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# **Investigation on the Effectiveness of EEG-BCI Techniques to Analyse Meditation**

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# Abstract

Electroencephalography (EEG), combined with computational approaches such as signal processing and machine learning, has emerged as a powerful tool for assessing meditation states. However, key gaps remain, particularly in analysing EEG data across multiple sessions and evaluating classification performance under both intra-subject and inter-subject (subject-independent) settings. This thesis addresses these challenges through both a systematic computational review and a series of novel experimental studies focused on EEG-based meditation classification.

First, a comprehensive review was conducted to systematically organise and evaluate EEG feature extraction and classification techniques used in meditation research. In addition, the review examined EEG preprocessing practices, brain wave frequency usage, and meditation and participant characteristics, providing a valuable computational reference for future researchers in the field.

The experimental component of this study used an online EEG dataset collected over multiple sessions for four mental tasks: Loving-Kindness Meditation directed toward the self (LKM-Self), toward others (LKM-Others), Pre-Resting (non-meditation), and Post-Resting. A Brain-Computer Interface (BCI) pipeline using Common Spatial Patterns (CSP) for feature extraction and Linear Discriminant Analysis (LDA) for classification achieved strong performance. Intra-subject, single-session meditation versus non-meditation classification achieved a mean accuracy of 99.5%. Using all four mental tasks, the results showed that Pre-Resting was the most distinguishable condition, while the remaining tasks exhibited more similar neural patterns. The research was then extended to intra-subject, multi-session classification, where pooled session data were used to assess classification consistency over time. These results

confirmed the presence of recurring neural patterns across sessions, similar to those observed in single-session analysis, and achieved a mean intra-subject, multi-session meditation versus non-meditation classification accuracy of 83.6%.

Building on this, a more advanced task was introduced to classify a new session pair, defined as a meditation session and a non-meditation session selected as a matched pair, after training on other session pairs from the same individual. To support this, following multiple tests to identify the best algorithms, three BCI pipelines were developed using CSP, Short-Time Fourier Transform (STFT), and their fusion (CSP + STFT), also referred to in this thesis as CSP-STFT fusion, with neural networks employed as the consistent classification algorithm. Across different experimental setups, CSP-STFT fusion yielded the highest performance, achieving an overall mean accuracy of 72.9% for intra-subject, multi-session classification. Further analysis showed that increasing the number of training session pairs (from 2 to 4) led to improved classification outcomes. The highest mean accuracy of 75.5% was achieved for LKM-Self versus non-meditation using four training session pairs, confirming the potential to classify new sessions based on prior data. These results demonstrate the feasibility of intra-subject, multi-session EEG classification for previously unseen session pairs.

In the final stage, the same three pipelines were evaluated under a subject-independent multi-session classification framework, allowing for direct comparison with intra-subject performance. A total of 9,900 independent tests were conducted to classify new session pairs across individuals. While overall accuracy was lower compared to intra-subject results, substantial variability was observed depending on session combinations. To highlight this, accuracies were divided into top 50% and bottom 50%, and the mean of each group was calculated. For example, in the classification of LKM-Self versus non-meditation using three training session pairs, the CSP + STFT pipeline achieved a mean accuracy of 62.3% overall, with 46.0% for the bottom 50% and 78.3% for the top 50%. This was lower than the intra-

subject accuracy of 72.1% under similar conditions, with similar trends observed across other tasks. Based on the mean accuracies obtained, the fusion approach outperformed individual methods in 83.3% of the cases. Additionally, increasing the number of training session pairs led to improved mean accuracies in approximately 75.0% of experiments, emphasizing the importance of training data volume in complex, subject-independent settings. The comparison between intra-subject and subject-independent outcomes confirmed that CSP-STFT fusion enhances classification robustness. Although subject-independent classification remains more challenging due to participant variability, the ability to obtain strong accuracies for certain training combinations is promising. These findings suggest that further research is needed to improve generalizability in real-world applications.

These findings provide a strong foundation for developing both personalized and subject-independent EEG-based Brain-Computer Interface (BCI) applications aimed at monitoring and enhancing meditation practice. The demonstrated effectiveness of combining spatial and time-frequency features, along with evidence of recurring neural patterns across sessions, highlights the potential for real-time, adaptive meditation support systems. Additionally, the methodologies and insights presented in this thesis offer valuable directions for future research in scalable BCI pipelines, continuous mental state tracking, and integration with multimodal neuroimaging approaches.

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# Chapter 1

## Introduction

### 1.1 Background and Motivation

Meditation has gained considerable attention in scientific research [1, 2] due to its reported benefits for mental well-being [3, 4], emotional regulation [5, 6], and cognitive performance [7, 8]. These outcomes have been increasingly supported by neurophysiological and behavioural studies, contributing to the growing integration of meditation practices into both clinical interventions and wellness programmes [9–11]. Among various forms of meditation, Loving-Kindness Meditation (LKM) [12, 13] has shown particular promise for enhancing compassion, reducing stress, and cultivating positive affect. LKM involves the deliberate practice of generating and directing feelings of compassion, love, and goodwill, typically beginning with oneself and progressively extending to others, such as close acquaintances, neutral individuals, and eventually all beings. Unlike concentration-based practices that focus primarily on attentional control, LKM emphasises affective and emotional regulation, with the aim of cultivating prosocial emotions through repeated mental practice. In experimental settings, LKM is commonly implemented using guided instructions that structure the sequence and duration of these contemplative phases, making it suitable for controlled EEG-based investigation.

To assess both long-term trait-level characteristics [14] and short-term meditative or non-meditative mental states [15], researchers have traditionally relied on interviews and questionnaires as psychological assessment tools [16, 17]. However, with increasing interest in reliable and objective evaluation techniques, there has been a corresponding shift toward neuroimaging and computational approaches to quantify the effects of meditation [18, 19].

Meditation is an umbrella term encompassing a wide range of contemplative practices; however, unless otherwise stated, the term “meditation” in this thesis is used specifically to refer to Loving-Kindness Meditation (LKM), which forms the exclusive focus of the experimental investigations.

In meditation research, it is important to distinguish clearly between state and trait effects, as they reflect fundamentally different aspects of meditative practice [14, 15]. State meditation refers to transient, short-term changes in mental and neural activity that occur during or immediately following a meditation session, whereas trait meditation reflects longer-term, stable changes associated with sustained practice over months or years. State effects are typically examined by comparing meditation with non-meditation conditions, while trait effects are studied through longitudinal designs or comparisons between practitioners with differing levels of experience. This distinction is particularly relevant in EEG-based studies, as state-level changes are more amenable to controlled experimental manipulation and classification, whereas trait-level effects are often confounded by individual variability. Accordingly, while both perspectives are acknowledged in this thesis, the experimental investigations primarily focus on state-level classification of meditation and non-meditation EEG, with multi-session analysis used to assess the stability of these state-related neural patterns over time.

The terms meditation and mindfulness are often used interchangeably in the literature, despite representing partially overlapping but distinct constructs. Meditation broadly refers to a family of structured mental practices designed to cultivate specific cognitive, emotional, or attentional states, whereas mindfulness is commonly defined as a quality of present-moment awareness that may be cultivated through certain meditation practices but can also be conceptualised as a dispositional trait or everyday cognitive style. To avoid conceptual ambiguity and potential jingle-jangle fallacies, this thesis adopts a practice-based definition of meditation, focusing on clearly defined contemplative techniques rather than abstract psychological constructs. In line

with commonly used typologies of meditation research, which distinguish between attentional, constructive, and deconstructive practices [20, 21], Loving-Kindness Meditation is categorised as a constructive meditation practice, characterised by the deliberate cultivation of affective and prosocial mental states. Throughout this thesis, the term meditation therefore refers specifically to Loving-Kindness Meditation as an explicit, guided mental practice, rather than to mindfulness as a general cognitive disposition.

Electroencephalography (EEG) has become a widely used technique for studying meditation due to its high temporal resolution, non-invasiveness, and portability [22, 23]. These features make EEG particularly suitable for capturing the subtle, time-sensitive changes in brain activity that occur during meditation [24, 25]. EEG enables the investigation of brain oscillations and connectivity patterns associated with different meditative and non-meditative mental states, offering insights into the neural mechanisms of mindfulness and concentration [26, 27]. In recent years, EEG has also been explored in Brain-Computer Interface (BCI) systems [28] aimed at mental state recognition, neurofeedback, and the development of adaptive meditation training tools [29]. These applications hold promise for personalizing meditation practices and may support long-term engagement through measurable progress tracking.

Despite these advantages, reliably classifying meditative states using EEG remains a complex challenge. EEG signals are inherently non-stationary, noisy, and subject-specific, which makes it difficult to extract stable features that generalize across different users and recording sessions [30, 31]. Feature extraction and classification techniques must therefore be carefully selected and optimised to account for this variability [22]. While a range of machine learning and signal processing methods have been developed for general EEG analysis, their application to meditation data is often fragmented and lacks a cohesive computational framework [32, 33]. Many existing studies have focused on small datasets, often using single-session designs for between-group comparisons such as novice versus expert [29, 34], or collecting multiple

sessions primarily for limited pairwise analyses, such as meditation versus non-meditation [35, 36] or before and after a meditation training programme [37, 38]. However, these studies rarely combine multiple sessions for comprehensive analysis, which limits the applicability of their findings to real-world scenarios where consistent performance across users and over extended time periods is essential. Real progress in meditation comes with continued practice across multiple sessions, making it especially valuable to understand meditation and non-meditation brain patterns across sessions, particularly when developing algorithms to support meditation progress.

A limitation observed in the literature is the continued over-reliance on traditional frequency-domain features, such as power spectral density measures, while more advanced spatial or time-frequency methods remain underexplored [27, 39]. Although methods like Common Spatial Patterns (CSP) and Short-Time Fourier Transform (STFT) have demonstrated strong performance in other BCI contexts, particularly in motor imagery tasks [22, 32], they have not been systematically evaluated or combined for meditation-related EEG classification. Furthermore, the effect of training data size, particularly the number of EEG sessions, on classification accuracy is rarely studied, even though such factors are crucial for building reliable meditation monitoring systems. This gap becomes especially important when developing BCI pipelines intended for multi-session or subject-independent settings, which more closely reflect real-world deployment. A BCI pipeline typically refers to a structured sequence of computational steps, including data preprocessing, feature extraction, and classification, designed to interpret brain signals for specific tasks or feedback systems.

The focus on Loving-Kindness Meditation in this thesis is deliberate and theoretically motivated. Compared to attentional practices such as focused attention or mindfulness-of-breath, LKM places a stronger emphasis on affective and emotional regulation, making it particularly relevant for mental-health-oriented applications of EEG-based assessment. In

addition, LKM is typically implemented using structured, guided protocols that clearly delineate meditation and non-meditation periods, which is advantageous for controlled EEG experiments and supervised classification. From a practical perspective, the publicly available dataset used in this study was specifically designed around LKM and includes multiple sessions per participant, a feature that is rare in meditation EEG research and essential for investigating cross-session classification. While comparing multiple meditation types is an important direction for future research, restricting the scope of this thesis to a single, well-defined meditation practice allows for deeper methodological investigation of session-level variability and classification robustness without introducing additional confounding factors.

This thesis is motivated by the need to bridge these gaps and move toward more generalizable and robust computational approaches for classifying Loving-Kindness Meditation (LKM) EEG data collected across multiple sessions and subjects. The research begins with a comprehensive computational review of the literature to identify dominant trends, overlooked techniques, and methodological weaknesses in existing EEG meditation studies. It then proceeds to achieve high single-session, intra-subject classification accuracies for LKM versus non-meditation and explores recurring neural patterns across multiple sessions for each individual, laying the foundation for robust personalized models. It subsequently develops and evaluates novel BCI pipelines using CSP, STFT, and their fusion, focusing on classifying LKM versus non-meditation states. These pipelines are assessed under both intra-subject and inter-subject conditions using multiple-session EEG data, addressing the variability across individuals and recording sessions that is often ignored in simpler models.

Although the core of this thesis lies in experimental development and evaluation, it also yields several theoretical and methodological insights relevant to EEG-based meditation research. These include the influence of training session count on classification accuracy, the viability and benefits of combining spatial and time-frequency feature extraction techniques, and a

comparative understanding of model performance in both personalized (intra-subject) and generalised (inter-subject) settings. All experimental investigations are conducted using a publicly available EEG dataset specifically collected for meditation research, ensuring consistency, transparency, and reproducibility. This dataset comprises clearly labelled, multiple-session EEG recordings covering Loving-Kindness Meditation and non-meditative control states, thereby providing a reliable foundation for the comparative analysis of different classification pipelines. The EEG dataset used in this study is publicly available at <https://doi.org/10.18112/openneuro.ds003816.v1.0.1> and was obtained from OpenNeuro.

The scope of this thesis is clearly defined: it focuses solely on EEG-based analysis and does not incorporate other modalities such as fNIRS or hybrid systems. By working within the constraints of a single, well-structured dataset and avoiding the variability introduced by multi-modal integration, the study maintains a high degree of experimental control while still addressing real-world challenges such as session-to-session variability and subject diversity. These design decisions reflect a deliberate balance between methodological precision and practical applicability, advancing the broader objective of developing scalable, generalizable EEG-based meditation classification systems with future potential in mental health support, neuroadaptive technology, and personalized wellness applications.

## 1.2 Problem Statement

The integration of electroencephalography (EEG) with computational algorithms such as signal processing and machine learning has shown significant promise for assessing meditation states, yet several critical gaps remain. Firstly, there is an absence of a comprehensive computational review that systematically categorizes and evaluates existing feature extraction and

classification techniques specifically for meditation-related EEG studies, which limits clarity on the current research landscape. Secondly, while intra-subject and inter-subject (subject-independent) EEG classification during meditation has been explored, most existing studies rely on pairwise session comparisons and overlook the temporal variability and consistency of neural patterns across multiple sessions. Thirdly, the generalizability of classification models across individuals (subject-independent classification) remains underexplored and challenging, especially in the context of multi-session meditation EEG data that tends to be highly individualized. Moreover, although numerous feature extraction techniques exist, few studies provide comparative evaluations of selected high-performing methods along with their fusion, such as the combination of spatial and time-frequency features, in both intra-subject and inter-subject multi-session EEG classification scenarios related to meditation. Finally, the impact of varying the number of training sessions on classification performance using multiple-session meditation EEG data is not well understood, which limits the practical deployment of such models in real-world neurofeedback or meditation monitoring applications.

This thesis addresses these issues through a combination of computational review and experimental evaluations, with a focus on designing and benchmarking EEG classification pipelines for meditation state detection across single and multiple sessions, and across both intra- and inter-subject contexts.

### 1.3 Research Objectives

The research objectives of this thesis are outlined below:

1. To conduct a comprehensive computational review of EEG-based feature extraction and classification techniques for meditation assessment to address a notable gap in the literature where such a review has not previously been presented.
2. To classify single-session, intra-subject meditation versus non-meditation EEG data with high accuracy using appropriate feature extraction and classification techniques, and to use the results to identify neural patterns associated with meditation and non-meditation mental tasks.
3. To investigate the presence of consistent neural patterns across multiple sessions within subjects for both meditation and non-meditation tasks using intra-subject classification.
4. To develop and evaluate BCI pipelines incorporating various feature extraction algorithms for intra-subject, multiple-session EEG classification to obtain optimal accuracies, where a new session pair is classified based on training from previous sessions. Furthermore, to investigate how the fusion of such successful feature extraction algorithms impacts classification performance.
5. To study how varying the number of training session pairs influences the classification accuracy of intra-subject, multiple-session meditation and non-meditation EEG data using the developed BCI pipelines.
6. To implement and evaluate subject-independent, multiple-session classification pipelines under conditions consistent with intra-subject classification, ensuring training and testing are conducted across different individuals.
7. To compare the performance of intra-subject and inter-subject multiple-session classification and investigate how changing the number of training session pairs affects classification accuracy in the subject-independent context.

## 1.4 Thesis Organization

This thesis is organised into six chapters, each addressing a distinct part of the research process:

- **Chapter 1: Introduction**

Introduces the background and motivation for the study, presents the problem statement, outlines the research objectives, and provides an overview of the thesis structure. It briefly touches on the methodological approach and scope of the study.

- **Chapter 2: A Computational Review of Feature Extraction and Classification Techniques for Meditation Assessment Using EEG**

Presents a systematic review of existing literature on EEG-based feature extraction and classification methods used for meditation assessment. It identifies methodological trends, summarizes commonly used techniques, highlights current gaps in the literature, and offers valuable insights and guidance for future research in the field of meditation EEG.

- **Chapter 3: Common Spatial Pattern for Classification of Loving Kindness Meditation EEG for Single and Multiple Sessions**

Investigates intra-subject classification of meditation and non-meditation EEG data using the Common Spatial Pattern (CSP) algorithm. It examines both single-session and multiple-session scenarios and evaluates the consistency of neural patterns across sessions within individuals.

- **Chapter 4: Novel Machine Learning-Driven Comparative Analysis of CSP, STFT, and CSP-STFT Fusion for EEG Data Classification Across Multiple Meditation and Non-Meditation Sessions in BCI Pipeline**

Develops and evaluates BCI pipelines using CSP, Short-Time Fourier Transform (STFT), and a fusion of both for classifying intra-subject, multiple-session EEG data. This chapter also investigates how varying the number of training sessions affects classification accuracy and explores the advantages of feature fusion.

- **Chapter 5: Machine Learning-Based Comparative Analysis of Subject-Independent EEG Data Classification Across Multiple Meditation and Non-Meditation Sessions**

Extends the classification framework to subject-independent scenarios, applying the same three BCI pipelines. It evaluates classification performance across individuals, compares results with intra-subject outcomes, and examines the effect of training session size on generalizability.

- **Chapter 6: Conclusion and Future Work**

Summarizes the research findings and key contributions across all chapters. It discusses the practical implications of the results, highlights limitations encountered during the study, and proposes future research directions to enhance EEG-based meditation state detection in real-world applications.

## STATEMENT OF CONTRIBUTION DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the student and the student's main supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the student's contribution as indicated below in the Statement of Originality.

Student name:	Nalinda Devaka Liyanagedera		
Name and title of main supervisor:	Professor Hans W. Guesgen, Chair in Computer Science		
In which chapter is the manuscript/published work?	Chapter 2		
Describe the contribution that the student and members of the supervisory team have made to the manuscript/published work: <sup>1</sup>			
The student conducted the systematic literature review, conceptualised the structure, designed the review methodology, extracted, categorised, and synthesised information from selected studies, and created visualisations in the form of summary tables. The student also wrote the original manuscript and contributed to reviewing and editing. The supervisory team contributed by reviewing and editing the manuscript and providing supervision throughout the work.			
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*This form should be placed at the beginning of each relevant thesis chapter.*

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## Chapter 2

# A Computational Review of Feature Extraction and Classification Techniques for EEG-Based Meditation Assessment

### Abstract

Meditation research using electroencephalography (EEG) has gained significant attention, with computational techniques playing a key role in feature extraction and classification. This review examines EEG-based meditation assessment by systematically analyzing 164 peer-reviewed studies. The selected studies were categorized based on meditation study characteristics, EEG preprocessing techniques, feature extraction methods, classification approaches, and EEG frequency bands utilised. Feature extraction methods were grouped into ten major categories based on their computational approaches, underlying mathematical principles, and relevance to EEG signal analysis in meditation studies. Frequency domain analysis contributed the most, accounting for 62.0% of extracted features. Classification techniques in 40 articles were analysed based on the number of methods used, grouping studies into those employing one, two, or three or more techniques. Support vector machines (55.0%) and artificial neural networks (47.5%) were among the most frequently used techniques, with some studies applying multiple methods. Alpha (90.2%) was the most frequently examined EEG frequency band in meditation studies, followed by Theta (77.4%). The findings highlight key trends, variations, and challenges in data acquisition, preprocessing, feature extraction, and classification. Due to methodological differences across studies, direct comparisons of classification accuracies were not possible. The review provides a structured synthesis of computational methods used in meditation EEG studies, identifies key research gaps, and discusses future directions,

emphasizing the need for standardized methodologies to enhance reproducibility and comparability.

Keywords: Feature Extraction, Classification, EEG (Electroencephalography), Meditation, BCI (Brain Computer Interface), Preprocessing

## 2.1 Introduction

### 2.1.1. Background on Meditation and EEG Neuroimaging

Meditation [40, 41], although practised for thousands of years, has gained significant popularity in modern stressful lifestyle due to scientific evidence supporting its ability to enhance self-awareness, reduce stress, and improve overall mental health [4, 5, 11]. Although there are many different meditation techniques that may differ in how they are practised, studies have been conducted on many of these techniques, demonstrating various similar benefits [1, 3, 7]. Studies show that there are short-term and long-term effects of meditation practice and referred to as ‘State’ and ‘Trait’ changes [15, 42].

Scientific methods used to study meditation include neurophysiological methods such as Electroencephalography (EEG) [43–46], Functional Magnetic Resonance Imaging (fMRI) [47], and Functional Near-Infrared Spectroscopy (fNIRS) [48]; physiological methods such as Heart Rate Variability [9], Cortisol Levels [49], and Blood Pressure; and psychological and behavioural methods such as Mindfulness and Meditation Scales, Questionnaires, and Interviews [16, 17, 50]. With the advancement of mobile phones and electronic technology, we have witnessed the development of meditation-supporting devices and mobile apps [18, 51, 52],

which have, in turn, increased the interest of both scientists and the general public in meditation [6, 53, 54].

EEG is a non-invasive neuroimaging technique that records electrical activity generated by neuronal oscillations in the brain [55, 56], collected through electrodes placed on the scalp [57]. EEG data collected over a certain duration consists of oscillatory signals over time. In most studies, this data is converted into the frequency domain, which is divided into five bands associated with specific cognitive and physiological states. These bands are Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), and Gamma (>30 Hz) [58–60]. The strength of these bands varies with different mental tasks, such as deep sleep, light sleep, meditation, wakeful rest, active thinking, and advanced problem-solving [56, 61].

Research on EEG in general has significantly flourished in the recent past due to improvements in hardware and software resources and reduction in prices. This includes improvements in EEG sensors and the processing power of devices. At the same time, with the development of feature extraction and classification algorithms [62–64], along with improvements in preprocessing and EEG data cleaning methods [30, 31, 65], there has been a significant improvement in the results obtained from raw EEG data [66–68].

EEG has been successfully used in various studies related to meditation, where different patterns in EEG data are mapped to various mental tasks associated with meditation. Some examples of such studies include comparisons between meditation and non-meditation [69, 70], novice and expert meditators [71, 72], different types of meditation [13, 73], various wavebands [74, 75], state and trait changes [26], and the effects of meditation training on novice meditators [76], among others.

Although studies on meditation EEG date back over 50 years [19, 77–79], research in this area is significantly less extensive compared to fields like motor imagery [28]. When examining

motor imagery EEG, previous research reveals a wealth of studies on computational methods, including feature extraction and classification [80–82]. The extensive body of research in motor imagery is well-documented in several review articles [22, 32]. In contrast, there are far fewer studies on computational methods, such as feature extraction and classification, in the context of meditation EEG. Furthermore, there are no systematic reviews that have been conducted to specifically examine these computational methods in meditation EEG, other than one instance of a review paper that lightly touches on machine learning methods used in meditation studies [2]. In this review, we explore how feature extraction and classification techniques have been effectively applied in various studies to analyse meditation EEG data, addressing a critical knowledge gap.

### 2.1.2. Overview Objectives of the Review

There is a significant body of research, including numerous original studies and review articles, published on meditation EEG. While many of these studies employ a variety of feature extraction and classification methods, existing review articles rarely focus specifically on the computational techniques involved in these processes. Recognizing this gap, the present review aims to address it. We selected peer-reviewed meditation EEG research articles published over the past 15 years, enabling us to trace the evolution of computational methods in feature extraction and classification. Additionally, this study captures important complementary aspects such as participant and meditation characteristics, data cleaning and preprocessing strategies, and the usage of frequency bands in meditation EEG research. Although this review maps a broad range of computational techniques used in meditation EEG research, a systematic literature review methodology was adopted to ensure transparency, replicability, and objective study selection. Unlike scoping reviews, which are primarily exploratory in nature, this work

applies predefined research questions, inclusion criteria, and structured synthesis to provide a reproducible computational reference for the field.

## 2.2 Methodology

### 2.2.1. Overview of the Systematic Literature Review Approach

A systematic literature review approach was used in this review to uphold the quality and reproducibility of our work in a transparent manner. The established guidelines in PRISMA were utilised for identifying, screening, and selecting research articles relevant to meditation EEG feature extraction and classification. This rigorous approach allowed us to capture a wide spectrum of studies and provided a comprehensive basis for our subsequent analysis.

### 2.2.2. Research Questions (RQ)

The review was built around the following research questions:

RQ1: What feature extraction methods have been used in EEG for meditation assessment?

RQ2: What classification techniques have been applied in meditation EEG studies, and how have their performances, study objectives, key findings, and limitations been evaluated in those studies?

RQ3: How have preprocessing and data cleaning techniques been used in studies that apply feature extraction and/ or classification methods in meditation EEG?

RQ4: What types of meditation techniques, participants, and EEG frequency bands have been used in studies that apply feature extraction and/ or classification methods in meditation EEG?

### 2.2.3. Search Strategy

A comprehensive search was conducted across multiple scientific databases, including Scopus, PubMed, SpringerLink, ScienceDirect, and IEEE Xplore. We used two sets of keywords along with Boolean operations in the search: “Meditation AND EEG AND Feature Extraction” and “Meditation AND EEG AND Classification.” The keyword searches were applied to the full searchable fields of the databases (including titles, abstracts, and indexed content), rather than being restricted to titles or abstracts alone, allowing studies primarily indexed under related terms such as mindfulness-based practices (e.g., MBSR or Vipassana) to be captured.

This review includes studies published between 2010 and 2024, covering a 15-year period to capture the evolution of computational techniques in meditation EEG analysis. This timeframe ensures the inclusion of recent advancements while providing sufficient historical context for understanding methodological trends.

We also applied filters to restrict the search to peer-reviewed articles published in English. This approach ensured that our search was both comprehensive enough to capture all relevant studies and selective enough to maintain quality and relevance.

#### 2.2.4. Inclusion and Exclusion Criteria

To determine which studies to include in the review, we defined clear inclusion and exclusion criteria. The inclusion criteria were as follows: studies that focused on EEG-based meditation assessment, employed computational methods for feature extraction and/or classification, and provided sufficient methodological details. The exclusion criteria included: studies that did not involve EEG data, were not peer-reviewed, or focused solely on subjective measures without any computational analysis. This systematic filtering process ensured that only studies relevant to our review's focus were included.

#### 2.2.5. Screening and Selection Process

The initial search using keywords and relevance yielded a large number of article titles along with their abstracts, from which duplicates and non-English articles were removed. Then, the selected article titles and abstracts were screened, and only those relevant to the review were retained. Next, the full-text versions of the selected studies were retrieved. After that, the remaining articles underwent a detailed full-text screening based on our inclusion and exclusion criteria. Finally, 164 research articles were selected for inclusion in this review.

A PRISMA flow diagram was used to illustrate the number of records at each stage: identification, screening, and final inclusion, ensuring a transparent account of the selection process. This is presented in Figure 2.1.

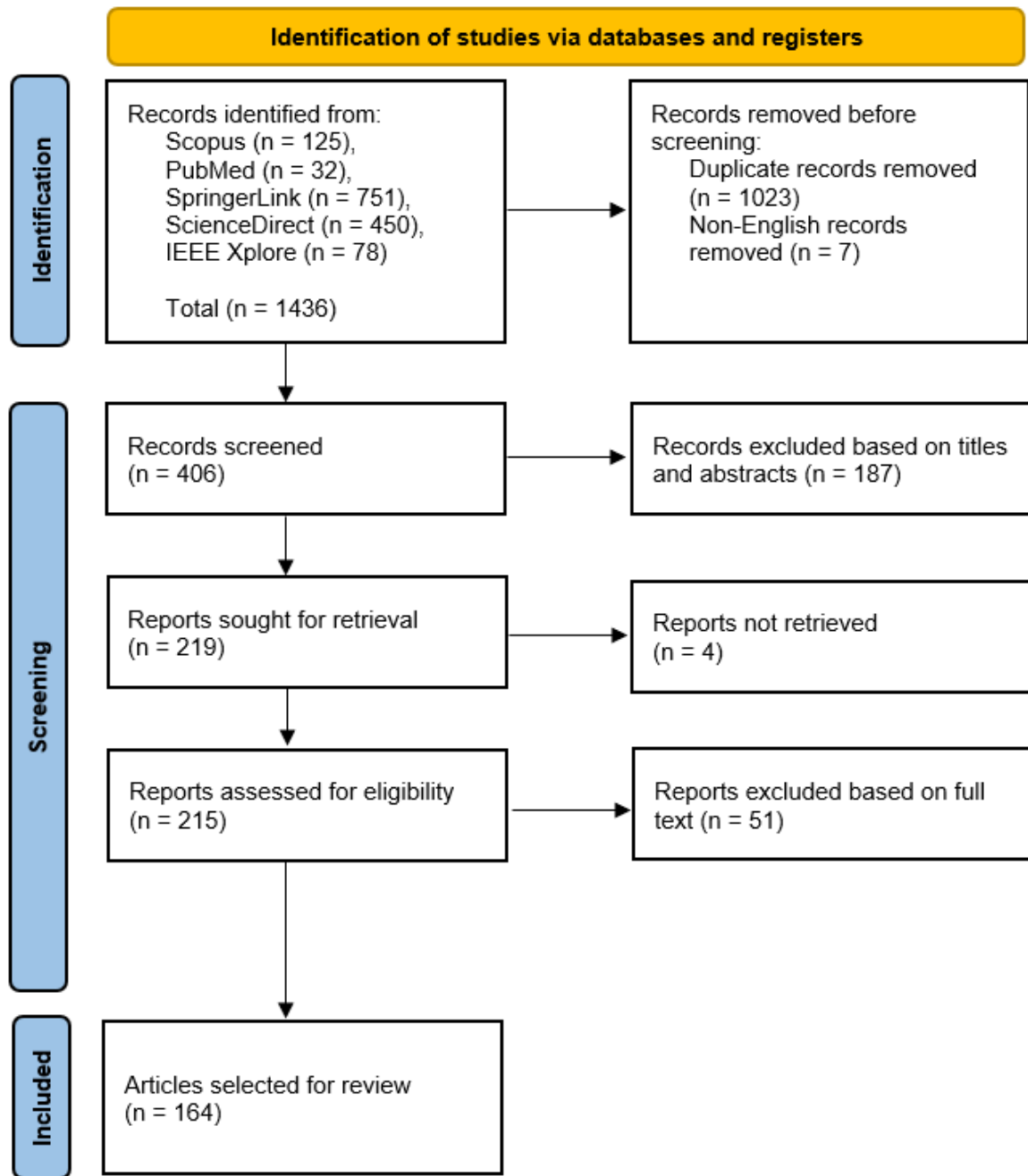


Figure 2.1 PRISMA flow diagram for selecting articles for the systematic review

### 2.2.6. Data Extraction and Categorization

For each selected study, we extracted key details such as participant characteristics, meditation characteristics (including techniques), EEG frequency bands, EEG preprocessing methods, and

EEG feature extraction and classification techniques. From studies that applied classification techniques, additional details, including the performance of pipelines, study objectives, key findings, and study limitations, were also extracted.

The extracted data were organised into structured tables to facilitate analysis:

Table 2.1: Summary of Participant and Meditation Details

Table 2.2: Types of Meditation Techniques Used

Table 2.3: Summary of EEG Preprocessing

Table 2.4: Summary of the Feature Extraction Methods Used

Table 2.5: Summary of the Performance of Pipelines and Classification Methods Used

This systematic data extraction allowed us to categorize the diverse methods into coherent groups for detailed analysis.

The summarized results are further analysed in the following sections of the review:

"Meditation Study Characteristics and Preprocessing" – Discusses participant details, meditation types, comparison group details, EEG preprocessing, and noise handling methods.

"Feature Extraction Techniques for Meditation EEG Assessment" – Reviews various feature extraction methods used in meditation EEG research, categorized based on computational approaches.

"Classification Techniques for Meditation EEG Assessment" – Explores machine learning and other classification techniques applied to meditation EEG data, highlighting pipeline performances.

By structuring the extracted data within these sections, this review provides a comprehensive analysis of computational methods used in meditation EEG research.

### 2.2.7. Data Synthesis and Analysis

After categorizing the extracted data, a structured synthesis was conducted to identify trends, gaps, and key insights in the use of feature extraction and classification techniques for meditation EEG assessment. This synthesis involved both qualitative and quantitative analyses, comparing study methodologies, extracted features, classification techniques, and reported outcomes.

Key findings were summarized through the following:

Table 2.6: Summary of Study Objectives, Key Findings, and Limitations – Provides a high-level overview of the main research questions addressed, significant findings, and reported limitations for studies that applied classification techniques.

Table 2.7: Summary of EEG Frequency Bands Used – Categorizes EEG frequency bands analysed in meditation studies, highlighting those most frequently associated with meditation.

The synthesized insights are further discussed in the "Conclusion" section under two subtopics:

"Recap of the Review's Major Insights" – Summarizes patterns in feature extraction and classification techniques across studies.

"Mapping Findings to Current and Future Meditation EEG Studies" – Connects the review's findings to broader trends in EEG-based neuroimaging and future research directions.

By structuring the synthesis through these tables and discussions, the review presents a comprehensive analysis of computational techniques in meditation EEG research, highlighting both established methodologies and areas requiring further exploration.

#### 2.2.8. Limitations of the Methodology

Finally, we acknowledge certain limitations in our review process. These include potential publication bias, variations in EEG data collection and preprocessing methods, and inconsistencies in the reporting of computational techniques. Additionally, the exclusion of non-English studies might limit the comprehensiveness of our review.

Regarding EEG data collection, significant differences exist among studies due to variations in devices, recording protocols, and participant-related factors. These include the types of meditation techniques used, number of participants, experience levels, comparison groups, and whether the study examined state and/or trait characteristics. Such differences inherently affect the EEG data collected and subsequently influence the reported performance metrics.

Furthermore, differences in preprocessing methods significantly impact results. These include the type of filtering methods applied, whether automated cleaning techniques were used, and whether manual cleaning with visual inspection was performed. Variations in these approaches can lead to inconsistencies in final outcomes.

Since our primary focus is on feature extraction and classification methods in EEG-based meditation studies, the reported performance metrics and classification accuracies were considered as given in the original studies. However, due to the substantial methodological differences between studies, we were unable to directly compare classification accuracies across studies. This remains the most significant limitation of our review.

## 2.3 Meditation Study Characteristics and Preprocessing

### 2.3.1. Meditation Study Characteristics

When reviewing research articles on feature extraction and classification of meditation EEG data, several dataset characteristics were found to substantially influence study outcomes. These include the type of meditation technique employed, whether the study examined state or trait effects, participant experience level (novice, intermediate, or expert), total sample size, and whether intra-subject or inter-subject analyses were performed. Such design choices directly affect EEG patterns, feature selection strategies, and reported classification performance. Therefore, as part of this literature review, detailed information related to meditation protocols and participant characteristics was systematically extracted from each article. Rather than providing a generic overview, this analysis highlights how meditation type, participant experience, and experimental design choices have been handled across prior studies, enabling more informed methodological decisions when designing new experiments.

The summary of meditation and participant details collected from 164 research articles is shown in Table 2.1 and Table 2.2. In Table 2.1, each line represents the details of a single research article along with the reference to the article. The first piece of information included in Table 2.1, in the column labelled ‘Meditation Type,’ is the type of meditation technique used in each of the studies. As mentioned in the introduction, there are many types of meditation techniques, and a study in a research article may use one or several meditation techniques depending on the study's requirements. It should be noted that meditation practices are inherently diverse, and attempts to categorise them into a small number of discrete styles are often approximate. Many techniques share common elements, and hybrid or overlapping practices are frequently

observed in both traditional and contemporary meditation research. The next piece of information collected is the state/trait characteristic of meditation used in each of the research articles. As explained in the introduction, state/trait characteristics refer to short-term/long-term changes occurring in participants practicing meditation. In feature extraction and classification, we aim to identify different groups related to meditation studies. Here, in most cases, the differences among these groups are related to the state/trait influence of meditation. Therefore, the state/trait characteristic related to each article is included in Table 2.1, under the column title ‘State/Trait’.

In meditation EEG data collection studies, the meditation experience of the participant is also a significant factor that contributes to the results. Therefore, for each article, we identified the participants' meditation experience level and included it in Table 2.1 under the column title ‘Experience Level’. When going through the articles, we identified three main groups of participants based on meditation experience level, which can be labelled as novice (or control), intermediate, and expert. Depending on the requirements of each study, we observed the use of one or more experience levels. At the same time, the number of participants involved in each study is also an important piece of information, and this is also included in Table 2.1 under the column title ‘Total No of Participants’. Here, when a research article focuses on more than one experience level, we noted the number of participants for each experience level used in the study.

Another important point in this type of research is whether the study conducts intra-subject, inter-subject, or both types of analyses. In intra-subject analysis, different instances of the same person are compared, while in inter-subject analysis, certain characteristics are compared among different participants. At the same time, a few instances were noticed where both comparisons were conducted in the same research article. Therefore, for each article, this information was also collected and included in Table 2.1 under the column title ‘Intra/Inter-

Subject Analysis'. As the final information under Table 2.1, we have included the comparison groups used in each of these studies under the column title 'Comparison Groups'. This information is included in Table 2.1 to explicitly document how prior studies structured their comparison groups and analytical scope, allowing readers to identify dominant experimental patterns and methodological gaps in the existing literature.

Table 2.2 summarizes the types of meditation techniques used in the 164 research articles we studied, identifying 39 different techniques. Of these, 152 articles explicitly stated the meditation techniques used, while the remaining 12 were excluded from this table. While many papers demonstrate the use of a single meditation technique, a few articles collected EEG data from participants practicing different meditation types, with a selected number of participants for each. Here we can see that, among 152 research articles, 37 articles have used Mindfulness Meditation in meditation EEG feature extraction and classification studies, which is 24.3%. Next, we observed Focused Attention Meditation and Vipassana Meditation, both techniques used in 14 research articles, which accounts for 9.2%. Out of the 39 meditation techniques used, 21 of them were used only once or twice among the 152 articles. In Table 2.2, the percentage represents how often each meditation technique was used per 100 papers. Since some research articles employed multiple techniques, the sum of the percentages exceeds 100.

### 2.3.2. Preprocessing

Preprocessing done in a well-planned manner is an important step in EEG pipeline development that significantly affects the performance of the pipeline. Therefore, in the research articles selected to study meditation EEG feature extraction and classification, certain characteristics related to preprocessing were also studied. The results of this study provide a consolidated view

of preprocessing practices used in meditation EEG research, revealing common design choices, inconsistencies, and underreported steps that directly influence reproducibility and pipeline performance. Under EEG preprocessing, the two main tasks are removing noise and artifacts from the raw EEG data and making modifications to the raw EEG data, such as splitting and filtering. This would result in a slightly modified EEG dataset that is much cleaner and easier to handle in the subsequent steps of the pipeline. Table 2.3 provides a summarized set of details on preprocessing related to the 164 research articles we reviewed.

In Table 2.3, the first piece of information for each article is the number of channels used in each study. The number of channels used to collect the EEG data plays a significant role in a study because the more electrodes used, the better the overall quality of the data collected. When going through the selected articles, we can see that some studies analyse the entire EEG dataset, while others break the EEG data into small segments called epochs, with analysis conducted independently on each epoch. Additionally, some studies that use epochs go a step further by using overlapping epochs. Overlapping epochs are used to minimize the effect of signal loss at the splitting points between epochs. In this case, the lost data will be included in the next adjacent epoch due to the overlapping. In Table 2.3, under the column 'Epoch Size (Overlap)', we have included both the epoch size and overlap size for each research article that used them in their studies.

Signal filtering methods are used to improve the quality and reduce the noise in EEG data. In addition to commonly discussed physiological and environmental noise, EEG recordings may also be affected by artefacts such as electrode–skin impedance variations, subject motion, amplifier saturation, and digitisation noise. The idea is to remove data related to certain frequency ranges that are not relevant to the study while retaining data from the frequency ranges that are important. Filtering therefore represents one component of a broader set of preprocessing strategies, which may be combined with other artefact-handling approaches

depending on data quality and study objectives. Additionally, filtering can be used to remove power line interference occurring at 50/60 Hz. If any filtering methods were applied in the research articles we reviewed, they are listed in the column 'Signal Filtering Methods' in Table 2.3.

When considering noise and artifact removal from EEG, this can be done either by using automated methods and algorithms or by observing the data graphically and manually identifying and removing artifacts. While reviewing past research articles, we observed instances where neither method was used, instances where one method was used, and instances where both methods were employed. In Table 2.3, the column 'Automated Artifact Removal' lists the methods used in a manuscript if automated cleaning was performed, while the column 'Manual Artifact Removal' indicates 'Yes' or 'Not Mentioned' to show whether manual cleaning was conducted in each of the research articles.

## 2.4 Feature Extraction Techniques for Meditation EEG Assessment

### 2.4.1. Introduction of Feature Extraction Techniques

In the study of meditation EEG, feature extraction is a critical section where crucial information is extracted for research purposes. Given the broad scope of this topic, we have categorized these features into ten groups for clarity. These categories are: Frequency Domain Analysis, Time-Frequency and Spectral Entropy Methods, Amplitude Features, Dimensionality Reduction and Decomposition, Phase and Synchrony Analysis, Entropy-Based Measures, Connectivity and Coherence Measures, Spatial, Microstate, Network and Topological Features, Statistical Features, and Advanced Modelling, Machine Learning, and Complex Features. In

the following sections, we will demonstrate how these different groups of features have been used efficiently in past literature to extract valuable information, while identifying various feature types for each of these feature categories.

#### 2.4.2. Frequency Domain Analysis

As the first category in meditation EEG feature extraction, we will examine “Frequency Domain Analysis”. Here, the EEG signal is converted into the frequency domain from its original time domain, allowing researchers to study the power distribution across different frequencies. In brain signal analysis, this frequency spectrum is typically divided into distinct bands: Delta (0.5-4 Hz), Theta (4-8 Hz), Alpha (8-13 Hz), Beta (13-30 Hz), and Gamma (>30 Hz). Changes in the power levels of these frequency bands are often associated with various mental tasks.

When we review research conducted on EEG, we can observe that a significant amount of work has used spectral analysis to understand oscillatory patterns in the participants. Meditation EEG research also follows this trend, and we can clearly observe many instances where Spectral Analysis [8, 35, 83–90] has been utilised in relevant research articles. Among the many methods used under this, the Power Spectral Density (PSD) [23, 29, 33, 36, 37, 90–122] is one of the most commonly used methods. The PSD represents the distribution of power across different frequencies in the EEG signal. It works by breaking the signal into frequency bands and quantifying the power (or energy) within each band. The power variations in these frequency bands can then be used as features to compare different mental states or meditation tasks. The Bartlett method [33] is an improved technique used to calculate the PSD of an EEG signal. It divides the signal into smaller, non-overlapping segments, calculates the PSD for each segment,

and then averages the resulting periodograms to obtain a smoother estimate with reduced variance.

Among the methods used to calculate the PSD, the Fast Fourier Transform (FFT) [12, 39, 93, 102, 103, 109–111, 121, 123–142] is the most commonly used technique in EEG feature extraction. FFT transforms EEG signals from the time domain into the frequency domain, allowing us to observe the strength (power) of different frequencies. At the same time, the Blackman-Harris window [33] is a tool that is used to enhance accuracy when extracting frequency strengths from EEG data. It applies smooth edges to the signal, reducing spectral leakage and errors when calculating the PSD using FFT. The Discrete Fourier Transform (DFT) [143], on the other hand, is used less with meditation EEG due to its higher computational complexity and lower memory efficiency. DFT provides the basic mathematical foundation of Fourier Transform and can produce reliable PSD outputs when dealing with smaller datasets without real-time requirements.

The Spectral Power Ratio (SPR) [92, 93, 105, 111, 137, 144–149] is a feature set derived from the PSD that can be used in classifying various meditation-related mental tasks. The SPR measures the power ratio between two frequency bands in EEG, and among the five bands mentioned, any two can be selected for this calculation, such as the Alpha/Beta Ratio, Theta/Beta Ratio, Delta/Theta Ratio, etc. Welch's Modified Periodogram [25, 36, 84, 103, 108, 137, 150, 151] is an improved method of calculating the PSD. The basic idea is that the EEG signal is segmented into small, often overlapping, windows, and a windowing function is applied before computing the periodogram for each segment using a method such as FFT. Then, the results of all windows are averaged to obtain a smooth and reliable PSD estimate, providing a clean feature set for further studies. Compared to Bartlett's method, Welch's approach further reduces variance while providing improved spectral smoothness through overlapping and windowing.

In some cases, specific sections of the PSD are used as features in meditation EEG analysis. PSD is divided into five bands, and you may refer to the features by the name of the band when you use a particular band's information as features. Also, there are instances where information from several bands is independently used in meditation EEG studies, and we can generally label this as Band Power [12, 25, 35, 96, 116, 140, 144, 147, 148, 151–162]. Instances can be observed where characteristics of individual frequency bands are used as features when studying and classifying various meditation-related EEG data. These instances can be referred to by the band names, and some recent research examples where the power of each band is used are Delta [163], Theta [134, 163, 164], Alpha [14, 27, 38, 98, 102, 117, 120, 127, 131, 134, 137, 139, 163, 165–169], Beta [133, 134, 163], and Gamma [134, 163, 170].

In spectral analysis, it is sometimes valuable to identify the frequency with the highest power, as this can help in understanding different mental states. In meditation EEG feature extraction studies, a few instances have been observed where this peak frequency was used, with studies employing methods such as the Frequency of the Main Peak [127, 165] and Instantaneous Peak Frequency Calculation [145].

Along with EEG spectral feature extraction, we observed Hanning Windowing [39, 103] as a helpful method for improving the quality of frequency-related features by reducing spectral leakage. In the process of converting EEG data into the frequency domain, the data is segmented into small-sized windows, which can create artificial frequencies at the edges of those windows, known as spectral leakage. The Hanning window minimizes this problem by smoothly tapering the edges of the window toward zero, thereby improving the accuracy of the obtained frequencies.

### 2.4.3. Time-Frequency and Spectral Entropy Methods

As the second category in meditation EEG feature extraction, we will examine “Time-Frequency and Spectral Entropy Methods”. Both these techniques are used to study how brain patterns change over time. Here, the Time-Frequency Distribution (TFD) shows how the power of each frequency changes over time, while the Spectral Entropy, which is derived from the Power Spectral Density (PSD), quantifies the signal randomness, allowing for the study of dynamic brain states in EEG data. TFD enables the examination of how a mental task, such as meditation, affects certain frequency bands over time and has been widely used in meditation EEG research [23, 38, 104, 118, 164, 171–174]. For example, when the mind relaxes during meditation, changes in the Alpha or Theta band powers may be observed, while an increase in the Gamma band might be associated with tasks involving heightened cognitive processing or problem-solving. Several methods are commonly used to obtain TFD in meditation EEG research, including Short-Time Fourier Transform, Discrete Wavelet Transform, Wavelet Transform, and Stockwell Transform.

The Short-Time Fourier Transform (STFT) [100, 118, 146, 175] is a method used to study how the strength of frequencies in EEG data changes over time. STFT breaks the data into small segments called windows (often overlapping) and applies the Fourier Transform on each window to get a frequency spectrum. STFT is capable of analyzing transient brain activities, such as those occurring during meditation, and supports Brain-Computer Interface (BCI) applications that require real-time EEG processing.

The Discrete Wavelet Transform (DWT) [89, 107, 128, 130, 148, 156, 165, 176–181] is another commonly used method for obtaining TFD patterns in meditation EEG data. DWT first breaks the signal into two components using low and high-pass filters to extract approximation and detail coefficients. These results are then downsampled to reduce the data size while retaining

the essential features of the signal. This process is repeated for multiple levels of decomposition until a clean time-frequency spectrum is obtained, especially for non-stationary signals like EEG. DWT is effective in reducing noise in the signal while preserving the important features.

The Continuous Wavelet Transform (CWT) [182, 183] uses a continuous range of scales, unlike the discrete set of scales used in DWT, when calculating the TFD for EEG. CWT provides a highly detailed decomposition of the EEG data, offering more precise time-frequency representations, although it has a higher computational cost than DWT. At the same time, we observe that various modified versions of the Wavelet Transform have been used in extracting features from meditation EEG data. Some examples include Stationary Wavelet Transform [152], Flexible Analytic Wavelet Transform [184], Complex Morlet Wavelet Convolution [29], Morlet Wavelet Transform [164], Morlet Wavelet Decomposition [185], Complex Continuous Wavelet Coherence [183, 186], and Wavelet Coherence [187].

The Stockwell Transform [33, 91] is another method used to analyse EEG data in both time and frequency simultaneously to obtain TFD. It combines features from the Fourier Transform and the Wavelet Transform. The method uses a frequency-dependent Gaussian window that changes in size, allowing it to capture high- and low-frequency activities very efficiently.

The Hilbert Transform [138, 188–190] closely aligns with time-frequency analysis techniques, as it produces an analytic signal for an EEG, from which amplitude and phase features are derived. The amplitude indicates how strong the signal is at a given time, while the phase shows the location in the signal cycle. Although not a TFD method, combining the Hilbert Transform with band-pass filters can isolate specific frequency bands, such as Alpha and Theta, which can be used in further studies. The Hilbert-Huang Transform [188] is a powerful signal processing method used to analyse nonlinear and non-stationary signals, such as EEG, consisting of two steps. In the first step, Empirical Mode Decomposition is performed, breaking the EEG signal

into simpler components called Intrinsic Mode Functions. In the second step, the Hilbert Transform is applied to these Intrinsic Mode Functions to obtain the amplitude feature set.

The Spectral Entropy [191] is a feature extraction method applied to EEG data to quantify the complexity and unpredictability of the power distribution across different frequency bands. Spectral Entropy for an EEG dataset is calculated by first using Fourier or Wavelet Transform to calculate the PSD, and then taking the Shannon Entropy of the normalised PSD, where Spectral Entropy is a value ranging between 0 and 1. A high Spectral Entropy indicates that the EEG signal is complex, and the brain is under stress or working hard. On the other hand, a low Spectral Entropy indicates a relaxed mind, where the brain waves are smoother.

#### 2.4.4. Amplitude Features

As the third category in meditation EEG feature extraction, we will examine “Amplitude Features”. In the study of meditation EEG features, we can observe instances where Amplitude [192], which is a fundamental characteristic of EEG, has been used. When we observe the EEG signal in the time domain, amplitude represents the height of a wave signal, and when many brain cells synchronize on a specific mental task, working together, the amplitude height increases. Some simple but powerful statistical measures used as meditation EEG features are Mean, Standard Deviation, Maximum and Minimum of Amplitude [147, 193–195]. These values have been successfully used in comparing the strength of brain waves during different mental tasks, such as meditation and non-meditation.

The Amplitude of the Main Peak [127, 165] is a feature used in some meditation EEG studies. Here, the height of the highest point in the EEG waveform is measured, which can be related to a mental task. A higher peak may indicate increased brain activity at a given instance, and it

is a simple and clear method to distinguish between two mental tasks at a basic level. On the other hand, Persistent Amplitude [191] is a slightly more advanced feature where the consistency of a signal's amplitude over time is measured. Persistent Amplitude checks if the amplitude remains stable or fluctuates over time, and this helps identify if the brain activity is stable or not, which is useful when studying brain behaviour under meditation.

In meditation EEG studies, amplitude-based features have revealed increased alpha-band amplitude during focused-attention practices and modulation of frontal activity during compassion-based meditation. These findings indicate that simple amplitude metrics can capture meaningful neural differences between meditation and non-meditation states.

#### 2.4.5. Dimensionality Reduction and Decomposition

As the fourth category in meditation EEG feature extraction, we will examine “Dimensionality Reduction and Decomposition”. Decomposition refers to breaking down a signal into components, while dimensionality reduction involves reducing the number of variables in a dataset while retaining the most important information. These techniques are very useful for extracting valuable information from EEG data, especially because EEG data is known to have high dimensionality, particularly when the number of channels increases, and often contains a lot of noise. Therefore, these methods allow the EEG data to be broken down into components, extracting the most important information while removing unnecessary and noisy elements. This enhances the capacity to understand various patterns in EEG data while reducing computational complexity. It should be noted that several techniques discussed in this section, such as PCA, CSP, and ICA, can serve different roles depending on how they are used in an analysis pipeline; in this review they are treated as feature extraction methods, although in other

contexts some of these techniques may also be used primarily for dimensionality reduction or classification support.

The Principal Component Analysis (PCA) [34, 143, 156, 182, 196–199] is a statistical method used to reduce the dimensions of complex EEG data. PCA transforms the given feature set into a new set of uncorrelated variables, called principal components, which capture the most variance in the data. The use of PCA increases the classification power of EEG data from various mental tasks by removing features that are not useful, reducing noise, and allowing focus on the most important features.

The Common Spatial Pattern (CSP) [200–202] is a method used to find patterns that can separate two mental tasks by analyzing the spatial information from multiple electrodes to identify the highest activity for each mental task. CSP computes a set of spatial filters, projecting the EEG data into two groups based on the two mental tasks and maximizing the variance between them. This allows dimensionality reduction by determining the number of top components selected. PCA captures the maximum variance in the overall data distribution using an unsupervised method, while CSP captures the biggest difference between the two mental tasks using a supervised method with labelled data.

The Filter Bank Common Spatial Pattern (FBCSP) [201] is an advanced version of CSP that applies multiple frequency filters to the EEG data before applying CSP. FBCSP allows focusing on specific frequency bands, where more attention can be given to extracting features. FBCSP is useful in studying complex mental tasks that involve clear distinctions across multiple frequency bands, although it comes with higher computational complexity. The Common Spatial Pattern with Tikhonov Regularization (TR-CSP) [203] improves the basic CSP by enabling it to handle noise and small variations in EEG data more effectively. Tikhonov

Regularization adds a penalty to large values in the covariance matrix inversion, helping to reduce overfitting, especially when the number of trials is limited, or the signals are noisy.

In meditation EEG studies, Independent Component Analysis (ICA) [8, 23, 25, 29, 36, 84, 88, 95, 100, 106, 108, 121, 122, 125, 129, 163, 164, 196, 204–208] is a method used in preprocessing and feature extraction. While PCA aims to maximize the variance, ICA focuses on maximizing the statistical independence of the components. ICA separates mixed EEG signals into their independent components. This isolates noise in the EEG data, such as eye blinks, muscle movements, and electrical interference, allowing them to be removed easily. After noise removal, the remaining components are related to various mental tasks, and based on the needs of the experiment, the necessary components can be selected as features. After selecting the components related to your study's mental tasks, you can either use them directly or apply other feature extraction techniques to the selected components to get a set of cleaner, mental task-specific features.

The ICA needs to run multiple iterations, and for large, complex EEG datasets, this can be computationally expensive. The Fast Independent Component Analysis (f-ICA) [209] provides a solution to this problem since it reduces the computational complexity by using a fixed number of iterations. This allows it to converge quickly and speed up the computation, making it ideal for real-time data processing, but it may have slightly lower accuracy than ICA.

On the other hand, Infomax ICA [129, 164], which is a variant of ICA, aims to increase the information extracted from a signal by maximizing the statistical independence of components extracted from EEG data. This method uses the Infomax principle, which is used for signal separation, and the algorithm focuses on maximizing the information of the components to increase their independence. Extended Infomax ICA [25] includes modifications to the basic

Infomax ICA, allowing it to handle complex situations, such as nonlinearities, more accurately. However, it comes with higher computational complexity and slower convergence

When analyzing EEG data, Empirical Mode Decomposition (EMD) [188] breaks down the signal into simpler, meaningful components called Intrinsic Mode Functions [188]. The EMD algorithm extracts components from the original EEG signal by identifying local maxima and minima. The first component contains the highest frequency, and subsequent components gradually contain lower frequencies, with each component having a varying amplitude. These components can be used as features to differentiate various mental tasks. The Surface Laplacian Transformation [208] focuses on extracting features from specific regions of the brain. It is a spatial filtering method that aims to minimize the effects of distant sources while enhancing the spatial resolution of the EEG signal by improving the representation of local activity.

#### 2.4.6. Phase and Synchrony Analysis

As the fifth category in meditation EEG feature extraction, we will examine “Phase and Synchrony Analysis”. In this review, phase-based synchrony and coupling methods are discussed separately due to their prominence in meditation EEG studies, while coherence-based connectivity measures and related approaches are covered in Section 2.4.8, and network-level representations are discussed later in the chapter. These features are commonly associated with vibration signals, such as EEG, where phase indicates the position of a wave at a given time, and synchrony provides a comparative measurement between phase values for different instances, such as channels, brain regions, and so on. A deeper understanding of this can be obtained when comparisons of certain channels or regions are focused on specific frequency

bands. Differences in values in these instances can be related to different mental tasks, such as meditation and non-meditation.

The Phase-Locking Value (PLV) [23, 33, 175, 189, 198, 210] is used to measure how well the phase of brain waves from two EEG channels is aligned over time. This value ranges between 0 and 1, where 0 means no phase synchronization and 1 means perfect phase synchronization. It provides features of how different regions interact with each other during a particular mental task, with varying PLV strengths for different mental tasks.

The Phase Coherence [154] also measures the coupling between the phase of various channels or brain regions over time. Although this is closely related to PLV, both differ in the calculation and sensitivity to noise, with PLV performing better in the presence of noise. Both PLV and Phase Coherence quantify phase synchrony by averaging the complex exponential of the phase difference; however, they mainly differ in the dimension over which the averaging is performed, with PLV typically averaging across trials or epochs, whereas Phase Coherence averages over time samples within a given window. On the other hand, Mean Phase Coherence [161] is obtained as a feature by calculating the Phase Coherence over a period of time or across a frequency band and then averaging the results. Operational Synchrony Measurement [14, 211] is a general term covering various techniques, such as Phase Locking Value (PLV) and Phase Coherence, used to evaluate the synchronization of EEG signals from different brain regions during meditation.

Another variation of PLV that is used to extract meditation EEG features is the Phase Lag Index (PLI) [198, 210, 212]. The PLI algorithm works specifically on non-zero-lag phase coupling, allowing it to detect the most accurate neural interactions. Since PLI does not consider zero-phase lag connections in the calculation, it is less sensitive to electromagnetic propagation

artifacts, making it perform better in the presence of noise compared to the other methods mentioned above.

At the same time, several other variations and extensions of PLV used to extract features in meditation EEG have been observed in recent literature. The Phase Synchrony Index (PSI) [132] offers more flexibility than PLV, as it can incorporate additional methods to measure synchronization. This makes it more adaptable to changes in brain activity over time and capable of working with different frequency ranges to capture more complex patterns. The Inter-Channel Phase Synchronization (ICPS) [104] is a broader method used to assess the synchronization between channels, while PSI provides a specific numerical value as a result. ICPS is more general and less specific, whereas PSI gives a particular result. ICPS may include PSI, PLV, and other methods as part of its broader approach. The Pairwise Phase Consistency (PPC) [113, 167] is a more robust, reliable version of PLV. PPC can handle noisier and more complex data while providing more accurate and stable results.

When doing meditation EEG-related research, although some studies focus generally on all frequency bands, there are instances where the focus is on specific frequency bands. In one such instance, Theta Phase Synchronization (TPS) [213] was performed, focusing on the Theta band (4-8 Hz). Here, the synchronization of Theta oscillations between different brain regions was analysed as a feature. At the same time, cross-frequency phase synchronization estimation [145] has been used to compare the synchronization between different frequency bands to identify the relationship between them, rather than examining synchronization within the same frequency band across different channels.

The Phase-Amplitude Coupling (PAC) [138, 144] is a feature extraction method used in EEG, where it measures the relationship between the phase of low-frequency bands (Delta or Theta) and the amplitude of high-frequency bands (Alpha, Beta, or Gamma). The idea here is that there

is a relationship between different frequency bands, and for various mental tasks, PAC tries to find this relationship by comparing the phase of one frequency band with the amplitude of another frequency band.

In meditation EEG research, phase- and synchrony-based metrics have shown increased long-range synchronization, particularly in the theta and alpha bands, during meditation practices. Frontal–parietal phase locking has been linked to sustained attention, while increased theta synchrony has been associated with affective processing. These findings indicate that phase-based features reflect functional interactions between brain regions that may not be captured by amplitude measures alone.

#### 2.4.7. Entropy-Based Measures

As the sixth category in meditation EEG feature extraction, we will examine “Entropy-Based Measures”. Entropy in EEG is used to check how complex the brain signal is over time. A low entropy value means the brain signals have simple, repeated patterns, and this can happen with a relaxed mind, such as during meditation or sleep. High entropy is observed when brain signals are continuously changing without any repeated patterns. Such complex, unpredictable brain patterns may occur in situations like stress or problem-solving. Shannon Entropy [156, 184, 214] is one of the simplest entropy methods used in meditation EEG. It measures the uncertainty or randomness of a signal and is calculated using the probability distribution of the signal amplitudes or spectral components. Although this method is simple to calculate and use, due to its high sensitivity to noise, thorough cleaning is required during the preprocessing stage.

Relative Entropy [149] measures the difference between two probability distributions, and in EEG studies, it can be used to compare two different mental tasks. This method is helpful in

detecting shifts in amplitude or frequency distributions but is sensitive to noise. Renyi Entropy [156] is a generalization of Shannon Entropy and has an adjustable parameter that allows control over the distribution characteristics, thus giving more freedom in EEG analysis for different brain states. Log Energy Entropy [184] specializes in measuring the logarithmic energy distribution of a signal, which can be specifically used in the Power Spectral Density (PSD) of EEG data. It can detect artifacts and is less sensitive to minor noise, but although it can identify the overall energy pattern, it may have challenges in identifying minor temporal or spatial variations in the EEG signal.

Although Shannon Entropy is used for discrete data, Differential Entropy [148], which is an extension of Shannon Entropy, can handle EEG data with continuous amplitude distributions. Differential Entropy has a certain computational challenge, especially for high-dimensional or noisy data, since it requires an estimation of the probability density function of the signal. Therefore, its accuracy depends on a smooth probability distribution that is not affected by noise. While Differential Entropy focuses on the overall unpredictability of the signal's distribution, Approximate Entropy [147, 148, 214, 215] quantifies the regularity or complexity of signal patterns over time and is used to measure the unpredictability or irregularity in EEG signals during different mental states. Approximate Entropy has low computational complexity, supports non-stationary signals, and can identify irregularities or noise in the signal. However, it may not perform well with short EEG data because its performance improves with longer time series to accurately assess regularity or complexity

Sample Entropy [37, 147, 148, 153, 162, 193, 214] is observed as one of the most frequently used entropy measures for EEG feature extraction in classifying various meditation-related mental tasks. It is an improved version of Approximate Entropy, and it can handle short EEG signals relatively well and produce fewer false positive results; however, it requires careful selection of parameters to avoid incorrect results. Fuzzy Entropy [216, 217] is a powerful

method that combines fuzzy logic with the entropy concept and is considered an improvement over both Approximate Entropy and Sample Entropy. Unlike strict classification into one of two categories, Fuzzy Entropy allows for a degree of membership. This flexibility enables it to effectively handle noisy, complex, and uncertain data, supporting both short and long-duration datasets. However, it has the drawback of relatively high computational complexity.

Other than the entropy methods mentioned above, several additional variations have also been used in meditation EEG feature extraction studies. These include Permutation Entropy [119, 148, 218], Sure Entropy [184], Threshold Entropy [184], Persistent Entropy [191], and Directed Phase Transfer Entropy [198]. Past studies show that entropy-based methods make a significant contribution to meditation EEG feature extraction, as they can quantify the complexity, irregularity, and unpredictability of brain signals. Their capability to analyse both short and long EEG recordings makes them valuable tools for understanding meditation-related mental states.

#### 2.4.8. Connectivity and Coherence Measures

As the seventh category in meditation EEG feature extraction, we will examine “Connectivity and Coherence Measures”. Here, connectivity indicates the interaction between brain regions, and coherence measures the correlation between signal oscillations at a given frequency. In EEG feature extraction, Coherence [37, 97, 109, 110, 115, 120, 141, 168, 192, 198, 210, 219] has been used to measure the functional connectivity between two signals or brain regions. It helps to understand the frequency-specific connectivity between EEG signals, measuring the degree to which two signals are linearly related in the frequency domain and aids in identifying synchronized brain activity. Coherence ranges between 0 and 1, where a value of 1 indicates strong synchronization between the signals, and a value of 0 indicates little to no relationship.

Coherence can be calculated for the entire frequency range or for specific frequency bands. It measures only linear relationships, and thus may miss nonlinear relationships in brain signals. Volume conduction effects may cause overlapping signals that are detected by multiple electrodes, and this can sometimes produce false connections in coherence.

The Magnitude-Squared Coherence (MSC) [142, 151] is an extension of the standard coherence method. Coherence calculates the correlation between two signals, but MSC squares the magnitude of the coherence, emphasizing the strength of the relationship between the two signals. While coherence indicates how much two signals are linearly related, MSC provides a more robust measure of the strength of that relationship. However, MSC shares the same limitations as coherence, primarily detecting linear relationships and missing any non-linear connections, and it also faces volume conduction effects.

The Imaginary Coherence [126, 205, 210], which is an extension of coherence, aims to address the issue of volume conduction in EEG signals. Standard coherence cannot distinguish between true functional connectivity and artificial connections caused by overlapping signals. Imaginary Coherence focuses on the imaginary part of the coherence, which represents the consistent non-zero phase lag between two signals. This phase lag plays a key role because neural interactions involve a time delay, thus providing a better way to reduce false connections caused by overlapping signals.

The Partial Directed Coherence (PDC) [220] is an advanced extension of coherence. When coherence shows only the degree of linear correlation between two signals, PDC enhances this by providing the directionality of interaction. This indicates which signal influences the other, and PDC applies Granger causality principles in the frequency domain to identify this relationship. In addition to identifying frequency-related relationships, PDC can distinguish if

one brain region influences and activates another region, providing a more detailed view of the brain network compared to standard coherence methods.

The Directed Transfer Function (DTF) [220, 221] works on the concept of Granger causality, which checks whether the activity in one brain region can predict the activity in another region. It identifies the direction of information flow between regions. Additionally, in a multichannel EEG dataset, DTF can be used to study how signals influence each other. Since DTF works in the frequency domain, these studies can be conducted on each frequency band separately. This method provides valuable features for analyzing meditation EEG data.

The Minimum Variance Distortionless Response (MVDR) Coherence [221] improves the accuracy of standard coherence by addressing the limitations caused by noise and overlapping signals. It uses a spatial filtering approach to reduce noise and interference from other brain regions, ensuring that the targeted pair remains more independent from those disturbances. MVDR Coherence reduces the impact of volume conduction and is particularly effective with complex EEG datasets containing a significant amount of noise.

#### 2.4.9. Spatial, Microstate, Network and Topological Features

As the eighth category in meditation EEG feature extraction, we will examine “Spatial, Microstate, Network and Topological Features.” A graph is a mathematical representation of a network with nodes and edges. In EEG studies, brain regions or channels are represented as nodes, and the connections between them are represented as edges. After mapping the EEG data onto a graph structure, graph-theoretic measures can be calculated on the modelled graph, providing features of the EEG data that can be mapped to different mental tasks, such as meditation and non-meditation.

In EEG feature extraction, Topographic Maps [8, 101, 179, 187, 206, 220, 222] are used to generate 2D maps that display the electrical activity across the scalp. Each point on this map represents an electrode placed on the scalp, and based on the colour of the point, we can observe the strength of the signal recorded at that location. When studying how meditation affects a person, we can observe how the colour patterns in the map change over time to understand the changes in the person's mental states.

On the other hand, Current Source Density (CSD) Transformation [98, 104, 126, 157] focuses on the signals coming from specific points on the scalp. This is done by reducing the effects of electrical activity from nearby sources, and this method can be used to focus our attention on specific regions of the brain and also to study how different brain regions interact during various mental tasks. CSD transformation, when focusing on one electrode, will subtract the signals measured from neighboring electrodes. It highlights areas of high brain activity while minimizing effects from less active signals.

LORETA (Low-Resolution Electromagnetic Tomography) [88, 157, 158, 160, 192, 223] is a powerful technique used to map 3D plots of brain activity from EEG data. When signals are collected from electrodes, each electrode produces a signal that contains the combined electrical activity from multiple locations in the brain. The signal will have a strong influence from the electrical activity at the location where the electrode is placed on the scalp, but it will also be affected by the electrical activity from adjacent locations on the scalp. LORETA is capable of removing the influences of nearby signals and providing a 3D plot to represent the electrical activity corresponding to each electrode location. LORETA is highly useful when studying brain behaviour during meditation, as it can clearly display the regions of the brain active during a specific mental task. LORETA allows us to observe any shifts in activity from one brain region to another, which can occur as a person progresses through a mental task such as meditation.

Graph Theoretical Measures [224] are an EEG feature extraction method that follows the concept of graph theory, where different regions of the brain are represented as nodes and the relationships between these brain regions are represented as edges. This type of mapping allows us to understand how different regions of the brain communicate or interact with each other. In this case, measurements may include the number of connections, the strength of connections, and the centrality in the network.

In EEG feature extraction, Microstate Analysis [186, 206, 225] is a method used to detect short, stable patterns of brain activity. These patterns are called microstates, and they can be considered the basic building blocks of brain activity, representing different mental states. To understand how mental states change over time in a person, the duration, frequency, and transitions between these microstates can be studied using the collected EEG data. These results are useful for understanding the mind of a person while meditating.

Persistent Homology Features [191] are another way of observing the shape and structure of brain signal patterns in meditation EEG data. These patterns are analysed to understand the duration and significance of each pattern in the whole signal, allowing us to gain insight into different meditative states. When studying various graphical representations of meditation EEG features, we come across Betti Areas and the Peak Location of Betti Curves [191] as well. A mathematical method called Topological Data Analysis is used to extract these features. Betti Areas represent the regions or space covered by these patterns, and the Peak Location of Betti Curves identifies the point where these patterns are the most significant.

#### 2.4.10. Statistical Features

As the ninth category in meditation EEG feature extraction, we will examine “Statistical Features”. When considering feature extraction from EEG data, statistical methods play a significant role. While some of these methods are advanced and complex, basic statistical measures are also commonly and effectively used in meditation EEG research. Since these basic methods are widely known, the details are not included here, and only the research articles that use them are mentioned. The most commonly used basic statistical methods for extracting features from meditation EEG data are Mean [85, 147, 148, 152, 174, 176, 184, 193–195, 215, 224], Maximum and Minimum [147, 176, 184, 193–195], Standard Deviation [85, 112, 147, 148, 152, 176, 184, 193–195, 215], Variance [37, 112, 152, 156, 170, 176, 202, 215], Interquartile Range (IQR) [152], and Root Mean Square [148, 170, 177, 184, 193, 215]. The above-mentioned methods have been observed in extracting amplitude-based, frequency-based, and time-domain features in meditation EEG studies.

Zero Crossing [148, 176] is a basic time-domain statistical method used to extract features from EEG data. Here, zero amplitude is considered as the baseline, and it counts how many times the signal crosses the baseline for the selected data. A lower number of crossings indicates a lower-frequency component, while a higher number indicates a higher-frequency component. Although this method is simple to compute, it is very sensitive to noise, as noise can easily shift the signal, leading to more frequent crossings of the baseline. On the other hand, the Zero-Crossing Rate [152, 193] is a variation of Zero Crossing that calculates the rate at which zero crossings occur, thus providing better insight into the signal's frequency. Higher Order Crossing [165] is an advanced variation of the above two, and it counts the number of passes through the baseline under specific conditions. The specific conditions may include using multiple

crossings within a single cycle or counting the crossings within a specified time period, etc., thus allowing the detection of more complex oscillatory patterns.

In meditation EEG feature extraction, Skewness [147, 184, 193, 215] quantifies the asymmetry of the amplitude distribution of the signal. The value can have positive or negative skewness, depending on whether there are more larger amplitudes or smaller amplitudes. Although skewness has been used to distinguish various meditation mental tasks, the presence of outliers in the dataset can create challenges. Kurtosis [147, 152, 156, 176, 184, 193, 215] is another statistical method that can be used to assess the shape of the distribution of the EEG signal amplitudes. It quantifies the "tailedness" of the signal's distribution, indicating how much the signal differs from a normal Gaussian distribution. While both skewness and kurtosis measure how the signal amplitude differs from a normal distribution, skewness specifically checks the asymmetry of the data distribution, focusing on how the bulk of the data behaves, while kurtosis specifically checks the peakedness and tail heaviness of the distribution, focusing on how deep the tails are.

Logarithmic Transformation [133, 135] is a feature extraction method that is applied by using a logarithmic function on an EEG signal. The aim of this is to compress the range of the signal to reduce the effect of extreme values while highlighting smaller changes, thus increasing sensitivity to them. This is applied to the amplitude distribution of the signal, and this transformation supports performing further statistical and machine learning methods. This method has the challenge of losing some information from the signal, which may or may not be important for a study. Logarithmic Energy [184] is an extension of Logarithmic Transformation that focuses on compressing the EEG signal power while increasing computational complexity. Logarithmic Energy is more resistant to noise and outliers and provides more information related to brain activity tasks compared to Logarithmic Transformation.

Hjorth Parameters [148, 151, 184, 215] are three statistical measures extracted as features from EEG data and labelled as activity, mobility, and complexity. Activity measures the overall power of the signal, while mobility focuses on the frequency of the signal by examining the rate of change in the signal's amplitude. Complexity is calculated using both activity and mobility and indicates the level of deviation from a simple sine wave, showing the degree of complexity of the EEG signal.

Event-Related Potentials (ERPs) [84, 132, 167, 171–173, 182, 206, 207, 213, 226] are time-domain, stimulus-locked averages of EEG signals rather than statistical features themselves; however, statistical descriptors such as peak amplitude, latency, and related measures are commonly extracted from ERP waveforms and used as features for analysis and classification. ERPs are measured electrical brain responses that are triggered by specific events or stimuli. Although these are directly related to EEG studies in sensory, cognitive, or motor events, we can observe instances where ERPs have been used in research related to meditation. In meditation research, studies are conducted to examine both state and trait changes resulting from the practice of meditation. State changes refer to temporary alterations in mental or neural activity, which can be assessed by comparing EEG data between meditative and non-meditative conditions. In contrast, trait changes are long-term, enduring effects that develop through sustained meditation practice over time. In studies investigating trait changes, event-related potentials (ERPs) are sometimes used as a key analytical tool. The idea here is to select two groups of people, where one group consists of experts in meditation with a lot of practice. All participants will receive the same set of triggers, such as visual, vocal, or a command to perform a task. Then, ERP performance can be checked in both groups, allowing us to understand trait changes resulting from long-term meditation practice.

Global Field Power (GFP) [225, 227] is an EEG feature extraction method used to calculate the overall strength of the electrical activity of the entire brain at a given time. GFP is calculated

by taking the root mean square of the EEG signals across all electrodes at a selected timepoint, which provides a measure of the overall signal intensity across the scalp. A higher GFP value indicates greater synchronization of brain activity across regions, while a lower GFP value indicates more scattered or less synchronized activity. By observing the change in GFP values over time, changes in different mental states or levels of meditation experience can be inferred.

Decorrelation Time [215] is a method that measures the time it takes for an EEG signal to lose its correlation with itself over time. Here, an autocorrelation function is applied to the EEG signal to analyse how the signal changes over time, and the time at which this autocorrelation falls below a certain threshold is identified as Decorrelation Time. This can be useful for examining how the electrical activity of the brain changes between non-meditative and meditative states.

#### 2.4.11. Advanced Modelling, Machine Learning, and Complex Features

As the tenth category in meditation EEG feature extraction, we will examine “Advanced Modelling, Machine Learning and Complex Features.” Here, we focus on methods that employ sophisticated mathematical and computational techniques to capture nonlinear and complex patterns and relationships in meditation EEG data. Autoregressive Modelling [24, 220] is an advanced feature extraction method that has been used in multiple instances of meditation EEG studies. This method assumes that the signal at a given time can be predicted using characteristics of previous sections of the signal. The model calculates coefficients that represent the relationships between past and present sections of the signal. These coefficients indicate the level of influence past signals have on the current section, and the coefficient values can be used as features in various studies.

In the Template Matching Procedure [29], EEG signals are compared with predefined patterns or templates. These templates may represent known brain patterns or mental tasks, and the aim is to check the level of similarity between the signal instance and one of these templates. This is achieved by dividing the EEG signal into small sections and checking how well each segment matches a template. The degree of similarity can be measured using metrics like correlation. In meditation EEG studies, if templates representing certain states of meditation are available, this method can be used to check the extent to which each instance of the meditation EEG data corresponds to these states.

The Highly Comparative Time-Series Analysis (HCTSA) [34] is an advanced method used to extract a large number of statistical and mathematical features from a time-series dataset, such as EEG. The extensive feature set, which may include hundreds or thousands of features, obtained from this method can be used to understand the differences between various meditation mental tasks. Among these features, HCTSA helps identify the most relevant features for distinguishing different mental states, making it useful for comparing meditative and non-meditative states.

As a machine learning algorithm, Linear Discriminant Analysis (LDA) has been used with EEG analysis primarily for EEG classification, but it has also been applied to tasks related to feature extraction in certain instances. In meditation EEG, LDA [196, 202] has been applied for dimensionality reduction and the enhancement of features obtained from various other methods. When extracting features from EEG data, many methods produce a large number of features due to the high number of electrodes and time points in EEG, creating challenges for tasks such as classification. LDA, as a dimensionality reduction method, can be significantly useful as it helps reduce the number of features while retaining the most prominent ones relevant to the targeted study. Thus, it improves the efficiency of algorithms designed to classify EEG data based on different mental tasks.

Artificial Neural Network (ANN) is an advanced machine learning method widely used for feature extraction and classification in datasets with complex nonlinear patterns. ANN [201, 202, 222, 228, 229], modelled after the structure and functionality of biological neural networks, has been applied in feature extraction from meditation EEG data. Depending on the task and expected performance, either raw EEG data or preprocessed data is used. An ANN typically consists of an input layer, an output layer, and a varying number of hidden layers, depending on the task. The neurons in the hidden layers are interconnected with adjustable weights, and these layers perform complex, nonlinear transformations of the input data to capture intricate patterns. Among the challenges of using ANNs are high computational complexity and the need for a significant amount of data to prevent overfitting.

Fractal Dimension (FD) [119, 148, 215, 230] is a method that quantifies the complexity and self-similarity of an EEG signal. FD uses mathematical tools such as the box-counting method, Higuchi's method, or Katz's method to capture the complexity of EEG signals associated with different mental tasks. FD has the capacity to capture nonlinear features efficiently; however, it faces challenges such as sensitivity to noise and high computational complexity.

The Hurst Exponent [152, 153] quantifies the degree of persistence or anti-persistence in time series data, such as EEG, indicating whether the signal continues in the same direction over time. The Hurst Exponent value ranges from 0 to 1. A value of 0.5 indicates a random walk (no persistence or anti-persistence), a value greater than 0.5 indicates persistence, and a value less than 0.5 indicates anti-persistence.

Detrended Fluctuation Analysis (DFA) [99, 105, 230] produces a similar output to the Hurst Exponent, staying within the range of 0 to 1. However, they differ in their methodologies for calculating these results. While the Hurst Exponent is typically computed using the statistical

properties of the range and variance of the EEG data, DFA involves detrending the signal by removing trends at different scales before analyzing the fluctuations.

#### 2.4.12. Summary of Feature Extraction Techniques

When going through past research articles on meditation EEG, we came across 163 relevant documents showing the use of feature extraction techniques to extract information. Since EEG feature extraction is a broad topic, we divided it down into ten sub-areas based on their characteristics. The selected ten subtopics are as follows: Frequency Domain Analysis, Time-Frequency and Spectral Entropy Methods, Amplitude Features, Dimensionality Reduction and Decomposition, Phase and Synchrony Analysis, Entropy-Based Measures, Connectivity and Coherence Measures, Spatial, Microstate, Network and Topological Features, Statistical Features, and Advanced Modelling, Machine Learning, and Complex Features. Various feature extraction methods identified in each of the studied papers were categorized under the most suitable subtopic among the ten we identified.

When we consider a single manuscript, it may use various types of feature extraction methods that yield the best results for the study conducted. Therefore, although we broke the feature extraction methods into 10 subtopics, a selected research paper may have a set of features that can be mapped into several of the 10 subtopics. This means for each research paper, we may identify a combination of the 10 topics being used for each study, such as one topic, two topics, three topics, etc. A summary of this was prepared for the 163 research articles, and it is given in Table 2.4. In this table, the column labelled 'Feature Extraction Methods Used' contains all the basic feature extraction methods used in each of the research articles. Then, each of these basic features was mapped to one of the ten topics. In Table 2.4, the column titles '1', '2', '3',

'4', '5', '6', '7', '8', '9', and '10' represent each of the 10 feature extraction subtopics in the order given above. Since each line in Table 2.4 represents a research article, each time a feature extraction method that falls into one of the above ten topics is identified, it is indicated with a '✓' in the corresponding column of the table. Table 2.4 gives a full summary of the 163 research articles where we extracted the feature extraction methods, and this will be highly valuable in getting an idea of how past research has been done on this topic.

## 2.5 Classification Techniques for Meditation EEG Assessment

### 2.5.1. Introduction of Classification Techniques

A review of the literature on classification techniques for meditation EEG revealed notable variation among studies. The main methods identified were Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Decision Trees and Random Forests, Linear Discriminant Analysis (LDA), and Artificial Neural Networks (ANNs). Some studies employed only one of these methods, while others applied two, three, or more. To better analyze their usage, the papers were grouped into three categories: those using one, two, or three or more classification methods.

Studies using a single classification method were further divided into five subgroups corresponding to the techniques listed above. Due to their complexity, no further categorization was applied to papers using two or more methods. As the focus was strictly on predictive classification algorithms, studies relying solely on statistical group separation or hypothesis-testing techniques (e.g., t-tests or ANOVA), which do not train models to classify unseen data, were excluded.

## 2.5.2. One Classification Method

As discussed earlier, studies on meditation EEG have employed several classification algorithms. Some used a single algorithm, while others applied multiple methods. This section focuses on studies that used only one classification algorithm, organized into five parts corresponding to the main techniques identified: Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Decision Trees and Random Forests, Linear Discriminant Analysis (LDA), and Artificial Neural Networks (ANNs).

### **Support Vector Machines (SVM)**

Support Vector Machine (SVM) is a supervised machine learning algorithm commonly used for classification. It identifies an optimal hyperplane that best separates data points into distinct classes. SVM performs effectively in high-dimensional spaces, making it well suited for EEG data, which are complex and feature-rich.

Ahani [33] used SVM to classify mindfulness meditation versus control conditions in novice meditators using combined EEG and respiration features, achieving an accuracy of 85%. Similarly, Bailey [34] classified expert meditators and non-meditators using time-series and frequency-band power features, attaining 67% accuracy. This study highlighted the importance of incorporating time-series features with SVM in meditation EEG analysis. Harne [152] employed SVM to classify EEG data recorded before and after OM mantra meditation. Among five frequency bands, the delta band achieved the highest accuracy (70.13%), suggesting a post-meditation brain state similar to deep sleep. This work was among the first to apply SVM for OM mantra EEG classification.

In another study [150] involving a participant with autism spectrum disorder, a Radial Basis Function (RBF) SVM classified pre- and post-mindfulness meditation EEG with an average accuracy of 80.76%, indicating positive effects of brief mindfulness practice on individuals with ASD. Han [218] applied two- and three-class SVM classifiers to distinguish meditation, attention, and relaxation states in expert and non-meditator EEG data. In pairwise comparisons, experts achieved 86.76%, 86.99%, and 80.59% accuracy, while non-meditators achieved 82.18%, 76.80%, and 67.87%. For three-class classification, accuracies were 74.31% (experts) and 62.16% (non-meditators), demonstrating superior performance in expert meditators using permutation entropy features.

Pandey [210] employed SVM to classify three meditation techniques, each compared with a control group. The highest accuracies were 84.76% (Gamma) for Himalayan Yoga, 90% (Alpha) for Isha Shoonya, and 84.76% (Theta) for Vipassana, representing the best-performing frequency ranges. Similarly, Gupta [191] combined EEG topological features with SVM to classify two meditation types, achieving up to 95% accuracy using Hodge spectral entropy, highlighting the value of topological data analysis in meditation research.

Ingle [196] used SVM to classify Vipassana meditation versus non-meditation EEG from novice meditators after four weeks of training. Three pipelines were tested using Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Linear Discriminant Analysis (LDA) before SVM classification. ICA + SVM and PCA + SVM each reached 93% accuracy, while LDA + SVM achieved the highest at 95%. The study underscored SVM's effectiveness for meditation EEG analysis and emphasized careful kernel parameter selection to prevent overfitting and underfitting.

## **k-Nearest Neighbors (k-NN)**

The k-Nearest Neighbors (k-NN) algorithm is another method used in meditation EEG classification. This section focuses on studies employing only this algorithm. In k-NN, a new data point is classified by identifying its k nearest neighbors based on feature similarity and assigning it the most common class label.

Jadhav [151] examined how meditation enhances emotional balance. EEG data for four emotions were collected before and after eight weeks of meditation training. Two-, three-, and four-class classifications were performed using k-NN, and post-training accuracies were significantly lower than pre-training, indicating improved emotional control after meditation.

Purnamasari [123] used k-NN to develop a real-time application for detecting stress levels during meditation. Features from Delta, Theta, Alpha, Beta, and Gamma bands were used, showing increased accuracy as more bands were included. The highest accuracy (80%) was achieved with  $k = 3$ . Similarly, Korde [209] built a BCI pipeline combining Independent Component Analysis (ICA) for feature extraction with k-NN for classification of mindfulness meditation and non-meditation EEG data, achieving 86.36% accuracy. Meditators showed more stable brain states than non-meditators.

## **Decision Trees and Random Forests**

Tree-based classification algorithms—such as Decision Trees, Random Forests, Bagged Trees, and Boosted Trees—are also used in meditation EEG studies. These methods employ a hierarchical structure where data are recursively split based on feature characteristics, with each

node representing a decision and each leaf a predicted outcome. Random Forests, in particular, combine multiple Decision Trees to improve accuracy and reduce overfitting.

Dadhich [184] used several tree-based algorithms, including Fine, Medium, Coarse, Boosted, and Bagged Trees, to classify meditation EEG for detecting mind wandering. The Bagged Tree Classifier achieved the highest accuracy of 92.41% in the alpha band, with novice meditators exhibiting greater mind wandering than experts. Pandey [230] applied Random Forest to distinguish EEG data before and after an eight-week Mindfulness-Based Stress Reduction (MBSR) program. Using Detrended Fluctuation Analysis (DFA), Higuchi Fractal Dimension (FD), and Katz FD for feature extraction, the best accuracy (70%) was achieved with Higuchi FD in frontal alpha bands, where right-frontal alpha waves had the greatest influence.

Huang [92] employed Random Forest to classify sitting and walking meditation EEG data using original power, power ratio, and nonlinear dynamics features. The highest accuracy (84.17%) was achieved when combining all three feature types. The study also noted challenges in collecting clean data during walking meditation due to motion artifacts and device limitations.

Tan [144] used Random Forest to classify Focused Attention Meditation and problem-solving EEG data. Subject-specific classifiers achieved an average accuracy of 93%, while a general classifier trained on pooled data achieved 74%, emphasizing the need for personalized training in meditation EEG classification. The study also highlighted the potential of such models for individualized meditation-support tools.

Edla [194] used a Random Forest classifier in a BCI pipeline to distinguish meditation from concentration (mental arithmetic) EEG data, achieving 75% accuracy. The model was successfully adapted to control a simple external device, demonstrating the potential for mind-state-driven home automation, though the author noted challenges in real-world implementation.

## **Linear Discriminant Analysis**

Linear Discriminant Analysis (LDA) is a supervised machine learning algorithm widely used for classification and dimensionality reduction. As discussed earlier under feature extraction, LDA finds a linear combination of features that best separates data classes by maximizing the ratio of between-class to within-class variance, assuming a shared covariance matrix. It has been effectively applied to meditation EEG data classification.

Wang [188] applied Fisher Linear Discriminant Analysis with Hilbert-Huang Transform features to classify relaxation meditation and tension imagination EEG, achieving ~90% accuracy. The study also linked relaxation to Alpha activity and tension to Beta activity. Panachakel [203] performed intra- and inter-subject classification of Rajayoga meditation versus resting EEG using Tikhonov-regularized CSP and LDA, obtaining 97.9% and 74.0% accuracy, respectively. The lower inter-subject performance was attributed to participant variability and limited session data. High-frequency (Gamma) bands were found to be more discriminative than lower frequencies.

Liyanagedera [200] combined Common Spatial Patterns (CSP) with LDA to classify four mind tasks related to Loving-Kindness Meditation (LKM): pre-rest, LKM-self, LKM-others, and post-rest. Six pairwise intra-subject comparisons were performed using single- and multi-session EEG. For meditation vs. pre-rest, accuracies of 99.5% (single session) and 83.6% (multi-session) were achieved. Results showed that pre-rest EEG differed slightly from other tasks and that EEG from repeated sessions shared common characteristics. The study emphasized the value of multi-session EEG analysis and highlighted the potential of training classifiers on previous meditation/rest data pairs to improve generalization.

## **Artificial Neural Networks (ANNs)**

Artificial Neural Networks (ANNs) are increasingly used for EEG analysis, particularly with large datasets exhibiting complex nonlinear patterns. Inspired by the structure of biological neurons, ANNs typically comprise input, hidden, and output layers. They are trained using known data, where weights are iteratively adjusted through forward and backward propagation. Once trained, the model classifies new data effectively.

Several studies have demonstrated the use of ANNs for meditation EEG classification. Munjal [204] applied a Convolutional Neural Network (CNN) to Shoonya meditation versus non-meditation EEG, testing models with and without Independent Component Analysis (ICA). Average accuracy improved from 70.16% (without ICA) to 99.50% (with ICA), underscoring the value of CNNs and EEG preprocessing for meditation studies.

Sharma [176] used a Multi-Layer Perceptron Neural Network (MLPNN) to classify EEG data from meditators and non-meditators before and after a three-month Yoga and Sudarshan Kriya training. Using statistical EEG features, accuracies of 87.2% (with 87.1% sensitivity and 87.4% specificity) were achieved, indicating positive neural effects of meditation training.

Panachakel [202] employed a deep learning model combining Common Spatial Patterns (CSP) for feature extraction, Linear Discriminant Analysis (LDA) for dimensionality reduction, and a Long Short-Term Memory (LSTM) network for classification of Rajayoga meditation EEG. Accuracies across frequency bands were Alpha – 79.1%, Beta – 86.5%, lower Gamma – 91.0%, and upper Gamma – 94.1%, marking a 15% improvement over prior work [203] and illustrating the strength of deep learning for meditation EEG classification.

Kaur [222] showed that Shallow Convolutional Neural Networks (SCNNs) effectively differentiate novice and experienced Himalayan Yoga meditators. Using 1D- and 2D-SCNN

models on 2s, 5s, and 10s segments, accuracies reached 2D-SCNN: 95.42–96.14% and 1D-SCNN: 99.45–99.48%, with 1D-SCNN outperforming 2D-SCNN.

Kora [128] investigated brain activation during Transcendental Meditation, Raja Yoga, and Mindfulness meditation using four deep neural network models. Over twelve weeks, EEG data collected across four sessions yielded accuracies of 99.4% (VGG-16), 98.8% (VGG-19), 97% (ResNet-18), and 95.2% (GoogleNet). The study also linked meditation to increased Alpha and decreased Delta power, confirming deep learning's capacity to capture EEG meditation dynamics.

Stapleton [95] explored the effect of a brief meditation session on novice meditators. Using a Riemannian geometry–based classifier, similar in approach to neural networks, pre- and post-meditation EEG were classified with 97% accuracy. Power spectral analysis showed increases in Theta (29%), Alpha (16%), Beta (17%), and Gamma (11%) with a 5% decrease in Delta, demonstrating measurable short-term effects of meditation.

This section reviewed studies employing a single classification algorithm with meditation EEG, highlighting the versatility and high performance of ANN-based approaches. The following section examines research integrating multiple classification algorithms in meditation EEG analysis.

### 2.5.3. Two Classification Methods

In this section, we review studies that employed two types of classification algorithms for meditation EEG analysis. Kaur [193] successfully used Support Vector Machine (SVM) and Random Forest (RF) to classify EEG data from two mind tasks—meditation and mind wandering. Four groups were tested: three with varying meditation experience and one novice

group. For the two mind tasks, SVM achieved accuracies of 94.92% (Himalayan Yoga Tradition), 96.29% (Vipassana), 93.70% (Isha Shoonya Yoga), and 96.48% (Control), while RF performed slightly better with 96.86%, 96.70%, 94.06%, and 94.62%, respectively. The study found that mind wandering produced more complex brain signals, while meditation showed less complexity and higher power levels. The author emphasized the potential of EEG-based meditation classification for developing EEG-guided meditation tools.

Shang [201] combined traditional and deep learning methods to study the effects of mindfulness-based stress reduction (MBSR) on novice meditators. EEG data were collected before and after an eight-week training program (MBSR1/REST1 and MBSR2/REST2). Four pipelines were tested: CSP + SVM, FBCSP + SVM, Shallow CNN, and Deep CNN. Mix-subject classification accuracies (Shallow, Deep, CSP, FBCSP) were as follows: MBSR1/REST1 (98.33%, 99.59%, 72.01%, 73.92%), MBSR2/REST2 (92.53%, 99.70%, 92.56%, 73.23%), MBSR1/MBSR2 (99.81%, 99.95%, 71.67%, 91.16%), and REST1/REST2 (99.88%, 99.78%, 93.98%, 95.13%). Deep learning achieved the highest accuracies, while inter-subject results were lower, indicating a need for further research on improving generalization.

Lee [127] used Artificial Neural Networks (ANN) and SVM to classify Tibetan Nyingmapa meditation EEG data. ANN accuracies ranged from 80% to 99%, peaking at 99.05%, while SVM started at 30% and reached 100% after optimization. The Alpha band was the key feature in both models, though the author noted the importance of testing across other meditation techniques for broader validation.

Liu [229] compared Feed-Forward Neural Networks (FFNN) and Convolutional Neural Networks (CNN) with traditional classifiers for mindfulness and non-meditation EEG data. Accuracies for meditation were: traditional 62.44%, CNN 63.19%, and FFNN 65.64%; for non-

meditation: traditional 60.57%, CNN 61.34%, and FFNN 63.25%. Deep learning outperformed traditional methods, with FFNN slightly surpassing CNN. The study noted that using only three EEG channels may have limited performance.

Karaiskou [148] addressed inter-subject variability using Riemannian Space Data Alignment (RSDA) to improve classification of breathing meditation and non-meditation EEG data. Support Vector Machine with Radial Basis Function Kernel (SVM-RBF) and EEGNet were used. Best accuracies obtained were: SVM-RBF 55.1%, SVM-RBF with RSDA 66.9%, EEGNet 57.4%, and EEGNet with RSDA 72.6%. RSDA improved both classifiers, demonstrating its potential for handling inter-subject differences in meditation EEG classification.

#### 2.5.4. Three or More Classification Methods

Recent studies have explored the use of multiple classification algorithms in meditation EEG analysis. Tibdewal [37] trained novice meditators for one month, collecting EEG data before and after training. Artificial Neural Network (ANN), k-Nearest Neighbors (KNN), and Support Vector Machine (SVM) were used, with accuracies of 72.5%, 82.5%, and 85.0%, respectively. SVM performed best, showing clear post-training improvements in brain patterns. However, the study was limited by its short duration and the absence of participants with varied meditation experience.

Devipriya [165] classified EEG data from novice, intermediate, and expert breathing meditators using ANN, SVM, and Fuzzy Kernel Least Square SVM (FKLSSVM), achieving accuracies of 91.25%, 93.93%, and 96.28%, respectively. Alpha power characteristics were key to the successful classifications. Lu [197] compared breathing meditation and mind-wandering EEG

for novice meditators using Linear Discriminant Analysis (72%), Naive Bayes (68%), SVM (75%), and KNN (76%), noting the best results with Alpha and Theta wave features. Rajalakshmi [147] studied yoga, meditation, and combined yoga-meditation EEG data using Linear SVM (91.67%), KNN (88.89%), and Multilayer Perceptron (89.58%). L-SVM performed best, and the author emphasized the need for broader participant groups and new features to improve generalization.

Singh [153] compared Himalayan Yoga (HT) and Hare Krishna mantra meditation (HKT) with control EEG using Support Vector Machine (SVM), Deep Neural Networks (DNN), and Random Forest (RF). The mean accuracies obtained were as follows: for HT vs. control, Band Power (BP) ranged from 91.1% to 100%, Sample Entropy (SE) from 67.4% to 72.3%, and Hurst Exponent (HE) from 67.0% to 72.0%; for HKT vs. control, BP reached 100%, SE ranged from 76.2% to 81.2%, and HE from 75.3% to 77.6%. All algorithms were effective, with BP features yielding the highest accuracies. Cruz [100] used five algorithms—Multilayer Perceptron, SVM, Logistic Regression, Decision Forest, and Naive Bayes—to classify pre- and post-meditation EEG. Accuracies dropped slightly after meditation (e.g., MLP: 74% → 69%), while Alpha power increased, indicating post-meditation calmness.

Baboo [198] compared expert and novice meditators and also healthy individuals vs. Parkinson's patients using SVM, Deep CNN, and Recurrent Neural Networks (RNN). Accuracies for meditators were 61%, 59%, and 56%; for patients, 52.17%, 60%, and 56%. k-Means and Graph Neural Networks performed poorly under study conditions. Pandey [101] proposed a lightweight CNN for classifying EEG from expert, novice, and control groups. It achieved 94.57% accuracy, close to deep models such as VGG16 (97.27%), ResNet50 (91.01%), MobileNet (90.75%), and MobileNetV2 (88.73%), while using fewer resources—making it suitable for real-time meditation support applications.

Chaudhary [155] classified EEG data for meditation and mind wandering using KNN (77.7%), Random Forest (68.6%), Quadratic Discriminant Analysis (73.8%), and Neural Network (73.83%). Average accuracy exceeded 70%, confirming distinct EEG patterns between meditation and mind wandering. Pandey [215] aimed to detect distractions such as mind wandering and sleepiness in novice meditators. EEG data were classified using ten algorithms, including AdaBoost, Decision Tree, Random Forest, and SVM variants. The Decision Tree achieved 77.1% for meditation vs. mind wandering, and Random Forest 85.8% for meditation vs. sleepiness, showing EEG's ability to detect these distractions.

#### 2.5.5. Summary of Classification Techniques

When looking at past research articles on meditation EEG, we found 40 relevant documents showing the use of classification techniques to separate the data, and a summary of this is given in Table 2.5. One important factor in these papers is the performance and classification accuracies related to those studies, and therefore, in Table 2.5, in the column 'Performance of Pipelines', this is noted for each of these 40 papers.

While observing the papers, we noticed that five main classification types were used: Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Decision Trees and Random Forests, Linear Discriminant Analysis (LDA), and Artificial Neural Networks (ANNs). In Table 2.5, the column titles '1', '2', '3', '4', and '5' represent each of the five classification methods in the order given above. Therefore, whenever a research article uses one of the above classification types, it is indicated with a '✓' in the corresponding column in Table 2.5. When going through the 40 articles, we noticed the use of various combinations of these five classification types in each paper, and a full summary of this can be observed in Table 2.5.

As shown in Table 2.5, we observed that Support Vector Machines and Artificial Neural Networks were the most commonly used classification methods. Out of the 40 papers, 22 used Support Vector Machines, which accounts for 55.0%, and Artificial Neural Networks were used 19 times, making up 47.5%. At the same time, Decision Trees and Random Forests, k-Nearest Neighbors, and Linear Discriminant Analysis were used 11, 8, and 7 times, respectively, which account for 27.5%, 20.0%, and 17.5%, respectively.

Across the reviewed studies, the strongest performance was most often reported when classifiers were paired with feature sets that capture both spectral and nonlinear characteristics of EEG, particularly when sufficient preprocessing and artifact handling were applied. Support Vector Machines and neural-network-based models were frequently selected due to their capacity to handle high-dimensional feature spaces; however, reported accuracies were highly dependent on study design and validation strategy. A repeated limitation across the classification literature is the lack of consistent evaluation protocols, where many studies rely on small sample sizes, single-session designs, or within-subject testing, making direct comparison of reported accuracies unreliable. Inter-subject and cross-session evaluation remains underexplored in meditation EEG classification, and only a small number of studies explicitly address generalization across participants, recording days, or meditation expertise levels. These gaps highlight the need for larger datasets, standardized validation (including cross-session and subject-independent testing), and clearer reporting of preprocessing and partitioning strategies when developing meditation EEG classification pipelines.

## 2.6 Conclusion

### 2.6.1. Recap of the Review's Major Insights

This review conducted a comprehensive computational analysis of recent meditation EEG studies, focusing on feature extraction and classification techniques. As the first review of its kind, it provides a broad summary of existing research, offering valuable guidance for future EEG-based meditation studies. Among 164 selected articles, 163 addressed feature extraction and 40 covered classification techniques, highlighting a clear imbalance between the two areas.

Although the main focus was on feature extraction and classification, several secondary factors were also reviewed for their influence on outcomes. Participant and meditation details were identified as key variables and summarized in Tables 2.1 and 2.2. Preprocessing methods varied notably across studies, underscoring their importance in EEG-based BCI pipelines; these methods are summarized in Table 2.3.

Feature extraction approaches showed considerable diversity, leading to their classification into ten categories: Frequency Domain Analysis, Time-Frequency and Spectral Entropy Methods, Amplitude Features, Dimensionality Reduction and Decomposition, Phase and Synchrony Analysis, Entropy-Based Measures, Connectivity and Coherence Measures, Spatial, Microstate, Network and Topological Features, Statistical Features, and Advanced Modeling, Machine Learning, and Complex Features (Table 2.4).

Of the 164 studies, 40 employed classification algorithms that fell into five primary groups: Support Vector Machines, k-Nearest Neighbors, Decision Trees and Random Forests, Linear Discriminant Analysis, and Artificial Neural Networks. Various combinations of these methods,

along with their pipeline performances, are summarized in Table 2.5. Table 2.6 provides one-row summaries of these articles, outlining objectives, key findings, and limitations.

EEG frequency bands—Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), and Gamma (>30 Hz)—were commonly analyzed. Some studies focused on specific bands, while others used the full EEG spectrum to observe differences in band-specific activity. In both cases, bands showing stronger associations with meditation outcomes were identified and summarized in Table 2.7. Studies that analyzed all bands without distinct differences were marked with a ‘✓’ across all columns.

This study reviewed 164 recent research articles related to feature extraction and classification methods used in meditation EEG. In this work, we presented valuable information on feature extraction, classification, study objectives, key findings, limitations, preprocessing and cleaning, meditation and EEG frequency details, and participant characteristics extracted from these research articles. This is the first time meditation EEG research articles have been analysed in such depth, making a significant and novel contribution to scientific research.

### 2.6.2. Mapping Findings to Current and Future Meditation EEG Studies

The biggest challenge encountered in this review, when examining past and present EEG meditation feature extraction and classification studies, was the inability to compare procedures and performance due to significant methodological differences. As a future direction, it is essential for meditation EEG researchers to develop standardized protocols and guidelines. Establishing a common framework would support more consistent research practices and facilitate meaningful comparisons of outcomes across studies.

In reviewing past research on EEG meditation, it is evident that in most cases, EEG data were collected independently by researchers. Unfortunately, much of this data is not publicly shared, which continues to hinder the progress of meditation EEG research. We therefore emphasize the importance of submitting collected EEG meditation data to public repositories. This would enable individuals with diverse expertise to access and analyse the data, leading to further advancements, replication studies, and improved cross-study comparisons in the field.

Furthermore, we observed that visual inspection and manual cleaning have been widely used in EEG cleaning and preprocessing in past research. Although the use of automated algorithms for EEG data cleaning has increased in recent years, manual methods remain prevalent in many studies. This highlights the need for continued advancements in the development of algorithms that can support EEG data cleaning. Such developments should aim to replicate the expertise involved in manual inspection, enabling reliable and consistent data processing. The application of these automated algorithms in future research will help establish a common foundation for EEG preprocessing in meditation studies.

When looking at the EEG frequency bands, our study shows that Alpha, Theta, and Beta bands are the most commonly used in meditation research, with Alpha being the most frequently analysed. This suggests that meditation may be primarily associated with these three bands, or that further research is needed to explore the potential roles of Delta and Gamma bands in meditation. The literature also highlights the importance of applying signal filtering methods and segmenting EEG data into epochs when conducting EEG-based meditation studies. Among the 39 meditation techniques examined in the selected studies, Mindfulness Meditation appeared most frequently, which may suggest that this method is particularly well-suited to EEG-based meditation research. Regarding the ‘State’ and ‘Trait’ changes influenced by meditation, a significant portion of the research focused on ‘State’ changes, with relatively

fewer studies addressing ‘Trait’ changes. This may indicate that studying ‘Trait’ changes is more challenging than investigating ‘State’ changes using EEG data.

We categorized meditation EEG feature extraction studies into ten sub-groups and observed that a significant proportion of research relied on frequency domain features (62.0%), while other methods were used at much lower rates. This dominance can be attributed to the long-standing use of frequency domain features in meditation research, whereas most of the other methods are relatively recent developments in the field of meditation EEG. This highlights numerous opportunities for future studies to explore these alternative techniques for feature extraction and analysis.

In meditation EEG classification, Support Vector Machines (SVMs) were the most commonly used algorithm (55.0%), followed by Artificial Neural Networks (ANNs) (47.5%). A key factor contributing to the rise in ANN usage is the growing application of machine learning in computational neuroscience, which has led to increased classification accuracy in recent years. However, to facilitate meaningful comparisons across meditation EEG classification studies, it is essential to establish a common foundation.

Therefore, our final conclusion is that researchers conducting meditation EEG studies should develop and adhere to standardized protocols for data collection, cleaning, and processing. Such practices would enable more consistent comparisons, support data sharing, and ultimately accelerate progress in the field.

Table 2.1 Summary of Participant and Meditation Details

No	Reference	Meditation Type	State/Trait	Experience Level	Total No of Participants	Intra/Inter-Subject Analysis	Comparison Groups
1	[33]	Mindfulness Meditation	State	Novice	34	Inter-Subject	Meditation group, Control group
2	[91]	Mindfulness Meditation	State	Novice	34	Intra-Subject/ Inter-Subject	Meditation group, Control group
3	[34]	Mindfulness Meditation	Trait	Novice (46), Expert (49)	95	Inter-Subject	Experienced Meditators, Non-Meditators
4	[152]	OM Mantra Meditation	State	Novice	23	Inter-Subject	Before OM Mantra Meditation, After OM Mantra Meditation.
5	[150]	Mindfulness Meditation	State	Novice	35	Intra-Subject	Pre-MF, Post-MF, TaskRest1, TaskRest2.
6	[218]	Yoga Meditation	State	Novice (20), Expert (20)	40	Inter-Subject	Advanced yoga meditators, Non-meditators.
7	[210]	Himalayan Yoga Meditation\ Isha Shoonya Meditation\ Vipassana Meditation	State	Control group and 3 Expert meditation groups (16 each)	64	Inter-Subject	Control Group, Himalayan Yoga Group, Isha Shoonya Group, Vipassana Group.
8	[191]	Autobiographical Self-Reflection Meditation\ Mantra Meditation	State	Novice (30 each)	90	Inter-Subject	Autobiographical Self-Reflection Group, Mantra-Based Meditation Group, Control Group
9	[151]	Focused Attention Meditation	State	Novice	11	Intra-Subject	Pre-meditation state, Post-meditation state
10	[123]	Not Mentioned	State	Not Mentioned	10	Inter-Subject	Patterns for different number of brain waves compared with each other
11	[209]	Mindfulness Meditation	State	Novice (11), Expert (11)	22	Inter-Subject	Mindfulness meditation group, Non-meditation group.
12	[227]	Kriya Yoga Meditation	State	Expert	23	Intra-Subject	Different stages/time in meditation
13	[184]	Himalayan Yoga Meditation	State	Novice (12), Expert (12)	24	Inter-Subject	Expert Meditators, Novice Meditators
14	[230]	Mindfulness Meditation	State	Novice	36	Inter-Subject	Before training meditation, After training meditation (8 Week)
15	[92]	Sitting Meditation\ Walking Meditation	State	Novice	20	Inter-Subject	Sitting Meditation, Walking Meditation.
16	[93]	Sitting Meditation\ Walking Meditation	State	Novice	20	Inter-Subject	Sitting Around, Sitting Meditation, Strolling, Walking Meditation.

17	[144]	Focused Attention Meditation	State	Novice (12), Expert (2)	14	Intra-Subject/ Inter-Subject	Focused Attention Meditation, Problem-Solving Task.
18	[83]	Open Monitoring Meditation	State	Novice (25), Expert (25)	50	Inter-Subject	Experienced Subjects, Inexperienced Subjects for meditation state and the background state
19	[188]	Concentrative Meditation	State	Not Mentioned	15	Inter-Subject	Meditation, Tension-imagination
20	[171]	Yoga Meditation	Trait	Expert (13), Control (15)	28	Inter-Subject	Long-term meditators, Novice control participants
21	[203]	Rajayoga Meditation	State	Expert	54	Intra-Subject/ Inter-Subject	Meditative state, Resting state
22	[94]	Mindfulness Meditation	State	Novice (42), Control (34)	76	Inter-Subject	Mindfulness-based stress reduction group, Waitlist control group
23	[200]	Loving Kindness Meditation	State	Expert	32	Intra-Subject	Pre-Resting, LKM-Self, LKM-Others, Post-Resting
24	[228]	Mindfulness Meditation	State	Novice, Expert	8	Inter-Subject	Experts and Novices: Meditation and Mind Wandering
25	[204]	Isha Shoonya Meditation	State	Expert (20), Control (31)	51	Inter-Subject	Isha Shoonya meditators, Control subjects.
26	[176]	Yoga Meditation\ Kriya Yoga Meditation	State	Novice (25), Control (25)	50	Inter-Subject	Meditation Group, Control Group: Before and after training
27	[95]	Open Monitoring Meditation	State	Novice	223	Inter-Subject	Pre-Meditation, Post-Meditation
28	[96]	Concentrative Meditation\ Analytical Meditation	State	Novice (9), Intermediate (6), Expert (8)	23	Intra-Subject/ Inter-Subject	Concentrative meditation, Analytical meditation, Beginners, Intermediate meditators, Advanced meditators
29	[37]	Not Mentioned	State	Novice	25	Inter-Subject	Before and After meditation training
30	[214]	Chan Meditation	State	Novice, Expert	Not Mentioned	Inter-Subject	Experienced Meditators, Noivce Meditators: Meditating State, Idle State, Talking State
31	[193]	Himalayan Yoga Meditation\ Isha Shoonya Meditation\ Vipassana Meditation	State	Expert (63), Control (31)	94	Inter-Subject	Himalayan Yoga practitioners, Isha Shoonya Yoga practitioners, Vipassana meditation practitioners, Control subjects.
32	[182]	Mindfulness Meditation	State	Novice	70	Intra-Subject	Mindfulness-Based Cognitive Therapy group, Cognitive Therapy group
33	[97]	Combination of several techniques	State	Expert	35	Inter-Subject	Theravada practitioners, Vajrayana practitioners: various combinations
34	[196]	Vipassana Meditation	State	Novice	50	Inter-Subject	Meditation State, Controlled (Normal) State: Before and after 4-week training

35	[125]	Focused Attention Meditation	State	Novice (12), Control (12)	24	Inter-Subject	Experimental neurofeedback group, Control group
36	[98]	Focused Attention Meditation	State\ Trait	Expert	60	Intra-Subject/ Inter-Subject	Active training participants, Waitlist control participants
37	[126]	Focused Attention Meditation\ Open Monitoring Meditation \ Loving Kindness Meditation	State	Expert	22	Intra-Subject/ Inter-Subject	Rest Condition, Focused Attention Meditation, Open Monitoring Meditation, Loving Kindness Meditation
38	[201]	Mindfulness Meditation	State	Novice	11	Intra-Subject/ Inter-Subject	Early Stage vs. Late Stage\ Resting State vs. Mindfulness Meditation State
39	[127]	Tibetan Nyingmapa Meditation	State	Novice (10), Intermediate (10), Expert (10)	30	Inter-Subject	Novice Group, Intermediate Group, Expert Group
40	[165]	Breathing Meditation	State	Novice, Intermediate, Expert	30	Inter-Subject	Novice Group, Intermediate Group, Expert Group
41	[177]	Kriya Yoga Meditation	State	Novice (15), Control (10)	25	Inter-Subject	Experimental meditation group, Control group
42	[202]	Rajayoga Meditation	State	Expert	54	Inter-Subject	Meditative state, Non-meditative state
43	[229]	Mindfulness Meditation	State	Novice (32), Control (28)	60	Inter-Subject	Meditation-trained group, Control group
44	[222]	Himalayan Yoga Meditation	State\ Trait	Novice (12), Expert (12)	24	Inter-Subject	Expert Meditators, Novice Meditators
45	[29]	Vipassana Meditation\ Mindfulness Meditation	Trait	Expert (16), Novice Control (19)	35	Inter-Subject	Experienced meditator group, Control group
46	[194]	Not Mentioned	State	Not Mentioned	40	Inter-Subject	Concentration, Meditation
47	[197]	Breathing Meditation	State	Novice	25	Intra-Subject	Breath focus, Mind wandering
48	[128]	Transcendental Meditation\ Rajayoga Meditation\ Mindfulness Meditation	State	Expert	52	Inter-Subject	Transcendental Meditation, RajaYoga Meditation, Mindfulness Meditation: Before and After
49	[147]	Yoga Meditation	State	Expert	30	Inter-Subject	Yoga, Meditation, Combined Yoga–Meditation
50	[99]	Focused Attention Meditation	State\ Trait	Novice (21), Expert (28)	49	Intra-Subject/ Inter-Subject	Meditation Practitioners, Novice Controls
51	[189]	Himalayan Yoga Meditation	Trait	Intermediate (12), Expert (12)	24	Intra-Subject/ Inter-Subject	Expert meditators, Intermediate meditators

52	[122]	Mindfulness Meditation	State	Novice	70	Inter-Subject	Mindfulness Training Group, Waiting List Group
53	[153]	Himalayan Yoga Meditation\ Mantra Meditation	State	Expert	32	Inter-Subject	Mantra Meditation, Himalayan Yoga, Control Group
54	[100]	Dharana Meditation	State	Not Mentioned	15	Inter-Subject	Pre-meditation, Post-meditation
55	[198]	Himalayan Yoga Meditation	State	Novice (12), Expert (12), Control (16), Parkinson (15)	55	Intra-Subject/ Inter-Subject	Expert Meditators, Novice Meditators, Healthy Controls, Parkinson's Disease Patients: multiple sessions
56	[154]	Mantra Meditation	State	Novice (10), Expert (10)	20	Intra-Subject/ Inter-Subject	Expert meditators, Novice meditators: Three sessions
57	[148]	Breathing Meditation	State	Novice (29), Expert (29)	58	Inter-Subject	Novice Meditators, Expert Meditators
58	[101]	Himalayan Yoga Meditation	State	Novice (12), Expert (12), Control (12)	36	Inter-Subject	Expert Meditators, Non-Expert Meditators, Control Subjects
59	[155]	Shamatha Meditation\ Zen Meditation	State	Expert	28	Inter-Subject	Compares different meditation types and styles
60	[215]	Breathing Meditation	State	Expert (29), Control (29)	58	Inter-Subject	Novice Meditators (Controls), Experienced Meditators
61	[174]	Himalayan Yoga Meditation\ Isha Shoonya Meditation\ Vipassana Meditation	State	Expert (16*3), Control (16)	64	Intra-Subject/ Inter-Subject	Control Group, Himalayan Yoga Meditation, Isha Shoonya Meditation, Vipassana Meditation: Meditation and Instructed mind-wandering
62	[149]	Himalayan Yoga Meditation	State\ Trait	Novice (12), Expert (12)	24	Inter-Subject	Expert meditators, Non-expert meditators.
63	[156]	Kriya Yoga Meditation	State	Intermediate to expert (23), Control (10)	33	Inter-Subject	Kriya Yoga Meditators, Non-Meditators (Control Group)
64	[178]	Theta Healing Meditation	State	Intermediate	20	Intra-Subject	During meditation, Post-meditation state
65	[186]	Calm Meditation\ Insight Meditation	Trait	Novice (7), Expert (7)	14	Intra-Subject	Experienced meditators, Novice (inexperienced) meditators
66	[163]	Body Scan Meditation\ Mantra Meditation	Trait	Intermediate (6), Expert (6)	12	Inter-Subject	Advanced Practitioners, Intermediate Practitioners: 2 meditation types, non-meditation
67	[183]	Calm Meditation\ Insight Meditation	Trait	Expert (7), Control (7)	14	Inter-Subject	Expert, Control: multiple meditation and non-meditation sessions
68	[224]	Body Scan Meditation	State	Novice	45	Inter-Subject	Body Scan Training group, Relaxation training control group: Before and after training

69	[220]	Kriya Yoga Meditation	State	Expert	23	Intra-Subject/ Inter-Subject	Experienced meditators
70	[179]	Kriya Yoga Meditation	State	Novice (10), Expert (23)	33	Inter-Subject	Meditators, Non-meditators.
71	[157]	Thoughtless Emptiness Meditation	State	Expert	29	Inter-Subject	Four different sessions
72	[84]	Open Monitoring Meditation \ Focused Attention Meditation	State	Novice (15), Expert (16)	31	Intra-Subject/ Inter-Subject	Expert meditation practitioners, Novice practitioners
73	[25]	Focused Attention Meditation	State	Expert	32	Intra-Subject/ Inter-Subject	Meditation, Mind-Wandering: two different settings
74	[164]	Mindfulness Meditation	State \ Trait	Novice (20), Control (20)	40	Intra-Subject	Mindfulness meditation group, Waitlist control group: Before and after Training
75	[102]	Thoughtless Emptiness Meditation	State	Novice to Expert	50	Inter-Subject	Novice, Intremediate, Expert groups were arranged
76	[129]	Himalayan Yoga Meditation \ Isha Shoonya Meditation \ Vipassana Meditation	State \ Trait	Expert (20, 27, 20), Control (32)	99	Inter-Subject	Vipassana Group, Himalayan Yoga Group, Isha Shoonya Group, Control Group: Meditation and Mind-wandering
77	[121]	Vipassana Meditation	State	Expert	16	Intra-Subject	Meditation, Control task
78	[103]	OM Mantra Meditation	State	Novice	23	Intra-Subject	Before OM mantra meditation, After OM mantra meditation
79	[23]	Vipassana Meditation	State	Expert	16	Intra-Subject	Meditation state, Control state (instructed mind-wandering)
80	[170]	Effortless Awareness Meditation	State	Novice (16), Expert (16)	32	Inter-Subject	Novice meditators, Experienced meditators: multiple different sessions
81	[85]	Inner Wisdom Meditation	State	Novice	6	Intra-Subject	Data collected for mutiple sessions/tasks
82	[130]	Not Mentioned	State	Novice (20), Expert (20)	40	Inter-Subject	Regular meditators, Non-meditators
83	[86]	Transcendental Meditation	State	Novice (6), Expert (6)	12	Inter-Subject	Advanced Meditation Practitioners, Control Group
84	[166]	Preksha Meditation	State	Novice (29), Control (26)	55	Inter-Subject	Preksha Meditation Group, Control Group: multiple session data
85	[131]	Body Scan Meditation	State	Novice	43	Inter-Subject	Meditation Group, Relaxation Training Group: multiple sessions
86	[169]	OM Mantra Meditation	State	Novice	20	Intra-Subject	Before meditation, After meditation
87	[104]	Mindfulness Meditation	Trait	Expert (22), Control (23)	45	Inter-Subject	Long-term meditators, Matched controls

88	[205]	Mindfulness Meditation\ Walking Meditation	State\ Trait	Novice (14), Control (15)	29	Inter-Subject	Meditation Group, Control Group: Before and after training
89	[195]	Theta Healing Meditation	State	Not Mentioned	9	Intra-Subject	Meditation, Post- meditation
90	[172]	Vipassana Meditation	Trait	Expert (31), Control (30)	61	Inter-Subject	Experienced meditators, Control group
91	[145]	Qigong Meditation\ Yoga Meditation	State	Expert	43	Intra-Subject/ Inter-Subject	Meditation, Rest, Arithmetic task
92	[120]	Transcendental Meditation	State\ Trait	Novice (38), Control (41)	79	Inter-Subject	Transcendental Meditation programme, Wait-list control group: Beginning and End
93	[219]	Transcendental Meditation	State	Expert	37	Intra-Subject	Listening to Vedic Recitation, Transcendental Meditation
94	[105]	Not Mentioned	State	Not Mentioned	27	Intra-Subject	Before training, After training
95	[106]	Rajayoga Meditation	State	Expert (21), Control (21)	42	Inter-Subject	Long-term meditators, Control group: In two sessions
96	[223]	Transcendental Meditation	State	Novice to Expert	87	Inter-Subject	Different task sessions including Meditation
97	[107]	Kriya Yoga Meditation	State	Novice (15), Control (10)	25	Inter-Subject	Meditation group, Control group: before and after training: rest and active
98	[158]	Breathing Meditation\ Body Scan Meditation	State	Novice (10), Control (10)	20	Intra-Subject/ Inter-Subject	Test Subjects, Normal controls: beginning and end of training
99	[159]	Focused Attention Meditation\ Body Scan Meditation	State	Novice	43	Intra-Subject	Meditation and non- meditation: different sessions
100	[14]	Kriya Yoga Meditation\ High- Vibration Meditation\ Zen Meditation\ Mindfulness Meditation\ Qigong Meditation	Trait	Novice (10), Expert (5)	15	Inter-Subject	Experienced Meditators, Novice Participants: different sessions
101	[132]	Focused Attention Meditation	State	Novice (21), Control (23)	44	Inter-Subject	Meditation Group, Control Group: multiple different sessions
102	[213]	Mindfulness Meditation	Trait	Expert (22), Control (22)	44	Inter-Subject	Experienced Meditators, Healthy Control Participants
103	[206]	Mindfulness Meditation	Trait	Expert (34), Control (28)	62	Inter-Subject	Experienced Meditators, Control Participants
104	[192]	Transcendental Meditation	State	Expert	26	Inter-Subject	Multiple different sessions

105	[124]	Transcendental Meditation	State\ Trait	Novice (9), Intermediate (3)	12	Intra-Subject/ Inter-Subject	Intermediate group, Novice group: Multiple different sessions
106	[133]	Open Monitoring Meditation	Trait	Novice (10), Expert (11)	21	Inter-Subject	Long-term meditators, First-time meditators: different instances
107	[108]	Mindfulness Meditation\ Loving Kindness Meditation	State	Novice (38), Expert (29)	67	Intra-Subject/ Inter-Subject	Long-term meditators, Novice participants: Multiple different sessions
108	[134]	Concentrative Meditation	State	Novice (10), Expert (10)	20	Inter-Subject	Experienced meditators, Novice meditators: Multiple different sessions
109	[135]	Open Monitoring Meditation	State\ Trait	Expert (10), Control (10)	20	Inter-Subject	Experienced meditators, Healthy controls: Multiple different sessions
110	[109]	Autogenic Meditation	State	Intermediate	14	Intra-Subject	Baseline condition, Meditation condition
111	[110]	Autogenic Meditation	State	Intermediate	13	Intra-Subject/ Inter-Subject	Baseline condition, Meditation condition
112	[111]	Breathing Meditation	State	Novice	58	Intra-Subject	Spontaneous breathing, Paced breathing
113	[136]	Vipassana Meditation	State	Expert	18	Intra-Subject	Beginning of meditation, Middle of meditation, End of meditation
114	[12]	Loving Kindness Meditation	State	Expert	1	Intra-Subject	Pre-resting task, Meditation task, Post-resting task
115	[143]	Concentrative Meditation	State	Novice to Intermediate	33	Intra-Subject	Meditation state, Non-meditation resting state
116	[175]	Mindfulness Meditation	State	Novice	82	Inter-Subject	Multiple different sessions
117	[36]	Mindfulness Meditation	State	Expert	32	Inter-Subject	Meditation, Mind-Wandering: multiple different sessions
118	[160]	Loving Kindness Meditation	State	Novice to Expert	41	Inter-Subject	Multiple different sessions
119	[87]	Focused Attention Meditation	State	Intermediate	1	Intra-Subject	Meditation, Mind-wandering.
120	[137]	Breathing Meditation	State	Not Mentioned	15	Intra-Subject	Rest Session, Stress Session, Meditation Session
121	[27]	Breathing Meditation	State	Novice (29), Expert (29)	58	Intra-Subject/ Inter-Subject	Experienced Meditators, Novices (Control Group): Meditation, rest multiple sessions
122	[112]	Not Mentioned	State	Not Mentioned	15	Intra-Subject	Before meditation, After a month of meditation
123	[138]	Himalayan Yoga Meditation\ Isha Shoonya Meditation\ Vipassana Meditation	State	Expert (24, 20, 19), Control (31)	94	Inter-Subject	Experienced Meditators (Himalayan Yoga, Vipassana, Isha Shoonya), Control Group (novice meditators): two data collection sessions

124	[38]	Mindfulness Meditation	State	Novice (21), Control (20)	41	Intra-Subject/ Inter-Subject	Treatment Group (8-week mindfulness training programme), Control Group (participants on a waitlist who did not receive the training): Multiple data collection sessions
125	[173]	Mindfulness Meditation	State\ Trait	Expert (16), Control (18)	34	Inter-Subject	Experienced Mindfulness Meditators, Non-Meditators (Healthy Controls)
126	[113]	Rajayoga Meditation	State\ Trait	Expert (27), Control (30)	57	Intra-Subject/ Inter-Subject	Long-term Meditators and Healthy Control Subjects: Before and after session data collection
127	[167]	Mindfulness Meditation	Trait	Expert (39), Control (36)	75	Inter-Subject	Experienced Meditators, Healthy Control Non-Meditators
128	[216]	Rajayoga Meditation	State	Expert	14	Inter-Subject	Multiple meditation and non-meditation sessions
129	[190]	Mindfulness Meditation	State	Novice	3	Intra-Subject	Mind Wandering (Control Condition), Mindfulness Meditation, Hypnosis
130	[180]	Focused Attention Meditation	State	Novice	20	Intra-Subject/ Inter-Subject	Pre-Meditation, Post-Meditation (after 8-week training)
131	[146]	Chi Meditation\ Yoga Meditation	State	Expert (8), Control (11)	19	Intra-Subject/ Inter-Subject	Experienced Meditators, Control Group of Non-Meditating Individuals
132	[88]	Buddhist Jhāna Meditation	State	Expert	29	Intra-Subject	Multiple different sessions
133	[212]	Mindfulness Meditation	State	Novice (16), Expert (16)	32	Inter-Subject	Novice meditators, Experienced meditators
134	[185]	Himalayan Yoga Meditation	State	Novice (12), Expert (12)	24	Inter-Subject	Expert practitioners, Non-expert practitioners
135	[207]	Mindfulness Meditation	State\ Trait	Intermediate (26), Control (23)	49	Intra-Subject/ Inter-Subject	Mindfulness Group, Control Group: Before and after 8 week training
136	[211]	Kriya Yoga Meditation	Trait	Novice	10	Intra-Subject	Pre-meditation condition, Post-meditation condition: 4-month training
137	[208]	Concentrative Meditation	State	Novice (12), Expert (12)	24	Inter-Subject	Experienced meditators, Novice control participants: Rest and meditation
138	[221]	Not Mentioned	State	Expert	30	Inter-Subject	Awake, Meditation, Drowsiness
139	[114]	Vipassana Meditation\ Loving Kindness Meditation	State	Novice (24), Expert (24)	48	Intra-Subject	Long-term Meditators, Meditation Novice Controls: Multiple session data collection
140	[8]	Focused Attention Meditation\ Open Monitoring	Trait	Novice (29), Expert (29)	58	Inter-Subject	Long-term Meditators, Meditation Novice Controls: Multiple session data collection

		Meditation \ Loving Kindness Meditation					
141	[115]	Mindfulness Meditation	Trait	Novice	66	Intra-Subject	Multiple session data collection before and after the 10 week training
142	[35]	Mindfulness Meditation	State	Novice	54	Intra-Subject	Meiditation, Non-meditation multiple sessions
143	[161]	Vipassana Meditation	State	Expert	2	Intra-Subject/ Inter-Subject	Pre-Meditaiton, Meditation, Post-meditation
144	[199]	Breathing Meditation	State	Novice (1), Intermediate (1), Expert (1)	3	Intra-Subject/ Inter-Subject	Multiple meditation sessions
145	[116]	Stabilizing Meditation\ Analytical Meditation	State	Expert	1	Intra-Subject	Multiple meditation and non-meditation sessions
146	[117]	Shamatha Meditation	State	Study (22), Control (22): Both with varying experience	44	Intra-Subject/ Inter-Subject	Beginning, middle, end of three-month training
147	[118]	Not Mentioned	State	Novice	6	Inter-Subject	Meditation state, Reading activity.
148	[119]	Vipassana Meditation	State\ Trait	Novice (24), Intermediate (22), Expert (21)	67	Inter-Subject	Novice, Intermediate, Expert: Multiple meditation and non-meditation sessions
149	[225]	Transcendental Meditation	State	Expert	20	Intra-Subject	Multiple meditation and non-meditation sessions
150	[226]	Focused Attention Meditation	State	Novice	29	Inter-Subject	Test group, Control group
151	[139]	Mindfulness Meditation	State\ Trait	Novice to Intermediate	201	Inter-Subject	Test group, Control group: multiple session data
152	[89]	Mindfulness Meditation	State	Novice (32), Control (16)	48	Inter-Subject	Meditation Group 1, Meditation Group 2, Control Group: Multiple session data collection
153	[140]	Mindfulness Meditation	State	Expert	1	Intra-Subject	Different meditation related mental tasks
154	[162]	Not Mentioned	State	Not Mentioned	10	Inter-Subject	Multiple meditation and non-meditation sessions
155	[217]	Rajayoga Meditation	State	Expert	15	Inter-Subject	Multiple meditation and non-meditation sessions
156	[90]	Rajayoga Meditation	State	Expert	52	Intra-Subject	Pre-Meditaiton, Meditation, Post-meditation
157	[168]	Mindfulness Meditation	State	Novice	11	Intra-Subject	Meditation, Rest condition: Before and after 8-week training
158	[24]	Mindfulness Meditation	State	Novice	37	Intra-Subject/ Inter-Subject	Multiple groups and sessions throughout 8-week training

159	[39]	Breathing Meditation	State	Expert	1	Intra-Subject	Meditation, Non-Meditation
160	[231]	Not Mentioned	State	Novice	10	Intra-Subject/ Inter-Subject	Meditation, Attention
161	[181]	Not Mentioned	State	Novice (5), Intermediate (5), Expert (1)	11	Inter-Subject	Expert meditator, Intermediate meditators, Non-meditators
162	[187]	Kriya Yoga Meditation	State	Novice (10), Expert (23)	33	Inter-Subject	Meditator group, Novice Control group
163	[141]	Transcendental Meditation\ Qigong Meditation	State	Novice (8), Expert (16)	24	Intra-Subject/ Inter-Subject	Transcendental Meditation Group, Qigong Group, Control Group: Multiple sessions
164	[142]	Mindfulness Meditation\ Mindlessness Meditation	State	Novice	24	Intra-Subject	Meditation task, Control task

Table 2.2 Types of Meditation Techniques Used

No	Meditation Type	Count	Percentage (%)
1	Mindfulness Meditation	37	24.3
2	Focused Attention Meditation	14	9.2
3	Vipassana Meditation	14	9.2
4	Himalayan Yoga Meditation	13	8.6
5	Breathing Meditation	10	6.6
6	Kriya Yoga Meditation	10	6.6
7	Transcendental Meditation	9	5.9
8	Rajayoga Meditation	8	5.3
9	Loving Kindness Meditation	7	4.6
10	Open Monitoring Meditation	7	4.6
11	Isha Shoonya Meditation	6	3.9
12	Yoga Meditation	6	3.9
13	Body Scan Meditation	5	3.3
14	Concentrative Meditation	5	3.3
15	Mantra Meditation	5	3.3
16	OM Mantra Meditation	3	2
17	Qigong Meditation	3	2
18	Walking Meditation	3	2
19	Analytical Meditation	2	1.3
20	Autogenic Meditation	2	1.3
21	Calm Meditation	2	1.3
22	Insight Meditation	2	1.3

23	Shamatha Meditation	2	1.3
24	Sitting Meditation	2	1.3
25	Theta Healing Meditation	2	1.3
26	Thoughtless Emptiness Meditation	2	1.3
27	Zen Meditation	2	1.3
28	Autobiographical Self-Reflection Meditation	1	0.7
29	Buddhist Jhāna Meditation	1	0.7
30	Chan Meditation	1	0.7
31	Chi Meditation	1	0.7
32	Dharana Meditation	1	0.7
33	Effortless Awareness Meditation	1	0.7
34	High-Vibration Meditation	1	0.7
35	Inner Wisdom Meditation	1	0.7
36	Mindlessness Meditation	1	0.7
37	Preksha Meditation	1	0.7
38	Stabilizing Meditation	1	0.7
39	Tibetan Nyingmapa Meditation	1	0.7

Table 2.3 Summary of EEG Preprocessing

No	Reference	No. of Channels	Epoch Size (Overlap)	Signal Filtering Methods	Automated Artifact Removal	Manual Artifact Removal
1	[33]	32	Not Mentioned	FIR linear phase Band-pass filter, High-pass filter, Low-pass filter	Independent Component Analysis	Not Mentioned
2	[91]	32	Not Mentioned	Band-pass filter (FIR linear phase filter)	Not Mentioned	Not Mentioned
3	[34]	64	30s	Band-pass filter	Automatic artifact removal, automatic epoch rejection.	Not Mentioned
4	[152]	16	Not Mentioned	Not Mentioned	Not Mentioned	Not Mentioned
5	[150]	21 or 32	1s	FIR Kaiser-windowed Band-pass filter.	Artifact Subspace Reconstruction, Independent Component Analysis	Yes
6	[218]	30	10s	Tenth-order Butterworth Band-pass filter	Common Average Reference	Not Mentioned
7	[210]	64	5s (2.5s overlap)	Not Mentioned	Not Mentioned	Not Mentioned
8	[191]	4	Not Mentioned	High-pass filter, Low-pass filter	Independent Component Analysis, Artifact Subspace Reconstruction	Not Mentioned

9	[151]	14	7s	Band-pass filter, FIR filter, Hamming window	Not Mentioned	Not Mentioned
10	[123]	1	Not Mentioned	Not Mentioned	Not Mentioned	Not Mentioned
11	[209]	14	Not Mentioned	Chebyshev filter, Notch filter	Daubechies Wavelet Transform	Not Mentioned
12	[227]	64	Not Mentioned	Band-pass Filter, Notch Filter	Wavelet Thresholding, Inverse Discrete Wavelet Transform	Not Mentioned
13	[184]	64	10s	High-pass filter	Not Mentioned	Yes
14	[230]	64	1s	Band-pass filter	Independent Component Analysis	Not Mentioned
15	[92]	14	10s	Not Mentioned	Not Mentioned	Yes
16	[93]	14	10s	Not Mentioned	Not Mentioned	Yes
17	[144]	21	2s (1s overlap)	Third-order Butterworth Band-pass filter	No	Yes
18	[83]	19	2s (1s overlap)	Not Mentioned	Not Mentioned	Not Mentioned
19	[188]	32	10s	Low-pass filter	Not Mentioned	Not Mentioned
20	[171]	32	1.55s	Band-pass filter	Independent Component Analysis	Yes
21	[203]	64	2s	Band-pass filter	Independent Component Analysis	Yes
22	[94]	64	Not Mentioned	Band-pass filter, Notch filter	Independent Component Analysis	Yes
23	[200]	127	2s (1s overlap)	High-pass filter, Low-pass filter	Not Mentioned	Not Mentioned
24	[228]	8	Not Mentioned	Not Mentioned	Not Mentioned	Not Mentioned
25	[204]	64	Not Mentioned	Band-pass filter	Independent Component Analysis	Not Mentioned
26	[176]	32	1s	Band-pass filter, Notch filter	Not Mentioned	Yes
27	[95]	19	2s	Band-pass filter, FIR filter	Independent Component Analysis	Yes
28	[96]	19	300s	High-pass filter, Low-pass filter	Independent Component Analysis	Yes
29	[37]	21	8s	FIR filter	Not Mentioned	Not Mentioned
30	[214]	8	Not Mentioned	Not Mentioned	Not Mentioned	Not Mentioned
31	[193]	72	1s	High-pass filter	Artifact Subspace Reconstruction algorithm, Independent Component Analysis	No
32	[182]	31	3.1s	Not Mentioned	Hybrid REG-ICA method	Yes
33	[97]	11	1s	High-Band pass filter, Notch filter	Not Mentioned	Yes
34	[196]	8	Not Mentioned	Line filter	Not Mentioned	Not Mentioned
35	[125]	64	1s (0.75s overlap)	High-pass filter	Automatic Source Reconstruction, Independent Component Analysis	Yes

36	[98]	88	2s (1s overlap)	Band-pass filter	Second-Order Blind Source Identification	Yes
37	[126]	64	4.096s (1.024s overlap)	Not Mentioned	Independent Component Analysis	Yes
38	[201]	128	5s	Band-pass filter, Notch filter	Automatic Artifact Removal method	Not Mentioned
39	[127]	6	30s, 60s, 90s, 120s, 150s (overlap of 2, 4, 8, 16, and 30 seconds)	High-pass filter, Band-pass filter, Notch filter	Not Mentioned	Yes
40	[165]	8	Not Mentioned	High-pass filter, Band-pass Filter, Notch Filter	Not Mentioned	Not Mentioned
41	[177]	14	Not Mentioned	Band-pass filter, Notch Filter	Not Mentioned	Not Mentioned
42	[202]	64	10s	Band-pass filter, Notch Filter	Independent Component Analysis	Yes
43	[229]	64	4s	Band-pass filter, Notch Filter	Not Mentioned	Yes
44	[222]	78	2s, 5s, 10s	High-pass filter, FIR filter	Not Mentioned	Not Mentioned
45	[29]	64	Not Mentioned	Band-pass filter	Independent Component Analysis, Template Matching Procedure.	Yes
46	[194]	1	Not Mentioned	Not Mentioned	Not Mentioned	Not Mentioned
47	[197]	1	Not Mentioned	Band-pass filter	Not Mentioned	Not Mentioned
48	[128]	2	1s	Band-pass filter	Not Mentioned	Yes
49	[147]	16	Not Mentioned	Band-pass filter	Not Mentioned	Yes
50	[99]	128 or 32	Not Mentioned	Bandpass filter (Butterworth FIR filter)	Independent Component Analysis	Yes
51	[189]	64	20s	Band-pass filter	Not Mentioned	Yes
52	[122]	16	2s	Band-pass filter, Notch filter	Independent Component Analysis	Yes
53	[153]	32 or 72	120s (15s overlap)	Butterworth Band-pass filter, Notch filter	Independent Component Analysis, automated artifact removal from EEGLAB	Yes
54	[100]	7	Not Mentioned	FIR filter	Independent Component Analysis	Yes
55	[198]	32 or 64	Epoch size not given	High-pass filter, Low-pass filter	Not Mentioned	Yes
56	[154]	32	10s (5s overlap)	Band-pass filter, Notch filter	Independent Component Analysis	Yes
57	[148]	19	1s, 2s, 3s, 4s, 5s	High-pass filter, Notch filter	Independent Component Analysis	Not Mentioned
58	[101]	64	2s, 4s, 6s	High-pass linear FIR filter	Independent Components Analysis, Artifact Subspace Reconstruction	Yes
59	[155]	16	5s (0.5s overlap)	Not Mentioned	Not Mentioned	Not Mentioned

60	[215]	19	5s	Band-pass filter	Not Mentioned	Not Mentioned
61	[174]	64	10s (5s overlap)	Not Mentioned	Not Mentioned	Not Mentioned
62	[149]	64	20s	High-pass filter, Line Noise Removal	Artifact Subspace Reconstruction, Adaptive Mixture Independent Component Analysis	Not Mentioned
63	[156]	64	1s (0.5s overlap)	Band-pass filter, Notch filter	Wavelet thresholding method	Not Mentioned
64	[178]	2	1s	High-pass filter, Low-pass filter	Not Mentioned	Not Mentioned
65	[186]	19	0.5s	Band-pass filter, Notch filter	Not Mentioned	Not Mentioned
66	[163]	25	5s	Band-pass filter	FASTER algorithm, Independent Component Analysis	Yes
67	[183]	19	Not Mentioned	Band-pass filter, Notch filter	Not Mentioned	Not Mentioned
68	[224]	28	Not Mentioned	High-pass filter, Low-pass filter	Not Mentioned	Yes
69	[220]	64	Not Mentioned	Band-pass filter, Notch filter	Wavelet thresholding method	Not Mentioned
70	[179]	64	Not Mentioned	Band-pass filter, Notch filter	Wavelet thresholding method	Not Mentioned
71	[157]	128	150s or 600s	Band-pass filter, Notch filter	Standard Regression Method	Yes
72	[84]	128	2s	Band-pass filter, Notch filter	Independent Component Analysis	Yes
73	[25]	31	1s	Band-pass filter, Notch filter	Independent Component Analysis	Yes
74	[164]	64	2.8s	High-pass filter, Low-pass filter	Independent Component Analysis	Yes
75	[102]	64	2s, 1s (0.5s overlap)	Band-pass filter	Not Mentioned	Yes
76	[129]	64	1s (0.5s overlap)	High-pass filter	Independent Component Analysis	Yes
77	[121]	19	2s	High-pass filter	Independent Component Analysis	Yes
78	[103]	16	1s	Band-pass filter	Not Mentioned	Not Mentioned
79	[23]	19	3s	High-pass filter	Independent Component Analysis	Yes
80	[170]	128	1s	Band-pass filter (IIR Butterworth filter)	Not Mentioned	Yes
81	[85]	1	Not Mentioned	Not Mentioned	Not Mentioned	Not Mentioned
82	[130]	2	Not Mentioned	Band-pass filter, Notch filter	Not Mentioned	Not Mentioned
83	[86]	1	Not Mentioned	Not Mentioned	Not Mentioned	Not Mentioned
84	[166]	32	Not Mentioned	High-pass filter, Low-pass filter	Not Mentioned	Yes
85	[131]	16	2s	Low-pass filter	Not Mentioned	Yes
86	[169]	Not Mentioned	Not Mentioned	Not Mentioned	Not Mentioned	Not Mentioned

87	[104]	64	4s	High-pass filter	Independent Component Analysis	Yes
88	[205]	19	Not Mentioned	High-pass filter	Independent Component Analysis	Not Mentioned
89	[195]	2	8s	Not Mentioned	Not Mentioned	Not Mentioned
90	[172]	32	1s	Band-pass filter	Not Mentioned	Yes
91	[145]	19	2s	Band-pass filter	Independent Component Analysis	Yes
92	[120]	32	2s	Band-pass filter, Low-pass filter	Not Mentioned	Yes
93	[219]	32	2s	Band-pass filter	Not Mentioned	Yes
94	[105]	8	30s	Band-pass filter, Notch filter	Not Mentioned	Yes
95	[106]	61	Not Mentioned	Band-pass filter, Notch filter	FASTICA algorithm (Fast Independent Component Analysis)	Yes
96	[223]	32	60s	Not Mentioned	Not Mentioned	Not Mentioned
97	[107]	14	Not Mentioned	Band-pass filter	Wavelet-based denoising technique	Not Mentioned
98	[158]	19	2s	Frequency Band Filter	Not Mentioned	Yes
99	[159]	6	0.1s	Butterworth Band-pass filter	Not Mentioned	Yes
100	[14]	21	60s	Band-pass filter, Notch filter	Not Mentioned	Yes
101	[132]	20	1s	Band-pass filter	Automated Artifact Rejection	Yes
102	[213]	64	1.1s	Band-pass filter	Independent Component Analysis	Not Mentioned
103	[206]	64	2s	Band-pass Filter, Band-stop Filter	Independent Component Analysis	Yes
104	[192]	32	2s	Band-pass filter	Not Mentioned	Not Mentioned
105	[124]	8	100s	High-pass filter, Low-pass filter	Not Mentioned	Yes
106	[133]	20	30s	High-pass filter, Low-pass filter, Notch filter	Independent Component Analysis	Yes
107	[108]	256	4s or 6s	Band-pass filter, High-pass filter	Independent Component Analysis	Yes
108	[134]	6	4s (2s overlap)	Band-pass filter, Notch filter	Not Mentioned	Yes
109	[135]	20	30s	High-pass filter, Low-pass filter, Notch filter	Independent Component Analysis	Yes
110	[109]	19	4s	Band-pass filter	Not Mentioned	Yes
111	[110]	19	4s	Band-pass filter	Independent Component Analysis	Yes
112	[111]	6	Not Mentioned	Notch filter	Not Mentioned	Not Mentioned
113	[136]	17	2s	High-pass filter, Low-pass filter, Notch filter	Not Mentioned	Yes
114	[12]	2	Not Mentioned	Notch filter	Not Mentioned	Yes

115	[143]	19	2s	Band-pass filter, Notch filter	Automated Artifact Rejection.	Yes
116	[175]	Two 32	2.5s	Band-pass filter	Independent Component Analysis	Yes
117	[36]	31	1s (0.5s overlap)	Band-pass filter	Independent Component Analysis	Yes
118	[160]	19	Not Mentioned	Not Mentioned	Standardized Artifact Rejection Algorithm	Yes
119	[87]	11	1s	High-pass filter	Not Mentioned	Yes
120	[137]	21	Not Mentioned	Band-pass filter	Not Mentioned	Not Mentioned
121	[27]	19	5s	Band-pass filter, FIR filter	Independent Component Analysis, Automatic Component Rejection	Yes
122	[112]	19	Not Mentioned	Band-pass filter	Not Mentioned	Not Mentioned
123	[138]	64	100s	Band-pass filter, FIR filter	Artifact Subspace Reconstruction	Yes
124	[38]	64	5s	Band-pass filter	Artifact Subspace Reconstruction, Independent Component Analysis	Not Mentioned
125	[173]	64	1s	Not Mentioned	Independent Component Analysis	Yes
126	[113]	64	0.5s (0.25s overlap)	High-pass filter, Low-pass filter, Notch filter	Independent Component Analysis	Yes
127	[167]	64	1.2s or 4s	Band-pass Filter, Band-stop Filter	Independent Component Analysis	Yes
128	[216]	64 or 8	0.5s	High-pass filter	Independent Component Analysis	Not Mentioned
129	[190]	128	1s	Band-pass filter	Not Mentioned	Not Mentioned
130	[180]	32	0.1s	Band-pass filter	ADJUST (Automatic Detection of EEG Artifacts)	Not Mentioned
131	[146]	Not Mentioned	Not Mentioned	Not Mentioned	Not Mentioned	Not Mentioned
132	[88]	31 or 21	1s, 4s, 8s, 16s, 32s, 64s (50% overlap for all)	Band-pass filter	Not Mentioned	Yes
133	[212]	128	2s	Butterworth IIR filter	Automated Artifact Rejection	Yes
134	[185]	64	10s	High-pass filter	Independent Component Analysis	Yes
135	[207]	64	6.8s, 3.5s, 1.2s	Band-pass filter, High-pass filter, Low-pass filter	Independent Component Analysis, Automated Artifact Rejection	Yes
136	[211]	19	60s	Band-pass filter	Automated Artifact Rejection	Yes
137	[208]	116	Not Mentioned	High-pass filter, Low-pass filter	Independent Component Analysis	Yes
138	[221]	30	30s	Band-pass Filter, Band-stop Filter	Automated Artifact Rejection	Not Mentioned
139	[114]	256	6s (3s overlap)	Band-pass filter, High-pass filter	Independent Component Analysis	Yes

140	[8]	256	6s	Band-pass filter, High-pass filter	Independent Component Analysis, Semi- Automatic Artifact Rejection	Yes
141	[115]	20	1s (0.5s overlap)	High-pass filter, Low-pass filter, Notch filter	Not Mentioned	Yes
142	[35]	6	6s	Band-pass filter, Notch filter	Semi-automatic artifact rejection	Yes
143	[161]	65	2.048s	Band-pass filter, Notch filter	Not Mentioned	Yes
144	[199]	128	Not Mentioned	Band-pass filter, Notch filter	Automated Artifact Rejection	Yes
145	[116]	64	2s (1s overlap)	Band-pass filter, High-pass filter	Not Mentioned	Yes
146	[117]	88	2s (1.5s overlap)	Band-pass filter	Semi-Automatic Artifact Removal	Yes
147	[118]	1	1s	Band-pass filter	Not Mentioned	Yes
148	[119]	128	120s	High-pass filter, Low-pass filter	Artifact Subspace Reconstruction (ASR) method	Yes
149	[225]	32	2s	Band-pass filter	Not Mentioned	Yes
150	[226]	64	1s	Band-pass filter	Not Mentioned	Yes
151	[139]	19	1.024s (0.512s overlap)	High-pass filter, Low-pass filter	Not Mentioned	Yes
152	[89]	Not Mentioned	1.25s	Not Mentioned	Not Mentioned	Not Mentioned
153	[140]	20	2.048 s	Butterworth Infinite Impulse Response (IIR) Filter	Automated Artifact Rejection	Yes
154	[162]	32	Not Mentioned	High-pass filter, Low-pass filter	Not Mentioned	Yes
155	[217]	64	0.5s	Band-pass filter, Notch filter	Independent Component Analysis	Not Mentioned
156	[90]	64	2s	Band-pass filter, Notch filter	Independent Component Analysis	Yes
157	[168]	128	0.8s	Band-pass filter	Independent Component Analysis	Yes
158	[24]	64	Not Mentioned	Band-pass filter, Notch filter	Independent Component Analysis	Yes
159	[39]	18	2s	Band-pass filter, Notch filter	Not Mentioned	Not Mentioned
160	[231]	1	Not Mentioned	Not Mentioned	Not Mentioned	Not Mentioned
161	[181]	9	2s (1s overlap)	Band-pass filter	Not Mentioned	Yes
162	[187]	64	Not Mentioned	Not Mentioned	Not Mentioned	Yes
163	[141]	16	30s	Not Mentioned	Not Mentioned	Not Mentioned
164	[142]	4	0.6s	Band-pass filter, Notch filter	Independent Component Analysis	Yes

For Table 2.4 the numbers 1-10 represent: 1 - Frequency Domain Analysis, 2 - Time-Frequency and Spectral Entropy Methods, 3 - Amplitude Features, 4 - Dimensionality Reduction and Decomposition, 5 - Phase and Synchrony Analysis, 6 - Entropy-Based Measures, 7 - Connectivity and Coherence Measures, 8 - Spatial, Microstate, Network and Topological Features, 9 - Statistical Features, and 10 - Advanced Modelling, Machine Learning, and Complex Features.

Table 2.4 Summary of Feature Extraction Methods Used

No	Reference	Feature Extraction Methods Used	1	2	3	4	5	6	7	8	9	10
1	[33]	Power Spectral Density (PSD), Bartlett method, Blackman-Harris window, Stockwell transform, Phase Locking Value (PLV),	✓	✓			✓					
2	[91]	Power Spectral Density (PSD), Stockwell transform,	✓	✓								
3	[34]	Highly Comparative Time-Series Analysis (HCTSA), Principal Component Analysis (PCA),				✓						✓
4	[152]	Stationary Wavelet Transform (SWT), Mean, Standard Deviation, Variance, Interquartile Range (IQR), Kurtosis, Zero-Crossing Rate, Hurst Exponent, Band Power	✓	✓							✓	✓
5	[150]	Welch's Modified Periodogram,	✓									
6	[218]	Permutation Entropy						✓				
7	[210]	Coherence, Imaginary Coherence, Phase Lag Index (PLI), Phase Locking Value (PLV),					✓		✓			
8	[191]	Persistent Homology Features, Betti Areas and the Peak Location of Betti Curves, Persistent Entropy, Persistent Amplitude, Spectral Entropy		✓	✓			✓		✓		
9	[151]	Hjorth Parameters, Band Power, Welch's Modified Periodogram, Magnitude-Squared Coherence (MSC),	✓						✓		✓	
10	[123]	Fast Fourier Transform (FFT),	✓									
11	[209]	Fast Independent Component Analysis (f-ICA)				✓						
12	[227]	Global Field Power (GFP)									✓	

13	[184]	Flexible Analytic Wavelet Transform (FAWT), Logarithmic Energy, Skewness, Mean, Maximum and Minimum, Standard Deviation, Root Mean Square, Kurtosis, Hjorth Parameters, Log Energy Entropy, Sure Entropy, Shannon Entropy, Threshold Entropy		✓				✓			✓	
14	[230]	Detrended Fluctuation Analysis (DFA), Fractal Dimension (FD)										✓
15	[92]	Power Spectral Density (PSD), Spectral Power Ratio (SPR),	✓									
16	[93]	Fast Fourier Transform (FFT), Power Spectral Density (PSD), Spectral Power Ratio (SPR),	✓									
17	[144]	Band Power, Spectral Power Ratio (SPR), Phase-Amplitude Coupling (PAC)	✓				✓					
18	[83]	Spectral Analysis	✓									
19	[188]	Hilbert-Huang Transform, Empirical Mode Decomposition (EMD), Intrinsic Mode Functions, Hilbert Transform,		✓		✓						
20	[171]	Event-Related Potentials (ERPs), Time-Frequency Distribution (TFD)		✓							✓	
21	[203]	Common Spatial Pattern with Tikhonov Regularization (TR-CSP)				✓						
22	[94]	Power Spectral Density (PSD),	✓									
23	[200]	Common Spatial Pattern (CSP),				✓						
24	[228]	Artificial Neural Network (ANN)										✓
25	[204]	Independent Component Analysis (ICA),				✓						
26	[176]	Discrete Wavelet Transform (DWT), Mean, Maximum and Minimum, Standard Deviation, Variance, Zero Crossing, Kurtosis,		✓							✓	
27	[95]	Power Spectral Density (PSD), Independent Component Analysis (ICA),	✓			✓						
28	[96]	Band Power, Power Spectral Density (PSD),	✓									
29	[37]	Variance, Sample Entropy, Power Spectral Density (PSD), Coherence	✓					✓	✓		✓	
30	[214]	Shannon Entropy, Approximate Entropy, Sample Entropy						✓				
31	[193]	Mean, Standard Deviation, Maximum and Minimum of Amplitude, Root Mean Square, Kurtosis, Skewness, Zero-Crossing Rate, Sample Entropy			✓			✓			✓	
32	[182]	Event-Related Potentials (ERPs), Continuous Wavelet Transform (CWT), Principal Component Analysis (PCA),		✓		✓					✓	
33	[97]	Power Spectral Density (PSD), Coherence	✓						✓			
34	[196]	Principal Component Analysis (PCA), Independent Component				✓						✓

		Analysis (ICA), Linear Discriminant Analysis (LDA),											
35	[125]	Fast Fourier Transform (FFT), Independent Component Analysis (ICA),	✓			✓							
36	[98]	Power Spectral Density (PSD), Alpha, Current Source Density (CSD) Transformation	✓							✓			
37	[126]	Fast Fourier Transform (FFT), Imaginary Coherence, Current Source Density (CSD) Transformation	✓						✓	✓			
38	[201]	Common Spatial Pattern (CSP), Filter Bank Common Spatial Pattern (FBCSP), Artificial Neural Network (ANN)				✓							✓
39	[127]	Fast Fourier Transform (FFT), Alpha, Amplitude of the Main Peak, Frequency of the Main Peak	✓		✓								
40	[165]	Alpha, Amplitude of the Main Peak, Frequency of the Main Peak, Higher Order Crossing, Discrete Wavelet Transform (DWT),	✓	✓	✓							✓	
41	[177]	Discrete Wavelet Transform (DWT), Root Mean Square,		✓								✓	
42	[202]	Common Spatial Pattern (CSP), Variance, Linear Discriminant Analysis (LDA), Artificial Neural Network (ANN)				✓						✓	✓
43	[229]	Artificial Neural Network (ANN)											✓
44	[222]	Artificial Neural Network (ANN), Topographic Maps								✓			✓
45	[29]	Independent Component Analysis (ICA), Template Matching Procedure, Complex Morlet Wavelet Convolution, Power Spectral Density (PSD),	✓	✓		✓							✓
46	[194]	Mean, Standard Deviation, Maximum and Minimum of Amplitude				✓						✓	
47	[197]	Principal Component Analysis (PCA),				✓							
48	[128]	Fast Fourier Transform (FFT), Discrete Wavelet Transform (DWT),	✓	✓									
49	[147]	Mean, Standard Deviation, Maximum and Minimum of Amplitude, Skewness, Kurtosis, Band Power, Spectral Power Ratio (SPR), Approximate Entropy, Sample Entropy	✓			✓			✓			✓	
50	[99]	Power Spectral Density (PSD), Detrended Fluctuation Analysis (DFA)	✓										✓
51	[189]	Hilbert Transform, Phase Locking Value (PLV),		✓				✓					
52	[122]	Power Spectral Density (PSD), Independent Component Analysis (ICA),	✓			✓							

53	[153]	Sample Entropy, Hurst Exponent, Band Power,	✓					✓				✓
54	[100]	Power Spectral Density (PSD), Short-Time Fourier Transform (STFT), Independent Component Analysis (ICA),	✓	✓		✓						
55	[198]	Coherence, Phase Lag Index (PLI), Phase Locking Value (PLV), Directed Phase Transfer Entropy, Principal Component Analysis (PCA),				✓	✓	✓	✓			
56	[154]	Band Power, Phase Coherence	✓					✓				
57	[148]	Mean, Standard Deviation, Root Mean Square, Zero Crossing, Hjorth Parameters, Permutation Entropy, Approximate Entropy, Sample Entropy, Differential Entropy, Fractal Dimension (FD), Band Power, Spectral Power Ratio (SPR), Discrete Wavelet Transform (DWT),	✓	✓				✓			✓	✓
58	[101]	Power Spectral Density (PSD), Topographic Maps	✓							✓		
59	[155]	Band Power,	✓									
60	[215]	Mean, Standard Deviation, Variance, Root Mean Square, Skewness, Kurtosis, Fractal Dimension (FD), Decorrelation Time, Hjorth Parameters, Approximate Entropy						✓			✓	✓
61	[174]	Mean, Time-Frequency Distribution (TFD)		✓							✓	
62	[149]	Relative Entropy, Spectral Power Ratio (SPR)	✓					✓				
63	[156]	Variance, Kurtosis, Band Power, Shannon Entropy, Renyi Entropy, Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA),	✓	✓		✓		✓			✓	
64	[178]	Discrete Wavelet Transform (DWT),		✓								
65	[186]	Complex Continuous Wavelet Coherence, Microstate Analysis		✓						✓		
66	[163]	Delta, Theta, Alpha, Beta, Gamma, Independent Component Analysis (ICA),	✓			✓						
67	[183]	Complex Continuous Wavelet Coherence, Continuous Wavelet Transform (CWT),		✓								
68	[224]	Graph Theoretical Measures, Mean								✓	✓	
69	[220]	Directed Transfer Function (DTF), Partial Directed Coherence (PDC), Autoregressive Modelling,							✓	✓		✓
70	[179]	Discrete Wavelet Transform (DWT), Topographic Maps		✓						✓		
71	[157]	Band Power, LORETA (Low-Resolution Electromagnetic Tomography), Current Source Density (CSD) Transformation	✓							✓		
72	[84]	Event-Related Potentials (ERPs), Spectral Analysis, Welch's Modified	✓			✓					✓	

		Periodogram, Independent Component Analysis (ICA),											
73	[25]	Independent Component Analysis (ICA), Extended Infomax ICA, Welch's Modified Periodogram, Band Power,	✓			✓							
74	[164]	Independent Component Analysis (ICA), Infomax ICA, Time-Frequency Distribution (TFD), Morlet wavelet transform, Theta,	✓	✓		✓							
75	[102]	Fast Fourier Transform (FFT), Power Spectral Density (PSD), Alpha,	✓										
76	[129]	Fast Fourier Transform (FFT), Independent Component Analysis (ICA), Infomax ICA,	✓			✓							
77	[121]	Power Spectral Density (PSD), Fast Fourier Transform (FFT), Independent Component Analysis (ICA),	✓			✓							
78	[103]	Fast Fourier Transform (FFT), Power Spectral Density (PSD), Welch's Modified Periodogram, Hanning Windowing	✓										
79	[23]	Time-Frequency Distribution (TFD), Independent Component Analysis (ICA), Power Spectral Density (PSD), Phase Locking Value (PLV),	✓	✓		✓	✓						
80	[170]	Gamma, Variance, Root Mean Square,	✓									✓	
81	[85]	Spectral Analysis, Mean, Standard Deviation	✓									✓	
82	[130]	Fast Fourier Transform (FFT), Discrete Wavelet Transform (DWT),	✓	✓									
83	[86]	Spectral Analysis	✓										
84	[166]	Alpha,	✓										
85	[131]	Fast Fourier Transform (FFT), Alpha,	✓										
86	[169]	Alpha	✓										
87	[104]	Time-Frequency Distribution (TFD), Current Source Density (CSD) Transformation, Power Spectral Density (PSD), Inter-Channel Phase Synchronization (ICPS)	✓	✓			✓			✓			
88	[205]	Independent Component Analysis (ICA), Imaginary Coherence				✓			✓				
89	[195]	Mean, Standard Deviation, Maximum and Minimum of Amplitude,			✓							✓	
90	[172]	Event-Related Potentials (ERPs), Time-Frequency Distribution (TFD)		✓								✓	
91	[145]	Instantaneous Peak Frequency Calculation, Spectral Power Ratio (SPR), cross-frequency phase synchronization estimation	✓				✓						

92	[120]	Alpha, Coherence, Power Spectral Density (PSD)	✓						✓			
93	[219]	Coherence							✓			
94	[105]	Power Spectral Density (PSD), Spectral Power Ratio (SPR), Detrended Fluctuation Analysis (DFA)	✓									✓
95	[106]	Power Spectral Density (PSD), Independent Component Analysis (ICA),	✓			✓						
96	[223]	LORETA (Low-Resolution Electromagnetic Tomography)								✓		
97	[107]	Discrete Wavelet Transform (DWT), Power Spectral Density (PSD),	✓	✓								
98	[158]	LORETA (Low-Resolution Electromagnetic Tomography), Band Power,	✓							✓		
99	[159]	Band Power,	✓									
100	[14]	Operational Synchrony Measurement, Alpha	✓				✓					
101	[132]	Fast Fourier Transform (FFT), Event-Related Potentials (ERPs), Phase Synchrony Index (PSI)	✓				✓				✓	
102	[213]	Event-Related Potentials (ERPs), Theta Phase Synchronization (TPS)					✓				✓	
103	[206]	Event-Related Potentials (ERPs), Independent Component Analysis (ICA), Topographic Maps, Microstate Analysis				✓				✓	✓	
104	[192]	EEG Amplitude, Coherence, LORETA (Low-Resolution Electromagnetic Tomography)			✓				✓	✓		
105	[124]	Fast Fourier Transform (FFT),	✓									
106	[133]	Fast Fourier Transform (FFT), Beta, Logarithmic Transformation	✓									✓
107	[108]	Power Spectral Density (PSD), Welch's Modified Periodogram, Independent Component Analysis (ICA),	✓			✓						
108	[134]	Fast Fourier Transform (FFT), Theta, Alpha, Beta, Gamma	✓									
109	[135]	Fast Fourier Transform (FFT), Logarithmic Transformation	✓									✓
110	[109]	Fast Fourier Transform (FFT), Coherence, Power Spectral Density (PSD),	✓						✓			
111	[110]	Fast Fourier Transform (FFT), Coherence, Power Spectral Density (PSD),	✓						✓			
112	[111]	Fast Fourier Transform (FFT), Power Spectral Density (PSD), Spectral Power Ratio (SPR),	✓									
113	[136]	Fast Fourier Transform (FFT),	✓									
114	[12]	Fast Fourier Transform (FFT), Band Power,	✓									
115	[143]	Principal Component Analysis (PCA), Discrete Fourier Transform	✓			✓						

116	[175]	Short-Time Fourier Transform (STFT), Phase Locking Value (PLV),		✓			✓					
117	[36]	Independent Component Analysis (ICA), Power Spectral Density (PSD), Welch's Modified Periodogram,	✓			✓						
118	[160]	Band Power, LORETA (Low-Resolution Electromagnetic Tomography)	✓						✓			
119	[87]	Spectral Analysis	✓									
120	[137]	Fast Fourier Transform (FFT), Welch's Modified Periodogram, Alpha, Spectral Power Ratio (SPR)	✓									
121	[27]	Alpha	✓									
122	[112]	Standard Deviation, Variance, Power Spectral Density (PSD),	✓								✓	
123	[138]	Fast Fourier Transform (FFT), Hilbert Transform, Phase-Amplitude Coupling (PAC)	✓	✓			✓					
124	[38]	Time-Frequency Distribution (TFD), Alpha,	✓	✓								
125	[173]	Event-Related Potentials (ERPs), Time-Frequency Distribution (TFD)		✓							✓	
126	[113]	Power Spectral Density (PSD), Pairwise Phase Consistency (PPC),	✓				✓					
127	[167]	Event-Related Potentials (ERPs), Pairwise Phase Consistency (PPC), Alpha	✓				✓				✓	
128	[216]	Fuzzy Entropy						✓				
129	[190]	Hilbert Transform,		✓								
130	[180]	Discrete Wavelet Transform (DWT),		✓								
131	[146]	Short-Time Fourier Transform (STFT), Spectral Power Ratio (SPR),	✓	✓								
132	[88]	Independent Component Analysis (ICA), LORETA (Low-Resolution Electromagnetic Tomography), Spectral Analysis	✓			✓				✓		
133	[212]	Phase Lag Index (PLI)					✓					
134	[185]	Morlet Wavelet Decomposition,		✓								
135	[207]	Event-Related Potentials (ERPs), Independent Component Analysis (ICA),				✓					✓	
136	[211]	Operational Synchrony Measurement					✓					
137	[208]	Independent Component Analysis (ICA), Surface Laplacian Transformation,				✓						
138	[221]	Minimum Variance Distortionless Response (MVDR) Coherence, Directed Transfer Function (DTF)							✓			
139	[114]	Power Spectral Density (PSD),	✓									
140	[8]	Spectral Analysis, Independent Component Analysis (ICA), Topographic Maps	✓			✓				✓		

141	[115]	Power Spectral Density (PSD), Coherence	✓						✓			
142	[35]	Spectral Analysis, Band Power,	✓									
143	[161]	Mean Phase Coherence, Band Power,	✓				✓					
144	[199]	Principal Component Analysis (PCA),				✓						
145	[116]	Power Spectral Density (PSD), Band Power,	✓									
146	[117]	Power Spectral Density (PSD), Alpha,	✓									
147	[118]	Time-Frequency Distribution (TFD), Short-Time Fourier Transform (STFT), Power Spectral Density (PSD),	✓	✓								
148	[119]	Power Spectral Density (PSD), Fractal Dimension (FD), Permutation Entropy	✓					✓				✓
149	[225]	Global Field Power (GFP), Microstate Analysis							✓	✓		
150	[226]	Event-Related Potentials (ERPs)								✓		
151	[139]	Fast Fourier Transform (FFT), Alpha	✓									
152	[89]	Discrete Wavelet Transform (DWT), Spectral Analysis	✓	✓								
153	[140]	Fast Fourier Transform (FFT), Band Power,	✓									
154	[162]	Band Power, Sample Entropy	✓					✓				
155	[217]	Fuzzy Entropy						✓				
156	[90]	Spectral Analysis, Power Spectral Density (PSD),	✓									
157	[168]	Alpha, Coherence	✓						✓			
158	[24]	Autoregressive Modelling										✓
159	[39]	Fast Fourier Transform (FFT), Hanning Windowing	✓									
160	[181]	Discrete Wavelet Transform (DWT)		✓								
161	[187]	Wavelet Coherence, Topographic Maps		✓						✓		
162	[141]	Fast Fourier Transform (FFT), Coherence	✓						✓			
163	[142]	Fast Fourier Transform (FFT), Magnitude-Squared Coherence (MSC),	✓						✓			
	Total		101	40	8	36	19	17	18	20	35	18
	Percent age (%)		62.0	24.5	4.9	22.1	11.7	10.4	11.0	12.3	21.5	11.0

For Table 2.5 the numbers 1-5 represent: 1 - Support Vector Machines (SVM), 2 - k-Nearest Neighbors (k-NN), 3 - Decision Trees and Random Forests, 4 - Linear Discriminant Analysis (LDA), and 5 - Artificial Neural Networks (ANNs)

Table 2.5 Summary of Performance of Pipelines and Classification Methods Used

No	Reference	Performance of Pipelines	1	2	3	4	5
1	[33]	Support Vector Machine (SVM) was used for the classification of meditation and control. When using EEG alone, the accuracy was 78%, but using only respiration signals produced a slightly lower result than combining both. EEG and respiration signals combined produced the best result, with an 85% classification accuracy.	✓				
2	[34]	When using SVM for the classification of expert meditators and non-meditators, 7,381 advanced time-series features from hctsa resulted in an accuracy of 67%. The traditional EEG frequency measures produced an accuracy of 56%.	✓				
3	[152]	The classification accuracy for the Gamma, Beta, Alpha, Theta, and Delta bands was 42.26%, 48.33%, 61.11%, 50.72%, and 70.13%, respectively, when classifying EEG data collected before and after OM mantra meditation.	✓				
4	[150]	Radial Basis Function Support Vector Machine (RBF SVM) was used to classify pre- and post-mindfulness meditation EEG data. Results indicate an average accuracy of 80.76%, with 78.24% for pre-meditation and 82.14% for post-meditation data.	✓				
5	[218]	A three-class and two-class SVM classifiers were used to classify meditation, attention, and relaxation for expert meditator and non-meditator EEG data. Expert meditators obtained higher classification accuracies than non-meditators for all instances, including both the comparison of the three classes together and the pairwise comparison.	✓				
6	[210]	Support Vector Machine (SVM) was used in pairwise classification for the control group and each of the meditation groups. The accuracy results are as follows: Himalayan Yoga - 84.76% for Gamma, Isha Shoonya - 90% for Alpha, and Vipassana - 84.76% for Theta.	✓				
7	[191]	EEG topological features were used with SVM to classify two meditation types. The results obtained were as follows: persistent entropy - 72%, Betti area - 82%, persistent amplitude - 83%, Hodge spectral entropy - 88%, and combined features - 95%.	✓				
8	[151]	EEG data were collected for four emotions before and after an eight-week meditation programme. Two-, three-, and four-class classification accuracies were calculated before training and then after training using k-Nearest Neighbors. In all instances, classification accuracies dropped significantly, indicating improved emotional balance after the meditation training.		✓			
9	[123]	Using the k-Nearest Neighbor (k-NN) algorithm, classification was done to detect how the power of delta, theta, alpha, beta, and gamma waves changes with time. This was done to identify the change in stress levels while meditating. The highest accuracy of 62.5% was obtained when using four bands (delta,		✓			

		theta, alpha, and beta). The change in k in the algorithm affected the accuracy, with a peak of 80% obtained when k = 3					
10	[209]	The BCI pipeline in this study used features derived from ICA and statistical methods, followed by the k-nearest neighbors (k-NN) algorithm for classification. An accuracy of 86.36% was achieved when classifying meditation and non-meditation EEG data.		✓			
11	[184]	The results show that mind-wandering was detected in meditation EEG. In the BCI pipeline, several machine learning methods, namely Decision Tree Classifiers (Fine Tree, Medium Tree, Coarse Tree) and Ensemble Classifiers (Ensemble Boosted Tree, Ensemble Bagged Tree), were tested. The best classification accuracy of 92.41% was achieved by the Ensemble Bagged Tree Classifier for the alpha band with the O1-Oz channels.			✓		
12	[230]	The study used several feature extraction methods independently (Detrended Fluctuation Analysis (DFA), Higuchi Fractal Dimension (FD), and Katz FD) along with a Random Forest (RF) classifier in the BCI pipelines. The best classification accuracy of 70% was obtained with Higuchi FD using frontal region alpha bands.			✓		
13	[92]	For each of the BCI pipelines, Random Forest was used as the classifier to separate sitting and walking meditation EEG data. Among the single features used (original power features, power ratio features, and non-linear dynamics features), original power features produced the best accuracy of 83.96%. A multi-feature model combining these features was also used in the study, achieving the highest accuracy of 84.17%.			✓		
14	[144]	The study builds BCI pipelines to classify Focused Attention Meditation and problem-solving tasks EEG data using Random Forest Classifiers. The study was tested with individual classifiers specific to each subject, and an average accuracy of 93% was obtained for all the subjects. Next, a general classifier for all subjects was tested but produced a lower accuracy of 74%.			✓		
15	[188]	The study focused on classifying EEG data collected for two mental tasks: relaxation meditation and tension imagination. The BCI pipeline was modelled with features extracted using the Hilbert-Huang Transform (HHT) and Fisher Linear Discriminant Analysis for classification, achieving a success rate of about 90% accuracy.				✓	
16	[203]	Rajayoga meditation and resting EEG data were classified by using Tikhonov regularization CSP for feature extraction and Linear Discriminant Analysis (LDA) for classification. Here, an accuracy of 97.9% was obtained for intra-subject classification, and an accuracy of 74.0% was obtained for inter-subject classification.				✓	
17	[200]	Classification was done using Common Spatial Patterns and Linear Discriminant Analysis, comparing six pairs taken from four mind tasks (pre-rest, post-rest, and two meditation tasks). Only intra-subject analysis was done with the EEG data, first for a single session, then using a pool of data from multiple sessions. For a single session, the best accuracy of 99.8% was obtained, and for multiple sessions, the best accuracy of 85.9% was obtained.				✓	
18	[204]	Convolutional Neural Network models were tested with and without Independent Components Analysis (ICA) to classify Shoonya meditation with non-meditation EEG data. Without ICA, an average accuracy of 70.16% and with ICA, an average accuracy of 99.50% (for three models) were obtained. The					✓

		results indicate the use of ICA significantly increases the classification accuracy.					
19	[176]	The study successfully used various statistical parameters obtained from EEG data collected from meditators and non-meditators. A Multi-Layer Perceptron Neural Network (MLPNN) was used for classification, achieving 87.1% sensitivity, 87.4% specificity, and 87.2% accuracy.					✓
20	[95]	The study collected pre-meditation and post-meditation EEG data and used a machine learning method similar to a neural network for classification. The study used a Riemannian geometry-based classifier, which achieved a classification accuracy of 97%.					✓
21	[37]	EEG data collected before and after the meditation training were classified using Artificial Neural Network (ANN), k-Nearest Neighbors (KNN), and Support Vector Machine (SVM). The accuracy obtained for ANN, KNN, and SVM was 72.5%, 82.5%, and 85.0%, respectively. SVM performed best, followed by KNN and then ANN.	✓	✓			✓
22	[193]	The study uses Support Vector Machine (SVM) and Random Forest (RF) to classify EEG data from meditation and mind-wandering tasks. The classification accuracies for Himalayan Yoga Tradition, Vipassana, Isha Shoonya Yoga, and the control group were 94.92%, 96.29%, 93.70%, and 96.48% for SVM, and 96.86%, 96.70%, 94.06%, and 94.62% for RF, respectively.	✓		✓		
23	[196]	The study uses Support Vector Machines (SVM) for classification in three pipelines, each tested with a different feature extraction method. The combination of Independent Component Analysis + SVM and Principal Component Analysis + SVM both achieved an accuracy of 93%. However, Linear Discriminant Analysis + SVM provided the highest accuracy at 95%.	✓				
24	[201]	EEG data for meditation and rest states were collected at the beginning (MBSR1, REST1) and end (MBSR2, REST2) of the training, and various pairwise classifications were performed. These classifications were tested using traditional machine learning pipelines (CSP + SVM, FBCSP + SVM) and deep learning pipelines (Shallow ConvNet, Deep ConvNet). Significant mix-subject classification accuracies were obtained for the following pairs in this order (Shallow, Deep, CSP, FBCSP): MBSR1/REST1 (98.33%, 99.59%, 72.01%, 73.92%), MBSR2/REST2 (92.53%, 99.70%, 92.56%, 73.23%), MBSR1/MBSR2 (99.81%, 99.95%, 71.67%, 91.16%), REST1/REST2 (99.88%, 99.78%, 93.98%, 95.13%)	✓				✓
25	[127]	The study tested the performance of Artificial Neural Network (ANN) and Support Vector Machine (SVM) under various conditions. These different conditions produced varying levels of accuracy, with ANN ranging from 80% to 99%, achieving a peak value of 99.05%. On the other hand, SVM accuracies began in the range of 30%, but with proper adjustments, they reached up to 100%. With optimal conditions, both methods demonstrated good results.	✓				✓
26	[165]	The study used Fuzzy Kernel Least Square Support Vector Machine (FKLSSVM), Support Vector Machine (SVM), and Artificial Neural Network (ANN) in classifying breathing meditation EEG data. The result accuracies showed ANN at 91.25%, SVM at 93.93%, and FKLSSVM achieving the highest classification accuracy of 96.28%.	✓				✓
27	[202]	The study used a pipeline with Common Spatial Pattern (CSP) for feature extraction and Linear Discriminant Analysis (LDA) for dimensionality reduction. Then, a Long Short-Term Memory					✓

		(LSTM) neural network was used for classification. The results for the bands were as follows: Alpha - 79.1%, Beta - 86.5%, lower Gamma - 91.0%, and upper Gamma - 94.1%.					
28	[229]	Feed-forward neural networks (FFNN) and convolutional neural networks (CNN) were tested in this study to compare them with traditional methods. For the meditation group, the identification accuracy was as follows: traditional - 62.44%, CNN - 63.19%, FFNN - 65.64%. For the non-meditation control group, the identification accuracy was: traditional - 60.57%, CNN - 61.34%, FFNN - 63.25%.					✓
29	[222]	The study used 1D-SCNN (Shallow Convolutional Neural Networks) and 2D-SCNN to classify experienced and novice Himalayan Yoga meditation EEG data. Studies were conducted on various models of the two for segment lengths of 2s, 5s, and 10s, with the best accuracies obtained as follows: 2D-SCNN (2s - 95.42%, 5s - 95.73%, 10s - 96.14%) and 1D-SCNN (2s - 99.45%, 5s - 99.48%, 10s - 99.45%).					✓
30	[194]	The study successfully built a machine learning pipeline to classify meditation and concentration EEG data using a Random Forest Classifier with an accuracy of 75%.			✓		
31	[197]	Meditation and mind-wandering EEG data were classified using multiple classifiers, where Alpha and Theta features made a significant contribution. The accuracies obtained were as follows: Linear Discriminant Analysis – 72%, Naive Bayes – 68%, Support Vector Machines – 75%, and k-Nearest Neighbors – 76%.	✓	✓		✓	
32	[128]	The study tested how well different deep learning models can classify EEG data collected during meditation (Transcendental Meditation, Raja Yoga, and Mindfulness). The accuracies obtained were 99.4% for VGG-16, 98.8% for VGG-19, 97% for ResNet-18, and 95.2% for GoogleNet.					✓
33	[147]	The study tested the performance of machine learning algorithms to classify EEG data from yoga, meditation, and combined yoga-meditation. The best accuracies obtained were as follows: Linear Support Vector Machine: 91.67%, k-Nearest Neighbors: 88.89%, and Multilayer Perceptron: 89.58%.	✓	✓			✓
34	[153]	EEG data collected for Himalayan Yoga (HT) and Hare Krishna mantra meditation (HKT) were compared with a control group (CTR). The mean classification accuracies when using the features Sample Entropy (SE), Hurst Exponent (HE), and Band Power (BP) for Support Vector Machines (SVM), Deep Neural Networks (DNN), and Random Forest (RF) are as follows. For HT vs. CTR: HE (SVM = 71.9%, DNN = 67.0%, RF = 72.0%), SE (SVM = 67.4%, DNN = 70.2%, RF = 72.3%), BP (SVM = 91.1%, DNN = 100%, RF = 100%); and for HKT vs. CTR: HE (SVM = 75.3%, DNN = 78.1%, RF = 77.6%), SE (SVM = 76.2%, DNN = 81.2%, RF = 79.4%), BP (SVM = 100%, DNN = 100%, RF = 100%).	✓		✓		✓
35	[100]	Pre- and post-meditation EEG data were independently classified using five classification methods, and their accuracies are as follows: Multilayer Perceptron (pre: 74%, post: 69%), Support Vector Machine (pre: 70%, post: 61%), Logistic Regression (pre: 75%, post: 68%), Decision Forest (pre: 68%, post: 52%), and Naive Bayes (pre: 64%, post: 57%).	✓		✓		✓
36	[198]	Classification accuracies for expert and novice meditators, as well as for healthy individuals and patients, are as follows: Support Vector Machine (61%, 52.17%), Deep Convolutional Neural Networks (59%, 60%), Recurrent Neural Networks (56%, 56%). k-Means Clustering and Graph Neural Networks did not perform successfully in the study.	✓				✓

37	[148]	Meditation and non-meditation EEG data were classified using Support Vector Machines with a Radial Basis Function Kernel (SVM-RBF) or EEGNet while testing Riemannian Space Data Alignment (RSDA), and the best accuracies obtained are as follows: SVM-RBF: 55.1%, SVM-RBF with RSDA: 66.9%, EEGNet: 57.4%, and EEGNet with RSDA: 72.6%.	✓				✓
38	[101]	Algorithms were tested to classify EEG data collected from expert meditators, novice meditators, and the control group. The proposed lightweight CNN model achieved an accuracy of 94.57%. Random Forest, as a traditional method, achieved 64.3%. Accuracy for several deep learning models: VGG16 = 97.27%, ResNet50 = 91.01%, MobileNet = 90.75%, and MobileNetV2 = 88.73%.	✓		✓	✓	✓
39	[155]	Mind-wandering and meditation EEG data were classified using several algorithms, and the best accuracies obtained are as follows: K-Nearest Neighbors = 77.7%, Random Forest = 68.6%, Quadratic Discriminant Analysis = 73.8%, and Neural Network = 73.83%.	✓	✓	✓	✓	✓
40	[215]	Ten algorithms were used to classify EEG data to compare meditation vs. mind-wandering and meditation vs. sleepiness. For mind-wandering, the best classification accuracy of 77.1% was obtained by the Decision Tree classifier. For sleepiness, the best classification accuracy of 85.8% was obtained by the Random Forest classifier.	✓	✓	✓	✓	✓
	Total		22	8	11	7	19
	Percent age (%)		55.0	20.0	27.5	17.5	47.5

Table 2.6 Summary of Study Objectives, Key Findings, and Limitations

No	Reference	Study Objective	Key Findings	Study Limitations
1	[33]	The aim of the study was to assess how well EEG and respiration signals, together, can be used to successfully classify two instances of meditation and control conditions for a selected group of people. The researchers hypothesized that EEG and respiration data could identify changes occurring in a person during mindfulness meditation, allowing for the identification of meditation quality.	The best classification accuracy was obtained when using EEG and respiration signals together, indicating the importance of using multiple physiological signals when classifying mindfulness meditation, especially when trying to classify meditation versus non-meditation participants, which can provide future options for identifying how well a meditation session went. Results show a high increase in power in Beta and Theta waves, while a small increase in alpha wave during meditation.	This study was done on novice meditators; therefore, the use of expert meditators in future studies could give significantly better results. The data collection order might have influenced the results, and future studies should aim to minimize this effect. The study uses two physical measurements and suggests using other types to improve the results.
2	[34]	The study investigates whether time-series analysis methods outperform	When using 7,381 time-series features, 405 features successfully distinguished	A small sample size and the use of only one session limited the broader

		traditional frequency band power measures in assessing brain activity during meditation. It also aims to differentiate expert meditators from non-meditators by examining resting-state brain patterns using EEG.	the two groups and produced the best classification accuracy of 67% for expert meditators and non-meditators. This shows that advanced time-series analysis outperformed traditional methods. Meditators exhibited more stable EEG patterns.	understanding of the study. The use of PCA might hide some information. This study focused on only one type of meditation.
3	[152]	The study aims to classify EEG data collected before and after OM mantra meditation for novice meditators using SVM. It also aims to identify the variation in the delta band, which is linked with deep sleep.	The study discovered that OM mantra meditation has the highest effect in the Delta band, thus producing the highest classification accuracy of 70.13% when comparing before and after meditation. The paper states that this research is among the first to use SVM to classify OM mantra meditation EEG.	The study used a small sample size with a narrow age range of 18 to 22 for the selected participants, and only a single session of data was collected. Additionally, it was conducted only with OM mantra meditation, and no control group was used in the study.
4	[150]	The study investigated how a short mindfulness meditation session affects a person with Autism Spectrum Disorder (ASD). Before and after meditation, EEG data was classified using SVM to identify brain pattern differences, aiming to address the limitations of self-report measurements.	SVM was successfully used to classify pre- and post-mindfulness meditation EEG data with an average accuracy of 80.76%. The study shows that a brief mindfulness meditation session has positive effects on a young person with Autism Spectrum Disorder (ASD).	The main study limitations are the lack of a control group, the collection of only a single session of data, and the small sample size.
5	[218]	The study looks at how permutation entropy (PE) features from EEG data can be used to classify different mental states, such as meditation, attention, and relaxation. It aims to identify objective methods to assess meditation that will be useful in meditation brain-computer interface (BCI) studies.	The study found that permutation entropy features obtained from EEG can be successfully used to classify the three classes of meditation, attention, and relaxation for expert meditators and non-meditators using SVM. It also found variability in the quality of meditation among expert meditators, indicating the need for tools to support and improve meditation.	Variability in the meditation levels of the expert meditators might have affected the study. Additionally, a small sample size and challenges in identifying features related to the attention task were noted.
6	[210]	The study looks at how three meditations (Himalayan Yoga, Isha Shoonya, and Vipassana) affect the brain connectivity by comparing the results with a control group. It aims to measure functional connectivity and use graph theory methods to identify brain activity differences for various frequency bands.	The study on each of the three meditation techniques showed a unique increase in activity in certain frequency bands and also in certain regions of the brain, thus giving high classification accuracies associated with those conditions.	Small sample size, using only a single session of data, and lack of diversity in the participants were some limitations of this study. Also, the challenge of using a lab to stimulate a real-world meditation experience was a limitation that was mentioned.

7	[191]	The study uses EEG data to investigate unique topological features in two different meditation types, with the aid of a control group. The aim was to achieve high classification accuracies using SVM.	The study found clear differences in EEG signal patterns between two types of meditation. For certain features, such as Hodge spectral entropy, high accuracies like 95% were achieved, indicating the importance of topological data analysis in studying meditation.	High computational power is needed to analyse topological data, and subjectively choosing parameters are two limitations in this study. Additionally, using only two meditation states and the chance of the machine learning model overfitting are additional challenges in this study.
8	[151]	This study focuses on understanding how meditation can enhance emotions in a person, improving overall well-being. Positive and negative emotions were assessed by collecting EEG data before and after an eight-week meditation programme.	The study found that regular meditation improves emotional coherence across negative and positive emotions. The reduction in classification accuracies after meditation training indicates greater self-awareness and control over various emotions	Using a small sample size, variations in emotional responses, and differences in meditation experience among participants were some limitations. Additionally, only short meditation sessions were conducted during the 8-week training, which limited the depth of meditation experience.
9	[123]	The aim of the study was to develop a real-time stress level detection system during meditation. This was tested by using delta, theta, alpha, and beta waves and classifying these signals with the k-Nearest Neighbor (k-NN) algorithm.	The k-Nearest Neighbor (k-NN) algorithm was successfully used to detect stress levels, achieving 80% accuracy when $k = 3$ , while developing an app that runs during meditation. The app provided real-time feedback on stress levels.	The biggest challenge was the unreliable connection from the EEG device to the smartphone, creating errors in machine learning classification. Also, some major challenges existed regarding the quality of the signals obtained from the EEG device.
10	[209]	The study looked at how mindfulness meditation affects brain activity by examining EEG data. ICA, along with statistical methods, was tested for feature extraction, and these features were analysed to classify meditation and non-meditation.	A k-nearest neighbors classifier was successfully used with a classification accuracy of 86.36% in distinguishing between meditators and non-meditators. The study found a significant difference between the two groups, with meditators showing more stable brain states.	Meditation EEG data contains significant noise and artifacts, requiring extensive cleaning. However, this multi-step cleaning process may lead to the loss of important information from the EEG dataset. This introduces another challenge: collecting high-quality, low-error EEG data during the experimental stage.
11	[184]	The study focuses on building a machine learning system to detect mind-wandering during a meditation session. EEG data was segmented into components using flexible analytic wavelet transform (FAWT), and features identified from this were used to classify meditation and mind-wandering.	The study was successful in detecting mind wandering during meditation with a high classification accuracy of 92.41%. The paper states that statistical analysis indicates that expert meditators showed lower mind wandering than novice meditators. This work can be further improved for developing machine learning apps to monitor and support meditation.	The method depends heavily on high-quality EEG data, meaning noisy data makes it less reliable. It might be overtrained for the selected dataset, hence may require adjustments for new datasets. Further studies are needed to generalize the resulting method.
12	[230]	The study investigates how EEG signals change before	The study showed that Higuchi Fractal Dimension,	Variation in EEG data occurs across individuals due to

		and after an 8-week mindfulness-based stress reduction programme. The study aims to identify the most effective nonlinear methods with EEG meditation, analyse how frequency bands behave with meditation, and determine which parts of the scalp are most active during meditation.	along with the Random Forest classifier, was effective in classifying EEG data before and after mindfulness training, with an accuracy above 70%. Alpha frequency band, especially from the right frontal region, were the most prominent for classification.	differences in meditation experience levels among participants, which negatively affects the study. The author highlights the importance of future studies that consider each individual independently to ensure differences among participants do not impact the results.
13	[92]	The study aims to distinguish between sitting meditation and walking meditation EEG data. It proposes using various feature extraction methods, either individually or with joint features, along with a Random Forest classifier to separate the two mental tasks.	When trying to classify sitting meditation and walking meditation EEG data, among the three features used alone, the most successful was original power features. But when all three features were combined and used together, they produced the best classification accuracy of 84.17%. Walking meditation presented additional challenges due to body movements that affected the study.	Studying walking meditation has challenges due to additional errors that may be present in the collected EEG data. Also, fixed EEG devices are more advanced than mobile EEG devices in many ways, which can result in differences in EEG data quality. Additionally, the meditation experience level of the participants may vary, adding a challenge to building a common BCI pipeline.
14	[144]	The aim of the study is to classify EEG data collected for Focused Attention Meditation and problem-solving tasks. This research tries to improve the understanding of the behaviour of the brain in ways that would help enhance meditation practice.	When it comes to classifying EEG data for Focused Attention Meditation and problem-solving tasks, individual Random Forest Classifiers were highly successful, achieving an average accuracy of 93%. On the other hand, general Random Forest Classifiers did not perform as well. The variations in meditation among participants were captured effectively when individual attention was given to each participant's EEG data.	The practice of Focused Attention Meditation is unique to each person, so it's impractical to design a common BCI pipeline that supports all. Although individual classifiers worked well for each participant, this approach needs to be further tested with multiple session data from the same person. Also, noise in EEG data can affect the outcomes of these types of studies.
15	[188]	The study examines EEG data collected for two mind tasks: relaxation meditation and a tension imagination task. The aim was to successfully classify the two mind tasks so that the knowledge gained could be used in future studies in consciousness, especially when studying different types of mental tasks.	The study shows the capability of using EEG data to classify the two mental tasks: relaxation meditation and tension imagination using the Hilbert-Huang Transform and Fisher Linear Discriminant Analysis. Additionally, the study identified the connection between relaxation during meditation and Alpha waves, and tension with Beta waves.	The study only focused on two mind tasks and needs to be tested on other mind tasks. The small sample size limits the generalization of the results. Various artifacts in EEG data create a challenge in classification accuracy. Finally, the individual differences among the participants can affect the development of a successful BCI pipeline.
16	[203]	The study focuses on classifying EEG data from a	The study successfully used the Linear Discriminant	Variability among the participants reduced the

		meditative state and a resting state for Rajayoga meditation. The findings aim to enhance the understanding related to meditation and will help in developing tools to facilitate meditation practice.	Analysis classifier with Rajayoga meditation and resting EEG data and obtained an accuracy of 97.9% for intra-subject and 74.0% for inter-subject classifications. The study showed that high frequency bands such as Gamma were more effective in the classification than the low frequency bands. The results indicated the challenge of generalizing the classification pipeline across different individuals with different meditation experience.	classification accuracy significantly for inter-subject classification when compared with intra-subject. Using only a single session of data for each participant prevented any study of session variability similar to the study done on subject variability when conducting classification.
17	[200]	The study aims to classify EEG data from loving-kindness meditation (LKM) and non-meditation instances for both single and multiple sessions. The study uses Common Spatial Patterns (CSP) for feature extraction and Linear Discriminant Analysis (LDA) for classification. The study tries to find mental patterns related to four meditation-related mind tasks EEG data.	For meditation and rest classification for a single session, a high accuracy of 99.5% was obtained, and for a pool of multiple session data, this was 83.6%. The results show that the pair of Common Spatial Pattern and Linear Discriminant Analysis works well with meditation EEG data, but further improvements are needed in multiple session studies. The results also show that out of the four mind tasks used, pre-rest EEG data was slightly different from the other three, as indicated by the classification accuracy differences. Additionally, multiple sessions exhibit some common characteristics across each mind task.	The lack of details about the level of meditation experience of the participants prevented the study from conducting inter-subject studies (where independent analysis would be conducted for each participant). Challenges in cleaning EEG data were noted. The lower classification accuracy in multiple sessions suggests the need for further studies. An improvement could be to, instead of using a pooled dataset from multiple sessions, attempt to classify new session data after training on a separate set of multiple-session data.
18	[204]	The study aims to classify EEG data collected from Isha Shoonya meditation experts while practicing meditation and a control group while conducting a non-meditation mind task. Studies were done with and without Independent Components Analysis (ICA) while using Convolutional Neural Network (CNN) models for the classification. The study attempts to improve the detection of meditation by optimizing the performance of CNNs.	The study shows that a Convolutional Neural Network can be used to classify EEG data of Shoonya meditation and non-meditation. The use of Independent Components Analysis in the preprocessing significantly increased the classification accuracy. The author says that this study can be expanded to clinical applications such as detecting schizophrenia and epilepsy.	The use of a small sample size may pose challenges in generalizing the results. The control group may have high variations in mental states, which might affect the study. It is important to ensure there is no overfitting and to test the method on other types of meditation techniques.
19	[176]	The study examines how effectively meditators and	The study found that the practice of combined Yoga	The sample size may have some limitations when

		non-meditators can be classified based on various statistical measures obtained from EEG data collected from the two groups. The study uses a meditation practice consisting of combined Yoga and Sudarshan Kriya, along with a control group, to collect the EEG data, and aims to support the automation of meditation assessment.	and Sudarshan Kriya changes EEG activity, indicating positive effects on brain function. A Multi-Layer Perceptron Neural Network (MLPNN), along with statistical measures obtained from meditation/non-meditation EEG, was able to successfully classify the two groups. After the three-month meditation training, an increase in the EEG parameters was observed.	generalizing the results to a broader population. The three-month duration may not be sufficient to capture brain wave changes from meditation. Focusing only on certain statistical parameters might hide some information available in the EEG data. The author emphasizes the importance of using advanced processing techniques and larger sample sizes as improvements for this study.
20	[95]	The study investigates how a short meditation session affects novice meditators by analyzing EEG to identify altered states of consciousness. The study expects to use changes in various frequency band power patterns during meditation to understand how meditation can affect the brain activity of individuals.	The study found that even a short meditation session significantly modified the EEG patterns in novice meditators. Theta, Alpha, Beta, and Gamma power levels increased by 29%, 16%, 17%, and 11%, respectively, while Delta power decreased by 5%. Additionally, the machine learning classifier successfully achieved a 97% accuracy in classifying pre-meditation and post-meditation data.	Variability in the session durations created challenges in the analysis. Since a control group was not used, isolating meditation-specific changes was challenging. The lack of clinical screening limited the understanding of the mental states of the participants.
21	[37]	The study aims to identify how meditation affects brain activity. A group was trained daily over a month, and EEG data were collected before and after the training. The two sets of EEG data were classified using three methods to understand the changes in brain activity affected by the meditation practice.	EEG data collected before and after meditation training were successfully classified using three algorithms, with the best accuracy reaching 85% by Support Vector Machine. The study showed an improvement in mental states after the one-month meditation training. Additionally, there was a significant increase in the strength of Theta and Alpha waves and a decrease in the strength of Delta and Beta waves following the meditation training.	The small sample size and the use of a limited set of statistical methods for feature extraction may restrict the findings. Since the study focuses on novice meditators, it does not account for individuals with different levels of meditation experience. Additionally, the one-month training duration does not capture long-term effects of meditation. By focusing only on the front part of the brain, the study misses insights on whole-brain activity.
22	[193]	The study aims to classify EEG data collected while performing a meditation task and a mind-wandering task to identify specific brain patterns related to meditation. For this study, three groups of participants were used, consisting of varying levels of expertise in three meditation techniques and one novice group who	The study successfully classified meditation and mind-wandering EEG data using Support Vector Machine (SVM) and Random Forest (RF). They also found that meditation is related to less complex brain signals with high power levels, while more complex signals were observed for mind-wandering. The author	The difference in the sample size and experts in the three meditation techniques having different levels of expertise. Focusing the signals on the whole brain might hide some information available in certain regions of the brain. The author notes that only features related to the timing of the EEG signals were focused on, and thus other

		were not experts in any meditation technique.	states that the knowledge gained here can be useful when developing EEG-guided meditation tools in the future.	types of features related to meditation EEG might have been missed.
23	[196]	The study aims to build a BCI pipeline to classify EEG signals recorded during Vipassana meditation and non-meditation sessions. Three pipelines were prepared to test Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Linear Discriminant Analysis (LDA) for feature extraction, and each was combined with Support Vector Machines (SVM) for classification. The study aims to understand how EEG and mental patterns behave while meditating compared to non-meditative states.	The study successfully used Support Vector Machines (SVM) to classify meditation and non-meditation EEG sessions. Additionally, Linear Discriminant Analysis performed best with SVM when compared to either Independent Component Analysis or Principal Component Analysis. However, all three pipelines demonstrated significantly high accuracies.	The author mentions the small sample size and the need to increase the size to generalize the results. Additionally, the author states that methods like LDA + SVM took longer to train, which makes them less practical. Furthermore, sensitivity to kernel choices for the SVM classifier can create overfitting and underfitting.
24	[201]	The study aims to explore the effects of mindfulness-based stress reduction (MBSR) meditation on novice meditators. For this, an eight-week training was conducted, and EEG data was collected at the beginning and end of the training during both resting and meditation tasks. Various pairwise combinations of these tasks were then tested using traditional machine learning and deep learning pipelines to study how the meditation training impacted the participants.	The study shows that the short mindfulness meditation training had significant effects which were visible in the collected EEG data. When testing various pairwise (meditation/rest, meditation1/meditation2, rest1/rest2) classifications with several machine learning algorithms, some accuracies were obtained that were very close to 100%. However, for the inter-subject classifications, significantly low accuracies were obtained. The study showed that SVM and neural networks were successful in classifying various instances of meditation/non-meditation EEG data.	Small sample size and the differences among the participants were noted by the author as limitations. Also, the authors say not having enough sessions of EEG data was a challenge in the study. The author also highlights the need for large datasets to properly apply the machine learning algorithms. In the inter-subjects, most of the classification accuracies were close to 50% or below, which is a significant weakness in a binary classification study.
25	[127]	The study aims to use artificial intelligence techniques (ANN, SVM) to understand the effect of Tibetan Nyingmapa meditation. It used novice, intermediate, and expert meditators, and EEG data were collected for both meditation sessions and non-meditation baseline sessions. The study aims to obtain high classification accuracies	The study found that both artificial neural networks (ANN) and support vector machine (SVM), under optimal conditions, produced accuracies over 98%. The key features contributing to these accuracies came from the Alpha band. The study highlights the value of using artificial intelligence in studying meditation EEG.	The study talks about the challenges faced with complexity in the EEG data. The author states that ANN models can encounter local minima, which might hinder achieving optimal results. Additionally, since the study focused on one meditation type, the findings may not generalize to other meditation types.

		to demonstrate the value of using artificial intelligence in meditation EEG analysis.		
26	[165]	The study focuses on classifying meditation EEG data based on the experience level of the participants. The study used novice, intermediate, and expert meditators in breathing meditation. This is targeted by using features in the Alpha band and testing three types of machine learning algorithms. The author expects to contribute to meditation EEG research by quantifying experience through classifications.	The study successfully used three machine learning algorithms (FKLSSVM, SVM, ANN) to classify breathing meditation EEG data for participants with three levels of experience. Among them, FKLSSVM achieved the highest accuracy of 96.28%. Additionally, the Alpha band was noted to have the highest impact as a feature in the classification process.	Small sample size and collecting only a single session of data may not be sufficient to capture all information related to this study. Also, restrictions in feature selection might have caused the loss of some valuable features available in the EEG data that might be useful for the study.
27	[202]	The study aims to classify Rajayoga meditation and non-meditation EEG data using a deep learning model. The study expects to detect the different brain activity characteristics in the two mind states using machine learning techniques.	When classifying meditation and non-meditation EEG data, classification accuracies of Alpha - 79.1%, Beta - 86.5%, lower Gamma - 91.0%, and upper Gamma - 94.1% were obtained. By using a neural network for classification, an increase of 15% in accuracy was achieved compared to previous work, indicating the value of using deep learning techniques for meditation EEG.	The study focused on inter-subject classification of meditation and non-meditation; hence, the variability among the EEG data collected due to differences in the meditation experience levels of the participants created challenges. The study only focused on Rajayoga meditators; therefore, the results cannot be generalised to all meditation types.
28	[229]	The study aims to assess how well deep learning algorithms can classify EEG data collected from a mindfulness meditation group and a control group. The meditation group followed an eight-week meditation training. The study seeks to compare the results with those from traditional classification methods.	The study showed that deep learning methods outperformed the traditional methods when detecting meditation and non-meditation EEG data. At the same time, Feed-Forward Neural Networks (FFNN) outperformed Convolutional Neural Networks (CNN). The study demonstrates the value of using deep learning methods with meditation EEG.	The dataset was limited, having only one session of small sized data per mind task for each person, and this is not enough for a comprehensive analysis. The analysis was done using only three channels, which is not sufficient for a complete study. Some limitations existed because of the noise in the EEG data.
29	[222]	The aim is to investigate if Shallow Convolutional Neural Networks (SCNNs) are successful in classifying experienced and novice Himalayan Yoga meditation EEG data. The author assumes that success in this area will be useful for research in building real-time applications for wearable	The study showed that Shallow Convolutional Neural Networks (SCNN) were highly successful in classifying experienced and novice Himalayan Yoga meditation EEG data. Also, 1D-SCNN performed better than 2D-SCNN in this classification.	Limited sample size restricted the comprehensive study. There is the risk of overfitting when the complexity of the model increases. The author shows that the lack of publicly available meditation EEG data also creates a challenge in this type of research.

		EEG devices to support meditation.		
30	[194]	The study aims to develop a BCI pipeline to classify EEG data collected from concentration and meditation using a Random Forest Classifier. Additionally, the study examines the ability to use this classification skill to control external devices (home automation) using mental states.	The study successfully built a machine learning pipeline to classify meditation and concentration EEG data using a Random Forest Classifier. The developed model demonstrated the capability to control a basic external device with a binary task.	Small sample size and the EEG device used, which had only one electrode, might have affected the data quality and created challenges for classification. Since the data was collected in a controlled environment, applying it in a real-world situation may be more challenging. The study only used two mind states rather than a range of mental states, which limited its capabilities.
31	[197]	The study aims to classify breathing meditation and mind-wandering EEG data for novice meditators using several machine learning techniques.	The study showed that meditation and mind-wandering EEG data classification was successfully done using Linear Discriminant Analysis, Naive Bayes, Support Vector Machines, and k-Nearest Neighbors. Also, a significant contribution of Alpha and Theta features was noted.	The variability among the individuals created differences in individual EEG patterns, which created a challenge in classification. Small sample size and limited data quality were also challenges faced, as mentioned by the author.
32	[128]	The study tries to find how the brain activates (on selected brain waves) under different meditation conditions. EEG data were collected for Transcendental Meditation, Raja Yoga, and Mindfulness Meditation at four different instances during a twelve-week training session and analysed using several classification techniques to understand the collected data.	The study found that meditation causes changes to brain activities, such as changes in the strength of Delta and Alpha waves. Additionally, the study was able to successfully classify different conditions related to meditation tasks using four types of artificial neural networks, with the VGG-16 model achieving the highest accuracy of 99.4%. The study showed the value of using EEG data to understand meditation.	The study mentions that the small sample size is a limitation and suggests collecting data from a diverse group of people with varying levels of meditation experience. Additionally, the author says that a twelve-week training period is insufficient to properly understand the effects of meditation.
33	[147]	The study aims to classify EEG data collected for three mind tasks: yoga, meditation, and combined yoga-meditation. The study uses three machine learning algorithms: linear support vector machine, K-nearest neighbor, and multilayer perceptron to identify the best performing classifier.	The study was successful in classifying EEG data collected from yoga, meditation, and combined yoga-meditation using the classifiers Linear Support Vector Machine, k-Nearest Neighbors, and Multilayer Perceptron, with the best accuracy obtained for Linear Support Vector Machine: 91.67%. The study used 50 features extracted from the EEG for the classification.	EEG data were complex and hard to extract information from. Also, the author states the need to identify and use new features to improve accuracies. There is a need for a broad group of participants to collect data so that the results can be generalised.
34	[153]	The study examines brain patterns of Himalayan Yoga	Himalayan Yoga and Hare Krishna mantra meditation	Due to the small sample size and the fact that participants

		(HT) and Hare Krishna mantra meditation (HKT) compared to a control group. Here, features such as Sample Entropy, Hurst Exponent, and Band Power, taken from EEG data, were classified using three machine learning algorithms: Support Vector Machines, Deep Neural Networks, and Random Forest.	EEG data were successfully classified against the control data using Support Vector Machines (SVM), Deep Neural Networks (DNN), and Random Forest. The features Sample Entropy (SE), Hurst Exponent (HE), and Band Power (BP) obtained from EEG data were independently and successfully used, with the BP feature producing the best accuracies for the three machine learning algorithms.	were selected based on certain conditions, there is a challenge in generalizing the results. Also, the study only focused on two types of meditation, leaving an opportunity to study other types. The study should also explore other types of features and classification methods to gain a better understanding.
35	[100]	The study explores how brain activities are impacted by breathing meditation, especially in the Alpha region. To test this, pre-meditation and post-meditation EEG data were classified using five algorithms: Multilayer Perceptron, Support Vector Machine, Logistic Regression, Decision Forest, and Naive Bayes.	The five classification algorithms used were successful in showing that there is a difference in brain activity between pre- and post-meditation. This is shown by the reduction in classification accuracies for post-meditation EEG data when using all five algorithms. Additionally, the study found an increase in Alpha wave power strength in post-meditation when compared with pre-meditation.	The small sample size, challenges with electrodes, and possible artifacts are some limitations mentioned by the author when generalizing the results.
36	[198]	The study focuses on using several machine learning algorithms to classify novice and expert meditators, as well as healthy individuals and patients with Parkinson's disease, using EEG data collected in all instances.	The study successfully used several machine learning algorithms to compare novice and expert meditators, as well as healthy participants and patients, using EEG data. The Deep Convolutional Neural Network achieved the best mean accuracy of 59.5% in the study. k-Means Clustering and Graph Neural Networks were not successful.	The author notes that the low quality of equipment used in the study affected the results. Additionally, a small sample size was identified as a limitation for obtaining optimal results.
37	[148]	The study attempts to classify breathing meditation and non-meditation EEG data while addressing the challenge of using inter-subject data. Here, Riemannian Space Data Alignment was tested to reduce the differences among participants, while using Support Vector Machines with a Radial Basis Function Kernel or EEGNet for classification.	Support Vector Machines with a Radial Basis Function Kernel (SVM-RBF) and EEGNet were successful in classifying meditation and non-meditation EEG data. Riemannian Space Data Alignment (RSDA) was able to increase the accuracy of both classifiers, indicating support for inter-subject classification. The best accuracy of 72.6% was obtained for EEGNet with RSDA.	The author says that high variability in the EEG data among various participants posed some challenges, especially with the lower-performing participants. Additionally, Riemannian Space Data Alignment's inability to accommodate geometric transformations placed limitations on the study.

38	[101]	The study proposes a lightweight Convolutional Neural Network (CNN) to classify EEG data collected from expert meditators, novice meditators, and the control group. The study aims to show that this method can work effectively so that it can be used in real-time due to its low complexity.	The introduced Convolutional Neural Network (CNN) outperformed traditional methods in classifying EEG data collected from expert meditators, novice meditators, and the control group, achieving an accuracy of 94.57%. At the same time, this new method performed similarly well to several deep learning models while maintaining low complexity.	Complexity and available artifacts created challenges in extracting features properly, thus impacting performance. The study uses a specific mind task and needs to be tested on different mind tasks and datasets to generalize the results. The author states that the results obtained depended on sample size, which should be increased in future studies.
39	[155]	The study aims to classify EEG data collected during mind-wandering and while practicing one of four meditation variations, using experts in each meditation variation. Several classification algorithms are used in the study to distinguish between meditation and mind-wandering.	The study used four variations of meditation and mind-wandering EEG data and successfully classified meditation and mind-wandering using several algorithms, achieving an average accuracy greater than 70%. This demonstrated the neural pattern differences between meditation and mind-wandering. Among the algorithms used, K-Nearest Neighbors produced the best accuracy of 77.7%.	The study focuses only on expert meditators; hence, the study should be extended to include novice meditators and non-meditators. Since the participants were selected from specific regions and meditation types, future studies should be conducted using a more diverse population to generalize the findings.
40	[215]	The aim of the study is to explore methods for identifying distractions during breathing meditation for novice meditators, which could be useful in developing applications to guide them. In this study, distractions such as sleepiness and mind-wandering were independently compared with meditation using EEG data, while testing ten different classification algorithms.	The study was successful in showing that EEG data can be used to detect mind-wandering and sleepiness during meditation. Ten classification algorithms were successfully used in the study, with the Random Forest classifier and the Decision Tree classifier producing the best results.	Since the study was conducted on novice meditators, the results may not be applicable to expert meditators, as there are certain brain wave pattern differences between novice and expert meditators. Additionally, using a small sample size and a limited number of electrodes might have missed capturing complex patterns that are useful for the comparison.

Table 2.7 Summary of EEG Frequency Bands Used

No	Reference	Delta	Theta	Alpha	Beta	Gamma
1	[33]		✓	✓	✓	
2	[91]		✓	✓	✓	
3	[34]			✓		
4	[152]	✓	✓	✓	✓	✓

5	[150]		✓	✓	✓	
6	[218]	✓	✓	✓	✓	✓
7	[210]	✓	✓	✓	✓	✓
8	[191]	✓	✓	✓	✓	✓
9	[151]		✓	✓	✓	
10	[123]	✓	✓	✓	✓	
11	[209]	✓	✓	✓	✓	✓
12	[227]					✓
13	[184]	✓	✓	✓	✓	
14	[230]		✓	✓		
15	[92]	✓	✓	✓	✓	✓
16	[93]	✓	✓	✓	✓	✓
17	[144]	✓	✓	✓	✓	✓
18	[83]			✓		
19	[188]			✓	✓	
20	[171]	✓	✓		✓	✓
21	[203]			✓	✓	✓
22	[94]			✓		
23	[200]	✓	✓	✓	✓	✓
24	[228]	✓	✓	✓	✓	✓
25	[204]	✓	✓	✓	✓	✓
26	[176]	✓	✓	✓	✓	✓
27	[95]	✓	✓	✓	✓	✓
28	[96]	✓	✓	✓	✓	✓
29	[37]	✓	✓	✓	✓	
30	[214]	✓	✓	✓	✓	
31	[193]	✓	✓	✓	✓	✓
32	[182]			✓	✓	
33	[97]	✓	✓	✓	✓	✓
34	[196]	✓	✓	✓	✓	
35	[125]		✓	✓	✓	✓
36	[98]			✓	✓	
37	[126]	✓	✓	✓	✓	
38	[201]	✓	✓	✓	✓	✓
39	[127]			✓		
40	[165]			✓		
41	[177]		✓	✓	✓	✓
42	[202]			✓	✓	✓
43	[229]			✓		
44	[222]					✓
45	[29]			✓	✓	
46	[194]	✓	✓	✓	✓	✓
47	[197]		✓	✓		

48	[128]		✓	✓	✓	
49	[147]	✓	✓	✓	✓	✓
50	[99]	✓	✓	✓	✓	✓
51	[189]	✓	✓	✓	✓	✓
52	[122]		✓	✓	✓	
53	[153]			✓		✓
54	[100]	✓	✓	✓	✓	✓
55	[198]	✓	✓	✓	✓	✓
56	[154]		✓	✓		
57	[148]		✓	✓	✓	
58	[101]		✓	✓		
59	[155]	✓	✓	✓	✓	✓
60	[215]	✓	✓	✓	✓	
61	[174]					✓
62	[149]	✓	✓	✓	✓	✓
63	[156]	✓	✓	✓	✓	✓
64	[178]		✓	✓		
65	[186]	✓	✓	✓	✓	✓
66	[163]	✓	✓	✓	✓	✓
67	[183]	✓	✓	✓	✓	✓
68	[224]		✓			
69	[220]	✓	✓	✓	✓	✓
70	[179]	✓	✓	✓	✓	✓
71	[157]			✓	✓	✓
72	[84]			✓		✓
73	[25]	✓	✓	✓	✓	✓
74	[164]		✓			
75	[102]	✓	✓	✓	✓	✓
76	[129]			✓		✓
77	[121]	✓	✓	✓	✓	✓
78	[103]	✓	✓	✓	✓	✓
79	[23]	✓	✓	✓		✓
80	[170]	✓	✓	✓	✓	✓
81	[85]	✓	✓	✓	✓	✓
82	[130]	✓	✓	✓	✓	✓
83	[86]					✓
84	[166]			✓		
85	[131]			✓		
86	[169]			✓		
87	[104]		✓			
88	[205]		✓	✓		
89	[195]		✓			
90	[172]		✓			

91	[145]		✓	✓		
92	[120]			✓		
93	[219]	✓	✓	✓	✓	✓
94	[105]		✓	✓	✓	✓
95	[106]		✓	✓		
96	[223]		✓	✓	✓	
97	[107]		✓	✓		✓
98	[158]	✓	✓	✓	✓	✓
99	[159]		✓	✓		
100	[14]			✓		
101	[132]		✓	✓	✓	
102	[213]		✓			
103	[206]	✓	✓			
104	[192]		✓	✓	✓	✓
105	[124]	✓	✓	✓	✓	
106	[133]				✓	
107	[108]	✓	✓	✓	✓	✓
108	[134]		✓	✓	✓	✓
109	[135]		✓			✓
110	[109]	✓	✓	✓	✓	✓
111	[110]	✓	✓	✓	✓	
112	[111]		✓	✓	✓	
113	[136]		✓	✓		✓
114	[12]	✓	✓	✓	✓	✓
115	[143]	✓	✓	✓	✓	
116	[175]		✓			
117	[36]	✓	✓	✓	✓	✓
118	[160]			✓	✓	✓
119	[87]	✓	✓	✓	✓	✓
120	[137]	✓	✓	✓	✓	✓
121	[27]		✓	✓	✓	
122	[112]	✓	✓	✓		
123	[138]			✓		✓
124	[38]		✓	✓		
125	[173]	✓		✓		
126	[113]	✓	✓	✓	✓	✓
127	[167]		✓	✓		
128	[216]	✓	✓	✓	✓	✓
129	[190]	✓	✓	✓		✓
130	[180]		✓	✓	✓	
131	[146]	✓	✓	✓	✓	✓
132	[88]	✓	✓	✓		✓
133	[212]		✓	✓	✓	

134	[185]		✓	✓		
135	[207]	✓	✓	✓	✓	✓
136	[211]			✓		
137	[208]	✓	✓	✓	✓	✓
138	[221]	✓	✓	✓	✓	✓
139	[114]	✓	✓	✓		✓
140	[8]	✓	✓	✓	✓	✓
141	[115]		✓	✓	✓	
142	[35]	✓	✓	✓	✓	✓
143	[161]		✓	✓		✓
144	[199]					✓
145	[116]			✓	✓	✓
146	[117]			✓	✓	
147	[118]	✓	✓	✓	✓	✓
148	[119]	✓	✓	✓	✓	✓
149	[225]	✓	✓	✓	✓	
150	[226]	✓	✓	✓	✓	✓
151	[139]			✓		
152	[89]			✓		
153	[140]	✓	✓	✓	✓	✓
154	[162]	✓	✓	✓		
155	[217]	✓	✓	✓		
156	[90]	✓	✓	✓		
157	[168]			✓		
158	[24]			✓	✓	
159	[39]		✓	✓	✓	✓
160	[231]	✓	✓	✓	✓	✓
161	[181]	✓	✓	✓	✓	✓
162	[187]	✓	✓	✓	✓	
163	[141]		✓	✓	✓	
164	[142]		✓	✓	✓	
	Total	83	127	148	107	89
	Percentage (%)	50.6	77.4	90.2	65.2	54.3

## STATEMENT OF CONTRIBUTION DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the student and the student's main supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the student's contribution as indicated below in the Statement of Originality.

Student name:	Nalinda Devaka Liyanagedera
Name and title of main supervisor:	Professor Hans W. Guesgen, Chair in Computer Science
In which chapter is the manuscript/published work?	Chapter 3

Describe the contribution that the student and members of the supervisory team have made to the manuscript/published work:<sup>1</sup>

The student analysed and interpreted the data, validated results, visualised findings, and wrote the original manuscript. Moreover, conceptualising, designing the methodology, and developing the necessary software were carried out by the student. The student also contributed to the review and editing of the manuscript. The supervisory team contributed by reviewing and editing the manuscript and providing supervision throughout the work.

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# Chapter 3

## Common spatial pattern for classification of loving kindness meditation EEG for single and multiple sessions

### Abstract

While a very few studies have been conducted on classifying loving kindness meditation (LKM) and non-meditation electroencephalography (EEG) data for a single session, there are no such studies conducted for multiple session EEG data. Thus, this study aims to classify existing raw EEG meditation data from single and multiple sessions in order to derive meaningful inferences that can support the development of algorithms for meditation practice. In this analysis, data have been collected on Pre-Resting (before-meditation), Post-Resting (after-meditation), LKM-Self and LKM-Others for 32 participants and hence allowing us to conduct six pairwise comparisons for the four mind tasks. Common Spatial Patterns (CSP) is a feature extraction method widely used in motor imaginary brain computer interface (BCI), but not in meditation EEG data. Therefore, using CSP in extracting features from meditation EEG data and classifying meditation/non-meditation instances, particularly for multiple sessions will create a new path in future meditation EEG research. The classification was done using Linear Discriminant Analysis (LDA) where both meditation techniques (LKM-Self and LKM-Others) were compared with Pre-Resting and Post-Resting instances. The results show that for a single session of 32 participants, around 99.5% accuracy was obtained for classifying meditation/Pre-Resting instances. For the 15 participants when using five sessions of EEG data, around 83.6% accuracy was obtained for classifying meditation/Pre-Resting instances. The results demonstrate the ability to classify meditation/Pre-Resting data. Most importantly, this classification is possible for multiple session data as well. In addition to this, when comparing

the classification accuracies of the six mind task pairs; LKM-Self, LKM-Others and Post-Resting produced relatively lower accuracies among them than the accuracies obtained for classifying Pre-Resting with the other three. This indicates that Pre-Resting has some features giving a better classification indicating that it is different from the other three mind tasks.

Keywords: BCI (brain computer interface), EEG (electroencephalography), Meditation, Classification, CSP (common spatial patterns), LDA (linear discriminant analysis)

### 3.1 Introduction

As defined by Thomas et al. [1], meditation simply means targeting mental and emotional control by focusing the mind on a thought, activity or an object resulting in a clear and calm mind. Meditation is known to have multiple benefits such as depression reduction, stress reduction, anxiety reduction and as an attentional training to bring improved insight into one's own mental activity [5]. To investigate latent neural patterns associated with meditation-related mental states, scientific methods such as heart rate analysis, brain waves, brain imaging, and questionnaires [9, 16, 17, 232, 233] have been used and in this study, brain wave data collected on multiple meditation sessions using electroencephalography (EEG) were used. EEG is a test used to monitor the electrical activity of the brain and has been successfully used in studying various types of meditation [33, 182, 234]. The present work is aimed at achieving a classification for loving kindness meditation (LKM) EEG data for a variety of instances. The selected EEG dataset consists of four types of mind tasks, two meditation and two resting (one before meditation and one after meditation). The study was conducted using EEG data of 32 participants for a single session and 15 participants for 5 sessions. The analysis was done for

both single session and multi-session instances. A machine learning approach was used to get the results in which Common spatial patterns (CSP) was used for feature extraction and Linear discriminant analysis (LDA) was used for classification. The classification was done for all six pairs of the four mind tasks that gave a better understanding of the LKM EEG dataset.

### 3.1.1. EEG BCI background

In recent years, research has been conducted to develop various sensor devices that can read information from the human body and can be used for operations in the outside world. This involves a broad area where sensors may try to detect features such as heartbeat, breath, eye movement, brain waves, etc. The field in which brain waves are used for communicating with a computational device is known as brain computer interface (BCI) [28]. The brain functions by transferring information between brain cells known as neurons in the form of electrical signals and chemicals. These electrical signals at a given time indicate how a brain functions and both researchers and doctors have been using the behaviour of these signals as a tool to understand the functionality of the brain. Electroencephalography (EEG) which is one such method used to measure this electrical activity in millivolts, measures the voltage changes produced from the flow of ionic current among neurons of a brain. The patterns of electrical activity occurring in the brain are known as brain waves. These brain waves are basically classified into five categories which are defined based on the frequency strength and are assigned to different activities occurring in the brain such as deep sleeping, meditating, creativity, alertness, problem solving, etc. Although there are small variations in the boundaries of these bands, the mostly used set of frequencies among researchers are Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz) and Gamma (> 30 Hz) [73, 77, 121].

EEG data are collected by placing electrodes along the scalp and collecting data for a certain period of time. The international 10–20 system [57] of electrode placement is an internationally recognised numbering system used to identify locations on the scalp when placing electrodes of an EEG device on the scalp. The electrodes placement is designated by numbers and letters to represent the area of the brain underneath the electrode, Fp: pre-frontal region, F: frontal region, P: parietal region, T: temporal region, O: occipital region and C: central region [8, 58, 235]. To represent electrodes placed on the boarder of any of the two regions, the letters of both regions are used [26, 59] (FC/frontal-central region, FT/frontal-temporal region, CP/central-parietal region, TP/temporal-parietal region and PO/parietal-occipital region) and AF is used between Fp and F [236]. The numbers represent the position on the scalp with odd numbers for the left hemisphere and even numbers for the right hemisphere. When collecting EEG data any number of electrodes can be used, placed in any pattern in international 10–20 system and in most of the studies an electrode count of 4, 8, 16, 32, 64, 128 or 256 has been used.

### 3.1.2. EEG signal processing with machine learning techniques

EEG data contain a variety of information about the brain activity for a given instance and pattern extraction and deriving information from them are complex processes. This is basically due to the fact that the raw EEG data can contain high levels of noise (low signal-to-noise ratio) and thus it needs to follow multiple steps to process the signals to extract the valuable information hidden in the raw EEG data. The steps involve data acquisition, signal preprocessing and artifact removal, feature extraction, classification, and control interface, which in a general EEG-BCI pipeline refers to the stage where classification outputs are used to provide feedback or control an external system; however, this study focuses only on the signal processing and classification stages [22]. When considering signal preprocessing and

artifact removal, EEG data are commonly affected by noise originating from multiple sources, including external environmental interference such as electromagnetic effects from surrounding electrical equipment, as well as physiological artefacts arising from bodily activities such as eye movements, eye blinks, and jaw movements. Here, usually a suitable filtering technique can be used to remove noise coming from internal body functions and a high pass filter [33] can be used to remove unwanted lower frequencies such as frequencies less than 0.5 Hz. A low pass filter [33] can be used to remove unwanted higher frequencies such as frequencies greater than 60 Hz. To remove the external electromagnetic noises, 50 Hz band stop filter [165] can be used.

For signal processing and feature extraction from EEG data, sometimes advanced algorithms such as common average reference (CAR), independent component analysis (ICA), principal component analysis (PCA), Fourier transformation (FT), linear discriminant analysis (LDA), common spatial pattern (CSP) can be used depending on the problem type [32, 64, 196]. In CAR, to reduce the noise, the average value of all the electrodes is removed from all the electrodes. On the other hand, ICA is a special case of blind source separation, where the observed EEG signals are assumed to be linear mixtures of underlying, statistically independent and non-Gaussian source signals. A commonly used analogy is the “cocktail party problem,” which describes the separation of individual sound sources from a mixture of voices recorded by multiple microphones. In EEG artifact removal, ICA [30, 31] attempts to decompose the recorded channel data into independent components, some of which correspond to physiological artifacts such as eye blinks or muscle activity, allowing these components to be identified and removed. In feature extraction, ICA can also be used to reduce source mixing by separating dominant neural sources, rather than assuming that the recorded EEG channels themselves are statistically independent.

Principal component analysis (PCA) [30, 143] tries to reduce the number of variables in a dataset. When doing this task, some information may get lost in the dataset. So, PCA tries to reduce the data size while losing minimum information as possible. This size reduction allows various machine learning algorithms to work efficiently. In EEG data processing, PCA can be used not only for cleaning the data, but also for extracting features.

Fourier transformation (FT) [237, 238] can be seen as a feature extraction method used in many EEG-related experiments. FT is a mathematical transformation of data that will convert a vibration signal into its frequency domain. So, the result will show how each frequency has contributed to the original vibration signal.

Common spatial pattern (CSP) [45, 62, 81, 82] is a multivariate signal processing method used in EEG feature extraction methods that tries to maximize the variance of one mind task while trying to minimize the variance of the other mind task. The idea is to identify a set of spatial filters that will maximize the variance between two mind tasks in EEG. The algorithm starts by dividing the dataset based on the two mind tasks and then calculate a covariance matrix for each mind task. After that a pooled covariance matrix is calculated using all the covariance matrices. Then, the spatial filters that give a maximum covariance difference between the two mind tasks are calculated using generalised eigen vectors obtained from the pooled matrix. These spatial filters are sorted in the descending order of eigen values obtained from the pooled covariance matrix. After that, each mind task EEG dataset is passed through the spatial filters to get the spatially filtered features for each mind task. These features get ranked according to their strength of separating the two mind tasks and the strongest features will be used in classifying a new EEG dataset.

With CSP as a feature extraction algorithm, linear discriminant analysis (LDA) [46, 80] as a classification algorithm has been used, especially in the area of motor imagery BCI. LDA is a

machine learning algorithm that will either calculate or use an already built pooled covariance matrix to calculate the feature set, which in other words, when using the algorithm alone, LDA itself will calculate a feature set for the classification model. However, when the feature set calculated by CSP is available, LDA can take it as an input and directly use that for the classification model. Lotte et al. in his review paper conducted a study regarding classification algorithms for EEG-based brain–computer interfaces [32] and gives a summary of all the methods and algorithms used under BCI for feature extraction and classification. Among the above-mentioned algorithms, CSP is one of the best performing feature extraction algorithms for EEG in motor imagery. As shown in another review paper based on motor imagery EEG [22], the classification algorithm LDA has produced high performance in motor imagery BCI. Although this combination of CSP and LDA has been used to analyse EEG data in many experiments such as motor imagery, this machine learning pair has not been used for studying meditation EEG datasets for multiple sessions. The lack of research for using CSP and LDA to study meditation EEG is well demonstrated in a review paper [76].

### 3.1.3. Study of meditation using EEG

Effects of meditation on humans can be divided into two types, namely state and trait while EEG has been used to study both cases [15, 26]. States are temporary changes and traits are long-term/permanent changes happening in a person doing meditation. To identify state [42, 61] characteristics, a person needs to collect data for meditation and non-meditation instances either for the same group of people or for a meditation group and a control group. The brain wave characteristic difference between meditation and non-meditation instances is one example of state changes in the brain. Trait [14, 17] changes are permanent modifications which are visible in a person after practicing meditation for a long time. Trait characteristics can be

identified by comparing brain functionality of long-term meditators with non-meditators/novice meditators. This can be detected when they are staying relaxed without meditating or while doing meditation. Studies have been conducted comparing different instances of the same meditation technique such as meditation vs non-meditation, novice meditators meditating vs expert meditators meditating, using EEG data [78].

Although there are many meditation techniques, past research shows that they are categorized in to either 2 or 3 different types of groups based on the characteristics they possess. Cahn et al. [26] divide meditation into two types, mindfulness and concentrative depending on how the person focuses his/her attention in meditation. Some meditation techniques fall into either one of these two techniques or somewhere in the middle where it will have a portion of characteristics from both mindfulness and concentrative methods. Mindfulness meditation simply allows any type of emotion, thought or a feeling to appear and disappear from mind without any forceful control over it. The person will be an observer looking at the mind without any attachment, dislike or analysis and some examples are Vipassana [50, 232, 239] and Zen [240, 241] meditations. On the other hand, in concentrative meditation a person will have a special focus or an attention towards a specific mental task. This can be a body sensation like breath, body movement like walk, a repeated sound (a word or a sentence know as a mantra) or imagining of a particular symbol or picture, etc. Some examples are yoga and samatha (breath, etc.) meditations [141, 176]. However, some meditation techniques such as loving kindness [12, 13] and transcendental [242, 243] will have characteristics of both mindfulness and concentrative methods. Loving kindness meditation (LKM) which is also known as Metta meditation works by generating positive thoughts such as kindness, love, compassion towards oneself or others without getting too attached to anything. This can be achieved by repeating a phrase or couple of phrases that may wish someone to be happy or wish someone to be free

from suffering. Research shows that LKM has many benefits that improves physical and mental health such as reducing depression, stress and even improving the immunity of the body [12].

#### 3.1.4. Summarizing the importance of this study

Scientifically understating how a brain works when doing meditation is an ongoing research trend in the field of meditation. Studies show that various characteristics were identified in EEG signals that map with various characteristics of meditation [1, 26, 40, 41]. As an example, when considering EEG data collected for a group of people when meditating and when not meditating, analysed EEG data show pattern difference between the two groups [79]. Moreover, there are studies that discuss about multiple benefits gained from practicing meditation [11]. Some studies show how practice of meditation supports in improving mental health [3, 13]. However, it is important to have a proper guidance for the meditation. Brandmeyer et al. [19] talks about the need of some devices/programmes that can indicate how well a person is performing in meditation. The author indicates, with such facilities a person can monitor his/her progress in meditation and alter the practice according to the progress. Therefore, it has been emphasized that there is a need for monitoring tools in the research community. There have been scientific studies to understand the usefulness of apps that support meditation [6, 52, 54]. These studies show that these apps offer many benefits for the people using them [18, 53]. However, the biggest disadvantage of most of the apps available for meditation support is that the apps are not capable of knowing if the person is properly progressing in the meditation [51]. Therefore, the support and guidance an already available app can offer a person is highly limited. Taken together, it emphasizes the importance of classifying meditation/ non-meditation EEG data with high accuracy and more importantly, to study if the classification of meditation/ non-meditation is possible for multiple sessions using EEG data. This can result in developing

algorithms that can understand various stages in meditation, hence can guide a person in meditation. Recent studies have shown the results of classifying EEG meditation/non-meditation data. Ahani et al. [33] has classified mindfulness meditation EEG data using Stockwell transform and support vector machine with an accuracy of 85.0%. At the same time, Tee et al. [178] achieved a classification accuracy of 96.9% for theta healing meditation using discrete wavelet transform and logistic regression. However, for LKM such results have not been reported so far. In both cases, the studies were conducted only for a single session EEG data. It is well understood that a study of multiple session classification is needed. Therefore, this study was done for loving kindness meditation for multiple sessions and CSP was used in feature extraction, and this is a significantly new approach.

## 3.2 Methods

### 3.2.1. Dataset description

For the current study, an online EEG dataset relevant to LKM was chosen which has been titled as “The Effect of Buddhism Derived Loving Kindness Meditation on Modulating EEG: Long-term and Short-term Effect”. The dataset has been publicly available since 2021–09-24 onwards. The dataset was collected by the team of Ven. GoonFui Wong, Junling Gao and Rui Sun with a funding of Faculty Research Fund of Faculty of Education in HKU. The project has been ethically approved by the University of Hong Kong Human Research Ethics Committee under the reference number: EA210145. The dataset DOI is “[https://doi.org/10.18112/open\\_neuro.ds003816.v1.0.1](https://doi.org/10.18112/open_neuro.ds003816.v1.0.1)”.

Brainvision—ActiCHamp (Brain Products, German) EEG device was used for the data collection. The device has 127 EEG channels placed on the international 10–20 system and one ECG channel for collecting the data [236]. To keep a good signal-to-noise ratio, all electrodes impedance was kept under 20 kOhm and the sampling rate was 1000.

EEG data have been collected using 48 participants having previous experience in meditation and were used for the two main mind tasks: meditation and non-meditation separately. Out of these 48 participants, 15 participants were used in multiple session data collection. For these 15 participants, 8–10 data collection sessions were conducted within a 2-month period. In each session, the data were collected for each person for six types of tasks with eyes closed. The meditation method used was loving kindness meditation (LKM). The six tasks were pre-resting, post-resting, radiating LKM to self, radiating LKM to others, visualize self and visualize others.

In this analysis the interest is to classify rest state EEG data with meditation EEG data. For that, EEG data of four mind tasks out of the six available tasks were selected. The selected four instances were pre-resting, post-resting, radiating LKM to self, radiating LKM to others where the first two are resting instances: one before the meditation sessions and the other after finishing all the meditation sessions. LKM to self and LKM to others are two types of meditations where a person meditates loving kindness thoughts to oneself and to others, respectively. In the current work, the labels Pre-Resting, Post-Resting, LKM Self and LKM Others are used for them.

The original dataset consists of 6467 files having a size of 53.97 GB and with 48 total number of participants from which 15 were used in multiple session data collection. With these details, two types of studies were conducted for the given dataset. One is to study the meditation/ non-meditation EEG data for 48 participants for a single session while the other is to study the meditation/ non-meditation EEG data for 15 participants for multiple sessions.

When considering the original dataset, each EEG data collected for a single instance (single mind task) has produced 6 files. (A single data collection session consists of six of these mind tasks (instances), which means 36 files for a single data collection session.) One out of the six files for each instance contains the raw EEG data and the other five files contain supporting data for the raw EEG data. In the original dataset a sample of those six files, for an instance called 'aaa' were labelled as: `aaa_eeg.eeg`, `aaa_eeg.json`, `aaa_eeg.vhdr`, `aaa_eeg.vmrk`, `aaa_channels.tsv`, `aaa_events.tsv`. To read EEG data for a single instance, the corresponding EEG file and the supporting files were used together.

### 3.2.2. Methods of experiment

As the first step, readability of both the raw data and supporting files were checked. A very few data collection instances, in which one or more of the six needed files were corrupted, the entire session was removed from our analysis. In this study, a person/session was selected only if all four mind tasks were not corrupted. The analysis was conducted using the python language and the mne package in python was used to read the raw data using `read_raw_brainvision`. Out of 48 participants that can be considered for a single session, there were 32 people whose files were readable without being corrupted, for all 4 instances. Therefore, for the single session analysis raw data of these 32 participants was used.

Similarly, the mne package was used to read raw data for the 15 participants where data were collected in multiple sessions consisting about 8, 9 or 10 sessions. For these 15 participants, it was observed that 5 to 9 sessions were properly readable (for a selected good session, EEG data were properly readable for all four instances it has.). Therefore, when studying EEG data for multiple sessions, the data of five sessions (Table 3.1) were used for these 15 participants to

allow fairness among all 15 participants. When there were more than 5 good-quality sessions available, the 5 sessions with the largest file sizes were selected and used in this study.

Table 3.1 The five sessions selected for each of the 15 participants when in multiple session analysis

Count	Participant No	Session Numbers					
1	1	1	7	8	9	10	
2	3	1	2	5	6	10	
3	7	1	2	3	8	10	
4	8	1	4	5	6	8	
5	11	2	3	4	9	10	
6	12	1	2	3	4	8	
7	14	1	3	5	6	8	
8	37	3	4	7	9	11	
9	38	1	2	3	7	10	
10	39	1	5	6	7	9	
11	41	3	5	7	8	9	
12	42	1	3	6	7	10	
13	43	1	2	3	4	5	
14	44	1	3	4	6	7	
15	45	1	5	7	8	9	

In summary, using the loving kindness meditation EEG dataset (Pre-Resting, Post-Resting, LKM Self and LKM Others) two studies were conducted using the available readable data. In the first study, EEG data for 32 participants involved with a single session were used. For the second study, EEG data for 15 participants collected in 5 sessions were used. As the next step, cleaning of this readable raw EEG data is elaborated below.

The raw data consist of 128 channels from which one was an ECG channel. The ECG channel was removed, and the remaining 127 EEG channels were taken. Under the 10–20 montage, 4–5 channels were renamed accordingly to match the montage ‘standard\_1005’. The dataset was filtered using a high pass filter of 0.5 Hz and a low pass filter of 45 Hz that gave the cleaned EEG dataset a frequency range starting from 0.5 Hz to 45 Hz. This frequency range contains 5 frequency bands that are used in studying meditation EEG; Delta (0.5–4 Hz), Theta (4–8 Hz),

Alpha (8–13 Hz), Beta (13–30 Hz), Lower Gamma (30–45 Hz). The applied filtering attenuated power-line interference at 50 Hz, which is common in the country where the data were collected.

Something that is very common in many EEG meditation data analyses is to visually inspect the data and manually remove selected sub-parts based on waveform appearance. This approach is highly questionable, as the identification of faulty segments can vary between researchers and lacks scientific reproducibility. In this study, standard automated preprocessing steps such as filtering were applied; however, no additional manual or visually guided artefact rejection was performed. Therefore, when a raw EEG dataset was selected for analysis, the entire recording was retained without removing sub-parts solely based on visual inspection. This design choice allows other researchers to repeat the same procedure in future experiments.

Each selected EEG dataset was broken down into epochs of 2 s size with 1 s overlap. With a sampling rate of 1000, an epoch of 2 s will contain sufficient information for the feature extraction and classification. When an EEG data is broken into epochs, some information near to the splitting location gets lost. To avoid this, an overlapping of 1 s was used and this would put the separation location of one epoch placed in the middle of the adjacent epoch.

Here, two studies were conducted on the four mind tasks Pre-Resting, Post-Resting, LKM Self and LKM Others using the relevant EEG epochs. A pairwise comparison was done among these four mind tasks creating six pairs. They are (Pre-Resting/LKM Self), (Pre-Resting/ LKM Others), (Pre-Resting/Post-Resting), (LKM Self/LKM Others), (Post-Resting/LKM Self) and (Post-Resting/LKM Other). These six pairs were used in single session study and in multi-session study where the results can be used to understand some characteristics of meditation EEG data.

The first study was conducted on the EEG data of 32 participants for a single session. A session consists of four mind tasks Pre-Resting, Post-Resting, LKM Self and LKM Others. Thus, six pairwise analysis was conducted. As an example, one pair is used in the explanation, as elaborated below, since the same procedure is applicable for all the six pairs. Moreover, the same procedure was conducted for all the 32 participants.

For a single person, the pair “Pre-Resting/LKM Self” was selected. Here, EEG data were read, filtered and broken into two groups of epochs. Then the dataset was divided into training and testing sets where 70% was used for the training and 30% for testing. For the training and testing, a machine learning pipeline was built using Python scikit-learn library which consists of three steps. As the first step in the pipeline, a covariance matrix was estimated for the input data using Oracle Approximation Shrinkage (OAS). Then as the second step, common spatial pattern (CSP) with (nfilter = 8) was used for the feature extraction. Here, eight spatial filters were used in the CSP filter bank, while reducing the dimensionality of covariance matrix to extract the most relevant features. As the final component of the pipeline, linear discriminant analysis (LDA) was used as the classification algorithm. The entire pipeline—including OAS covariance estimation, CSP feature extraction, and LDA—was fitted using only the training dataset, and the learned parameters were then applied to the test data to calculate LDA scores for the testing data, enabling classification. The prediction accuracy for the test data was calculated using `balanced_accuracy_score` in Python. This procedure was conducted 25 times, and the average accuracy across the 25 tests for a single pair for a single person was calculated. A similar procedure was conducted for the remaining 5 pairs for the given person to calculate the prediction accuracies. This calculation was conducted on all selected 32 participants and the results are shown in Table 3.2.

Table 3.2 Average prediction accuracy (%) after conducting 25 tests each for 32 participants with single session using CSP and LDA (train 70%, test 30%)

Count	Participant No	Pre-Resting / LKM Self	Pre-Resting / LKM Others	Pre-Resting / Post-Resting	LKM Self / LKM Others	Post-Resting / LKM Self	Post-Resting / LKM Other
1	1	100 ± 0	100 ± 0	100 ± 0	100 ± 0	100 ± 0	94.6 ± 3.4
2	2	100 ± 0	100 ± 0	100 ± 0	100 ± 0	100 ± 0	98.8 ± 1.8
3	3	100 ± 0	100 ± 0	100 ± 0	100 ± 0	81.9 ± 6.5	80.3 ± 4.4
4	5	100 ± 0	100 ± 0	100 ± 0	99.8 ± 0.6	99.7 ± 0.8	98.2 ± 1.8
5	6	100 ± 0	99.9 ± 0.1	100 ± 0	98.6 ± 1.2	100 ± 0	99.9 ± 0.1
6	7	100 ± 0	100 ± 0	100 ± 0	100 ± 0	100 ± 0	95.1 ± 2.8
7	8	99.3 ± 0.8	100 ± 0	100 ± 0	99.9 ± 0.4	97.2 ± 1.1	99.5 ± 0.6
8	11	99.4 ± 2.0	100 ± 0	100 ± 0	98.1 ± 1.6	99.7 ± 0.9	100 ± 0
9	12	98.6 ± 3.1	99.4 ± 0.3	100 ± 0	98.7 ± 2.2	100 ± 0	90.8 ± 6.1
10	13	98.6 ± 4.1	99.9 ± 0.2	99.7 ± 0.6	88.5 ± 6.6	94.5 ± 5.1	98.1 ± 1.7
11	14	100 ± 0	99.9 ± 0.3	100 ± 0	100 ± 0	99.7 ± 0.5	100 ± 0
12	17	97.5 ± 2.5	99.5 ± 1.0	98.4 ± 2.7	91.1 ± 5.3	99.2 ± 0.8	90.5 ± 4.6
13	18	99.8 ± 0.5	100 ± 0	100 ± 0	65.7 ± 8.5	92.4 ± 3.8	98.7 ± 2.0
14	19	100 ± 0	100 ± 0	99.7 ± 1.6	95.3 ± 4.8	97.7 ± 2.6	95.5 ± 4.6
15	21	100 ± 0	99.5 ± 1.7	100 ± 0	79.6 ± 8.1	99.5 ± 0.6	99.3 ± 1.5
16	22	100 ± 0	100 ± 0	100 ± 0	99.0 ± 0.7	96.9 ± 3.9	94.1 ± 6.4
17	23	100 ± 0	100 ± 0	100 ± 0	100 ± 0	100 ± 0	99.3 ± 1.1
18	24	100 ± 0	100 ± 0	100 ± 0	97.8 ± 2.5	97.3 ± 2.1	93.1 ± 4.0
19	25	100 ± 0	99.1 ± 1.2	99.8 ± 0.5	82.2 ± 8.5	98.4 ± 1.3	80.4 ± 7.3
20	28	98.1 ± 2.2	99.3 ± 1.0	97.9 ± 1.7	99.9 ± 0.1	94.6 ± 2.4	99.4 ± 1.4
21	29	98.2 ± 2.7	100 ± 0	100 ± 0	99.1 ± 1.7	99.2 ± 0.5	84.8 ± 3.5
22	33	97.8 ± 1.6	100 ± 0	100 ± 0	87.9 ± 6.9	88.8 ± 7.4	96.0 ± 4.6
23	36	98.5 ± 0.7	100 ± 0	100 ± 0	98.7 ± 0.8	100 ± 0	100 ± 0
24	37	100 ± 0	100 ± 0	100 ± 0	100 ± 0	100 ± 0	74.4 ± 5.3
25	38	100 ± 0	100 ± 0	100 ± 0	99.4 ± 1.1	100 ± 0	100 ± 0
26	39	95.1 ± 2.1	100 ± 0	100 ± 0	87.3 ± 6.5	100 ± 0	100 ± 0
27	40	99.9 ± 0.2	100 ± 0	99.9 ± 0.3	93.7 ± 4.7	98.4 ± 2.4	93.1 ± 3.1
28	41	99.9 ± 0.6	99.9 ± 0.4	99.6 ± 1.2	99.8 ± 0.9	100 ± 0	99.9 ± 0.5
29	42	99.8 ± 0.4	99.9 ± 0.3	99.4 ± 1.3	99.6 ± 1.0	98.8 ± 0.5	85.7 ± 3.8
30	43	100 ± 0	100 ± 0	100 ± 0	99.4 ± 1.0	99.9 ± 0.3	99.2 ± 1.2
31	44	100 ± 0	92.3 ± 4.3	99.1 ± 1.2	98.5 ± 0.7	99.2 ± 0.5	99.6 ± 0.4
32	45	98.4 ± 2.4	100 ± 0	100 ± 0	100 ± 0	100 ± 0	99.1 ± 1.1
Mean Accuracy		99.3	99.6	99.8	95.6	97.9	94.9

The second study was conducted on the EEG data collected from the 15 participants for multiple sessions where each session consists of four mind tasks Pre-Resting, Post-Resting, LKM Self and LKM Others. Here, per person five sessions were selected (Table 3.1) for the study of behaviour of EEG meditation data for multiple sessions. In this test, prediction accuracy was calculated for each person for all six mind task pairs. They are (Pre-Resting/ LKM Self), (Pre-Resting/LKM Others), (Pre-Resting/ Post-Resting), (LKM Self/LKM Others), (Post-Resting/ LKM Self) and (Post-Resting/LKM Other). When considering a single pair such as Pre-

Resting/LKM Self for a single person, corresponding EEG data for the five sessions were used. These EEG data for the five sessions for a given pair, were read, filtered, broken down into epochs with the labels of the two mind tasks. In this case, one group will have epochs of Pre-Resting EEG data of five sessions and the other group will have epochs of LKM Self EEG data of five sessions. Then the dataset was divided into training and testing sets where 70% was used for the training and 30% for testing. Similar to the first study (above-mentioned), a machine learning pipeline with CSP and LDA was used for feature extraction and classification and the average prediction accuracy for 25 experiments was calculated for the test dataset. This was repeated for all six pairs for a single person and the calculation was conducted on all 15 participants and the results are shown in Table 3.3. Using 70% of the data for training is the standard procedure; however, there are cases where a favourable train–test split may lead to artificially high classification accuracy on the remaining 30% of the data. In such cases, the observed performance may reflect chance alignment between training and testing samples rather than genuine generalisation. This type of overfitting due to data partitioning can be examined by reducing the training dataset size and increasing the testing dataset size, and then comparing classification accuracies obtained under different training–testing ratios. One such case is illustrated here, where the entire second experiment was repeated using 20% of the data for training and the remaining 80% for testing, and the corresponding prediction accuracies are shown in Table 3.4.

Table 3.3 Average prediction accuracy (%) after conducting 25 tests each for 15 participants with 5 sessions using CSP and LDA (train 70%, test 30%)

Count	Participant No	Pre-Resting / LKM Self	Pre-Resting / LKM Others	Pre-Resting / Post-Resting	LKM Self / LKM Others	Post-Resting / LKM Self	Post-Resting / LKM Other
1	1	83.2 ± 3.0	89.3 ± 2.5	93.8 ± 1.9	74.7 ± 4.2	82.2 ± 2.9	80.8 ± 2.8
2	3	90.9 ± 4.4	93.7 ± 2.6	94.9 ± 3.2	67.5 ± 2.6	78.6 ± 2.0	74.2 ± 2.9
3	7	82.8 ± 1.6	80.1 ± 2.2	67.0 ± 4.8	79.4 ± 1.6	67.2 ± 1.7	73.4 ± 2.4
4	8	85.8 ± 2.2	86.4 ± 2.1	91.0 ± 1.6	85.0 ± 2.7	86.6 ± 2.0	76.5 ± 2.1
5	11	85.9 ± 4.7	84.8 ± 5.2	85.6 ± 3.2	79.9 ± 1.9	75.8 ± 2.9	84.8 ± 2.5
6	12	80.5 ± 2.1	88.1 ± 2.0	81.6 ± 2.2	86.2 ± 2.3	79.4 ± 7.4	84.0 ± 2.6

7	14	80.4 ± 2.2	79.8 ± 2.7	90.2 ± 3.7	63.9 ± 4.6	71.6 ± 4.0	75.9 ± 4.4
8	37	70.6 ± 2.2	78.8 ± 1.6	75.6 ± 3.9	72.7 ± 2.7	77.8 ± 1.4	62.0 ± 4.6
9	38	74.7 ± 2.1	89.2 ± 3.6	94.0 ± 2.2	79.0 ± 2.4	76.9 ± 4.2	87.9 ± 1.8
10	39	91.7 ± 3.5	91.2 ± 3.2	83.6 ± 7.0	78.3 ± 4.4	75.2 ± 5.0	78.4 ± 4.8
11	41	89.4 ± 2.2	72.8 ± 5.4	89.8 ± 3.0	87.5 ± 1.2	82.0 ± 2.2	77.2 ± 3.1
12	42	82.0 ± 3.4	83.9 ± 2.9	85.1 ± 2.8	65.0 ± 2.9	80.6 ± 4.6	69.7 ± 1.6
13	43	83.4 ± 5.1	83.6 ± 5.2	82.1 ± 2.5	76.9 ± 3.7	70.3 ± 3.8	69.7 ± 3.9
14	44	81.3 ± 4.3	73.1 ± 3.3	85.6 ± 4.3	77.8 ± 3.1	83.6 ± 2.2	85.0 ± 2.1
15	45	78.0 ± 2.9	90.5 ± 2.4	89.4 ± 4.0	75.6 ± 2.9	79.1 ± 6.4	79.1 ± 2.7
Mean Accuracy		82.7	84.4	85.9	76.6	77.8	77.2

Table 3.4 Average prediction accuracy (%) after conducting 25 tests each for 15 participants with 5 sessions using CSP and LDA (train 20%, test 80%)

Count	Participant No	Pre-Resting / LKM Self	Pre-Resting / LKM Others	Pre-Resting / Post-Resting	LKM Self / LKM Others	Post-Resting / LKM Self	Post-Resting / LKM Other
1	1	79.7 ± 3.8	86.6 ± 2.7	90.7 ± 4.8	68.9 ± 4.3	82.2 ± 5.8	82.4 ± 2.8
2	3	91.2 ± 4.5	90.0 ± 4.0	92.7 ± 4.3	66.9 ± 4.2	79.4 ± 5.7	72.7 ± 6.8
3	7	82.0 ± 2.4	78.9 ± 3.1	68.2 ± 4.2	78.8 ± 2.5	66.7 ± 1.1	72.7 ± 2.3
4	8	86.2 ± 1.2	86.5 ± 1.6	90.8 ± 1.3	79.6 ± 5.3	84.6 ± 3.0	75.8 ± 3.4
5	11	80.8 ± 5.8	78.9 ± 5.2	86.6 ± 3.3	78.9 ± 1.4	79.3 ± 3.5	83.9 ± 1.3
6	12	80.2 ± 1.3	85.4 ± 3.9	81.1 ± 2.6	86.0 ± 2.9	81.5 ± 6.2	84.2 ± 2.5
7	14	78.9 ± 3.4	80.0 ± 2.0	88.4 ± 6.1	64.8 ± 4.0	72.2 ± 4.2	73.9 ± 6.6
8	37	68.5 ± 4.4	79.7 ± 1.6	75.9 ± 3.2	67.8 ± 3.7	76.5 ± 2.1	69.6 ± 6.4
9	38	78.1 ± 4.8	90.3 ± 3.6	91.0 ± 3.5	77.5 ± 2.9	80.8 ± 4.7	84.2 ± 4.8
10	39	90.6 ± 3.0	91.0 ± 2.7	81.8 ± 6.5	84.5 ± 6.6	75.6 ± 3.1	75.7 ± 3.9
11	41	89.7 ± 3.1	82.4 ± 7.3	89.5 ± 3.4	84.8 ± 2.9	84.8 ± 5.5	80.7 ± 4.8
12	42	79.7 ± 3.3	80.7 ± 4.0	85.2 ± 3.1	65.3 ± 3.2	75.7 ± 5.1	69.5 ± 2.4
13	43	83.2 ± 6.0	85.3 ± 5.9	79.7 ± 3.5	76.9 ± 4.9	68.9 ± 5.2	71.0 ± 4.7
14	44	83.2 ± 5.1	75.4 ± 6.9	86.7 ± 4.2	76.3 ± 4.1	74.7 ± 5.7	83.2 ± 3.4
15	45	78.6 ± 3.2	89.3 ± 1.4	90.0 ± 2.9	71.0 ± 5.1	80.9 ± 5.0	72.8 ± 5.9
Mean Accuracy		82.0	84.0	85.2	75.2	77.6	76.8

### 3.3 Results

The first objective of this study was to evaluate how well meditation EEG data can be classified from non-meditation EEG data. For this purpose, two meditation tasks—LKM-Self and LKM-Others—were analysed in relation to two non-meditation baseline conditions. The two non-meditation mind tasks were labelled as Pre-Resting and Post-Resting. Pre-Resting refers to the initial resting-state condition in which the participant remains at rest without performing meditation. This is followed by the two meditation mind tasks (LKM-Self and LKM-Others).

Finally, the fourth mind task, Post-Resting, corresponds to a resting-state condition recorded after completion of the two meditation tasks. The initial analysis examined how well each meditation task could be classified against each non-meditation condition. Subsequently, classification between the two meditation tasks was evaluated. Finally, classification between the two non-meditation conditions (Pre-Resting and Post-Resting) was examined.

Each individual result in Tables 3.2–3.4 shows the average prediction accuracy for each participant for a given pair of mind tasks. The six mind task pairs are (Pre-Resting/ LKM Self), (Pre-Resting/LKM Others), (Pre-Resting/ Post-Resting), (LKM Self/LKM Others), (Post-Resting/ LKM Self) and (Post-Resting/LKM Other). The average value for each instance was calculated by conducting 25 experiments and averaging the obtained prediction accuracies.

Table 3.2 contains the average prediction accuracy for 32 participants after conducting 25 tests per participant. Original dataset had 48 participants, from which 32 participants had usable EEG data which were used for the analysis. A machine learning pipeline with CSP and LDA was used to get the results where 70% of the data were used for the training and 30% for the testing. The last row of Table 3.2 shows the average prediction accuracy calculated for all 32 participants. Here a single prediction accuracy per each pair of mind tasks indicates the performance of the algorithms used as well as some characteristics of the EEG meditation dataset that is being studied here.

The average classification accuracy obtained for Pre-Resting/LKM Self is 99.3% and for Pre-Resting/LKM Others is 99.6%. This gives an average of 99.5% for classifying meditation/Pre-Resting instances. At the same time, Post-Resting/LKM Self and Post-Resting/LKM other obtained 97.9% and 94.9%, respectively. Thus, giving an average of 96.4% for classifying meditation/Post-Resting instances. Pre-Resting/Post-Resting classification has given a high accuracy of 99.8%, but LKM Self/LKM Others has given a slightly lower accuracy of 95.6%.

After obtaining a high classification accuracy for the single session case, the conditions were evaluated for multiple sessions. The purpose is to test if some similar characteristics are shared among multiple sessions for a selected mind task for a given person. For checking this, 5 sessions were selected and a pool of epochs for each mind task was created. Using this, the classification accuracy for two mind tasks was checked where data from 5 sessions were used. The results are shown in Tables 3.3 and 3.4. Table 3.3 demonstrates the results of accuracies obtained where 70% of the data have been used for training and the rest for the testing, whereas in Table 3.4, 20% of the data were used for training and 80% of the data for testing. With such a huge reduction in the training data, less than 1% reduction in the accuracy for five out of the six tests was observed. The remaining one has less than 1.5% reduction in the accuracy. This is remarkable because 20% training data out of five sessions will on the average have data size of one session. This implies that only few data are enough to do the classification without a heavy loss in accuracy.

Table 3.3 contains the average prediction accuracy for 15 participants after conducting 25 tests. Original dataset had 48 participants, from which 15 participants were selected for collecting EEG data for multiple sessions containing 8 to 10 sessions. For all these 15 participants, 5 or more sessions were in good readable condition. Therefore, among these good-quality EEG data sessions, the largest 5 sessions were used in this analysis. CSP and LDA algorithms were used for feature extraction and classification. Here, 70% of the data were used for the training and 30% for the testing. The last row of Table 3.3 shows the average prediction accuracy calculated for all 15 participants which shows the prediction accuracy per each pair of mind tasks. Here a single prediction accuracy per each pair of mind tasks indicates the performance of the algorithms used as well as some characteristics of the EEG meditation dataset.

Table 3.4 contains the average prediction accuracy for 15 participants after conducting 25 tests and this study differs from the study where the results are shown in Table 3.3 by only one

condition, which is the training and testing dataset sizes. A machine learning pipeline with CSP and LDA was used to get the results where 20% of the data were used for the training and 80% for the testing.

Since Tables 3.3 and 3.4 have almost similar results, only one of them is explained here (Table 3.3). The multiple session classification was done using the data of 15 participants for 5 sessions. The results show that the pairs (Pre-Resting/LKM Self), (Pre-Resting/LKM Others) and (Pre-Resting/Post-Resting) have relatively higher accuracies compared to the other pairs (LKM Self/LKM Others), (Post-Resting/LKM Self) and (Post-Resting/LKM Other). Here the average classification accuracy obtained for Pre-Resting/LKM Self is 82.7% and for Pre-Resting/ LKM Others is 84.4%. This gives an average of 83.6% for classifying meditation/Pre-Resting instances. At the same time, Post-Resting/LKM Self and Post-Resting/LKM Others obtained 77.8% and 77.2%, respectively. Thus, giving an average of 77.5% for classifying meditation/Post-Resting instances. Pre-Resting/Post-Resting classification has given a relatively high accuracy of 85.9%, but LKM Self/LKM Others has given a slightly lower accuracy of 76.6%. When comparing the first three pairs and the other three pairs an accuracy reduction of 5% – 8% can be observed.

Figure 3.1 gives the comparison plot of average accuracy difference between first three accuracy columns and last three accuracy columns for Table 3.2. This plot is for the single session classification using 32 participants. Figure 3.2 gives the comparison plot of average accuracy difference between first three accuracy columns and last three accuracy columns for Table 3.3. This plot is for the multiple session classification using 15 participants.

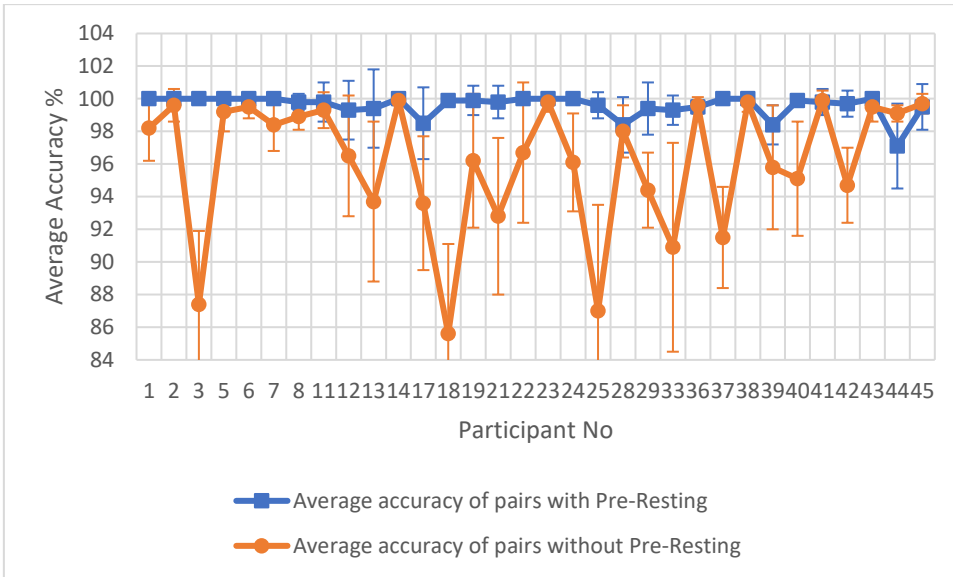


Figure 3.1 Comparison of average of first three accuracy columns (Average accuracy of pairs with Pre-Resting) with average of last three accuracy columns (Average accuracy of pairs without Pre-Resting) for the 32 participants in Table 3.2 for single session classification

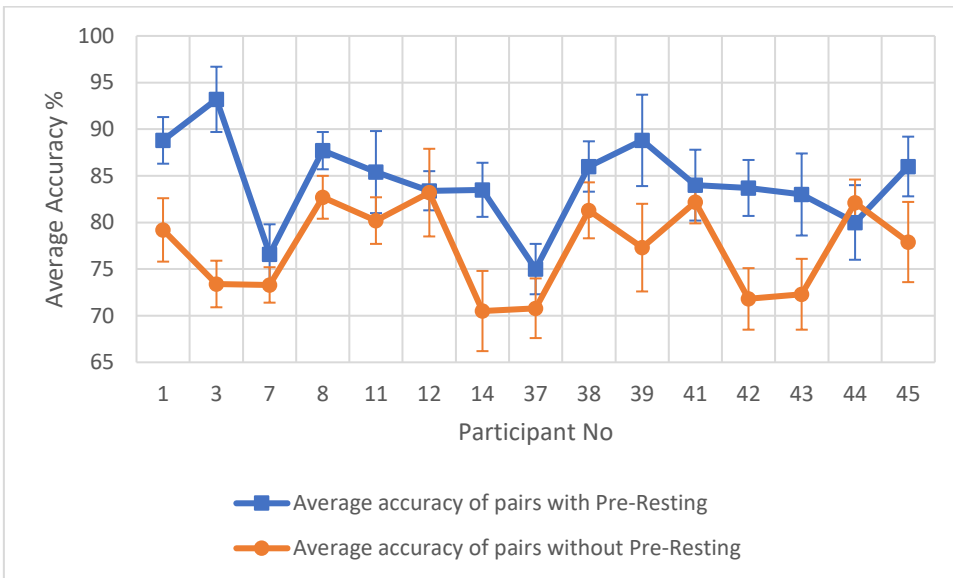


Figure 3.2 Comparison of average of first three accuracy columns (Average accuracy of pairs with Pre-Resting) with average of last three accuracy columns (Average accuracy of pairs without Pre-Resting) for the 15 participants in Table 3.3 for multiple session classification

### 3.4 Discussion

An EEG dataset collected from Loving Kindness Meditation for single and multiple sessions was used in this study and the dataset is currently available online. The most significant factor of the dataset is that it is a large dataset consisting of several meditation/non-meditation mind tasks collected for multiple sessions for multiple users. This gave the opportunity to study several patterns related to meditation EEG data for both single session and multiple sessions. The results we obtained in this study shows that good classification accuracy can be obtained for some instances, whereas for other instances this accuracy is slightly lower than the high accuracy ones, where all pairs were given similar analysis conditions. Based on these values we can understand some mind tasks have more similarities among them which make them hard to separate while the other mind tasks are easily separable owing to their differences. This is a valuable information that we can observe from the result set, which will be clearly explained below. At the same time, obtaining a very high accuracy for separating meditation and rest before meditation is also a high achievement in this study.

The ability to classify two pools of epochs from multiple sessions related to meditation mind tasks has a huge benefit, as explained in the introduction. With a 20% training data, a classification accuracy around 83% was obtained for the remaining 80% of the testing data (Table 3.4). This shows that some common characteristics are available among meditation multiple sessions. One such explanation we can give for this is we used 20% of the data taken from ten sessions where both groups contained five sessions each. Then, this 20% was used for the training and the remaining 80% from the ten groups were used for testing. Only 20% of training data and the large testing data (80%) produce an accuracy greater than 80% when doing the classification, thus giving the idea that some similarity is available among the five sessions of each group. Similarly, common characteristics are available among Pre-Resting multiple

sessions. This indicates that if such similar characteristics could be identified for the current dataset, it is possible to use that knowledge to identify whether the new session is meditation or non-meditation. This paves the path for a future research opportunity where you use multiple sessions of meditation/ non-meditation EEG data for training an algorithm and using that algorithm to determine into which category (meditation or non-meditation) a new mind task dataset will fall. At the moment, that is the biggest limitation in this study since you can only use data from the pool of epochs for testing and this does not currently support EEG data from a new session determining if this new data is a meditation or if it is a non-meditation session.

#### 3.4.1. Understanding the EEG meditation dataset based on the results obtained

When considering the 4 mind tasks, Pre-Resting is the starting session where EEG data are collected before starting any meditation practice. On the other hand, Post-Resting is a resting session where EEG data are collected after finishing a meditation session. Pre-Resting and Post-Resting are not totally equal because as an example if a person's mind gets calm when meditating, in the Post-Resting instance, immediately after a meditation session, this calmness might be still slightly lingering. This can be supported if Post-Resting has more similarities with the meditation sessions and also if it has some differences with Pre-Resting instance. LKM Self, LKM Others are two meditation sessions done in the middle in between Pre-Resting and Post-Resting instances. Where meditation loving kindness is done to oneself or others and the corresponding data were collected.

When looking at Tables 3.2–3.4, a pattern similarity in all 3 of them can be observed. For all three tables, when considering the six columns used for classification accuracies for the 6 pairs, the first 3 columns give higher accuracies compared to the remaining 3 columns. This difference

is 2–4% for Table 3.2. But in Tables 3.3, 3.4, the difference has increased up to 5–8%. Here, the prediction accuracy difference was obtained while using similar conditions for all instances including the feature extraction and classification algorithms. Although the method of analysis is similar for all the six pairs, they exhibit two levels of accuracies. This implies the following facts. Firstly, a higher prediction accuracy between a pair indicates there is a larger difference between the two and a smaller similarity between the two. On the other hand, for a pair, if the prediction accuracy has reduced it means that there is a smaller a difference and a larger similarity between the two in the pair, when comparing with a higher prediction accuracy.

The classification accuracy difference between first three accuracy columns and last three accuracy columns of Tables 3.2 and 3.3 are clearly demonstrated in Figures 3.1 and 3.2. Figure 3.1 contains the summary of the single-session 32-participant accuracy data shown in Table 3.2. Here, for each participant ‘Average accuracy of pairs with Pre-Resting’ was calculated using the first three accuracy columns of Table 3.2 and ‘Average accuracy of pairs without Pre-Resting’ was calculated using the last three accuracy columns of Table 3.2. The results show that out of the 32 participants, 28 participants have a higher accuracy average for the first three accuracy columns compared with the last three accuracy columns in Table 3.2. Among these 4 remaining participants, 3 of them have a marginal difference and only the participant no. 44 falls out of this pattern with a big value. The 28 participants out of 32 in Figure 3.1 clearly indicate that the first three column average accuracy is larger than the last three column average accuracy in Table 3.2. This observation is further proven by Figure 3.2. Figure 3.2 contains the summary of the multiple session 15 participant accuracy data shown in Table 3.3. Here, for each participant ‘Average accuracy of pairs with Pre-Resting’ was calculated using the first three accuracy columns of Table 3.3 and ‘Average accuracy of pairs without Pre-Resting’ was calculated using the last three accuracy columns of Table 3.3. The results show that out of the 15 participants, 14 participants have a higher accuracy average for the first three accuracy

columns compared with the last three accuracy columns in Table 3.3. The only participant that deviated from this pattern was participant no 44, which is the same participant that gave a significant difference in Figure 3.1. The 14 participants out of 15 in Figure 3.2 clearly indicate that first three column average accuracy is larger than the last three column average accuracy in Table 3.3.

The results suggest that the 3 pairs; (Pre-Resting/LKM Self), (Pre-Resting/LKM Others) and (Pre-Resting/Post-Resting) have produced higher classification accuracies. The first two pairs compare Pre-Resting instance with a two meditation instances. This proves that a higher classification accuracy can be achieved for a Pre-Resting instance and a meditation session. On the other hand, the higher classification accuracy between Pre-Resting/Post-Resting indicates that there is a higher difference between the two instances.

In terms of the last two columns in the three tables, we can see that in both instances it exhibits lower accuracies compared to first three accuracy columns. This indicates that when comparing EEG of each meditation and Post-Resting instance, they have more similarity than comparing with Pre-Resting and meditation instances. At the same time the pair LKM Self/LKM Others, having a low classification accuracy, indicates both these meditation techniques have some shared characteristics.

Concluding remarks for Tables 3.2–3.4, we can observe that the instance Pre-Resting, when comparing with LKM Self, LKM Others and Post-Resting, gives the highest classification accuracies. This shows that Pre-Resting has a big difference from the other three. In the pairwise comparison among LKM Self, LKM Others and Post-Resting only a lower classification accuracy is obtained. This indicates that the difference among these three is low and the similarity is high when compared with Pre-Resting; suggesting that the EEG collected for the two meditation sessions and the Post-Resting session are almost similar to each other.

Meditation may cause certain significant changes in a person including the EEG data patterns. This is divided into two types namely 'states' and 'traits' [26]. 'States' are temporary changes happening when meditating compared to the rest instance before beginning the meditation. 'Traits' are some permanent changes that happens to a person doing meditation for a long time. The high EEG difference mentioned above, between the Pre-Resting instance and a meditation session (LKM Self or LKM Others) equals to a 'states' change. The high EEG difference between Pre-Resting and Post-Resting indicates a significant difference between the two. Furthermore, the similarity (low difference) between Post-Resting and a meditation session (LKM Self or LKM Others) indicates that they have some common characteristics. But the difference between Pre-Resting and Post-Resting is not a 'trait' change and it is a 'state' change because it is more of a temporary relaxation happening in a person after a meditation session.

In this study, the participants are described as experienced meditators, and the analysis assumes relative stability of meditation-related EEG patterns across sessions. Rather than modelling changes in meditation proficiency or neural activity over time, EEG data from multiple sessions are pooled under the assumption that the underlying meditative and non-meditative states remain comparable across recordings. This assumption supports the interpretation of the observed differences as state-related effects rather than longitudinal trait changes.

### 3.4.2. Limitations of the study due to dataset characteristics

The dataset used in this study is of good-quality EEG data which we obtained after cleaning the original dataset and we selected four mind tasks for the analysis. The dataset was originally collected using 45 participants for one session and out of which 15 participants were used to collect multiple sessions. But one significant limitation of the collected dataset is, for the 45

participants the level of experience of meditation had not been collected as a measurement. The participants are said to be experienced meditators, but the level of experience of doing meditation is missing. Because of this lack of information, we can only study the state characteristics of the participants, and we cannot study the trait characteristics of the participants related to the meditation tasks. Hence, one significant limitation of the dataset is, we can only study state characteristics and not the trait characteristics. As a result, while trait-related changes cannot be explicitly analysed, the assumption of stable meditation-related EEG patterns in experienced meditators allows multi-session data to be combined for state-based classification.

### 3.5 Conclusion

This study was conducted to classify EEG data on four mind tasks, namely two types of meditation, pre-resting before meditation and post-resting after meditation using CSP and LDA as the classification algorithms. The results show that CSP and LDA combination was very successful in classifying a single session EEG data on meditation and Pre-Resting mind task (average accuracy = 99.5%). For the multiple session instance, although CSP and LDA does some decent classification even for a 20% training data, further research needs to be done to increase the classification accuracy.

Relatively higher classification accuracies were obtained for the pairs (Pre-Resting/LKM Self), (Pre-Resting/LKM Others) and (Pre-Resting/Post-Resting) when comparing with the pairs (LKM Self/LKM Others), (Post-Resting/LKM Self) and (Post-Resting/LKM Other). The results indicates that Pre-Resting has a larger difference compared with Post-Resting, LKM Self

and LKM Others. On the other hand, among Post-Resting, LKM Self and LKM Others there seems to be a lesser difference.

The results show the hidden characters among EEG data of meditation-related mind tasks. These hidden characters are vital in research endeavour involving developing useful algorithms that can help to get a better picture of a new meditation mind task when compared with previous mind tasks.

## STATEMENT OF CONTRIBUTION DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the student and the student's main supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the student's contribution as indicated below in the Statement of Originality.

Student name:	Nalinda Devaka Liyanagedera
Name and title of main supervisor:	Professor Hans W. Guesgen, Chair in Computer Science

In which chapter is the manuscript/published work?	Chapter 4
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Describe the contribution that the student and members of the supervisory team have made to the manuscript/published work:<sup>1</sup>

The student analysed and interpreted the data, validated results, visualised findings, and wrote the original manuscript. Moreover, conceptualising, designing the methodology, and developing the necessary software were carried out by the student. The student also contributed to the review and editing of the manuscript. The supervisory team contributed by reviewing and editing the manuscript and providing supervision throughout the work.

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## Chapter 4

# Novel machine learning-driven comparative analysis of CSP, STFT, and CSP-STFT fusion for EEG data classification across multiple meditation and non-meditation sessions in BCI pipeline

### Abstract

This study focuses on classifying multiple sessions of loving kindness meditation (LKM) and non-meditation electroencephalography (EEG) data. This novel study focuses on using multiple sessions of EEG data from a single individual to train a machine learning pipeline, and then using a new session data from the same individual for the classification. Here, two meditation techniques, LKM-Self and LKM-Others were compared with non-meditation EEG data for 12 participants. Among many tested, three BCI pipelines we built produced promising results, successfully detecting features in meditation/ non-meditation EEG data. While testing different feature extraction algorithms, a common neural network structure was used as the classification algorithm to compare the performance of the feature extraction algorithms. For two of those pipelines, Common Spatial Patterns (CSP) and Short Time Fourier Transform (STFT) were successfully used as feature extraction algorithms where both these algorithms are significantly new for meditation EEG. As a novel concept, the third BCI pipeline used a feature extraction algorithm that fused the features of CSP and STFT, achieving the highest classification accuracies among all tested pipelines. Analyses were conducted using EEG data of 3, 4 or 5 sessions, totaling 3960 tests on the entire dataset. At the end of the study, when considering all the tests, the overall classification accuracy using SCP alone was 67.1%, and it was 67.8% for STFT alone. The algorithm combining the features of CSP and STFT achieved an overall classification accuracy of 72.9% which is more than 5% higher than the other two pipelines. At

the same time, the highest mean classification accuracy for the 12 participants was achieved using the pipeline with the combination of CSP STFT algorithm, reaching 75.5% for LKM-Self/ non-meditation for the case of 5 sessions of data. Additionally, the highest individual classification accuracy of 88.9% was obtained by the participant no. 14. Furthermore, the results showed that the classification accuracies for all three pipelines increased with the number of training sessions increased from 2 to 3 and then to 4. The study was successful in classifying a new session of EEG meditation/ non-meditation data after training machine learning algorithms using a different set of session data, and this achievement will be beneficial in the development of algorithms that support meditation.

Keywords: Machine learning, Classification, BCI (brain computer interface), EEG (Electroencephalography), Loving kindness meditation (LKM), Multiple session, CSP (Common spatial patterns), STFT (short time Fourier transform), Neural network

## 4.1 Introduction

### 4.1.1. Background of the study

In recent years, meditation has gained significant popularity among people due to several reasons including, increase in scientific research on meditation [1, 2], publicity on evidence of many mental health/ physical health/ social benefits gained when doing meditation [3, 7, 8], improvements in technological devices/ apps that supports meditation [6, 53, 54], certain schools, universities, workplaces, hospitals, prisons, sports teams introducing meditation for their stakeholders [4, 11], not to mention increased stress levels in many people in the modern

world [5]. Some scientific methods used in the study of meditation include neuroimaging techniques such as EEG (Electroencephalography) [26], fMRI (Functional Magnetic Resonance Imaging) [47], PET (Positron Emission Tomography) [10], fNIRS (Functional Near-Infrared Spectroscopy) [48], Physiological Measurements such as Heart Rate Variability [9], Cortisol Levels [49] and Psychological Assessments such as Questionnaires, and Interviews [16, 17]. Among those various techniques, in this study we used EEG to understand certain meditation/ non-meditation characteristics.

Our research interest lies in the contribution to the development of algorithms and software [51, 52] aimed at understating the characteristics of a new meditation session. Understanding these characteristics will allow us to know how progressive a meditation session is [18]. In other words, this type of research could lead to future possibilities of developing algorithms or software that can guide a person [19] towards good progress in meditation. A progress of something must be measured as a value between two instances or locations. In this case, any such progress in meditation for a person must be compared and measured either against a non-meditation session as the baseline or against a previous meditation session as the baseline. This comparison needs be tested independently on individuals first and if it is successful, further studies can then identify common baselines that can be used to compare the progress of any individual. Therefore, as an initial step in understanding these characteristics in a new meditation session, we should be able to distinguish between a meditation session and a nonmeditation session [78, 79, 176] for the same person.

This study involves using multiple-session [200, 244] meditation/ non-meditation EEG data for 12 participants, training machine learning algorithms [66, 67, 245] using multiple session data for each participant and then, testing the trained algorithms using a new meditation/ non-meditation pair. Here, intra-subject [63] analysis is performed where each algorithm is trained and tested on each participant independently. The use of multiple session meditation/ non-

meditation EEG data to classify a new meditation/ non-meditation pair for the same person using machine learning techniques is a novel research concept that was successfully implemented and described in this paper.

#### 4.1.2. Related work

Electroencephalography (EEG) is a method used to study brain functions by recording the electrical activity that occurs when neurons in the brain communicate with each other [55]. When the brain focuses on a specific mind task or is at rest, a large number of neurons work together synchronously sending signals [56]. EEG electrodes [57, 236] are placed on the scalp to detect the voltage patterns resulting from these electrical activities. EEG data collected over a certain duration consists of a series of vibration signals, known as brain waves. One way to study these brain waves is by analyzing their frequencies [60]. The changing brainwave patterns can be broken down into subcategories, each representing a specific frequency. The strength of each frequency varies with the brain wave patterns over time. Research and studies on brainwaves have identified several frequency ranges based on certain common characteristics related to specific mind tasks and brain functions. Although there are some minor differences, the commonly used frequency bands include Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz) and Gamma (> 30 Hz) [73, 77, 121]. There have been significant research showing that the Theta [104, 172, 175, 235] and Alpha [74, 136, 246] frequency bands are strongly associated with meditation/ non-meditation mind tasks and in our study, we emphasized the importance to these frequency bands.

The brain computer interface (BCI) pipeline [28] consists of the steps of data collection, preprocessing, feature extraction and selection, classification, and application [22, 32]. In

preprocessing, cleaning and artifact removal on the collected data are mainly targeted [30, 31]. Sometimes these raw data are directly taken for cleaning, but in some cases, the data are broken down using signal decomposition methods [247, 248] to perform the cleaning efficiently. There are two main types of noise, one type is the noise added from the external environment, such as electromagnetic effects from the surroundings. This noise can be minimized by using a high pass filter to remove unwanted lower frequencies below 0.5 Hz and by using a low pass filter to remove unwanted frequencies above 45 Hz [33]. At the same time, there are instances where a 50 Hz band stop filter can be used to eliminate the external electromagnetic noise at that frequency [165]. The second type of noise in EEG data comes from various bodily activities such as eye movement, eye blinking, head or jaw movements, breathing etc [30]. A small portion of this noise will be removed when performing frequency filters, and any remaining artifacts will be removed manually [31]. This can be achieved firstly by plotting channel spectra [103] to identify bad channels or epochs followed by adjusting them. Secondly this is done by running independent component analysis (ICA) [64, 196], to look for components related to errors and to remove them.

After preprocessing, which reduces the noise in the EEG data, the next step in a BCI pipeline is feature extraction [32, 37]. The idea here is to extract important patterns hidden in the EEG data. This is a complex task because, even after cleaning, EEG is known to have a low signal-to-noise ratio. Therefore, to get meaningful information from EEG, advanced signal processing methods such as Common Spatial Patterns (CSP) [45, 62, 82], Short Time Fourier Transform (STFT) [184, 249, 250], wavelet transform [184], and Event Related Potentials (ERPs) [232] are used. Additionally, Geometrical Features [251], which focus on the spatial and morphological properties of the EEG signals, and Graphical Features [252], which represent connectivity patterns in brain networks, are also employed to extract meaningful insights from EEG data. CSP, as a signal processing method in EEG, focuses on the differences between two

mind tasks by creating filters that highlight these differences making it easier to separate the two tasks. CSP is a very powerful EEG feature extraction algorithm mainly used for motor imagery [22, 81], but we adopted CSP with meditation EEG in this study, as well as in our previous study [200]. The full procedure of spatial filters maximizing the variance of the two mind tasks, supported by covariance matrices and their eigen vectors, along with the remaining steps in the CSP process that ranks the spatially filtered features of the two mind tasks, is clearly described in our previous manuscript [200].

STFT [249], on the other hand checks how different frequencies change over time, and this is done by using the mathematical technique known as Fourier Transformation [237, 238] on EEG data. In signal processing, Fourier Transformation decomposes the signal into all the frequencies it is made up of, while indicating the strength of each frequency. In STFT, EEG data is broken down into short overlapping time segments, and for each time segment, the strength of each frequency related to the EEG data are identified using Fourier Transformation. This method is very useful for analyzing EEG data because it allows us to obtain a feature set that shows how brain waves, such as alpha, beta, theta behave over time. In general, a feature extraction algorithm tries to identify a feature set that is unique to the mathematical or statistical approach that algorithm follows. Hence, one feature extraction algorithm may capture certain patterns that another algorithm might fail to capture, and vice versa. Therefore, there can be instances where a fusion of two feature extraction algorithms produces better results than using each algorithm alone. Similar to CSP, although STFT is also a well-established feature extraction algorithm for EEG in general, both of these algorithms are significantly new when it comes to extracting features from meditation EEG.

The next step in a BCI pipeline after feature extraction is classification [68, 178, 253]. Classification algorithms can be statistical methods, machine learning methods, rule-based methods or a combination of the above [32]. Because of its high accuracy and efficiency with

large data, machine learning, subset of artificial intelligence, is gaining high popularity in the research and industrial communities. Random forests, support vector machines, neural networks, decision trees and logistic regression are some of the top-level machine learning algorithms used for classification [66, 245, 254]. Among these, when it comes to classifying complex datasets like EEG, images and voice that require high level abstraction and feature learning capabilities, neural networks [255–259] are on the top of the list. In our study, a multi-layer perceptron (MLP) [147, 253, 254] was used as the neural network for classification, providing a common ground to compare various feature extraction algorithms. An MLP functions similarly to neuron interactions in the brain and consists of an input layer, a couple of hidden layers, and an output layer where each layer has a number of nodes called neurons. MLPs are usually trained using a supervised learning approach [66]. In training, the input data are first passed through the network towards the output, a process known as forward propagation. Here, the network's output is compared with the actual output, and an error is calculated. This error is then propagated backward, known as backpropagation. The optimization algorithm in the MLP iteratively updates the weights to improve performance. MLPs consist of an activation function that determines whether a neuron should fire or not, and they have a high capacity to approximate complex functions.

Up to now, most of the classification studies on EEG meditation involved using 2 sessions [1, 76, 78]. These two sessions can be from a single person, either during meditation or while not meditating [79, 176]. Another method involves collecting meditation EEG data from novices [143] and experts [72] to compare the two groups. The third method involves using a group of people who are not familiar with meditation and training them for a certain period of time, while simultaneously collecting EEG data at the beginning and end of the training [26]. All these studies are based on the “state” and “trait” characteristics [15] related with meditation, which refers to the changes happening in a person when practicing meditation. These changes have

been identified with various methods such as EEG, heartbeat rate, fMRI, fNIRS etc [9, 44, 48]. However, in our study, we focus solely on brainwave patterns using EEG [26, 76, 182] data.

#### 4.1.3. Meditation in the study

“State” refers to temporary changes that occur in a person while meditating compared to not meditating. “Trait” refers to permanent changes that occur in a person who has been meditating for a long time [14]. Studies have shown that even a person new to meditation can experience significant “state” improvements after a short period of meditation training, such as a couple of months [42, 61]. A characteristic of state changes is that they can manifest quickly for novice meditators. For expert meditators, while state changes still occur, they might be less pronounced over short periods because experts are already at a higher baseline level of meditative experience. Therefore, for very short periods, state changes might appear minimal and less significant in experts compared to novices [26].

For this study an online EEG data collected in a duration of 2 months from 12 expert meditators was used. Since the participants are labelled as experts [71, 133, 134, 185], based on past study records, we assume that there should be a significant “state” characteristic available when comparing meditation and non-meditation instances for these participants. At the same time, since they are expert meditators [71, 133, 134, 185], as past studies indicate, the assumption is made that any improvements in the state characteristic that can happen during this short period of data collection are minimum. Therefore, we expect that there is a small “state” characteristic difference among the sessions of meditation data used for each of these participants. At the same time, we expect a significant state characteristic difference between meditation and non-meditation data. In other words, an assumption is made that for each person, meditation sessions

are almost similar in characteristics among themselves, and the non-meditation sessions are also similar in characteristics among themselves, while the two mind tasks will have some significant differences between them. Our aim was to use these differences in “state” characteristic between the two mind tasks as the feature set in our study to train and classify multiple sessions of meditation/ non-meditation EEG data. With these assumptions in mind, the importance of this study is summarized as follows.

#### 4.1.4. Importance of this study

Using multiple session meditation data to train a machine learning algorithm and classify an unknown session data for a given person is a novel concept that hasn't been studied so far to the best of our knowledge. At the same time, two feature extraction algorithms CSP and STFT which have not been significantly used with meditation EEG was tested in this study. Most importantly, this study stands out because of using a combined feature set of CSP and STFT in one BCI pipeline for meditation EEG data. Furthermore, with this study we were able to understand how meditation EEG data classification behaves with different number of training session. Thus, this whole study will have a significant impact on future research on developing algorithms to support and guide people to successfully improve their meditation skills.

## 4.2 Methods

### 4.2.1. Dataset description and overview

An EEG dataset available online was used in this study where the data was collected while practicing loving kindness meditation (LKM) [12, 13]. The dataset DIO is <https://doi.org/10.18112/openneuro.ds003816.v1.0.1>. A comprehensive description on the dataset has been given in our previous manuscript [200] and a summary of the dataset related to this study is given as follows. The dataset consists of EEG data of 48 participants who have previous experience in meditation. Out of these participants, 15 participants were used to collect data for multiple sessions, that is 8–10 sessions on different days in a period of two months, and the rest of the participants were used to collect data only for a single session. When considering a single data collection session, the EEG data was collected for six mind tasks which produced six EEG data files. The six mind tasks were pre-resting, LKM-Self, LKM-Others, post-resting, visualize self and visualize others. Out of the EEG data collected for these six mind tasks for a single session, only three mind tasks were used in this study, and they are pre-resting (will be referred as non-meditation), LKM-Self, LKM-Others. In pre-resting, the EEG data was collected at the beginning of the session as the first mind task before starting the meditation tasks. LKM-Self and LKM-Others are the two meditation mind tasks where the EEG data was collected when a person has loving, kindness thoughts either towards oneself or for others.

For the current study only a subset of the entire dataset was used according to our research interest. Our research interest was to classify meditation/ non-meditation EEG data for multiple sessions. As the non-meditation task, we used the pre-rest dataset. To compare with this non-meditation task, we used two meditation mind tasks independently and they are LKM-Self and

LKM-Others. In other words, we did two studies, one to classify non-meditation/ LKM-Self and the other to classify non-meditation/LKM-Others. Since we were studying the classification of multiple session data, we used the data of the 15 participants where data was collected on 8–10 sessions.

In this study we assumed each of the 15 participants to be independent from one another. Therefore, the classification training and testing was done independently for each participant. This is mainly because we do not have the level of meditation expertise of each participant. Although all the participants are labelled as experts in meditation, in the absence of a measurement to indicate their level of expertise, all participants were considered independently from one another in this study. In this study, machine learning techniques were used to classify each mind task pair (meditation/ non-meditation). When we checked the dataset, we noticed that some session EEG data for some mind tasks had significantly smaller file sizes than others. To give an equal opportunity in an algorithm among the selected session data, and to increase the training and testing strength, we decided to use the largest five EEG files for each mind task for each participant and eliminate smaller data files. Using the largest five files that will contain the highest amount of data for a selected session combination will be useful for training and testing the machine learning algorithms, especially when session data for training and testing are interchanged in different tests. Therefore, as the first step, for each participant we selected the five largest EEG files for each of the three mind tasks non-meditation, LKM-Self and LKM-Others. Here, we only considered the individual file size of each mind task without considering the session number and the total file size for a given session.

#### 4.2.2. Data preprocessing and cleaning

The next task was to do a cleaning and preprocessing for the selected EEG data. The initial cleaning and the preprocessing on the EEG data was done using EEGLAB [31] in MATLAB and a similar procedure was conducted on each individual EEG file as explained below. After reading an EEG file as the first step, the channel locations [236] were added to the EEGLAB. Then a baseline correction was done on each EEG file by removing the epoch baseline [31]. To detect any bad channels visually, channel spectra [103] was plotted and after identifying the bad channels, they were removed using the “interpolate electrodes” method in EEGLAB [260]. Here, each removed channel was replaced with a new channel by EEGLAB based on the characteristics of the remaining good channels and this is done to make sure the remaining tasks can be done on the total channel size.

After that, the EEG data was filtered using “Basic FIR filter” in EEGLAB while using 2 Hz and 45 Hz as filter borders. This filtering (low pass/ high pass filters) removed the noise coming from very low frequency and moreover, the 50 Hz noise coming from external electronic devices and electricity from the country that the data was collected [261, 262]. Then, independent component analysis (ICA) [58] was done on the EEG data where ICA was implemented with principal component analysis (PCA) [64, 196] with the value 32 by using the function in EEGLAB. We can observe that PCA has been successfully used with other algorithms for cleaning EEG data, and one such example is MSPCA [247, 248, 263]. Since there are 127 channels in the original dataset, PCA is used for dimensionality reduction to facilitate the smooth process of ICA. By using this function in EEGLAB, the ICA components were plotted and after careful study, bad components were removed to clean the EEG dataset [31]. For each mind task, the cleaned dataset was saved as a new EEG file in “.eeg” format with two supporting files “.vhdr” and “.vmrk”. In the cleaning process we identified that out of 15

participants, there were only 12 participants with good data, the other three participants were observed to have a lot of errors in their EEG dataset and in some cases, the file sizes were comparatively very small. Therefore, from the initial cleaning and preprocessing with EEGLAB, we selected 12 participants out of the 15 total participants. Past studies [43, 264] show that good generalization depends on using a large number of participants, however we conducted our study with the available participant data. In the selected dataset, each participant had three mind tasks with five EEG files per task. Therefore, at the end of this cleaning process, we obtained 180 ( $12 \times 3 \times 5$ ) EEG files to be used in the next stage of our study. For the next stage of our study, we used the python environment to develop BCI pipelines [28] and after reading some of these saved files into a one of the developed pipelines, we conducted further processing and analysis.

#### 4.2.3. BCI pipeline modelling

At this stage we had EEG data for two meditation tasks and one non-meditation mind task. Our aim was to study how effectively a classification can be achieved for meditation/ non-meditation data when using multiple session EEG data. With the available data, we were able to do two studies, one with LKM-Self/ non-meditation EEG data and the other with LKM-Others/ non-meditation EEG data. After the initial cleaning process was done using the EEGLAB, the subsequent stages of data processing were started with the 180 EEG files. In each experiment, the study was conducted individually for each participant using a selected pipeline, and this process was repeated for all the participants for all pipelines. For a single participant 15 EEG files were used, that is comprised of 5 EEG files for the five sessions per each of the three mind tasks and were taken into the BCI pipeline. After reading the file set for a single participant, various feature extraction and classification algorithms were used to see how well

they perform [22, 32]. Then the same procedure was conducted on the 12-participant data and the classification accuracies were observed. Based on the performance, certain feature extraction algorithms combined with classification algorithms produced good results. With this knowledge gathered, we finetuned the BCI pipelines that used these algorithms, which displayed good classification accuracies for multiple session EEG data. The following sections elaborates on these steps in modelling the pipelines.

With the initial findings about the most supportive feature extraction and classification algorithms for our task, further studies were conducted after preparing three BCI pipelines. To proceed further, three BCI pipelines were used and for feature extraction we used one out of Common Spatial Patterns (CSP) [45, 62, 82], Short Time Fourier Transform (STFT) [249, 250] and a fusion of CSP and STFT in each pipeline. Then, each one of these feature extraction algorithms was followed by a neural network [255–257] for the classification and the use of neural network gave a common ground to compare performance of the three feature extraction algorithms tested for multiple session meditation EEG data. All three pipelines have a common section at the beginning where the reading of 15 EEG files followed by some basic cleaning conducted on the EEG data. `Read_raw_brainvision` available in `mne` package in python was used to read the EEG files [265, 266]. Each file had data of 127 EEG channels and 1 ECG channel in the original dataset. Since the study was done using EEG data, ECG channel was removed, and the remaining EEG channels were used in the montage 'standard\_1005'. As the first step after reading and cleaning the EEG data, each EEG file was broken down into epochs [31] of 2s size with a 1s overlap [65]. The 1s overlap was used to make sure that the data that can get lost when splitting the EEG data is preserved because the splitting end of one epoch will be placed in the middle of the adjacent epoch. The following sections elaborates how each of these pipelines was implemented in a step-by-step approach.

Since the same procedure was conducted for the analysis between the pairs of LKM-Self, versus non-meditation and LKM-Others versus non-meditation, only the explanation relevant to one pair is given. As mentioned above, the first study was to see the classification of multiple session EEG data of LKM-Self and non-meditation. When working with each participant, the largest 5 data files for both LKM-Self sessions and non-meditation sessions were selected for our study. These ten EEG data sessions are independent from each other except they correspond to the two mind tasks performed by the same person. Herein, our aim was to keep two files, one from each mind task for the testing and remaining multiple session files from both mind tasks for the training. When testing, we studied how machine learning methods can be used in classifying a new session with EEG data from the two mind tasks, using the training knowledge obtained from some different sessions. With the available 5 sessions of EEG data, we did the study for 3, 4 and 5 session instances. As the first step, 5 sessions of EEG data available for of LKM-Self and non-meditation were paired based on data size similarity, which means, the largest LKM-Self and non-meditation were paired, then the next two were paired etc. to make sure there will be similar amount of data for both training and testing from both mind tasks. Then these pairs were used in the training and testing. For example, if a random selection is made among these pairs, there will be a chance of having a pair with one as the largest session in one mind task and the other as the smallest session in the other mind task. Therefore, random pairing in this case could negatively impact training and testing with the machine learning algorithms due to biased data sizes and this was eliminated by pairing the mind task EEG data based on size.

#### 4.2.4. Varied number of sessions

The procedure for using 3 session data was done as follows. As mentioned above, LKM-Self and non-meditation EEG data were paired based on their size. Here, we selected 3 pairs of EEG

data, using 2 pairs for the training and the remaining pair for the testing. For each set of 3 pairs, we conducted 3 tests, where one pair becomes the testing data while the other two becomes the training data. Since we had 5 pairs from which we used 3 pairs, we used all possible selection combinations for selecting 3 pairs out of 5 pairs in our experiment. This gave a total of 10 different combinations and per selected combination, we did 3 tests. Therefore, altogether 30 tests were conducted on the 5 pairs of LKM-Self and non-meditation EEG data to test a pipeline developed for selected machine learning training/ testing algorithms for a single participant. This test was repeated for all 12 participants using the developed BCI pipeline.

Next, training and testing was done using 4 pairs of EEG data. In this case 3 pairs were used for the training and the remaining pair was used for the testing. Similar to above procedure, when using 4 pairs, 4 tests were conducted where each time one pair out of the 4 pairs was used as the testing set. Since we had 5 pairs available, we selected 4 pairs and used all possible combinations for selecting these 4 pairs. There are 5 possible ways to select 4 pairs out of 5 and since one such 4 pairs were tested 4 time, a total of 20 tests were conducted on the 5 pairs of LKM-Self and non-meditation EEG data for a selected BCI pipeline. This was repeated for all 12 participant EEG data.

The third test was conducted using all 5 pairs of LKM-Self and non-meditation EEG data. Here, 4 pairs of session data were used for the training and the remaining pair was used for the testing. This was repeated while each time a new pair was used for the testing. In this case a total of 5 tests were conducted for 5 pairs of LKM-Self and non-meditation EEG data for the selected BCI pipeline and the procedure was repeated for the EEG data of all 12 participants. Based on the session size, a total of 55 ( $30 + 20 + 5$ ) tests were conducted for each participant. This was done on all 12 participants across the 3 pipelines for two meditation mind tasks, resulting in a total of 3960 tests conducted in our entire study ( $55 \text{ tests per participant} * 12 \text{ participants} * 3 \text{ pipelines} * 2 \text{ meditation tasks}$ ).

These studies allowed us to understand how multiple session EEG data can be used to train a machine learning algorithm and test the trained algorithm by performing classification on a new session EEG dataset. At the same time, the study allowed us to understand how these machine learning pipelines behave when the number of training sessions increases in a multiple session classification study. This concludes the description on the common section of the three BCI pipelines where the training and testing was done using 3 pairs, 4 pairs and 5 pairs of LKM-Self and non-meditation EEG data. The following section will explain the part where the three BCI pipelines have their unique characteristics.

#### 4.2.5. Feature extraction and classification

Each of the three BCI pipelines used in our study has their unique characteristics based on how feature extraction algorithms were used in them. In our study, advanced signal processing algorithms were used for the feature extraction and machine learning algorithms were used for the classification. In all three pipelines, neural networks were used for the classification. To be more precise, a multi-layer perceptron (MLP) with two hidden layers with a size of 20 for each layer, a logistic activation function, `max_iter = 1000` and `random_state = 42` was used in each of the three pipelines for the classification [147, 253, 254]. For the feature extraction in the first pipeline Common Spatial Patterns (CSP) was used and for the second pipeline Short Time Fourier Transform (STFT) was used. Most importantly, for the third pipeline a fusion of CSP and STFT was used as the algorithm for the feature extraction from EEG data.

A pipeline starts by reading a portion of EEG files (the ones saved after cleaned and preprocessed by EEGLAB) for the three mind tasks and splitting them into epochs of 2s. Using this dataset, analysis was done for the pair LKM-Self and non-meditation and for the pair LKM-

Others and non-meditation independently. When considering LKM-Self and non-meditation in the pipeline with CSP used for feature extraction, the procedure starts by taking the epochs of 5 sessions for the two mind tasks. Here, depending on how many sessions were used for the analysis, dataset is divided into train and test data, where one pair of session data is used for the testing and the remaining pairs were used for the training. Since it is needed to keep records of both training and testing data, each epoch of data had a label to indicate which mind task each epoch represents. Each data epoch is a 2D (dimension) array where one side represents the number of channels, and the other side represents the individual data elements for a single channel. In this case, there are 127 channels and 2000 data points which contains 1000 Hz data for 2s time interval. In the pipeline, this 2D array dataset for a single epoch is grouped into a 3D array where the number of epochs becomes the magnitude of the third dimension and we had a 1D label set with the size same as the number of epochs, where one label is used to represent each epoch. This 3D dataset with the shape (# of epochs, 127 of channels, 2000 of datapoints) and 1D labels set with the shape (# of epochs) are then processed and reshaped accordingly to satisfy the algorithms used in the pipeline.

As the next step with the CSP pipeline, a covariance matrix [267, 268] was calculated using the training dataset and the corresponding labels where Ledoit-Wolf shrinkage estimator [269] was used for the matrix regularization. A CSP object with four spatial filters ( $nfilter = 4$ ) was initialised. In CSP, a spatial filter represents a weight vector spanning all EEG channels and projects the multi-channel EEG signal into components that maximise variance for one class while minimising it for the other; thus, CSP operates on the multichannel signal jointly rather than on individual channels independently. The CSP model was fitted using only the training data, and four discriminative spatial filters were obtained. The resulting spatial filter matrix had a shape of (4, 127), corresponding to four spatial filters across the 127 EEG channels, and these

filters represent the spatial patterns that are most discriminative between the two mind tasks [270]. This result was kept aside to be used shortly.

Then the 3D training and testing datasets with the shape (# of epochs, 127, 2000) were taken and reshaped as 2D arrays (# of epochs x 127, 2000) and principal component analysis (PCA) [64, 196] was applied with (n\_components = 127). The datasets were reshaped to 2D because that shape change allowed us to use PCA on the data and PCA was applied on the training/testing data to reduce the dimensionality [271, 272] from 2000 to 127. The results obtained from PCA were reshaped to obtain 3D arrays of the shape (# of epochs, 127, 127). These two training/testing arrays were multiplied with the reshaped spatial patterns array described in the above paragraph to get a feature set for training and testing with the shape (# of epochs, 127, 4). These training/testing feature sets were then reshaped as (# of epochs x 127, 4) along with the corresponding label set to satisfy the shape of the neural network. The MLP we used had 4 input nodes and it had two hidden layers with each one having 20 nodes. While checking various combinations, we noticed that the above pattern gave optimal results, thus it was used. As described above, this experiment was conducted while using 3, 4 and 5 multiple session EEG data. At the same time, this was conducted in classifying LKM-Self, non-meditation pair and also with the pair LKM-Others, non-meditation using the first BCI pipeline (CSP pipeline) we developed.

The second pipeline was developed while using STFT for feature extraction and MLP for the classification. As explained above, the pipeline starts by reading a portion of the cleaned EEG data of the three mind tasks and breaking them into epochs of 2s. At this point the training/testing data had the shape (# of epochs, 127, 2000) and labels set had the shape (# of epochs). Then the 3D training/testing data were converted to 3D STFT data. In this case each epoch is broken into multiple timeslots and an average value per frequency value (whole numbers) was calculated for the frequency points from 0 to 45 and the shape of the results were as (# of

epochs, 127, 46). These training/ testing features were reshaped into 2D (# of epochs x 127, 46). Then, these feature sets were used in the training and testing of the neural network while changing the range of the frequency used to get the optimal solution. By doing this study, we noticed that the ten frequencies in the range [4:13] gave the best result and it was used in our study. The frequency band 4–8 Hz is referred as Theta [104, 172, 175, 235] and the frequency band 8–13 Hz is referred as Alpha [74, 136, 246] in brain wave frequency studies. Therefore, the selected frequency range in this study contains information of Theta and Alpha waves of the brainwaves. With this knowledge, we used the training/ testing dataset (# of epochs x 127, 10) along with the corresponding labels in the neural network. Therefore, the MLP in the second pipeline had 10 input nodes and it had two hidden layers with each one having 20 nodes. The STFT pipeline was implemented for 3, 4 and 5 multiple session EEG data and the classification accuracies were calculated for LKM-Self, nonmeditation pair and also for the pair LKM-Others and non-meditation.

The third pipeline was modelled with the fusion of CSP and STFT for the features. This algorithm follows the steps of the above two algorithms when using CSP alone and STFT alone to get two feature sets for the training/ testing data. In this pipeline, after following the steps explained with the above two pipelines, we came to the point of having a training/ testing feature set for CSP with the shape of (# of epochs x 127, 4) and a training/ testing feature set for STFT with the shape of (# of epochs x 127, 10). As the next step under this pipeline, we joined these two feature sets to get a combined feature set of CSP and STFT with the shape of (# of epochs x 127, 14). Then, this feature set obtained for the training/ testing data along with the matching label set were used with the neural network with 14 input nodes and did the classification. The MLP in the third pipeline had two hidden layers with each one having 20 nodes. Using the third pipeline (fusion of CSP and STFT) along with the multilayer perceptron, analysis was conducted to study the classification accuracies for LKM-Self, non-meditation pair and for the

pair LKM-Others and non-meditation using the cleaned EEG data. This study was conducted using multiple session EEG data and this was done for multiple sessions of 3, 4 and 5. A summary of the procedure is shown in Figure 4.1.

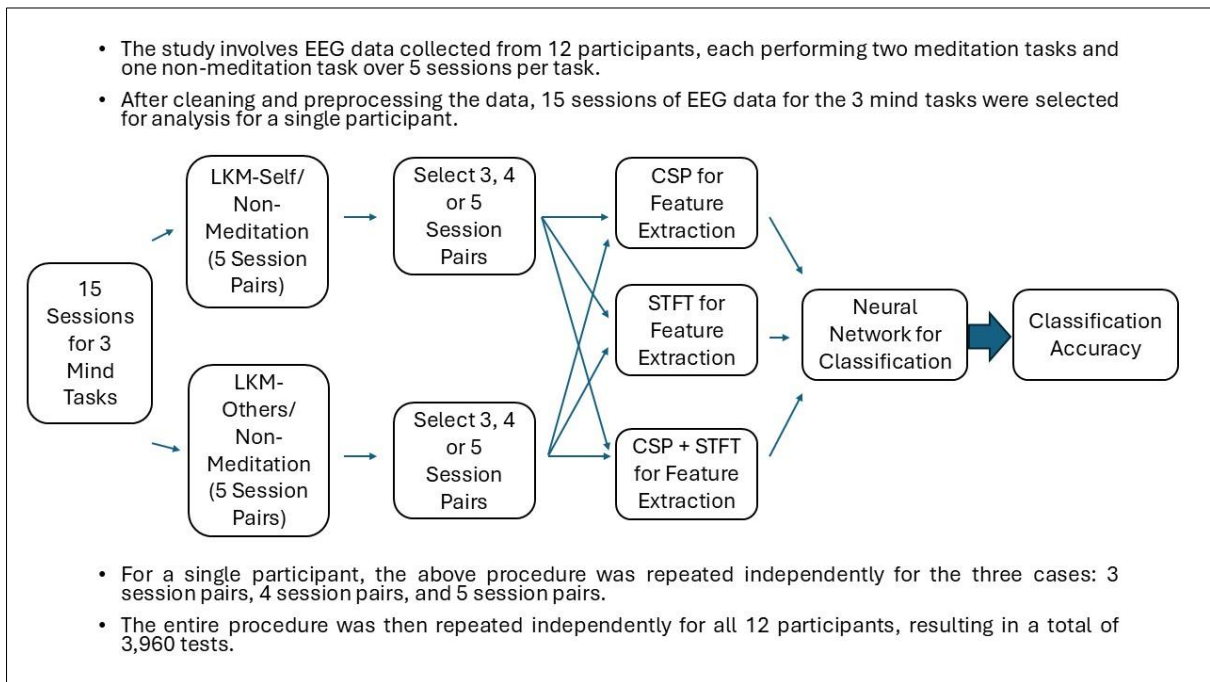


Figure 4.1 Summary of the methodology for EEG data classification across multiple meditation and non-meditation sessions

### 4.3 Results

The main target of this study was to see how well feature extraction and classification algorithms can be used with multiple session meditation/ non-meditation EEG data. Here, after training a machine learning algorithm using multiple session EEG data, we studied the performance of the trained algorithm in classifying a new meditation/ non-meditation session for the same subject. Data collected for 12 participants was used in this study. The results obtained can be divided into two main parts since one study was conducted using LKM-Self

and non-meditation EEG data and the second study was conducted using LKM-Others and non-meditation EEG data. At the same time, the results can be divided based on the three feature extraction methods (CSP, STFT or the fusion of CSP and STFT) used in this study. Furthermore, the results can be divided based on the number of sessions used in this study. We used either 3, 4 or 5 sessions and out of which 2, 3 or 4 sessions were used for the training while using the remaining session pair for the testing. Therefore, with this change in the number of training sessions, we were able to study how classification accuracies changed. In our study, we used Leave-One-Session-Out Cross-Validation, and the average and standard deviation were used to calculate the accuracy and uncertainty for each participant.

Table 4.1 shows the average classification accuracies obtained for LKM-Self and non-meditation when using 3 sessions of EEG data for the study where 2 sessions were used for the training and 1 session for the testing. The results were obtained by analyzing the EEG data of the 12 participants using CSP, STFT and a fusion of CSP and STFT as the feature extraction algorithms, and Figures 4.2 and 4.3 demonstrate the performance comparison. Figure 4.2 graphically shows the results given in Table 4.1; Figure 4.3 gives the normalised classification accuracies that allow us not only to compare performance of the three algorithms for each person, but also to compare this individual change among all participants, which is a visual improvement of Figure 4.2. Figure 4.3 is prepared by setting the lowest classification accuracy among the three algorithms for each person to 0 and the other two accuracies are proportionally plotted by considering the largest change (among all pairwise comparisons for all 12 participants) set to 100, and all the other changes scaled proportionally between 0 and 100. In Figure 4.3, participant 12 shows the highest accuracy difference among the three algorithms, while participant 11 shows the lowest accuracy difference among the three algorithms (the top value in the graph is the smallest for participant 11 compared to the top values for all other participants). In the meantime, Table 4.1 shows that for all participants, the mean classification

accuracy for CSP is at 66.7% and for STFT it is 67.3%. For the selected 12 participants, we observed the fusion of CSP and STFT gave a better mean classification accuracy of 72.1%. When considering the performance of CSP alone and STFT alone, we observed almost similar mean accuracies. Out of these 12 participants, 10 participants demonstrated the highest accuracy levels when using CSP and STFT together which is 83.3% of probability of total participants. In terms of CSP alone and STFT alone, the highest accuracy level was demonstrated by only one person in each instance which is a probability of 8.3% of total participants of the study and this is visible in Figure 4.3.

Table 4.1 Average accuracy (%) calculated independently for each of the 12 participants when classifying LKM-Self/ non-meditation EEG data using one of the three algorithms CSP, STFT or (CSP + STFT) per test for the case of 3 sessions of data

Count	Participant No	CSP	STFT	CSP + STFT
1	1	78.3 ± 5.4	73.4 ± 8.3	79.1 ± 7.2
2	3	61.2 ± 11.6	63.8 ± 13.4	61.7 ± 14.2
3	7	61.7 ± 9.9	64.5 ± 8.6	67.5 ± 9.7
4	8	79.2 ± 4.9	70.9 ± 5.4	79.0 ± 4.7
5	11	63.8 ± 8.7	62.4 ± 9.7	64.1 ± 8.6
6	12	57.6 ± 21.6	74.6 ± 15.4	79.9 ± 16.7
7	14	81.6 ± 6.9	78.6 ± 5.2	86.3 ± 3.8
8	38	65.5 ± 11.9	53.7 ± 10.7	66.4 ± 11.4
9	42	71.0 ± 7.6	67.6 ± 5.3	73.4 ± 5.6
10	43	59.1 ± 8.8	60.4 ± 11.9	65.8 ± 9.1
11	44	63.3 ± 12.6	79.0 ± 8.7	79.5 ± 8.1
12	45	58.6 ± 7.3	58.1 ± 14.7	62.4 ± 13.1
Mean Accuracy		66.7	67.3	72.1

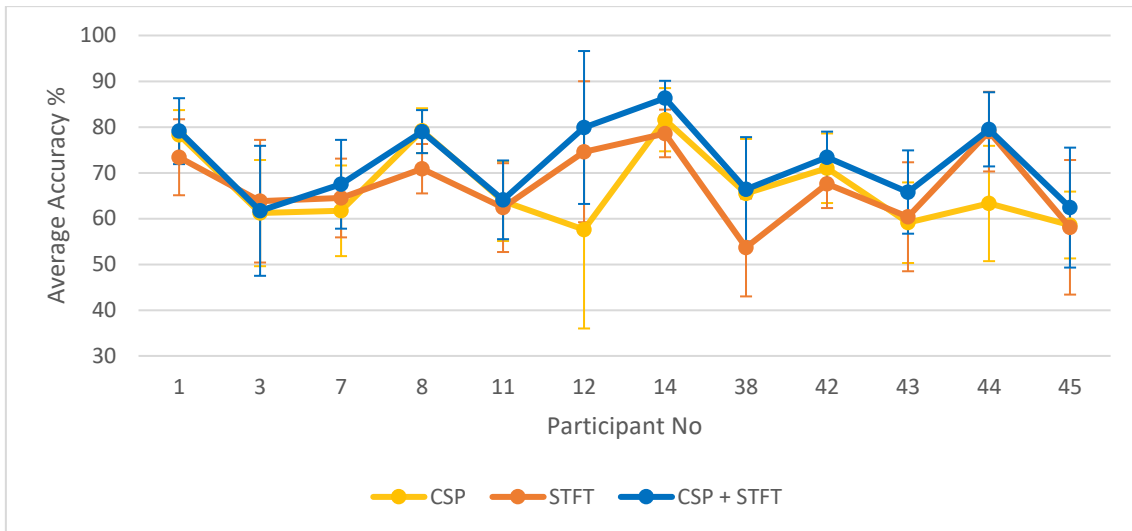


Figure 4.2 Comparison of average classification accuracies for LKM-Self/ non-meditation EEG data when using the three algorithms CSP, STFT and (CSP + STFT) for the case of 3 sessions of data

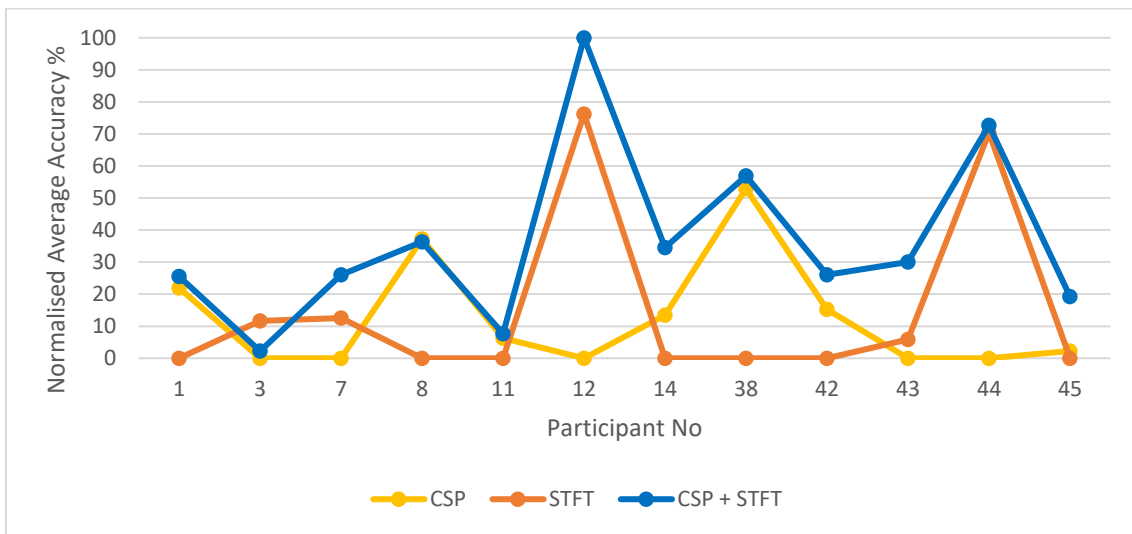


Figure 4.3 Relative comparison of normalised average classification accuracies for LKM-Self/ non-meditation EEG data when using the three algorithms CSP, STFT and (CSP + STFT) for the case of 3 sessions of data

Table 4.2 shows the average classification accuracies obtained for LKM-Others and non-meditation when using 3 sessions of EEG data for the study where 2 sessions were used for the

training and 1 session for the testing. The results were obtained using the EEG data of the 12 participants while using CSP, STFT and fusion of CSP and STFT, and Figures 4.4 and 4.5 demonstrate the performance comparison. Figure 4.4 graphically shows the results given in Table 4.2; Figure 4.5 gives the normalised classification accuracies that allow us to compare performance of the three algorithms for each person and compare this change among all participants. Table 4.2 shows that for all participants, the mean classification accuracy for CSP is at 65.1% and for STFT it is 65.7%. Furthermore, we observed that the fusion of CSP and STFT demonstrates a better mean classification accuracy of 70.7% for all the participants and this is better than the mean accuracies obtained when using the algorithms alone (difference of 5.0%). When considering the performance of CSP alone and STFT alone, we observed very similar mean accuracies. Out of these 12 participants, 10 participants gave the highest accuracy levels when using CSP and STFT together which is 83.3% of probability in terms of the total number of participants. Regarding CSP alone and STFT alone the highest accuracy level was demonstrated by only one person for each algorithm which is a probability of 8.3% for the study (see Figure 4.5).

Table 4.2 Average accuracy (%) calculated independently for each of the 12 participants when classifying LKM-Others/ non-meditation EEG data using one of the three algorithms CSP, STFT or (CSP + STFT) per test for the case of 3 sessions of data

Count	Participant No	CSP	STFT	CSP + STFT
1	1	72.9 ± 14.1	74.0 ± 10.9	76.1 ± 13.9
2	3	60.0 ± 10.7	60.2 ± 11.8	65.1 ± 9.3
3	7	56.0 ± 12.5	59.3 ± 11.3	64.0 ± 11.3
4	8	72.8 ± 13.5	62.6 ± 14.7	72.1 ± 13.0
5	11	64.0 ± 8.4	66.8 ± 5.9	69.7 ± 6.9
6	12	61.7 ± 26.3	71.4 ± 18.7	78.3 ± 19.0
7	14	79.5 ± 9.5	75.2 ± 7.7	81.7 ± 7.3
8	38	67.6 ± 5.8	59.5 ± 6.1	68.7 ± 5.2
9	42	69.8 ± 9.1	64.1 ± 10.1	72.0 ± 9.5
10	43	52.9 ± 10.6	68.2 ± 15.3	70.0 ± 14.5
11	44	67.9 ± 11.3	74.3 ± 8.3	72.9 ± 9.4
12	45	56.5 ± 15.1	53.3 ± 15.0	57.7 ± 12.6
Mean Accuracy		65.1	65.7	70.7

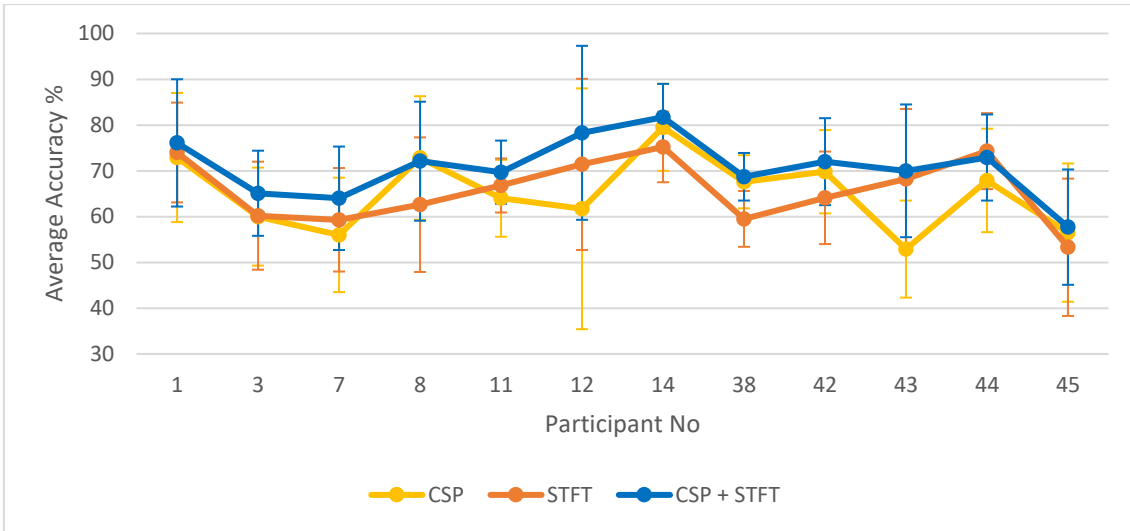


Figure 4.4 Comparison of average classification accuracies for LKM-Others/ non-meditation EEG data when using the three algorithms CSP, STFT and (CSP + STFT) for the case of 3 sessions of data

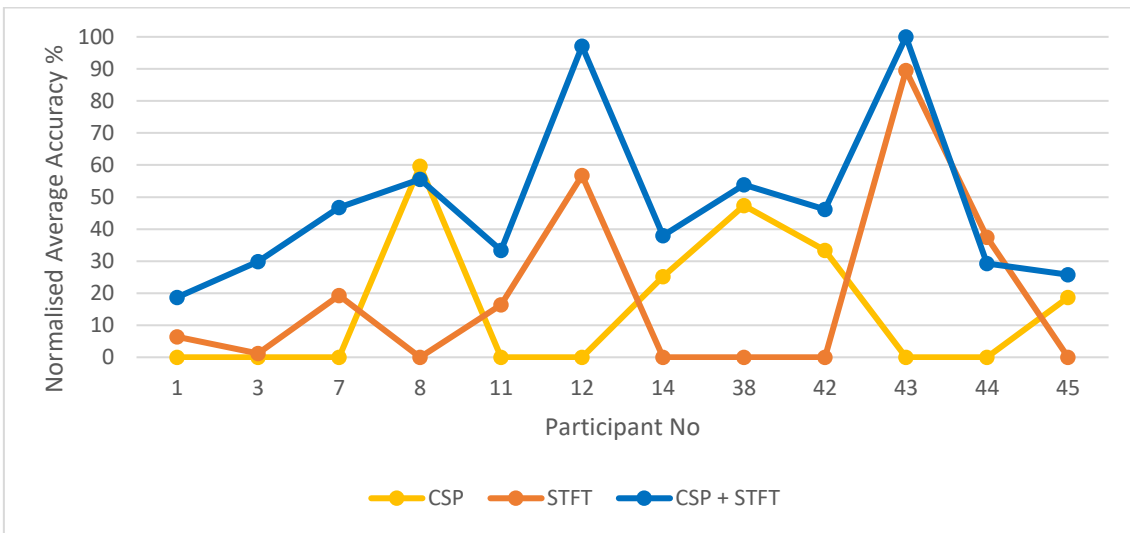


Figure 4.5 Relative comparison of normalised average classification accuracies for LKM-Others/ non-meditation EEG data when using the three algorithms CSP, STFT and (CSP + STFT) for the case of 3 sessions of data

Table 4.3 shows the average classification accuracies obtained for LKM-Self and non-meditation when using 4 sessions of EEG data for the study where 3 sessions were used for the training and 1 session for the testing. Here, one of the three algorithms CSP, STFT or fusion of

CSP and STFT was used on data available for 12 participants. Figure 4.6 graphically shows the results given in Table 4.3; Figure 4.7 gives the normalised classification accuracies that allow us to compare performance of the three algorithms for each person and compare this change among all participants and this is a visual improvement of Figure 4.6. In Figure 4.7 we can observe participant 12 shows the highest accuracy difference among the three algorithms which is given by the fusion of CSP and STFT. Table 4.3 shows that for the 12 participants, the mean classification accuracy for CSP was 68.4% and for STFT it was 69.1%. For the selected 12 participants, we observed the fusion of CSP and STFT gives the best mean classification accuracy among the three algorithms which is 74.2% for the 12 participants, 5.1% greater than the other two. In the meantime, we observed CSP and STFT alone produced similar mean accuracies. By looking at Figure 4.7 we can see that out of the 12 participants, 9 participants showed the highest accuracy level when using CSP and STFT together which is a probability of 75.0% of total participants. At the same time, in this study STFT alone gave the highest accuracy on 2 participants which is 16.7% and CSP alone gave the highest accuracy for 1 person which is 8.3%.

Table 4.3 Average accuracy (%) calculated independently for each of the 12 participants when classifying LKM-Self/ non-meditation EEG data using one of the three algorithms CSP, STFT or (CSP + STFT) per test for the case of 4 sessions of data

Count	Participant No	CSP	STFT	CSP + STFT
1	1	78.5 ± 5.1	73.9 ± 8.1	79.8 ± 6.9
2	3	62.6 ± 8.7	67.9 ± 6.5	65.0 ± 10.9
3	7	62.1 ± 9.5	65.7 ± 8.2	69.3 ± 10.3
4	8	79.6 ± 4.8	72.2 ± 4.0	79.5 ± 3.8
5	11	67.3 ± 9.2	65.2 ± 9.0	67.5 ± 8.3
6	12	59.5 ± 17.0	78.7 ± 11.8	84.0 ± 14.2
7	14	82.5 ± 6.6	79.8 ± 3.9	87.6 ± 3.2
8	38	66.9 ± 10.8	57.0 ± 9.6	68.5 ± 9.8
9	42	73.0 ± 8.5	68.4 ± 3.8	75.9 ± 5.9
10	43	61.9 ± 10.5	61.5 ± 11.7	69.5 ± 7.5
11	44	65.6 ± 13.2	79.8 ± 8.9	79.3 ± 8.9
12	45	61.4 ± 7.1	58.8 ± 14.7	64.5 ± 12.5
Mean Accuracy		68.4	69.1	74.2

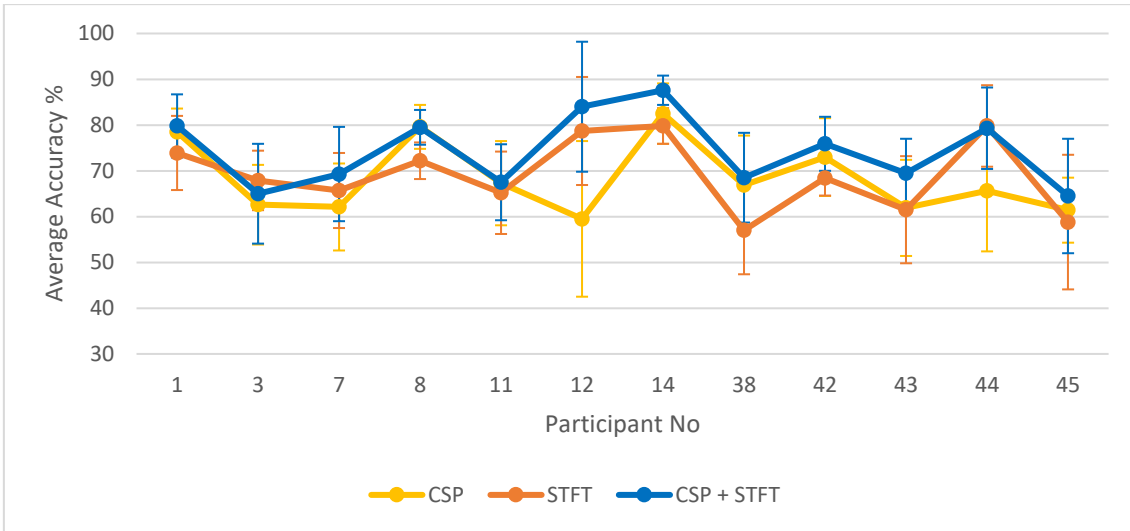


Figure 4.6 Comparison of average classification accuracies for LKM-Self/ non-meditation EEG data when using the three algorithms CSP, STFT and (CSP + STFT) for the case of 4 sessions of data

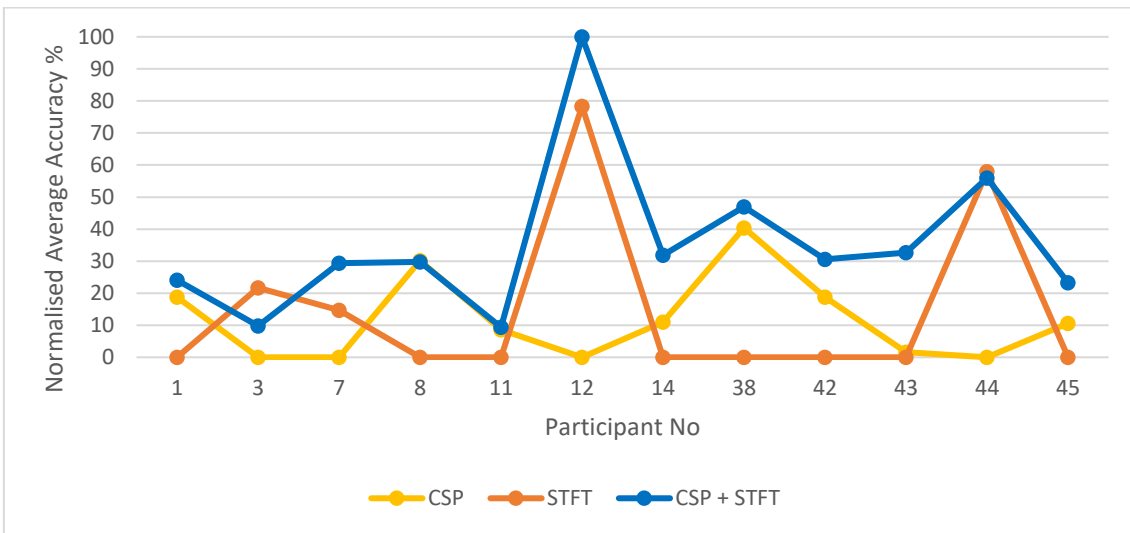


Figure 4.7 Relative comparison of normalised average classification accuracies for LKM-Self/ non-meditation EEG data when using the three algorithms CSP, STFT and (CSP + STFT) for the case of 4 sessions of data

Table 4.4 shows the average classification accuracies obtained for the 12 participants when using the mind tasks LKM-Others and non-meditation. Here, 4 sessions of EEG data were used for the study where 3 sessions were used for the training and 1 session for the testing. One of

the three algorithms CSP, STFT or fusion of CSP and STFT was used in the implementation and Figures 4.8 and 4.9 displays the comparisons of the performances. Figure 4.8 graphically shows the results given in Table 4.4; Figure 4.9 gives the normalised classification accuracies that allow us to compare performance of the three algorithms for each person and compare this change among all participants. Table 4.4 shows that for the 12 participants, the highest mean classification accuracy was obtained for the algorithm with the fusion of CSP and STFT, which is 72.0%. When using CSP alone and STFT alone, they were giving slightly lower mean accuracies (~ 5% difference) when compared to the use of fusion of CSP and STFT and those accuracies were 66.2% and 66.8% respectively. Out of these 12 participants, 10 participants demonstrate the highest accuracy level when using CSP and STFT together which is 83.3% of the total study. For both CSP alone and STFT alone, the highest accuracy was demonstrated only by 1 person which is a probability of 8.3% for this study and all this is shown in Figure 4.9.

Table 4.4 Average accuracy (%) calculated independently for each of the 12 participants when classifying LKM-Others/ non-meditation EEG data using one of the three algorithms CSP, STFT or (CSP + STFT) per test for the case of 4 sessions of data

Count	Participant No	CSP	STFT	CSP + STFT
1	1	73.9 ± 14.5	75.1 ± 11.1	76.8 ± 14.6
2	3	62.7 ± 6.0	62.3 ± 7.6	66.4 ± 7.2
3	7	55.1 ± 13.1	59.1 ± 11.7	65.0 ± 11.8
4	8	74.2 ± 13.7	63.8 ± 14.4	73.9 ± 12.7
5	11	66.0 ± 8.9	68.5 ± 5.3	72.0 ± 7.0
6	12	61.2 ± 22.7	72.4 ± 18.8	77.5 ± 20.6
7	14	81.1 ± 9.6	76.1 ± 6.5	83.6 ± 5.8
8	38	69.3 ± 8.7	60.3 ± 4.0	71.7 ± 6.0
9	42	69.1 ± 11.2	66.0 ± 9.2	72.4 ± 10.3
10	43	56.4 ± 8.8	69.3 ± 14.8	72.1 ± 13.2
11	44	69.6 ± 8.5	76.2 ± 7.5	75.0 ± 6.1
12	45	55.3 ± 16.7	52.3 ± 15.3	57.9 ± 14.4
Mean Accuracy		66.2	66.8	72.0

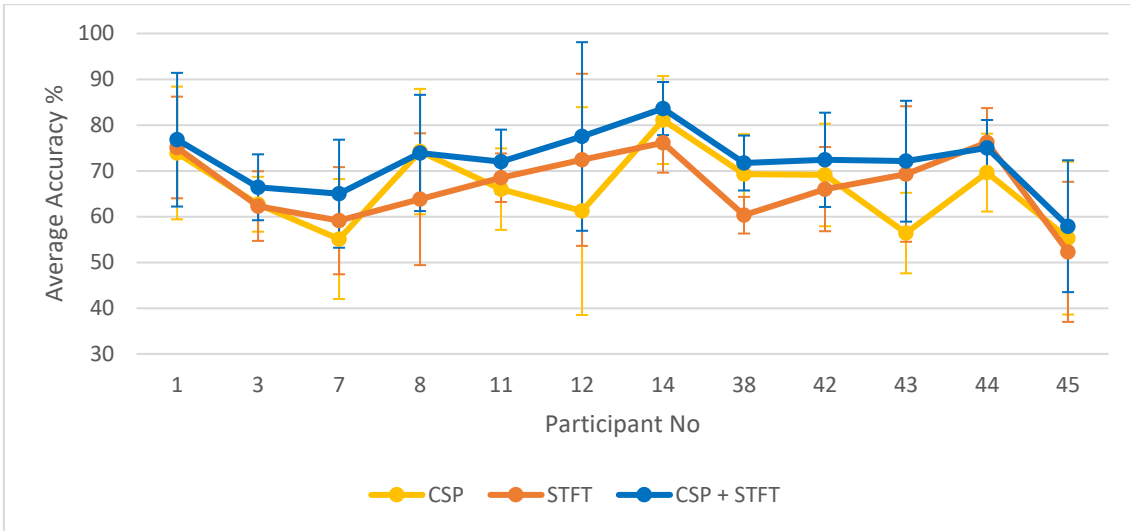


Figure 4.8 Comparison of average classification accuracies for LKM-Others/ non-meditation EEG data when using the three algorithms CSP, STFT and (CSP + STFT) for the case of 4 sessions of data

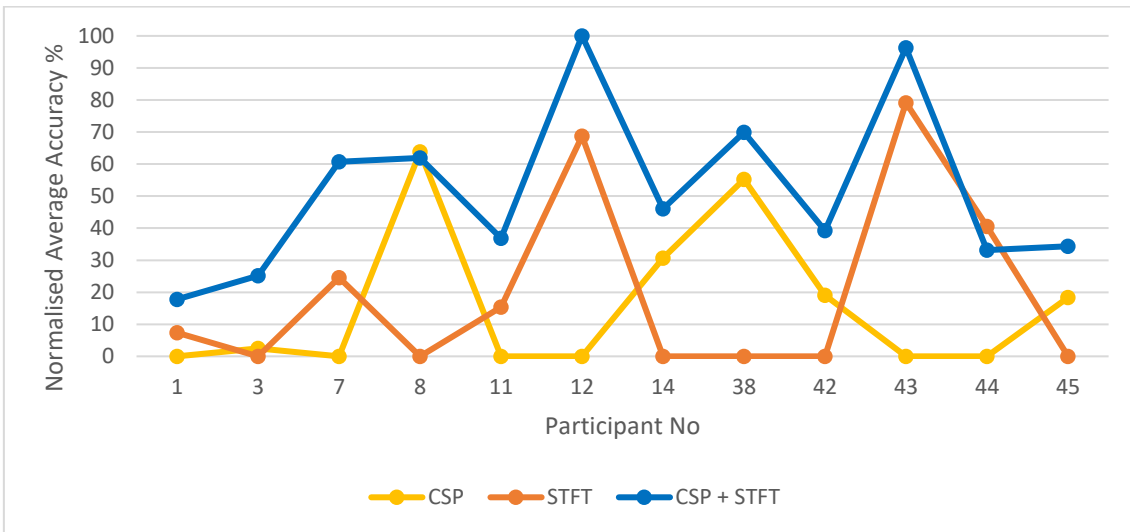


Figure 4.9 Relative comparison of normalised average classification accuracies for LKM-Others/ non-meditation EEG data when using the three algorithms CSP, STFT and (CSP + STFT) for the case of 4 sessions of data

Table 4.5 shows the average classification accuracies obtained for LKM-Self and non-meditation when using 5 sessions of EEG data for the study where 4 sessions were used for the training and 1 session for the testing. In Table 4.5, the average classifications accuracies and their errors for the 12 participants are shown for the three algorithms CSP, STFT or fusion of

CSP and STFT, and Figure 4.10 gives a graphical representation of the results. Figure 4.11 shows the normalised classification accuracies that demonstrates a good comparison on the performance of the three algorithms for each person and among all participants. Table 4.5 shows that for the 12 participants, the mean classification accuracy for CSP was 69.5% and for STFT it was 70.4%. For the selected 12 participants, we observed that the fusion of CSP and STFT gave the best mean classification accuracy among the three algorithms which is 75.5%. Here, the performance difference between CSP alone and STFT alone is less than 1.0%. However, when considering CSP and STFT fusion, the accuracy this produced is greater than 5.1% when compared with CSP alone and STFT alone. When studying the Figure 4.11, it is observed that out of 12 participants, 10 participants gave the best accuracy level when using CSP and STFT together which is 83.3% of the total participants. CSP alone and STFT alone gave the highest accuracy once per each algorithm and this probability is 8.3%. for the study.

Table 4.5 Average accuracy (%) calculated independently for each of the 12 participants when classifying LKM-Self/ non-meditation EEG data using one of the three algorithms CSP, STFT or (CSP + STFT) per test for the case of 5 sessions of data

Count	Participant No	CSP	STFT	CSP + STFT
1	1	78.4 ± 5.0	74.8 ± 7.3	80.0 ± 6.8
2	3	61.5 ± 7.5	69.5 ± 4.8	65.9 ± 4.9
3	7	63.3 ± 10.6	66.8 ± 8.3	69.9 ± 11.7
4	8	81.3 ± 4.0	72.7 ± 4.2	81.7 ± 3.1
5	11	68.5 ± 9.2	66.3 ± 8.3	69.4 ± 7.2
6	12	60.2 ± 15.1	79.8 ± 6.1	86.1 ± 8.7
7	14	83.9 ± 7.0	80.3 ± 3.9	88.9 ± 2.9
8	38	72.8 ± 10.3	59.4 ± 9.3	71.1 ± 8.6
9	42	75.1 ± 6.8	70.6 ± 2.1	78.4 ± 5.0
10	43	60.4 ± 12.2	64.1 ± 7.1	69.7 ± 3.8
11	44	69.8 ± 15.2	80.3 ± 9.1	80.8 ± 8.5
12	45	58.6 ± 6.8	59.9 ± 15.2	64.4 ± 12.6
Mean Accuracy		69.5	70.4	75.5

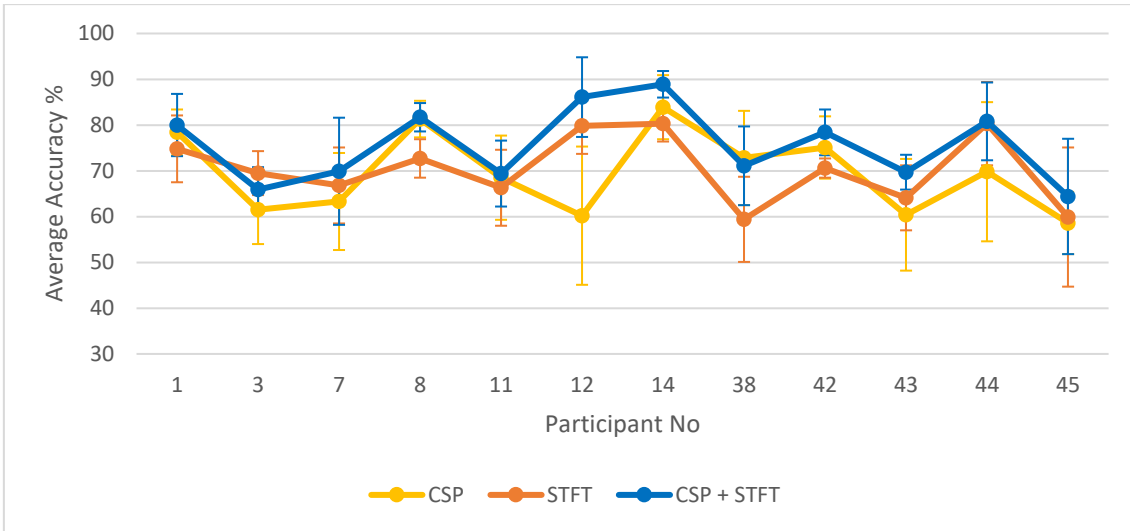


Figure 4.10 Comparison of average classification accuracies for LKM-Self/ non-meditation EEG data when using the three algorithms CSP, STFT and (CSP + STFT) for the case of 5 sessions of data

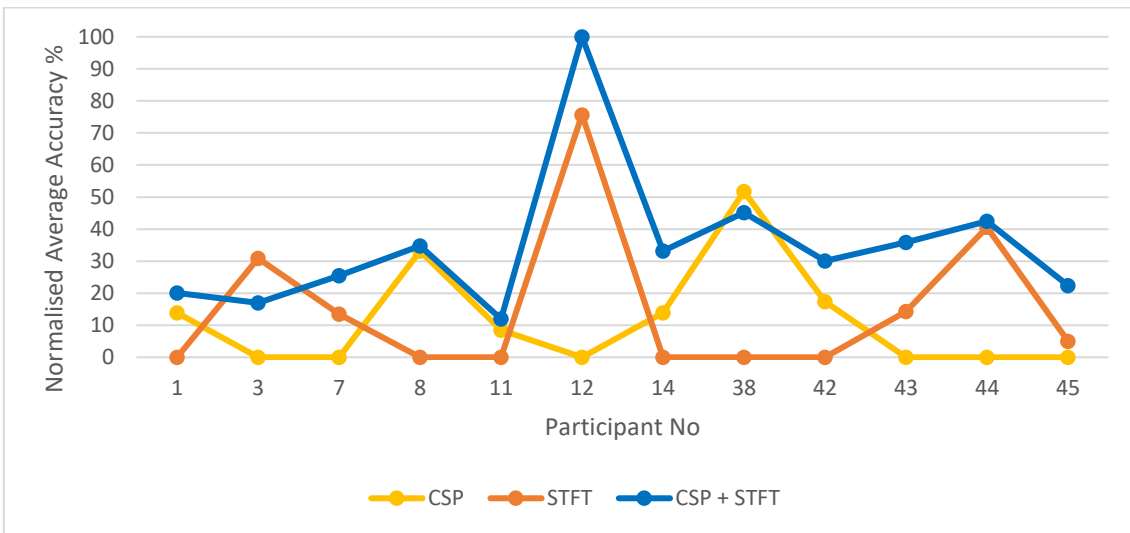


Figure 4.11 Relative comparison of normalised average classification accuracies for LKM-Self/ non-meditation EEG data when using the three algorithms CSP, STFT and (CSP + STFT) for the case of 5 sessions of data

Table 4.6 shows the average classification accuracies obtained for the 12 participants when using the mind tasks LKM-Others and non-meditation. Here, 5 sessions of EEG data were used for the study where 4 sessions were used for the training and 1 session for the testing. Figures

4.12 and 4.13 gives a clear picture of how the classification algorithms work when using the three algorithms CSP, STFT or fusion of CSP and STFT. Table 4.6 shows that for the selected 12 participants the mean accuracy for the three algorithms CSP, STFT or fusion of CSP and STFT are 66.5%, 67.3 and 73.0% respectively. Here, we can see a 5.7% difference between the highest two results and a 0.8% difference between the lowest two results. At the same time, it is observed that out of the 12 participants, 10 participants obtained the highest classification accuracy when using CSP and STFT together for feature extraction. This probability is 83.3% of the total participants and only one person per instance got the highest accuracy when using CSP alone and STFT alone, which is a probability of 8.3% and this is shown in Figure 4.13.

Table 4.6 Average accuracy (%) calculated independently for each of the 12 participants when classifying LKM-Others/ non-meditation EEG data using one of the three algorithms CSP, STFT or (CSP + STFT) per test for the case of 5 sessions of data

Count	Participant No	CSP	STFT	CSP + STFT
1	1	74.9 ± 15.0	76.0 ± 10.4	78.4 ± 13.4
2	3	60.3 ± 4.0	62.4 ± 4.5	65.8 ± 6.0
3	7	55.8 ± 14.2	60.2 ± 11.6	64.4 ± 13.2
4	8	76.3 ± 12.3	66.2 ± 14.3	75.7 ± 13.0
5	11	66.9 ± 9.4	68.8 ± 5.1	72.5 ± 6.0
6	12	60.8 ± 17.8	73.3 ± 19.5	79.7 ± 22.4
7	14	82.2 ± 9.7	76.7 ± 5.8	84.5 ± 6.6
8	38	71.0 ± 8.7	60.1 ± 3.0	72.4 ± 6.1
9	42	71.6 ± 13.4	66.8 ± 8.4	75.1 ± 10.3
10	43	55.8 ± 7.2	69.6 ± 14.0	73.9 ± 13.5
11	44	69.8 ± 4.0	76.8 ± 8.1	75.9 ± 4.3
12	45	53.0 ± 18.9	50.6 ± 16.8	58.2 ± 15.6
Mean Accuracy		66.5	67.3	73.0

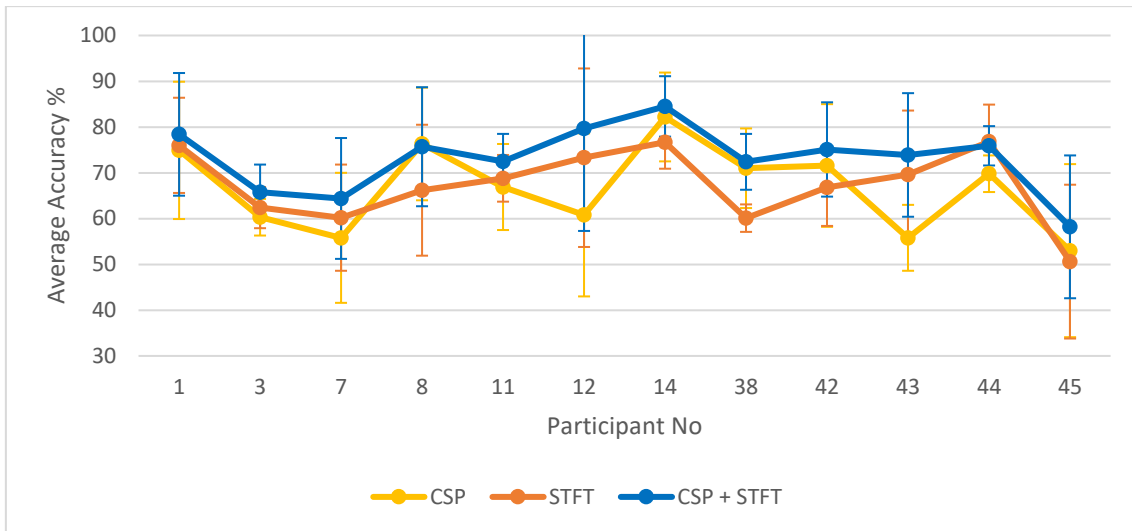


Figure 4.12 Comparison of average classification accuracies for LKM-Others/ non-meditation EEG data when using the three algorithms CSP, STFT and (CSP + STFT) for the case of 5 sessions of data

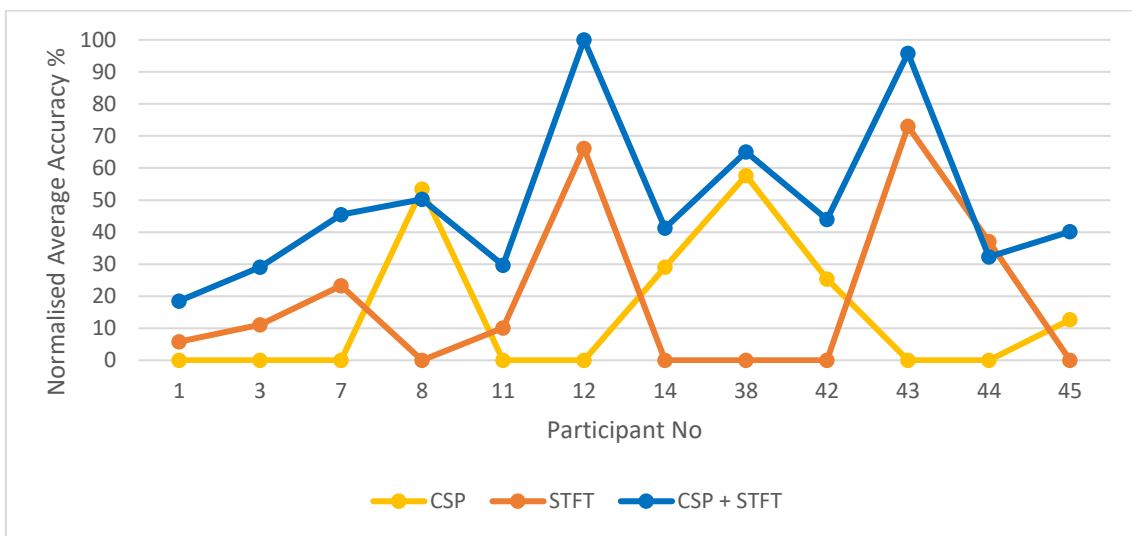


Figure 4.13 Relative comparison of normalised average classification accuracies for LKM-Others/ non-meditation EEG data when using the three algorithms CSP, STFT and (CSP + STFT) for the case of 5 sessions of data

## 4.4 Discussion

This study successfully showed that for a given person, multiple session meditation/ non-meditation EEG data can be used for training machine learning algorithms and those trained algorithms can be used to successfully classify a new session of meditation/ non-meditation EEG data for the same person. Although further improvements are needed to increase the classification accuracies, to the best of our knowledge, this is the first time an attempt has been made successfully to use multiple session data to train an algorithm and to classify an unknown session of meditation/ non-meditation EEG data. The study was done for two meditation techniques (LKM Self and LKM Others) and one non-meditation mind task. Therefore, two studies were conducted, one for LKM Self and non-meditation EEG data and the second one for LKM Others and non-meditation EEG data. Hence, our findings are supported by two independent studies where EEG data of two meditation tasks were used.

Although the participants used in the data collection were labelled as experts in meditation, the data does not provide the level of meditation expertise as a measurement for these participants. This lack of information pushed us to do only intra-subject analysis and prevents us from doing any inter-subject analysis. For example, if there was a measurement for the expert level of the meditators and some of them fall into the same level, we could have done inter-subject classification by taking multiple session meditation data from those participants and comparing that with multiple session non-meditation data among those same level participants. That would have allowed us to first study on intra-subject multiple session classification and then extend it to inter-subject multiple session classification. On the other hand, if there was a measurement for the expert level of the meditators in the dataset, and moreover, if the participants fall into two or more levels, we could have used that to study the “trait” characteristics of the participants using the level difference values among those participants. Unfortunately, with the limited

information available without any values to represent the expert levels, only intra-subject analysis was done where each participant was considered independent from one another.

The majority of the classification studies done in the past with meditation/ non-meditation EEG data were done on two session data, rather than on multiple sessions. However, in our previous study, we introduced the novel research idea of using multiple session EEG data to a certain level. In our previous study, we used EEG data from 5 sessions for the same person, creating separate pools of epochs for meditation and non-meditation EEG data. Then, from that pool we selected a certain percentage randomly for the training and the remaining for the testing. In that case, both training and testing datasets were expected to have epochs of all 5 sessions of meditation and non-meditation EEG data since the data was randomly selected. In this current study, we went a step further where multiple session meditation/ non-meditation EEG data from one person were used for training the algorithms and a different session EEG data from the same person was used in the classification. In the previous study, we showed the occurrence of similar characteristics not only in multiple session meditation EEG data but also in multiple session non-meditation EEG data. However, since in our previous study, we were using data from a pool of data for training and testing, it was not supporting the classification of a new session of meditation/ non-meditation EEG data. In this new study we were able to show that this is achievable, where a new session of meditation/ non-meditation EEG data can be classified by an algorithm trained using a different set of meditation/ non-meditation EEG multiple session data for the same person.

#### 4.4.1. Analysis based on the type of algorithm used

In this study, three pipelines were used to train and classify multiple session meditation/ non-meditation EEG data. This was achieved using several feature extraction and classification algorithms in the initial stage to see how well the classifications perform. Through initial analysis, we identified that for the classification, a multilayer perceptron was generating good results, and hence, it was used to proceed further. Since our aim was to identify good feature extraction algorithms, to keep the same ground for comparison, neural network was used as the classification algorithm with different feature extraction algorithms. When checking for various feature extraction algorithms, we identified that CSP and STFT were generating good results. We then introduced a new feature extraction algorithm that fuses CSP and STFT and this new algorithm generated better results than using CSP alone and STFT alone. Hence, results obtained at the end of our study turned out to be notable because they proved that multiple session EEG data meditation/ non-meditation tasks from a selected person can successfully classify a new unknown session for that individual. Additionally, the fusion of CSP and STFT produced better results compared to using CSP or STFT alone.

The studies were done on LKM Self/ non-meditation and LKM Others/ non-meditation EEG data independently for three cases of 3, 4 or 5 sessions and out of which 2, 3 or 4 sessions were used for the training while using the remaining session pair for the testing. Tables 4.1, 4.3 and 4.5 show the results for LKM Self/ non-meditation for the use of 2, 3, and 4 training sessions and Tables 4.2, 4.4 and 4.6 show the results for LKM Others/ non-meditation for the use of 2, 3, and 4 training sessions. When checking these tables, it is visible that classification accuracies of certain participants were noticeably higher than some other participants. One obvious reason for this could be due to unexpected noise of some EEG files which persisted even after the multistep comprehensive cleaning. The other possible reason is, for some participants, there

might be a big difference in the wave patterns between meditation/ non-meditation EEG data, whereas others may not have much of a difference and this depends on the expert level of the meditators. Past studies have shown that at the start of learning meditation, there will not be much of a difference between meditation and non-meditation brain patterns for novice meditators. But when you consider an expert meditator, you tend to see considerable differences in mind patterns between meditation and non-meditation [71, 133, 134, 185]. However, since we do not have a measurement level that indicates the expert levels of the participants, to compare the results, it cannot be confirmed that the noticeable classification differences among the participants is related to the expert level. Therefore, to compare the performance of the three algorithms, we calculated the mean accuracy for all the 12 participants and this value was used in the comparison of the three algorithms.

When considering LKM Self/ non-meditation classification, the highest mean accuracy was obtained using the algorithm with the fusion of CSP and STFT, for the three instances when using 2, 3 and 4 sessions for training and the results obtained are depicted in Tables 4.1, 4.3 and 4.5 respectively. As shown in Tables 4.1, 4.3 and 4.5, the best results obtained were 72.1%, 74.2% and 75.5% respectively, when using CSP + STFT for feature extraction. When considering the mean classification accuracies calculated for all 12 participants across each of the three training session sizes, for all instances, CSP alone showed the lowest classification accuracies and STFT alone demonstrated slightly higher accuracies compared to CSP alone (with differences of 0.6%, 0.7%, 0.9% for the three session sizes, respectively). On the other hand, CSP + STFT combination significantly outperformed STFT alone in classification accuracies when using 2, 3 and 4 sessions for training, with differences of 4.8%, 5.1% and 5.1%, respectively. While the mean accuracy difference between CSP alone and STFT alone is less than 1%, the mean accuracy of CSP + STFT combination is on the average 5.0% higher

than CSP alone and STFT alone for LKM Self/ non-meditation classification and this a significant finding.

When considering LKM Others / non-meditation classification, the highest mean accuracy was obtained when using the algorithm with the fusion of CSP and STFT for the three instances of using 2, 3 and 4 sessions for training. These results are given in Tables 4.2, 4.4 and 4.6 respectively, with mean accuracies of 70.7%, 72.0% and 73.0% for each case. When considering the mean classification accuracies calculated for all 12 participants across each of the three training session sizes, CSP alone gave the lowest classification accuracies and STFT alone showed slightly higher accuracies compared to CSP alone (with differences of 0.6%, 0.6%, 0.8% for the three session sizes, respectively). However, CSP + STFT combination gave the highest mean accuracy across all three session sizes, significantly higher than STFT alone (with differences of 5.0%, 5.2%, 5.7% for the three session sizes, respectively). While the mean accuracy difference between CSP alone and STFT alone is less than 1%, the mean accuracy of the CSP + STFT combination is on average 5.3% higher than CSP alone and STFT alone for LKM Others/ non-meditation classification and this also a significant finding.

The overall average of the classification accuracy when using CSP alone for all instances is calculated as 67.1%. Similarly, overall average of the classification accuracy when using STFT alone for all instances is calculated as 67.8% and when using CSP + STFT combined the result was 72.9%. Therefore, when considering all instances, using CSP alone and STFT alone generated classification accuracies with a difference less than 1%. The results show that the best classification accuracy can be obtained when using the fusion of CSP and STFT for the feature extraction and then using that information in the classification. This classification accuracy is more than 5% greater than using CSP alone and STFT alone and this is a notable increase in the classification accuracy.

#### 4.4.2. Analysis based on the number of training sessions used

While working on the main research topic that focused on studying how well machine learning algorithms can be used in classifying multiple session meditation/ nonmeditation EEG data, by rearranging the results shown in Tables 4.1, 4.2, 4.3, 4.4, 4.5 and 4.6, a different pattern was observed. This pattern displayed that higher the number of training sessions (training data size), the higher the calculated classification accuracy when using a certain algorithm set for the feature extraction and classification. The classification accuracies shown in Tables 4.1, 4.2, 4.3, 4.4, 4.5 and 4.6, were generated using the same file size for training while using different algorithms and the results are separated into LKM Self/ non-meditation and LKM Others/ nonmeditation. To add an alteration, in this new comparison, all the results were grouped according to the algorithm used, separately for LKM Self/ non-meditation and for LKM Others/ non-meditation. It allowed us to compare the classification accuracies for different numbers of training sessions within a given algorithm and a mind task pair. The results indicated that the increase in the number of training sessions used in the machine learning algorithm increases the average classification accuracy and the following section explains this for each algorithm and meditation type.

Table 4.7 shows the average classification accuracies obtained for LKM-Self and non-meditation when using the algorithm CSP in the pipeline for the three cases of 3 sessions, 4 sessions and 5 sessions of data and the Figure 4.14 shows the results graphically. When using 3, 4, and 5 sessions, 2, 3, and 4 sessions were used respectively for the training and the remaining one session was used in the testing. The mean classification accuracies for these three cases are 66.7%, 68.4% and 69.5% respectively and this suggests that there is an increase in the mean classification accuracy with the increase in the number of training sessions. Figure 4.15

gives the normalised classification accuracies of the Table 4.7, and this figure allows us not only to compare classification accuracies for the three session sizes for each person, but also to compare this change among all participants and this is a visual improvement of Figure 4.14. Figure 4.15 is prepared by putting the lowest classification accuracy among the three for each participant to 0 and the other two are proportionally plotted by giving the largest change among all participants to have a value 100, and all the other values changing proportionally in between 0 and 100. When considering the individual participants, using 4 sessions has increased the classification accuracy of all 12 participants when compared with 3 sessions and in other words 100% of total participants. At the same time, using 5 sessions has increased the classification accuracy for 8 participants out of 12 when compared with 4 sessions, and this is a 66.7% increase.

Table 4.7 Average accuracy (%) calculated independently for each of the 12 participants when classifying LKM-Self/ non-meditation EEG data using the algorithm CSP for the three cases of 3 sessions, 4 sessions and 5 sessions of data

Count	Participant No	3 Sessions	4 Sessions	5 Sessions
1	1	78.3 ± 5.4	78.5 ± 5.1	78.4 ± 5
2	3	61.2 ± 11.6	62.6 ± 8.7	61.5 ± 7.5
3	7	61.7 ± 9.9	62.1 ± 9.5	63.3 ± 10.6
4	8	79.2 ± 4.9	79.6 ± 4.8	81.3 ± 4.0
5	11	63.8 ± 8.7	67.3 ± 9.2	68.5 ± 9.2
6	12	57.6 ± 21.6	59.5 ± 17.0	60.2 ± 15.1
7	14	81.6 ± 6.9	82.5 ± 6.6	83.9 ± 7.0
8	38	65.5 ± 11.9	66.9 ± 10.8	72.8 ± 10.3
9	42	71.0 ± 7.6	73.0 ± 8.5	75.1 ± 6.8
10	43	59.1 ± 8.8	61.9 ± 10.5	60.4 ± 12.2
11	44	63.3 ± 12.6	65.6 ± 13.2	69.8 ± 15.2
12	45	58.6 ± 7.3	61.4 ± 7.1	58.6 ± 6.8
Mean Accuracy		66.7	68.4	69.5

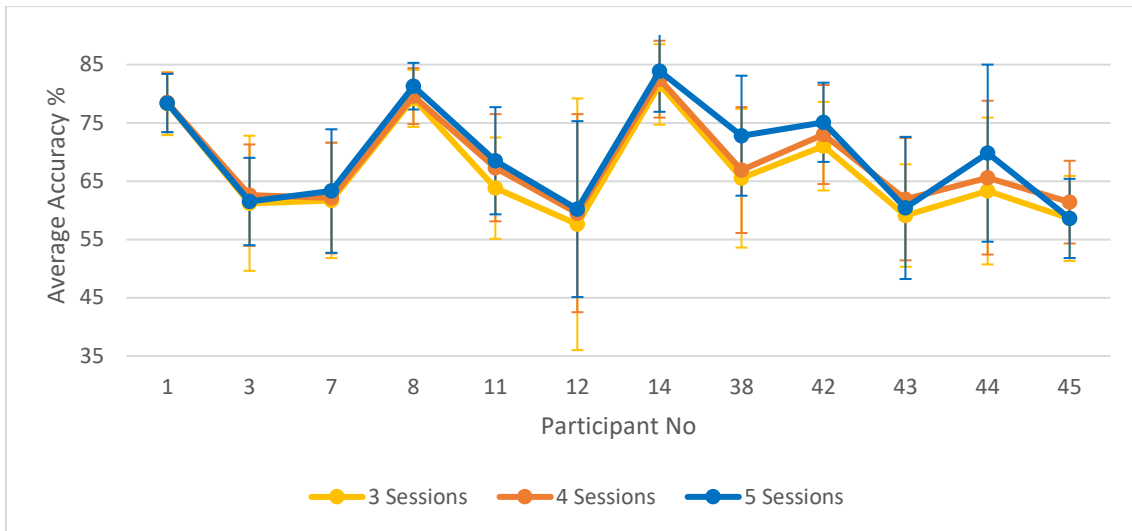


Figure 4.14 Comparison of average classification accuracies for LKM-Self/ non-meditation EEG data when using the algorithm CSP for the three cases of 3 sessions, 4 sessions and 5 sessions of data

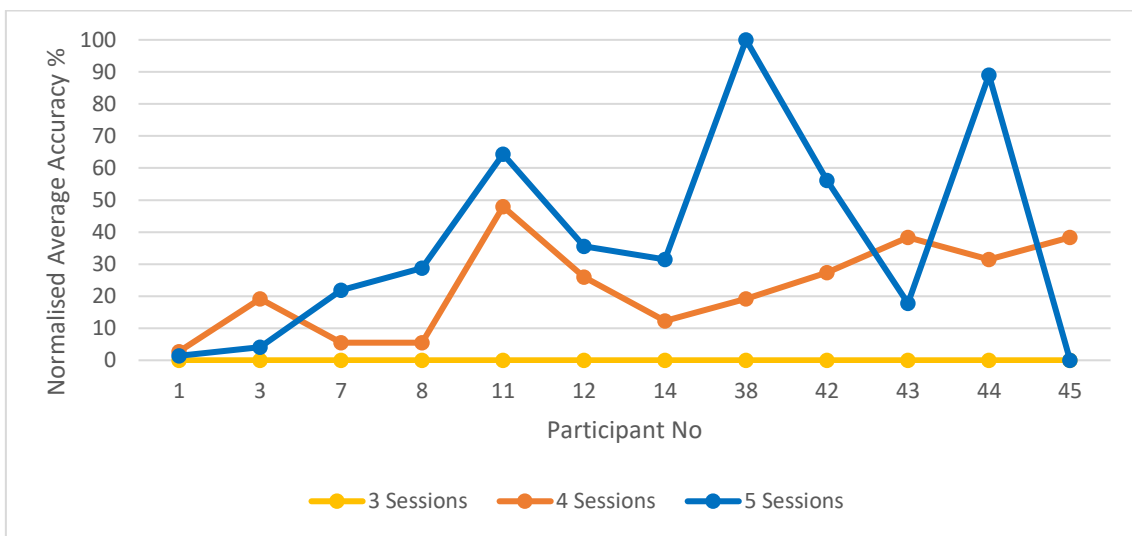


Figure 4.15 Relative comparison of normalised average classification accuracies for LKM-Self/ non-meditation EEG data when using the algorithm CSP for the three cases of 3 sessions, 4 sessions and 5 sessions of data

Table 4.8 shows the average classification accuracies obtained for LKM-Self and non-meditation when using the algorithm STFT in the pipeline for the three cases of 3 sessions, 4 sessions and 5 sessions of data and Figure 4.16 shows the results graphically. The mean

classification accuracies for the three cases are 67.3%, 69.1% and 70.4% respectively and this indicates an increase in the mean classification accuracy with the increase in the training data size. Figure 4.17 gives the normalised classification accuracies of the Table 4.8, and this figure allows us to compare classification accuracies for the three session sizes for each person, as well as the change among all participants and this is a visual improvement of Figure 4.16. When considering the individual participants, using 4 sessions has increased the classification accuracy of all 12 participants when compared with 3 sessions and this is a 100% increase. Similarly, using 5 sessions has increased the classification accuracy of all 12 participants when compared with 4 sessions, and this is also a 100% increase.

Table 4.8 Average accuracy (%) calculated independently for each of the 12 participants when classifying LKM-Self/ non-meditation EEG data using the algorithm STFT for the three cases of 3 sessions, 4 sessions and 5 sessions of data

Count	Participant No	3 Sessions	4 Sessions	5 Sessions
1	1	73.4 ± 8.3	73.9 ± 8.1	74.8 ± 7.3
2	3	63.8 ± 13.4	67.9 ± 6.5	69.5 ± 4.8
3	7	64.5 ± 8.6	65.7 ± 8.2	66.8 ± 8.3
4	8	70.9 ± 5.4	72.2 ± 4.0	72.7 ± 4.2
5	11	62.4 ± 9.7	65.2 ± 9.0	66.3 ± 8.3
6	12	74.6 ± 15.4	78.7 ± 11.8	79.8 ± 6.1
7	14	78.6 ± 5.2	79.8 ± 3.9	80.3 ± 3.9
8	38	53.7 ± 10.7	57.0 ± 9.6	59.4 ± 9.3
9	42	67.6 ± 5.3	68.4 ± 3.8	70.6 ± 2.1
10	43	60.4 ± 11.9	61.5 ± 11.7	64.1 ± 7.1
11	44	79.0 ± 8.7	79.8 ± 8.9	80.3 ± 9.1
12	45	58.1 ± 14.7	58.8 ± 14.7	59.9 ± 15.2
Mean Accuracy		67.3	69.1	70.4

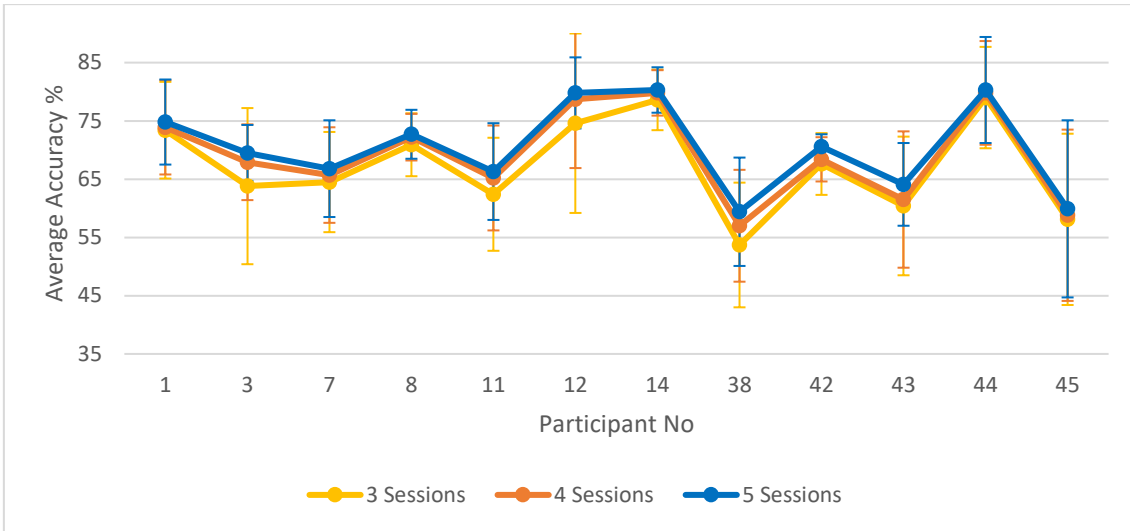


Figure 4.16 Comparison of average classification accuracies for LKM-Self/ non-meditation EEG data when using the algorithm STFT for the three cases of 3 sessions, 4 sessions and 5 sessions of data

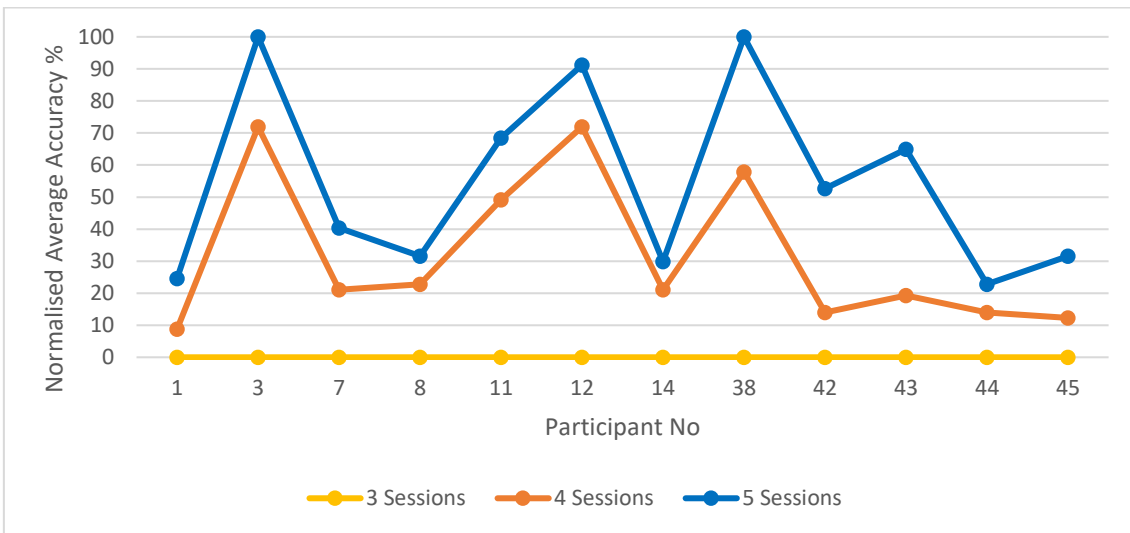


Figure 4.17 Relative comparison of normalised average classification accuracies for LKM-Self/ non-meditation EEG data when using the algorithm STFT for the three cases of 3 sessions, 4 sessions and 5 sessions of data

Table 4.9 shows the average classification accuracies obtained for LKM-Self and non-meditation when using the algorithm with CSP and STFT fusion in the pipeline for the three cases of 3 sessions, 4 sessions and 5 sessions of data and the Figure 4.18 shows the results

graphically. The mean classification accuracies for the three cases are 72.1%, 74.2% and 75.5% respectively and this shows an increase in the mean classification accuracy with the increase in the number of training sessions. Figure 4.19 demonstrates the normalised classification accuracies of the Table 4.9 and by observing Figure 4.19 we can see that using 4 sessions has increased the classification accuracy for 11 participants out of 12 when compared with 3 sessions and this is a 91.7% increase. Similarly, using 5 sessions has increased the classification accuracy for 11 participants out of 12 when compared with 4 sessions, and this is a 91.7% increase.

Table 4.9 Average accuracy (%) calculated independently for each of the 12 participants when classifying LKM-Self/ non-meditation EEG data using the algorithm (CSP + STFT) for the three cases of 3 sessions, 4 sessions and 5 sessions of data

Count	Participant No	3 Sessions	4 Sessions	5 Sessions
1	1	79.1 ± 7.2	79.8 ± 6.9	80.0 ± 6.8
2	3	61.7 ± 14.2	65.0 ± 10.9	65.9 ± 4.9
3	7	67.5 ± 9.7	69.3 ± 10.3	69.9 ± 11.7
4	8	79.0 ± 4.7	79.5 ± 3.8	81.7 ± 3.1
5	11	64.1 ± 8.6	67.5 ± 8.3	69.4 ± 7.2
6	12	79.9 ± 16.7	84 ± 14.2	86.1 ± 8.7
7	14	86.3 ± 3.8	87.6 ± 3.2	88.9 ± 2.9
8	38	66.4 ± 11.4	68.5 ± 9.8	71.1 ± 8.6
9	42	73.4 ± 5.6	75.9 ± 5.9	78.4 ± 5.0
10	43	65.8 ± 9.1	69.5 ± 7.5	69.7 ± 3.8
11	44	79.5 ± 8.1	79.3 ± 8.9	80.8 ± 8.5
12	45	62.4 ± 13.1	64.5 ± 12.5	64.4 ± 12.6
Mean Accuracy		72.1	74.2	75.5

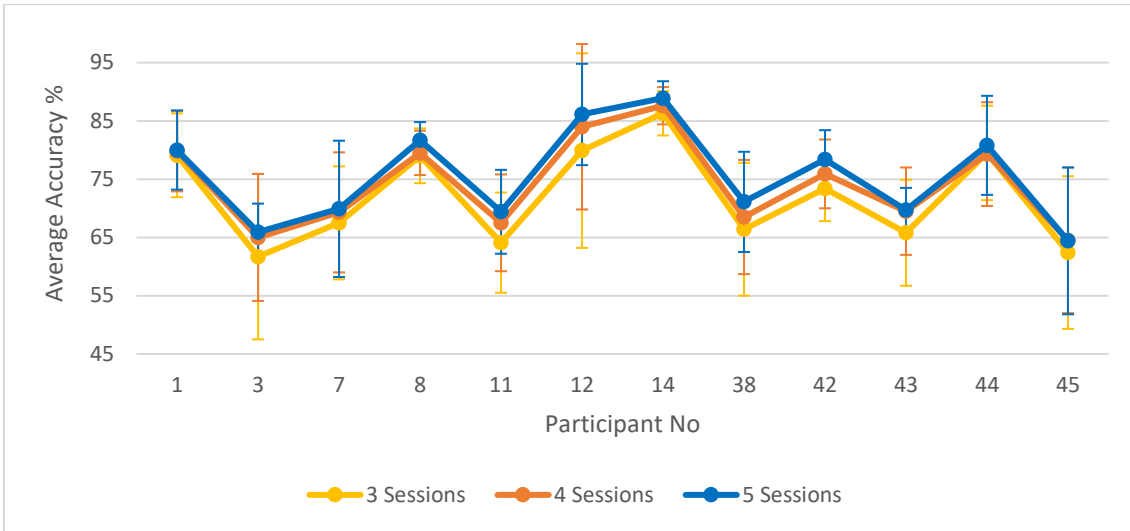


Figure 4.18 Comparison of average classification accuracies for LKM-Self/ non-meditation EEG data when using the algorithm (CSP + STFT) for the three cases of 3 sessions, 4 sessions and 5 sessions of data

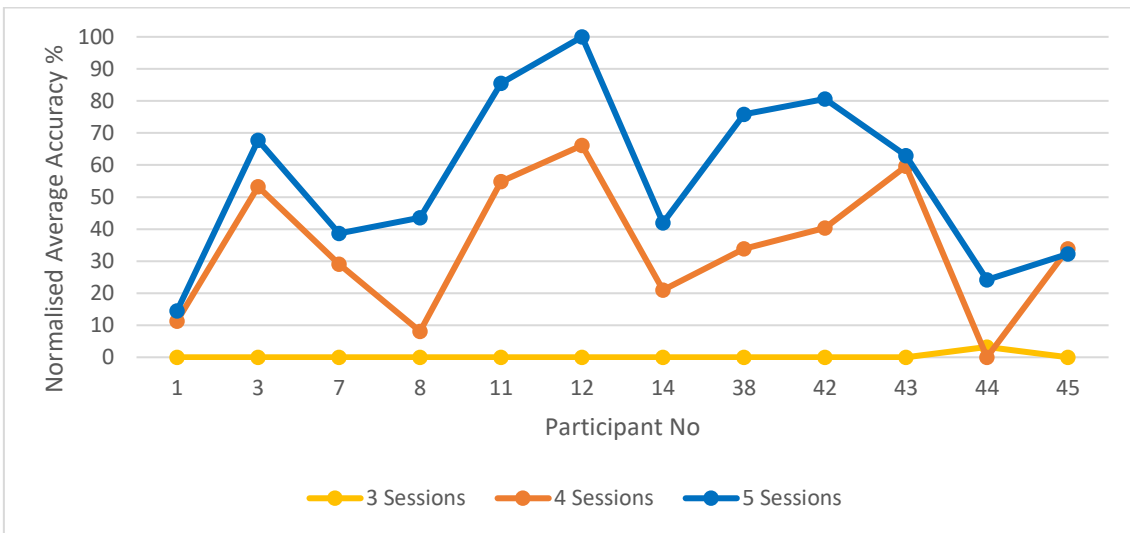


Figure 4.19 Relative comparison of normalised average classification accuracies for LKM-Self/ non-meditation EEG data when using the algorithm (CSP + STFT) for the three cases of 3 sessions, 4 sessions and 5 sessions of data

Table 4.10 shows the average classification accuracies obtained for LKM-Others and non-meditation when using the algorithm CSP in the pipeline for the three cases of 3 sessions, 4 sessions and 5 sessions of data and the Figure 4.20 shows the results graphically. The mean

classification accuracies for the three cases are 65.1%, 66.2% and 66.5% respectively and this indicates an increase in the mean classification accuracy with the increase in the number of training sessions. Normalised classification accuracies of the Table 4.10 given in Figure 4.21, demonstrates that using 4 sessions has increased the classification accuracy for 8 participants out of 12 when compared with 3 sessions and this is a 66.7% increase. Similarly, using 5 sessions has increased the classification accuracy for 8 participants out of 12 when compared with 4 sessions, and this is also a 66.7% increase.

Table 4.10 Average accuracy (%) calculated independently for each of the 12 participants when classifying LKM-Others/ non-meditation EEG data using the algorithm CSP for the three cases of 3 sessions, 4 sessions and 5 sessions of data

Count	Participant No	3 Sessions	4 Sessions	5 Sessions
1	1	72.9 ± 14.1	73.9 ± 14.5	74.9 ± 15.0
2	3	60.0 ± 10.7	62.7 ± 6.0	60.3 ± 4.0
3	7	56.0 ± 12.5	55.1 ± 13.1	55.8 ± 14.2
4	8	72.8 ± 13.5	74.2 ± 13.7	76.3 ± 12.3
5	11	64.0 ± 8.4	66.0 ± 8.9	66.9 ± 9.4
6	12	61.7 ± 26.3	61.2 ± 22.7	60.8 ± 17.8
7	14	79.5 ± 9.5	81.1 ± 9.6	82.2 ± 9.7
8	38	67.6 ± 5.8	69.3 ± 8.7	71 ± 8.7
9	42	69.8 ± 9.1	69.1 ± 11.2	71.6 ± 13.4
10	43	52.9 ± 10.6	56.4 ± 8.8	55.8 ± 7.2
11	44	67.9 ± 11.3	69.6 ± 8.5	69.8 ± 4.0
12	45	56.5 ± 15.1	55.3 ± 16.7	53.0 ± 18.9
Mean Accuracy		65.1	66.2	66.5

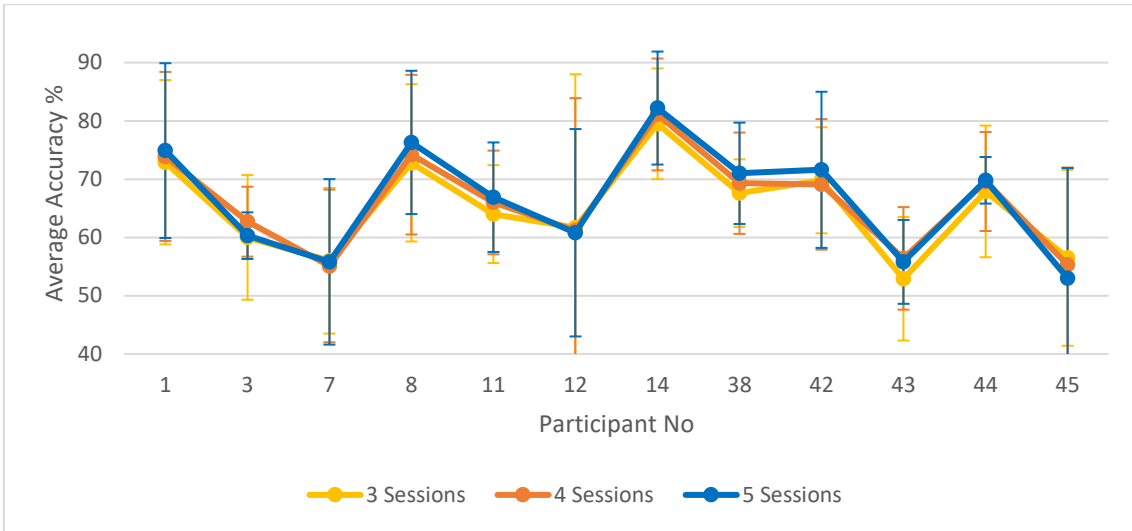


Figure 4.20 Comparison of average classification accuracies for LKM-Others/ non-meditation EEG data when using the algorithm CSP for the three cases of 3 sessions, 4 sessions and 5 sessions of data

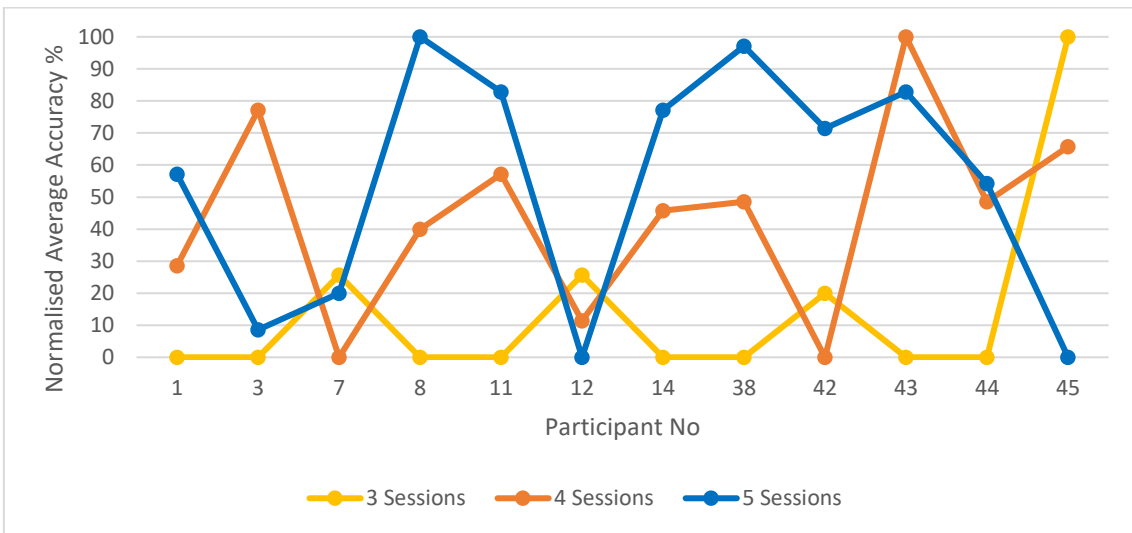


Figure 4.21 Relative comparison of normalised average classification accuracies for LKM-Others/ non-meditation EEG data when using the algorithm CSP for the three cases of 3 sessions, 4 sessions and 5 sessions of data

Table 4.11 shows the average classification accuracies obtained for LKM-Others and non-meditation when using the algorithm STFT in the pipeline for the three cases of 3 sessions, 4 sessions and 5 sessions of data and the Figure 4.22 shows the results graphically. The mean

classification accuracies for the three cases are 65.7%, 66.8% and 67.3% respectively and this indicates an increase in the mean classification accuracy when increasing the number of training sessions. Furthermore, normalised classification accuracies of the Table 4.11 given in Figure 4.23, demonstrates that using 4 sessions has increased the classification accuracy for 10 participants out of 12 when compared with 3 sessions and this is 83.3% of the total participants. Similarly, using 5 sessions has increased the classification accuracy for 10 participants out of 12 when compared with 4 sessions, and this is also an 83.3% increase.

Table 4.11 Average accuracy (%) calculated independently for each of the 12 participants when classifying LKM-Others/ non-meditation EEG data using the algorithm STFT for the three cases of 3 sessions, 4 sessions and 5 sessions of data

Count	Participant No	3 Sessions	4 Sessions	5 Sessions
1	1	74.0 ± 10.9	75.1 ± 11.1	76.0 ± 10.4
2	3	60.2 ± 11.8	62.3 ± 7.6	62.4 ± 4.5
3	7	59.3 ± 11.3	59.1 ± 11.7	60.2 ± 11.6
4	8	62.6 ± 14.7	63.8 ± 14.4	66.2 ± 14.3
5	11	66.8 ± 5.9	68.5 ± 5.3	68.8 ± 5.1
6	12	71.4 ± 18.7	72.4 ± 18.8	73.3 ± 19.5
7	14	75.2 ± 7.7	76.1 ± 6.5	76.7 ± 5.8
8	38	59.5 ± 6.1	60.3 ± 4.0	60.1 ± 3.0
9	42	64.1 ± 10.1	66.0 ± 9.2	66.8 ± 8.4
10	43	68.2 ± 15.3	69.3 ± 14.8	69.6 ± 14.0
11	44	74.3 ± 8.3	76.2 ± 7.5	76.8 ± 8.1
12	45	53.3 ± 15.0	52.3 ± 15.3	50.6 ± 16.8
Mean Accuracy		65.7	66.8	67.3

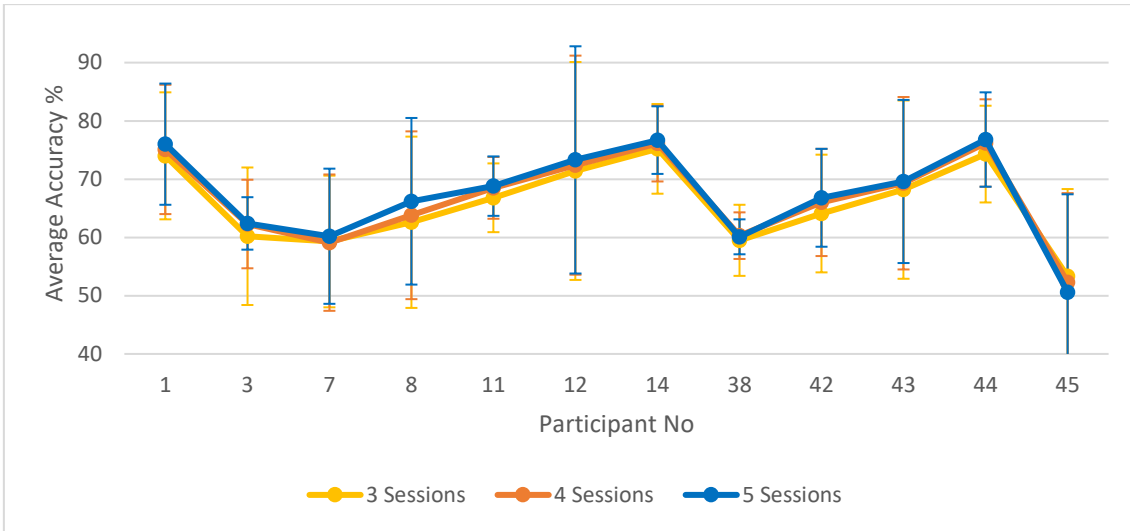


Figure 4.22 Comparison of average classification accuracies for LKM-Others/ non-meditation EEG data when using the algorithm STFT for the three cases of 3 sessions, 4 sessions and 5 sessions of data

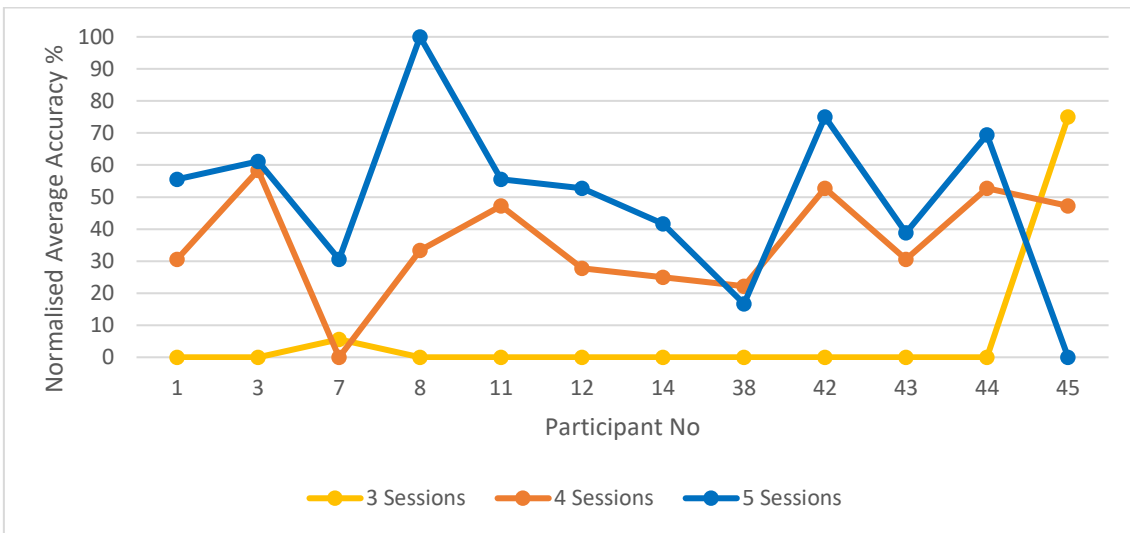


Figure 4.23 Relative comparison of normalised average classification accuracies for LKM-Others/ non-meditation EEG data when using the algorithm STFT for the three cases of 3 sessions, 4 sessions and 5 sessions of data

Table 4.12 shows the average classification accuracies obtained for LKM-Others and non-meditation when using the algorithm CSP and STFT fusion in the pipeline for the three cases of 3 sessions, 4 sessions and 5 sessions of data and Figure 4.24 shows the results graphically.

The mean classification accuracies for the three cases are 70.7%, 72.0% and 73.0% respectively and this indicates an increase in the mean classification accuracy with the increase of the number of training sessions. Moreover, normalised classification accuracies of the Table 4.12 given in Figure 4.25, demonstrates that using 4 sessions has increased the classification accuracy for 11 participants out of 12 when compared with 3 sessions and this is an increase of 91.7%. At the same time, using 5 sessions has increased the classification accuracy for 10 participants out of 12 when compared with 4 sessions, and this is an increase of 83.3%.

Table 4.12 Average accuracy (%) calculated independently for each of the 12 participants when classifying LKM-Others/ non-meditation EEG data using the algorithm (CSP + STFT) for the three cases of 3 sessions, 4 sessions and 5 sessions of data

Count	Participant No	3 Sessions	4 Sessions	5 Sessions
1	1	76.1 ± 13.9	76.8 ± 14.6	78.4 ± 13.4
2	3	65.1 ± 9.3	66.4 ± 7.2	65.8 ± 6.0
3	7	64.0 ± 11.3	65.0 ± 11.8	64.4 ± 13.2
4	8	72.1 ± 13.0	73.9 ± 12.7	75.7 ± 13.0
5	11	69.7 ± 6.9	72.0 ± 7.0	72.5 ± 6.0
6	12	78.3 ± 19.0	77.5 ± 20.6	79.7 ± 22.4
7	14	81.7 ± 7.3	83.6 ± 5.8	84.5 ± 6.6
8	38	68.7 ± 5.2	71.7 ± 6.0	72.4 ± 6.1
9	42	72.0 ± 9.5	72.4 ± 10.3	75.1 ± 10.3
10	43	70.0 ± 14.5	72.1 ± 13.2	73.9 ± 13.5
11	44	72.9 ± 9.4	75.0 ± 6.1	75.9 ± 4.3
12	45	57.7 ± 12.6	57.9 ± 14.4	58.2 ± 15.6
Mean Accuracy		70.7	72.0	73.0

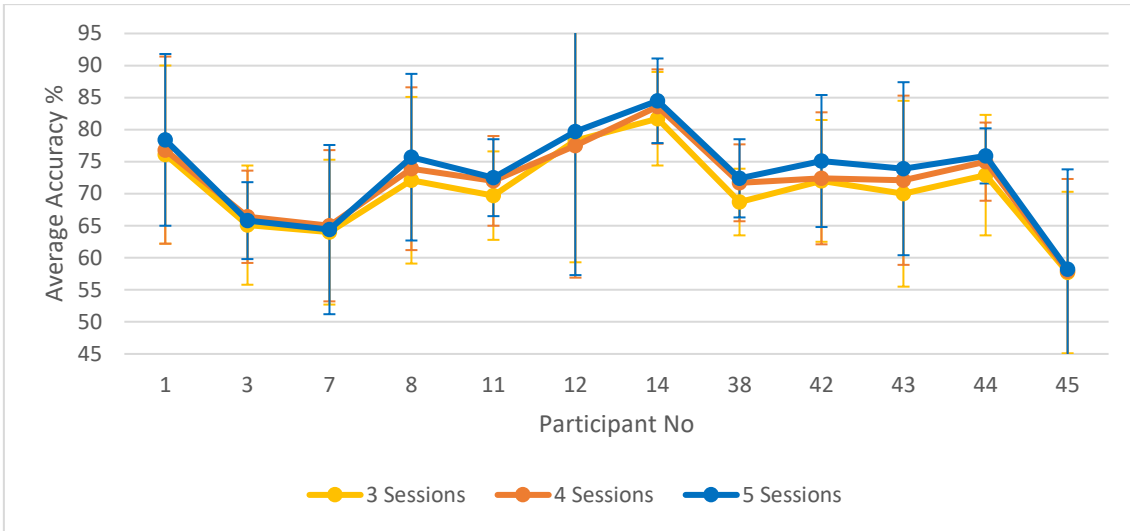


Figure 4.24 Comparison of average classification accuracies for LKM-Others/ non-meditation EEG data when using the algorithm (CSP + STFT) for the three cases of 3 sessions, 4 sessions and 5 sessions of data

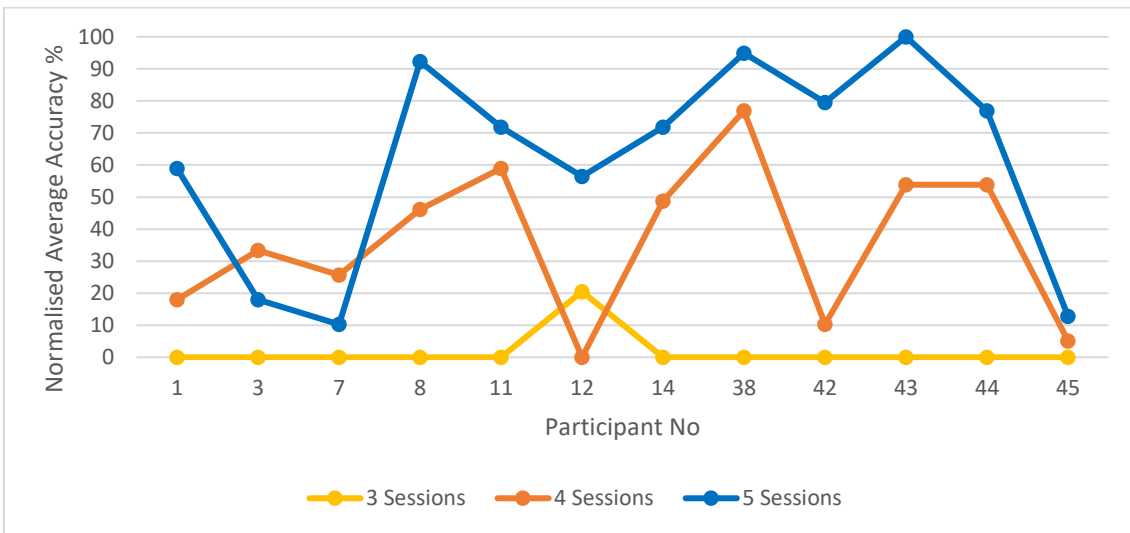


Figure 4.25 Relative comparison of normalised average classification accuracies for LKM-Others/ non-meditation EEG data when using the algorithm (CSP + STFT) for the three cases of 3 sessions, 4 sessions and 5 sessions of data

When summarizing the above results, the lowest mean accuracy was obtained when using 3 sessions in the study. At the same time, the highest mean accuracy was obtained when using 5 sessions whereas using 4 sessions stood at a middle mean accuracy level. This shows that when

the number of training sessions increases, the classification accuracy increases. Furthermore, the following section shows how this pattern behaves for individual participant classification accuracies. Out of 72 instances for the 12 participants, in 64 instances, using 4 sessions was giving a higher classification accuracy than using 3 sessions and the percentage of this is 88.9% when training the machine learning algorithms. Similarly, out of 72 instances for the 12 participants, in 59 instances, using 5 sessions was giving a higher classification accuracy than using 4 sessions and the percentage of this is 81.9%. These two percentage results further prove that use of more sessions for training a machine learning algorithm increases the classification accuracy of that algorithm.

#### 4.4.3. Limitations of the study and future work

The study was conducted using an online EEG dataset and some limitations were based on the characteristics of the dataset. Our interest was only with the multiple session EEG data which has been collected for 15 participants for 8–10 sessions. Due to errors in some files and due to having comparatively smaller file sizes, our analysis was conducted only for 12 participants using the largest 5 files for each mind task and our analysis was limited to these boundaries. At the same time, although the participants were labelled as experts in meditation, since there was no indication of this expert level as a value, we only did intra-subject analysis, and we could not do any inter-subject analysis. Also, as described previously, lack of quantified meditation expert level of the participants forced us to study only the “state” characteristic of the meditation EEG data and we were not able to study the “trait” characteristic of the meditation EEG data. Since this is the first time a study was conducted to classify multiple session meditation/ non-meditation EEG data, further studies can be conducted for improving the classification

accuracies so the studies can support the identification of new meditation/ non-meditation states with much ease. At the same time, for future work, if multiple session EEG data can be collected from participants in the same expert level, such data can be used to study if machine learning can be used for classifying multiple session EEG data as an inter-subject analysis. Similarly, if the data was collected for participants with multiple expert levels, then this can be used to study the “trait” characteristic of the meditation EEG data.

## 4.5 Conclusion

In this study, we were able to demonstrate successful classification of multiple session meditation/ nonmeditation EEG data. LKM-Self, non-meditation pair and LKM-Others, non-meditation pair were independently tested here. While keeping a neural network in all instances as the classification algorithm, the features of meditation EEG were successfully extracted using CSP, STFT and fusion of CSP and STFT. Use of CSP and STFT for meditation EEG is a significantly new approach, and fusion of CSP and STFT notably improved the results. Most importantly, by conducting 3960 tests, we were able to show that for a given person, after training a BCI pipeline with multiple session meditation/ non-meditation EEG data, we could successfully classify a new session for the same person. This creates an opportunity for initiating research developing algorithms to support a person to progress in meditation expertise, especially when such progress usually comes with many sessions of meditation practice. Future studies need to be done to improve the classification accuracies, to achieve multiple session inter-subject classification and, to identify characteristics to monitor how meditation EEG changes (progresses) over time.

## STATEMENT OF CONTRIBUTION DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the student and the student's main supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the student's contribution as indicated below in the Statement of Originality.			
Student name:	Nalinda Devaka Liyanagedera		
Name and title of main supervisor:	Professor Hans W. Guesgen, Chair in Computer Science		
In which chapter is the manuscript/published work?	Chapter 5		
Describe the contribution that the student and members of the supervisory team have made to the manuscript/published work: <sup>1</sup>			
The student analysed and interpreted the data, validated results, visualised findings, and wrote the original manuscript. Moreover, conceptualising, designing the methodology, and developing the necessary software were carried out by the student. The student also contributed to the review and editing of the manuscript. The supervisory team contributed by reviewing and editing the manuscript and providing supervision throughout the work.			
Please select one of the following three options:			
<input checked="" type="radio"/>	<p>The manuscript/published work is published or in press</p> <p>Please provide the full reference of the research output:</p> <p>Nalinda D. Liyanagedera, Corinne A. Bareham, Heather Kempton, Hans W. Guesgen, "Machine Learning-Based Comparative Analysis of Subject-Independent EEG Data Classification Across Multiple Meditation and Non-Meditation Sessions," Sensors (MDPI), 11 Nov. 2025. <a href="https://doi.org/10.3390/s25226876">https://doi.org/10.3390/s25226876</a></p>		
<input type="radio"/>	<p>The manuscript is currently under review for publication</p> <p>Please provide the name of the journal:</p>		
<input type="radio"/>	<p>It is intended that the manuscript will be published, but it has not yet been submitted to a journal</p>		
Student's signature:	<p>Nalinda Liyanagedera</p> <p><small>Digitally signed by Nalinda Liyanagedera Date: 2026.02.15 11:23:31 +13'00'</small></p>	Main supervisor's signature:	<p>Hans W Guesgen</p> <p><small>Digitally signed by Hans W Guesgen Date: 2026.02.15 11:53:11 +13'00'</small></p>
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## Chapter 5

# Machine learning-based comparative analysis of subject-independent EEG data classification across multiple meditation and non-meditation sessions

### Abstract

In this study, subject-independent (inter-subject), multiple-session electroencephalography (EEG) data classification was tested for Loving-Kindness Meditation (LKM) and non-meditation. This is a novel study that extends our previous work on intra-subject, multiple-session classification. Here, two meditation techniques, LKM-Self and LKM-Other, were independently compared with non-meditation. For each mental task, five sessions of data collected from each of the twelve participants were placed in a common data pool, from which randomly selected session data were used for training and testing the machine learning algorithms. Three previously tested BCI pipelines were used. In each case, feature extraction was performed using Common Spatial Patterns (CSP), Short-Time Fourier Transform (STFT), or a fusion of CSP and STFT, followed by classification using a neural network structure. The study was further divided into three cases, where two, three, or four session pairs were used to train the algorithms, and the remaining session pair was used for testing. For each individual instance, the test was repeated thirty times to generalize the results. Thus, a total of 9,900 independent tests were conducted for the entire dataset. The mean classification accuracies obtained in this study were lower than those reported in our previous intra-subject classification study. For example, in LKM-Self/non-meditation classification using three session pairs with the CSP + STFT pipeline, the mean accuracy for all tests was 62.3%, with the bottom 50% at 46.0% and the top 50% at 78.3%, demonstrating variability across session selections. The corresponding intra-subject classification result for the same instance was 72.1%. For all other

instances, a similar pattern was observed. Furthermore, when considering all the mean accuracies obtained, in 83.3% of the instances, CSP + STFT produced better classification accuracies than CSP or STFT alone. At the same time, in 75.0% of the instances, increasing the number of training session pairs led to improved classification accuracies. This study demonstrates that subject-independent, multiple-session EEG classification of meditation and non-meditation is feasible for specific session combinations. Further research is needed to confirm these findings across larger and more diverse participant groups. These findings provide a foundation for developing subject-independent algorithms that can guide long-term meditation practice.

Keywords: EEG (Electroencephalography), BCI (brain computer interface), Machine learning, Subject independence, Classification, Meditation, Multiple session, CSP (Common spatial patterns), STFT (short time Fourier transform), Neural network

## 5.1 Introduction

Electroencephalography (EEG) has emerged as a highly effective non-invasive method for measuring human cognitive activities and mental states, with applications ranging from neurorehabilitation to mindfulness training [7]. In recent years, advances in sensor technology and machine learning have supported the development of systems that interpret brain activity patterns, particularly those that aim to achieve subject-independent analysis [2, 67, 245]. Among these applications, meditation assessment has received significant attention due to its relevance to mental health [3], stress reduction [5], and cognitive enhancement [7, 8]. However, a major challenge in developing generalised EEG-based systems for such purposes lies in the

variability of brain signals across individuals and sessions [66]. This study focuses on subject-independent classification of EEG signals across multiple meditation and non-meditation sessions using machine learning techniques, with the goal of improving the robustness and reliability of EEG-based mental state monitoring systems [51, 52].

Meditation has been proven to cause both temporary and permanent changes in a person [4, 11] where “Trait” [14, 15] refers to the lasting changes that develop after long-term meditation practice. “State” [42, 61], on the other hand, refers to the temporary changes that occur while a person is meditating compared to when they are not. Since this study aims to classify meditation and non-meditation states, we focus on “State” characteristics. Many people who practise meditation aim to achieve progressively calmer mental states, and currently, psychological assessments such as mindfulness scales, questionnaires, and interviews have demonstrated such progressive differences among individuals who practise meditation [16, 17].

At the same time, neuroimaging techniques such as EEG [26, 76, 182], fMRI (Functional Magnetic Resonance Imaging) [47], fNIRS (Functional Near-Infrared Spectroscopy) [48], and PET (Positron Emission Tomography) [10], along with physiological measurements such as heart rate variability [9] and cortisol levels [49], have been used to understand various characteristics of meditation/non-meditation. A significant number of studies have been conducted using EEG to examine different aspects of meditation/non-meditation [1, 78, 79], and some of these studies highlight the importance of developing software systems that can support individuals in practicing meditation, particularly in guiding them toward progress [6, 53, 54]. At the most basic level, the calmness achieved through meditation can be identified by comparing brain patterns during meditation and non-meditation, with non-meditation serving as a baseline [78, 176]. However, since meditation skills improve over time with repeated practice, understanding states such as calmness requires computational analysis and recognition of patterns in multiple-session meditation/non-meditation EEG data [18, 19].

We recognized the importance of studying patterns in multiple-session meditation/non-meditation EEG data [69, 200, 244]. Our earlier work [200], showed that while meditation sessions share similar EEG characteristics, they are clearly distinguishable from non-meditation sessions. As a next step, in our following study [69], we successfully classified intra-subject, multiple-session meditation/non-meditation EEG data. When developing a system that can monitor and distinguish brain pattern differences between meditation and non-meditation EEG data, it is more practical and user-friendly to design it as a subject-independent system, since such systems do not require personal calibration or prior data collection from each individual user, making them easier to use and more accessible in real-world applications. Therefore, as the next step in our study, in this paper we plan to test subject-independent, multiple-session meditation/non-meditation EEG data classification and compare this performance with the outcomes of our previous intra-subject classification study [69].

EEG is a method used to measure the electrical activity of the brain [55, 56] by placing electrodes on the scalp at predefined locations [57]. Studies have shown that the EEG signals collected in this manner, which consist of vibration-like patterns, can correlate with different mental tasks [63]. One common method for analysing EEG data is to first transform it into the frequency domain [60], where, based on specific characteristics, the signal is divided into five frequency bands: Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), and Gamma ( $> 30$  Hz) [73, 77, 121]. Based on past research, the Theta [104, 172, 175, 235] and Alpha [74, 136, 246] bands are most commonly associated with meditation/non-meditation studies, and they were utilised in our study as well. EEG mainly consists of non-linear and complex data; therefore, extracting meaningful patterns from it is a lengthy and challenging process, commonly referred to as the Brain-Computer Interface (BCI) pipeline [28].

A BCI pipeline consists of multiple steps that can generally be broken down into data collection, preprocessing, feature extraction, classification, and application [22, 32]. Preprocessing

involves cleaning and artifact removal of the collected EEG data, and modifying it into a different structure or a simpler format, such as through dimensionality reduction [30, 31]. Since EEG data are complex and have a low signal-to-noise ratio, this cleaning and preprocessing step plays a significant role in the entire study. After the data is cleaned and converted into the desired format, the next step is feature extraction [32, 37]. The aim here is to extract important information hidden in the EEG data that can be used for valuable future tasks. Even after thorough cleaning, a certain amount of noise still remains in the EEG data. Because of this, advanced signal processing methods such as Short Time Fourier Transform (STFT) [249, 250], Common Spatial Patterns (CSP) [45, 62, 82], and Event-Related Potentials (ERPs) [232] are used in feature extraction.

After feature extraction, the next step in the BCI pipeline is classification and application [68, 178, 253]. When we go through past work, notable classification algorithms used with meditation EEG include Support Vector Machines (SVM) [147], Linear Discriminant Analysis (LDA) [196], Artificial Neural Networks (ANNs) [254], Decision Trees, Random Forests [245], and k-Nearest Neighbors (k-NN) [66]. Among these, SVMs and ANNs were the most commonly used methods, with ANNs being significantly utilised by researchers in the recent past. The use of ANNs has increased not only with EEG but also in many research scenarios involving large, nonlinear datasets with high computational complexity that require processing to extract meaningful patterns [255]. This is because ANNs can function as deep learning algorithms that learn from data, adapt to new information, and model complex non-linear relationships [257]. An ANN structure behaves similarly to neuron interactions in the brain, and a basic ANN consists of an input layer, an output layer, and a number of hidden layers, where each layer contains one or more nodes depending on the problem it is designed to solve. An ANN is first trained on a dataset before being used on a new dataset, and training occurs by sending signals forward and backward through the network while optimizing the internal

weights to learn from the training data [256]. After a significant amount of analysis, in our previous study on intra-subject multiple-session classification, we used ANNs to ensure consistent conditions during classification while comparing the performance of different feature extraction methods [69]. In this study, we intend to use the proven BCI pipelines from our previous study, allowing us to compare the performance of intra-subject and inter-subject multiple-session meditation/non-meditation classification on common ground.

This study aims at the novel task of evaluating how effectively subject-independent EEG data classification can be achieved for multiple-session meditation and non-meditation EEG data. This work extends our previously published study [69], where we first demonstrated that multiple-session meditation and non-meditation EEG data exhibit common characteristics within each group. Following that, we successfully performed intra-subject classification of multiple-session meditation and non-meditation EEG data. As a continuation of these studies, this work focuses on subject-independent classification of multiple-session meditation and non-meditation EEG data.

By focusing on both multiple-session meditation and subject-independent classification, this study adds significant value to scientific research. Past studies show a growing demand and interest in achieving subject-independent EEG data classification, particularly in areas such as motor imagery [32, 81]. Such an advancement would enable the development of applications that can be trained on existing data and used by new individuals without further modifications. Unfortunately, no prior research exists on subject-independent, multiple-session meditation EEG classification. Therefore, this study represents a key milestone in initiating and encouraging the development of algorithms that can support apps guiding individuals in their meditation progress. The value of such an app is particularly significant when it is subject-independent and supports multiple-session meditation practice, as true progress in meditation can only be achieved through consistent long-term practice.

## 5.2 Methods

This study is an extension of our previous work [69], where we successfully demonstrated intra-subject, multi-session EEG data classification for meditation and non-meditation states. In this work, we test how subject-independent, multi-session EEG data classification for meditation and non-meditation states performs compared to our previous study. Since we aim to compare the results of inter-subject classification with our earlier intra-subject classification, this study follows a procedure similar to our previous work, where the only difference is that, instead of using EEG sessions from the same person for training and testing on the selected machine learning algorithms, EEG sessions from different participants were used. Since the data preprocessing and construction of the BCI pipelines were done similarly to our previous study, only the most important steps are summarized here, and readers can refer to our earlier paper [69] for the full description. At the same time, the parts of the procedure that are unique to this study are thoroughly explained in this methods section.

This study uses an EEG dataset available online, with the dataset DOI as follows: <https://doi.org/10.18112/openneuro.ds003816.v1.0.1>. A description of the dataset can be found in one of our previous research articles [200]. The dataset is labelled as experienced meditators [72, 133, 185], but since there is no measurement of experience level, such as years of practice, we assume there may be varying levels of experience among the expert participants. In this study, five sessions of EEG data collected per mental task for each of the 12 participants were used, which is a subset of the above online dataset. The study uses both meditation and non-meditation EEG data. Two meditation types were used in this study: loving-kindness meditation [12, 13] on oneself (LKM-Self) and on others (LKM-Others). Therefore, for each participant, 15 sessions of EEG data were used, with 5 sessions per meditation type and 5 sessions of non-

meditation data. Two independent classification tests were conducted: one for LKM-Self vs. non-meditation and the other for LKM-Others vs. non-meditation. Altogether, 180 (15 \* 12) sessions of EEG data were used in this study, and these 180 sessions were the highest-quality sessions selected from the original dataset after initial cleaning and screening.

The selected 180 sessions of EEG data were further cleaned and preprocessed using EEGLAB [31, 260] in MATLAB. A "Basic FIR filter" was applied to extract the data between 2 Hz and 45 Hz, and bad channels were identified and corrected [33, 165]. Independent component analysis (ICA) [58, 64, 196] was then performed on each EEG data session, and cleaning was done by selecting the appropriate components through visual inspection [31, 103]. Since the original EEG data had 127 channels, principal component analysis (PCA) [64, 196] was used along with ICA to achieve dimensionality reduction [271, 272], allowing ICA to run smoothly. The cleaned EEG data sessions were saved in ".eeg" file format for use in the BCI pipelines developed using Python [265, 266].

In our previous study [69], intra-subject classification was performed using 5 session pairs of EEG data for the two compared meditation/non-meditation mental tasks for a selected participant. Since we plan to compare the results of the two studies, in this study, we are also using 5 session pairs of EEG data for the mental tasks. After selecting these 10 sessions, we used three sizes of training data to match our previous study in order to compare the results. Therefore, in this study, we used 2 session pairs, 3 session pairs, or 4 session pairs of EEG data for training the machine learning algorithms in independent analyses.

The cleaned data consists of 180 sessions from 12 participants. Since we are working on intra-subject classification, we first modelled this dataset into three groups corresponding to the three mental tasks. Specifically, 60 sessions of data were assigned to LKM-Self, LKM-Others, and non-meditation, with each group containing 5 sessions of EEG data from a single participant.

Two independent studies were conducted to classify LKM-Self vs. non-meditation and LKM-Others vs. non-meditation. Since the procedures were the same for both cases, the description is provided only for the LKM-Self vs. non-meditation classification.

For all independent tests conducted, the first task was to randomly select 5 participants per mental task, ensuring that each participant contributed at most one session for that task. Since each participant had 5 sessions of data per mental task, 1 session was then randomly selected from the available 5 for each chosen participant. In this way, each mental task contained data from 5 different participants. Among the two mental tasks, a single participant's data might appear in one or both tasks, depending on the random selection. The selected 5 meditation and 5 non-meditation sessions were then paired randomly to create 5 meditation/non-meditation session pairs. This selection process was repeated each time a pair of meditation/non-meditation mental tasks were used to study their classification strength.

For the LKM-Self vs. non-meditation pair, three independent studies were conducted, each using a different number of training session pairs. These studies were evaluated using three independent BCI pipelines. In this study, we used the same three BCI pipelines that produced the best performance in our previous work [69] on intra-subject multiple-session meditation/non-meditation EEG classification. Since, as part of our study, we intend to compare the performance of intra-subject and inter-subject classifications, we used the same BCI pipelines. Here, each of these EEG session data was broken down into epochs of 2s size with a 1s overlap [65]. The main difference among these three BCI pipelines is the method used for feature extraction. The three BCI pipelines use either Common Spatial Patterns (CSP) [45, 62, 82], Short-Time Fourier Transform (STFT) [249, 250], or a fusion of CSP and STFT in each pipeline for feature extraction.

To give some background on the feature extraction methods used in the three BCI pipelines, Common Spatial Patterns (CSP) identifies spatial filters that maximize variance differences between two mental tasks, capturing discriminative patterns across EEG channels. Short-Time Fourier Transform (STFT) analyzes the spectral content of EEG signals over short time windows, allowing the extraction of frequency-based features such as theta and alpha bands, which are relevant to meditation. The third pipeline combines CSP and STFT, taking advantage of both spatial and spectral information, providing a richer feature representation for classification. These methods are critical for the current study, as they enable the BCI pipelines to extract complementary information from multi-session EEG data and differentiate meditation from non-meditation states effectively.

In this study, EEG data were analyzed across several frequency ranges to identify the most effective band for meditation and non-meditation classification. Consistent with our previous findings [69], the theta and alpha frequency range (4–13 Hz) again produced the best classification performance. In all three BCI pipelines, artificial neural networks [256, 257] were used as the classification algorithms, providing a common ground to compare the performance of the three feature extraction algorithms. We tested several network configurations and activation functions, and similar to our previous study, a compact multi-layer perceptron (MLP) with two hidden layers of 20 nodes and a logistic activation function provided the best performance. Although EEG data are high-dimensional, dimensionality-reduction techniques reduced the feature set to a maximum of 14 inputs for each BCI pipeline. For this compact input, the two 20-node hidden-layer structure offered the highest accuracy with low computational cost, while increasing network size did not improve performance. Since we used three different training sizes on three different BCI pipelines, we conducted nine different studies. Also, since this was done for the classification of LKM-Self vs. non-meditation and

LKM-Others vs. non-meditation independently, this adds up to eighteen different studies that we conducted.

All the tests conducted started with a random selection of 5 pairs of EEG session data for the selected meditation/non-meditation mental tasks. Then, three different studies were conducted based on the number of session pairs used for the training of the machine learning algorithms. In the following sections, each of these three studies is explained one after the other.

The first study was conducted using 2 EEG data session pairs for training and 1 EEG data session pair for testing the BCI pipelines. The study starts by randomly selecting 5 EEG data session pairs for the LKM-Self and non-meditation mental tasks. In this study, 3 out of 5 session pairs were selected at a time, with 2 pairs used for training and the remaining session pair used for testing. Here, interchanging the testing session pair gave 3 tests for the selected 3 session pairs. Using the selected 5 pairs, multiple tests were conducted on various selection combinations of 3 session pairs out of 5. With different selection combinations, a total of 30 tests were conducted for each randomly selected 5 session pairs of LKM-Self/non-meditation. This random selection of 5 session pairs of EEG data for LKM-Self and non-meditation was repeated for 30 independent experiments, resulting in 900 tests. Since 900 tests were conducted on one type of BCI pipeline, and we used 3 independent BCI pipelines in our study, the total number of tests conducted was 2700. Therefore, for these 3 BCI pipelines, a total of 2700 (900 \* 3) tests were conducted on the classification of LKM-Self vs non-meditation using 3 session pairs of EEG data in the study.

The second study was conducted using 3 EEG data session pairs for training and 1 EEG data session pair for testing the BCI pipelines. The study begins by randomly selecting 5 EEG data session pairs for the LKM-Self and non-meditation mental tasks. In this study, 4 out of the 5 session pairs were selected at a time, with 3 pairs used for training and the remaining session

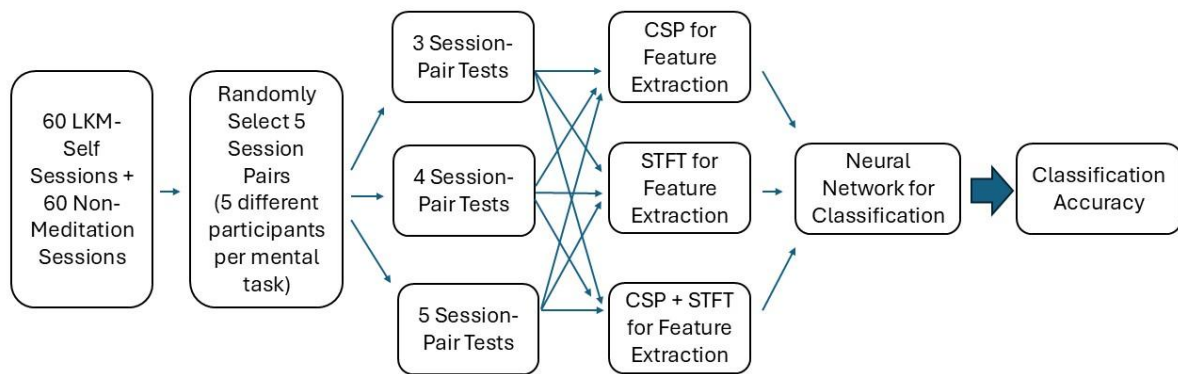
pair used for testing. Here, interchanging the testing session pair gave 4 tests for the selected 4 session pairs. Using the selected 5 pairs, multiple tests were conducted on various selection combinations of 4 session pairs out of 5. With different selection combinations, a total of 20 tests were conducted for each randomly selected 5 session pairs of LKM-Self/non-meditation. This random selection of 5 session pairs of EEG data for LKM-Self and non-meditation was repeated for 30 independent experiments, resulting in 600 tests. Since 600 tests were conducted on one type of BCI pipeline, and we used 3 independent BCI pipelines in our study, the total number of tests conducted was 1800. For these 3 BCI pipelines, a total of 1800 ( $600 * 3$ ) tests were conducted on the classification of LKM-Self vs non-meditation using 4 session pairs of EEG data in the study.

The third study was conducted using 4 EEG data session pairs for training and 1 EEG data session pair for testing the BCI pipelines. The study begins by randomly selecting 5 EEG data session pairs for the LKM-Self and non-meditation mental tasks. In this study, out of the 5 session pairs selected at a time, 4 pairs were used for training, and the remaining session pair was used for testing. Here, interchanging the testing session pair gave 5 tests for the randomly selected 5 session pairs of LKM-Self/non-meditation. This random selection of 5 session pairs of EEG data for LKM-Self and non-meditation was repeated for 30 independent experiments, resulting in 150 tests. Since 150 tests were conducted on one type of BCI pipeline, and we used 3 independent BCI pipelines in our study, the total number of tests conducted was 450. For these 3 BCI pipelines, hence, 450 ( $150 * 3$ ) tests were conducted on the classification of LKM-Self vs. non-meditation using 5 session pairs of EEG data in the study.

When considering all three studies with different numbers of session pairs tested on the 3 BCI pipelines, a total of 4950 ( $2700 + 1800 + 450$ ) tests were conducted to study the classification of LKM-Self vs non-meditation. A similar approach was used to study the classification of LKM-Others vs non-meditation, thus a total of 9900 ( $4950 * 2$ ) independent tests were

conducted in our study for testing inter-subject multiple session meditation and non-meditation EEG data classification. The full description of the implementation of the 3 BCI pipelines is provided in our previous research article [69], and a summary of the procedure is shown in Figure 5.1. That work clearly describes the steps for using CSP, STFT, and the fusion of CSP and STFT for feature extraction. It also describes how deep learning was achieved using artificial neural networks with 2 hidden layers to match each of the feature sets and obtain optimal outcomes.

- The study involves EEG data collected from 12 participants, each performing two meditation tasks and one non-meditation task over five sessions per task.
- After cleaning and preprocessing the data, 120 sessions were used for the LKM-Self vs. non-meditation tests.



- Random selection of five session pairs was freshly drawn for each run in every branch, and each run was repeated 30 times for generalization.
- The entire procedure was then repeated independently for LKM-Others vs. non-meditation, resulting in a total of 9,900 tests for the entire study.

Figure 5.1 Workflow of inter-subject EEG classification across multiple meditation and non-meditation sessions with different training–testing setups

### 5.3 Results

In this study, we evaluated the effectiveness of subject-independent multiple-session EEG data classification for distinguishing between meditation and non-meditation states. We plan to

compare these findings with our previous research on intra-subject multiple-session EEG data classification. The results are mainly divided into two parts, as we independently compared non-meditation with two meditation techniques: LKM-Self and LKM-Others. Each of these comparisons was tested under three conditions, based on the number of EEG session pairs used specifically 3, 4, and 5 session pairs for both LKM-Self/non-meditation and LKM-Others/non-meditation classification tasks.

As a result, six tables were generated to present the findings from these six studies. For each study, three independent classification tests were conducted using three different BCI pipelines, which employed CSP, STFT, or a fusion of CSP and STFT for feature extraction. Accordingly, each of the six tables includes the classification accuracies achieved by all three pipelines. Each study was repeated independently 30 times to generalize the findings and improve result reliability. Leave-One-Session-Out Cross-Validation was applied, and the average and standard deviation were computed to report the classification accuracy and associated uncertainty for each test.

Table 5.1 presents the average classification accuracies obtained for LKM-Self vs. non-meditation EEG data using 3 session pairs, based on 30 independent experiments conducted for each of the three BCI pipelines with different feature extraction methods: CSP, STFT, and a fusion of CSP and STFT. Each of these 30 experiments consists of 30 independent tests, and each row in the table shows the average accuracy and uncertainty for those 30 tests across the three BCI pipelines. For all 2700 ( $30 * 30 * 3$ ) tests conducted, 2 session pairs were used for training the machine learning algorithm, and 1 session pair was used for testing the algorithm. The “Mean Accuracy (All Tests)” provides the average accuracy and uncertainty for all 900 tests conducted for each BCI pipeline. Since we observed a significant level of uncertainty for each pipeline across the 900 tests, we calculated the “Mean Accuracy (Bottom 50%)” and the

“Mean Accuracy (Top 50%)” from these 900 tests. These mean accuracies and uncertainties are displayed at the bottom of Table 5.1.

Table 5.2 follows the same description as provided for Table 5.1, with the only difference being the use of the meditation mental task LKM-Others instead of LKM-Self. Therefore, Table 5.2 presents the average classification accuracies obtained for LKM-Others vs. non-meditation EEG data using 3 session pairs, based on 30 independent experiments conducted for each of the three BCI pipelines employing different feature extraction methods: CSP, STFT, and a fusion of CSP and STFT. Each BCI pipeline consists of 900 tests, adding up to a total of 2700 tests. The table also includes the results for “Mean Accuracy (All Tests)”, “Mean Accuracy (Bottom 50%)”, and “Mean Accuracy (Top 50%)”.

Table 5.1 Average accuracy (%) calculated independently for each of the 30 experiments conducted for classifying LKM-Self/ non-meditation EEG data using one of the three algorithms CSP, STFT or (CSP + STFT) per test for the case of 3 session pairs of data

Experiment No	CSP	STFT	CSP + STFT
1	66.3 ± 12.0	59.5 ± 15.5	50.6 ± 25.1
2	57.7 ± 15.1	59.1 ± 10.2	77.8 ± 11.3
3	60.4 ± 9.2	47.4 ± 16.6	72.1 ± 17.7
4	61.4 ± 20.3	79.1 ± 11.0	60.1 ± 19.3
5	71.7 ± 9.0	61.0 ± 14.2	68.9 ± 8.6
6	45.3 ± 14.8	46.4 ± 15.3	77.0 ± 9.2
7	51.6 ± 16.1	72.3 ± 13.1	59.0 ± 20.1
8	63.6 ± 21.9	69.2 ± 11.9	57.5 ± 20.0
9	52.4 ± 16.0	47.5 ± 23.2	54.9 ± 15.6
10	50.2 ± 21.5	64.0 ± 14.7	57.9 ± 14.0
11	45.8 ± 15.1	55.0 ± 11.5	45.0 ± 13.8
12	56.6 ± 15.5	62.6 ± 11.7	68.6 ± 16.7
13	53.6 ± 16.4	53.7 ± 22.8	48.2 ± 22.8
14	47.8 ± 15.1	57.9 ± 16.9	57.5 ± 9.6
15	55.0 ± 12.2	48.3 ± 20.9	74.4 ± 9.8
16	63.7 ± 9.0	50.3 ± 22.8	72.0 ± 15.3
17	54.3 ± 25.4	64.0 ± 19.0	63.0 ± 26.8
18	54.9 ± 17.9	47.0 ± 21.1	80.2 ± 10.5
19	63.2 ± 17.0	65.9 ± 19.0	51.2 ± 21.0
20	54.2 ± 14.8	49.5 ± 19.6	59.8 ± 17.7
21	50.1 ± 24.1	61.5 ± 21.0	65.4 ± 11.0
22	69.9 ± 21.6	58.9 ± 14.5	63.3 ± 14.3
23	51.6 ± 10.7	54.8 ± 21.6	57.8 ± 18.4
24	59.4 ± 10.7	54.5 ± 17.1	44.5 ± 21.0
25	58.0 ± 19.4	57.8 ± 15.5	65.2 ± 13.6
26	59.4 ± 18.3	62.5 ± 17.1	78.3 ± 9.7

27	52.5 ± 10.2	55.6 ± 10.6	51.3 ± 10.8
28	47.0 ± 22.0	54.4 ± 13.3	54.5 ± 19.3
29	56.1 ± 14.1	50.9 ± 20.7	52.8 ± 18.8
30	49.0 ± 18.3	50.9 ± 24.1	79.7 ± 10.9
Mean Accuracy (All Tests)	56.1 ± 18.0	57.4 ± 19.1	62.3 ± 19.6
Mean Accuracy (Bottom 50%)	41.7 ± 12.0	41.7 ± 11.7	46.0 ± 13.2
Mean Accuracy (Top 50%)	70.4 ± 9.7	73.1 ± 9.8	78.3 ± 8.7

Table 5.2 Average accuracy (%) calculated independently for each of the 30 experiments conducted for classifying LKM-Others/ non-meditation EEG data using one of the three algorithms CSP, STFT or (CSP + STFT) per test for the case of 3 session pairs of data

Experiment No	CSP	STFT	CSP + STFT
1	67.0 ± 17.8	46.8 ± 19.7	75.1 ± 10.3
2	55.1 ± 23.9	52.7 ± 23.3	76.1 ± 10.3
3	49.9 ± 16.0	52.7 ± 14.4	52.4 ± 24.8
4	49.5 ± 24.4	50.2 ± 19.8	78.9 ± 17.9
5	67.0 ± 14.2	60.0 ± 12.6	78.1 ± 14.8
6	45.7 ± 15.7	49.2 ± 20.4	78.1 ± 13.5
7	63.7 ± 24.0	51.2 ± 14.3	45.2 ± 24.1
8	54.7 ± 11.3	52.6 ± 19.1	63.1 ± 27.2
9	67.7 ± 20.5	54.7 ± 19.7	66.9 ± 18.9
10	50.7 ± 17.0	57.1 ± 18.2	58.2 ± 12.2
11	58.3 ± 10.3	54.3 ± 17.6	50.4 ± 15.8
12	68.0 ± 8.8	57.1 ± 19.1	51.0 ± 22.5
13	55.7 ± 20.7	56.0 ± 16.9	76.4 ± 8.5
14	52.5 ± 16.8	58.3 ± 19.8	56.6 ± 23.1
15	51.0 ± 15.9	67.0 ± 13.3	53.7 ± 18.5
16	56.8 ± 6.4	50.9 ± 17.4	55.9 ± 15.8
17	46.6 ± 19.8	62.2 ± 16.0	65.9 ± 18.6
18	53.8 ± 9.2	47.7 ± 20.7	60.4 ± 18.5
19	52.5 ± 14.6	56.9 ± 17.0	58.5 ± 15.2
20	58.1 ± 15.7	59.7 ± 14.6	72.9 ± 18.9
21	50.2 ± 19.5	43.4 ± 21.5	64.5 ± 14.0
22	65.9 ± 16.3	60.8 ± 15.3	64.1 ± 20.1
23	56.9 ± 16.9	70.8 ± 8.4	54.9 ± 16.3
24	56.1 ± 15.7	53.7 ± 21.9	53.4 ± 27.7
25	63.7 ± 13.5	61.6 ± 14.5	53.3 ± 15.6
26	65.1 ± 16.0	66.7 ± 10.6	66.6 ± 19.6
27	53.8 ± 17.2	56.9 ± 17.6	62.7 ± 18.8
28	62.0 ± 24.1	47.5 ± 14.2	61.0 ± 17.5
29	59.8 ± 9.3	60.6 ± 18.4	51.8 ± 24.5
30	51.9 ± 11.8	59.0 ± 10.7	63.2 ± 17.0
Mean Accuracy (All Tests)	57.0 ± 18.0	56.0 ± 18.4	62.3 ± 20.9
Mean Accuracy (Bottom 50%)	42.7 ± 11.8	40.8 ± 11.4	45.0 ± 14.1
Mean Accuracy (Top 50%)	71.3 ± 10.0	71.1 ± 9.3	79.7 ± 8.5

The results shown in Tables 5.3–5.6 follow the same structure and reporting format as described for Tables 5.1 and 5.2, with the only differences being the number of session pairs (4 and 5 instead of 3) and the meditation task (LKM-Self or LKM-Others). Each table presents the average accuracies and uncertainties across the three BCI pipelines (CSP, STFT, and CSP–

STFT fusion), including “Mean Accuracy (All Tests),” “Mean Accuracy (Bottom 50%),” and “Mean Accuracy (Top 50%).”

Table 5.3 Average accuracy (%) calculated independently for each of the 30 experiments conducted for classifying LKM-Self/ non-meditation EEG data using one of the three algorithms CSP, STFT or (CSP + STFT) per test for the case of 4 session pairs of data

Experiment No	CSP	STFT	CSP + STFT
1	67.4 ± 11.4	44.7 ± 10.4	62.0 ± 12.5
2	57.9 ± 16.8	52.3 ± 17.7	72.1 ± 19.4
3	67.2 ± 19.4	53.4 ± 19.1	60.1 ± 28.0
4	69.0 ± 22.2	66.5 ± 19.6	71.4 ± 10.4
5	62.5 ± 10.8	65.6 ± 18.5	54.3 ± 21.9
6	55.9 ± 18.1	57.5 ± 16.3	58.4 ± 12.1
7	65.8 ± 11.9	58.9 ± 19.0	54.7 ± 8.3
8	61.6 ± 14.2	69.0 ± 9.2	46.4 ± 18.7
9	52.0 ± 15.2	49.7 ± 18.0	58.6 ± 25.5
10	60.0 ± 16.9	53.2 ± 15.0	57.1 ± 16.4
11	62.9 ± 19.7	52.7 ± 15.6	68.8 ± 13.2
12	57.9 ± 15.6	44.8 ± 11.0	63.2 ± 12.9
13	65.1 ± 11.7	61.5 ± 19.9	63.2 ± 10.6
14	54.0 ± 17.4	62.8 ± 16.9	71.2 ± 20.3
15	52.0 ± 15.2	52.4 ± 18.5	55.4 ± 25.0
16	58.2 ± 20.3	55.2 ± 16.9	47.4 ± 11.3
17	49.8 ± 12.0	56.5 ± 15.4	49.6 ± 17.1
18	53.2 ± 17.9	56.7 ± 12.2	69.6 ± 15.1
19	52.3 ± 23.1	54.8 ± 24.3	55.4 ± 16.6
20	52.5 ± 14.0	66.0 ± 15.0	68.7 ± 12.9
21	53.2 ± 17.0	50.2 ± 22.9	66.4 ± 14.3
22	57.4 ± 11.9	55.1 ± 16.1	62.6 ± 22.8
23	64.8 ± 14.5	67.1 ± 12.1	79.1 ± 8.6
24	56.2 ± 15.9	46.0 ± 13.4	58.1 ± 16.2
25	68.0 ± 8.6	62.6 ± 14.2	70.8 ± 12.7
26	56.0 ± 22.7	62.3 ± 15.3	72.8 ± 7.5
27	66.0 ± 8.4	63.0 ± 14.9	65.1 ± 12.6
28	59.2 ± 9.2	54.2 ± 11.5	73.8 ± 8.2
29	67.0 ± 17.0	75.0 ± 9.7	64.0 ± 19.5
30	44.5 ± 19.3	67.0 ± 10.2	76.8 ± 13.0
Mean Accuracy (All Tests)	59.0 ± 17.3	57.9 ± 17.7	63.2 ± 18.4
Mean Accuracy (Bottom 50%)	45.1 ± 11.9	43.3 ± 10.7	48.7 ± 13.7
Mean Accuracy (Top 50%)	72.9 ± 8.4	72.5 ± 9.2	77.7 ± 8.3

Table 5.4 Average accuracy (%) calculated independently for each of the 30 experiments conducted for classifying LKM-Others/ non-meditation EEG data using one of the three algorithms CSP, STFT or (CSP + STFT) per test for the case of 4 session pairs of data

Experiment No	CSP	STFT	CSP + STFT
1	76.4 ± 6.8	42.6 ± 11.1	75.8 ± 7.4
2	43.3 ± 15.1	72.5 ± 15.3	68.9 ± 25.6
3	61.4 ± 25.4	50.3 ± 15.7	63.6 ± 18.9
4	45.2 ± 22.5	43.5 ± 17.2	63.4 ± 20.3

5	75.6 ± 20.7	48.6 ± 16.7	70.8 ± 10.3
6	45.6 ± 17.2	62.9 ± 24	56.2 ± 20.8
7	63.9 ± 14.5	81.0 ± 10.2	55.2 ± 17.3
8	68.0 ± 8.6	78.9 ± 15.5	44.8 ± 15.4
9	47.8 ± 14.0	63.9 ± 19.2	55.3 ± 17.8
10	69.4 ± 7.2	40.5 ± 14.7	53.6 ± 16.3
11	57.2 ± 19.6	54.7 ± 14.1	65.2 ± 19.3
12	67.4 ± 18.4	75.5 ± 14.5	70.1 ± 12.3
13	55.8 ± 16.7	54.3 ± 10.8	60.4 ± 18.8
14	49.4 ± 14.5	53.5 ± 13.3	64.2 ± 15.9
15	56.4 ± 18.0	59.7 ± 17.7	65.5 ± 15.7
16	70.0 ± 9.7	78.0 ± 10.4	51.6 ± 14.0
17	41.6 ± 14.4	54.4 ± 14.3	69.2 ± 8.0
18	66.7 ± 7.7	62.3 ± 12.0	63.3 ± 16.6
19	43.6 ± 12.6	68.1 ± 12.4	70.2 ± 17.9
20	48.8 ± 15.1	64.2 ± 13.1	65.5 ± 11.7
21	64.6 ± 16.4	68.8 ± 20.2	57.3 ± 16.0
22	51.2 ± 14.3	62.3 ± 15.8	57.6 ± 14.2
23	70.3 ± 12.5	54.5 ± 19.5	69.3 ± 13.1
24	56.8 ± 13.6	46.9 ± 14.9	43.1 ± 16.3
25	60.1 ± 19.1	72.7 ± 10.7	52.2 ± 19.9
26	68.4 ± 10.8	66.9 ± 13.3	72.4 ± 10.4
27	57.5 ± 10.5	61.9 ± 13.6	42.9 ± 15.9
28	42.7 ± 16.6	45.2 ± 16.7	60.4 ± 11.3
29	63.8 ± 15.9	59.3 ± 16.6	62.9 ± 16.9
30	56.1 ± 12.7	49.8 ± 14.7	72.7 ± 9.5
Mean Accuracy (All Tests)	58.2 ± 18.4	59.9 ± 18.9	61.5 ± 18.2
Mean Accuracy (Bottom 50%)	43.3 ± 12.8	44.0 ± 11.4	46.8 ± 13.3
Mean Accuracy (Top 50%)	73.0 ± 8.7	75.8 ± 9.1	76.1 ± 7.5

Table 5.5 Average accuracy (%) calculated independently for each of the 30 experiments conducted for classifying LKM-Self/ non-meditation EEG data using one of the three algorithms CSP, STFT or (CSP + STFT) per test for the case of 5 session pairs of data

Experiment No	CSP	STFT	CSP + STFT
1	66.1 ± 12.4	36.5 ± 12.6	36.3 ± 12.2
2	52.9 ± 12.1	66.9 ± 15.0	52.5 ± 18.3
3	63.6 ± 8.3	66.5 ± 12.6	72.0 ± 8.6
4	66.5 ± 17.0	79.8 ± 14.6	72.5 ± 9.8
5	62.9 ± 9.1	57.2 ± 14.2	73.3 ± 13.5
6	60.9 ± 15.8	63.3 ± 14.0	51.2 ± 14.0
7	57.4 ± 16.2	55.0 ± 9.5	57.6 ± 19.1
8	57.0 ± 12.5	74.5 ± 16.1	74.9 ± 12.9
9	61.2 ± 9.9	61.1 ± 18.7	43.4 ± 22.4
10	63.4 ± 18.3	54.4 ± 16.1	57.6 ± 16.8
11	72.0 ± 9.4	65.8 ± 8.6	42.3 ± 10.0
12	61.0 ± 22.0	66.8 ± 16.6	55.6 ± 15.8
13	60.7 ± 16.0	59.3 ± 12.5	71.9 ± 11.2
14	69.4 ± 13.3	53.9 ± 15.5	74.7 ± 9.5
15	58.4 ± 10.4	52.6 ± 10.1	70.3 ± 17.4
16	68.1 ± 20.0	66.2 ± 18.6	56.7 ± 18.3
17	57.7 ± 10.8	71.3 ± 19.4	75.0 ± 16.5
18	38.7 ± 14.2	56.1 ± 8.8	87.5 ± 8.5
19	56.0 ± 15.7	69.8 ± 6.8	71.3 ± 20.4
20	48.1 ± 15.7	66.2 ± 13.1	49.6 ± 12.1
21	56.6 ± 3.6	45.8 ± 9.0	63.2 ± 7.6
22	58.8 ± 4.3	48.0 ± 9.3	61.5 ± 20.0

23	60.4 ± 26.3	62.4 ± 13.9	43.9 ± 4.0
24	63.8 ± 11.8	50.8 ± 19.1	74 ± 15.2
25	71.9 ± 12.9	63.4 ± 11.1	62.7 ± 11.0
26	64.5 ± 12.7	72.1 ± 10.0	59.3 ± 6.6
27	50.0 ± 11.3	50.8 ± 21.2	67.9 ± 10.2
28	73.6 ± 14.7	71.9 ± 9.3	50.7 ± 11.8
29	63.6 ± 13.8	58.7 ± 15.2	62.8 ± 11.8
30	66.8 ± 10.2	57.1 ± 22.8	57.4 ± 7.2
Mean Accuracy (All Tests)	61.1 ± 15.9	60.8 ± 17.2	61.6 ± 18.3
Mean Accuracy (Bottom 50%)	48.6 ± 11.8	46.7 ± 10.5	46.5 ± 11.2
Mean Accuracy (Top 50%)	73.5 ± 7.7	74.9 ± 8.9	76.8 ± 9.1

Table 5.6 Average accuracy (%) calculated independently for each of the 30 experiments conducted for classifying LKM-Others/ non-meditation EEG data using one of the three algorithms CSP, STFT or (CSP + STFT) per test for the case of 5 session pairs of data

Experiment No	CSP	STFT	CSP + STFT
1	65.7 ± 14.0	71.7 ± 7.0	51.2 ± 17.8
2	60.6 ± 21.3	64.4 ± 12.0	61.7 ± 12.4
3	71.2 ± 12.0	54.9 ± 13.4	54.2 ± 17.6
4	71.8 ± 18.7	70.7 ± 15.2	54.5 ± 13.9
5	58.6 ± 12.6	49.8 ± 16.7	51.5 ± 17.3
6	55.5 ± 21.1	56.4 ± 6.1	60.9 ± 11.9
7	66.9 ± 6.7	49.7 ± 16.6	55.9 ± 12.2
8	51.1 ± 8.4	66.2 ± 17.7	64.6 ± 15.3
9	56.8 ± 8.4	67.6 ± 13.0	39.5 ± 7.6
10	57.5 ± 19.3	73.5 ± 11.8	77.5 ± 10.8
11	43.8 ± 8.9	44.3 ± 16.0	65.8 ± 10.3
12	57.4 ± 13.2	69.2 ± 15.9	69.7 ± 9.1
13	60.9 ± 13.2	56.4 ± 22.1	73.0 ± 9.1
14	70.1 ± 11.7	51.7 ± 14.4	74.0 ± 10.1
15	53.0 ± 8.8	56.2 ± 19.0	52.4 ± 13.6
16	48.7 ± 14.9	66.0 ± 16.2	61.4 ± 16.7
17	57.4 ± 18.4	70.5 ± 22.6	58.0 ± 11.2
18	41.9 ± 16.8	67.3 ± 23.9	73.9 ± 9.2
19	73.2 ± 10.1	59.7 ± 9.9	63.0 ± 20.0
20	62.6 ± 6.6	77.9 ± 11.5	29.1 ± 10.0
21	52.7 ± 4.8	69.6 ± 7.0	51.6 ± 13.7
22	63.7 ± 13.0	56.2 ± 7.0	57.9 ± 9.4
23	70.8 ± 6.0	54.3 ± 21.2	71.4 ± 19.2
24	63.1 ± 10.0	53.8 ± 26.0	77.1 ± 7.3
25	66.4 ± 16.0	52.2 ± 24.2	50.3 ± 12.6
26	71.9 ± 13.9	65.8 ± 12.2	71.5 ± 8.8
27	49.4 ± 13.6	54.2 ± 9.8	57.4 ± 17.5
28	64.1 ± 6.5	74.8 ± 9.8	63.5 ± 8.6
29	66.0 ± 9.3	67.2 ± 9.1	67.2 ± 6.8
30	66.7 ± 11.3	65 ± 17.5	62.2 ± 7.5
Mean Accuracy (All Tests)	60.7 ± 15.6	61.9 ± 18.0	60.7 ± 16.8
Mean Accuracy (Bottom 50%)	48.5 ± 11.3	47.6 ± 13.2	47.4 ± 11.9
Mean Accuracy (Top 50%)	72.8 ± 8.0	76.2 ± 8.3	74.1 ± 8.1

To support the tabulated results (Tables 5.1–5.6), Figures 5.2–5.5 provide a visual summary of the mean classification accuracies obtained across the three BCI pipelines (CSP, STFT, and CSP

+ STFT). These figures illustrate the overall performance trends for LKM-Self vs non-meditation and LKM-Other vs non-meditation classification under different session pair conditions (3, 4, and 5).

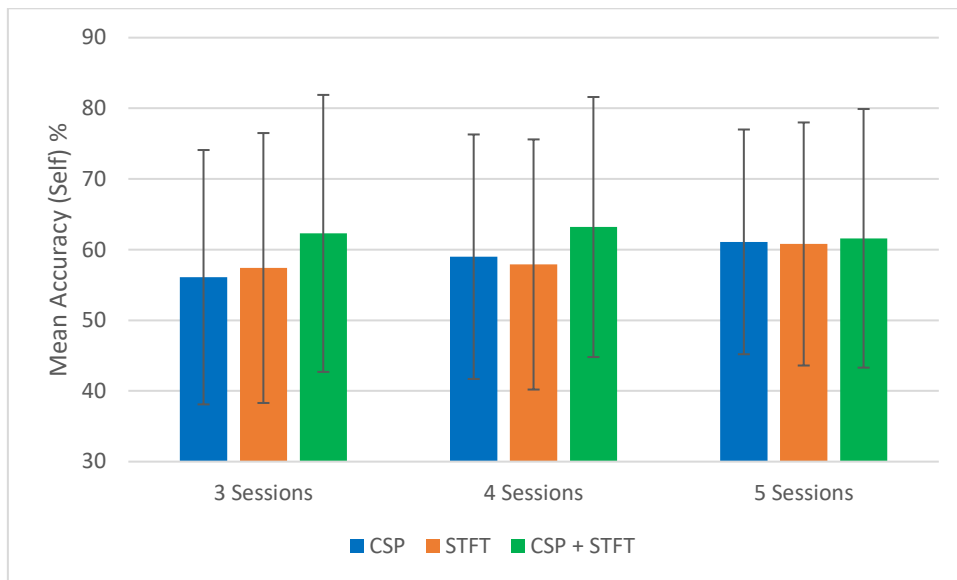


Figure 5.2 Comparison of mean classification accuracies for LKM-Self/ non-meditation when using the three algorithms CSP, STFT or (CSP + STFT) for the cases of 3, 4 or 5 session pairs of EEG data

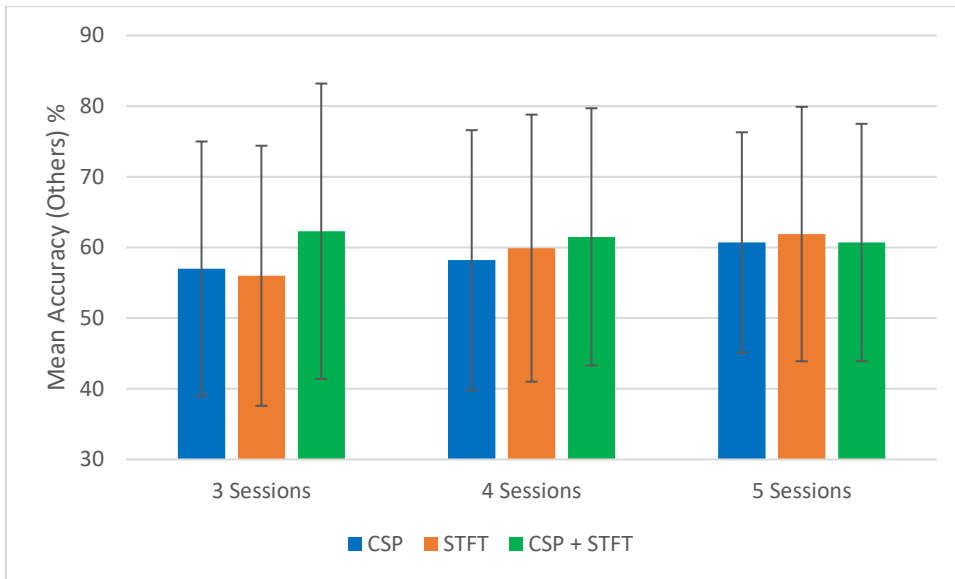


Figure 5.3 Comparison of mean classification accuracies for LKM-Others/ non-meditation when using the three algorithms CSP, STFT or (CSP + STFT) for the cases of 3, 4 or 5 session pairs of EEG data

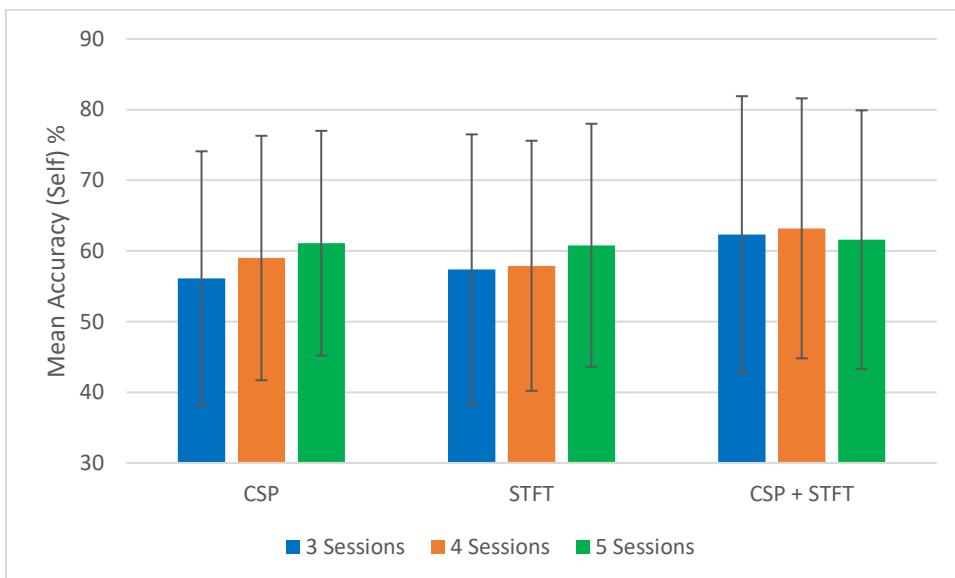


Figure 5.4 Comparison of mean classification accuracies for LKM-Self/ non-meditation when using 3, 4 or 5 session pairs of EEG data for the three algorithms CSP, STFT or (CSP + STFT)

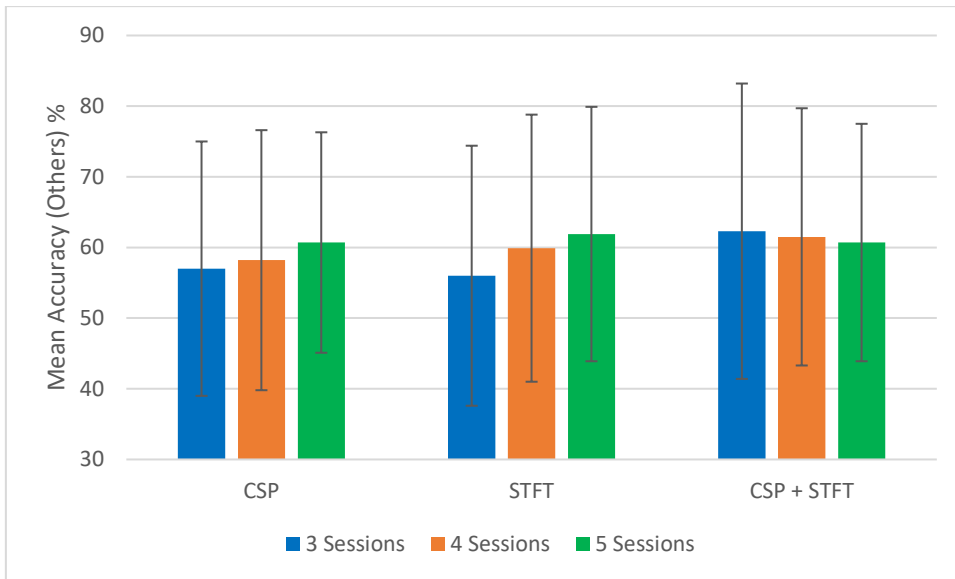


Figure 5.5 Comparison of mean classification accuracies for LKM-Others/ non-meditation when using 3, 4 or 5 session pairs of EEG data for the three algorithms CSP, STFT or (CSP + STFT)

## 5.4 Discussion

In this study, we evaluated the performance of inter-subject (subject-independent), multi-session EEG data classification for meditation and non-meditation states and compared it with our previous work on intra-subject, multi-session EEG data classification for the same states. Six separate studies were conducted, resulting in six tables of outcomes. These included the LKM-Self vs non-meditation study and the LKM-Others vs non-meditation study, each performed using three, four, and five EEG session pairs. Since each of these six independent studies was tested using three different BCI pipelines, each table contains three columns corresponding to these pipelines. The main difference among the three pipelines lies in the use of different feature extraction algorithms namely, CSP, STFT, and CSP + STFT. With three pipelines applied across the six studies, a total of 18 (6 \* 3) outcomes are presented in the six result tables (Tables 5.1–5.6).

In the six tables, there are 30 lines of results, and each result represents the average classification accuracy along with the corresponding error for a single random selection of 5 session pairs. As described in the methods section, after randomly selecting 5 session pairs of meditation/non-meditation EEG data, each pipeline was tested on all possible combinations of those 5 pairs, with classification accuracy computed for each instance (for the 3, 4, and 5 session pairs used independently in the pipeline, the total number of possible combinations was 30, 20, and 5, respectively). These classification accuracies were then used to calculate the average classification accuracy and the associated error. This is reported as a single result in each table, and for 30 such tests, 30 results are shown for each BCI pipeline.

Our aim was to obtain a mean accuracy for each of the BCI pipelines using the results in the six tables, so that the results could be compared with the mean accuracies obtained in our previous studies on intra-subject classification. Therefore, we calculated the overall average for each pipeline, based on 30 independent tests. In the tables, these results are labelled as “Mean Accuracy (All Tests).” For the tables containing results of 3, 4, and 5 session pairs, these overall averages and errors for each pipeline were calculated using classification accuracy results obtained from 900, 600, and 150 independent tests, respectively. The total number of tests conducted for the entire study was 9,900  $((900 + 600 + 150) \times 3 \times 2)$ .

After obtaining the 18 overall mean accuracy values for the six tables, they were compared with the corresponding instances from our previous studies. We observed that the mean accuracy for each instance in this study was lower than the corresponding accuracy in the previous study for the same instance. This suggests that inter-subject classification produced lower classification accuracy than intra-subject classification. Additionally, a significant finding in this study was the high level of error observed when calculating these mean accuracy values. These results opened a new perspective in our study, revealing that some instances yield high classification

accuracies, while others yield low classification accuracies when conducting inter-subject, multi-session meditation/non-meditation classification.

Compared to our previous study, the reduced classification accuracies along with the high errors in this study demonstrate that some tests produced high classification accuracies, while others resulted in low classification accuracies. One possible explanation, which should be tested in future research, is that this variability may be related to differences in meditation experience levels among the participants, since session selection was performed randomly. Although the dataset was labelled as consisting of experienced meditators, the actual experience level such as years of practice was not measured. We therefore hypothesize that a range of experience levels may have existed among the so-called experienced meditation participants. If this were the case, we would expect some selection combinations to yield high classification accuracies, while others would result in lower accuracies. High accuracies could occur when the random selection included meditation EEG sessions from participants with similarly high levels of meditation experience, whereas low accuracies could result when the random selection mixed EEG data from participants with varying levels of experience.

To test this assumption for the 18 studies shown in Tables 5.1–5.6, after calculating the “Mean Accuracy (All Tests)”, we also computed the “Mean Accuracy (Bottom 50%)” and “Mean Accuracy (Top 50%)”. For each BCI pipeline, the classification accuracies were divided into two equal groups: the lower 50% and the upper 50%, and the mean accuracy and corresponding error were calculated for each group. These calculations were performed across the 18 independent studies, and the resulting values are presented at the bottom of Tables 5.1–5.6. The results show the mean accuracies of both the top and bottom 50% of the accuracy values obtained when testing each BCI pipeline for each of the three training sizes used in the study.

At a glance, we can observe a significant difference in classification accuracy between the mean accuracies calculated from the top and bottom halves of the results. This indicates that classification accuracy depends on the data selected for the classification. If accuracy were not influenced by the choice of sessions, the difference between the top 50% and bottom 50% would not be substantial. Since we used random selection, some combinations yielded significantly high classification accuracies, while others resulted in notably low accuracies. This was reflected in the large variance among the calculated classification accuracies for all tests within a single BCI pipeline model and further evidenced by the substantial difference between the mean accuracies of the top 50% and the bottom 50%.

The summary of the classification accuracy results (“Mean Accuracy (All Tests)”) presented in Tables 5.1–5.6 is further elaborated in Figures 5.2–5.5. Additionally, we compared the results obtained in this study (“Mean Accuracy (All Tests)”, “Mean Accuracy (Bottom 50%)”, and “Mean Accuracy (Top 50%)”) with those from our previous study, and this comparison is illustrated in Figures 5.6–5.11. In the following sections, these figures are explained individually.

First, we focus on the performance trends of the 18 different studies, which we label as “Mean Accuracy (All Tests).” When calculating the mean accuracies, in the cases of 3, 4, or 5 session pairs, they were computed using accuracies obtained from 900, 600, and 150 tests, respectively. Figures 5.2–5.5 present the comparison of mean classification accuracies for LKM-Self/non-meditation and LKM-Others/non-meditation using the three algorithms: CSP, STFT, and CSP + STFT, across 3, 4, and 5 session pairs of EEG data.

For LKM-Self/non-meditation (Figures 5.2 and 5.4), the CSP + STFT pipeline significantly outperforms the others for 3- and 4-session pairs, and performs slightly better in the 5-session pair case. An increase in the number of training pairs generally improves accuracy for CSP and

STFT, while for CSP + STFT, the improvement is seen mainly when comparing 3 to 4 session pairs. Overall, in 5 out of 6 cases where session pairs increased, classification accuracy improved.

For LKM-Others/non-meditation (Figures 5.3 and 5.5), CSP + STFT outperforms the others in the 3- and 4-session pair cases, while STFT performs best in the 5-session pair case. As with LKM-Self, increasing session pairs usually improved classification accuracy for CSP and STFT, but not consistently for CSP + STFT. Here, 4 out of 6 cases showed improvements.

By comparing both meditation types, we see that in 9 out of 12 instances (75.0%), an increase in the number of training session pairs led to higher classification accuracy. These findings are consistent with our previous intra-subject study, where increasing training session pairs improved classification accuracy in all 12 comparisons (100%).

The performance of the three BCI pipelines (CSP, STFT, and CSP + STFT) was further tested using pairwise t-tests (Table 5.7). The results indicate that CSP + STFT performs significantly better than CSP ( $t(5) = -3.15$ ,  $p = 0.025$ ), while CSP + STFT is marginally better than STFT ( $t(5) = -2.43$ ,  $p = 0.059$ ), though not statistically significant at  $\alpha = 0.05$ . No significant difference was found between CSP and STFT ( $t(5) = -0.59$ ,  $p = 0.581$ ).

Table 5.7 Paired t-test results comparing classification accuracies across methods (d.f. = 5 for all comparisons)

<b>Comparison</b>	<b>t-stat</b>	<b>p-value</b>
CSP vs CSP + STFT	-3.15	0.025
STFT vs CSP + STFT	-2.43	0.059
CSP vs STFT	-0.59	0.581

Next, the results obtained in this study are compared with those from our previous study, and Figures 5.6–5.11 have been prepared to provide the corresponding comparisons. The results

from this study include "Mean Accuracy (All Tests)", "Mean Accuracy (Bottom 50%)", and "Mean Accuracy (Top 50%)", as shown in Tables 5.1–5.6. These are compared with the matching experimental results from our previous study, labelled as "Mean Accuracy (Intra-Subject, Previous Study)". Each graph allows for a comparison of the performances of the three BCI pipelines: CSP, STFT, and CSP + STFT, for a selected meditation type and session pair count.

Figure 5.6 presents the classification accuracies for LKM-Self/non-meditation using 3 session pairs of EEG data with the three algorithms: CSP, STFT, or (CSP + STFT), while Figure 5.7 shows the corresponding results for LKM-Others/non-meditation. Similarly, Figure 5.8 displays the classification accuracies for LKM-Self/non-meditation using 4 session pairs, and Figure 5.9 presents the same for LKM-Others/non-meditation. Finally, Figures 5.10 and 5.11 show the classification accuracies for LKM-Self and LKM-Others/non-meditation, respectively, when using 5 session pairs of EEG data with the three algorithms.

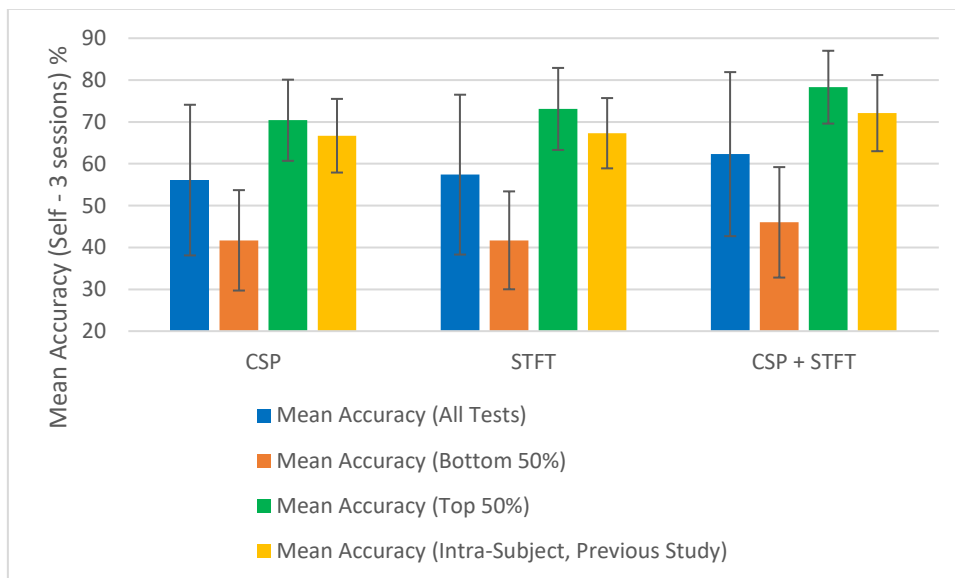


Figure 5.6 Comparison of mean inter-subject (All Tests, Bottom 50%, Top 50%) and intra-subject (previous study) classification accuracies for LKM-Self/ non-meditation when using 3 session pairs of EEG data for the three algorithms CSP, STFT or (CSP + STFT)

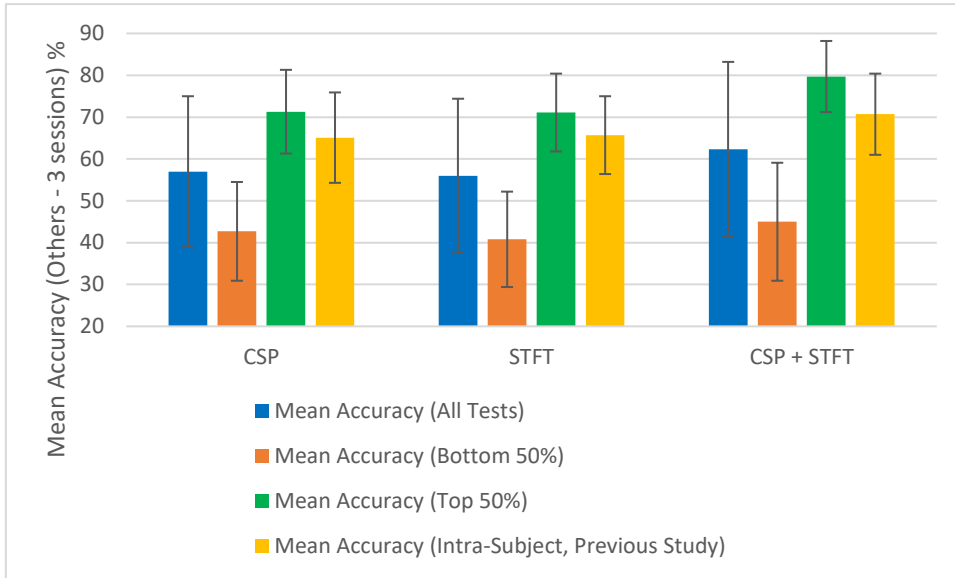


Figure 5.7 Comparison of mean inter-subject (All Tests, Bottom 50%, Top 50%) and intra-subject (previous study) classification accuracies for LKM- Others/ non-meditation when using 3 session pairs of EEG data for the three algorithms CSP, STFT or (CSP + STFT)

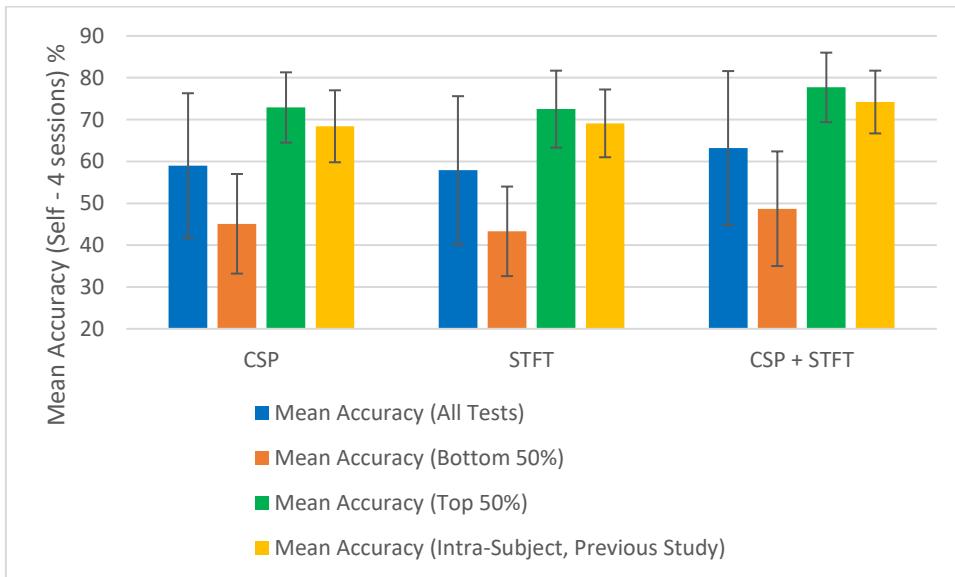


Figure 5.8 Comparison of mean inter-subject (All Tests, Bottom 50%, Top 50%) and intra-subject (previous study) classification accuracies for LKM-Self/ non-meditation when using 4 session pairs of EEG data for the three algorithms CSP, STFT or (CSP + STFT)

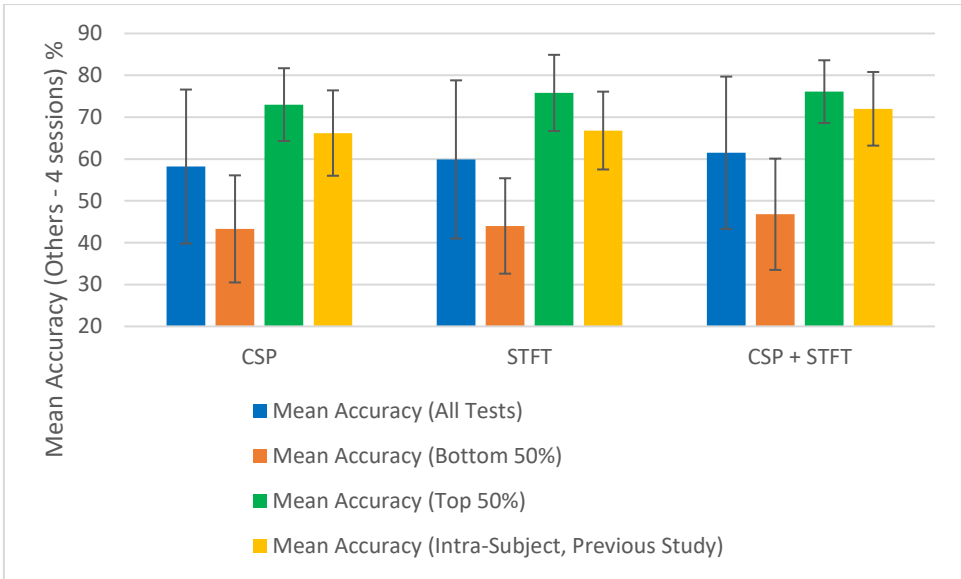


Figure 5.9 Comparison of mean inter-subject (All Tests, Bottom 50%, Top 50%) and intra-subject (previous study) classification accuracies for LKM- Others/ non-meditation when using 4 session pairs of EEG data for the three algorithms CSP, STFT or (CSP + STFT)

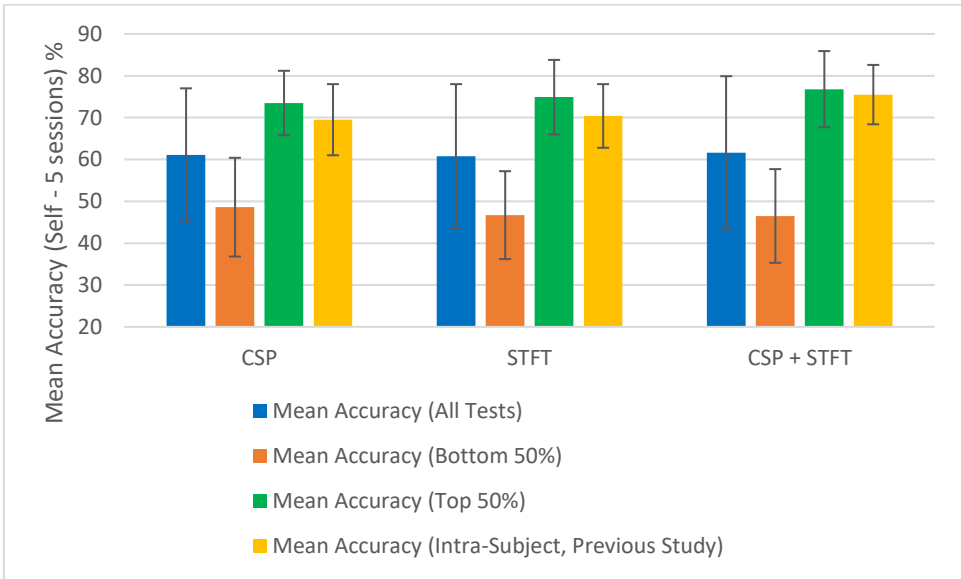


Figure 5.10 Comparison of mean inter-subject (All Tests, Bottom 50%, Top 50%) and intra-subject (previous study) classification accuracies for LKM-Self/ non-meditation when using 5 session pairs of EEG data for the three algorithms CSP, STFT or (CSP + STFT)

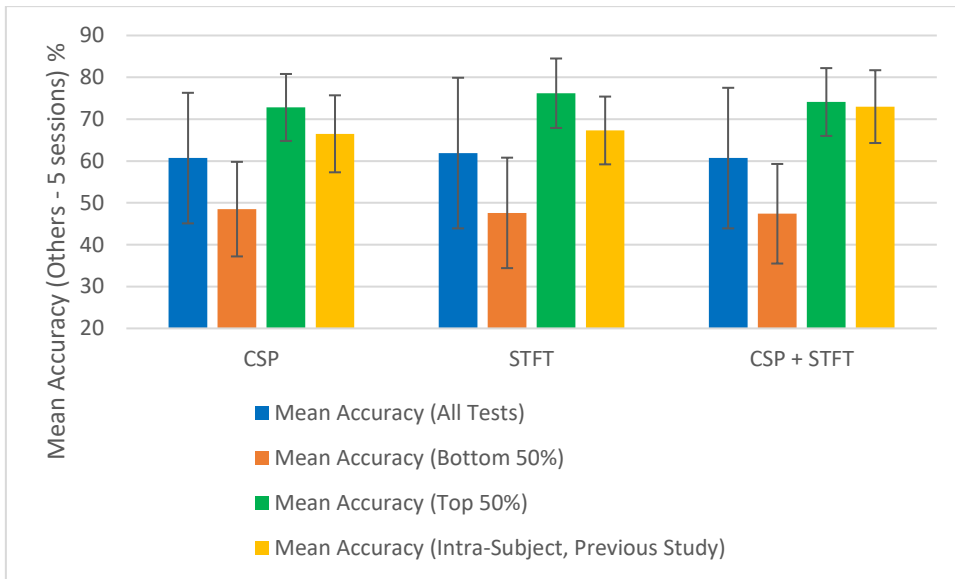


Figure 5.11 Comparison of mean inter-subject (All Tests, Bottom 50%, Top 50%) and intra-subject (previous study) classification accuracies for LKM- Others/ non-meditation when using 5 session pairs of EEG data for the three algorithms CSP, STFT or (CSP + STFT)

When we look at Figures 5.6–5.11 for the 18 different study instances (3 BCI pipelines  $\times$  2 meditation types  $\times$  3 training session pair sizes), we observe several recurring patterns. Therefore, we will address these patterns one by one and provide a general explanation as follows.

The first observation we can elaborate on for all these 18 study instances is that the mean accuracy (all tests) in this study yielded lower classification accuracies compared to the same instances in our previous study on intra-subject classification. This is clearly understandable, as this study tested inter-subject (subject-independent) classification, meaning EEG multi-session data from different participants were used for training and testing the algorithms. In contrast, the previous study conducted a single test using multi-session data from a single person for both training and testing. This highlights that when using meditation EEG data from multiple participants, extracting meaningful information and applying it to classification algorithms becomes more complex, as such data involve greater variability than multi-session

data from a single individual. Nevertheless, we were able to demonstrate that good classification performance is achievable in certain instances. Therefore, we can conclude that further research is necessary to generalize these results and achieve high mean accuracies for subject-independent classification using multiple-session meditation/non-meditation EEG data.

The second significant factor we observed in this study was that the mean accuracy (all tests) for these 18 studies exhibited significantly high error values, or in other words, variability. This suggests that the classification accuracies had a wider distribution around the mean values. What this indicates is that, while the mean accuracies in this study were lower than those in our previous study, there were individual instances that yielded relatively good accuracies, as well as those that resulted in relatively poor accuracies. These studies were conducted using a random selection of session pairs, and the high variance reveals that certain selection combinations produced good classification accuracies. Although we ensured that for each mental task, the session data were always selected from different participants, some sessions still displayed significantly higher levels of match, leading to higher classification accuracies. The underlying reasons for obtaining high accuracy for certain selection combinations and low accuracy for others remain to be explored.

One assumption we can make is that although the selected participants are labelled as expert meditators, they may still exhibit differences, falling within a range of expertise at the expert level. When the randomly selected data came from participants with similar levels of meditation skills, using session data from these participants tended to produce higher classification accuracies. Although this may or may not be the case, what remains significant is that there were individual instances that resulted in high classification accuracies. Therefore, future studies should be conducted to better understand the reasons why some session combinations fail to yield good classification accuracies, and to develop solutions to address these issues.

Such studies will make a meaningful contribution toward achieving subject-independent, multiple-session meditation/non-meditation classification.

To further illustrate the significance of some session combinations yielding high accuracies and others yielding low accuracies, we divided the entire accuracy result set into two equal parts and calculated the mean accuracy for each part. For each pipeline, when the number of session pairs used was 3, 4, and 5, the number of tests conducted for each was 900, 600, and 150, respectively. In each case, this set was divided in half, with the largest half of the values placed in one group and the smallest half in another group. Then, using these selected test values, the mean and error for each group were calculated. These mean values ("Mean Accuracy (Bottom 50%)" and "Mean Accuracy (Top 50%)") are shown in Figures 5.6–5.11, enabling us to compare them with the full mean accuracies of this study, "Mean Accuracy (All Tests)," and the results of the past study, "Mean Accuracy (Intra-Subject, Previous Study)".

When examining Figures 5.6–5.11, we observe a significant difference between the mean accuracies of the bottom 50% and the top 50%, indicating that some session pair combinations yield better classification accuracies than others. Although the overall mean accuracies (all tests) in this study were lower than the corresponding values in the previous study, the mean accuracies of the top 50% were consistently higher than those of the past intra-subject classification. This further suggests that the top 50% of results in this inter-subject classification study outperformed those from the previous intra-subject study. Therefore, these positive findings highlight the importance of future research aimed at identifying the factors contributing to lower-performing combinations and improving the overall effectiveness of subject-independent, multiple-session meditation/non-meditation classification.

Additionally, we tested the results of the 3-, 4-, and 5-session pairs independently to examine whether bimodality was present in the classification accuracies obtained in our study (Table

5.8). Hartigan’s Dip Test was used, and for the 3-session case, unimodality was rejected, indicating bimodal characteristics among the 5,400 test results. In contrast, the 4- and 5-session cases, which together consisted of 4,500 tests (3,600 + 900), failed to reject unimodality, indicating a lack of statistically significant bimodality. When generalizing across the entire dataset, we can conclude that although a hint of bimodality is visible, further research is needed to confirm this characteristic in multiple-session meditation/non-meditation EEG data.

Table 5.8 Hartigan’s Dip Test results for classification accuracy distributions across different session-pair conditions

<b>Session Pair Type</b>	<b>No. of Tests</b>	<b>Dip Statistic</b>	<b>p-value</b>
3-session pairs	5,400	0.0077	0.0347
4-session pairs	3,600	0.0085	0.0831
5-session pairs	900	0.0152	0.1793

Furthermore, such findings that improve multiple-session classification will contribute to the future development of subject-independent EEG meditation-guiding apps. This is because progress in meditation is achieved through rigorous practice across multiple sessions, and therefore, any algorithm intended to support a person’s meditation progress should be capable of distinguishing patterns across sessions, specifically differentiating between meditation and non-meditation states. Although current research on such apps that support mental calmness and relaxation is still in its early stages, there is significant attention and high demand even for the most basic apps currently available. For these reasons, this study on subject-independent, multiple-session meditation/non-meditation classification holds great significance in current EEG research.

## 5.5 Limitations

This study was conducted using an EEG dataset available online and we acknowledge some limitations connected with the dataset. Although the dataset is a large, multiple-session, good-quality EEG dataset, the number of participants is relatively small (12), and detailed characteristics such as age, gender, physical conditions, and meditation experience values are not available. Even though the dataset labels participants as “experts,” the level of meditation experience has not been independently validated, and differences within the expert group may exist. We acknowledge that these factors can have an impact on the classification accuracies in our study. In the subject-independent setting considered in this study, additional variability may also arise from differences between recording sessions collected weeks or months apart, which may further influence classification performance when combined with inter-subject differences.

In addition, after analysis we identified a best-performing frequency range that was applied to all participants. While this approach provided a common ground to support subject-independent classification, it did not account for individually defined frequency ranges. Since peak outcomes for each participant may slightly deviate from the generalized range, this choice may have reduced the overall classification accuracies. We therefore highlight that future studies should explore algorithms that optimize for individualized frequency ranges while still aiming for subject-independent generalization.

Finally, although multiple EEG cleaning methods were applied in EEGLAB, including bad channel removal, ICA, and visual inspection, we accept that EMG activity cannot be completely ruled out. Subtle contributions may still remain, particularly in the lower frequency bands due to eye movements or muscle tension. Future studies should therefore consider more advanced artifact removal techniques or complementary physiological monitoring to further minimize EMG influence in EEG-based meditation classification.

## 5.6 Conclusion

This study explored a novel task of subject-independent (inter-subject) classification of meditation and non-meditation using multiple-session EEG data. In this research, 18 different studies, each comprising multiple tests, were conducted, totalling 9,900 independent tests. The results obtained were compared with our previous study on intra-subject classification. The mean classification accuracies for inter-subject classification were lower than those for intra-subject classification, which may be due to the increased complexity of recognizing patterns when EEG data from multiple participants are used together. Nevertheless, achieving good classification accuracies for certain session combinations selected from multiple participants highlights the future potential for high-accuracy, subject-independent classification of multiple-session meditation/non-meditation EEG data. To address the limitations and challenges identified in this study, we suggest the following improvements as directions for future work.

As future work, we emphasize the importance of conducting research to achieve high classification accuracies for subject-independent, multiple-session meditation/non-meditation EEG data, which would enable the development of meditation-guiding algorithms. Future studies could also include additional evaluation metrics such as AUC and F1-score to provide a more comprehensive assessment of classification performance. Such studies should first collect data from expert meditators with the same level of experience and skill, ideally with a sample size of around 25–30 participants, and then gather data from those with two levels of experience. Meditation expertise should be assessed using standardized experience metrics. Data from the same experience level can be used to test and improve classification accuracies, while data with two levels of experience can help identify features that distinguish between the

levels. These features can then be used in studies to assess improvements in meditation practices.

When trying to identify the level of meditation experience of a person participating in EEG data collection, one method that can be used is to obtain a measurement of the duration of past meditation practice, preferably in years or months. The challenge with this approach is that some individuals may progress well in meditation within a shorter time compared to others. At the same time, an expert meditator may experience physical or mental challenges on the day of data collection, which could affect the success of the meditation session. Therefore, it is better to accompany the experience-level measurement with a psychological assessment of the meditation session, such as a questionnaire or a mindfulness and meditation scale, and to collect both types of data alongside the EEG recordings. Such data would be highly useful when studying subject-independent, multi-session EEG meditation/non-meditation classification. Furthermore, collecting data such as heart rate variability and blood oxygen level changes, in addition to EEG data during meditation/non-meditation sessions, can provide valuable features that may help achieve higher classification accuracies.

# Chapter 6

## Conclusion and Future Work

### 6.1 Summary of the Research Work

This thesis investigated the effectiveness of EEG-based Brain-Computer Interface (BCI) techniques to process and classify meditative and non-meditative states, with a focus on both intra-subject and inter-subject (subject-independent) classification using multiple-session EEG data. The study began with a computational review, presented in Chapter 2, of existing feature extraction and classification techniques applied to meditation-related EEG data. The review revealed a strong emphasis on frequency-domain features in existing literature, highlighting a notable gap in the exploration of more advanced or combined methods. Although addressing this was not an explicitly stated objective, the study indirectly responded to this gap by evaluating CSP, STFT, and their fusion, thereby providing comparative insights through the development of multiple BCI pipelines.

Following the review, Chapter 3 examined the application of Common Spatial Pattern (CSP) for feature extraction and Linear Discriminant Analysis (LDA) for classification of EEG data from an online dataset collected during Loving-Kindness Meditation (LKM). The work initially focused on single-session, intra-subject classification to investigate the consistency of neural patterns within individuals. In addition to binary meditation versus non-meditation classification, pairwise comparisons among four mental tasks (LKM-Self, LKM-Others, Pre-Resting, and Post-Resting) were conducted to explore their distinctiveness. This analysis was then extended to multi-session, intra-subject classification, using pooled session data to assess whether consistent patterns could be identified across time. The results confirmed the presence

of stable neural characteristics within individuals, with Pre-Resting consistently showing greater distinctiveness compared to the other mental tasks.

Building upon this, Chapter 4 developed and evaluated three distinct BCI pipelines using CSP, Short-Time Fourier Transform (STFT), and their fusion (CSP-STFT). These pipelines were tested under intra-subject multiple-session classification scenarios, where a new meditation/non-meditation EEG session pair was classified after training on session pairs from the same individual. The performance of the pipelines was further analysed by varying the number of training sessions, and results showed that increasing the training data generally improved classification accuracy. The fusion method consistently outperformed the individual methods in most cases, demonstrating its potential for enhancing classification robustness.

Finally, Chapter 5 extended the evaluation to a subject-independent framework, where training and testing datasets were drawn from different individuals without overlapping sessions for the same mental task. These pipelines were then applied to multiple-session EEG data from different individuals and evaluated across various meditation and non-meditation conditions. Although the overall classification accuracy was relatively low, the top 50% of results showed promising performance, suggesting that some session combinations yielded notably better outcomes. The fusion of CSP and STFT outperformed individual methods in 83.3% of the cases, reinforcing its robustness. Additionally, increasing the number of training sessions improved accuracy in approximately 75.0% of instances, indicating that training data volume plays a significant role in subject-independent scenarios. The analysis provided valuable insights into the performance differences between intra-subject and inter-subject classification, supporting the development of more generalizable models for meditation assessment.

Across the experimental chapters, classification performance changed systematically as the level of generalization increased, with accuracies decreasing as the task moved from single-

session intra-subject settings to cross-session and finally to subject-independent scenarios. In Chapter 3, single-session intra-subject classification using CSP + LDA achieved a mean accuracy of 99.5% for meditation versus Pre-Resting, while pooled multi-session intra-subject classification reduced to a mean accuracy of 83.6% when five sessions were used. In Chapter 4, when classifying an unseen session pair from the same individual, the CSP + STFT pipeline achieved mean accuracies of 72.1%, 74.2%, and 75.5% for LKM-Self/non-meditation using 3, 4, and 5 sessions, respectively, with corresponding mean accuracies of 70.7%, 72.0%, and 73.0% for LKM-Others/non-meditation. In Chapter 5, subject-independent multiple-session classification produced lower mean accuracies, typically in the range of 60–63% depending on task and training size, with noticeably higher variability across tests. Overall, these results confirm that moving from single-session to cross-session and finally to subject-independent evaluation substantially increases the difficulty of meditation EEG classification.

The feature-extraction methods used in this thesis contribute complementary information. CSP primarily captures spatial discrimination by learning filters that emphasize channel patterns that differ between meditation and non-meditation, while STFT captures time–frequency structure by representing how spectral content evolves over short windows within a session. The fusion of CSP and STFT combines spatial and time–frequency characteristics within a single feature set, and this consistently produced higher accuracies than using either method alone. For example, in Chapter 4, CSP + STFT improved mean accuracies by approximately 5–6% compared to CSP or STFT individually across the 3–5 session cases, demonstrating the practical value of feature fusion for improving cross-session robustness. Furthermore, in the subject-independent, multiple-session analysis presented in Chapter 5, the CSP + STFT pipeline outperformed the individual CSP or STFT pipelines in 83.3% of the tested instances, reinforcing the robustness and generalization capability of the fusion approach under more challenging inter-subject conditions.

## 6.2 Key Findings and Contributions

This thesis makes several original contributions to the domain of EEG-based meditation classification and BCI research. A comprehensive literature review was conducted using a systematic approach to examine the computational methods used for feature extraction and classification in meditation EEG studies. In addition to these core areas, the review also summarizes important supporting aspects such as EEG preprocessing techniques, meditation types, participant information, and the frequency bands commonly associated with meditation-related EEG. To the best of our knowledge, this is the first time a broad, in-depth review has been carried out that considers all significantly important peer-reviewed research articles written in English over the past 15 years focusing on computational methods in meditation EEG. As such, the review addresses a notable research gap and can serve as a valuable reference for future researchers planning studies in this domain.

The second novel contribution of this study was the successful classification of single-session, intra-subject meditation and non-meditation EEG data, achieving a high accuracy of 99.5%. These findings were published in a journal paper. In addition, the study evaluated classification performance across all six pairwise combinations of four mental tasks, LKM-Self, LKM-Others, Pre-Resting, and Post-Resting, related to meditation and non-meditation. The results revealed a distinctive pattern: the three pairwise comparisons that involved Pre-Resting (Pre-Resting vs LKM-Self, Pre-Resting vs LKM-Others, and Pre-Resting vs Post-Resting) achieved higher classification accuracies than the three comparisons conducted solely among LKM-Self, LKM-Others, and Post-Resting. This indicates that Pre-Resting is more readily distinguishable from the other tasks, showing that there are slight but noticeable differences in the brain activity patterns.

Progress in meditation comes with the practice of multiple sessions, yet there has been a notable lack of EEG-based research focused on this area. This represents a significant research gap, especially when attempting to understand how meditation and non-meditation EEG data behave across multiple sessions. Studies that identify recurring patterns and achieve reliable classification accuracies in such settings are highly valuable for developing applications that support meditation progress. Therefore, the next set of novel contributions and key findings in this thesis relate to the analysis of different stages in multi-session meditation and non-meditation EEG data. These investigations were built upon the background knowledge gained through the single-session classification studies.

As the first multi-session study, intra-subject analysis was performed by constructing separate data pools using EEG data from multiple sessions for each mental task. Random samples were selected from these pools to conduct meditation versus non-meditation classification. Although the classification accuracies were noticeably lower than in the single-session analysis, the results were still significant, yielding an overall mean intra-subject, multi-session meditation versus non-meditation classification accuracy of 83.6%. These findings demonstrated the presence of common neural characteristics across meditation sessions and across non-meditation sessions. Additionally, pairwise classification was performed using pooled multi-session data for all possible combinations of the four mental tasks related to meditation and non-meditation: LKM-Self, LKM-Others, Pre-Resting, and Post-Resting. The novel pattern observed in the single-session classification also emerged here: Pre-Resting appeared more distinct from the other three tasks, which were more similar to each other. As a novel outcome of this study, it was shown that even when using data from multiple sessions, successful classification of meditation and non-meditation states is achievable, and key neural patterns identified in single-session data remain consistent.

As the next novel multi-session study, intra-subject classification was performed in which, for a single person, a new meditation/non-meditation EEG session pair was classified after training a BCI pipeline using a couple of session pairs from the same individual. After an initial round of testing, based on the best performance observed among the tested classification methods, an artificial neural network was selected as the classification algorithm to provide a consistent basis for comparing different feature extraction techniques. BCI pipelines were then constructed using various feature extraction methods, including fusion approaches that combined multiple methods. Among the pipelines tested, those built using CSP and STFT individually were able to successfully classify the new session pair. Notably, the pipeline that used a fusion of CSP and STFT achieved even better performance, with an overall mean intra-subject, multi-session classification accuracy of 72.9%, and all results were published in a journal paper. The fusion approach often outperformed the individual methods, showing potential for enhanced classification robustness. As a novel contribution, this study demonstrated that cross-session intra-subject classification of a new meditation/non-meditation session pair is feasible, and that fusing CSP and STFT features leads to superior performance compared to using either method alone.

As this study is the first to use multiple-session meditation/non-meditation EEG data to classify a new session pair, a further novel investigation was conducted to investigate how the performance of the three best-performing BCI pipelines changes when the number of training session pairs is varied. This type of insight can be significantly valuable when planning and developing algorithms aimed at distinguishing meditation from non-meditation, particularly in applications designed to guide users through long-term meditation progress. For this study, 2, 3, and 4 session pairs were tested, and the results clearly showed that, in most cases, increasing the number of training sessions generally improved classification accuracy. Among these, the best performance was observed when using four training session pairs for LKM-Self versus

non-meditation, achieving the highest mean accuracy of 75.5% and highlighting the benefit of larger training sets in capturing session-level neural patterns. As a novel contribution, this study demonstrated that increasing the number of training session pairs enhances the classification accuracy of multiple-session, intra-subject meditation/non-meditation EEG data.

This study was further extended to investigate the novel objective of subject-independent, multiple-session meditation/non-meditation EEG data classification. In this analysis, the previously developed three successful BCI pipelines were reused under conditions similar to intra-subject classification, enabling a meaningful comparison between the two scenarios. Care was taken during data selection to ensure that multiple sessions from the same individual were not included for the same mental task across training and testing. Although the overall mean classification accuracy in this study was relatively low, the results showed substantial variance. This led to a more detailed analysis by calculating the mean accuracies of the top 50% and bottom 50% of all classification results. The top 50% yielded comparatively high mean accuracies, indicating that certain combinations of session selections led to promising performance, while others did not. Consistent with earlier findings, the fusion of CSP and STFT outperformed the individual methods in 83.3% of the cases. The results of this novel subject-independent, multiple-session classification revealed relatively low but promising accuracies, with certain session combinations yielding notably better performance. These findings offer a valuable foundation for developing more generalizable models in future studies.

Since inter-subject and intra-subject multiple-session classification studies were conducted under similar conditions, their performances can be directly compared. When considering the mean accuracies across all tests, inter-subject (subject-independent) classification showed relatively lower accuracies with higher variance. This is understandable, as the use of data sessions from different individuals naturally results in a more complex and diverse data pool compared to one created from multiple sessions of the same individual. In inter-subject

classification, if the selected sessions differ in the level or quality of the mental task, the classification performance may decline. On the other hand, sessions that represent similar levels within the same mental task are likely to yield higher accuracies. Compared to intra-subject classification, the inter-subject (subject-independent) results demonstrated lower but still promising accuracy, especially when considering the top 50%, providing a basis for developing more generalizable models in future work.

Finally, in the subject-independent, multiple-session meditation/non-meditation classification task, the impact of changing the number of training sessions in the BCI pipeline was examined. Consistent with the trends observed in the intra-subject analysis, increasing the number of training session pairs led to improved classification accuracy in approximately 75.0% of the cases. These findings suggest that training data volume plays a significant role even in more complex subject-independent scenarios. The key findings and contributions discussed throughout this section collectively enhance both the theoretical understanding and practical development of EEG-based meditation classification systems.

Across Chapters 3–5, the experimental findings can also be interpreted within the broader state–trait framework introduced in Chapter 1. The classification tasks investigated in this thesis primarily target state-level meditation effects, defined as transient neural patterns occurring during meditation relative to non-meditation conditions. The high single-session intra-subject accuracies demonstrate that these state-related differences are strongly detectable under controlled conditions. The subsequent multi-session and subject-independent analyses extend this by examining the stability and reproducibility of these state-related neural signatures across time and across individuals, without claiming trait-level inference. In parallel, the consistent improvement achieved through CSP–STFT fusion represents a central methodological contribution of this thesis. By integrating spatial filtering (CSP) with time–frequency representations (STFT), the fusion approach captures complementary characteristics of

meditation EEG signals, thereby improving robustness under increasingly challenging generalization settings.

When interpreting these findings in relation to prior work, the literature reviewed in Chapter 2 shows that many meditation EEG studies primarily focus on binary comparisons between two mental conditions (e.g., meditation vs rest) [136, 151, 164] or between two participant groups (e.g., meditators vs non-meditators) [33, 34, 184]. Although such studies often report strong classification accuracies, their evaluation frameworks typically do not examine cross-session prediction, systematic multi-session pooling, or subject-independent generalization across recording days. In contrast, this thesis explicitly quantified performance across progressively harder settings, including pooled multi-session testing [200], cross-session prediction of unseen session pairs [69], and subject-independent evaluation using multiple sessions [273]. This comparison is important because it clarifies that high accuracies in simple experimental setups do not necessarily transfer to cross-session or subject-independent use cases, which are more aligned with practical meditation-support applications. The consistent benefit of CSP–STFT fusion observed in Chapters 4 and 5 aligns with broader BCI research [22, 32], where integrating spatial and time–frequency representations improves robustness under increased generalization requirements.

### 6.3 Limitations of the Study

While the research yielded meaningful insights and novel findings, it is important to acknowledge certain limitations. One key limitation is related to the meditation type used in the experiments. This study focused exclusively on EEG data collected during the practice of Loving-Kindness Meditation (LKM), as it was the most suitable publicly available dataset

aligned with the study's multi-session and classification-focused objectives. As a result, the findings may not be directly generalizable to other meditation forms such as mindfulness, breathing-based meditation, or transcendental meditation. However, it is worth noting that LKM is a well-established and widely studied meditation technique, and its selection in this study is supported by previous research that has demonstrated its effectiveness in generating distinct and measurable neural patterns.

The second limitation of this study relates to participant sample size. It is well known that in machine learning, larger datasets typically lead to better model performance and more generalizable outcomes. However, in practice, there are challenges that make it difficult to obtain large volumes of high-quality EEG data. This study used an online dataset collected from expert meditators, and assembling such a dataset presents challenges in recruiting suitable participants. Furthermore, datasets with multiple-session recordings add an extra layer of complexity in terms of scheduling and participant availability. Despite these practical challenges, the dataset utilised in this study remains among the larger publicly available multi-session EEG datasets related to meditation. Nevertheless, we acknowledge that the number of participants and sessions, while sufficient for the intended experimental analyses, may still limit the broader generalizability of the findings.

The original study plan included collecting additional EEG data using breath-focused meditation to broaden the scope of the research. Ethics approvals (Application IDs: 4000023183 and SOA 22/63) were obtained from the Massey University Ethics Committee. However, due to COVID-19 restrictions and subsequent logistical challenges related to EEG equipment procurement, it was not feasible to complete new data collection within the available timeframe. While the use of a high-quality public dataset ensured methodological consistency, the absence of newly collected data limited the opportunity to design the experiment more flexibly and include additional meditation types.

When considering the analysis of meditation studies in general, a significant number of research efforts have been conducted using EEG. However, we acknowledge that using only EEG for the analysis of meditation can be considered a limitation. Other physiological and neuroimaging methods such as fMRI, fNIRS, heart rate variability, and cortisol level measurements have also been used in meditation research. From this perspective, the use of EEG in combination with another neuroimaging modality, such as a multimodal fusion with fNIRS, could potentially enhance classification performance. Therefore, the exclusive focus on EEG, without multimodal integration, represents a limitation of this study.

Another limitation of this study lies in the use of a fixed preprocessing strategy across all experiments. While applying a standardized preprocessing pipeline ensures consistency and fairness when comparing different feature extraction and classification methods, it also means that the impact of all alternative preprocessing or noise reduction strategies was not fully explored. To some extent, various preprocessing techniques such as artifact cleaning and epoching were tested during the initial stages of the study to achieve optimal outcomes. However, not all possible methods or parameter combinations were examined. Given that EEG signal quality and classification performance can be highly sensitive to the chosen preprocessing steps, some of the data used in this study may have yielded different results under alternative preprocessing strategies. Although the most suitable preprocessing techniques were selected for the dataset as a whole, certain individual data instances may have benefited from alternative methods; however, this was not systematically tested.

This study successfully used the fusion of CSP and STFT features, which outperformed using each method individually. Although this is a novel approach in multi-session meditation and non-meditation EEG classification, we acknowledge that more sophisticated fusion strategies, either at the feature level or decision level, could potentially offer even better results. While the

CSP-STFT fusion demonstrated improved performance, the use of more advanced fusion techniques was not explored, and this is recognised as a limitation of the present study.

## 6.4 Implications and Applications

The findings from this thesis hold several implications for both research and practical applications. The systematic computational review conducted in this study provides a structured and reproducible overview of EEG-based feature extraction and classification techniques used in meditation research. By consolidating methodological trends, reporting practices, and performance patterns across 164 studies, the review offers a reference framework that can assist researchers in identifying established approaches, methodological gaps, and underexplored areas. This contributes to improving experimental design and promoting greater methodological consistency in future meditation EEG studies.

Sustained meditation practice typically involves repeated sessions over extended periods, making cross-session consistency an important consideration for practical monitoring systems. The classification pipelines developed in this study provide a methodological foundation for future real-time meditation monitoring systems aimed at supporting structured meditation practice. Furthermore, the inclusion of subject-independent, multiple-session classification addresses a key challenge in developing systems that can potentially support users without extensive per-session calibration.

Various clinical and mental health monitoring practices already utilise neuroimaging techniques, including EEG, to assess patient progress over time. In many of these applications, measurements taken during an initial session are compared with subsequent recordings to track changes in neural or physiological states. The multi-session classification framework developed

in this thesis may contribute to enhancing such systems by enabling structured and objective monitoring across repeated visits. These methods could potentially be adapted for use in stress reduction programmes, cognitive training regimens, and therapeutic interventions where longitudinal neural assessment is relevant.

Although this thesis focuses on meditation, EEG-based BCI is a broader field with diverse applications. The subject-independent classification framework, session-based experimental design, and feature-fusion strategy presented in this work can serve as a conceptual and methodological reference for future EEG-BCI systems that aim to improve generalization across sessions and individuals. As such, the impact of this work may extend beyond meditation into other domains of mental state classification and adaptive neurotechnology.

## 6.5 Future Work

This thesis has laid the groundwork for several structured future research directions. One important extension is to evaluate additional meditation techniques under multi-session and subject-independent classification settings. Since this study focused exclusively on Loving-Kindness Meditation (LKM), future work should investigate whether the cross-session patterns and generalization behaviours observed in this thesis remain consistent across other meditation forms, such as focused attention, breath-based meditation, or transcendental meditation. Such comparative investigations would clarify whether the observed state-level neural signatures and fusion benefits are meditation-specific or represent broader meditative phenomena.

Another key direction involves expanding dataset scale and diversity. The subject-independent results in Chapter 5 demonstrated increased variability and reduced mean accuracy compared to intra-subject settings, highlighting the importance of larger and more heterogeneous datasets.

Future studies should therefore include greater participant numbers, wider age distributions, varied levels of meditation expertise, and longer longitudinal recordings. These improvements would enable more reliable evaluation of generalization across individuals and sessions, and provide a stronger foundation for developing robust meditation EEG classification frameworks.

From a methodological perspective, this thesis used a multi-layer perceptron as a consistent baseline classifier to compare different feature extraction approaches. However, the decreasing accuracies observed under progressively harder generalization conditions suggest that further investigation into advanced learning strategies is warranted. Future work may explore deep learning architectures, transfer learning, domain adaptation techniques, and representation-learning approaches specifically designed to address cross-session and cross-subject variability. Importantly, such investigations should maintain consistent evaluation protocols to ensure fair comparison across feature extraction strategies.

Another promising direction is the refinement of feature-fusion methodologies. While the CSP–STFT fusion demonstrated consistent improvements across Chapters 4 and 5, including outperforming individual methods in 83.3% of subject-independent cases, more sophisticated fusion strategies could be explored. Future studies may investigate hierarchical feature fusion, attention-based weighting mechanisms, or hybrid feature–decision level integration to further enhance robustness under subject-independent conditions.

Multimodal integration also represents a significant opportunity for future research. Although this thesis focused exclusively on EEG, combining EEG with complementary modalities such as fNIRS, heart rate variability, or other physiological markers may improve robustness and reduce ambiguity in mental state discrimination. Future work should systematically evaluate whether multimodal fusion improves cross-session and cross-subject generalization beyond what is achievable with EEG alone.

Finally, implementation of a real-time experimental BCI prototype could serve as an important validation step. Developing a real-time system based on the best-performing pipeline would allow testing of cross-session stability under practical conditions. Incorporating adaptive learning and incremental model updating mechanisms may help address session variability observed in subject-independent scenarios. Such experimental validation would provide insight into how laboratory-level classification performance translates into continuous, real-world meditation monitoring environments.

## References

1. Thomas JW, Cohen M (2014) A Methodological review of meditation research. *Front Psychiatry* 5:. <https://doi.org/10.3389/fpsy.2014.00074>
2. Kora P, Meenakshi K, Swaraja K, Rajani A, Raju MS (2021) EEG based interpretation of human brain activity during yoga and meditation using machine learning: A systematic review. *Complement Ther Clin Pract* 43:. <https://doi.org/10.1016/j.ctcp.2021.101329>
3. Hankey A, Shetkar R (2016) Self-transcending meditation is good for mental health: Why this should be the case. *International Review of Psychiatry* 28:236–240. <https://doi.org/10.1080/09540261.2016.1191449>
4. Lutz A, Slagter HA, Dunne JD, Davidson RJ (2008) Attention regulation and monitoring in meditation. *Trends Cogn Sci* 12:163–169. <https://doi.org/10.1016/j.tics.2008.01.005>
5. Grossman P, Niemann L, Schmidt S, Walach H (2004) Mindfulness-based stress reduction and health benefits: A meta-analysis. *J Psychosom Res* 57:35–43. [https://doi.org/10.1016/S0022-3999\(03\)00573-7](https://doi.org/10.1016/S0022-3999(03)00573-7)
6. Bostock S, Crosswell AD, Prather AA, Steptoe A (2019) Mindfulness on-the-go: Effects of a mindfulness meditation app on work stress and well-being. *J Occup Health Psychol* 24:127–138. <https://doi.org/10.1037/ocp0000118>
7. Chiesa A, Calati R, Serretti A (2011) Does mindfulness training improve cognitive abilities? A systematic review of neuropsychological findings. *Clin Psychol Rev* 31:449–464. <https://doi.org/10.1016/j.cpr.2010.11.003>
8. Ferrarelli F, Smith R, Dentico D, Riedner BA, Zennig C, Benca RM, Lutz A, Davidson RJ, Tononi G (2013) Experienced Mindfulness Meditators Exhibit Higher Parietal-Occipital EEG Gamma Activity during NREM Sleep. *PLoS One* 8:. <https://doi.org/10.1371/journal.pone.0073417>

9. Nasrolahzadeh M, Mohammadpoory Z, Haddadnia J (2019) Analysis of heart rate signals during meditation using visibility graph complexity. *Cogn Neurodyn* 13:45–52. <https://doi.org/10.1007/s11571-018-9501-5>
10. Magan D, Yadav RK, Bal CS, Mathur R, Pandey RM (2019) Brain plasticity and neurophysiological correlates of meditation in long-term meditators: A Fluorodeoxyglucose positron emission tomography study based on an innovative methodology. *Journal of Alternative and Complementary Medicine* 25:1172–1182. <https://doi.org/10.1089/acm.2019.0167>
11. Davis DM, Hayes JA (2011) What Are the Benefits of Mindfulness? A Practice Review of Psychotherapy-Related Research. 48:198–208. <https://doi.org/10.1037/a0022062>
12. Wong G, Sun R, Adler J, Yeung KW, Yu S, Gao J (2022) Loving-kindness meditation (LKM) modulates brain-heart connection: An EEG case study. *Front Hum Neurosci* 16:. <https://doi.org/10.3389/fnhum.2022.891377>
13. Rana N (2015) Mindfulness and Loving-Kindness Meditation: A Potential Tool for Mental Health and Subjective Well-Being. *Indian Journal of Positive Psychology* 6:189
14. Fingelkurts AA, Fingelkurts AA, Kallio-Tamminen T (2016) Trait lasting alteration of the brain default mode network in experienced meditators and the experiential selfhood. *Self and Identity* 15:381–393. <https://doi.org/10.1080/15298868.2015.1136351>
15. Medvedev ON, Krägeloh CU, Narayanan A, Siegert RJ (2017) Measuring Mindfulness: Applying Generalizability Theory to Distinguish between State and Trait. *Mindfulness (N Y)* 8:1036–1046. <https://doi.org/10.1007/s12671-017-0679-0>
16. Lau MA, Bishop SR, Segal Z V. (2010) The Toronto Mindfulness Scale: Development and Validation. *J Clin Psychol* 66:430–441. <https://doi.org/10.1002/jclp.20326>
17. Davis KM, Lau MA, Cairns DR (2009) Development and preliminary validation of a trait version of the toronto mindfulness scale. *J Cogn Psychother* 23:185–195. <https://doi.org/10.1891/0889-8391.23.3.185>

18. Crivelli D, Fronza G, Venturella I, Balconi M (2019) Supporting Mindfulness Practices with Brain-Sensing Devices. Cognitive and Electrophysiological Evidences. *Mindfulness* (N Y) 10:301–311. <https://doi.org/10.1007/s12671-018-0975-3>
19. Brandmeyer T, Delorme A (2013) Meditation and neurofeedback. *Front Psychol* 4:3–5. <https://doi.org/10.3389/fpsyg.2013.00688>
20. Nash JD, Newberg A, Awasthi B (2013) Toward a unifying taxonomy and definition for meditation. *Front Psychol* 4:. <https://doi.org/10.3389/fpsyg.2013.00806>
21. Nash JD, Newberg AB (2023) An updated classification of meditation methods using principles of taxonomy and systematics. *Front Psychol* 13:. <https://doi.org/10.3389/fpsyg.2022.1062535>
22. Singh A, Hussain AA, Lal S, Guesgen HW (2021) A comprehensive review on critical issues and possible solutions of motor imagery based electroencephalography brain-computer interface. *Sensors* 21:1–35. <https://doi.org/10.3390/s21062173>
23. Cahn BR, Delorme A, Polich J (2013) Event-related delta, theta, alpha and gamma correlates to auditory oddball processing during vipassana meditation. *Soc Cogn Affect Neurosci* 8:100–111. <https://doi.org/10.1093/scan/nss060>
24. Kim J, Jiang X, Forenzo D, Liu Y, Anderson N, Greco CM, He B (2022) Immediate effects of short-term meditation on sensorimotor rhythm-based brain–computer interface performance. *Front Hum Neurosci* 16:. <https://doi.org/10.3389/fnhum.2022.1019279>
25. Matiz A, Crescentini C, Fabbro A, Budai R, Bergamasco M, Fabbro F (2019) Spontaneous eye movements during focused-attention mindfulness meditation. *PLoS One* 14:1–19. <https://doi.org/10.1371/journal.pone.0210862>
26. Cahn BR, Polich J (2006) Meditation states and traits: EEG, ERP, and neuroimaging studies. *Psychol Bull* 132:180–211. <https://doi.org/10.1037/0033-2909.132.2.180>

27. Rodriguez-Larios J, Bracho Montes de Oca EA, Alaerts K (2021) The EEG spectral properties of meditation and mind wandering differ between experienced meditators and novices. *Neuroimage* 245:. <https://doi.org/10.1016/j.neuroimage.2021.118669>
28. Singh A, Lal S, Guesgen HW (2019) Reduce calibration time in motor imagery using spatially regularized symmetric positives-definite matrices based classification. *Sensors* 19:. <https://doi.org/10.3390/s19020379>
29. Jiang X, Lopez E, Stieger JR, Greco CM, He B (2021) Effects of Long-Term Meditation Practices on Sensorimotor Rhythm-Based Brain-Computer Interface Learning. *Front Neurosci* 14:. <https://doi.org/10.3389/fnins.2020.584971>
30. Urigüen JA, Garcia-Zapirain B (2015) EEG artifact removal - State-of-the-art and guidelines. *J Neural Eng* 12:. <https://doi.org/10.1088/1741-2560/12/3/031001>
31. Delorme A, Makeig S (2004) EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *J Neurosci Methods* 134:9–21. <https://doi.org/10.1016/j.jneumeth.2003.10.009>
32. Lotte F, Bougrain L, Cichocki A, Clerc M, Congedo M, Rakotomamonjy A, Yger F (2018) A review of classification algorithms for EEG-based brain-computer interfaces: A 10 year update. *J Neural Eng* 15:. <https://doi.org/10.1088/1741-2552/aab2f2>
33. Ahani A, Wahbeh H, Nezamfar H, Miller M, Erdogmus D, Oken B (2014) Quantitative change of EEG and respiration signals during mindfulness meditation. *J Neuroeng Rehabil* 11:87
34. Bailey NW, Fulcher BD, Caldwell B, Hill AT, Fitzgibbon B, van Dijk H, Fitzgerald PB (2024) Uncovering a stability signature of brain dynamics associated with meditation experience using massive time-series feature extraction. *Neural Networks* 171:171–185. <https://doi.org/10.1016/j.neunet.2023.12.007>
35. Goldstein MR, Turner AD, Dawson SC, Segal Z V., Shapiro SL, Wyatt JK, Manber R, Sholtes D, Ong JC (2019) Increased high-frequency NREM EEG power associated with mindfulness-based interventions for chronic insomnia: Preliminary findings from

- spectral analysis. *J Psychosom Res* 120:12–19.  
<https://doi.org/10.1016/j.jpsychores.2019.02.012>
36. Matiz A, Crescentini C, Bergamasco M, Budai R, Fabbro F (2021) Inter-brain co-activations during mindfulness meditation. Implications for devotional and clinical settings. *Conscious Cogn* 95:. <https://doi.org/10.1016/j.concog.2021.103210>
  37. Tibdewal MN, Nagbhide DN, Mahadevappa M, Ray AK, Dhoke A, Malokar M (2022) Multi-feature extraction, analysis, and classification for control and meditators' electroencephalogram. *Signal Image Video Process*. <https://doi.org/10.1007/s11760-022-02191-6>
  38. Rodriguez-Larios J, Wong KF, Lim J (2024) Assessing the effects of an 8-week mindfulness training program on neural oscillations and self-reports during meditation practice. *PLoS One* 19:. <https://doi.org/10.1371/journal.pone.0299275>
  39. Colgan DD, Memmott T, Klee D, Ernst L, Han SJ, Oken B (2019) A single case design to examine short-term intracranial EEG patterns during focused meditation. *Neurosci Lett* 711:134441. <https://doi.org/10.1016/j.neulet.2019.134441>
  40. Travis F, Shear J (2010) Focused attention, open monitoring and automatic self-transcending: Categories to organize meditations from Vedic, Buddhist and Chinese traditions. *Conscious Cogn* 19:1110–1118.  
<https://doi.org/10.1016/j.concog.2010.01.007>
  41. Wahbeh H, Sagher A, Back W, Pundhir P, Travis F (2018) A Systematic Review of Transcendent States Across Meditation and Contemplative Traditions. *Explore* 14:19–35. <https://doi.org/10.1016/j.explore.2017.07.007>
  42. Aftanas LI, Golosheikin SA (2003) Changes in cortical activity during altered states of consciousness: study of meditation by high resolution EEG. *Fiziol Cheloveka* 29:18–27
  43. Yu X, Aziz MZ, Sadiq MT, Fan Z, Xiao G (2021) A New Framework for Automatic Detection of Motor and Mental Imagery EEG Signals for Robust BCI Systems. *IEEE Trans Instrum Meas* 70:. <https://doi.org/10.1109/TIM.2021.3069026>

44. Hagerty MR, Isaacs J, Brasington L, Shupe L, Fetz EE, Cramer SC (2013) Case study of ecstatic meditation: fMRI and EEG evidence of self-stimulating a reward system. *Neural Plast* 2013:. <https://doi.org/10.1155/2013/653572>
45. Ang KK, Chin ZY, Wang C, Guan C, Zhang H (2012) Filter bank common spatial pattern algorithm on BCI competition IV datasets 2a and 2b. *Front Neurosci*. <https://doi.org/10.3389/fnins.2012.00039>
46. Schlögl A, Lee F, Bischof H, Pfurtscheller G (2005) Characterization of four-class motor imagery EEG data for the BCI-competition 2005. *J Neural Eng* 2:. <https://doi.org/10.1088/1741-2560/2/4/L02>
47. Ramli N, Kuok SS, Tan LK, Tan YQ, Tan LF, Goh KJ, Kadir KAA, Seow PC, Goh SY (2019) Effect of mindfulness meditation on brain-computer interface: fMRI perspective. *Neurol Asia* 24:343–353. <https://doi.org/10.1016/j.concog.2013.10.010>
48. Izzetoglu M, Shewokis PA, Tsai K, Dantoin P, Sparango K, Min K (2020) Short-term effects of meditation on sustained attention as measured by fNIRS. *Brain Sci* 10:1–16. <https://doi.org/10.3390/brainsci10090608>
49. Kamei T, Toriumi Y, Kimura H, Kumano H, Ohno S, Kimura K (2000) Decrease in serum cortisol during yoga exercise is correlated with alpha wave activation. *Percept Mot Skills* 90:1027–1032. <https://doi.org/10.2466/pms.2000.90.3.1027>
50. Zeng X, Li M, Zhang B, Liu X (2014) Revision of the Philadelphia Mindfulness Scale for Measuring Awareness and Equanimity in Goenka's Vipassana Meditation with Chinese Buddhists. *J Relig Health* 54:623–637. <https://doi.org/10.1007/s10943-014-9870-y>
51. Roquet CD, Sas C (2018) Evaluating mindfulness meditation apps. In: *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, Montreal, QC, Canada, 21–26 April
52. Flett JAM, Hayne H, Riordan BC, Thompson LM, Conner TS (2019) Mobile Mindfulness Meditation: a Randomised Controlled Trial of the Effect of Two Popular

- Apps on Mental Health. *Mindfulness* (N Y) 10:863–876.  
<https://doi.org/10.1007/s12671-018-1050-9>
53. Huberty J, Green J, Glissmann C, Larkey L, Puzia M, Lee C (2019) Efficacy of the mindfulness meditation mobile app “calm” to reduce stress among college students: Randomized controlled trial. *J Med Internet Res* 21:. <https://doi.org/10.2196/14273>
  54. Qu C, Sas C, Daudén Roquet C, Doherty G (2020) Functionality of Top-Rated Mobile Apps for Depression: Systematic Search and Evaluation. *JMIR Ment Health* 7:e15321. <https://doi.org/10.2196/15321>
  55. Bareham CA, Allanson J, Roberts N, Hutchinson PJA, Pickard JD, Menon DK, Chennu S (2018) Longitudinal bedside assessments of brain networks in disorders of consciousness: Case reports from the field. *Front Neurol* 9:. <https://doi.org/10.3389/fneur.2018.00676>
  56. Chennu S, Annen J, Wannez S, Thibaut A, Chatelle C, Cassol H, Martens G, Schnakers C, Gosseries O, Menon D, Laureys S (2017) Brain networks predict metabolism, diagnosis and prognosis at the bedside in disorders of consciousness. *Brain* 140:2120–2132. <https://doi.org/10.1093/brain/awx163>
  57. Jurcak V, Tsuzuki D, Dan I (2007) 10/20, 10/10, and 10/5 systems revisited: Their validity as relative head-surface-based positioning systems. *Neuroimage* 34:1600–1611. <https://doi.org/10.1016/j.neuroimage.2006.09.024>
  58. Scheeringa R, Bastiaansen MCM, Petersson KM, Oostenveld R, Norris DG, Hagoort P (2008) Frontal theta EEG activity correlates negatively with the default mode network in resting state. *International Journal of Psychophysiology* 67:242–251. <https://doi.org/10.1016/j.ijpsycho.2007.05.017>
  59. Özerdem A, Güntekin B, Atagün I, Turp B, Başar E (2011) Reduced long distance gamma (28-48 Hz) coherence in euthymic patients with bipolar disorder. *J Affect Disord* 132:325–332. <https://doi.org/10.1016/j.jad.2011.02.028>

60. Newson JJ, Thiagarajan TC (2019) EEG Frequency Bands in Psychiatric Disorders: A Review of Resting State Studies. *Front Hum Neurosci* 12:1–24.  
<https://doi.org/10.3389/fnhum.2018.00521>
61. Fell J, Axmacher N, Haupt S (2010) From alpha to gamma: Electrophysiological correlates of meditation-related states of consciousness. *Med Hypotheses* 75:218–224.  
<https://doi.org/10.1016/j.mehy.2010.02.025>
62. Lotte F, Guan C (2011) Regularizing common spatial patterns to improve BCI designs: Unified theory and new algorithms. *IEEE Trans Biomed Eng* 58:355–362.  
<https://doi.org/10.1109/TBME.2010.2082539>
63. Singh A, Lal S, Guesgen HW (2019) Small Sample Motor Imagery Classification Using Regularized Riemannian Features. *IEEE Access* 7:46858–46869.  
<https://doi.org/10.1109/ACCESS.2019.2909058>
64. Subasi A, Gursoy MI (2010) EEG signal classification using PCA, ICA, LDA and support vector machines. *Expert Syst Appl* 37:8659–8666.  
<https://doi.org/10.1016/j.eswa.2010.06.065>
65. Jung TP, Makeig S, Westerfield M, Townsend J, Courchesne E, Sejnowski TJ (2001) Analysis and visualization of single-trial event-related potentials. *Hum Brain Mapp* 14:166–185. <https://doi.org/10.1002/hbm.1050>
66. Hosseini MP, Hosseini A, Ahi K (2021) A Review on Machine Learning for EEG Signal Processing in Bioengineering. *IEEE Rev Biomed Eng* 14:204–218.  
<https://doi.org/10.1109/RBME.2020.2969915>
67. Qiu L, Zhong Y, He Z, Pan J (2022) Improved classification performance of EEG-fNIRS multimodal brain-computer interface based on multi-domain features and multi-level progressive learning. *Front Hum Neurosci* 16:.  
<https://doi.org/10.3389/fnhum.2022.973959>
68. Al-Saegh A, Dawwd SA, Abdul-Jabbar JM (2021) Deep learning for motor imagery EEG-based classification: A review. *Biomed Signal Process Control* 63:.  
<https://doi.org/10.1016/j.bspc.2020.102172>

69. Liyanagedera ND, Bareham CA, Kempton H, Guesgen HW (2025) Novel machine learning-driven comparative analysis of CSP, STFT, and CSP-STFT fusion for EEG data classification across multiple meditation and non-meditation sessions in BCI pipeline. *Brain Inform* 12:4. <https://doi.org/10.1186/s40708-025-00251-4>
70. Tei S, Faber PL, Lehmann D, Tsujiuchi T, Kumano H, Pascual-Marqui RD, Gianotti LRR, Kochi K (2009) Meditators and non-meditators: EEG source imaging during resting. *Brain Topogr* 22:158–165. <https://doi.org/10.1007/s10548-009-0107-4>
71. Brefczynski-Lewis JA, Lutz A, Schaefer HS, Levinson DB, Davidson RJ (2007) Neural correlates of attentional expertise in long-term meditation practitioners. *Proc Natl Acad Sci U S A* 104:11483–11488. <https://doi.org/10.1073/pnas.0606552104>
72. Winter U, LeVan P, Borghardt TL, Akin B, Wittmann M, Leyens Y, Schmidt S (2020) Content-Free Awareness: EEG-fcMRI Correlates of Consciousness as Such in an Expert Meditator. *Front Psychol* 10:1–11. <https://doi.org/10.3389/fpsyg.2019.03064>
73. Dunn BR, Hartigan JA, Mikulas WL (1999) Concentration and mindfulness meditations: Unique forms of consciousness? *Applied Psychophysiology Biofeedback* 24:147–165. <https://doi.org/10.1023/A:1023498629385>
74. Lee DJ, Kulubya E, Goldin P, Goodarzi A, Girgis F (2018) Review of the neural oscillations underlying meditation. *Front Neurosci* 12:1–7. <https://doi.org/10.3389/fnins.2018.00178>
75. Lagopoulos J, Xu J, Rasmussen I, Vik A, Malhi GS, Eliassen CF, Arntsen IE, Sæther JG, Hollup S, Holen A, Davanger S, Ellingsen Ø (2009) Increased theta and alpha EEG activity during nondirective meditation. *Journal of Alternative and Complementary Medicine* 15:1187–1192. <https://doi.org/10.1089/acm.2009.0113>
76. Deolindo CS, Ribeiro MW, Aratanha MA, Afonso RF, Irmischer M, Kozasa EH (2020) A Critical Analysis on Characterizing the Meditation Experience Through the Electroencephalogram. *Front Syst Neurosci* 14:1–29. <https://doi.org/10.3389/fnsys.2020.00053>

77. Banquet JP (1973) Spectral analysis of the EEG in meditation. *Electroencephalogr Clin Neurophysiol* 35:143–151. [https://doi.org/10.1016/0013-4694\(73\)90170-3](https://doi.org/10.1016/0013-4694(73)90170-3)
78. Brandmeyer T, Delorme A, Wahbeh H (2019) The neuroscience of meditation: classification, phenomenology, correlates, and mechanisms. *Prog Brain Res* 244:1–29. <https://doi.org/10.1016/bs.pbr.2018.10.020>
79. Fingelkurts AA, Fingelkurts AA, Kallio-Tamminen T (2015) EEG-guided meditation: A personalized approach. *J Physiol Paris* 109:180–190. <https://doi.org/10.1016/j.jphysparis.2015.03.001>
80. Tariq M, Trivailo PM, Simic M (2019) Classification of left and right knee extension motor imagery using common spatial pattern for BCI applications. In: *Procedia Computer Science*. Elsevier B.V., pp 2598–2606
81. Mingai Li, Chunting Zhang, Songmin Jia, Yanjun Sun (2018) Classification of Motor Imagery Tasks in Source Domain. In: *International Conference on Mechatronics and Automation*
82. Thomas KP, Lau CT, Vinod AP, Guan C, Ang KK (2009) A New Discriminative Common Spatial Pattern Method for Motor Imagery Brain—Computer Interfaces. *IEEE Trans Biomed Eng* 56:2730–2733. <https://doi.org/10.1109/TBME.2009.2026181>
83. Dmitrieva LA, Kuperin YA, Smetanin NM (2018) Differentiation of brain waves patterns in different states by multifractal analysis. *Proceedings of the International Conference Days on Diffraction, DD 2018* 76–81. <https://doi.org/10.1109/DD.2018.8552936>
84. Fucci E, Abdoun O, Caclin A, Francis A, Dunne JD, Ricard M, Davidson RJ, Lutz A (2018) Differential effects of non-dual and focused attention meditations on the formation of automatic perceptual habits in expert practitioners. *Neuropsychologia* 119:92–100. <https://doi.org/10.1016/j.neuropsychologia.2018.07.025>
85. Pittayapruerk P, Boonyahotra V, Sittiprapaporn P (2017) Electroencephalographic studies of inner wisdom meditation training program. *ECTI-CON 2017 - 2017 14th International Conference on Electrical Engineering/Electronics, Computer,*

Telecommunications and Information Technology 21–24.

<https://doi.org/10.1109/ECTICon.2017.8096163>

86. Rubik B (2011) Neurofeedback-enhanced gamma brainwaves from the prefrontal cortical region of meditators and non-meditators and associated subjective experiences. *Journal of Alternative and Complementary Medicine* 17:109–115.  
<https://doi.org/10.1089/acm.2009.0191>
87. Delorme A, Grandchamp R, Curot J, Barragan-Jason G, Denuelle M, Sol JC, Valton L (2021) Effect of meditation on intracerebral EEG in a patient with temporal lobe epilepsy: A case report. *Explore* 17:197–202.  
<https://doi.org/10.1016/j.explore.2020.11.005>
88. Dennison P (2019) The human default consciousness and its disruption: Insights from an EEG study of buddhist Jhāna meditation. *Front Hum Neurosci* 13:1–28.  
<https://doi.org/10.3389/fnhum.2019.00178>
89. Ren J, Huang ZH, Luo J, Wei GX, Ying XP, Ding ZG, Wu Y Bin, Luo F (2011) Meditation promotes insightful problem-solving by keeping people in a mindful and alert conscious state. *Sci China Life Sci* 54:961–965. <https://doi.org/10.1007/s11427-011-4233-3>
90. Sharma K, Achermann P, Panwar B, Sahoo S, Pascual-Marqui RD, Faber PL, Ganesan RA (2023) High Theta–Low Alpha Modulation of Brain Electric Activity During Eyes-Open Brahma Kumaris Rajyoga Meditation. *Mindfulness (N Y)* 14:1674–1688.  
<https://doi.org/10.1007/s12671-023-02163-y>
91. Ahani A, Wahbeh H, Miller M, Nezamfar H, Erdogmus D, Oken B (2013) Change in physiological signals during mindfulness meditation. *International IEEE/EMBS Conference on Neural Engineering, NER* 1378–1381.  
<https://doi.org/10.1109/NER.2013.6696199>
92. Huang M, Ye L, Chen J, Fu R, Zhou C (2021) Feature Representation for Meditation State Classification in EEG Signal. In: *Proceedings - 11th International Conference on Information Technology in Medicine and Education, ITME 2021*. Institute of Electrical and Electronics Engineers Inc., pp 267–270

93. Huang M, Chen J, Zhou C (2019) Feature extraction and calibration of EEG signals in sitting and walking meditation. In: IEEE 2nd International Conference on Knowledge Innovation and Invention (ICKII). IEEE, p 613
94. Stieger JR, Engel S, Jiang H, Cline CC, Kreitzer MJ, He B (2021) Mindfulness Improves Brain-Computer Interface Performance by Increasing Control over Neural Activity in the Alpha Band. *Cerebral Cortex* 31:426–438.  
<https://doi.org/10.1093/cercor/bhaa234>
95. Stapleton P, Dispenza J, McGill S, Sabot D, Peach M, Raynor D (2020) Large effects of brief meditation intervention on EEG spectra in meditation novices. *IBRO Rep* 9:290–301. <https://doi.org/10.1016/j.ibror.2020.10.006>
96. Neri B, Callara AL, Vanello N, Menicucci D, Zaccaro A, Piarulli A, Laurino M, Norbu N, Kechok J, Sherab N, Gemignani A (2024) Report from a Tibetan Monastery: EEG neural correlates of concentrative and analytical meditation. *Front Psychol* 15:.  
<https://doi.org/10.3389/fpsyg.2024.1348317>
97. Amihai I, Kozhevnikov M (2014) Arousal vs. relaxation: A comparison of the neurophysiological and cognitive correlates of Vajrayana and Theravada meditative practices. *PLoS One* 9:.  
<https://doi.org/10.1371/journal.pone.0102990>
98. Skwara AC, King BG, Zanesco AP, Saron CD (2022) Shifting Baselines: Longitudinal Reductions in EEG Beta Band Power Characterize Resting Brain Activity with Intensive Meditation. *Mindfulness (N Y)* 13:2488–2506.  
<https://doi.org/10.1007/s12671-022-01974-9>
99. Irmischer M, Houtman SJ, Mansvelder HD, Tremmel M, Ott U, Linkenkaer-Hansen K (2018) Controlling the Temporal Structure of Brain Oscillations by Focused Attention Meditation. *Hum Brain Mapp* 39:1825–1838. <https://doi.org/10.1002/hbm.23971>
100. Cruz MV, Jamal S, Wahl C, Sethuraman SC (2024) Investigating the impact of mindful breathing meditation on brain waves: a study on young adults. *Neuropsychological Trends* 19–44. <https://doi.org/10.7358/neur-2024-035-cruz>

101. Pandey P, Miyapuram KP (2021) BRAIN2DEPTH: Lightweight CNN Model for Classification of Cognitive States from EEG Recordings. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). Springer Science and Business Media Deutschland GmbH, pp 394–407
102. Hinterberger T, Schmidt S, Kamei T, Walach H (2014) Decreased electrophysiological activity represents the conscious state of emptiness in meditation. *Front Psychol* 5:1–14. <https://doi.org/10.3389/fpsyg.2014.00099>
103. Harne BP, Hiwale AS (2018) EEG Spectral Analysis on OM Mantra Meditation: A Pilot Study. *Applied Psychophysiology Biofeedback* 43:123–129. <https://doi.org/10.1007/s10484-018-9391-7>
104. Jo HG, Malinowski P, Schmidt S (2017) Frontal theta dynamics during response conflict in long-term mindfulness meditators. *Front Hum Neurosci* 11:1–11. <https://doi.org/10.3389/fnhum.2017.00299>
105. Lee YJ, Kim HG, Cheon EJ, Kim K, Choi JH, Kim JY, Kim JM, Koo BH (2019) The Analysis of Electroencephalography Changes Before and After a Single Neurofeedback Alpha/Theta Training Session in University Students. *Applied Psychophysiology Biofeedback* 44:173–184. <https://doi.org/10.1007/s10484-019-09432-4>
106. Sharma K, Chandra S, Dubey AK (2018) Exploration of Lower Frequency EEG Dynamics and Cortical Alpha Asymmetry in Long-term Rajyoga Meditators. *Int J Yoga* 11:30–36. [https://doi.org/10.4103/ijoy.IJOY\\_11\\_17](https://doi.org/10.4103/ijoy.IJOY_11_17)
107. Chandra S, Sharma G, Mittal A, Jha D (2016) Effect of Sudarshan Kriya (meditation) on gamma, alpha, and theta rhythm during working memory task. *Int J Yoga* 9:72. <https://doi.org/10.4103/0973-6131.171715>
108. Dentico D, Bachhuber D, Riedner BA, Ferrarelli F, Tononi G, Davidson RJ, Lutz A (2018) Acute effects of meditation training on the waking and sleeping brain: Is it all about homeostasis? *European Journal of Neuroscience* 48:2310–2321. <https://doi.org/10.1111/ejn.14131>

109. Kim DK, Rhee JH, Kang SW (2014) Reorganization of the brain and heart rhythm during autogenic meditation. *Front Integr Neurosci* 7:1–9. <https://doi.org/10.3389/fnint.2013.00109>
110. Kim DK, Lee KM, Kim J, Whang MC, Kang SW (2013) Dynamic correlations between heart and brain rhythm during autogenic meditation. *Front Hum Neurosci* 7:1–8. <https://doi.org/10.3389/fnhum.2013.00414>
111. Park YJ, Park YB (2012) Clinical utility of paced breathing as a concentration meditation practice. *Complement Ther Med* 20:393–399. <https://doi.org/10.1016/j.ctim.2012.07.008>
112. Tibdewal MN, Nagbhide DN, Thakare KB (2020) Analysis of Electroencephalogram for Cognitive Effects of Human Being before and after Meditation. In: 2020 International Conference on Industry 4.0 Technology (I4Tech). IEEE
113. Pradeep Kumar G, Sharma K, Adarsh A, Manvi A, Ramajayam G, Ramakrishnan AG (2023) Functional reorganization of the brain in distinct frequency bands during eyes-open meditation. *Conscious Cogn* 116:. <https://doi.org/10.1016/j.concog.2023.103590>
114. Dentico D, Ferrarelli F, Riedner BA, Smith R, Zennig C, Lutz A, Tononi G, Davidson RJ (2016) Short Meditation Trainings Enhance Non-REM Sleep Low-Frequency Oscillations. *PLoS One* 11:1–19. <https://doi.org/10.1371/journal.pone.0148961>
115. Shanok NA, Reive C, Mize KD, Jones NA (2019) Mindfulness Meditation Intervention Alters Neurophysiological Symptoms of Anxiety and Depression in Preadolescents. *J Psychophysiol*. <https://doi.org/10.1027/0269-8803/a000244>
116. Luft CDB, Zioga I, Banissy MJ, Bhattacharya J (2019) Spontaneous visual imagery during meditation for creating visual art: An EEG and brain stimulation case study. *Front Psychol* 10:1–14. <https://doi.org/10.3389/fpsyg.2019.00210>
117. Sagar M, Zanesco AP, King BG, Bridwell DA, MacLean KA, Aichele SR, Jacobs TL, Wallace BA, Saron CD, Miikkulainen R (2015) Mean-field thalamocortical modeling of longitudinal EEG acquired during intensive meditation training. *Neuroimage* 114:88–104. <https://doi.org/10.1016/j.neuroimage.2015.03.073>

118. Anwar D, Naik V, Gupta A, Sharma SK (2017) Detecting meditation using a dry mono-electrode EEG sensor. In: 9th International Conference on Communication Systems and Networks (COMSNETS). IEEE
119. Kakumanu RJ, Nair AK, Venugopal R, Sasidharan A, Ghosh PK, John JP, Mehrotra S, Panth R, Kutty BM (2018) Dissociating meditation proficiency and experience dependent EEG changes during traditional Vipassana meditation practice. *Biol Psychol* 135:65–75. <https://doi.org/10.1016/j.biopsycho.2018.03.004>
120. Travis F, Valosek L, Konrad A, Link J, Salerno J, Scheller R, Nidich S (2018) Effect of meditation on psychological distress and brain functioning: A randomized controlled study. *Brain Cogn* 125:100–105. <https://doi.org/10.1016/j.bandc.2018.03.011>
121. Cahn BR, Delorme A, Polich J (2010) Occipital gamma activation during Vipassana meditation. *Cogn Process* 11:39–56. <https://doi.org/10.1007/s10339-009-0352-1>
122. Luo M, Gan Q, Huang Z, Jiang Y, Li K, Wu M, Yang D, Shao H, Chen Y, Fu Y, Chen Z (2024) Changes in Mental Health and EEG Biomarkers of Undergraduates Under Different Patterns of Mindfulness. *Brain Topogr* 37:75–87. <https://doi.org/10.1007/s10548-023-01026-y>
123. Purnamasari PD, Fernandya A (2019) Real time EEG-based stress detection and meditation application with K-nearest neighbor. *IEEE Region 10 Humanitarian Technology Conference, R10-HTC 2019-Novem*:49–54. <https://doi.org/10.1109/R10-HTC47129.2019.9042488>
124. Tomljenović H, Begić D, Maštrović Z (2016) Changes in trait brainwave power and coherence, state and trait anxiety after three-month transcendental meditation (TM) practice. *Psychiatr Danub* 28:63–72
125. Brandmeyer T, Delorme A (2020) Closed-Loop Frontal Midline $\theta$  Neurofeedback: A Novel Approach for Training Focused-Attention Meditation. *Front Hum Neurosci* 14:. <https://doi.org/10.3389/fnhum.2020.00246>
126. Yordanova J, Kolev V, Mauro F, Nicolardi V, Simione L, Calabrese L, Malinowski P, Raffone A (2020) Common and distinct lateralised patterns of neural coupling during

- focused attention, open monitoring and loving kindness meditation. *Sci Rep* 10:.  
<https://doi.org/10.1038/s41598-020-64324-6>
127. Lee YH, Hsieh YJ, Shiah YJ, Lin YH, Chen CY, Tyan YC, GengQiu J, Hsu CY, Chen SCJ (2017) A cross-sectional evaluation of meditation experience on electroencephalography data by artificial neural network and support vector machine classifiers. *Medicine (United States)* 96:.  
<https://doi.org/10.1097/MD.0000000000006612>
  128. Kora P, Rajani A, Chinnaiah MC, Madhavi KR, Swaraja K, Meenakshi K (2021) EEG-Based Brain-Electric Activity Detection During Meditation Using Spectral Estimation Techniques. In: *Lecture Notes in Networks and Systems*. Springer Science and Business Media Deutschland GmbH, pp 687–693
  129. Braboszcz C, Rael Cahn B, Levy J, Fernandez M, Delorme A (2017) Increased gamma brainwave amplitude compared to control in three different meditation traditions. *PLoS One* 12:1–27. <https://doi.org/10.1371/journal.pone.0170647>
  130. Gupta N, Sood N, Saini I (2018) Statistical Feature Based Comparison of EEG in Meditation for Various Wavelet. *ICSCCC 2018 - 1st International Conference on Secure Cyber Computing and Communications* 73–77.  
<https://doi.org/10.1109/ICSCCC.2018.8703266>
  131. Fan Y, Tang YY, Tang R, Posner MI (2014) Short Term Integrative Meditation Improves Resting Alpha Activity and Stroop Performance. *Applied Psychophysiology Biofeedback* 39:213–217. <https://doi.org/10.1007/s10484-014-9258-5>
  132. Yoshida K, Takeda K, Kasai T, Makinae S, Murakami Y, Hasegawa A, Sakai S (2020) Focused attention meditation training modifies neural activity and attention: longitudinal EEG data in non-meditators. *Soc Cogn Affect Neurosci* 15:215–224.  
<https://doi.org/10.1093/scan/nsaa020>
  133. Tanaka GK, Maslahati T, Gongora M, Bittencourt J, Lopez LCS, Demarzo MMP, Budde H, Teixeira S, Basile LF, Campayo JG, Cagy M, Ribeiro P, Velasques B (2015) Effortless attention as a biomarker for experienced mindfulness practitioners. *PLoS One* 10:1–13. <https://doi.org/10.1371/journal.pone.0138561>

134. Lee YH, Shiah YJ, Chen SCJ, Wang SF, Young MS, Lin CL (2015) Improved emotional stability in experienced meditators with concentrative meditation based on electroencephalography and heart rate variability. *Journal of Alternative and Complementary Medicine* 21:31–39. <https://doi.org/10.1089/acm.2013.0465>
135. Tanaka GK, Peressutti C, Teixeira S, Cagy M, Piedade R, Nardi E, Ribeiro P, Velasques B (2014) Lower trait frontal theta activity in mindfulness meditators. *Arq Neuropsiquiatr* 72:687–693. <https://doi.org/10.1590/0004-282X20140133>
136. Marasinghe C, Tennakoon V, Mahawithanage STC (2021) EEG Characteristics During Mindfulness Meditation Among Buddhist Monks in a Sri Lankan Forest Monastery. *Mindfulness (N Y)* 12:3026–3035. <https://doi.org/10.1007/s12671-021-01762-x>
137. Attar ET, Balasubramanian V, Subasi E, Kaya M (2021) Stress Analysis Based on Simultaneous Heart Rate Variability and EEG Monitoring. *IEEE J Transl Eng Health Med* 9:. <https://doi.org/10.1109/JTEHM.2021.3106803>
138. Sihn D, Kim J, Kim SP (2024) Meditation-type specific reduction in infra-slow activity of electroencephalogram. *Biomed Eng Lett* 14:823–831. <https://doi.org/10.1007/s13534-024-00377-0>
139. Moynihan JA, Chapman BP, Klorman R, Krasner MS, Duberstein PR, Brown KW, Talbot NL (2013) Mindfulness-Based Stress Reduction for Older Adults: Effects on Executive Function, Frontal Alpha Asymmetry and Immune Function. *Neuropsychobiology* 68:34–43. <https://doi.org/10.1159/000350949>
140. Chowdhury A, van Lutterveld R, Laukkonen RE, Slagter HA, Ingram DM, Sacchet MD (2023) Investigation of advanced mindfulness meditation “cessation” experiences using EEG spectral analysis in an intensively sampled case study. *Neuropsychologia* 190:. <https://doi.org/10.1016/j.neuropsychologia.2023.108694>
141. Kato T, Kawano K (2017) Physiological Investigation on EEG Coherency during Yoga Meditation and Qigong Exercise. *Journal of International Society of Life Information Science* 35:99. [https://doi.org/10.18936/islis.35.2\\_99](https://doi.org/10.18936/islis.35.2_99)

142. Bigliassi M, Galano BM, Lima-Silva AE, Bertuzzi R (2020) Effects of mindfulness on psychological and psychophysiological responses during self-paced walking. *Psychophysiology* 1–17. <https://doi.org/10.1111/psyp.13529>
143. Duda AT, Clarke AR, De Blasio FM, Rout TW, Barry RJ (2023) The Effects of Concentrative Meditation on the Electroencephalogram in Novice Meditators. *Clin EEG Neurosci* 54:130–140. <https://doi.org/10.1177/15500594211065897>
144. Tan G, Wang S, Vierge V, Mu W, Wang M, Greco L, Mounier H, Chaillet A (2022) An EEG Classifier to Discriminate Between Focused Attention Meditation and Problem-solving. In: *Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics*. Institute of Electrical and Electronics Engineers Inc., pp 1954–1960
145. Rodriguez-Larios J, Faber P, Achermann P, Tei S, Alaerts K (2020) From thoughtless awareness to effortful cognition: alpha - theta cross-frequency dynamics in experienced meditators during meditation, rest and arithmetic. *Sci Rep* 10:1–11. <https://doi.org/10.1038/s41598-020-62392-2>
146. Alawieh H, Dawy Z, Yaacoub E, Abbas N, El-Imad J (2019) A Real-Time ECG Feature Extraction Algorithm for Detecting Meditation Levels within a General Measurement Setup. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS* 99–103. <https://doi.org/10.1109/EMBC.2019.8857832>
147. Rajalakshmi A, Sridhar SS (2024) Classification of yoga, meditation, combined yoga–meditation EEG signals using L-SVM, KNN, and MLP classifiers. *Soft comput* 28:4607–4619. <https://doi.org/10.1007/s00500-024-09695-y>
148. Karaiskou AI, Varon C, Alaerts K, De Vos M (2023) Cross-Subject Mindfulness Meditation EEG Decoding. In: *2023 IEEE International Conference on Metrology for eXtended Reality, Artificial Intelligence and Neural Engineering, MetroXRINE 2023 - Proceedings*. Institute of Electrical and Electronics Engineers Inc., pp 781–786
149. Pandey P, Miyapuram KP (2020) Classifying Oscillatory Signatures of Expert vs NonExpert Meditators. In: *International Joint Conference on Neural Networks (IJCNN)*. IEEE

150. Susam BT, Riek NT, Beck K, Eldeeb S, Hudac CM, Gable PA, Conner C, Akcakaya M, White S, Mazefsky C (2022) Quantitative EEG Changes in Youth With ASD Following Brief Mindfulness Meditation Exercise. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 30:2395–2405.  
<https://doi.org/10.1109/TNSRE.2022.3199151>
151. Jadhav N, Manthalkar R, Joshi Y (2017) Effect of meditation on emotional response: An EEG-based study. *Biomed Signal Process Control* 34:101–113.  
<https://doi.org/10.1016/j.bspc.2017.01.008>
152. Harne BP, Dhekekar RS, Bobade Y, Hiwale A (2019) SVM classification of EEG signal to analyze the effect of OM Mantra meditation on the brain. In: *IEEE 16th India Council International Conference (INDICON)*
153. Singh S, Gupta V, Reddy TK, Behera L, Samanta S (2023) Meditative State Classification Using Neuronal Multi-IMF Band Power and Complexity Features. In: *2023 National Conference on Communications, NCC 2023*. Institute of Electrical and Electronics Engineers Inc.
154. Singh S, Gupta V, Reddy TK, Bhushan B, Behera L (2022) Meditation and Cognitive Enhancement: A Machine Learning Based Classification Using EEG. In: *Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics*. Institute of Electrical and Electronics Engineers Inc., pp 1973–1978
155. Chaudhary S, Pandey P, Miyapuram KP, Lomas D (2022) Classifying EEG Signals of Mind-Wandering Across Different Styles of Meditation. In: *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. Springer Science and Business Media Deutschland GmbH, pp 152–163
156. Shaw L, Routray A (2016) Statistical features extraction for multivariate pattern analysis in meditation EEG using PCA. In: *IEEE EMBS International Student Conference: Expanding the Boundaries of Biomedical Engineering and Healthcare, ISC*

157. Schoenberg PLA, Ruf A, Churchill J, Brown DP, Brewer JA (2018) Mapping complex mind states: EEG neural substrates of meditative unified compassionate awareness. *Conscious Cogn* 57:41–53. <https://doi.org/10.1016/j.concog.2017.11.003>
158. Hata M, Hayashi N, Ishii R, Canuet L, Pascual-Marqui RD, Aoki Y, Ikeda S, Sakamoto T, Iwata M, Kimura K, Iwase M, Ikeda M, Ito T (2019) Short-term meditation modulates EEG activity in subjects with post-traumatic residual disabilities. *Clin Neurophysiol Pract* 4:30–36. <https://doi.org/10.1016/j.cnp.2019.01.003>
159. Kosunen I, Salminen M, Järvelä S, Ruonala A, Ravaja N, Jacucci G (2016) RelaWorld: Neuroadaptive and immersive virtual reality meditation system. *International Conference on Intelligent User Interfaces, Proceedings IUI 07-10-Marc:208–217*. <https://doi.org/10.1145/2856767.2856796>
160. Viczko J, Tarrant J, Jackson R (2021) Effects on Mood and EEG States After Meditation in Augmented Reality With and Without Adjunctive Neurofeedback. *Front Virtual Real* 2:.. <https://doi.org/10.3389/frvir.2021.618381>
161. Berkovich-Ohana A (2017) A case study of a meditation-induced altered state: increased overall gamma synchronization. *Phenomenol Cogn Sci* 16:91–106. <https://doi.org/10.1007/s11097-015-9435-x>
162. Sen N, Misra IS (2023) Meditation Effects on Human Stress Relief Using Frequency and Non-Linear Features of EEG Signal. In: *2023 2nd International Conference on Ambient Intelligence in Health Care, ICAIHC 2023*. Institute of Electrical and Electronics Engineers Inc.
163. Thomas J, Jamieson G, Cohen M (2014) Low and then high frequency oscillations of distinct right cortical networks are progressively enhanced by medium and long term Satyananda Yoga meditation practice. *Front Hum Neurosci* 8:1–13. <https://doi.org/10.3389/fnhum.2014.00197>
164. Nyhus E, Engel WA, Pitfield TD, Vakkur IMW (2019) Increases in Theta Oscillatory Activity During Episodic Memory Retrieval Following Mindfulness Meditation Training. *Front Hum Neurosci* 13:1–14. <https://doi.org/10.3389/fnhum.2019.00311>

165. Devipriya A, Nagarajan N (2018) A Novel Method of Segmentation and Classification for Meditation in Health Care Systems. *J Med Syst* 42:.. <https://doi.org/10.1007/s10916-018-1062-y>
166. Shreyas Pragya S, C Sanchette P (2018) Impact of preksha meditation on alpha waves in EEG. *Indian J Clin Anat Physiol* 5:519–524. <https://doi.org/10.18231/2394-2126.2018.0119>
167. Bailey NW, Baell O, Payne JE, Humble G, Geddes H, Cahill I, Hill AT, Chung SW, Emonson M, Murphy OW, Fitzgerald PB (2023) Experienced Meditators Show Multifaceted Attention-Related Differences in Neural Activity. *Mindfulness* (N Y) 14:2670–2698. <https://doi.org/10.1007/s12671-023-02224-2>
168. Gao J, Sun R, Leung HK, Roberts A, Wu BWY, Tsang EW, Tang ACW, Sik HH (2023) Increased neurocardiological interplay after mindfulness meditation: a brain oscillation-based approach. *Front Hum Neurosci* 17:.. <https://doi.org/10.3389/fnhum.2023.1008490>
169. Anand H (2014) Effect of meditation ( ' OM ' chanting ) on alpha EEG and galvanic skin response : Measurement of an altered state of consciousness. *Indian Journal Of Positive Psychology* 5 (3):255–259
170. van Lutterveld R, Houlihan SD, Pal P, Sacchet MD, McFarlane-Blake C, Patel PR, Sullivan JS, Ossadtchi A, Druker S, Bauer C, Brewer JA (2017) Source-space EEG neurofeedback links subjective experience with brain activity during effortless awareness meditation. *Neuroimage* 151:117–127. <https://doi.org/10.1016/j.neuroimage.2016.02.047>
171. Katyal S, Hajcak G, Flora T, Bartlett A, Goldin P (2020) Event-related potential and behavioural differences in affective self-referential processing in long-term meditators versus controls. *Cogn Affect Behav Neurosci*. <https://doi.org/10.3758/s13415-020-00771-y>
172. Andreu CI, Palacios I, Moënné-Loccoz C, López V, Franken IHA, Cosmelli D, Slagter HA (2019) Enhanced response inhibition and reduced midfrontal theta activity in

- experienced Vipassana meditators. *Sci Rep* 9:1–11. <https://doi.org/10.1038/s41598-019-49714-9>
173. Luo X, Zhao J, Zhao D, Wang L, Hou Y, Liu Y, Zeng J, Yuan H, Lei X (2024) Differences in attentional function between experienced mindfulness meditators and non-meditators. *Front Psychiatry* 15:.. <https://doi.org/10.3389/fpsy.2024.1341294>
  174. Singh S, Pandey P, Chaudhary S, Miyapuram KP, Lomas J (2022) Towards the development of personalized and generalized interfaces for brain signals across different styles of meditation. In: *ACM International Conference Proceeding Series*. Association for Computing Machinery
  175. Deng X, Yang M, Chen X, Zhan Y (2023) The role of mindfulness on theta inter-brain synchrony during cooperation feedback processing: An EEG-based hyperscanning study. *International Journal of Clinical and Health Psychology* 23:.. <https://doi.org/10.1016/j.ijchp.2023.100396>
  176. Sharma H, Raj R, Juneja M (2019) EEG signal based classification before and after combined Yoga and Sudarshan Kriya. *Neurosci Lett* 707:134300. <https://doi.org/10.1016/j.neulet.2019.134300>
  177. Chandra S, Sharma G, Sharma M, Jha D, Mittal AP (2017) Workload regulation by Sudarshan Kriya: an EEG and ECG perspective. *Brain Inform* 4:13–25. <https://doi.org/10.1007/s40708-016-0055-1>
  178. Tee JL, Phang SK, Chew WJ, Phang SW, Mun HK (2020) Classification of meditation states through EEG: A method using discrete wavelet transform. In: *AIP Conference Proceedings, Proceedings of the 13th International Engineering Research Conference, Subang Jaya, Malaysia*. American Institute of Physics Inc.
  179. Shaw L, Routray A (2017) Topographical Sub-bands Analysis of EEG during Short Kriya Yoga Meditation. In: *2017 14th IEEE India Council International Conference (INDICON)*. IEEE
  180. Taori T, Gupta S, Manthalkar R, Gajre S (2024) Mindfulness Intervention Affects Cognitive Abilities of Students: A Time–Frequency Analysis Using EEG. In: *Lecture*

Notes in Electrical Engineering. Springer Science and Business Media Deutschland GmbH, pp 219–233

181. Gaurav G, Sahani AK, Sahoo A (2019) An EEG based Quantitative Analysis of Absorbed Meditative State. International IEEE/EMBS Conference on Neural Engineering, NER 2019-March:57–60. <https://doi.org/10.1109/NER.2019.8717094>
182. Bostanov V, Ohlrogge L, Britz R, Hautzinger M, Kotchoubey B (2018) Measuring Mindfulness: A Psychophysiological Approach. *Front Hum Neurosci* 12:1–22. <https://doi.org/10.3389/fnhum.2018.00249>
183. Kopal J, Vyšata O, Burian J, Schätz M, Procházka A, Vališ M (2014) Complex continuous wavelet coherence for EEG microstates detection in insight and calm meditation. *Conscious Cogn* 30:13–23. <https://doi.org/10.1016/j.concog.2014.07.015>
184. Dadhich A, Patel J, Tiwari R, Verma R, Mishra P, Jain JK (2024) A flexible analytic wavelet transform and ensemble bagged tree model for electroencephalogram-based meditative mind-wandering detection. *Healthcare Analytics* 5:. <https://doi.org/10.1016/j.health.2023.100286>
185. Brandmeyer T, Delorme A (2018) Reduced mind wandering in experienced meditators and associated EEG correlates. *Exp Brain Res* 236:2519–2528. <https://doi.org/10.1007/s00221-016-4811-5>
186. Kopal J, Vyšata O, Burian J, Schätz M, Procházka A, Vališ M (2017) EEG Synchronizations Length During Meditation. *J Med Biol Eng* 37:220–229. <https://doi.org/10.1007/s40846-017-0219-3>
187. Shaw L, Routray A (2017) Topographical pattern analysis using wavelet based coherence connectivity estimation in the distinction of meditation and non-meditation EEG. 25th European Signal Processing Conference, EUSIPCO 2017 2017-Janua:1554–1558. <https://doi.org/10.23919/EUSIPCO.2017.8081470>
188. Wang H, Song A, Li B, Xu B, Li Y (2015) Psychophysiological classification and experiment study for spontaneous EEG based on two novel mental tasks. *Technology and Health Care* 23:S249–S262. <https://doi.org/10.3233/THC-150960>

189. Pandey P, Gupta P, Miyapuram KP (2021) Brain Connectivity Based Classification of Meditation Expertise. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). Springer Science and Business Media Deutschland GmbH, pp 89–98
190. Bauer PR, Sabourdy C, Chatard B, Rheims S, Lachaux JP, Vidal JR, Lutz A (2022) Neural dynamics of mindfulness meditation and hypnosis explored with intracranial EEG: A feasibility study. *Neurosci Lett* 766:.  
<https://doi.org/10.1016/j.neulet.2021.136345>
191. Gupta KV, Beuria J, Behera L (2024) Characterizing EEG signals of meditative states using persistent homology and Hodge spectral entropy. *Biomed Signal Process Control* 89:.  
<https://doi.org/10.1016/j.bspc.2023.105779>
192. Travis F (2011) Comparison of coherence, amplitude, and eLORETA patterns during Transcendental Meditation and TM-Sidhi practice. *International Journal of Psychophysiology* 81:198–202. <https://doi.org/10.1016/j.ijpsycho.2011.06.011>
193. Kaur K, Khandnor P (2023) Temporal-domain Analysis of Meditation and Mind-wandering EEG Signals for Different Meditation Traditions. In: 2023 7th International Conference on Computer Applications in Electrical Engineering-Recent Advances: Sustainable Transportation Systems, CERA 2023. Institute of Electrical and Electronics Engineers Inc.
194. Edla DR, Mangalorekar K, Dhavalikar G, Dodia S (2018) Classification of EEG data for human mental state analysis using Random Forest Classifier. *Procedia Comput Sci* 132:1523–1532. <https://doi.org/10.1016/j.procs.2018.05.116>
195. Tee JL, Leong WY (2018) EEG extraction for meditation. *Journal of Engineering Science and Technology* 13:2125–2135
196. Rahul Ingle, Oimbe S, Kehri V, Awale RN (2018) Classification of EEG Signals during Meditation and Controlled State Using PCA, ICA, LDA and Support Vector Machines. *International Journal of Pure and Applied Mathematics* 118:3179–3190

197. Lu S, Wang T (2022) Online EEG Classification of Meditative States for Wearable Devices using Machine Learning. In: Proceedings - 2022 12th International Conference on Information Technology in Medicine and Education, ITME 2022. Institute of Electrical and Electronics Engineers Inc., pp 358–361
198. Baboo GK, Dubey S, Baths V (2023) Comparative Study of Neural Networks (G/C/RNN) and Traditional Machine Learning Models on EEG Datasets. In: Cognitive Science and Technology. Springer, pp 163–177
199. Jin J, Dauwels J, Vialatte FB, Cichocki A (2014) Synchrony analysis of paroxysmal gamma waves in meditation EEG. In: ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings. pp 4703–4707
200. Liyanagedera ND, Hussain AA, Singh A, Lal S, Kempton H, Guesgen HW (2023) Common spatial pattern for classification of loving kindness meditation EEG for single and multiple sessions. *Brain Inform* 10:. <https://doi.org/10.1186/s40708-023-00204-9>
201. Shang B, Duan F, Fu R, Gao J, Sik H, Meng X, Chang C (2023) EEG-based investigation of effects of mindfulness meditation training on state and trait by deep learning and traditional machine learning. *Front Hum Neurosci* 17:. <https://doi.org/10.3389/fnhum.2023.1033420>
202. Panachakel JT, Pradeep Kumar G, Ramakrishnan GA, Sharma K (2021) Automated classification of EEG into meditation and non-meditation epochs using common spatial pattern, linear discriminant analysis, and LSTM. In: IEEE Region 10 Annual International Conference, Proceedings/TENCON. Institute of Electrical and Electronics Engineers Inc., pp 215–218
203. Panachakel JT, Govindaiah PK, Sharma K, Ganesan RA (2021) Binary classification of meditative state from the resting state using EEG. In: Proceedings of the 2021 IEEE 18th India Council International Conference, INDICON 2021. Institute of Electrical and Electronics Engineers Inc.
204. Munjal R, Varshney T, Choudhary A, Dhiman R (2023) Convolutional Neural Network Based Models for Identification of Brain State Associated with Isha Shoonya Meditation. In: Proceedings - 4th IEEE 2023 International Conference on Computing,

- Communication, and Intelligent Systems, ICCIS 2023. Institute of Electrical and Electronics Engineers Inc., pp 387–392
205. Lee D, Kang DH, Ha N hyun, Oh C young, Lee U, Kang SW (2018) Effects of an Online Mind–Body Training Program on the Default Mode Network: An EEG Functional Connectivity Study. *Sci Rep* 8:1–8. <https://doi.org/10.1038/s41598-018-34947-x>
  206. Bailey NW, Freedman G, Raj K, Sullivan CM, Rogasch NC, Chung SW, Hoy KE, Chambers R, Hased C, Van Dam NT, Koenig T, Fitzgerald PB (2019) Mindfulness meditators show altered distributions of early and late neural activity markers of attention in a response inhibition task. *PLoS One* 14:1–26. <https://doi.org/10.1371/journal.pone.0203096>
  207. Incagli F, Tarantino V, Crescentini C, Vallesi A (2020) The Effects of 8-Week Mindfulness-Based Stress Reduction Program on Cognitive Control: an EEG Study. *Mindfulness (N Y)* 11:756–770. <https://doi.org/10.1007/s12671-019-01288-3>
  208. DeLosAngeles D, Williams G, Burston J, Fitzgibbon SP, Lewis TW, Grummett TS, Clark CR, Pope KJ, Willoughby JO (2016) Electroencephalographic correlates of states of concentrative meditation. *International Journal of Psychophysiology* 110:27–39. <https://doi.org/10.1016/j.ijpsycho.2016.09.020>
  209. Korde KS, Paikrao PL, Jadhav . N. S. (2019) Analysis of EEG Signals and Biomedical Changes Due to Meditation on Brain by Using ICA for Feature Extraction. In: *ICICCS : Second International Conference on Intelligent Computing and Control Systems*. Institute of Electrical and Electronics Engineers, p 1721
  210. Pandey P, Gupta P, Miyapuram KP (2022) Exploration of Brain Network Measures Across Three Meditation Traditions. *NeuroRegulation* 9:113–126. <https://doi.org/10.15540/NR.9.3.113>
  211. Fingelkurts AA, Fingelkurts AA, Kallio-Tamminen T (2016) Long-term meditation training induced changes in the operational synchrony of default mode network modules during a resting state. *Cogn Process* 17:27–37. <https://doi.org/10.1007/s10339-015-0743-4>

212. van Lutterveld R, van Dellen E, Pal P, Yang H, Stam CJ, Brewer J (2017) Meditation is associated with increased brain network integration. *Neuroimage* 158:18–25.  
<https://doi.org/10.1016/j.neuroimage.2017.06.071>
  
213. Payne JR, Baell O, Geddes H, Fitzgibbon B, Emonson M, Hill AT, Van Dam NT, Humble G, Fitzgerald PB, Bailey NW (2020) Experienced Meditators Exhibit No Differences to Demographically Matched Controls in Theta Phase Synchronization, P200, or P300 During an Auditory Oddball Task. *Mindfulness* (N Y) 11:643–659.  
<https://doi.org/10.1007/s12671-019-01287-4>
  
214. Lin H, Li Y (2017) Using EEG data analytics to measure meditation. In: *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. Springer Verlag, pp 270–280
  
215. Pandey P, Rodriguez-Larios J, Miyapuram KP, Lomas D (2023) Detecting moments of distraction during meditation practice based on changes in the EEG signal. In: *APSCON 2023 - IEEE Applied Sensing Conference, Symposium Proceedings*. Institute of Electrical and Electronics Engineers Inc.
  
216. Kumar GP, Sharma K, Ramakrishnan AG, Adarsh A (2021) Increased Entropy of Gamma Oscillations in the Frontal Region during Meditation. In: *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*. Institute of Electrical and Electronics Engineers Inc., pp 787–790
  
217. Pradeep KK, Angarai Ganesan R, Sharma K (2020) Fuzzy entropy as a measure of EEG complexity during Rajayoga practice in long-term meditators. In: *2020 IEEE 17th India Council International Conference, INDICON 2020*. Institute of Electrical and Electronics Engineers Inc.
  
218. Han Y, Huang W, Huang H, Xiao J, Li Y (2020) Assessing meditation state using EEG-based permutation entropy features. In: *IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)*. IEEE
  
219. Travis F, Parim N, Shrivastava A (2017) Higher theta and alpha1 coherence when listening to Vedic recitation compared to coherence during Transcendental Meditation practice. *Conscious Cogn* 49:157–162. <https://doi.org/10.1016/j.concog.2017.02.002>

220. Shaw L, Routray A (2018) Topographical assessment of neurocortical connectivity by using directed transfer function and partial directed coherence during meditation. *Cogn Process* 19:527–536. <https://doi.org/10.1007/s10339-018-0869-2>
221. Dissanayaka C, Ben-Simon E, Gruberger M, Maron-Katz A, Sharon H, Hendler T, Cvetkovic D (2015) Comparison between human awake, meditation and drowsiness EEG activities based on directed transfer function and MVDR coherence methods. *Med Biol Eng Comput* 53:599–607. <https://doi.org/10.1007/s11517-015-1272-0>
222. Kaur K, Khandnor P, Khosla A (2024) Classification of Meditation Expertise from EEG Signals Using Shallow Neural Networks. In: *Communications in Computer and Information Science*. Springer Science and Business Media Deutschland GmbH, pp 169–185
223. Travis F, Parim N (2017) Default mode network activation and Transcendental Meditation practice: Focused Attention or Automatic Self-transcending? *Brain Cogn* 111:86–94. <https://doi.org/10.1016/j.bandc.2016.08.009>
224. Xue SW, Tang YY, Tang R, Posner MI (2014) Short-term meditation induces changes in brain resting EEG theta networks. *Brain Cogn* 87:1–6. <https://doi.org/10.1016/j.bandc.2014.02.008>
225. Faber PL, Travis F, Milz P, Parim N (2017) EEG microstates during different phases of Transcendental Meditation practice. *Cogn Process* 18:307–314. <https://doi.org/10.1007/s10339-017-0812-y>
226. Chan RW, Alday PM, Zou-Williams L, Lushington K, Schlesewsky M, Bornkessel-Schlesewsky I, Immink MA (2020) Focused-attention meditation increases cognitive control during motor sequence performance: Evidence from the N2 cortical evoked potential. *Behavioural Brain Research* 384:112536. <https://doi.org/10.1016/j.bbr.2020.112536>
227. Shaw L, Routray A (2020) EEG Traced Microstates Detection during Meditation-A State of Consciousness. In: *2020 IEEE 15th International Conference on Industrial and Information Systems, ICIIS 2020 - Proceedings*. Institute of Electrical and Electronics Engineers Inc., pp 253–257

228. Shejwadkar MA, Ashok Kumar R (2023) Unraveling the Mysteries of Mind-Wandering and Meditation: A Comprehensive Investigation using Deep Learning. In: International Conference on Recent Advances in Science and Engineering Technology, ICRASET 2023. Institute of Electrical and Electronics Engineers Inc.
229. Liu B (2022) Deep Learning for Meditation's Impact on Brain-Computer Interface Performance. In: 2022 International Communication Engineering and Cloud Computing Conference, CECCC 2022. Institute of Electrical and Electronics Engineers Inc., pp 64–69
230. Pandey P, Miyapuram KP (2021) Nonlinear EEG analysis of mindfulness training using interpretable machine learning. In: Proceedings - 2021 IEEE International Conference on Bioinformatics and Biomedicine, BIBM 2021. Institute of Electrical and Electronics Engineers Inc., pp 3051–3057
231. Sravanth KR, Peddi A, Sagar GS, Gupta B, Chakraborty C (2018) Comparison of Attention and Meditation Based Mobile Applications by Using EEG Signals. 6th Global Wireless Summit, GWS 2018 260–265.  
<https://doi.org/10.1109/GWS.2018.8686634>
232. Delgado-Pastor LC, Perakakis P, Subramanya P, Telles S, Vila J (2013) Mindfulness (Vipassana) meditation: Effects on P3b event-related potential and heart rate variability. *International Journal of Psychophysiology* 90:207–214.  
<https://doi.org/10.1016/j.ijpsycho.2013.07.006>
233. Dziembowska I, Izdebski P, Rasmus A, Brudny J, Grzelczak M, Cysewski P (2016) Effects of Heart Rate Variability Biofeedback on EEG Alpha Asymmetry and Anxiety Symptoms in Male Athletes: A Pilot Study. *Applied Psychophysiology Biofeedback* 41:141–150. <https://doi.org/10.1007/s10484-015-9319-4>
234. West MA (1980) Meditation and the EEG. *Psychol Med* 10:369–375.  
<https://doi.org/10.1017/S0033291700044147>
235. Tang YY, Tang R, Rothbart MK, Posner MI (2019) Frontal theta activity and white matter plasticity following mindfulness meditation. *Curr Opin Psychol* 28:294–297.  
<https://doi.org/10.1016/j.copsyc.2019.04.004>

236. NEW actiCAP and actiCHamp caps now with an improved and unified layout. <https://pressrelease.brainproducts.com/uol/>. Accessed 13 Mar 2023
237. Widmann A, Schröger E, Maess B (2015) Digital filter design for electrophysiological data - a practical approach. *J Neurosci Methods* 250:34–46. <https://doi.org/10.1016/j.jneumeth.2014.08.002>
238. Barry RJ, Clarke AR, Johnstone SJ, Magee CA, Rushby JA (2007) EEG differences between eyes-closed and eyes-open resting conditions. *Clinical Neurophysiology* 118:2765–2773. <https://doi.org/10.1016/j.clinph.2007.07.028>
239. Lukseng T, Siripornpanich V, Chutabhakdikul N (2020) Long-Term Vipassana Meditation Enhances Executive Function in Adult Meditators. *Siriraj Med J* 72:352–360
240. Murata T, Koshino Y, Omori M, Murata I, Nishio M, Sakamoto K, Horie T, Isaki K (1994) Quantitative EEG Study on Zen Meditation (Zazen). *Psychiatry Clin Neurosci* 48:881–890. <https://doi.org/10.1111/j.1440-1819.1994.tb03090.x>
241. Yu X, Fumoto M, Nakatani Y, Sekiyama T, Kikuchi H, Seki Y, Sato-Suzuki I, Arita H (2011) Activation of the anterior prefrontal cortex and serotonergic system is associated with improvements in mood and EEG changes induced by Zen meditation practice in novices. *International Journal of Psychophysiology* 80:103–111. <https://doi.org/10.1016/j.ijpsycho.2011.02.004>
242. Travis F, Haaga DAF, Hagelin J, Tanner M, Arenander A, Nidich S, Gaylord-King C, Grosswald S, Rainforth M, Schneider RH (2010) A self-referential default brain state: Patterns of coherence, power, and eLORETA sources during eyes-closed rest and transcendental meditation practice. *Cogn Process* 11:21–30. <https://doi.org/10.1007/s10339-009-0343-2>
243. Travis F (2001) Autonomic and EEG patterns distinguish transcending from other experiences during Transcendental Meditation practice. *International Journal of Psychophysiology* 42:1–9. [https://doi.org/10.1016/S0167-8760\(01\)00143-X](https://doi.org/10.1016/S0167-8760(01)00143-X)

244. Collura TF, Guan J, Tarrant J, Bailey J, Starr F (2010) EEG biofeedback case studies using live Z-score training and a normative database. *J Neurother* 14:22–46. <https://doi.org/10.1080/10874200903543963>
245. Sharma H, Raj R, Juneja M (2022) An empirical comparison of machine learning algorithms for the classification of brain signals to assess the impact of combined yoga and Sudarshan Kriya. *Comput Methods Biomech Biomed Engin* 25:721–728. <https://doi.org/10.1080/10255842.2021.1975682>
246. Vivot RM, Pallavicini C, Zamberlan F, Vigo D, Tagliazucchi E (2020) Meditation Increases the Entropy of Brain Oscillatory Activity. *Neuroscience* 431:40–51. <https://doi.org/10.1016/j.neuroscience.2020.01.033>
247. Sadiq MT, Yu X, Yuan Z, Aziz MZ, Rehman N ur, Ding W, Xiao G (2022) Motor Imagery BCI Classification Based on Multivariate Variational Mode Decomposition. *IEEE Trans Emerg Top Comput Intell*. <https://doi.org/10.1109/TETCI.2022.3147030>
248. Sadiq MT, Yu X, Yuan Z, Zeming F, Rehman AU, Ullah I, Li G, Xiao G (2019) Motor Imagery EEG Signals Decoding by Multivariate Empirical Wavelet Transform-Based Framework for Robust Brain-Computer Interfaces. *IEEE Access* 7:171431–171451. <https://doi.org/10.1109/ACCESS.2019.2956018>
249. Kiyimik MK, Güler I, Dizibüyük A, Akin M (2005) Comparison of STFT and wavelet transform methods in determining epileptic seizure activity in EEG signals for real-time application. *Comput Biol Med* 35:603–616. <https://doi.org/10.1016/j.combiomed.2004.05.001>
250. Shovon TH, Nazi Z Al, Dash S, Hossain F (2019) Classification of Motor Imagery EEG Signals with multi-input Convolutional Neural Network by augmenting STFT. In: *International Conference on Advances in Electrical Engineering (ICAEE) Dhaka, Bangladesh, 26–28 September*
251. Akbari H, Sadiq MT, Payan M, Esmaili SS, Baghri H, Bagheri H (2021) Depression Detection Based on Geometrical Features Extracted from SODP Shape of EEG Signals and Binary PSO. *Traitement du Signal* 38:13–26. <https://doi.org/10.18280/TS.380102>

252. Akbari H, Sadiq MT, Jafari N, Too J, Mikaeilvand N, Cicone A, Serra-Capizzano S (2023) Recognizing seizure using Poincaré plot of EEG signals and graphical features in DWT domain. *Bratislava Medical Journal* 124:12–24.  
[https://doi.org/10.4149/BLL\\_2023\\_002](https://doi.org/10.4149/BLL_2023_002)
253. Craik A, He Y, Contreras-Vidal JL (2019) Deep learning for electroencephalogram (EEG) classification tasks: A review. *J Neural Eng* 16:. <https://doi.org/10.1088/1741-2552/ab0ab5>
254. Amin HU, Malik AS, Ahmad RF, Badruddin N, Kamel N, Hussain M, Chooi WT (2015) Feature extraction and classification for EEG signals using wavelet transform and machine learning techniques. *Australas Phys Eng Sci Med* 38:139–149.  
<https://doi.org/10.1007/s13246-015-0333-x>
255. Nasrolahzadeh M, Mohammadpoory Z, Haddadnia J (2024) A novel method for distinction heart rate variability during meditation using LSTM recurrent neural networks based on visibility graph. *Biomed Signal Process Control* 90:.  
<https://doi.org/10.1016/j.bspc.2023.105822>
256. Subasi A, Alkan A, Koklukaya E, Kiymik MK (2005) Wavelet neural network classification of EEG signals by using AR model with MLE preprocessing. *Neural Networks* 18:985–997. <https://doi.org/10.1016/j.neunet.2005.01.006>
257. Michelucci U (2018) *Applied deep learning: A case-based approach to understanding deep neural networks*. Apress Media LLC
258. Sadiq MT, Akbari H, Siuly S, Li Y, Wen P (2022) Alcoholic EEG signals recognition based on phase space dynamic and geometrical features. *Chaos Solitons Fractals* 158:.  
<https://doi.org/10.1016/j.chaos.2022.112036>
259. Sadiq MT, Aziz MZ, Almogren A, Yousaf A, Siuly S, Rehman AU (2022) Exploiting pretrained CNN models for the development of an EEG-based robust BCI framework. *Comput Biol Med* 143:. <https://doi.org/10.1016/j.combiomed.2022.105242>

260. Liu R, Wang Z, Qiu J, Wang X (2023) Assigning channel weights using an attention mechanism: an EEG interpolation algorithm. *Front Neurosci* 17:.  
<https://doi.org/10.3389/fnins.2023.1251677>
261. Corcoran AW, Alday PM, Schlesewsky M, Bornkessel-Schlesewsky I (2018) Toward a reliable, automated method of individual alpha frequency (IAF) quantification. *Psychophysiology* 55:. <https://doi.org/10.1111/psyp.13064>
262. Bailey NW, Hill AT, Biabani M, Murphy OW, Rogasch NC, McQueen B, Miljevic A, Fitzgerald PB (2023) RELAX part 2: A fully automated EEG data cleaning algorithm that is applicable to Event-Related-Potentials. *Clinical Neurophysiology* 149:202–222.  
<https://doi.org/10.1016/j.clinph.2023.01.018>
263. Sadiq MT, Yu X, Yuan Z, Aziz MZ (2020) Motor imagery BCI classification based on novel two-dimensional modelling in empirical wavelet transform. *Electron Lett* 56:1367–1369. <https://doi.org/10.1049/el.2020.2509>
264. Sadiq MT, Yu X, Yuan Z, Aziz MZ, Siuly S, Ding W (2021) Toward the Development of Versatile Brain–Computer Interfaces. *IEEE Transactions on Artificial Intelligence* 2:314–328. <https://doi.org/10.1109/tai.2021.3097307>
265. Gramfort A, Luessi M, Larson E, Engemann DA, Strohmeier D, Brodbeck C, Parkkonen L, Hämäläinen MS (2014) MNE software for processing MEG and EEG data. *Neuroimage* 86:446–460. <https://doi.org/10.1016/j.neuroimage.2013.10.027>
266. Jas M, Larson E, Engemann DA, Leppäkangas J, Taulu S, Hämäläinen M, Gramfort A (2018) A reproducible MEG/EEG group study with the MNE software: Recommendations, quality assessments, and good practices. *Front Neurosci* 12:.  
<https://doi.org/10.3389/fnins.2018.00530>
267. Cohen MX (2022) A tutorial on generalized eigendecomposition for denoising, contrast enhancement, and dimension reduction in multichannel electrophysiology. *Neuroimage* 247:. <https://doi.org/10.1016/j.neuroimage.2021.118809>

268. Congedo M, Barachant A, Bhatia R (2017) Riemannian geometry for EEG-based brain-computer interfaces; a primer and a review. *Brain-Computer Interfaces* 4:155–174. <https://doi.org/10.1080/2326263X.2017.1297192>
269. Brier MR, Mitra A, McCarthy JE, Ances BM, Snyder AZ (2015) Partial covariance based functional connectivity computation using Ledoit-Wolf covariance regularization. *Neuroimage* 121:29–38. <https://doi.org/10.1016/j.neuroimage.2015.07.039>
270. von Wegner F, Laufs H (2018) Information-theoretical analysis of EEG microstate sequences in python. *Front Neuroinform* 12:.. <https://doi.org/10.3389/fninf.2018.00030>
271. Chatterjee C (2022) *Adaptive Machine Learning Algorithms with Python: Solve Data Analytics and Machine Learning Problems on Edge Devices*. Apress Media LLC
272. Janzamin M, Ge R, Kossaiji J, Anandkumar A (2019) Spectral learning on matrices and tensors. In: *Foundations and Trends in Machine Learning*. Now Publishers Inc, pp 393–536
273. Liyanagedera ND, Bareham CA, Kempton H, Guesgen HW (2025) Machine Learning-Based Comparative Analysis of Subject-Independent EEG Data Classification Across Multiple Meditation and Non-Meditation Sessions. *Sensors* 25:6876. <https://doi.org/10.3390/s25226876>