JSPM's

Rajarshi Shahu College of Engineering, Pune.

(An Autonomous Institute Affiliated to Savitribai Phule Pune University, approved by AICTE, accredited by NBA (UG Programs), Accredited by NAAC with "A" Grade)

Engineering Design and Innovation- II

Report on

Bridging Consciousness and the Subconscious: EEG Across States of Awareness

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Third Year B.Tech – [2024-25]

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Department of Information Technology

C E R T I F I C A T E

This is to certify that Mr. Yash Lende, Mr. Yatharth Pawar, Ms. Sakshi Bhagat, Ms. Sarthaki Joshi has successfully completed EDI– II project entitled **Bridging Consciousness and the Subconscious : EEG Across States of Awareness** my supervision, in the partial fulfillment of Third Year B.Tech Information Technology.

Date:

Place:

Prof. Jayesh Sarwade	**Dr. Nihar M. Ranjan**
Guide	**HoD, IT department, RSCOE**

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ABSTRACT

KEYWORDS: EEG, Meditation, Brainwaves, Mindfulness, Cognitive Function, Behavioral Neuroscience, Neuroplasticity.

Electroencephalography (EEG) is a powerful tool for recording the electrical activity of the brain through electrodes placed on the scalp. This technique is widely used in clinical contexts to diagnose various neurological conditions, including epilepsy, sleep disorders, and encephalopathies.

In recent years, the convergence of ancient meditation practices with modern neuroscience has fostered a growing field of contemplative neuroscience. This project explores the relationship between meditation techniques and their corresponding EEG spectral amplitudes to understand how different states of awareness influence cognitive and neural connectivity. Using EEG data recorded during various meditation practices, the study focuses on spectral changes in theta, alpha, and gamma bands, examining how these oscillations correlate with attentional and cognitive states. Through signal preprocessing, feature extraction, and the application of machine learning models, the project aims to classify meditation states and identify neural patterns unique to each technique.

The findings suggest that experienced meditators exhibit higher neural synchrony and stronger oscillatory power, especially in the alpha and gamma bands, reflecting improved cognitive stability and mindfulness. These insights highlight the potential of EEG-based analysis in decoding consciousness and demonstrate the effectiveness of machine learning in advancing neurophysiological research.

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Chapter 1: Introduction

1.1 EEG Generation from the Brain

When neurons are activated, they produce synaptic currents which then induce a magnetic field measurable by EMG and a secondary electrical field over the scalp measurable by EEG. The human head consists of different layers including the scalp, skull, brain and many other thin layers in between. The skull attenuates the signals approximately one hundred times more than the soft tissue. On the other hand, most of the noise is generated either within the brain (internal noise) or over the scalp (system noise or external noise).Therefore, only large populations of active neurons can generate enough potential to be recordable using the scalp electrodes. These measurements are then amplified greatly before further processing.

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1.2 EEG Applications

- Monitoring alertness, coma, and brain death;
- Locating areas of damage following head injury, stroke, and tumor;
- Testing afferent pathways (by evoked potentials);
- Monitoring cognitive engagement (alpha rhythm);
- Producing biofeedback situations;
- Controlling anesthesia depth (servo anesthesia);
- Investigating epilepsy and locating seizure origin;
- Testing epilepsy drug effects;
- Assisting in experimental cortical excision of epileptic focus;
- Monitoring the brain development;
- Testing drugs for convulsive effects;
- Investigating sleep disorders and physiology;

1.3 Characteristics of EEG signals

EEG signals reflect often brain rhythms that reflect the current state of the brain for example sleep or wakefulness. The main characteristics that are used to make inferences about the brain rhythms are the frequency and amplitude of the signal. These characteristics are however not independent of other factors and often change with age and also show variations from person to person.
The main brain waves distinguished by frequency are listed below.

1.3.1 Delta Waves

Delta waves lie within the range of 0.5–4 Hz. These waves are primarily associated with deep sleep and may be present in the waking state. It is very easy to confuse artefact signals caused by the large muscles of the neck and jaw with the genuine delta response. This is because the muscles are near the surface of the skin and produce large signals, whereas the signal that is of interest originates from deep within the brain and is severely attenuated in passing through the skull. Signal processing methods need to be applied to distinguish genuine delta responses from artefacts.

1.3.2 Theta Waves

Theta waves lie within the range of 4–7.5 Hz. They are generally associated with access to subconscious material and creative inspiration or deep meditation. The theta wave plays an important role in infancy and childhood. Larger contingents of theta wave activity in the waking adult are abnormal and are caused by various pathological problems. The changes in the rhythm of theta waves have been used in maturational and emotional studies.

1.3.3 Alpha Waves

Lie in the range of 8-13 Hz and are mostly recorded over the posterior part of the brain called the occipital region of the brain. Most commonly they are rounded or sinusoidal in shape but in rare cases observed to have sharp negative peaks with rounded positive peaks. Alpha waves have been thought to indicate both a relaxed awareness without any attention or concentration. The alpha wave is the most prominent rhythm in the whole realm of brain activity and possibly covers a greater range than has been previously documented. Peaks have been observed in both the beta and the other ranges while in an alpha setting, showing alpha characteristics. The normal amplitude of the alpha wave is around 50uV. The origin and the significance of the alpha wave is an active research area.

1.3.4 Beta Waves

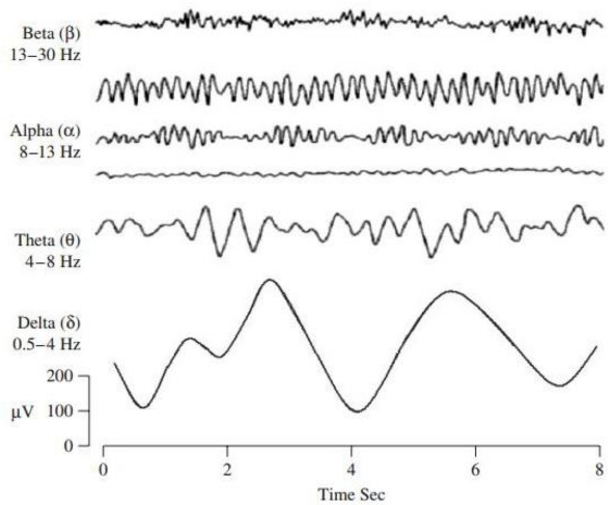
A beta wave is the electrical activity of the brain varying within the range of 14–26 Hz. A beta wave is the usual waking rhythm of the brain associated with active thinking, active attention, focus on the outside world, or solving concrete problems, and is found in normal adults. A high-level beta wave may be acquired when a human is in a panic state. Rhythmical beta activity is encountered chiefly over the frontal and central regions. Importantly, a central beta rhythm can be blocked by motor activity or tactile stimulation. The amplitude of beta rhythm is normally under 30μV.

1.3.5 Gamma Waves

The frequencies above 30 Hz correspond to the gamma range. Although the amplitudes of these rhythms are very low and their occurrence is rare, detection of these rhythms can be used for confirmation of certain brain diseases. The regions of high EEG frequencies and highest levels of cerebral blood flow (as well as oxygen and glucose uptake which are relevant to fMRI measurements) are located in the frontocentral area. The gamma wave band has also been proved to be a good indication of event-related synchronization (ERS) of the brain and can be used to demonstrate the locus for right and left index finger movement, right toes, and the rather broad and bilateral area for tongue movement.

The image shows the various types of waves described above and their frequency bands. Note that here the gamma waves are included in the beta range. This is a somewhat prevalent practice and the gamma waves are sometimes called fast beta waves.

These rhythms are cyclic in nature and correspond to the steady state responses of the brain, in addition to this transients such as an event-related potential (ERP) and containing positive occipital sharp transient (POST) signals (also called rho (ρ) waves) may be observed in EEG signals. Artefacts caused by the eye interference such as fluttering of eyelids may be similar to an alpha rhythm in the posterior part of the brain and need to be filtered out. Other extraneous signals may be caused by any bone defects or brain malfunction.



1.4 EEG Recording Systems

1.4.1 Requirements and Current Standards

Electroencephalography (EEG) is a pivotal tool in understanding brain functions and examining cognitive processes like memory. In your study, EEG plays a central role in investigating the effects of intermittent theta-burst stimulation (iTBS) on working memory performance. The EEG system used in this study, along with the electrodes and standards followed, ensure high-quality and reliable data acquisition to support the investigation of neural correlates of cognitive functions.

The EEG recording electrodes and their proper function are crucial for acquiring high quality data. Different types of electrodes are often used in the EEG recording systems, such as:

- disposable (gel-less, and pre-gelled types);
- reusable disc electrodes (gold, silver, stainless steel, or tin);
- headbands and electrode caps;
- saline-based electrodes;
- Needle electrodes.

In this study, EEG data was recorded using a **128-electrod**e R-Net MR cap, which offers high-density electrode coverage for accurate neural activity capture. The electrode setup follows the international 10-20 system with additional electrodes placed to ensure optimal signal detection across relevant brain regions. Specifically, the system includes electrodes such as Fp1, Fp2, Fz, Cz, Pz, and others, ensuring comprehensive coverage of both frontal and parietal areas, which are key for examining the dorsolateral prefrontal cortex **(DLPFC)** activity involved in working memory tasks.

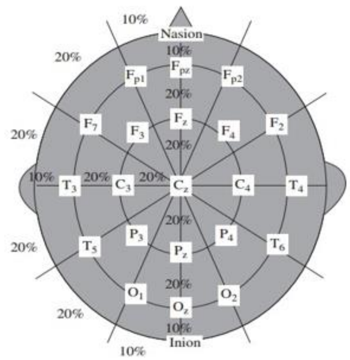
The system meets international standards, **including IEEE 1033-2018, ISO 13485**, and IEC 60601-1, ensuring data quality, safety, and compliance with clinical research protocols. The setup allows for high-resolution data collection, critical for analyzing event-related potentials (ERPs) and power spectral densities (PSDs) before and after the application of intermittent theta-burst stimulation (iTBS) on participants.

1.4.2 Modes of Recording

For the EEG recordings in this study, the differential mode was used, where each electrode pair records the difference in voltage between two electrodes. This method allows for capturing the neural activity at specific brain regions while minimizing common noise. In our setup, the electrodes are positioned according to the international 10-20 system and are supplemented with additional electrodes for better signal accuracy, particularly in the frontal and parietal regions critical for working memory tasks.

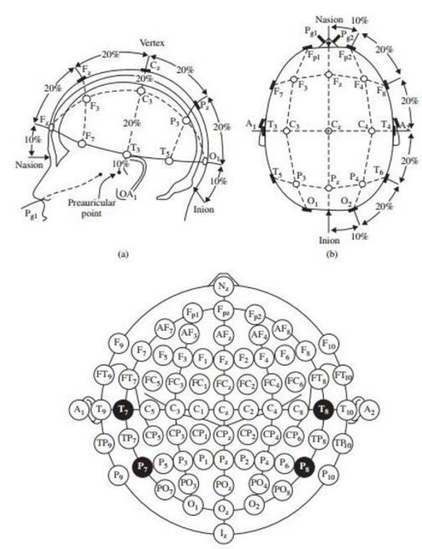
1.4.3 Electrode Placement Standards

The diagram below represents the placement of 21 electrodes in a standard recommended system called the 10-20 system.



Several other recording systems exist for example, in the Maudsley electrode positioning system, the conventional 10–20 system has been modified to capture better the signals from epileptic foci in epileptic seizure recordings. The only difference between this system and the 10–20 conventional system is that the outer electrodes are slightly lowered to enable better capturing of the required signals. The advantage of this system over the conventional one is that it provides a more extensive coverage of the lower part of the cerebral convexity which is important for epilepsy studies. Many systems have been proposed by researchers over the years mostly to cater to various specialized needs.

The diagram in the right shows a more detailed diagram of the 10-20 system for the placement of 75 electrodes around the skull:



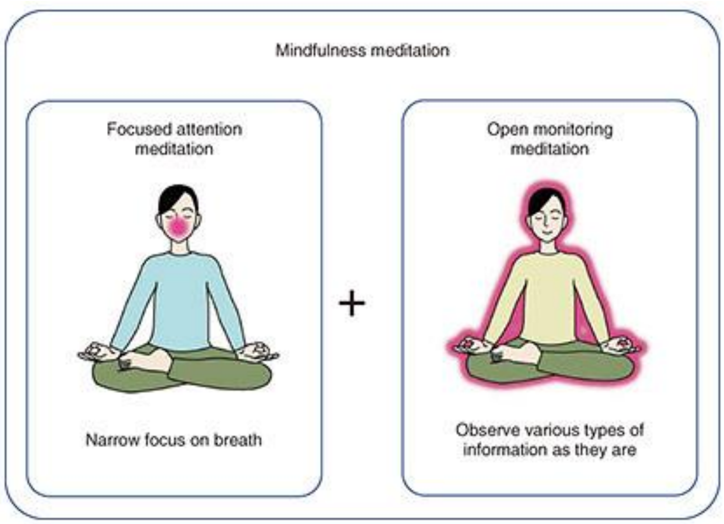
1.5 Types of Meditation

1.5.1 Focused Attention Meditation

The It is a common meditation practice that involves the practitioner continuously main-taining focus on a particular object in the present time such as the breath, a mantra, or some external stimulus. Various cultures all over the world practice this clinical form of meditation in accordance with their specific scriptures and archives. This form of meditation is associated with Gamma wave activity (>30 Hz) Long-railed practice of FAM cultivates strong connectivity within the brain, thus resulting in better cognitive performance.

1.5.2 Open Monitoring Meditation

OMM is the opposite of FAM, it causes the practitioner to detach from their autobio-graphical memory [10]. FAM and OMM can help reduce mind wandering and sponta-neous thoughts and are widely practiced getting rid of exasperation and vexation. In OMM, meditators keep a detached yet present consciousness of whatever that occurs in their present experience. While maintaining this consciousness all emotions, physical sensations and thoughts are not considered interruptions but just elements to be wit-nessed. However, if practitioners react to the present phenomena they are distracted from the consciousness. During OMM, redirecting attention from distracting elements is more difficult than in FAM, as there is no specific target object to maintain a focus on, instead, practitioners just need to refrain from reacting to external stimuli.



1.5.3 Automatic Self-Transcending

Automatic Self-Transcending (AST) refers to a category of meditation practices that allow the mind to effortlessly settle into a state of deep inner silence beyond thought. Unlike the previous techniques, FAM or OMM, AST does not require the performer to engage actively, such as maintaining focus on an object or monitoring ongoing experi-ences. Instead, it involves shifting attention and awareness inwards thereby leading to a state of pure consciousness. Chanting of the mantras, which is a key practice in many cultures, is an example of the Transcendental Meditation technique.

Chapter 2: Aim and Objectives

Aim: To analyze EEG-based neural dynamics across meditation states and associate their relationship with respective Brainwaves

2.1 Problem Statement

Meditation is known to influence brain activity, but it is unclear how different meditation techniques uniquely affect brainwave patterns. Most studies treat meditation as a single activity rather than comparing distinct techniques. This project aims to analyze EEG data collected during various meditation practices and use data science and machine learning to identify and classify the brainwave patterns associated with each technique

2.2 Key Gaps

- The causal mechanisms behind EEG changes during meditation are not fully understood.
- The long-term persistence of meditation-induced brain changes is unclear.
- Distinguishing correlation from causation in brainwave shifts remains challenging

2.3 Our study

- Using EEG + ML to compare three main types of meditation,
- Matching each to its dominant brainwave pattern,
- Investigating why these changes happen (not just what happens),
- And considering whether changes are temporary or Persistant (reversible)

Chapter 3: Literature Survey

Author	Year	Objective	Methods used	Dataset	Key Findings	Performance Metrics	Limitations
Braboszcz et al.	2017	Investigate EEG activity differences across meditation traditions.	EEG analysis, gamma wave detection.	Meditators & control group (N = varied).	Higher gamma amplitudes in meditators.	Gamma wave amplitude comparison.	Small sample size, cross-sectional.
R. M. Vivot et al.	2020	Analyze entropy changes in EEG due to meditation.	Entropy estimation, ML classifiers.	EEG from 3 meditation traditions.	Vipassana increased entropy most (alpha & gamma bands).	Entropy changes across meditation types.	Limited to specific meditation traditions.
Padmavathi Kora et al.	2021	Systematic review of EEG-based meditation research.	Review of past studies on EEG & meditation.	Multiple prior EEG studies.	Summarized EEG-based insights on meditation.	Qualitative insights from literature.	Lack of experimental validation.
Nike Walter & Thilo Hinterberger	2022	Explore EEG complexity & criticality in meditation.	Spectral, complexity, and criticality analysis.	EEG recordings from expert meditators.	EEG complexity effectively mapped meditation states.	EEG feature differentiation metrics.	Findings may not generalize to beginners.
Baoxiang Shang et al.	2023	Examine mindfulness effects using DL & ML.	Deep learning & ML for EEG feature extraction.	EEG recordings from mindfulness trainees.	EEG features with mindfulness training.	Deep learning classification accuracy.	Training effects not tracked long-term.
Alexander T. Duda et al.	2024	Analyze EEG spectral changes in mindfulness meditation.	EEG spectral analysis (theta, alpha, beta).	40 participants ,6-week intervention.	Increased theta, alpha, beta amplitudes.	Spectral power analysis.	Short-term study, limited participants.
Amit Bernstein et al.	2024	Use ML to characterize EEG changes in focused meditation.	XGBoost classifier for EEG pattern recognition.	26 meditators, EEG recordings.	83% accuracy in distinguishing states.	83% accuracy, 79% AUC-ROC, 74% F1-score	Focused only on experienced meditators.
Nicco Reggente et al.	2024	Decoding meditation depth using EEG data.	Self-reporting & EEG probing techniques.	34 Vipassana meditators, self-reported depth.	Novel method improved meditation depth decoding.	Correlation between EEG features & depth.	Self-reported depth may introduce bias.

Chapter 4: Proposed System

4.1 Overview

The proposed system focuses on analyzing EEG signals collected during different meditation states and classifying them using machine learning and deep learning techniques. The system follows a step-by-step pipeline, including EEG data acquisition, preprocessing, feature extraction, and classification.

4.2 System Workflow

EEG Data Acquisition:

1) EEG Data Acquisition is the first and most important step in the system workflow. In this phase, brain signals are collected from the user while performing different meditation techniques
2) EEG signals are recorded using the 10-20 international electrode placement system.
3) Electrodes placed at frontal, temporal, parietal, and occipital regions capture brain wave activity during meditation.
4) Process Steps:
   a) EEG Device Setup
   - Place EEG electrodes or headset on the user's scalp at specific positions (based on 10-20 system).
   - Ensure proper connection for accurate signal capturing.

   b) Signal Recording During Meditation
   - Ask the user to perform different meditation techniques like:Mindfulness Meditation ,Breathing Meditation ,Focused Attention Meditation ,Relaxation State.

   c) Data Collection Parameters
   - Frequency range: 0.5 Hz – 50 Hz
   - Sampling Rate: 128 Hz / 256 Hz / 512 Hz (depending on device)
   - Duration: 5-15 minutes per session

   d) Storage of Raw EEG Signals
   - Store EEG signals in a database or file (CSV, EDF, or MAT format) for further analysis.
5) To capture high-quality brain signals that represent different mental states during meditation. This raw EEG data will be used for pre-processing, feature extraction, and machine learning model training.

4.3 Preprocessing:

1) Preprocessing is a crucial step in the system workflow to clean and prepare the raw EEG data for further analysis. The raw EEG signals often contain noise and unwanted artifacts that need to be removed for accurate results.
2) Process Steps:

i. Noise Removal

- Remove external noise and artifacts caused by: Eye blinks , Muscle movements , Power-line interference , Body movements

- Techniques used:Bandpass Filter (Example: 0.5 Hz – 50 Hz) and Notch Filter (to remove 50/60 Hz electrical noise)

ii. Artifact Removal Techniques :

- Independent Component Analysis (ICA), Principal Component Analysis (PCA) and Manual visual inspection (if required)

iii. Signal Normalization

a) Normalize the EEG signal values for better performance of machine learning models.

b) Example: Min-Max Scaling or Z-score normalization.

iv. Segmentation of EEG Data

Divide the EEG signal into smaller time windows (segments) for feature extraction.

Example: 2 seconds or 5 seconds window size.

3) Noise and artifacts (eye blinks ,muscle movements) are removed using Independent Component Analysis (ICA) and bandpass filtering.
4) To convert noisy raw EEG signals into clean, smooth, and structured data so that important brain wave features can be easily extracted and analyzed.

4.3 Feature Extraction:

1) Techniques like Fourier Transform (FT), Wavelet Transform (WT), and Power Spectral Density (PSD) are used to extract EEG features.
2) Feature Extraction is the process of extracting meaningful information (features) from pre-processed EEG signals. These features represent the brain activity patterns and help in identifying different meditation states.
3) Raw EEG data is high-dimensional and difficult to analyze directly.
4) Features help convert complex signals into numerical values that can be easily processed by Machine Learning models.
5) To generate a compact and informative feature set from EEG signals that captures the brain's response during different meditation techniques for accurate classification.
6) Common Features Extracted from EEG Signals:
    a. Time Domain Features.
    b. Frequency Domain Features.
    c. Entropy Features.
    d. Statistical Features.
    e. Wavelet Transform Features.

4.4 Classification Models:

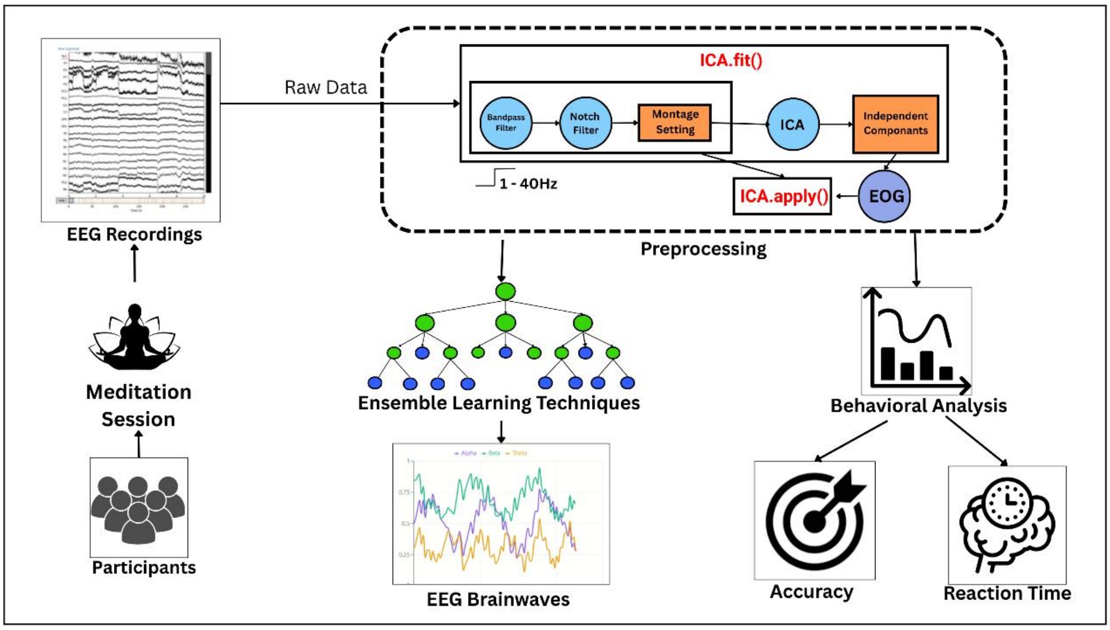
1) **Conventional ML Models**: Logistic Regression, Support Vector Machine (SVM), k-nearest Neighbors (k-NN).
2) In this step, Machine Learning (ML) or Deep Learning (DL) models are used to classify the EEG signals into different meditation states based on the extracted features.
3) To automatically predict or identify the mental state of a person during meditation using EEG data.

4) Deep Learning Models: Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Artificial Neural Network (ANN).
5) To develop an intelligent and automated system that can classify real-time EEG signals into correct meditation states, providing valuable feedback to users or mental health professionals.

4.5 Visualization & Analysis:

1) EEG signals are visualized to identify patterns linked to different meditation techniques.
2) Visualization and Analysis is the final step where the results of EEG signal classification and brain activity patterns are presented in a clear and understandable format using graphs, charts, and dashboards.
3) To help users, researchers, or healthcare professionals easily interpret the brain activity and meditation states based on EEG data analysis.
4) To present EEG analysis results in a user-friendly and interactive manner, allowing better understanding of meditation effects on brain activity and enabling further cognitive or clinical research.
5) Techniques Used for Visualization:
    a) Brain Wave Plots:
        1. Visual representation of different brain waves (Delta, Theta, Alpha, Beta, Gamma) over time.
        2. Helps to observe changes in brain activity during meditation sessions.
    b) Power Spectral Density (PSD) Graphs:
        1. Shows the power of each frequency band.
        2. Identify which brain wave dominates during specific meditation techniques.
    e) Confusion Matrix:
        1. Visual representation of the performance of classification models.
        2. Shows correctly and incorrectly classified states.
    f) Accuracy & Loss Graphs:
        1. Plots showing the model's accuracy and loss over training epochs
        2. Helps in evaluating model performance.
    g) Real-Time Dashboard:
        1. Display real-time meditation state detection.
        2. Show metrics like:Relaxation Level , Focus Level , Stress Detection ,Meditation Progress Over Time.

4.3 Block Diagram of Proposed System



Chapter 5: System Requirement Study

5.1 Hardware Requirements

- EEG Headset with 10-20 electrode system
- High-performance GPU (for deep learning models)
- Data storage (Minimum 500GB HDD/SSD)
- High-speed computing system

5.2 Software Requirements

- Programming Languages: Python, MATLAB
- Libraries & Frameworks: TensorFlow, Keras , Scikit-Learn, EEGLAB (for EEG preprocessing)
- Data Processing Tools: Numpy, Pandas, OpenCV
- Visualization Tools: Matplotlib, Seaborn

Chapter 6: Architecture

6.1 Data Collection and Properties

Raw EEG data for all participants is imported into the analysis pipeline using the appropriate libraries (e.g., *MNE-Python*). Each participant's dataset contains multiple files, including EEG signals, channel metadata, and event markers. Upon import, channel information (electrode labels, sampling rate, and sensor type) is automatically read and verified to ensure consistency across datasets.

Since some meditation sessions include additional physiological signals (e.g., respiration, GSR), synchronization is performed to align all recorded streams on a common timeline. Event markers embedded during data acquisition are used to segment the EEG into meaningful intervals corresponding to baseline, meditation, and post-meditation phases. This ensures that feature extraction and analysis are performed on accurately time-aligned EEG segments across all participants and meditation groups.

6.2 Signal Cleaning and Artifact removal

The EEG signals are often contaminated by various types of noise and artifacts, which can distort the data and compromise the validity of the analysis.

6.2 1 Common EEG Artifacts Observed

EEG data is frequently contaminated by a variety of artifacts, which can be categorized into:

- **Eye Movement Artifacts (EOG):**
  These arise from eye blinks and movements, typically visible as sharp deflections in the EEG signal. The frontal electrodes, especially near the Fp1 and Fp2 locations, are highly sensitive to these artifacts.
- **Muscle Artifacts (EMG):**
  These result from muscle contractions, particularly from facial muscles, and can affect the signal in the frontal and central regions.
- **Powerline Noise:**
  This is a common artifact caused by electrical interference from power lines, typically at 50 Hz (or 60 Hz, depending on the region).
- **Electrode Pop Artifacts:**
  These occur when there is poor contact or loose electrodes, leading to sudden jumps or spikes in the EEG signal.

6.2.2 Filtering Techniques

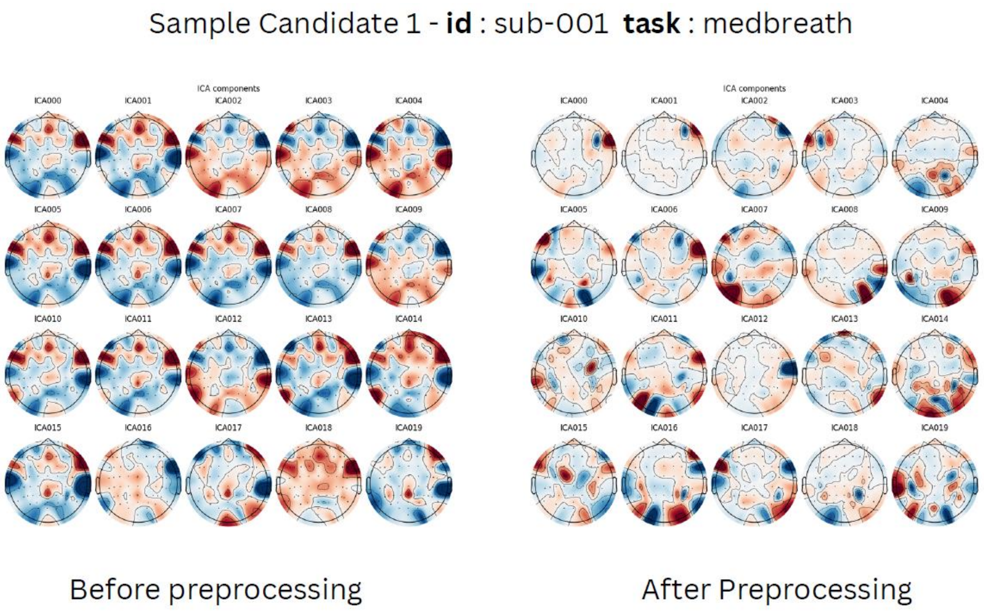
To clean the EEG data, several filtering techniques are applied to reduce the influence of noise and artifacts. These include:

- **Bandpass Filtering (1-40 Hz):** This filter removes frequencies outside the typical range for EEG, typically between 1 Hz and 40 Hz. It helps to retain the relevant brain activity while filtering out low-frequency drift and high-frequency noise.
- **Notch Filtering (50 Hz):** A notch filter is applied to remove powerline interference, which typically appears as a 50 Hz noise in the sign

ICA (Independent Component Analysis) was used as a computational technique to separate mixed signals into their independent components. In the context of EEG data, ICA was particularly effective for identifying and removing artifacts, such as those caused

Here Filtering takes place in following 7 steps

1. Bandpass Filtering (1-40 Hz)
2. Set EEG Montage (10-20 system)
3. Remove Powerline Noise (50 Hz Notch Filter)
4. Run ICA for Artifact Removal
5. Use Fp1 (or Fp2) as EOG Proxy Channel for Artifact Removal
6. Extract Events from Annotations
7. Create Epochs Aligned to Each Event Type



Filtering Signals and Artifacts

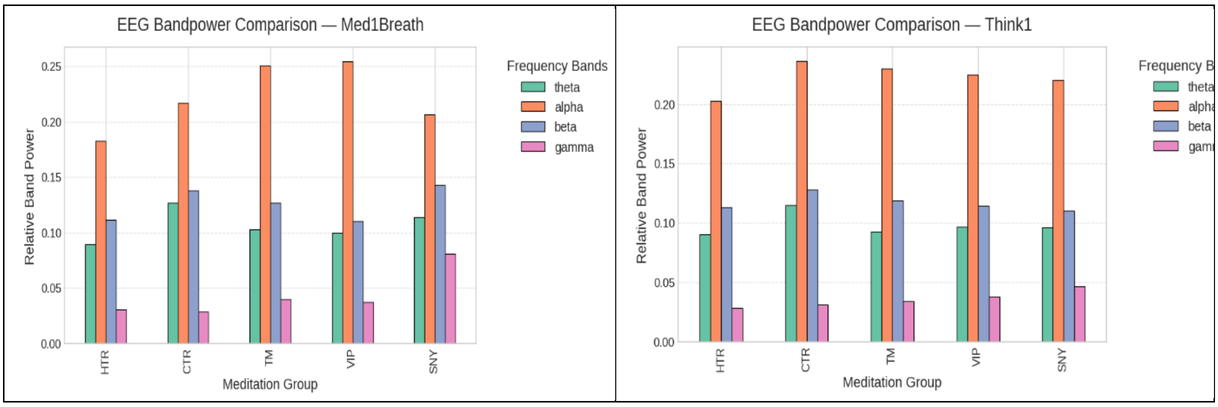
6.3 Feature Extraction (Power Spectrum Density)

After the EEG data is cleaned using ICA and segmented into relevant meditation intervals, the signals are transformed into the frequency domain to extract features that represent brainwave activity. Power Spectral Density (PSD) is computed using **Welch's method**, which provides a stable estimation of how signal power is distributed across different frequency bands. From the PSD values, the average power of each brainwave band (delta, theta, alpha, beta, gamma) is calculated for every EEG channel. These features form the input dataset for statistical analysis and machine learning, enabling the comparison of meditation techniques based on their unique neural signatures.

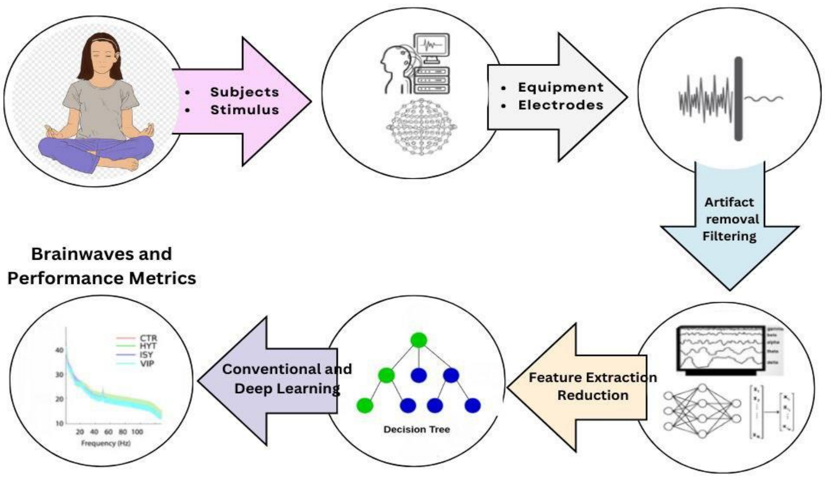
Step No.	**Feature Extraction Action**	**Description / Output**
1. PSD Computation	Apply Welch's method to compute PSD for each EEG channel.	Converts signal from time-domain → frequency-domain.
2. Frequency Band Segmentation	Divide PSD into standard EEG bands: • Delta (0.5–4 Hz) • Theta (4–8 Hz) • Alpha (8–13 Hz) • Beta (13–30 Hz) • Gamma (>30 Hz)	Helps identify dominant brain activity relevant to cognitive/meditative states.
3. Band Power Extraction	Calculate mean power value within each band for every channel.	Converts PSD spectrum into a numeric feature vector.

6.4 Data Analysis

The first plot shows how brainwave activity varies across four tasks (two meditation-related and two thinking tasks) within the control (CTR) group. Delta power remains dominant across all tasks, indicating a relaxed or low-engagement state, while alpha and theta remain moderately stable. Beta and gamma power stay consistently low, reflecting minimal cognitive load or focused engagement. This suggests that the control group does not exhibit notable modulation of brainwave activity based on task type, possibly due to the absence of meditation training



The second plot compares the **Think1 task** across all meditation groups (HTR, CTR, TM, VIP, SNY). Here, alpha remains the highest across all groups, which indicates calm wakefulness during a cognitive activity. However, meditation-trained groups (HTR, TM, VIP, SNY) show relatively higher theta power compared to the control group. Theta activity is linked to internalized focus, sustained attention, and meditative awareness. Meanwhile, the control group shows a slightly stronger beta response, reflecting a more typical cognitively driven processing style during thinking tasks. Gamma power remains low overall, but shows a slight increase in the SNY group, indicating deeper cognitive integration.

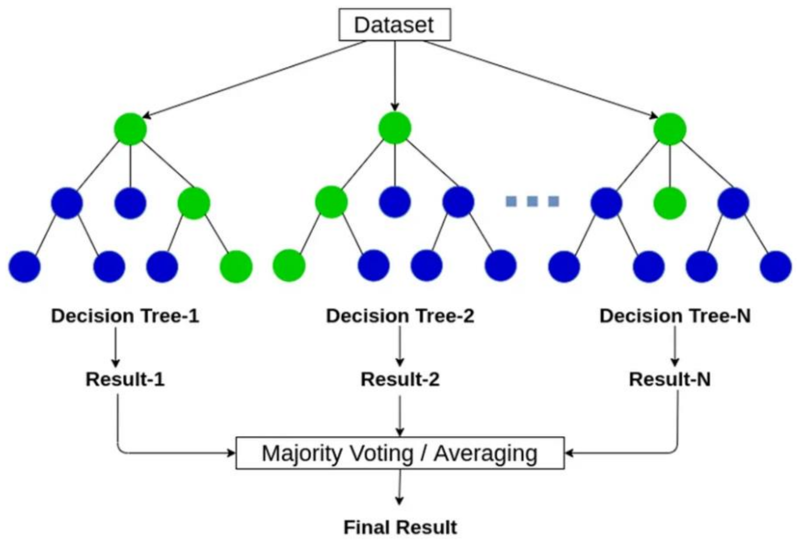


Chapter 7: Algorithm

In the context of EEG data analysis, Random Forest was employed to classify the features extracted from EEG signals recorded during cognitive tasks (2-back and 3-back) in both the active and sham iTBS groups before and after stimulation.

7.1Random Forest Classifier

The Random Forest classifier builds multiple decision trees, where each tree is trained on a randomly selected subset of data. It creates an ensemble by using different combinations of input data and features, ensuring that each tree is diverse. This diversity reduces the risk of overfitting, a common problem in single decision tree



How does Random Forest algorithm work?

The random forest algorithm operates in the following steps:

Step-1 : Bootstrap Sampling (Bagging):

From the original training dataset, multiple bootstrap samples are generated. A bootstrap sample is a random sample drawn with replacement, meaning that the same data point may appear more than once in a sample, while others may not appear at all.

Each decision tree in the random forest is trained on a different bootstrap sample.

Step-2 : Random Feature Selection:

At each node of the decision tree, instead of considering all features (as in standard decision trees), the algorithm randomly selects a subset of features. This adds additional randomness and helps decorrelate the trees, making the final model more generalizable.

This random feature selection is a key difference between random forests and bagging with decision trees.

Step-3 : Grow Decision Trees:

Each tree in the forest is grown to the maximum extent without pruning. The goal is to let each tree overfit its particular bootstrap sample.

Step-4 : Aggregation:

For classification, the predictions of all trees are combined using majority voting. The class that gets the most votes becomes the final prediction.

For regression, the predictions of all trees are averaged to produce the final output.

Key Hyperparameters of Random Forests

Tuning the hyperparameters of a random forest model can have a significant impact on its performance. The main hyperparameters include:

1. Number of Trees (n_estimators):

This parameter specifies how many trees the random forest should include. More trees generally improve accuracy, but they also increase computational cost.

2. Number of Features to Consider (max_features):

Controls how many features the algorithm should consider when making splits at each node. Options include:

- "**auto":** Use the square root of the number of features (default for classification).
- **"sqrt":** Same as "auto".
- **"log2":** Use the logarithm of the number of features.

An integer: Specify an exact number of features to consider.

3. Tree Depth (max_depth):

Limits the maximum depth of the individual trees. Shallow trees help reduce overfitting, but if trees are too shallow, the model may underfit.

4. Minimum Samples per Split (min_samples_split):

The minimum number of samples required to split an internal node. Higher values prevent trees from being too specific to small groups of data, reducing overfitting.

5. Minimum Samples per Leaf (min_samples_leaf):

The minimum number of samples required to be at a leaf node. It prevents overly small leaves, which can lead to overfitting.

5.3.1 Mathematical Explanation

The Random Forest classifier relies on decision trees as base learners. The classification process involves the following key mathematical concepts:

Decision Tree Split Criterion:

- **Gini Impurity:** Measures the impurity of a dataset. For a dataset DDD with classes CCC, it is calculated as:

$$I_{Gini}(D) = 1 - \sum_{i=1}^{C} P_i^2$$

Where P_i is the proportion of class i in D. The aim is to minimize Gini impurity for better splits.

- **Entropy:** Measures the disorder in a dataset. For dataset DDD, it is calculated as:

$$I_{Entropy}(D) = -\sum_{i=1}^{C} P_i \, log_2 \, P_i$$

The goal is to minimize entropy to achieve better splits.

- **Random Feature Selection:**

For each tree, only a random subset of features is considered at each split. This ensures diversity among trees and prevents overfitting.

- **Ensemble Voting:**

After training, each tree makes a prediction. The final prediction is determined by majority voting:

$$yRF = mode(y_1, y_2, y_3 \dots \dots y_n)$$

Where $y_1, y_2, y_3 \dots \dots y_n$ are the predictions from the T trees, and the mode selects the most frequent class.

- **Out-of-Bag (OOB) Error:**

OOB error provides an unbiased estimate of the model's performance, calculated as:

$$OOB\ Error = \frac{1}{N}\sum_{i=1}^{N} I(y_i \neq yRF_i)$$

Where y_i is the true class and yRF is the predicted class. This error is used for validation without needing a separate test set.

Chapter 8: Conclusions and Future scope

Result and Discussion:

The EEG data from multiple meditation traditions were analyzed with respect to changes in alpha (8–13 Hz) and gamma (>30 Hz) band power between meditation and non-meditative (thinking) conditions. The relative power differences (Δ values) provide insights into how neural oscillations vary across meditation styles.

These variations in frequency-band power highlight how each meditation form uniquely engages neural circuits related to attention and awareness. Shoonya meditation exhibited the most pronounced gamma enhancement, indicative of high cortical synchronization and sensory detachment. Vipassana meditation displayed the strongest alpha dominance, corresponding to deep relaxation and stable open monitoring. In contrast, the control and Himalayan Yoga groups maintained relatively flat spectral profiles, showing minimal oscillatory modulation.

Tradition	**Alpha (Meditation)**	**Gamma (Meditation)**	**Pattern Summary**
CTR	Moderate	Low	Baseline non-meditative pattern
HTR (Himalayan Yoga)	Low–moderate	Low	Calm and steady; minimal oscillatory variance
SNY (Shoonya)	Low	High gamma	Open-awareness state with strong parieto-frontal gamma coupling
TM (Transcendental Meditation)	High alpha, mild gamma	Moderate	Focused attention with inward-directed processing
VIP (Vipassana)	**Highest alpha**	High gamma	Somatic open-monitoring; strong alpha coherence

Table3 : Vipasana and Isha shoonya showing high gamma frequency

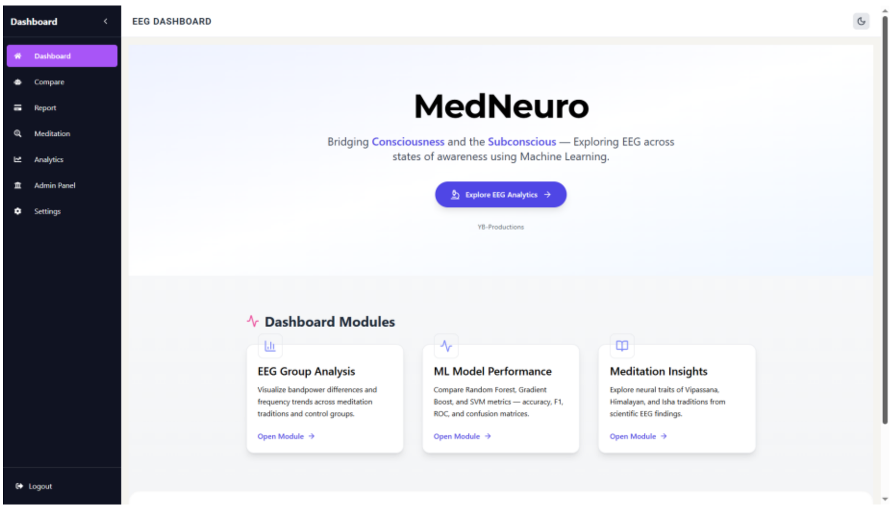


Fig: EEG Analytics Dashboard

Conclusion:

The study successfully demonstrated that different meditation techniques produce distinct EEG spectral patterns, reflecting varied cognitive and neural processes. While control participants showed negligible spectral variation, meditative states revealed significant modulations in alpha and gamma power, validating the hypothesis that meditation alters neural oscillatory dynamics.

Key findings indicate that:

- **Shoonya Meditation** enhances gamma-band synchronization, reflecting heightened awareness and open sensory monitoring.
- **Vipassana** shows pronounced alpha activity, associated with deep relaxation and cognitive stability.
- **Transcendental Meditation** exhibits balanced alpha–gamma coupling, characteristic of focused yet effortless attention.
- **Himalayan Yoga** maintains steady baseline activity, signifying emotional equilibrium without strong oscillatory transitions.

These outcomes align with contemporary contemplative neuroscience literature, suggesting that EEG-based analysis can reliably distinguish meditation types based on their spectral signatures. The integration of **EEG preprocessing, spectral analysis, and machine learning** establishes a scalable framework for identifying neural correlates of consciousne

Future Scope:

The findings of this study lay the groundwork for several promising directions in future research:

1. **Real-Time EEG Meditation Analysis** – Implementing wearable EEG devices to analyze meditation states in real-time for better insights into neural activity.
2. **Integration with Neurofeedback Systems** – Using EEG-based neurofeedback techniques to enhance meditation practices, allowing users to self-regulate brainwave activity for improved cognitive performance.
3. **Deep Learning for Advanced Classification** – Exploring the use of transformer models and graph neural networks (GNNs) to improve meditation state classification accuracy.
4. **Longitudinal Studies on Brain Plasticity** – Conducting long-term studies to determine whether EEG changes due to meditation persist over extended periods.
5. **Personalized Meditation Programs** – Using EEG data and AI-driven recommendation systems to tailor meditation practices to individuals based on their brainwave patterns.
6. **Clinical Applications in Mental Health** – Investigating the application of EEG-based meditation analysis in treating stress, anxiety, and neurological disorders, leading to non-invasive therapeutic interventions.
7. **Cross-Cultural Meditation Comparisons** – Expanding the study to analyze how meditation practices from different traditions influence EEG patterns differently.

Chapter 9: References

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Appendix A: Survey Paper with Plagiarism Report