Neuropsychological Trends

35
April 2024

Investigating the impact of mindful breathing meditation on brain waves: a study on young adults

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DOI: https://doi.org/10.7358/neur-2024-035-cruz

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ABSTRACT

Extensive evidence affirms meditation's impact on both physical and mental well-being, consistently highlighting increased alpha power during meditation. This study investigates how mindful breathing meditation affects brain waves in young adults, using EEG data from 15 participants. Focusing on boosting alpha wave power, the study shows a significant post-meditation increase. Data was processed with Finite Impulse Filters, Independent Component Analysis, Short-term Fourier analysis, and power spectral density analysis. The results highlight substantial alpha wave changes pre- and post-meditation. Additionally, data was preprocessed for machine learning-based classifiers (Support Vector Machine, Logistic Regression, Decision Forest, and Naïve Bayes) to categorize brain waves into Delta, Theta, Low Alpha, High Alpha, Low Beta, and High Beta. Comparative analysis reveals the strong impact of mindful breathing meditation and binaural beats on brain wave patterns. This research enhances our understanding of meditation's physiological effects on brain function, emphasizing its potential for improving mental well-being.

Keywords: brain computer interface; electroencephalograms (EEG); alpha waves; meditation; machine learning based classifier

1. Introduction

Meditation, a practice with a history spanning thousands of years, has been widely recognized for its positive impact on human well-being. It has shown various benefits, including stress reduction, improved mental health, increased focus, and attention, and enhanced emotional well-being. However, the specific effects of meditation can differ among individuals and different meditation practices. Four different types of meditation practices are there, which are defined by how attention is directed: Transcendental Meditation, mindfulness meditation, open-heart meditation, and Dharana Meditation. Transcendental Meditation is characterized by minimal internal chatter, while mindfulness meditation involves adopting an observer state of awareness, attentively observing thoughts, emotions, and physical sensations without attachment, and emphasizing present-moment awareness. Open heart meditation encompasses practices like loving-kindness, compassion, gratitude, and forgiveness-based meditations (Yordanova et al., 2020). Dharana meditation, the focus of our research, entails sustaining attention on a single object, such as the breath or a mantra. The emphasis lies in recognizing and redirecting the mind when it wanders from the focal point. Specifically, our study selected Dharana meditation with breathing as the chosen focal point.

Mindfulness-based neuroscience studies typically employ a longitudinal approach to investigate the effects of mindfulness practice instead of focusing solely on situational practice effects. In order to assess the effectiveness of mindfulness interventions, researchers commonly utilize objective measures of brain functions, such as electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) (Izzetoglu et al., 2020). Among various neuroimaging techniques, EEG has gained widespread popularity, particularly within the field of brain-computer interface research, due to its temporal resolution, versatility, non-invasiveness, and cost-effectiveness advantages (Jamal, Cruz, Chakravarthy, et al., 2023). Building upon the existing body of research, our present investigation aims to explore the neurophysiological impact of meditation by employing EEG. This method involves measuring the brain's electrical activity through electrodes placed on the scalp. The resulting recorded signals, which reflect different states of consciousness, yield extensive data that can shed light on the various states of consciousness.

The electrical patterns observed in EEG recordings can be categorized into five distinct brain waves, listed in ascending order of frequency: delta (0-4 Hz), theta (4-7 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-63 Hz) (Teplan, 2002). The dominance of a particular brain wave depends on the individual's state of consciousness during a specific task. The activity levels recorded for each of these EEG clusters are measured in microvolts. For each electrode used in the recording, the average power can be determined for the specified EEG bands. Delta waves, the slowest brain waves, are associated with deep therapeutic rest and dreamless sleep. Theta waves are linked to daydreaming and shallow-level sleep, as well as experiencing intense and raw emotions. Alpha waves are typically achieved through relaxation and meditation, serving as a “frequency bridge” between our conscious reasoning (beta) and intuitive (theta) mind (Bazanova & Vernon, 2014). They promote a state of calmness, deep relaxation, and contentment. Beta waves, characterized by low amplitude and high frequency, are commonly observed during wakefulness. In the field of neuroscience, gamma waves represent a more recent discovery, and ongoing research aims to deepen our understanding of their role (Jamal, Cruz & Kim, 2023).

This study aims to harness EEG data to explore the intricate characteristics of meditation and its profound impacts on brain activity. By meticulously analyzing these electrical signals, we intend to generate a dataset that captures the subject’s mental state engaging in meditation practices, both pre- and post-meditation stages. Even the raw EEG signals can provide valuable insights into the individual’s level of awareness. Our study is anticipated to reinforce the existing body of literature on the effects of meditation on the brain while also contributing to a deeper understanding of the distinctions between meditation and relaxation. To enhance the originality and significance of the research, instead of using preexisting data, the data was collected from a group of volunteers. The newly acquired dataset encompasses a diverse array of brain wave patterns. Machine learning models allow to interpret and classify the complex brain wave patterns. Five different classifiers: Multi-Layer Perceptron (MLP), Support Vector Machine (SVM), Logistic Regression (LR), Decision Forest (DF), and Naïve Bayes (NV) have been developed utilizing the collected dataset from the experiment. These classifiers were utilized to effectively categorize the brain waves into six distinct classes: Delta, Theta, Low Alpha, High Alpha, Low Beta, and High Beta. This rigorous classification process allowed for a more comprehensive understanding of the brain wave patterns and their corresponding classes. These versatile classifiers serve as benchmarks for complex models while making them suitable for diverse brain patterns recognition.

The rest of the paper is organized as follows: the Literature survey section provides an in-depth analysis of the existing research; in the methodology section the research hypothesis is presented, outlining the main objective of the study, the data collection procedure is described, including the sources of data and the methods employed to gather it. Additionally, the section covers the data preprocessing techniques used, such as filtering and artifact removal, which ensure the quality and reliability of the collected data. The statistical analysis techniques applied to the data are also detailed, followed by an explanation of the classification process using various Machine Learning algorithms. The Result and discussion section presents the findings of the study and provides a comparative analysis of the results obtained from the different Machine Learning algorithms utilized. The paper concludes with a summary of the key findings and their significance in relation to the research hypothesis. The conclusion highlights the contributions of the study to the existing body of knowledge, emphasizing its potential implications for the field.

2. Literature review

In EEG studies focused on meditation, a variety of analysis methods have been employed. One commonly used technique, as demonstrated by Bosworth (2019) is the application of the Fast Fourier Transform (FFT) to extract features from EEG data, particularly power in different frequency bands. This approach is widely utilized in EEG analysis, except for the Wavelet Transform (WT) which has also been employed in certain cases. Hagerty et al. (2013) showcased the use of power spectral distribution (PSD) as a means to capture the comprehensive content of EEG recordings, defining power levels within specific frequency bands using Welch's method. PSD, in conjunction with other methods, has proven effective in analyzing the power of brain waves in EEG data. In a comprehensive analysis conducted by Schoenberg et al. (2018), involving 30 experienced meditators, it was observed that power density decreased compared to their baseline results. This finding indicated that the state of self-referential function exhibited distinct activity when contrasted with executive-control processing (Schoenberg et al., 2018). Furthermore, researchers have discovered the significance of inter-hemispheric asymmetry in relation to specific frequencies, emphasizing the importance of neural coupling in the context of mindfulness meditation. Haupt's exploration of the differentiation between meditation and unique conscious responses, as distinct from states of relaxation, further reinforces the notion that mindfulness meditation warrants more comprehensive investigation and attention (Haupt, 2008). These collective findings underscore the potential and importance of mindfulness meditation across various populations and highlight the need for further research in this area.

Numerous comprehensive studies have been carried out to explore various facets of meditation practices and their potential outcomes. One notable study conducted by Wahbeh et al. (2018) delved into the specifics of transcendental meditation, which sets it apart from other forms of meditation by purportedly inducing an alternative state of consciousness that cannot be achieved through conventional means. The researchers aimed to gain a deeper understanding of this distinct claim and validate its authenticity through their study. In contrast to common misconceptions that often conflate meditation with relaxation, a study by Dunn et al. (1999) presented empirical evidence demonstrating that meditation produces outcomes that are not attainable through standard relaxation practices. These findings shed light on the unique and distinctive nature of meditation, highlighting its differentiation from relaxation techniques (Dunn et al., 1999).

Mindfulness meditation has been shown to be beneficial even for children, as it enhances their information-processing abilities and suggests a potential method for improving academic achievement (Vekety et al., 2022). In a comprehensive overview by Tarrant (2020) the concept of "Neuromeditation" was explored, which involves the utilization of technologies like electroencephalography (EEG) to enhance or improve meditation practices. This integration of feedback from meditation has directly contributed to the exploration of methodologies for studying different states of meditation. For instance, Dennison (2019) conducted research on jhāna meditation and found that it disrupts the Default Mode Network (DMN), an area of the brain associated with rest, while also enhancing focus and concentration. The diverse array of meditation practices poses challenges in isolating common patterns among them. Başar-Eroglu et al. (1996) identified the gamma band as potentially serving a broader functional role in cognitive processing, suggesting its involvement in a distinct system. Although the association of beta waves with attention and high levels of alertness is well-established, understanding their interaction with cognitive test responses can be elusive. Lim et al. (2019) demonstrated the crucial significance of the relationship between beta waves and theta waves in a concentration versus immersion test, where the specific brain lobes affected varied based on the activity performed. This research highlights the importance of comprehending how different brain regions collaborate to execute complex tasks.

Kaur and Singh (2015) discussed the implementation of the Short-Time Fourier Transform and windowing techniques for time-frequency analysis, involving multiple iterations of FFT to generate waveforms that depict temporal changes. These analysis methods significantly contribute to the comprehension of the frequency and temporal dynamics of EEG signals during meditation.

The hardware specifications of EEG systems play a critical role in accurately capturing brain signals during meditation research. Ahani et al. (2014) conducted a study on the effects of meditation on the elderly using a BioSemi in Common Mode Sense (CMS) system. Brandmeyer et al. (2019) highlighted the importance of hardware specifications by utilizing a 64-channel EEG system with a high sampling rate of 2048 Hz. A higher sampling rate allows for a larger range of frequencies to be analyzed, while an increased number of channels provides more detailed information about brain activity. These studies underscore the significance of employing standardized and high-quality EEG systems to ensure reliable data acquisition in meditation research. In some cases, researchers may employ down sampling techniques to reduce the sampling rate and focus on specific frequencies of interest. For instance, Pekala and Creegan (2020) utilized the Brain master Discovery 24E system, digitally scaling down the sampling rate from 1024 samples per second to 256 samples per second. This down sampling approach is commonly employed to reduce data volume while maintaining focus on specific frequency ranges that are of interest in the study.

The collection of large volumes of data has posed challenges in EEG studies focused on meditation, and as a result, methods for selecting the necessary data have evolved over time. This challenge has been addressed by employing common techniques such as the band-pass filter and independent component analysis (ICA) to filter out artifacts and unwanted data points. The band-pass filter allows for the selection of a specific range of frequencies of interest, eliminating all other frequencies. Additionally, Garland et al. (2022) emphasized using a notch filter to remove electrical components at 60 Hz (or 50 Hz in certain countries) to prevent potential artifacts caused by the proximity of these frequencies to EEG frequency bands. These filtering techniques are crucial for ensuring data quality and integrity in EEG recordings during meditation studies. By employing these methods, researchers can mitigate potential artifacts and enhance the reliability and validity of their findings.

Phase synchronization and independent component analysis (ICA) are essential components of EEG studies focusing on meditation. EEG research has extensively studied and discussed the analysis of waveform phases, with particular emphasis on its significance. Hebert et al. (2005) highlighted the importance of phase synchronization, which involves observing phase shifts within EEG recordings. Lutz et al. (2004) emphasized the use of data epochs, averaging power spectral distribution across electrodes, and employing ICA for artifact removal, providing valuable insights into topographical brain analysis during meditation. Developing topographical analysis methods is invaluable for understanding the underlying brain processes during meditation.

Another emerging approach involves utilizing machine learning techniques to classify meditation-related EEG data. Kora et al. (2021) explored various machine learning algorithms, including Support Vector Machine (SVM), Decision Trees, Artificial Neural Networks (ANN), and K-Nearest Neighbors (KNN), for interpreting EEG signals. These discussions have been instrumental in identifying the most effective algorithms for specific tasks and their applicability in an EEG setting. With EEG data, these algorithms demonstrated the capability to make predictions in meditation studies. Manjusha and Harikumar (2016) conducted a more detailed exploration of KNN and K-Means clustering. They applied both KNN's classification approach and K-Means clustering to EEG data to calculate epilepsy risk in patients. The study found that K-Means clustering exhibited better overall performance in predicting and identifying epilepsy risk. This suggests that K-Means clustering may also prove more efficient in discerning different outcomes in meditative practices.

Most of the research were conducted on preexisting dataset, hence, to enhance the novelty of the work, this study aims to strengthen the existing literature on the impact of meditation on the brain while also providing a deeper understanding of the differences between meditation and relaxation. To enhance the novelty and significance of our research, we collected data directly from a group of volunteers instead of relying on preexisting data. The data consisted of brain wave patterns, which underwent a thorough analysis and classification using five different classifiers: Multi-Layer Perceptron (MLP), Support Vector Machine (SVM), Logistic Regression (LR), Decision Forest (DF), and Naïve Bayes (NV). These classifiers were employed to effectively categorize the brain waves into six distinct classes: Delta, Theta, Low Alpha, High Alpha, Low Beta, and High Beta. Through this meticulous classification process, we achieved a more comprehensive understanding of the brain wave patterns and their respective classes.

3. Method

3.1 Experimental setup

To investigate the hypothesis that there would be a significant increase in alpha wave power density after the meditation stage compared to before meditation, an experiment was conducted involving fifteen volunteers. The research study has obtained required approval from the IRB committee to conduct the research on volunteers. The EEG signal data were collected using the DSI-7 Streamer EEG system from Wearable Sensing System. The experiment consisted of two stages: before meditation and after meditation. EEG signals were recorded from the participants during each stage using the DSI-7 Streamer EEG system. The DSI-7 Streamer is a wearable sensing device that allows for the acquisition of high-quality EEG data.

Prior to the meditation session, baseline EEG signals were recorded while the participants were in a relaxed state with their eyes open. Following the baseline recording, the participants practiced meditation for a predetermined duration by focusing on their breath while binaural beats is played to induce alpha wave activity. After the meditation session, EEG signals were recorded again to capture the post-meditation brain activity. The DSI-7 Streamer system collected EEG signals from 7 electrodes placed on the scalp of the participants. These signals were processed to extract the power density of alpha waves, which are typically associated with a relaxed and alert state. By comparing the alpha wave power density before and after the meditation stage, the experiment aimed to determine if there was a significant increase in alpha wave activity following meditation.

Once the data was collected, it underwent several pre-processing steps to ensure data quality and remove artifacts. Outliers and noisy data points can adversely affect the performance of classification models. Several data mining or analytical tools can be helpful in this process (Jamal, Elenin et al., 2023). Preprocessing techniques like outlier detection and removal help in identifying and eliminating these anomalies. These steps included Finite Impulse Response (FIR) filtering, independent component analysis (ICA), outlier detection, and removal. Following the pre-processing steps, a rigorous statistical analysis was conducted to examine the Power Spectrum Density (PSD) for the EEG data recorded before and after the meditation stage. The PSD plots were visualized and compared to validate the research hypothesis regarding changes in alpha wave activity.

To further analyze the data, the datasets were labelled based on frequency range in order to apply deep learning and machine learning-based classification methods. For deep learning-based analysis, Multi-Layer Perceptron (MLP) was developed and trained using both the before and after meditation datasets. Moreover, for machine learning based analysis, four popular traditional machine learning classification models were implemented: Support Vector Machine (SVM), Logistic Regression, Decision Forest, and Naïve Bayes. The classification models were trained and evaluated using appropriate performance metrics, such as classification accuracy, precision, and recall. The obtained results from the different classifiers were compared to assess their effectiveness in accurately classifying the EEG data before and after meditation. The complete research hypothesis is depicted in Figure 1.

By utilizing deep learning and traditional machine learning approaches, this analysis aimed to provide insights into the classification of EEG data and determine the extent to which the models could differentiate between pre- and post-meditation states. The performance metrics obtained from the classifiers helped assess the accuracy and efficacy of each model in classifying the EEG data.

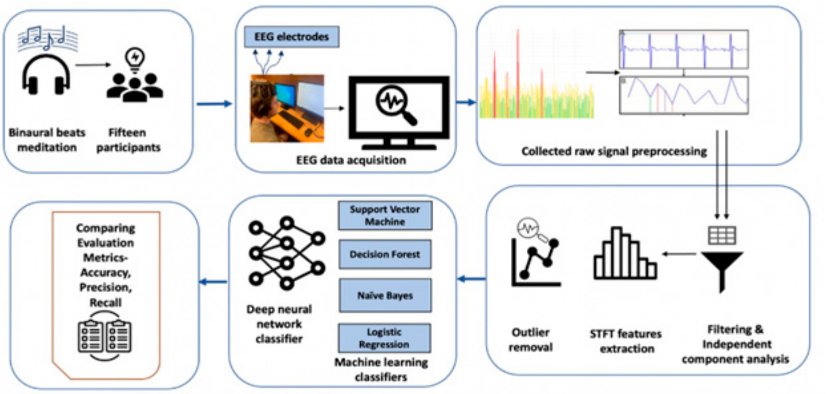

Figure 1. Fisheye view of the proposed methodology

3.2 Data collection

The examination of volunteers involved four different sessions, utilizing the DSI-7 Streamer EEG system from Wearable Sensing. This EEG system employs a dry electrode setup. It consists of seven channels, operating at a sampling rate of 300 Hz. Data collection was performed wirelessly using a Bluetooth connection and recorded through the DSI Streamer software, which was provided with the headset. All fifteen volunteers involved in the data collection procedure were between the ages of 17 to 25. Of the volunteers, there were 4 females and 11 males.

During the examination, volunteers were instructed to remain seated in a stationary position while the EEG system was carefully placed on their heads. To ensure good electrode contact, the DSI Streamer software was utilized to verify the quality of contact for each electrode site before initiating the recording process. Electrodes serve as conductors through which electrical signals are captured, and in the case of EEG systems, they are crucial components for data collection. These electrodes make contact with the scalp, and in the case of dry-EEG systems, they navigate through the hair to establish proper contact. Once satisfactory contact was confirmed, electrical activity from various scalp positions was recorded. The DSI-Streamer software provided a contact quality assurance check, indicated by green circles, to assess the quality of contact and signal prior to recording. To ensure good electrode contact, an impedance check was performed, which is crucial for the EEG setup process before data collection can commence. In this check, the Z(M) value, representing impedance, needed to be less than 1 and should not fluctuate by more than one. Meeting these criteria ensured that the electrodes had proper contact and signal quality, enabling reliable data collection.

The electrode positioning during the EEG recording followed the internationally recognized 10/20 system (Chatrian et al., 1985). Specifically, the following sites were recorded: LE, F4, C4, P4, P3, C3, and F3. This electrode configuration ensured adequate coverage of the occipital lobe, while also providing comprehensive sampling from other sites for a more thorough analysis of the volunteers' state. By including these specific electrode positions, the recording setup aimed to capture representative electrical activity from different regions of the brain, enabling a comprehensive examination of the participants' brain states during the study.

After ensuring good electrode contact, the volunteers were instructed to maintain a forward gaze without moving while a baseline EEG was recorded. This baseline EEG served as a reference for comparison with the subsequent examinations. The baseline recording lasted for exactly one minute. Following the baseline recording, participants were asked to close their eyes and focus on their breathing for one minute. This examination aimed to capture brain activity during a focused meditation on the breath.

Subsequently, binaural beats of alpha wave frequency were played while the participants' eyes remained closed, and they continued to focus on their breath. The binaural beats exposure duration was determined to ensure proper exposure to the music, and then a one-minute recording was taken during this period. Lastly, another one-minute examination with closed eyes was conducted, during which the volunteers once again focused on their breathing. Between each test, the volunteers were given brief periods of rest and time to reset.

3.3 Filtering and artifact removal

Once the data from all fifteen participants had been collected and stored in Comma Separated Values (CSV) format, it underwent preprocessing and filtering to target the frequencies of interest. To accomplish this, the Python library SciPy was utilized. By applying these preprocessing steps, the data was prepared for further analysis, targeting the specific frequency range of interest and removing any unwanted components. This preprocessing stage was crucial for ensuring the data's quality and suitability for subsequent analysis and interpretation.

First, a bandpass filter was applied using the Finite Impulse Response (FIR) filter in both the forward and backward directions. This approach helped mitigate any phase shift caused by the filtering process. The bandpass filter was designed to remove frequencies lower than 1 Hz and higher than 40 Hz, focusing on the specific frequency range of interest. After the application of the bandpass filter, the mean value was subtracted from the filtered data. This step effectively removed the DC (direct current) component from all the channels, ensuring that the data was centered around zero and eliminating any potential bias.

In addition to the filtering process, Independent Component Analysis (ICA) was performed on all of the channels to decompose the data into independent components as per equation 1. This decomposition allowed for more granular analysis of the data. To ensure the quality and accuracy of the components, the program automatically checked for absolute maximum values. If the maximum values exceeded five times the absolute minimum values, the corresponding component was excluded from the EEG data. This step helped to remove significant noise and artifacts that did not correspond to clean and accurate data.

$$y[n] = b_0 x[n] + b_1 x[n-1] + \cdots + b_N x[n-N] = \sum_{i=0}^{N} b_i \cdot x[n-i] \quad (1)$$

Once the data had undergone proper filtering and ICA, the Hann window method was employed to conduct Short-Time Fourier Analysis on each channel for each participant. The Hann windowing technique involves dividing the data into overlapping segments and applying a window function to each segment before performing a Fourier transform. It also ensures that the spectrogram, representing the brain wave frequencies over the time is aligned with the underlying data as possible. This method helps reduce spectral leakage and minimizes noise at the edges of the spectrogram, enhancing the accuracy of the analysis by reducing the presence of high-frequency artifacts.

The Short-Time Fourier Analysis (STFT) shown in equation 2 was applied to each channel, capturing the temporal and frequency information and their relationship to each other. This analysis produced a large number of data points, representing the frequencies present within the time span of the recording. The resulting data was then saved into CSV files, which contained the STFT of each channel along with its corresponding power values, providing a comprehensive representation of the data in terms of time and frequency. The STFT enables the use of spectral analysis and generate color maps of the largest power activities in respect to frequency. The method of applying the Short-Time Fourier Analysis was the same for outputting CSV files as it was for the spectrogram. In the case for the average spectrogram, the channels were combined and divided by the number of the channels to obtain the average spectrogram.

$$\mathrm{STFT}\{x(t)\}(\tau, \omega) \equiv X(\tau, \omega) = \int_{-\infty}^{\infty} x(t) w(t-\tau) e^{-i\omega t} dt \qquad (2)$$

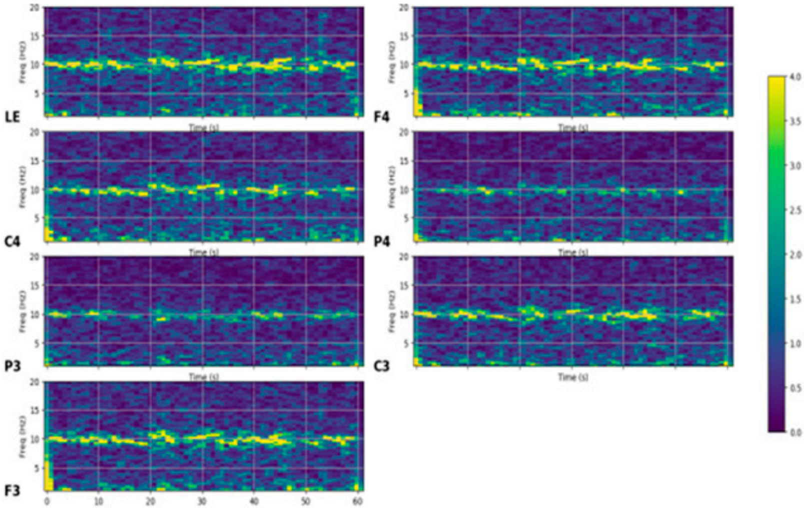

Figure 2. Color spectrogram of each individual channel

By utilizing these techniques, the analysis was able to capture both temporal and frequency information, allowing for a detailed examination of the EEG data and its power distribution across different frequencies over time. Figure 2 represents the spectrogram of each individual channel. These two different spectrograms visualize the differences between electrode sites and their overall effects.

3.4 Statistical analysis

To analyze the relative changes in overall frequency content, the average power spectral density (PSD) was calculated. Instead of using the Short-Time Fourier Transformation, a Fast Fourier Transformation (FFT) was applied to the entire dataset, separately for each channel. This process allowed for a comprehensive examination of the frequency composition. The FFT was performed on the entire dataset, encompassing all recordings, for each channel. Subsequently, the PSD values were calculated for each frequency bin. The PSD values were then averaged across all the volunteers within a specific test (e.g., before and after music). There is a total of 435 FFT values extracted from all initial datapoints.

Using the averaged PSD values, graphs were generated to visualize the channel-wise average PSD for both the "before" and "after" meditation conditions which is shown in Figure 3. The graph provides insights into the changes in frequency distribution before and after the mindful breathing meditation with the music stimulus. The graphs were appropriately scaled and presented to facilitate the interpretation of the results, allowing for a comparative analysis of the frequency content across different conditions. This approach enabled the examination of how the power distribution of different frequencies changed before and after the music intervention, providing valuable insights into the effects of the stimulus on brain activity. From Figure 3, it is evident that there is a significant increase in the power of alpha waves after the focal-based meditation on the breadth with binaural beats.

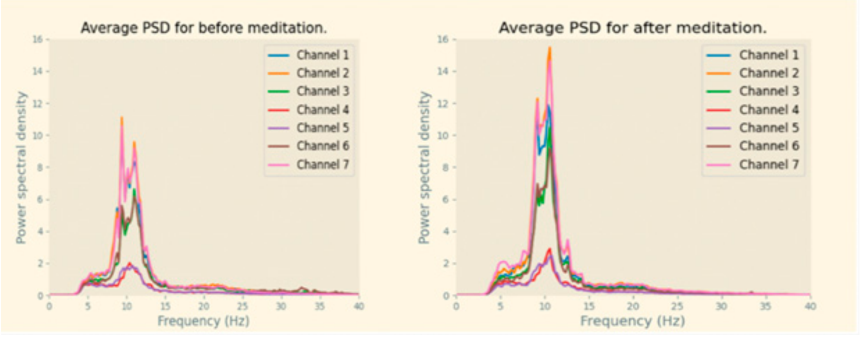

Figure 3. Comparison of average power spectral density before and after the meditation

During the analysis, outliers were identified in both the Delta and Theta frequency bands using the percentile-based threshold method. This process allows to focus on the necessary data segments which match the desired percentile range. These outliers were found to deviate significantly from the rest of the data points. Approximately 13% of data points in the Theta band and 10% in the Delta band were identified as outliers and subsequently removed from further analysis. This was done to ensure that the analysis focused on the representative data points and to minimize the influence of extreme values.

When examining the power values across all channels, there are changes observed across the low and high Alpha range implying the impact of meditation on brain activity. Such meditation practice often induces modifications in brain state while individual tends to enter a state with focused attention and elevated tranquillity. This promotes synchronization of neural activities which might lead to an increase of overall Alpha power bands. The statistical results are plotted in Figure 4 which represent the power comparison, the summation of power for before and after meditation. When examining the power values across all channels, the summation of power for the Low and High Alpha bands was found to be 1002.69 µV and

682.93 μV, respectively, in the before meditation scenario. In the after-meditation scenario, these values increased to 1645.28 μV for the Low Alpha band and 832.39 μV for the High Alpha band. This indicates that following meditation, there was an increase in power values for both Low and High Alpha bands, suggesting a higher level of activity in these frequency ranges compared to before the meditation stage. A similar pattern was observed in the High Beta and Gamma bands where High Beta values for before and after meditation are consecutively 83.30 μV and 96.62 μV. For Gamma, the values are 38.64 μV and 56.95 μV, respectively. This is obvious that the power values were higher after meditation compared to before meditation. However, in the Delta and Theta bands, the opposite trend was observed, with slightly higher power values before meditation compared to after meditation.

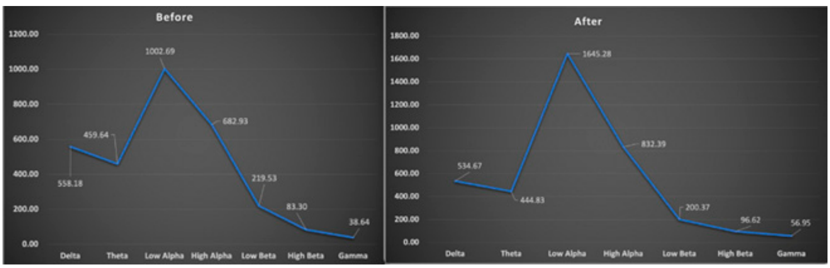

Figure 4. Power comparison plot before and after the meditation

3.5 Machine learning based classification

The preprocessed input data has been split into 70%-30% ratio for training and testing the models. Later, both traditional supervised machine learning and deep learning-based approaches were adopted for classifying brain wave labels. Supervised machine learning models can be trained by the labelled data and can predict class or categories from the target variables (Jamal & Wimmer, 2023). The classifier learns the relationship and pattern between the input features and target through the training process. In our experiment, multi-layer perceptron, support vector machine, logistic regression, decision forest and Naive Bayes models have been developed for predicting the brain wave labels. All these are supervised types of classifiers where the data labelling has been employed beforehand to train the models. Specifically, for SVM and Naïve Bayes, binary classes are developed, and then multiclass models are trained through one-vs-all techniques.

3.5.1 Data preprocessing for classification

For developing classification models, the dataset has been labelled into six classes or categories based on the frequency bands, i.e., Delta, Theta, Low Alpha, High Alpha, Low Beta, High Beta. However, due to the insignificant impact of Gamma before and after meditation, this class has been excluded from the output classes. Furthermore, the input features undergo a normalization technique to ensure consistent scaling. Normalization involves a linear transformation that maps the original variables to a new set of variables while preserving the same order of magnitude. The correlation among the variables or the predictive power of the features is kept unchanged in this process. In this experiment, Logistics normalization has been adopted to transform the variables in a range from 0 to 1. The formula for logistic normalization is shown in equation 3, where x denotes the original value and e represents Euler's number (2.718 approximate).

$$\text{Normalized value} = \frac{1}{(1 + e^{-x})} \qquad (3)$$

After normalizing the dataset, both deep learning and machine learning approaches have been undertaken to classify the brain waves. The final input dataset has a total of six classes. The feature distribution for both before and after meditation cases is presented in Figure 5ab.

(a) Before Meditation (b) After Meditation

Figure 5ab. Feature distribution before (a) and after (b) meditation

3.5.2 Multiclass neural network-based classification

A multiclass neural network consists of several input layers, hidden layers, and output layers. This is a kind of Artificial Neural Network (ANN) where the weights are adjusted during the training process (Agatonovic-Kustrin & Beresford, 2000). A multi-layer perceptron (MLP) neural network has been developed in this study where the number of hidden nodes is 100, and the learning rate is 0.01. The hidden layer's activation function is Rectified Linear Unit (ReLU), which introduces the non-linearity through the complex relationship of the network. Again, for the output layer, the SoftMax function is used as an activation function for converting the raw outputs of the network into probability scores for each class label where the summation of the score is up to 1. For measuring the discrepancy between the predicted class probability and true class label, the cross-entropy loss function is adopted in this network. Figure 6a shows the top-level structure of the neural network.

The overall accuracy for this classifier for pre-meditation and post-meditation datasets are respectively 74% and 69%. The precision rate is comparatively lower in before case (60%) than after meditation (70%) scenario indicating that the model has higher false positive predictions compared to the false negatives while employing pre-meditation stage's data. However, the recall has an opposite trend. Before and after meditation have consecutively 60% and 57% recall rates. Hence, the classifier's incorrect false negative rate is higher than false positive for post-meditation state.

3.5.3 The Support Vector Machine (SVM)

This structure is involved in training the model by optimizing all the parameters, i.e., bias terms and the coefficient, depending on the labelled training data. The trained SVM can then be used for predicting or classifying new and unseen samples. In this study, SVM one-vs-all technique has been adopted. A separate SVM classifier has been trained first for each of the classes treating that class as a positive class while combining all other classes into the negative class (Mathur & Foody, 2008). A decision boundary, a hyperplane, separates the categories in feature space. Figure 6b presents the diagram of SVM classifier.

The goal of this classifier is to find an optimal hyperplane that maximizes the margin between the support vectors of different classes. The optimization problem can be written as equation 4:

$$(w, b) = argmin \frac{|w|}{2} + C \frac{1}{n} \sum_{i=1}^{n} Zi \qquad (4)$$

The dual form for this classifier is stated below in equation 5 (Osuna, 1998):

$$\max \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \, \alpha_j y_i y_j x_i x_j \quad (5)$$

Here w and b are respectively weight and bias, and Zi presents the incorrectly classified points. The value of Zi is positive if any data point is incorrectly classified in positive or negative regions, otherwise, for the correctly classified points, it will remain zero. Moreover, α_i is greater than zero for support vectors and α_i=0 for non-support vectors. In our experiment, before meditation dataset could achieve 70% classification accuracy for this classifier with a similar precision and recall rates which is around 60%. And for after meditation state, the obtained accuracy is 61%. Here the precision (70%) is higher than recall rate (57%).

3.5.4 Logistic regression

This classifier works by fitting the data samples into some logistic functions while predicting the probability of any event occurrence. Depending on the multiple independent inputs, this algorithm can be developed as a multiclass classification model to predict more than two classes (Kwak & Clayton-Matthews, 2002). Logistic regression can handle the non-linear relationship between the input features and target outputs. The training process for multiclass logistic regression here is batch gradient descent which involves weight decay and learning rate.

The classifier has several input features (xi) and their related weights (wi) combined with bias (b). The net input passes through the sigmoid function where the output varies from 0 to 1. The output of the sigmoid function can be stated like as shown in equation 6.

$$\sigma(z) = p\ (y=1|x;\ w, b) \quad (6)$$

The parameters of the classifier are learned by using the maximum estimated likelihood. The cost function is presented in equation 7, where the class labels of training data are represented by y, features of training data are represented by x, and output is shown by h. The overall structural diagram of the logistic regression classifier is shown in Figure 6c.

$$C(\theta) = -\frac{1}{n} \sum_{m=1}^{n} [y^{(m)} \log\left(h_\theta\left(x^{(m)}\right)\right) + \left(1 - y^{(m)}\right) \log(1 - h_\theta(x^{(m)}))] \ (7)$$

As our study has a total of six class labels, multiclass logistic regression has been employed in this experiment. Logistic regression can handle the non-linear relationship between input features and output variables, based on the extracted features from EEG signal data, the emotional states are interpreted through this classifier. The training process for multiclass logistic regression here is batch gradient descent which involves weight decay and learning rate. To ensure the same input sets produce the same output sets and repeat the results overruns, the random seed generator has been employed as an integer in this case. The accuracy for before meditation case is 75% with 78% precision and 64% recall rate. Again, for after meditation stage, it could achieve 68% accuracy having 64% precision and 59% recall value.

3.5.5 Decision forest

Decision Forest is an ensemble learning technique which works by combining multiple decision trees to make predictions. This is one of the most used tree-based supervised learning classifiers where the final prediction is made by taking the average of individual trees (Rokach, 2016). This has benefits over a single decision tree in terms of overfitting issues. Decision forest might mitigate overfitting as it considers the average prediction. The classifier first selects some random samples from the dataset and creates a decision tree for all the samples. The prediction is made for all the trees and voting is performed for each predicted result using a mode. Finally, the highest-voted prediction is considered as the final prediction. The decision forester classifier diagram is presented in Figure 6d. For our experiment, the depth of the tree has been kept limited to avoid the risk of overfitting. The replication method here has been kept the input data the same creating some random nodes and diverse trees. It could achieve around 68% classification accuracy for pre-meditation and 52% accuracy for post-meditation case. Both precision and recall rates are similar for pre-meditation which is 56% for each.

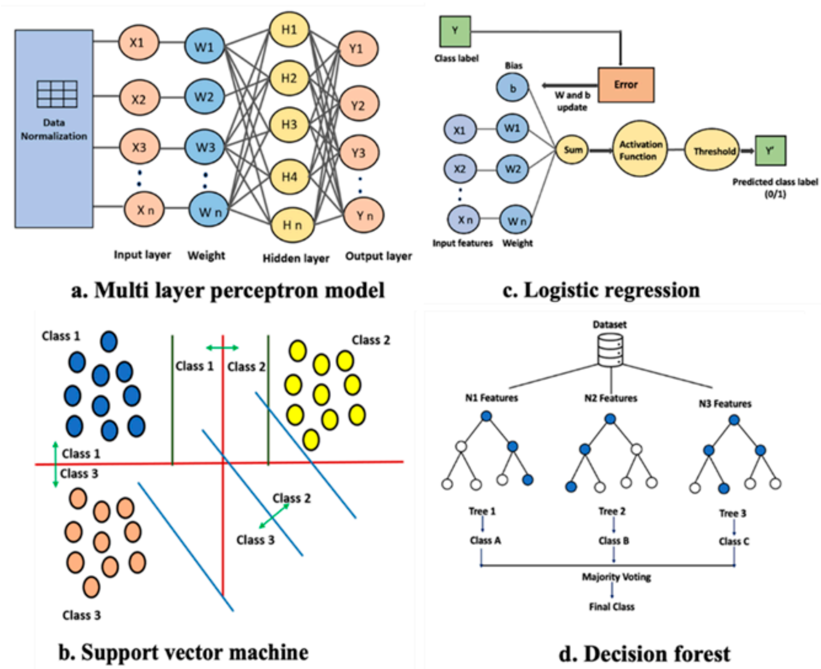

Figure 6ad. Classifier diagrams

3.5.6 Naïve Bayes

Another popular supervised algorithm Naïve Bayes (NV) has been applied to classify the brain wave labels. Utilizing the One vs All technique, a binary NV classifier has been trained first based on the maximum likelihood estimation principle from the training dataset. This classifier calculates the probability of each class from the input features utilizing the Bayes' theorem. It works on the Bayes' law or rule as below equation 8:

$$P(A|B) = \frac{P(B|A)P(B)}{P(B)} \qquad (8)$$

Here, P(A | B) is the posterior probability and P(B | A) is the likelihood probability.

Class with the highest probability is chosen as the predicted target. The used parameters here are feature likelihoods and class priors. In our experiment, NV classifier achieved 64% accuracy for before meditation dataset and 57% accuracy for after meditation dataset.

4. Results and discussion

The accuracy of all the classifiers is tabulated in table 1. The deep learning-based model, MLP, could achieve an overall 74% accuracy for the before-meditation dataset. Both precision and recall are 60% indicating that the model could classify an equal number of false positive and false negative samples. Whereas for the after-meditation dataset, the accuracy is slightly lower, which is around 69%. The precision and recall are, respectively, 70% and 57% here. While working with the traditional machine learning models, SVM obtained 70% and 61% accuracy for before and after scenarios. Logistic Regression (LR), Decision Forest (DF) and Naïve Bayes (NV) consecutively had 75%, 56% and 64% accuracy for before meditation dataset: however, for after meditation scenario, both 68%, 52% and 57% respectively.

A study for Alpha wave classification before and after meditation by Sharma et al. (2019) has achieved 87.2% accuracy using Artificial Neural Network (ANN). Moreover, while performing Kriya Yoga, the band energy comparison is presented before and after condition in the research work by Shaw and Routray (2016), where relative band energy in delta for meditators only are higher than non-meditators. The datasets employed in these studies are balanced for all the wave class there are a similar number of attributes, contributing to elevated classification accuracy. In our study, a decline in accuracy has been observed in the post-meditation scenario compared to the pre-meditation scenario. Upon investigating the factors contributing to this observation, one potential reason could be the presence of distinct patterns in the input features of the pre-meditation dataset. The after-meditation dataset, on the other hand, may exhibit more subtle changes and less variability, resulting in comparatively lower classification accuracy.

Another significant factor could be the timing of data collection, which occurred immediately after a one-minute break when the meditation music was turned off. It is possible that the effects of meditation on brain signals may not have fully manifested within this short timeframe. Furthermore, factors such as electrode placement, noise, and artifacts during the post-music session may have had a greater impact compared to the pre-music scenario. These factors should be taken into consideration in future studies to ensure a more balanced dataset, thereby aiming to achieve higher classification accuracy using machine or deep learning techniques.

Table 1. Classifiers' accuracy

Classifier	Before meditation			After meditation		
	Overall Accuracy	Precision	Recall	Overall Accuracy	Precision	Recall
MLP	74%	60%	60%	69%	70%	57%
SVM	70%	63%	60%	61%	60%	57%
DF	68%	56%	56%	52%	43%	42%
LR	75%	78%	64%	68%	64%	59%
NV	64%	57%	65%	57%	55%	54%

5. Conclusion

Meta-analyses focusing on electrophysiological changes during meditation consistently highlight increased alpha and theta power as characteristic markers of meditative states. To contribute to this body of knowledge, our research aimed to investigate the effect of meditation on the brain waves of 15 young volunteers. The collected EEG data were subjected to power spectral density analysis and general statistical analysis based on the power values, with the objective of understanding the impact of meditation on brain wave patterns. Obtained results revealed a significant alteration in alpha wave power before and after meditation. Moreover, the collected data was preprocessed to suit the requirements of machine learning and deep learning-based classifiers, including Support Vector Machine (SVM), Logistic Regression (LR), Decision Forest (DF), and Naïve Bayes (NV). These classifiers were employed to analyze the brain waves across six categories: Delta, Theta, Low Alpha, High Alpha, Low Beta, and High Beta. Notably, the findings demonstrated a significant increase in alpha wave power during breadth-focused meditation with alpha triggering binaural beats. The study also explored and compared the performance of different machine learning and deep learning classifiers using the collected dataset. In future studies, we aim to investigate the sustained effects of regular meditation practice on volunteers. Specifically, participants will be instructed to engage in daily meditation for a defined period, and the effects of meditation before and after this practice will be examined. This will provide further insights into the long-term impact of consistent meditation on brain wave patterns.

Availability of Data and Material

The data and materials used in this research are available upon request from the corresponding author.

Ethics Statement

This study was conducted following the ethical guidelines provided by Georgia Southern University. All participants provided informed consent, and ethical approval was obtained from the IRB.

Author's Contributions

Meenalosini Vimal Cruz contributed to the conception of the research, design of the study, resource collection, supervision of data collection and data analysis, manuscript drafting, and revising of the manuscript.
Suhaima Jamal contributed to the data analysis, implementing machine learning-based diagnosis, interpretation of results, and drafting and revising of the manuscript.
Camden Wahl contributed to the literature survey, the data collection and data analysis.
Sibi Chakkaravarthy Sethuraman contributed to the revising and proofreading of the manuscript.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Competing Interest

The authors declare no competing interests.

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