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# Enhancing Meditation Techniques and Insights Using Feature Analysis of Electroencephalography (EEG)

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## Abstract

Through a Bluetooth connection between the Muse 2 device and the meditation app, leveraging IoT capabilities. The methodology encompasses data collection, preprocessing, feature extraction, and model training, all while utilizing Internet of Things (IoT) functionalities. The Muse 2 device records EEG data from multiple electrodes, which is then processed and analyzed within a mobile meditation platform. Preprocessing steps involve eliminating redundant columns, handling missing data, normalizing, and filtering, making use of IoT-enabled techniques. Feature extraction is carried out on EEG signals, utilizing statistical measures such as mean, standard deviation, and entropy. Three different models, including Support Vector Machine (SVM), Random Forest, and Multi-Layer Perceptron (MLP), are trained using the preprocessed data, incorporating Internet of Things (IoT) based methodologies. Model performance is assessed using metrics like accuracy, precision, recall, and F1-score, highlighting the effectiveness of IoT-driven techniques. Notably, the MLP and Random Forest models demonstrate remarkable accuracy and precision, underlining the potential of this IoT-integrated approach. Specifically, the three models achieved high accuracies, with Random Forest leading at 0.999, followed by SVM at 0.959 and MLP at 0.99. This study not only contributes to the field of brain-computer interfaces and assistive technologies but also showcases a viable method to seamlessly integrate the Muse 2 device into meditation practices, promoting self-awareness and mindfulness with the added power of IoT technology.

**Keywords**: Brain-Computer Interfaces (BCIs), electroencephalography (EEG), IoT.

## الخلاصة

يقدم هذا البحث نظرة شاملة على ضم جهاز Muse 2 وتطبيق التأمل وتحليل بيانات مخطط كهربائية الدماغ (EEG) ودمج مفهوم انترنت الاشياء (IOT). استهدفت التقنية المقترحة تمكين المراقبة في الوقت الفعلي وتقييم نشاط الدماغ أثناء جلسات التأمل من خلال إنشاء اتصال بلوتوث سلس بين جهاز Muse2 وتطبيق التأمل والاستفادة من إمكانيات إنترنت الأشياء. تتضمن المنهجية جمع البيانات وتجهيزها واستخراج الميزات وتدريب النماذج باستخدام خوارزميات التعلم الآلي مع تسخير إمكانات أجهزة إنترنت الأشياء. يتم استخدام جهاز Muse 2 لجمع بيانات EEG من أقطاب كهربائية مختلفة والتي يتم تسجيلها وفحصها بعد ذلك على منصة متنقلة (التأمل). تُستخدم إشارات مخطط كهربية الدماغ لاستخراج الميزات باستخدام وسائل تشمل المتوسط والانحراف المعياري و entropy. تُدرب ثلاثة نماذج مختلفة: آلة المتجهات الداعمة (SVM) و Random Forest والشبكة العصبية ذات المستقبلات متعددة الطبقات (MLP) باستخدام البيانات المعالجة مسبقًا والمستخرجة من الميزات. يُقيم أداء النماذج باستخدام مقاييس مثل الضبط والدقة والاسترجاع ودرجة F1، مما يعرض فعالية التقنيات التي تعتمد على إنترنت الأشياء. تُظهر الدقة الممتازة والدقة التي حققتها نماذج MLP و Random Forest فائدة المنهجية المقترحة، والتي تجمع بين مبادئ إنترنت الأشياء وتحليل EEG حققت النماذج الثلاثة دقة عالية: Random Forest (٠,٩٩٩) وآلة المتجهات الداعمة (0.959) SVM والشبكة العصبية ذات المستقبلات متعددة الطبقات (0.99) MLP. تظهر نتائج ذات دقة عالية ويسلط الضوء على إمكانات إنترنت الأشياء. تفوقت Random Forest حيث تتحقق من صحة تحليل بيانات EEG ذات النسب العالية مع دمج إنترنت الأشياء بشكل كبير. لا يساهم هذا العمل في مجال واجهات الدماغ والحاسوب والتقنيات المساعدة فحسب بل يعرض أيضًا طريقة قابلة للتحقيق لدمج جهاز Muse2 في ممارسات التأمل لتحسين الوعي الذاتي واليقظة والاستفادة من قوة إنترنت الأشياء.

# INTRODUCTION

Brain-Computer Interfaces (BCIs) have ushered in a revolutionary era in human-technology interaction by enabling direct communication between the human brain and external devices. These interfaces harness the power of electroencephalography (EEG) devices to monitor and interpret mental activity, translating specific cognitive signals into actionable instructions for device control [1]. Among the various facets of BCI research, the utilization of EEG signals holds immense promise, as it paves the way for effective integration with the Internet of Things (IoT) and the creation of smart and accessible home environments [2]. The integration of BCIs and IoT technology has opened new avenues for enhancing the quality of life, convenience, and accessibility in daily living spaces. The IoT, characterized by interconnected objects equipped with sensors, software, and data exchange capabilities, has empowered the development of Smart Homes (SHs). These SHs can autonomously optimize the usage of a wide array of household products such as televisions, air conditioners, and lighting systems, ultimately improving our daily routines and overall well-being [3]. This study embarks on a compelling journey to unlock the potential of integrating the Muse 2 EEG device with meditation practices and IoT technology. The primary goal is to demonstrate how real-time EEG data analysis can be seamlessly integrated into the meditation experience, offering profound insights into its impact. By leveraging a comprehensive methodology encompassing data collection, preprocessing, feature extraction, and machine learning model training, the aim to shed light on the transformative possibilities of this integration The first stage in approach is to preprocess EEG data, which comprises duties like data cleaning, missing value management, normalization, and filtering. Subsequently, that used advanced statistical approaches to extract in methodology involves the preprocessing of EEG data, which includes tasks such as data cleaning, managing missing values, normalization, and filtering. Subsequently, that employed advanced statistical analysis methods to extract meaningful features from the EEG data. the investigation encompasses the training and evaluation of three machine learning models: Support Vector Machine (SVM), Random Forest (RF), and Multi-Layer Perceptron (MLP). These models are rigorously assessed using metrics such as accuracy, precision, recall, and F1-score, with the Random Forest model demonstrating superior performance across all metrics, underscoring its efficacy in EEG data analysis. A pivotal aspect of this study involves the seamless communication of translated user intentions from the EEG system to other IoT devices and systems. To facilitate this leverage, the publish-subscribe messaging mechanism MQTT (Message Queuing Telemetry Transport). MQTT empowers devices to communicate efficiently and reliably, forming the critical bridge between the EEG system and the broader IoT ecosystem [5]. The convergence of BCI and IoT technology holds great promise for revolutionizing human-computer interactions, particularly within the context of smart homes. The ability of the human mind to control appliances and equipment directly has the potential to significantly enhance convenience, accessibility, and the overall quality of life [6]. In the subsequent sections of this paper delve into a comprehensive exploration of the EEG interface, data analysis methodologies, and the intricacies of integrating this system with the MQTT-based IoT infrastructure. Through this work, the aim to illuminate the practical applications and real-world implications of this exciting technology, envisioning a future where the fusion of brain-computer interfaces and the Internet of Things transforms the way interact with environments [7].

## RELATED WORKS

This section presents an overview of several researchers' relevant work, which has helped to improve this discipline. Here are a few notable past works: SEONGHUN PARK [8]. In research comparing visual stimuli, for a brain-computer interface (BCI) in an augmented reality (AR) environment, the GSS stimulus was found to have the highest classification accuracy. Even though the AR-based BCI's performance was a little worse, it was still functional. In order to achieve high accuracy and information transfer rate, the researchers created a home appliance control system using the GSS stimulus. Overall, despite slightly lower performance compared to a conventional BCI, the GSS stimulus was ideal for the AR-based BCI, enabling usable control of home appliances. by Sharath V. N [9], It explores the integration of brain-computer interfaces (BCIs) with the internet of things (IoT), highlighting the advantages, difficulties, and applications of doing so. It investigates potential solutions and applications, puts emphasis on the value of effective communication, and suggests a conceptual framework for BCI-IoT integration. It highlights the considerable potential that results from BCIs and IoT integration, highlighting the opportunities for sophisticated interactions and improved functionality. Ullah, Mehar *et al.* [10] discussed the ways of Internet of Things (IoT) and brain-computer interfaces (BCIs) may be combined to improve healthcare. The development of healthcare facilities is the main topic of the paper's discussion of the potential advantages and applications of this integration. It offers a conceptual framework that fuses BCI with IoT technologies to facilitate real-time data processing, remote patient monitoring, and effective healthcare delivery. The study focuses advancement in the field and underscores the significance of secure communication and data privacy in this environment. Gao Xiaorong *et al.* [11], discusses ways the Internet of Things (IoT) and brain-computer interfaces (BCIs) may be combined to improve healthcare. The development of healthcare facilities is the main topic of the paper's discussion of the potential advantages and applications of this integration. It offers a conceptual framework that fuses BCI with IoT technologies to facilitate real-time data processing, remote patient monitoring, and effective healthcare delivery. The study focuses advancement in the field and underscores the significance of secure communication and data privacy in this environment. Hramov *et al.* [12], The work provides a thorough analysis of brain-computer interfaces (BCIs), focusing on its physical foundations, uses, and signal processing techniques. It covers a wide range of topics, such as methods to monitor brain activity and the different kinds and restrictions on BCIs. They highlight the use of BCIs in areas like robotics, brain state control, and rehabilitation. To fully realize the promise of BCIs and enhance human existence, they emphasize the significance of multidisciplinary collaboration and the integration of several scientific disciplines. Flesher [13], As a way to improve control over a robotic arm, it provides a novel BCI system that combines feedback from the skin. It shows through trials involving human subjects that adding tactile sensations considerably increases accuracy and effectiveness in operating the robotic arm. The tactile feedback was interpreted by the participants as coming from the robotic arm, resulting in a more natural and intuitive connection. The results show how sensory feedback can be included into BCIs, especially for uses like prosthetics and rehabilitation. This finding opens the door for further advancements in the sector and has significant implications for accurate and natural control in human-machine interactions. Ahamad [14] The goal of this study is to develop an effective BCI system that integrates machine learning and Internet of Things (IoT) technologies to enable direct brain-to-device connection. The suggested architecture improves the use of EEG data for signal analysis, categorization, and interpretation. Signal acquisition, preprocessing, feature extraction, machine learning methods, and IoT devices for data transfer and control are some of the system components covered in the article. Utilizing machine learning, the system adjusts to the unique brain patterns of each user, increasing the precision with which intents are deciphered. Real-time data transfer and seamless connectivity are made possible through IoT integration. The suggested system offers breakthroughs in human-machine interaction and has applications in gaming, assistive technology, and healthcare.

## Brain-Computer Interfaces (BCIs)

A common method in neuroscience and clinical neurology to identify changes in the electrical activity of the brain is electroencephalography (EEG). EEG caps are typically used with wet silver/silver chloride electrodes, which necessitates a lot of setup time and work. These electrodes have some drawbacks, such as a short wear time due to electrolyte instability. BCIs are a brand-new use for EEG technology. BCIs use the International 10/20 system to apply silver-chloride-coated metal discs to specific scalp locations. In order to identify each electrode's location in relation to the brain, it provides a number and a letter, such as F (for frontal lobe) and T (for temporal lobe). Dry contact electrodes need to be able pass through the hair layer, be biocompatible, electrochemically stable, and provide signal quality to be on par at wet electrodes [14]. Additional desirable qualities are long-term applicability, patient comfort, compatibility with bio-signal amplifiers, simplicity of usage, and patient preparation time. There have been three main categories of electrodes created:

1. multi-pin gold electrodes with titanium nitride coverings;
2. multi-pin polyurethane electrodes.

By gold-coating electrical precision brass pins and attaching them to an epoxy baseplate, gold multi-pin electrodes are produced.

This the endeavor's BCI configuration includes EEG data collecting, analog-to-digital conversion, digital signal processing, feature selection, and control of external mechatronic devices. Digital signal processing with filters is done in the second phase after the non-invasive EEG data is collected in the first step. To monitor individual brain waves and produce desired sounds, specific algorithms and mechatronics are created. PDR (Percussion Detection Rate) detection is carried out in the third phase using a special feature selection method [15]. Figure 1 depicts an open architecture that includes 8 bio potential input channels (brain (EEG), muscle (EMG), and heart (ECG), a high-powered analog front-end with 24-bit channel resolution up to 16khz sampling rate, and an accelerometer (st lis 3dh). 3 axis accelerometers, 16-bit data output, programmable, local SD storage with maximum data rate, and wireless communication [16].

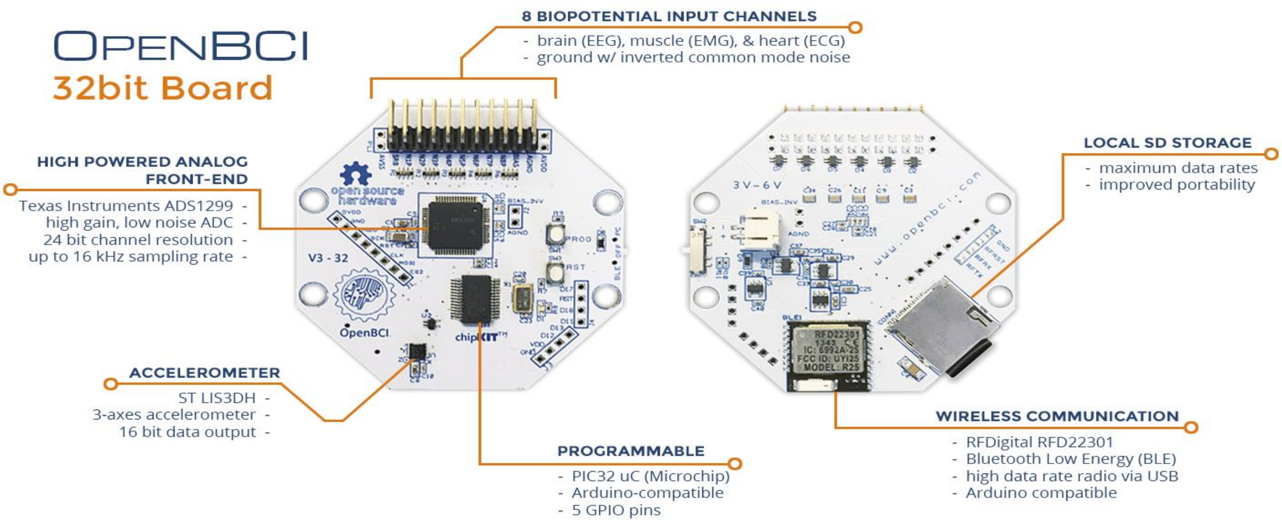


**Figure 1.** Open-source BCI solution of BCI system architecture is built using commonly used frameworks .

## Muse 2 Headband

*Comprehensive Academic Description*

By providing real-time feedback and tracking various physiological parameters, Muse 2 headband is a cutting-edge wearable technology that is intended to improve meditation practice. It includes a number of technological elements, such as EEG sensors, a heart rate monitor, an accelerometer, and breath tracking functionality [17]. EEG sensors on the Muse 2 headband are placed strategically on the scalp to record and examine brainwave activity related to relaxation and focused attention. Users can then make necessary adjustments after gaining insight into their mental states during meditation. Heart rate variability (HRV), a crucial sign of how the user's autonomic nervous system reacts to stress and relaxation. By assistance of this characteristic, individuals can more effectively comprehend their bodily responses and create stress-reduction strategies. The headband's built-in sensor enables it possible to observe movement during meditation. It encourages self-awareness and ideal alignment [18]. An intuitive user interface is provided by the Muse 2 headband's companion app, which connects to a smartphone or tablet via Bluetooth [19]. It offers a selection of guided meditation activities that may be customized to meet personal preferences and objectives. The headband's sensors provide real-time feedback combined with calming audio instructions. Users are able to evaluate their progress and make required modifications thanks to the Muse 2 headband's real-time feedback, which is based on the continuous monitoring and analysis of brainwave activity, heart rate, respiration, and body movement [20]. Each meditation session is also recorded and stored by the app, enabling users to track their progress over time and get individualized insights and advice. There are several advantages and potential uses for the Muse 2 headband. By providing rapid feedback and facilitating a deeper degree of concentration and relaxation, it enhances the practice of meditation with stress reduction by tracking HRV and promoting behaviors of controlled breathing. Furthermore, the employing of EEG sensors opens up the possibility of cognitive improvement [21]. The Muse 2 headband is an advanced piece of wearable technology that has transformed meditation practice. Its complex technical features and simple user interface give customers personalized teaching and real-time feedback, assisting individuals achieve a more profound and beneficial meditation session. It is a promising technique for fostering health and mindfulness because to its potential for stress reduction, cognitive improvement, and mental wellness. [22].

## MATERIALS AND METHODS

This section describes the methodology employed in the experiments results. The approach involves collecting data, extracting important features, analyzing it, and training models. The proposed approach provides a Bluetooth to connect a Muse 2 device with a meditation app for acquired EEG data. This algorithm attempts to optimize the Muse 2 device's integration into the meditation practice to provide users useful information about brain activity The proposed effort entailed using Bluetooth to pair a Muse 2 device with a meditation app and then analyzing EEG (electroencephalogram) data collected by the Muse 2 sensors. The process involves data preprocessing, feature extraction, and classification using machine learning models.

Based on the EEG data, the objective is to improve the meditative experience and offer real-time feedback. The data acquisition Analyzing brain activity and muscle movement is made possible by a process involving Bluetooth-enabled EEG signal capture using Open (BCI) and Muse devices. Experiments with the Inter axon Muse BCI device were also done to demonstrate the system's adaptability. The AF7 and AF8 electrodes on this device are similar to the Open (BCI) configuration. However, the Muse device does not employ TP9 or TP10 electrodes as shown in Figure 2. A comparison analysis is carried out using the Muse device to assess the potential impact of various BCI devices on the experimental outcomes, particularly in relation to the EMG component.

Figure 2 depicts the Inter axon Muse and the specific electrode placements based on the 10–20 International System, which allows for the recording of brain activity from various brain regions and facilitates accurate and reliable EEG measurements for brain-computer interface applications. The preprocessing techniques, including normalization and band-pass filtering, to enhance EEG data quality in BCI experiments. Feature extraction methods using entropy, standard deviation, and mean analysis are applied to EEG and EMG signals captured from specific electrodes. Classification of these signals is achieved using a Multi-Layer Perceptron (MLP)-based model, aiming to distinguish cognitive states and muscle activities with accuracy, contributing to the field of brain-computer interfaces and assistive technologies. The SVM, Random Forest (RF), and Multi-Layer Perceptron (MLP) architecture comprises input, hidden, and output layers, with the number of layers and neurons optimized through experimentation, as shown in Figure 3 and Algorithm1

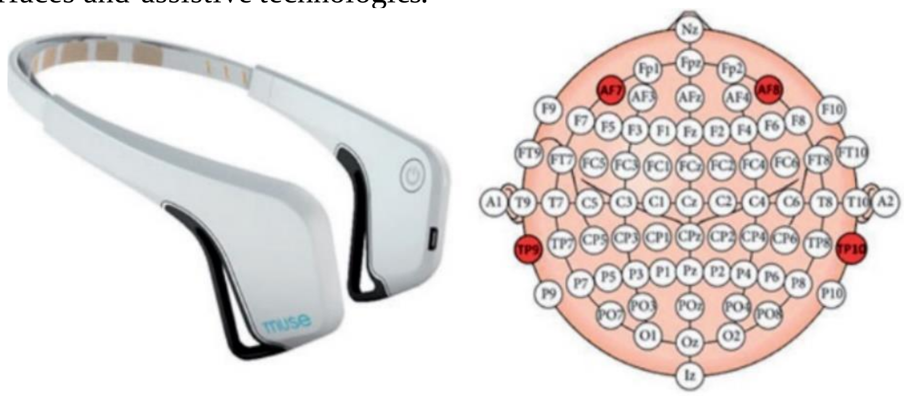


**Figure 2.** Muse2 Brain Computer Interface (BCI)

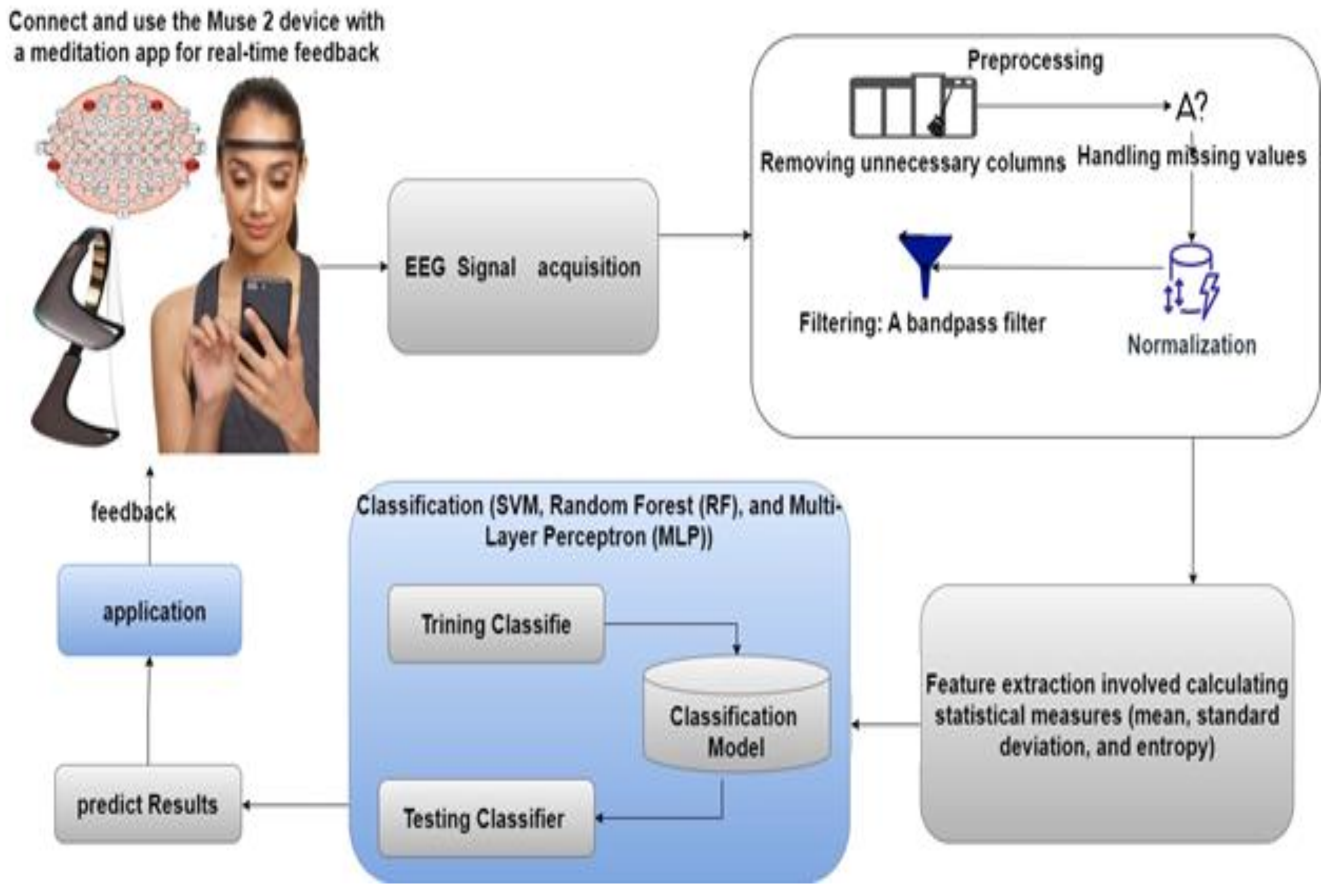


**Figure 3.** The block diagram of proposed work

**Algorithm 1.** The proposed model BCI Data Acquisition, Preprocessing, Feature Extraction, and Classification

step 1: Ensure the Muse 2 device is charged and turned on.
step 2: Enable Bluetooth on your device.
step 3: Install a compatible meditation application that supports Muse 2 integration.
step 4: Open the meditation application and go to the settings or device connection section.
step 5: Look for the option to connect or pair a device.
step 6: Select the Muse 2 device from the available devices list.
step 7: Follow the on-screen instructions to establish the Bluetooth connection.
step 8: Once connected, the application will start receiving data from the Muse 2 sensors.
step 9: The application may provide real-time feedback based on the received data.
step 10: Wear the Muse 2 device and use the meditation application to track and enhance meditation experience.
step 11: Data Acquisition: The EEG data was acquired using the Muse2 BCI device. The Muse2 device enables the collection of EEG signals from multiple electrodes. The data was captured on a mobile platform focused on meditation. The dataset includes various measurements recorded at different time points, such as Delta_TP9, Delta_AF7, Delta_AF8, Delta_TP10, Theta_TP9, Theta_AF7, Theta_AF8, Theta_TP10, Alpha_TP9, and others.
step 12: Data Preprocessing: The acquired data went through a preprocessing stage to prepare it for analysis. This stage involved several steps, including:

a) Removing unnecessary columns: Columns that were not relevant to the analysis or contained redundant information were removed from the dataset.
b) Handling missing values: If there were any (NaN) (Not a Number) values in the dataset, appropriate techniques were applied to handle them, such as imputation or deletion.
c) Normalization: Numeric data was normalized to ensure all features were on a similar scale. This step is important to avoid biases caused by differences in magnitude among features.
d) Filtering: A pass band filter was applied to remove unwanted frequency components from the EEG data. This step helps in isolating the desired brainwave activity.

step 13: Feature Extraction: After preprocessing, feature extraction was performed to derive meaningful information from the EEG signals. In this process, the means, standard deviations, and entropies of each data point were calculated. These measurements shed light on the central tendency, variability, and complexity of the EEG signal:

- Calculate statistical measures like mean, standard deviation, and entropy for each EEG channel.
- Perform calculations separately for each EEG channel, corresponding to different scalp locations.
- Combine results into feature vectors for specific time windows.

step 14: Modeling Training The preprocessed and feature-extracted data were used to train three different models, namely SVM, Random Forest (RF), and Multi-Layer Perceptron (MLP). The following steps were part of the training process:

a. Data splitting: To evaluate the performance of the model, the dataset was split into training and validation sets.
b. Model selection: The models for classification were SVM, Random Forest, and MLP.
c. Model training: To reduce the classification error, the connection weights between neurons were iteratively modified after the preprocessed data was input into each model.

Step 15: Performance Evaluation Several measures were used to assess how well the constructed models performed. Accuracy, Precision, Recall, and F1-score were some of these measurements. Precision calculated the percentage of genuine positive predictions among all positive predictions, whereas accuracy scored the classification findings' total correctness. Recall calculated the percentage of accurate predictions among all instances of actual success. The F1-score provided a fair evaluation of the effectiveness of the classification model by combining Precision and Recall into a single statistic.

## RESULTS AND DISCUSSION

This section presents the results of the experiments detailed. this part also includes an analysis of all the data acquired for each experiment.

### Data Acquisition

Data was gathered using a mobile platform specifically designed for meditation utilizing the muse 2 gadget. there are several measurements in the database that were made at various times. gyroscopic measurements, head band device on status, battery level, and other attributes are among the measurements and features that are included in each row, which corresponds to a particular timestamp, shown in Table 1.

Table 2 presents the EEG data collected from various channels over a period of time. It consists of 12,400 rows and 39 columns, including the Timestamp, Delta_TP9, Delta_AF7, Delta_AF8, Delta_TP10, Theta_TP9, Theta_AF7, Theta_AF8, Theta_TP10, Alpha_TP9, and other related features. Each row has a unique timestamp that shows when the data was recorded. The numerical numbers in the columns indicate the recorded EEG readings for the various channels. If there was no data available for that specific channel and date, the values in the table can contain NaN (Not a Number).

**Table 1.** Data from muse 2 in BCI of EEG.

| TimeStamp | Delta_TP9 | Delta_AF7 | ... | HSI_AF7 | HSI_AF8 | HSI_TP10 |
|---|---|---|---|---|---|---|
| 2023-02-02 11:12:57.660 | NaN | NaN | ... | 1.0 | 4.0 | 1.0 |
| 2023-02-02 11:12:57.741 | NaN | NaN | ... | 1.0 | 4.0 | 1.0 |
| 2023-02-02 11:12:57.762 | NaN | NaN | ... | 1.0 | 4.0 | 2.0 |
| 2023-02-02 11:12:59.661 | 1.019823 | -3.053491 | ... | 1.0 | 4.0 | 2.0 |
| 2023-02-02 11:13:00.426 | NaN | NaN | ... | NaN | NaN | NaN |
| ... | ... | ... | ... | ... | ... | ... |
| 2023-02-22 12:45:32.884 | NaN | NaN | ... | NaN | NaN | NaN |
| 2023-02-22 12:45:33.004 | 0.000000 | 0.000000 | ... | 4.0 | 4.0 | 4.0 |
| 2023-02-22 12:45:33.078 | NaN | NaN | ... | NaN | NaN | NaN |
| 2023-02-22 12:45:35.000 | 0.000000 | 0.000000 | ... | 4.0 | 4.0 | 4.0 |
| 2023-02-22 12:45:36.997 | 0.000000 | 0.000000 | ... | 4.0 | 4.0 | 4.0 |

**Table 2.** The preprocessing of data acquisition from muse 2 in BCI of EEG data

| Delta_TP9 | Delta_AF7 | Delta_AF8 | ... | HSI_AF8 | HSI_TP10 | Battery |
|---|---|---|---|---|---|---|
| 1.019823 | -3.053491 | 1.085578 | ... | 4.0 | 1.0 | 65.0 |
| 0.971511 | -3.053491 | 1.085578 | ... | 4.0 | 1.0 | 65.0 |
| 0.207826 | 0.0 | 0.0 | ... | 4.0 | 2.0 | 85.0 |
| 1.167421 | 0.0 | 0.0 | ... | 4.0 | 2.0 | 85.0 |
| 0.504791 | 0.0 | 0.0 | ... | 4.0 | 2.0 | 85.0 |
| ... | ... | ... | ... | ... | ... | ... |
| 0.0 | 0.0 | 0.0 | ... | 4.0 | 4.0 | 85.0 |
| 0.0 | 0.0 | 0.0 | ... | 4.0 | 4.0 | 85.0 |
| 0.0 | 0.0 | 0.0 | ... | 4.0 | 4.0 | 85.0 |
| 0.0 | 0.0 | 0.0 | ... | 4.0 | 4.0 | 85.0 |
| 0.0 | 0.0 | 0.0 | ... | 4.0 | 4.0 | 85.0 |

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## Preprocessing

This may happen if the EEG measurement wasn't captured or if there was a data collecting issue. These techniques include removing unnecessary columns that are not relevant to the analysis, normalizing the numeric data to ensure all features are on a similar scale, handling missing values, and applying a band-pass filter to remove unwanted frequency components from the EEG data. These steps are crucial for preparing the EEG data for further analysis and feature extraction in brain-computer interface (BCI) experiments. By performing these preprocessing steps, the data quality and reliability are improved, leading to more accurate and meaningful results in subsequent stages of EEG data analysis.

Table 2 shows the dataset after the preprocessing. It consists of 4800 rows and 37 columns. During the preprocessing stage, any NaN values (representing missing data), from Table 1, may have been dropped. Other preprocessing steps may have included normalization of the data to bring all features to a similar scale, reducing the impact of variations in magnitude and filtering by Fourier transform and band pass filter.

## Feature Extraction

In the feature extraction process, the mean, standard deviation, and entropy values are calculated for each row of the EEG data. This step aims to uncover meaningful information and characterize the underlying patterns within the raw EEG signals. The extracted features provide insights into the statistical properties, variability, and complexity of the EEG signals, The results of the feature extraction are summarized in Table 3.

Table 3 presents above provides statistical measures, including mean, standard deviation, and entropy, for each entry in the database. The table consists of 4800 rows and three columns: mean, STD (standard deviation), and entropy. The mean column represents the average value of the corresponding feature across the database. It provides an indication of the central tendency of the data. For example, in the first row, the mean values for the features are -0.888126, -0.281312, and -0.616305, respectively. The standard deviation (STD) column represents the variability or dispersion of the data around the mean. It quantifies how much the values deviate from the average. In the first row, the standard deviation values for the features are 9 825029, 23.501442, and 44.461825, respectively.

The entropy column measures the amount of information or uncertainty present in the data. Features characterizes the complexity or randomness of the feature values. Higher entropy values indicate greater uncertainty or more diverse patterns in the data. In the first row, the entropy values for the features are -139.487132, -727.673235, and -1481.483241, respectively.

**Table 3.** The Feature extraction of data acquisition from muse 2 in BCI of EEG data

| Data Point | Mean | Standard Deviation | Entropy |
|---|---|---|---|
| 3 | -2.233401 | 10.956679 | -75.772270 |
| 7 | -1.624145 | 23.902905 | -529.397990 |
| 17 | -1.955298 | 44.808705 | -1275.504747 |
| 21 | -3.775101 | 60.218001 | -1141.448122 |
| 25 | -20.051053 | 88.403643 | -465.200813 |
| ... | ... | ... | ... |
| 12393 | 84.466635 | 226.285910 | -29161.326863 |
| 12394 | 78.032281 | 239.451187 | -27564.114406 |
| 12396 | 64.707731 | 173.432776 | -21503.242473 |
| 12398 | 45.212987 | 146.412815 | -14689.795372 |
| 12399 | 4.429889 | 12.496414 | -861.804302 |

## Training Procedure

The training of the SVM, Random Forest (RF), and Multi-Layer Perceptron (MLP) model involves two main steps: data preprocessing and model training. In the data preprocessing step, the recorded EEG and EMG signals are preprocessed to remove noise, artifacts, and baseline drift. The signals are then divided into training and validation sets. The training model tuned as shown in Table 4 by feeding the preprocessed signals into the SVM, Random Forest (RF), and Multi-Layer Perceptron (MLP) and iteratively adjusting the connection weights between neurons to minimize the classification error as of the training process, while each column represents the training loss for a particular model.

**Table 4.** Hiper parameter tuning of Different Models (Multi-Layer Perceptron (MLP), SVM, Random Forest)

| Model | Hyper parameters Tuned |
|---|---|
| SVM | Regularization parameter (C)=1.1 |
| RF | Number of trees = 100, 200, 300 |
| | Maximum tree depth =30 |
| MLP | Number of hidden layers= 3 |
| | No. Nerouns per layer= 32, 64, 128 |
| | Learning rate= 0.01 |
| | Activation functions is Sigmoid |

For example, in the first row, the training processing of models SVM, Random Forest (RF), and Multi-Layer Perceptron (MLP) loss values for SVM, RF, and MLP are 0.65180434, 0.58347524, and 0.5444727, respectively. Observe a downward trend in the training loss values for each of the three models. This process is typically performed using back propagation, where the error is propagated backward through the network to update the weights.

Figure 4 shows the training loss values for three distinct models SVM, Random Forest (RF), and Multi-Layer Perceptron (MLP).

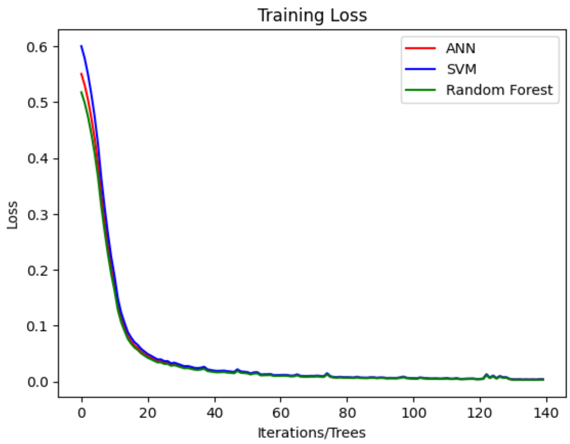


**Figure 4.** The training loss values for three distinct models SVM, Random Forest (RF), and Multi-Layer Perceptron (MLP).

For various training iterations or epochs, the training loss values are supplied. The mistake or difference between the model's anticipated outputs and the actual outputs during the training phase is represented by the training loss. The model's optimization goal is to reduce this loss and boost its ability to forecast the future. Lower training loss levels suggest higher accuracy and model fitting. In Figure 4, each row corresponds specific iteration or epoch.

## Performance Metrics

Table 5 shows that the models are increasingly performing better and more correctly fitting the training data Accuracy, precision, recall, and F1-score are just a few of the measures used to gauge how well the generated SVM, Random Forest (RF), and Multi-Layer Perceptron (MLP) model performs. Accuracy gauges how accurately the categorization outcomes are overall. The proportion of accurate positive forecasts among all positive predictions is measured by precision, whereas the proportion of accurate positive examples is measured by recall. The F1-score provides a fair evaluation of the performance of the classification model by combining accuracy and recall into a single parameter.

Performance statistics for the Multi-Layer Perceptron (MLP), SVM, and Random Forest models are shown in Table 5.

**Table 5.** Performance metrics of different models (Multi-Layer Perceptron (MLP), SVM, Random Forest)

| Model | Acc. | P. | Recall | F1-score |
|---|---|---|---|---|
| MLP | 0.9958333 | 0.995861 | 0.995833 | 0.9958287 |
| SVM | 0.959375 | 0.961858 | 0.959375 | 0.9588555 |
| Random Forest | 0.9989583 | 0.998961 | 0.998958 | 0.9989586 |

*Acc: Accuracy, P.: Precision

These metrics include the frequently used assessment metrics for machine learning, Accuracy, Precision, Recall, and F1-score. Accuracy represents the overall correctness of the model's predictions, indicating the proportion of correctly classified instances out of the total number of instances. Table 5 showing the results of MULTI-LAYER PERCEPTRON (MLP) model, the SVM model, and the Random Forest model which obtained accuracy values of 0.9958333, 0.959375, and 0.99989583 respectively. Precision measures the proportion of true positive predictions out of all positive predictions made by the model. It represents the model's ability to avoid false positives. The Precision values for the Multi-Layer Perceptron (MLP), SVM, and Random Forest models are 0.995861, 0.9618583, and 0.9989612, respectively. Recall, also known as sensitivity or true positive rate, measures the proportion of true positive predictions out of all actual positive instances in the database. It indicates the model's ability to find all relevant instances. The Recall values for the Multi-Layer Perceptron (MLP), SVM, and Random Forest models are 0.995833, 0.959375, and 0.998958, respectively.

F1-score is the harmonic mean of precision and recall. It provides a balanced measure of a model's performance, considering both precision and recall simultaneously. The F1-score values for the Multi-Layer Perceptron (MLP), SVM, and Random Forest models are 0.9958287, 0.9588555, and 0.9989586, respectively.

## CONCLUSIONS

This study employs an extensive approach, pairing a Muse 2 device with a meditation app via Bluetooth to analyze EEG data. The process encompasses data collection, preprocessing, feature extraction, and model training. The Muse 2 records EEG signals from multiple electrodes on a mobile meditation platform, yielding diverse metrics over time. Preprocessing enhances data quality by removing irrelevant columns, managing missing values, normalizing data for consistent scaling, and applying a band pass filter for focused brainwave activity. Feature extraction calculates statistical measures (mean, standard deviation, entropy) for each data point, revealing EEG signal complexity, variability, and central tendencies. Model training, utilizing SVM, Random Forest, and Multi-Layer Perceptron (MLP), adjusts neuron connection weights iteratively to minimize classification error. Performance metrics like accuracy, precision, recall, and F1-score gauge model effectiveness. Results indicate MLP achieved an accuracy of 0.9958, SVM scored 0.9594, and Random Forest excelled with 0.9990 accuracy, outperforming others. The study demonstrates the feasibility of using machine learning and the Muse 2 for enhanced meditation practices, offering insights into brain functioning during meditation.

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