# Mental State Recognition and Recommendation of Aids to Stabilize the Mind Using Wearable EEG

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# Mental State Recognition and Recommendation of Aids to Stabilize the Mind Using Wearable EEG

A dissertation submitted for the Degree of Master of Information Technology

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# Abstract

Emotions play an important role in the physical activities and mental health of the human. The ability to correctly determine and interpret the mental state of a person would offer new opportunities for medical and non-medical purposes. With the fast-evolving technology and the improvements in the field of emotion recognition, numerous studies have been carried out to overcome the challenges faced during the emotional recognition. The purpose of this project is to develop a solution to recognize the current mental state of a person by analyzing Electroencephalogram (EEG), which capable of detecting the electrical activity of the brain in real-time and determine five different emotions: happiness, sadness, calm, fear, and neutral emotions. Further, the presented web application provides the best remedy to balance an unstable mindset based on the emotional state determined. Dataset has collected from 33 participants including both males and females at the age between 20-50 years. EEG signals were acquired from each participant using EEG-headband called Muse in a quiet-controlled environment. Participants were advised to watch a five minutes video clip which consists of five videos in sequence, which allocated one minute for each class of mental state and the collected datasets were used for both train and test for different emotions after applying proper pre-processing techniques. The set of features is selected from the EEG data and applied different feature selection algorithms and mental state classification algorithms to compare their recognition accuracy and performance. From the tested multiple classification methods, the Random forest classifier achieved a maximum prediction accuracy of 87.12% and used to mental state recognition. Mood, the web-based application is developed to obtain the current mental state while prompting the best set of remedies based on user feedback collected.

*Keywords : Emotion, Emotion Recognition, Electroencephalogram (EEG), mental state classification, pre-processing, Random Forest, Muse headband, Item-based collaborative filtering*

# Declaration

The thesis is my original work and has not been submitted previously for a degree at this or any other university/institute.

To the best of my knowledge it does not contain any material published or written by another person, except as acknowledged in the text.

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under my supervision. The thesis has been prepared according to the format stipulated and is of acceptable standard.

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# List of Abbreviations

| Abbreviation | Description |
|---|---|
| EEG | Electroencephalogram |
| BCI | Brain Computer Interface |
| HCI | Human Computer Interface |
| DWT | Discrete Wavelet Transform |
| SVM | Support Vector Machine |
| KNN | K-Nearest Neighbor |
| ANN | Artificial Neural Network |
| CA | Classification Accuracy |
| LDA | Linear Discriminant Analysis |
| MBA | Mindfulness Based Application |
| CSV | Comma-Separated Values |
| OSC | Open Sound Control |
| UDP | User Datagram Protocol |
| RF | Random Forest |
| MLP | Multi-layer Perceptron |
| CSP | Common Spatial Patterns |
| FFT | Fast Fourier Transform |
| ED | Euclidean Distance |
| VR | Virtual Reality |
| JSON | JavaScript Object Notation |
| SDLC | Software Development Life Cycle |

# Chapter 1

# INTRODUCTION

This project aims to recognize different mental states of a human by analyzing discriminative Electroencephalography (EEG) based features by employed with appropriate classification methods. The mental state recognition model is capable of identifying the current mental state of a person by analyzing the brainwave patterns in real-time. Further, this constructed model is used in a web application, which displays the current emotional state along with set of recommendations of mindfulness techniques to stabilize the mind. This document provides comprehensive information about the approach that employed the use of machine learning technique to classify the brain signals to categorize set of mental states. Further, detailed about the developed web application that capable of recommending set of mindfulness techniques to that can be practiced to stabilize the mind.

## 1.1 Motivation

Every human being dreams to live a healthy life. Thus, more focus is given to physical health aspects such as regular exercises, practice yoga, having a healthy diet and many more. Yet, a very less number of them try to improve their psychological stability and goodness, which plays a major role in overall wellness. Considering the lifestyle that was before a couple of decades, current lifestyle has become very much busier, competitive, complex and hectic which leads to mental stress, depression and anxiety disorders. Thereby resulting in problems in their lives, families and working places that may affect negatively towards everyone related. Therefore managing the psychological wellness is very crucial throughout the lifespan of childhood to adulthood and beyond. There are various methods such as meditation, mindfulness exercises that can be practiced to keep the mental health in good condition. Meditation has been proven a very powerful practice that can be followed to control the mind and thoughts to mitigate the stress and anxiety. Mindfulness training is a collection of meditation, introspection which paying more attention to the present moment and try to control thoughts, feelings and be thoughtful in environment. It has been proven that, mindfulness has a significant positive impact on well-being and health, specifically helps to reduce the stress and depression among humans[1]. The term mindfulness majorly covers self-regulation approaches, movement meditation like yoga, breathing and visualization exercises. Grounding exercise is a technique that would help to reorient the mind into the present situation and the "5-4-3-2-1 game" [1] which is a common sensory awareness grounding exercise keeps people relax or get through difficult moments [2]. In the "5-4-3-2-1 game" focus on the look, feel, listen, smell, taste in the present moment.

Although mindfulness has become an effective tool to enhance your physical health and psychological well-being, it is very difficult to find an effective delivery medium that can reach a wider audience. A human mind consists of a variety of mental states and emotions during every waking moment of life. As there are different mindfulness techniques available nowadays, it is very difficult to find an effective mindfulness technique that is suitable for the present mental situation. Due to the lack of proper guidance to follow mindfulness meditation, it might negatively affect your mental health. With the evolving technology mindfulness, training has offered many advantages such as customizing the mindfulness training according to the participant needs, reaching an extensive range of interested practitioners, and addressing concerns bound with the time commitment. There is no shortage of meditation and mindfulness applications nowadays, which support you to control the anxiety, sleep better, and focus on the current situation. Moreover, a wide variety of mindfulness-based mobile/web applications has developed that seek to replicate the success of group intervention [3]. The major limitation of these applications is unable to identify the current emotional state of the person and provide proper meditation or mindfulness techniques to change the mental state. Most of the applications provide the user to engage with a set of activities or mindfulness techniques but do not visualize the accurate progression of how the mind has changed after the following set of activities. Further, most of the applications use different types of emotion detection modalities such as facial expressions, speech, text, and gestures to retrieve the emotional information of a human. However, these modalities can be lead to incorrect responses.

Due to these limitations of the existing solutions, it is required to have a proper way of recognizing the present mental state of the person and provide better mindfulness training. The project provides a novel approach to identify the mental state of a person with the use of an evolving brain-computer interface and accurately determine by analyzing the brainwaves. Other existing applications do not facilities such advanced techniques and mostly provide mindfulness training based on some recommendations, which might not precisely match with your current mental state. Further, this project provides a better platform for those applications to get recommendations to their applications based on brain wave analysis. Mood web application provides the current mental state of a person by capturing the brain waves in real-time and gives recommend aids to stabilize the stresses or depressed mind. Users can follow the training recommended and provide feedback to the system. This feedback is used to enhance the recommendation services hence provides quantitative and qualitative measurements for the mindfulness training recommendations. This novel approach is useful for the researchers or application developers who are developing mindfulness applications as the model is developed based on human physiological signals.

[1] Activity that helps to reorient the mindset from the negative thoughts or get rid of difficult moments by focusing the mind to the present moment. Mainly focused on what you can see, feel, listen, smell and taste in the present moment.

## 1.2 Aims and Objectives

As a remedy for the aforesaid problem identification, this work provides a better solution to identify the current mental state of a particular person and present some recommendations to balance an unstable mind while providing feedback for the followed medias(videos, audio, speeches or images) which helps to enhance the recommendations in a better way. This solution is capable of providing mindfulness activities in real-time by interpreting the brain signals. Mood web application connect with the Muse headband to accurately detect the emotional state. This application brings better user experience to life as this allows users to learn how to build their minds by practice through expert knowledge which accesses rich feedback experience to improve the learning. The long-term goal is to support humans to get rid of stressful minds triggering the existing state of their mind real-time. Further, this project aims to achieve the following objectives:

- Identify the current emotional state of the mindset of the person
- Based on the user feedback, provide set of recommended medias to balance an unstable mindset
- Visualize the change difference in mindset before and after the remedies been recommended
- Allow privileged users to control and upload medias to the system to collect user feedback

## 1.3 Scope

With the vast development of the technology, emotion detection has evolved in many ways, with the help of advanced sensors that capable of retrieving human physiological signals like cardiac activity, heart rate, neural feedback, skin conductance, etc [4]. The development of Brain-Computer Interfaces (BCIs) has become more comprehensive during the last decades that analyze physiological signals like EEG in areas like attention, lie-detection, stress, and emotion recognition. Such brain-computer interfacing would open up new platforms for human-machine communication including helping out people with physical or mental disorders. Recent researches have revealed that EEG, plays a major role when determining the emotions by tracking the patterns of brain activity [6]. To recognize the emotional states by analyzing the neural responses, it is required to implement a BCI system that creates a communication link between the brain and the computer by capturing, analyzing, and classifying the brain signals. With the greater availability of economical EEG devices, acquiring the brain signal is becoming a cost-effective method for the researchers and the consumer industry experts to develop novel applications with the help of neural responses. Interference is one of the dominant challenges in BCI applications and how instantly the emotion states are interpreted into a particular pattern of brain activity [7]. Furthermore, classifying the EEG signals is challenging due to the complexity, non-linearity, and randomness nature of the signals and it is difficult to determine the exact amount of data needed to properly identify different emotional states. This approach employs machine learning techniques to classify the emotional state using the EEG data captured using a research-grade brain-computer interface. The ability to autonomously detect mental state is useful for numerous purposes in different domains like healthcare, neuroscience, education, robotics, etc. This provides a different dimension of interaction between the device and the user which enables us to derive tangible information rather than depending on verbal communication.

This project is focused on collecting brain signals through EEG recordings from a commercially available device called Muse and then develop a machine learning model that uses to predict the corresponding mental state of the user. As described in the above section, this solution is aimed to achieve three main goals; identify the current cognitive state of the person using wearable electroencephalogram (EEG) device Muse, identify what is the best remedy to balance the cognitive states such as stress, anxiety, etc. In addition to that, this solution evaluates the accuracy of the recommendations via feedback getting from the users through the developed web application. A set of mindfulness training medias are recommended to reorient the mind into the present situation and keeps people relax or get through difficult moments. The Mood web application evaluates how the person responds to different types of inputs such as colorful graphics, images, videos, music, movies, and talks by analyzing the user feedback. And it is capable of predicting and tracking how the mental states have varied when interacting with each input by monitoring the EEG signal in real-time. Muse headband works through EEG-Neurofeedback technology, which uses seven finely tuned brain sensors; two sensors on the forehead, two behind the ear sensors, and three reference sensors. All seven sensors are used to capture the brain signals and analyze them properly to identify the mental state of a particular person. To differentiate and predict the mental states, sample brain signal data are collected from 33 individuals in a controlled and quiet environment. Both male and female participants are included at the age between 20 and 50 and taken verbal confirmation about their physical health condition. Further, Participants were advised to watch a five minutes video clip which consists of five different videos in sequence, which allocated one minute for each class of mental state, watch them without closing their eyes, to capture data for happy, sad, afraid, calm, and neutral mental states. Once sufficient data is been collected from different participants, pre-processing techniques are applied to remove unwanted pieces of information and filter only the relevant attributes to apply machine learning techniques. A range of electrical activities are captured using Muse devices and transforms it into easily understandable experiences. Collected brain signals are used to predict and track the mental states of the person. Different machine learning techniques are applied to the brain signal components to achieve maximum prediction accuracy and performance. Once the current mental state is recognized in real-time, the web application provides a set of mindfulness activities that the person should follow to set his or her mind is calm and settled. The Mood web application is capable of visualizing the current mental state of a person and provides the best set of recommended media such as videos, images, talks, relax music audio clips, motivational speeches, etc based on the mental state identified. Furthermore, users are allowed to provide feedback once they follow a particular mindfulness activity or media and that feedback will be useful for the improvements of the recommendation prompt to the person next time. Mood application is capable of visualizing how the user's mental states have changed over the day, week, or month and graphically represent it. These summary reports are useful for the user to understand how the mental states have fluctuated and further how the mindfulness activities have impacted to stabilize the mindset of a person. The users with administrative privileges have the capability of adding media to the application and they can evaluate how the users have engaged with media, whether it makes a considerable impact on their mindset; based on the feedback provided. Mood web application works with Muse headband to bring novel user experience to the life as this allows the user to learn how to build their mind by accessing rich feedback and practicing through expert education in deeper insights.

The remaining chapters are outlined with a detailed description of the developed model and about the web application. Starting from chapter two mainly provides a comprehensive review of relevant literature, explains more information about the background and overview of previous work based on a literature survey to identify the significance of the problem. Chapter three presents the design of the solution and implementation, hardware and software requirements, detailed research methodology. Chapter four gives the results of the work, sources for test data analysis, anticipated benefits, what the system will do the constraints under which it must operate to obtain optimal results, how the system interacts with the external factors. Chapter five provides a comprehensive summary of the project and future works are also presented. It also highlights a few improvements that could be made through future work.

# Chapter 2

# BACKGROUND

## 2.1 Literature Review

In recent years, real-time BCI has a significant improvement in providing a quality lifestyle for people. Due to that, the affective computing [1] has been widely researched for identification of human neural responses. With the numerous availability of economical EEG, the system and its increasing quality offer new possibilities for both medical and non-medical purposes. The ability of autonomous mental state recognition is useful in different domains like in healthcare, neuroscience, robotics, education, etc. It is difficult to measure the emotional condition by simply observing the person. Some components can be evaluated via some tools and techniques such as facial expressions, psychophysiological [2] aspects like brain responses to certain stimuli or tasks, conductance, etc. In Neurophysiological[3] studies, the signals are mapped according to the physiological changes on each emotion. Below contains some background information about different methods of identifying human mental states, methods, tools, and technologies that the researchers have used for previous works. Some of the prominent and noted researches are reviewed below.

Previous related researches [7][8][9][11] have shown sufficient evidence that human biological, psychological signals contain a considerable amount of information about emotion and attention which indicated the possibility of recognizing mental level by studying these signals. Researchers, Wan Ismail, M. Hanif, N.Hamzah from the University of Sultan Zainal Abidin, conducted research to identify the emotions of a person by analyzing brain waves. It is difficult to determine the mental state of a person by applying through face recognition techniques or analyzing the behavior of the person. Due to that, these researchers have employed with brain waves and tried to identify the relationship

[1]The study that considers the development of systems/devices that can determine, interpret and process human affects where popular among computer science, psychology, and cognitive science disciplines

[2]Branch of neuroscience which use to understand how a person's physiological responses and interactions affect one another

[3]Branch of neuroscience and physiology that considers the study of the functioning of the nervous system.

between the EEG signals and human emotions. Their study proves that human emotion detection can determined by analyzing the brain waves via EEG signals. This conclusion has tremendously helpful for my research study to finalize a proper methodology to identify the emotions. In addition to that, they developed software that can detect human emotions and used EEG signals to form a relationship between EEG signals and emotions. In this study, emotions are identified either through EEG neuroimaging, functional magnetic resonance imaging (fMRI)[8]. Through brain waves, the collected data are contributed to classifying the emotion felt by the respondent by analyzing the brain waves before and during the process of emotion detection. Further, this research was conducted to experiment and understand how the brain waves change in different emotions such as happy, angry, surprised, and sad. As per their findings that obtained through the process carried out was revealed that the emotion detection of a person could not describe only by analyzing facial reaction. But with the analysis of brain waves, they were able to identify the appropriate emotions of the respondent although the person is trying to unrelieved it. Their main objectives of this study are to implement a classification model which identifies different emotions of a person by studying the brain waves and examine the relationship between the human emotions through facial and the electricity flow of a brain signal. The methodology they followed was helpful for my analysis and it consists of four stages. At the initial stage both EEG and visual data are extracted at the same time from the participant, and then recorded the entire session which included the captured image along with the EEG data. At the third stage applied proper pre-processing techniques, feature extraction, and classification is performed and then artificial intelligence techniques are applied to the emotional face in the final stage. During the data recording process, they used Cap EEG which placed on the head of the participant to collect the brain signals. As per the research published by the Journal of Undergrad Neuroscience Education, the quality and comfort level of the EEG Cap is low compared to individual electrodes [33]. The drawback mentioned in the research were analyzed when selecting an appropriate EEG device to proceed with the data recording step.

Affective/Cognitive computing is an emerging research field and Rashima Mahajan, Dipali Bansal, Shweta Singh researchers have analyzed in the context of human-neural response[4]. They have explored and evaluated different types of emotion assessment modalities like facial expressions, speech, text, gestures, and human physiological responses. The main focus of their study is to explore how the EEG signals can be used to describe the feelings, thoughts, and unspoken words of a person. They have developed an EEG-based, real-time BCI system to analyze and classify human emotions by evoking visual stimuli or external audio. In EEG-base emotion classification, it measures the millivolt range of an electrical signal by placing the number of electrodes on the scalp of the test subject and the electrical waveform is transformed into a set of features by involving different machine-learning algorithms. It is required to trained sets of features by properly labeling them and the machine learning model will return the current emotion which is being sensed. To collect and measure the electrical signals there are EEG neuroheadset-set available by integrating a set of electrodes. For this study, they have used such an EEG neuroheadset unit called EMOTIV to collect EEG data. Among various commercial EEG sets, they have selected EMOTIV EEG Neuroheadset because of its better resolution, capable of achieving a higher bit rate and it is a comparatively more user-friendly interface. For the primary process and analysis of the acquired EEG signals, they have used MATLAB based advanced brain mapping toolbox. EEG-Lab toolbox and BCILAB plugin have provided a perfect platform for the analysis and classification of emotional states using the acquired EEG signals. Independent Component Analysis (ICA) algorithm of EEGLAB is capable of identifying the emotional states of distinct emotional states of the brain signals discovered from the headband. After the data were mapped to a feature set several classification algorithms like Bayesian statistical classifier, Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), K-nearest neighbor, and artificial intelligence tools like Artificial Neural Network (ANN) were applied. Their study proposes a portable, real-time approach to retrieve emotional state from neural response by capturing spectral and temporal variations in the EEG using EMOTIV EEG headset. This EEG acquisition using consists of 14-channel electrode sensors (AF3, AF4, FC5, FC6, F3, F4, F7, F8, T7, T8, P7, P8, O1, and O2) which arranged according to the standard positions of the scalp as shown in Figure A.1. One of the important observation found in their research study is, that the emotional changes are more associate with the frontal scalp region. Signal processing is done using EEGLab, the plugin BCILAB in MATLAB. Their training procedure is involved with labeling the emotions according to the participant's feedback. Similar approach is selected and applied for my research work as well. Several classification algorithms were applied but out of those artificial neural network and support vector machines classifiers performed well in terms of flexibility, processing time. Finally, as the solution researchers have implemented a real-time BCI system that can translate different brain states into operative control signals.

Another research is conducted by Dr.Aparna Ashtaputre, to investigate and map the relationship between brain waves and emotions. This study reveals and tries to differential Happy and Sad emotions by analyzing the brain waves and the results showed a clear difference in Alpha waves in between these emotions. The EEG-based connectivity pattern was detected by using Quadratic Discriminant Analysis[4]. As per the results of the study, Alpha waves indicate a high value in Happy state compared to Sad state[20]. Alpha waves are useful for overall mental calmness, alertness of the mind or body integration. Beta waves are important for effective functioning throughout the but it can also translate into anxiety, stress, and restlessness. According to the Brainwave, angry emotional reactions are very clear on the right side of the brain that involves Theta waves. The theta waves indicate stress relief and deep relaxation or it can be linked to pressure on human emotions. Hence, the theta waves are indicated if a particular person is experiencing an angry emotion. Furthermore, this study revealed that the real emotion of a person cannot be revealed and described only by using facial reaction but the brain wave analysis would provide more accurate and true emotion although the respondent is trying to unrevealed. The neurons of the brain construct a rhythmic signal which can be divided into several bands [20]. The following table depicts several bands of brain signals, their frequencies, and their relevant activities involved.

[4] A statistical procedure used to classify an unknown individual and the probability of their classification into a certain group

Table 2.1: EEG frequency bands & relevant activity involved [4]

| Name | Frequency Range | Activity |
|---|---|---|
| δ (Delta) | 0 - 3Hz | Deep Sleep |
| θ (Theta) | 4 - 7Hz | Drowsiness or Meditation |
| α (Alpha) | 8 - 12Hz | Eyes closed, Quiet, Resting |
| β (Beta) | 13 - 30Hz | Attention or focused on specific task |
| γ (Gamma) | 30 - 40Hz | High level mental processing, binding of senses |

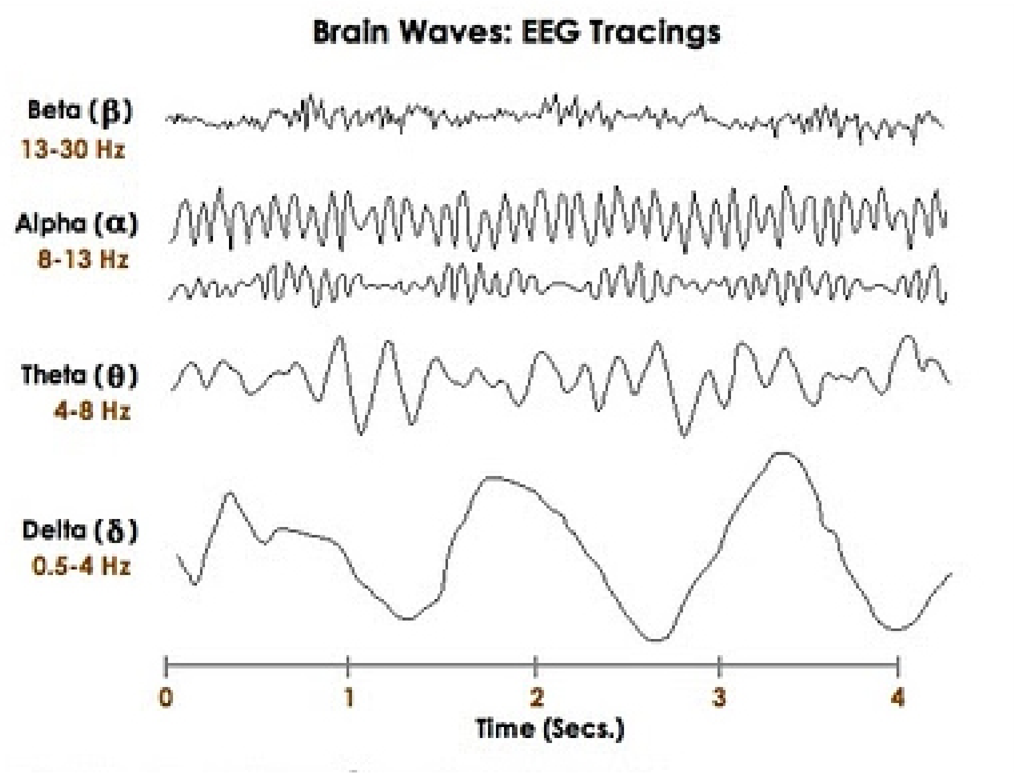


Figure 2.1: Brain Waves - EEG Trace [22]

Several previous works have studied and investigated in the context of real-time mental state recognition by analyzing EEG data. There are different types of consumer-grade, economical EEG system, or wearable are available to acquire the EEG data. These EEG systems are used to capture the electrical activity of the brain over a while. Some systems are capable of amplifying, digitalizing, and output an enhanced signals. Below table depicts the comparison between four headsets provided by different manufacturers.

Table 2.2: A Comparison of different EEG headsets

| Specifications | Emotiv EEG [14] | Neurosky Mindwave[15] | Xwave with Neurosky[16] | Muse[17] |
|---|---|---|---|---|
| Cost | $750 | $99.99 | $90 | $269 |
| Channels | 14 | 1(1-ref, 1-gnd) | 1(1-ref, 1-gnd) | 4 |
| Bandwidth | 0.2-45 Hz | 3-100 Hz | 3-100 Hz | 2-50 Hz |
| Resolution | 16-bits | 12-bits | 8-bits | - |
| Sampling rate | 128 Hz | 512 Hz | - | 220-500 Hz |
| Battery type | Li-poly | AAA | Lithium | Lithium |
| Battery life | 12hrs | 8hrs | 6hrs | 4.5hrs |
| Remarks | Capture 4 Mental states, 5 EEG bands | Capture 2 mental states | Extracts 8-EEG band data | Detects positive and negative emotions, 5 bands of brain waves |

Several electrodes are placed in the EEG headset and depending on the brain responses consumers need to select the EEG system which satisfies at least the minimum required electrodes. The sampling rate indicates the number of samples can be collected within a second. Muse headband is specially developed for meditation purposes. It consists of four channels, two electrodes, and one reference. More features about Muse headband is covered in the methodology section. There are some open-source EEG systems are available, OpenBCI is one of the most popular EEG systems that can provide a maximum of sixteen channels. It can achieve a 256Hz sampling rate and flexible in electrode placement. The EMOTIV Epoc is considered as the first consumer EEG system related to the market. It consists of 14 channels and provides a 2048Hz sampling rate. Further EMOTIV manufactures related second product as EMOTIV Insight which is known as a more economical option for EMOTIV users. It provides a 126-256Hz sampling rate and consists of five channels. Neurosky is known as the original consumer EEG system available in the market.

In psychological signal-based emotion, classification is attempted to recognize different emotions like happiness, sadness, anxiety, fear, disgust, surprise, anger and excitement among others. Numerous research works have proved that the classification of emotions can be obtained by analyzing EEG data. As per the previously published works, statistical features of EEG are obtained and applied machine learning techniques to classify different mental states [5],[9],[10]. Emotion modeling can be categorized into three domains such as time, frequency, and combination of time and frequency domains. Event-related potentials (ERPs) are mainly considered in Time domain emotional modeling. Frequency domain emotional modeling is achieved by learning the features, power spectrum analysis of alpha, beta, theta, gamma, and delta frequency bands. Common Spatial Patterns (CSPs) is widely used for feature extraction in EEG based classification which provides 74.8% accuracy with linear support vector machine (SVM)[34]. The pre-processed features retrieved from Fast Fourier Transform (FFT) produced 85.7% classification accuracy using

SVMs. The combination of frequency and time improves the power spectrum analysis at predefined time period when measuring brain waves. Several machine learning algorithms such as k-Nearest Neighbors (kNN) are used for emotion classification with different Time-Frequency analysis methods. Discrete wavelet transform (DWT) [11],[12],[13] and lifting based wavelet transform combined with spatial filtering to obtain the emotion related features of EEG data and used to classify happiness, sadness, fear and disgust emotions using Fuzzy C-Means clustering [4]. A group of researchers including Jordan J.Bird conducted a study on mental state classification using an EEG based BCI system, Muse headband by applying different classifiers such as Bayesian Networks, SVM, and Random forest which achieved an accuracy of 87% [7]. EEG-based feature extraction is challenging due to its complexity, non-stationary, non-linear, and randomness. The signals remain static within short intervals and a short-time windowing approach is used to identify important features from the EEG signals. During this study, they observed that the signals show non-stationary behavior during eye blinking, changes in alertness, and when the transitions happening between mental states [7]. This is an interesting and important observation for my study that helps to avoid such interference, randomness from the signals. During the data acquisition session, the participants are advised to avoid eye blinking and keep the alertness throughout the period. In this study, the data acquisition process is carried out using the Muse headband and after that, several feature selection algorithms like Shannon Entropy, max-min features in temporal sequences, time-frequency based fast Fourier transform (FFT), statistical techniques are used. To provide a better representation for the raw data in a specific time period, they used a set of statistical features which useful to justify the efficiency of the set of features in pattern recognition. The statistical features are; Mean value of the sequence, computed for the given set of data values acquired with the time window. Further, standard deviation, third, fourth order of statistical moments which gives the skewness measure. To increase the diversity of the features, minimum and maximum values are captured within a one second time window. The temporal features are determined by dividing the initial time window of one second into 0.25 seconds, which creates four batches. Then compute the min, max and mean values of each batch, then calculated Euclidean Distance (ID) of all mean values derived 18 features by considering the distance. Finally, they derived 30 features by adding four max, four min, and four mean values to the 18 features. 150 of temporal features are extracted within one second of the short window time for five signals. That temporal features are further reduced to 144 features to build a 12x12 matrix to compute the log-covariance for the features. Entropy is an other uncertainty measure commonly used in BCI application since it provides better efficiency in the context of random, non-linear signal processing. FFT is important when extracting the features based on the frequency spectrum of a give time frame. After the above process, they have used several feature selection algorithms like oneR, Information Gain, Correlation, Symmetrical Uncertainty, and Evolutionary Algorithm to create five different data sets to categorize three states such as neutral, relaxing, and concentrating. Finally, they applied some classification algorithms on the pre-processed data-sets, like SVM, Random Forest, Multilayer Perceptron (MLP) and Naive Bayes and evaluated the accuracy of the model. Below table depicts some of the previous studies on human mental state recognition using EEG signals and classification methods they have used.

Table 2.3: Previous studies based on human emotion recognition using EEG

| Reference | Feature Engineering Techniques | Classification Method | Method | Dataset |
|---|---|---|---|---|
| A Real-Time Set Up for Retrieval of Emotional States from Human Neural Responses [4] | Independent Component Analysis algorithm (ICA) | SVM, ANN | BCI for human emotion recognition using Emotiv EEG Neuroheadset | Fs: 128Hz / No of Electrodes: 6 (AF3, AF4, F3, F4, FC5, FC6) |
| A Study on Mental State Classification using EEG-based Brain-Machine Interface[7] | Shannon Entropy, Log Covariance, Statistical Techniques, Max Min Features, Time-Frequency based on FFT | Random Forest classifier along with dataset created by oneR attribute selector CA+ 87.16% Naive Bayes Classifier data set created using symmetrical uncertainty CA+ 51.49% | Using Muse headband recognizing 3 states (relaxed, neutral, concentrating) by using low tempo music and a shell game | Fs: 200Hz / No.of Electrodes: 4 (AF8, AF7, TP9, TP10) |
| Mental State Recognition via Wearable EEG [18] | DWT, Power Correlation | SVM, Logistic Regression (LR), Deep Belief Network (DBN) | Using Muse Headband, A Video clip | Fs: 220 Hz / No.of Electrodes: 4 (FP1, FP2, TP9, TP10) |
| Mental state and emotion detection from musically stimulated EEG. Brain Informatics [19] | Time Domain, Frequency Domain, Time-Frequency | SVM,CA+ 83.33% | By using Musical Stimulus | Fs: 256 Hz / No.of Electrodes: 10 -20 |

## 2.2 A Review of Similar Systems

Mindfulness meditation provides significant benefits to maintain a better physical or mental health and well-being of a human. Hence mindfulness meditation apps have been developed in the last couple of years which assuring to provide better sleep, keep the attention, combat anxiety, and more. As per the Wall Street Journal, there are more than 2000 new meditation apps have launched to the different app markets between 2015 and 2018 [35]. There are some application available which are completely free to use, which rest of them include a free version with some options where users need to upgrade to experience the premium features. There are some journals, research studies available that provide comprehensive comparisons between the applications in terms of availability, accuracy, expenses, and features. However, most of them are hidden from under-laying architecture and the technology used for each application. The main objective of this study is to develop a Mindfulness-Based Application (MBA) that potentially offers an alternative delivery medium for meditation practice in everyday life by employed with BCI. Hence several similar application which is already in the app markets has been evaluated and measured the effectiveness of them. The findings indicates that less number of applications only provides mindfulness training while most of them provides reminders for meditation. Furthermore, research study expanded to the technologies embedded in each mindfulness apps, such as integrating with wearable devices, virtual reality (VR) which use to enhance the self awareness and attention. Muse, Spire, WellBe are some of the wearable devices available to enhance the meditation process and well-being experience.

Muse has introduced two different headbands to the market, called Muse 2 and Muse S integrated with multiple sensors that provide real-time feedback on brain activities, breathing, heart rate, and body movements to keep consistent mind during the meditation [17]. Spire is designed by Standford University's Calming Technologies Lab, which measures the breathing patterns, counting steps, and recognize the tension level of the person [36]. The Spire embedded sensors monitor the breathing pattern and the mobile application synchronized with these data and notify the users when the stress level is higher than the optimal value. Being, is another mindfulness tracker which can differentiate bad stress by tracking the blood pressure, sleep cycles and heart rate. The main drawback of Being is, it consists of a comparatively huge watch face which leads discomfort to wear throughout the day [36]. WellBe is a comfortable wearable solution over Being, and it monitors the heart rate level. Apple Watch, Samsung Gear fit and Mi fit are widely used fitness bands and watches that can monitor the heart rate. EMOTIV Insight, Neurosky Mindwave are some of the EEG based wearables aggregates with alpha and gamma signals and helps for meditation, deep sleep, and concentration. Many of these wearable APIs are available for the developers to create their own customized applications, games based on EEG signals. Nowadays there are some wearables that exist to enhance the lucid dreaming which the subject is aware that they are dreaming [37]. Neuroon open sleep mask is on the lucidcatcher that provides guided meditation along with EEG. Furthermore, there are limited number of VR based meditation apps available that provides an immersive experience using existing VR headset such as Playstation VR, Oculus rift, Oculus Quest, etc. More details and images of these wearable devices are included in the appendix section.

There are a considerable amount of meditation and mindfulness apps available on the apple app store and google play store. The findings indicate that most of the applications are focused on a guided meditation to the users relaxed and claimed. There are a limited number of applications that support monitoring intrinsic meditation and measure the effectiveness of the training at the same time. Most of the applications are not capable of identifying the current mental state of a person and guiding them according to the current mental state. Claudia D. Roquet, Corina Sas from Lancaster University conducted a research to evaluate the mindfulness meditation apps. A set of free Mindfulness-Based Applications (MBAs) are searched from the iTunes app store by using keywords such as meditation, mindfulness, well-being and mindful [38]. At the initial stage, more than 280 apps were identified which are included in the Health category. As per their findings, most of the applications were quite generic focus on the usability aspects of the interfaces rather than the context of training content. They considered specific cognitive strategies such as concentration, objects attention in terms of physical, conceptual, body posture, and meditation processes such as extrinsic (which depends on an instructor or process) and self-reliant which is known as intrinsic. Further, their findings indicate that there is a lack of diversification on the techniques offered in each application and the context they are employed. The following table is extracted from their study with provide a better comparison between different MBAs in terms of the meditation type, cognitive strategies, attention and meditation process employed.

Table 2.4: Evaluation of MBAs and the meditation techniques used

| App Name | Meditation Type | Cognitive Strategies | Objects of attention | Intrinsic / Extrinsic |
|---|---|---|---|---|
| Calm | Guided Meditation | Concentration, Introspection, Noting, | Body | Extrinsic |
| Insight Timer | Self-reliant Meditation | Concentration | Sound | Intrinsic |
| Mindfulness Daily | Guided Meditation | Introspection, Focused, Attention | Body | Extrinsic |
| Headspace | Guided Meditation | Focused attention, Introspection | Body | Extrinsic |

By clearly analyzing these previous works, identified several drawbacks of each applications and tried to present some solution through this study. The findings indicate that most of the applications are focused on a guided meditation to the users relaxed and claimed. There are a limited number of applications that support monitoring intrinsic meditation and measure the effectiveness of the training at the same time. Furthermore, most of the applications are not capable of identifying the current mental state of a person and guiding them according to the current mental state.

# Chapter 3

# METHODOLOGY

This section comprised with a detailed description about the methodology followed to achieve above stated objective of the project. By gathering background information upon environments using past research works, brainstorming sessions, having continues discussion with the supervisor and advisor came up with proper approaches, which are defined in each sub sections.

This project proposes an approach to analyze neural responses in real-time and classify mental states human. The main initiative of this work is to collect the appropriate EEG data and finalize the data-set. Later applied relevant data pre-processing techniques in order to reduce noise and other irrelevant artifacts from the data. Several feature selection methods are followed and different classification algorithms are applied to implement this mental state recognition model.

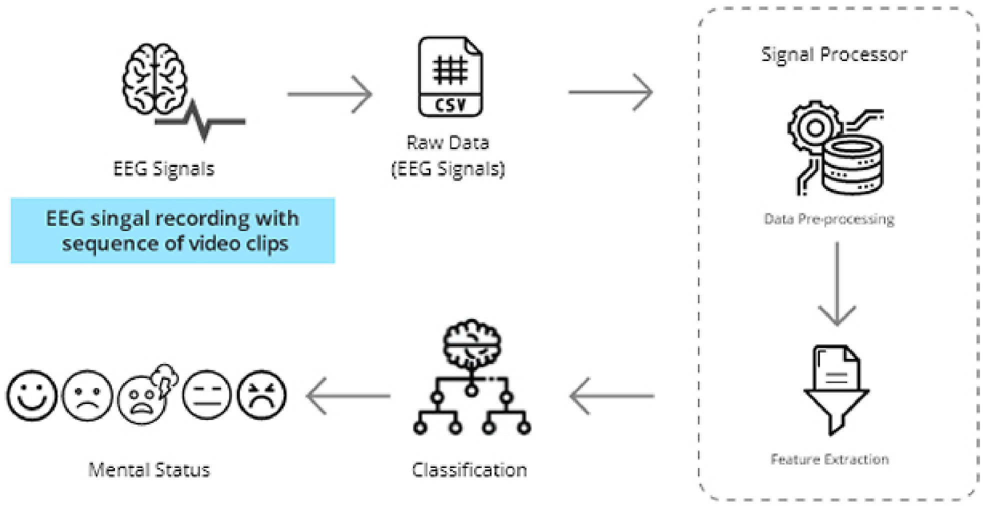


Figure 3.1: The block diagram of the EEG based human emotion recognition system

Figure 3.1 depicts the main activities involved in the development of the mental state recognition model. Initially, it is required to select the proper data acquisition method to capture brain activity and store the raw data based on the captured time for signal processing. The data acquisition process is described more in section 3.2. Then relevant data pre-processing techniques are applied to the raw data to extract important features from the brain signals. Feature extraction and selection algorithms and sections 3.3 and 3.4 elaborate more details on that. A set of classifiers is used to classify different mental states and selected the most appropriate classification algorithms by considering the prediction accuracy and processing time. The following sections provide more details about each step mentioned in the block diagram.

## 3.1 Experimental Environment

### 3.1.1 Hardware Interface

Muse2, EEG sensing device is used as the main hardware interface for the data acquisition step. Muse2 headband equipped to collect real-time EEG signals that provide feedback based on brain activity, breathing, heart rate, and body movements. This device is widely popular among neuroscience researchers and meditation practitioners. It is capable of interpreting mental activities via advanced signal processing. This headband fits in the middle of the forehead and keeps it steady around the back of your ears, as a pair of glasses. Users are allowed to adjust the arms of the headband and keep it tighter or looser according to the user's preference.


Figure 3.2: Muse - Brain sensing headband [17]

This EEG sensing device is comprised of five dry application sensors, TP9, AF7, TP10, AF8 to record brain wave activity, and one used as a reference point(NZ). The Figure 3.3 depicts sample live stream of four sensors embedded in Muse device. The X-axis indicates the time reading in seconds and Y-axis measured in micro-volts on each sensors at t=0. Right AUX is discarded as it does not have a device and simply produce noise.

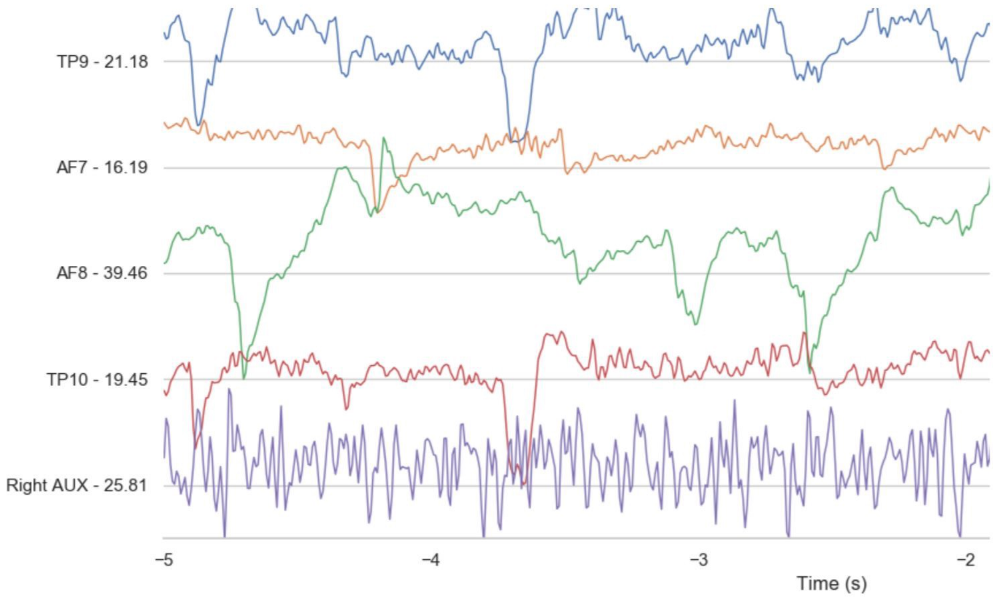


Figure 3.3: Sample live EEG stream of the Muse sensors [6]

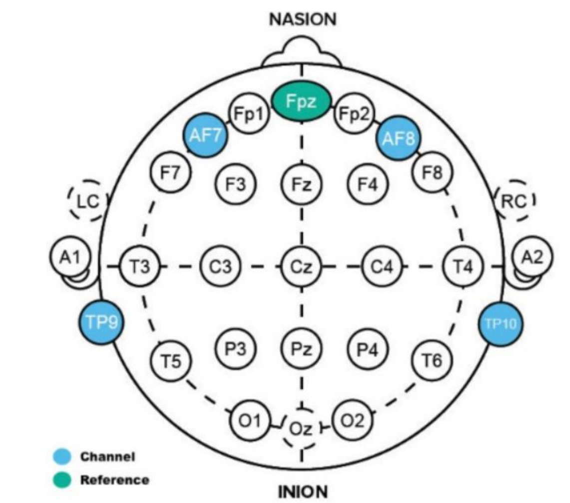


Figure 3.4: Muse EEG Electrodes placement according to the 10-20 International Standard [6]

Figure 3.4 shows how the electrodes are placed on the Muse devices according to the 10-20 Electrode placement standard. The channels unique to the Muse system are highlighted other channels are shared between multiple channel systems.

### 3.1.2 Software Interface

1. Muse Direct

   Muse Direct is available on the Apple app store which allows the users to streamed and recorded raw EEG data anytime and anywhere. This allows collecting with multiple Muse device via Bluetooth connectivity and records EEG signals simultaneously from multiple people. With its rich graphical user interface, users can start verifying their algorithms or related works without building an entire application to capture raw EEG data. Some of the important features of Muse Direct application is listed below:

   - Allows to connect with multiple headbands via Bluetooth
   - Provides rich graphical interface and easy to use
   - Stream raw data in real-time to one or many computers simultaneously
   - Single click recording
   - Provides Raw EEG data, accelerometer, battery, ppg, gyroscope, and DRL/REF
   - Embedded with built-in algorithms: headband indicator, band powers, data quality indicator, blink event, jaw clench event, and "is user wearing headband" indicator [24]

2. Muse Lab

   Muse Lab is a data recording and visualization tool that streaming from Muse headband. It obtains the data over OSC streaming from Muse Direct and it is not directly connected to the Muse device itself, users must run both Muse Direct and Muse Lab. Furthermore, users can save and load configuration files which helps keep track of a specific setup. Muse lab facilitates users to annotate the data via specific markers, differentiate them using different colors, and filter them accordingly. More details about the Muse Direct and Muse Lab are described with the aid of a set of screenshots in the appendix section.

3. Muse Player

   Muse Player is a command-line tool for recording, replaying and converting EEG and accelerometer data from the Muse device. It also used to convert the native Muse file format (.muse) to different formats such as CSV, MATLAB (HDF5) and .txt (OSC replay). Muse Player is capable of acquiring Muse data in different formats and outputs them into different formats. Furthermore, Muse Direct Cloud can be used as an alternative solution for the Muse player to convert muse files into different formats such as JSON, Muse, CSV, etc.

## 3.2 Data Acquisition

1. Participants

   A total of 33 adults, age between 20-50 years (both male and female) were involved with this experiment. The physical condition of each participant was confirmed by asking a set of questions at the initial stage of the experiment session. Their verbal confirmation helps to find the appropriate audience who are free from neurological abnormalities or mental disorders.

2. Environmental Setup

   The data acquisition session was conducted in a controlled and quiet environment where the subjects were advised to sit comfortably on a chair as depicted in the below figure. Further, the participants were informed to avoid unnecessary movements and facial muscle movements to prevent the interference of electromyographic signals. In addition to that participants were advised to keep their eyes open during any of the tasks. As a result of blinking & closing eyes provides interference to the AF7 and AF8 sensors which cause unnecessary patterns of spikes into account.

Figure 3.5: A test subject is participating in the data acquisition task

The participants were informed to watch a video clip which consist of five, one minutes of small videos clips to acquire EEG data. A black screen was placed in between each video. When the participant is watching the video, EEG signals were captured using MUSE headband with the help of Muse Direct mobile app and Muse Lab. Further subjects were informed to answer for the evaluation by providing the emotions they have experienced.

Figure 3.6: Sequence of video clips used to collect data

The acquired data were streamed to the Muse Lab which is an instance running on the computer and the communication is handle between the computer and the headband via User Datagram Protocol (UDP). By using the Muse Player application collected data (.MUSE file) are converted into CSV file format and the following image depicts the sample Dataset.

| A | B | C | D | E | F | G | H | I | J |
|---|---|---|---|---|---|---|---|---|---|
| 1549587887 | /notch_filtered_eeg | 944.5393 | 744.3879 | 696.82214 | 935.9357 | | | | |
| 1549587887 | /variance_eeg | 3919.851 | 1441.418 | 362.21472 | 5007.477 | | | | |
| 1549587887 | /variance_notch_filtered_eeg | 3758.058 | 1433.429 | 343.3517 | 4869.955 | | | | |
| 1549587887 | /eeg | 952.5275 | 714.3956 | 720.0366 | 954.9451 | nan | nan | | |
| 1549587887 | /notch_filtered_eeg | 969.1539 | 725.0555 | 705.8109 | 930.0339 | | | | |
| 1549587887 | /variance_eeg | 3919.851 | 1441.418 | 362.21472 | 5007.477 | | | | |
| 1549587887 | /variance_notch_filtered_eeg | 3758.058 | 1433.429 | 343.3517 | 4869.955 | | | | |
| 1549587887 | /eeg | 958.5714 | 707.9487 | 718.4249 | 951.3187 | nan | nan | | |
| 1549587887 | /notch_filtered_eeg | 974.6968 | 715.8239 | 719.03296 | 958.9796 | | | | |
| 1549587887 | /variance_eeg | 3919.851 | 1441.418 | 362.21472 | 5007.477 | | | | |
| 1549587887 | /variance_notch_filtered_eeg | 3758.058 | 1433.429 | 343.3517 | 4869.955 | | | | |
| 1549587887 | /eeg | 970.2564 | 734.5421 | 713.9927 | 958.1685 | nan | nan | | |
| 1549587887 | /notch_filtered_eeg | 965.5723 | 717.4895 | 719.74194 | 960.9782 | | | | |
| 1549587887 | /variance_eeg | 3919.851 | 1441.418 | 362.21472 | 5007.477 | | | | |
| 1549587887 | /variance_notch_filtered_eeg | 3758.058 | 1433.429 | 343.3517 | 4869.955 | | | | |
| 1549587887 | /eeg | 978.718 | 752.2711 | 713.9927 | 963.0037 | nan | nan | | |
| 1549587887 | /notch_filtered_eeg | 965.0449 | 735.1414 | 719.8062 | 955.0245 | | | | |
| 1549587887 | /variance_eeg | 3919.851 | 1441.418 | 362.21472 | 5007.477 | | | | |
| 1549587887 | /variance_notch_filtered_eeg | 3758.058 | 1433.429 | 343.3517 | 4869.955 | | | | |
| 1549587887 | /eeg | 979.5238 | 752.2711 | 716.0073 | 960.5861 | nan | nan | | |
| 1549587887 | /notch_filtered_eeg | 972.8121 | 745.8861 | 719.2519 | 963.403 | | | | |
| 1549587887 | /variance_eeg | 3919.851 | 1441.418 | 362.21472 | 5007.477 | | | | |
| 1549587887 | /variance_notch_filtered_eeg | 3758.058 | 1433.429 | 343.3517 | 4869.955 | | | | |
| 1549587887 | /eeg | 977.1062 | 745.4213 | 714.3956 | 961.392 | nan | nan | | |
| 1549587887 | /notch_filtered_eeg | 977.523 | 746.612 | 714.6218 | 964.2277 | | | | |
| 1549587887 | /variance_eeg | 3919.851 | 1441.418 | 362.21472 | 5007.477 | | | | |
| 1549587887 | /variance_notch_filtered_eeg | 3758.058 | 1433.429 | 343.3517 | 4869.955 | | | | |
| 1549587887 | /eeg | 980.7326 | 729.304 | 720.0366 | 954.5421 | nan | nan | | |
| 1549587887 | /notch_filtered_eeg | 981.7429 | 749.8084 | 709.0493 | 960.8354 | | | | |

Figure 3.7: Sample Raw Dataset

Sample data set (EEG) data from Muse 2 device consists of raw EEG data, Accelerometer data, Muscle Movement as Blinks and Jaw Clenches, etc. These raw EEG data as delta, alpha, theta, gamma, and delta. These frequencies are based on specific frequency ranges or called as frequency bands and the Delta band (1 – 4 Hz), the Theta band (4 – 8 Hz), the Alpha band (8 – 13 Hz), the Beta band (13 – 30 Hz), the Gamma band ($>$ 30 Hz) as shown Figure 2.1. Depending on the individual factors, internal states, stimulus properties, and research classifiers, these frequency bands might show slight differences in frequencies. However, the signal is a mixture of several underlying base frequencies, which capable of reflecting certain affective, cognitive, or attentional states.

## 3.3 Data Pre-processing

The EEG signals are consists of noises and several other unnecessary artifacts. Pre-preprocessing the EEG is mainly involved with reducing or removing these unnecessary artifacts to increase the signal quality. The noises can be added to the signal due to the interference, existence of electronic amplifiers, and power line interferences. These unnecessary artifacts are originated from the noncerebral region of the brain. These artifacts mainly appear when blinking or jogging your eyes, and moving head, shoulders, fingers, and legs. The brain signals which are involved in determining emotions are alpha, beta, delta, theta, and gamma. The following list contains the data coming from Muse device in CSV file format collected over the data acquisition process. During the process of feature selection, the most accurate and appropriate data are going to be used and those unnecessary artifacts, features have to be eliminated in the pre-processing stage. A detailed description of these data is explained in appendix section B.

- $/eeg$
- $/acc(xyzmovementofthehead)$
- $/gyro$
- $/ppg$
- $/variance-eeg$
- $/drlref$
- $/notch-filtered-eeg$
- $/variance-notch-filtered-eeg$
- $/elements/blink(eyeblinking)$
- $/elements/touching_{f}orehead(signalqualitygood/ok/bad)$
- $/elements/jaw-clench(movements)$
- $/elements/alpha-absolute$

- $/elements/beta-absolute$
- $/elements/theta-absolute$
- $/elements/delta-absolute$
- $/elements/gamma-absolute$
- $/elements/horseshoe$
- $/elements/is-good$
- $/batt$
- $/muse/annotation$

Mainly Python language and pandas library were used to pre-process the data and the following procedures are applied. *Derive useful features:* Some of the useful indicators are derived from the existing data-set such as EEG, alpha, beta, theta, delta, gamma, and muse annotation. *Inconsistent columns:* Data-set itself contains columns that are irrelevant or useless columns that can drop them to give more focus on the other columns that are most useful for the analysis. Beta and Alpha brain waves are considered the most important waves useful for emotion detection. So other than the raw EEG values absolute and relative values of the beta and alpha waves have to be used as the features [20]. *Missing Values:* Collected data-set contains several missing values, some of the columns had NAN values and those values are being replaced by the mean of that particular column. *Remove the outliers:* In statistics, an outlier is a data point that significantly differs from other observations. Those outliers are existed due to the errors in the experiments or the variability in the measurements. Keeping those abnormal values negatively affected the accuracy of the model, hence required to eliminate those values. By clearly analyzing the data-set corresponding to each person, required pre-processing steps were followed to prepare accurate data-set for the model implementation.

## 3.4 Feature Extraction

EEG based feature extraction is challenging due to the complexity of the signal, non-stationary, non-linear, and random. The signals remain static within short intervals and a short-time windowing approach is used to extract important features from the EEG signals [7]. The signals show non-stationary behavior during eye blinking, changes in alertness, and when the transitions happening between mental states [7]. This subsection outlines the different techniques used to select a set of features from the non-stationary EEG signals to recognize different classes of mental states. Raw dataset consists of 103 features and different feature extraction techniques are applied to extract the best set of features among them. Feature extraction is carried out to reduce the number of features included in the dataset and created a new dataset to apply classification algorithms. Initially feature selection techniques are applied by ranking them according to their importance for the analysis and eliminated unwanted features from the dataset. To provide a better representation of the raw data in a particular time period, this project uses statistical features that to justify the efficiency of the set of features. The statistical features are; Mean value of the sequence, computed for the given set of data values acquired with the time window. Means values are calculated for EEG, PPG, alpha, beta, theta, gamma, delta absolute, and relative values at each second. *Shannon Entropy and Log-Energy Entropy:* Entropy is considered as an uncertainty measure and widely used in BCI applications. Shannon entropy is calculated for each features to select best set of features among existing 103 features. Shannon entropy is given by [25]:

$$h = \sum_j S_j \times \log(S_j),$$

where h is a particular feature computed in every one sec. and $S_j$ is normalized element of this temporal window. Then, split the window into two which compute the log-energy entropy as shown in below [25]:

$$\log e = \sum_j \log(S_i^2) + \log(S_j^2)$$

where $i$ represents the normalized element of the first sub window (0 - 0.5sec.) and $j$ represents the normalized element for the second sub window (0.5 - 1 sec.)

Furthermore, Linear Discriminant Analysis (LDA) used as the forwarding feature selection method. LDA can reduce feature dimensionality. LDA is a method based on the means of the intra-class and inter-class which evaluate the maximum linear separability between classes [16]. During the feature extraction process, 28 of features are identified as important features for the classification out of existing 103 features. EEG1, EEG2, EE3, EE4, blink, PPG1, PPG2, PPG3, alpha, beta absolute and relative, variance in EEG1, EEG2, EEG3, EEG4, variance-notch-filtered for EEG1, EEG2, EEG3, EEG4 and jaw clench are some of the features extract from the data set.

## 3.5 Emotion Classification

In this step, several classification algorithms are applied and trained to classify different mental states. The training process involved the labeling of mental states according to the feedback taken from the participants. In this scenario, the classification task was to predict the class labels happy, sad, afraid, calm, neutral from samples of EEG recorded by invoking through a video clip. In the first approach, the model is trained and tested on data from only a few participants. K-Fold cross-validation is performed in the data from the k sessions. Then train the model on data from all participants. Cross-validation is important when it comes to evaluating the performance of the model in which some portion of the data-set is used to train the model. This involved 70% of labeled data is allocated for training the model and the remaining 30% is used to evaluate the trained model. K-fold cross-validation method helps to improve the process by dividing the same data-set in multiple times by keeping several iterations of training folds and testing folds. For this multi-class classification problem, several methods can be used for this classification such as Support Vector Machine (SVM) [26] [27], k Nearest Neighbor (kNN) [28], Multi-Layer Perceptron (MLP) [29] and Random-Forest [30]. *Support Vector Machine*

*(SVM):* is a supervised machine learning algorithm which mostly used for classification problems. In SVM, each data points are plotted in n-dimensional space where n indicates the number of features and finds the hyper-plane or line which segregates into classes. The scikit-learn SVM library is used to perform the SVM classification to the processed data-set [26]. A set of Tuning parameter values are used to improve the performance of the model. "kernel", "gamma" and "C" parameters are given the high impact on the model. The kernel parameter is an important function that transforms low dimensional input space to higher space, or not makes the problem into a separable problem. The parameter values, 'rbf', 'linear', 'sigmoid','precomputed', 'poly' are used to specify the kernel type and the default value is 'rbf'. For this classification, the kernel type is kept as the default value. The parameter gamma indicates the kernel coefficient for 'poly', 'sigmoid' and 'rbf'. For this classification, gamma parameter values is assigned as 'auto'. The classification report and histograms of the SVM classification are detailed in the Results section. *k Nearest Neighbor (kNN):* is known as a supervised machine learning algorithm that relies on labeled data as input to learn and produce output for the unlabeled data [28]. In this classification, emotions are labeled as 'afraid', 'calm', 'neutral', 'happy' and 'sad' which appears in the last column of the data-set. These classes are annotated during the data acquisition step with the help of the annotation feature in the Muse Lab application. The kNN involved in calculating the ED or the straight line distance between the data points. The kNN algorithm runs several times for different k values, which reduces the number of errors in the classification and improve the accuracy of the model. The sklearn-neighbors library is used by importing the KNeighborsClassifier module to classify the processed data-set using the kNN algorithm. The 'n_neighbors' argument is used to pass the number of neighbors required in the KNeighborsClassifier() function. The algorithms run for different n_neighbors values and evaluate the prediction accuracy of each session. The classification report and histograms of the kNN classification are presented in the Results section. *Random Forest:* is a popular supervised algorithm that can be used for both regression and classification [30]. This creates decision trees for randomly selected data samples and evaluate the prediction accuracy for each tree and select the best tree. The sklearn, ensemble RandomForestClassifier module is imported to perform random forest classification by passing set of arguments to theRandomForestClassifier() function. An argument "n_estimators" indicates the number of trees in the forest and random_state argument refers to the randomness when building the tree. The classification report and the related histogram is presented in the Results section. Several classification algorithms are applied to the pre-processed data set to identify the best classifier model in terms of prediction accuracy and performance. Random forest classifier achieved a maximum prediction accuracy of 87.12% and this classifier model is used to proceed with mental state recognition.

## 3.6 Implementation of Mood Web Application

The Mood, web-based application is developed by integrating the mental state classification model that capable of identifying the current mental state of the user and provide some recommendation based on the identified mental state. As an example when the user is in a sad situation Mood application provides set of recommendations which help the user to get rid of that situation. The high-level architecture diagram of the Mood application is depicted below.

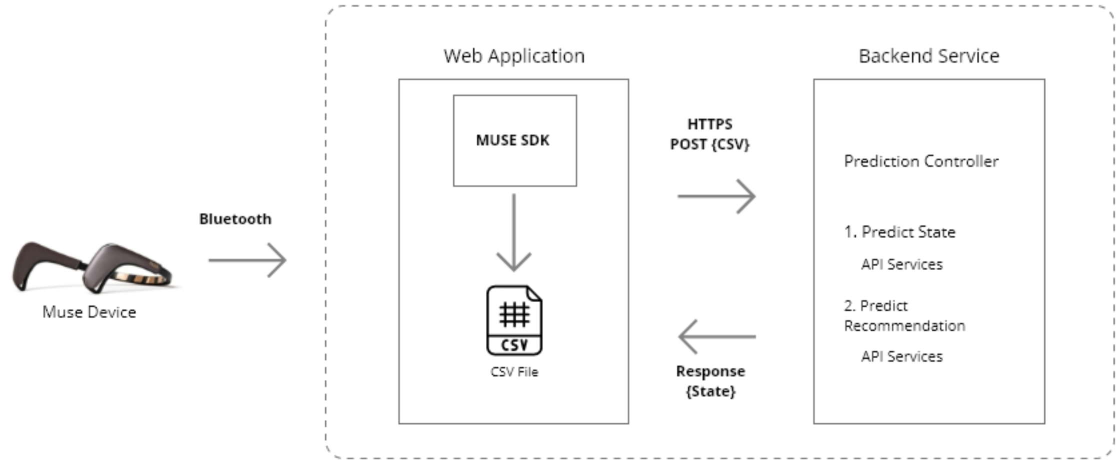


Figure 3.8: High-Level Architecture of the Mood Application

A Java application was developed to capture data in real-time with the aid of Open Sound Control (OSC) protocol and store the processed stream of data in a database. That stream data is sent to the trained model to obtain the emotional state of that particular time. Users can wear Muse headband while accessing the Mood web application via Bluetooth connectivity. Muse Lab provides real-time EEG data in .muse format and it converts to CSV format via that Java application. That file is sent to the Prediction controller to retrieve the current mental state. The acquired data from the device were streamed to a web browser with the help of the developed java executable and MuseIO application. The UDP is used to handle the communication between the Muse device and the MuseLab application. The EEG data is passed to a database and Python client fetches the data stream from the database for further data processing. The classifier model predicts the emotional state by analyzing the data stream of that particular time frame and returns the state to the Mood application. Database connection is created to keep the stream data and predicted the mental state of that particular person. This will create a communication channel between the device and the system. The main objective of this project is to provide the best set of mindfulness activities to balance an unstable mindset of a person by analyzing the current emotional state. The Mood web application prompts the best set of remedies like image, audio, and video clips based on the Item collaborative filtering method, to help users to balance an unstable mindset. The recommendation services are further improved based on the feedback provided by the user. Some of the user interfaces of the Mood application are attached in the appendix section. Further below sub sections provide a detailed description of the frontend and backend implementation work carried out, RestAPI details, Database details, and main functionalities of the Mood web application.

### 3.6.1 Main Use Cases

This section provides a detailed description of the main use cases considered when developing the Mood application. At the design stage of SDLC, the following main use cases and main actors of the system were identified.

- Login

  Actors: Admin & Normal User

  Description: Users are allowed to access the system by providing the correct username/email address and password. The system will validate the login credentials and prompt an error message for incorrect details. The system will navigate to the home page if the user provides correct login information to the system.

- Create an Account

  Actors: Normal User

  Description: Anyone can create an account in Mood by providing the correct username, email address, password, and able to perform basic actions such as retrieve the current mental state, view media, add feedback, ratings for the media, and view summary information. An error message will display if the user provides an email address that is already registered with the system.

- Display current mental state

  Actors: Normal User/Registered User

  Description: Mood registered users are allowed to retrieve the current mental state while wearing the Muse device. The system will prompt the current mental state as Happy, Sad, Afraid, Calm, and Neutral.

- Display recommended medias

  Actors: Normal User/Registered User

  Description: Mood registered user is allowed to view a set of recommended media based on the current mental state identified by the system.

- View media

  Actors: Normal User/Registered User

  Description: Mood registered user are allowed to view recommended medias by clicking the recommendation card in the carousel panel.

- Add feedback and rating to the media

  Actors: Normal User/Registered User

  Description: Mood registered user is allowed to add feedback on the media they followed and give a rating based on the experience they get from that media. The rating can be added from 1 to 5 and by clicking the submit button it will be added to the system.

- View feedback and rating to the media

  Actors: Normal User/Registered User

  Description: Mood registered user is allowed to view all the feedback and ratings added by the interacted users.

- Display summary details

  Actors: Admin User and Normal User/Registered User

  Description: Mood normal users can see an overview of engagement with the application which indicates total no. of interactions with the system, total view, and feedback provided for the media.

- Report generation

  Actors: Admin User and Normal User/Registered User

  Description: Mood admin user is allowed to generate a summary of the interaction chart which visualizes how the Mood users have engaged with the media in a particular duration. Further, the admin user is capable of generating a summary of the feedback chart which visualizes how the users have added feedback to the media in a particular duration. Mood user is allowed to generate the "My Mood" chart which visualizes how the mental states have changed over the time period. Charts can be generated for a particular date range, for the current month and week.

- Change password

  Actors: Admin User and Normal User/Registered User

  Description: Users are allowed to change their password by navigating to the profile section and entering the old password and the new password. The system will update the password once the user confirmed.

- Upload a media to the system

  Actors: Admin User

  Description: Admin user is allowed to upload media to the system by adding media title, URL, media type, duration, and recommended mental state. Once the user confirmed the upload, particular media will be displayed in the Media section.

- List all medias

  Actors: Admin User

  Description: Admin user is allowed to view all the media details added in the system. The table contains Media name, type, URL, duration, total no. of views, average ratings, review counts of the particular media.

- Delete a media

  Actors: Admin User

  Description: Admin user is allowed to delete particular media from the system if there is no interaction exists for the media.

### 3.6.2 User Interface Design

At the design stage of the SDLC, a set of main user interfaces were identified and then created Wireframes to identify the user flow, user interaction properly. After finalizing the wireframes based on the requirements, UI mockups and prototype were designed using Adobe XD tool. The screenshots of all the design user interfaces are attached in Appendix section C. Before moving to the implementation stage of the SDLC, required development languages and technologies were identified. Ant design UI framework is selected to develop the UI components of Mood application as it provides high quality React UI components to build rich user interfaces. Mood user interfaces are built upon a basic React skeleton as it provides more flexibility in developing rich, complex user interfaces in Javascript. Furthermore, the chrome developer tool and integrated react developer tools were utilized to identify, debug the issues occurred during implementation. UI responsiveness in different screen sizes and cross-browser compatibility were considered to provide better user experience to the Mood application users.

### 3.6.3 RestAPI Design

In the implementation stage of SDLC, Restful web service was developed using Java microservices framework called Spring boot. Furthermore, Apache Maven is used to building and manage the Java-based project and also helps maintain a set of required dependency modules. MySQL is used to maintain the database of the Mood application and required entities, tables were identified at the initial stage of the Design phase. In addition to that Hibernate object-relational mapping tool is used as a framework that maps the object-oriented domain model to a relational database. The following are the main entities involved with the Mood database.

- Media - Hold the information related to the Medias; media id, name, URL, duration, type, recommended mood type are the main columns of the Media table
- User - Hold the information related to the User; user id, full name, email address, role, profile image url are the main columns of the User table
- User Media Feedback - Hold the information related to Feedback and ratings given by the user for a particular media. Feedback id, media id, rating value, review, created date and updated date are the main columns of the Feedback table
- User Media View - Keep the records once user is interacted with a particular media; view id, user id, media id, viewed date are the main columns of the View table
- User Mood - Keeps all the logged Mood types for a particular user. mood id, user id, mood type, logged dates are the main columns for the Mood table

The following are the main endpoints developed and deployed to interact with the Mood web application.

1. User Sign-up

   Description: This api is used to register users to the system.

URI: /api/v1/user

HTTP Method: POST

2. User Login

   Description: This api is used to login to an already registered user.

   URI: /api/v1/user/login

   HTTP Method: POST

3. View User

   Description: This api is used to get user information.

   URI: /api/v1/user/userId

   HTTP Method: GET

4. Change Password

   Description: This api is used to change the existing password.

   URI: /api/v1/user/password

   HTTP Method: PUT

5. Update user

   Description: This api is used to update already existing user information.

   URI: /api/v1/user

   HTTP Method: PUT

6. Add Media

   Description: This api is used to add media to the system. Only the admin can add media.

   URI: /api/v1/media

   HTTP Method: POST

7. View Media

   Description: This api is used to get single media information.

   URI: /api/v1/media/mediaId/userId

   HTTP Method: GET

8. Delete Media

   Description: This api is used to delete a media.

   URI: /api/v1/media/mediaId

   HTTP Method: DELETE

9. List Media

   Description: This api is used to get list of media.

   URI: /api/v1/media/all/page/size

   HTTP Method: GET

10. Add Feedback

    Description: This api is used to add media feedback to the system.

    URI: /api/v1/media/feedback

    HTTP Method: POST

11. List Feedback

    Description: This api is used to get the list of media feedback.

    URI: /api/v1/user/media/feedback/mediaId/page/size

    HTTP Method: GET

12. Add User Media View

    Description: This api is used to add user media views to the system.

    URI: /api/v1/media/view/userId/mediaId

    HTTP Method: POST

13. List User Media View

    Description: This api is used to get list of user media view.

    URI: /api/v1/user/media/views/userId/page/size

    HTTP Method: GET

14. Add User Mood

    Description: This api is used to add user mood to the system.

    URI: /api/v1/user/mood/userId/mood

    HTTP Method: POST

15. User Mood Summary

    Description: This api is used to get the user mood summary.

    URI: /api/v1/user/mood/summary/userId/option

    HTTP Method: GET

16. User Overview

    Description: This api is used to get the user overview.

    URI: /api/v1/user/overview/userId

    HTTP Method: GET

17. Application Overview

    Description: This api is used to get the application overview.

    URI: /api/v1/app/overview

    HTTP Method: GET

18. Application Overview

    Description: This api is used to get the application overview.

    URI: /api/v1/app/overview

    HTTP Method: GET

### 3.6.4 Application Deployment

In terms of application deployment process, Mood application is hosted in local environment and rendered in a web browser. Craco and NPM configuration are used to deploy the Mood react app in localhost with the support of Yarn and NPM. Furthermore, backend micro services are deployed using Maven configurations. Mood web application supports and renders in any web browser; Google chrome, Firefox, Safari etc.

# Chapter 4

# EVALUATION

## 4.1 Testing

A testing was conducted on the developed solution to verify whether all the functional and non-functional aspects are fulfilled against defined requirements. At the initial stage of this study, separate test cases were created to cover all the test scenarios for all individual components that exist and the Mood web application. Some of the test cases are presented in the below section. Those test cases are executed to verify the defects of the system. The defects, issues encountered using the testing phase is corrected and re-run the test cases. The following listed tests were conducted on the system.

- Component Testing

  The emotion detection model was tested in multiple ways such as using different participants based on their age, gender to evaluate the accuracy of the model in terms of all these constraints. Furthermore, increased the number of test subject involved and verify how the model reacts to such condition. The real-time signal streaming application also tested with the help of MuseIO applications.

- Integration Testing

  User interface and the responsiveness of the Mood web application is tested using chrome developer tools. Mood web application is tested on different web browsers mainly on Chrome, Firefox after integrating home page, mood page, and feedback pages.

- System Testing

  This test was conducted to verify whether the system is free from defects or not. Once all the components are an integrated system and it verifies whether all the requirements are met. Further, consider the functionalities of the system and performance aspects as well.

The following are the test cases executed for to verify whether the model is working properly for different scenarios. Furthermore, as depicted in Figure 4.15 and 4.16; test cases were executed in terms of validating the functionality of the Mood web application for both admin and normal user.

| **Test Case #** | **1** |
|---|---|
| Description | Emotion detection is working for both male and female |
| Expected Result | Emotion type is changing for both male and female successfully |
| Actual Results | Emotion type is chaning for both male and female successfully |
| Status | Pass |

Figure 4.1: Test-Case 01

| **Test Case #** | **2** |
|---|---|
| Description | Emotion detection is working for the people who are in the age above 20 |
| Expected Result | Emotion type is changing successfully for the age category above 20 |
| Actual Results | Emotion type is changing successfully for the age category above 20 |
| Status | Pass |

Figure 4.2: Test-Case 02

| **Test Case #** | **3** |
|---|---|
| Description | Emotion detection is working for the people who are in the age below 50 |
| Expected Result | Emotion type is changing successfully for the age category below 20 |
| Actual Results | Emotion type is changing successfully for the age category below 20 |
| Status | Pass |

Figure 4.3: Test-Case 03

| **Test Case #** | **4** |
|---|---|
| Description | Emotion detection is working for the people who are in the age between 20 and 50 |
| Expected Result | Emotion type is changing successfully for the age category between 20 and 50 |
| Actual Results | Emotion type is changing successfully for the age category between 20 and 50 |
| Status | Pass |

Figure 4.4: Test-Case 04

| Test Case ID | Scenario | Test Steps | Test Data | Expected Result | Actual Result | Pass / Fail |
|---|---|---|---|---|---|---|
| U001 | Login to the System as a normal user | Go to the login web page<br>Enter User Name<br>Enter Password<br>Click on Login Button | User Name :<br>aruni@gmail.com<br>Password : aruni@123 | User should be able to login to the system<br>ONLY user privileged portal should be displayed | User successfully logged in to the user portal | Pass |
| U002 | Unsuccessful Login | Go to the login web page<br>Enter User Name<br>Enter Password<br>Click on Login Button | Invalid User Name<br>Valid Password | User should NOT be able to login to the system | Displayed an error message and user couldn't log into the system | Pass |
| U003 | Display mental state type | **Precondition:**<br>User should wear the Muse headband<br><br>**Test Steps :**<br>Go to the login web page<br>Enter login details<br>Navigate to the "For you" page | User Name :<br>aruni@gmail.com<br>Password : aruni@123 | User should be able to login to the system<br>Predicted mental state type should be displayed as Happy, Sad, Afraid, Calm or neutral | Display the mental state and highlighted the emoji icon placeholder | Pass |
| U004 | Display recommendations | **Precondition:**<br>User should wear the Muse headband<br><br>**Test Steps :**<br>Go to the login web page<br>Enter login details<br>Navigate to the "For you" page<br>Display the recommedations cards | User Name :<br>aruni@gmail.com<br>Password : aruni@123 | User should be able to login to the system<br>Higlight the emotion type<br>Display the recommendation cards in a carousel view with media type, title, durtaion and rating value | Display recommendation cards in a carousel view; with media type, title, rating value and duration | Pass |
| U005 | Add feedback, rating to a media | **Precondition:**<br>User should wear the Muse headband<br><br>**Test Steps :**<br>Go to the login web page<br>Enter login details<br>Navigate to the "For you" page<br>Display the recommedations cards<br>Click on recommedation card | User Name :<br>aruni@gmail.com<br>Password : aruni@123 | User should be able to login to the system<br>Higlight the emotion type<br>Display the recommendation cards in a carousel view with media type, title, durtaion and rating value<br>Recommendation card should be clickable<br>User should navigate to the media details page<br>User should be able to enter feedback<br>User should be able to click on stars and add rating<br>User should be able to submit the feedback upon click on submit button | Display recommendation cards in a carousel view; with media type, title, rating value and duration<br>User navigate to the media details page (verify the contents)<br>Media played<br>User is able to add feedback and click on added rating | Pass |

Figure 4.5: Test Cases - Normal User

| Test Case ID | Scenario | Test Steps | Test Data | Expected Result | Actual Result | Pass / Fail |
|---|---|---|---|---|---|---|
| A001 | Login to the System as an admin | Go to the login web page<br>Enter User Name<br>Enter Password<br>Click on Login Button | User Name : admin@gmail.com<br>Password : admin@123 | User should be able to login to the system<br>ONLY admin privileged portal should be displayed | User successfully logged in to the admin portal | Pass |
| A002 | Upload a media | **Precondition:**<br>User should login to the system with correct creditials<br><br>**Test Steps:**<br>User should navigate to "Upload" section | Media Title: Test name<br>Media URL: https://www.youtube.com/embed/D4BZshNWJMc?list=PLQ_PIlf6OzqLWt6qvrnhKgGyQby0VvvJc<br>Media Type: Video<br>Duration: 1hr 2min 23 sec<br>Recommended for: Sad | User should be able to successfully add a media to the system<br>Successfully added toast message should be displayed | Successfully added a media to the system<br>Media can be viewed in Media Table<br>Displayed "Media successfully added" message | Pass |
| A003 | Delete a media | **Precondition:**<br>User should login to the system with correct creditials<br><br>**Test Steps:**<br>User should navigate to "Medias" section | Select already interacted and not interact medias<br>Interacted:<br>4 Beautiful Soundtracks \| Relaxing Piano<br>Not Interacted:<br>Best Relaxing Music (Ocean Waves) | User should not be able to delete already interacted media<br>User should be able to delete not interacted media<br>Successfully deleted toast should be displayed<br>Unable to delete this media toast message should display | User is unable to delete already interact media and "Unable to delete this media" toast message displayed<br>User is able to delete not interacted media and "Successfully delete this media" toast message displayed | Pass |
| A004 | Change password | **Precondition:**<br>User should login to the system with correct creditials<br><br>**Test Steps:**<br>User should navigate to "Profile" section | User Name : admin@gmail.com<br>Password : admin@123<br>New Password: admin@1234 | Successfully Changed your password toast message should be displayed | Successfully Changed your password toast message is displayed | Pass |
| A005 | Summary report generation | **Precondition:**<br>User should login to the system with correct creditials<br><br>**Test Steps:**<br>User should navigate to "Summary" section | Date range<br>This Month<br>This Week | Charts should generate according to the date range selected<br>Summary of Interaction, Feedback charts should displayed according to the user select (This week or This month) | Charts displayed correctly as per the selection | Pass |

Figure 4.6: Test Cases - Admin User

## 4.2 Results

In this study, the classification model has been built that required to provide higher quality, from a data analysis perspective. Before proceed with the final deployment of the model, it is required to completely evaluate the classification model. The following review steps are executed to evaluate the model and achieves the objectives of the study. Th following metrics are used to evaluate the classification model.

- Accuracy

  Accuracy is used to measure the quality of the classifier model. Accuracy is derived by considering the proportion of number of correct predictions and total number of predictions [31].

$$Accuracy = \frac{Number of correct predictions}{Total number of predictions}$$

- F-measure

  This statistical metric is also known as the F1-score which can derive using the following equation. This also interpreted as a weighted average of recall and precision. [31].

$$F1 = 2 \times \frac{precision \times recall}{precision + recall}$$

- Recall

  The following equation derived how the recall is calculated. This statistical metric calculates how many actual positives are captured from the model by labeling them as True positive [31].

$$Recall = \frac{true positive}{true positive + false negative}$$

- Precision

  Precision metric refers to the number of actual positives divided by sum of the all true positives and false positives as indicated below [32].

$$Precision = \frac{true positive}{true positive + false positive}$$

The pre-processed data set is applied to several classification algorithms as mentioned above chapter 3. Results for each classification algorithm are presented in the following summary table. The classification accuracy was evaluated by considering accuracy, recall, precision, f1-score statistical metrics.

Table 4.1: Summary of accuracy for classification algorithms

| **Model** | **SVM** | **kNN** | **MLP** | **Random Forest** |
|---|---|---|---|---|
| Emotion Detection | 70.13% | 78.35% | 59.39 % | 87.12% |

In SVM, each data points are plotted in n-dimensional space where n indicates the number of features and finds the hyper-plane or line which segregates into classes. The scikit-learn SVM library is used to perform the SVM classification to the processed data-set. A set of Tuning parameter values are used to improve the performance of the model such as gamma values is initialized as "auto" and kernel value kept as default. The following figures 4.5 and 4.6 depict the confusion matrix and the classification report for the SVM algorithm. The kNN is known as a supervised machine learning algorithm that relies on labeled data as input to learn and produce output for the unlabeled data [28]. In this classification, emotions are labeled as 'afraid', 'calm', 'neutral', 'happy' and 'sad' which appears in the last column of the data-set. These classes are annotated during the data acquisition step with the help of the annotation feature in the Muse Lab application. The kNN involved in calculating the ED or the straight line distance between the data points. The kNN algorithm runs several times for different k values, which reduces the number of errors in the classification and improve the accuracy of the model. The sklearn-neighbors library is used by importing the KNeighborsClassifier module to classify the processed data-set using the kNN algorithm. The 'n_neighbors' argument is used to pass the number of neighbors required in the KNeighborsClassifier() function. The algorithms run for different n_neighbors values and evaluate the prediction accuracy of each session. The classification report, confusion matrix, and histograms of the kNN classification are depicted in Figures 4.7 and 4.8. The highest accuracy was achieved using the Random Forest algorithm. Figure 4.9 depicts the classification report and confusion matrix for each emotion for the testing data test. Figure 4.10 indicates a histogram chart for emotion prediction.

| Predicted-emotion | 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| Actual-emotion | | | | | |
| 0 | 70 | 0 | 0 | 1 | 2 |
| 1 | 9 | 57 | 2 | 0 | 3 |
| 2 | 2 | 16 | 14 | 1 | 24 |
| 3 | 6 | 3 | 4 | 65 | 1 |
| 4 | 7 | 17 | 11 | 0 | 50 |

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| afraid | 0.74 | 0.96 | 0.84 | 73 |
| calm | 0.61 | 0.80 | 0.70 | 71 |
| happy | 0.45 | 0.25 | 0.32 | 57 |
| neutral | 0.97 | 0.82 | 0.89 | 79 |
| sensitive | 0.62 | 0.59 | 0.61 | 85 |
| accuracy | | | 0.70 | 365 |
| macro avg | 0.68 | 0.68 | 0.67 | 365 |
| weighted avg | 0.69 | 0.70 | 0.69 | 365 |

Figure 4.7: Classification Report and Confusion Matrix for the SVM

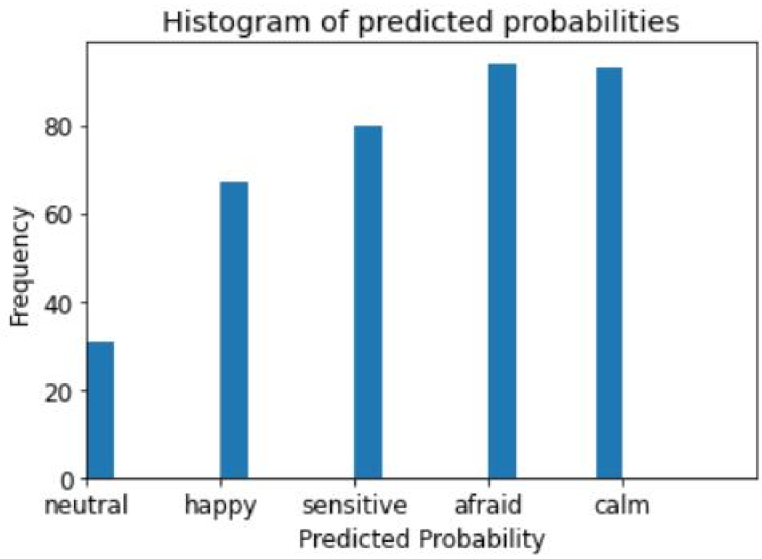


Figure 4.8: Histogram of predicted emotion probabilities

```
Predicted-emotion   0   1   2   3   4
Actual-emotion
0                  70   1   1   1   0
1                   2  57   2   0  10
2                   0   5  36   1  15
3                   7   2   0  70   0
4                   1  14  17   0  53
              precision    recall  f1-score   support

           0       0.88      0.96      0.92        73
           1       0.72      0.80      0.76        71
           2       0.64      0.63      0.64        57
           3       0.97      0.89      0.93        79
           4       0.68      0.62      0.65        85

    accuracy                           0.78       365
   macro avg       0.78      0.78      0.78       365
weighted avg       0.78      0.78      0.78       365

0.7835616438356164
```

Figure 4.9: Classification Report and Confusion Matrix for the kNN

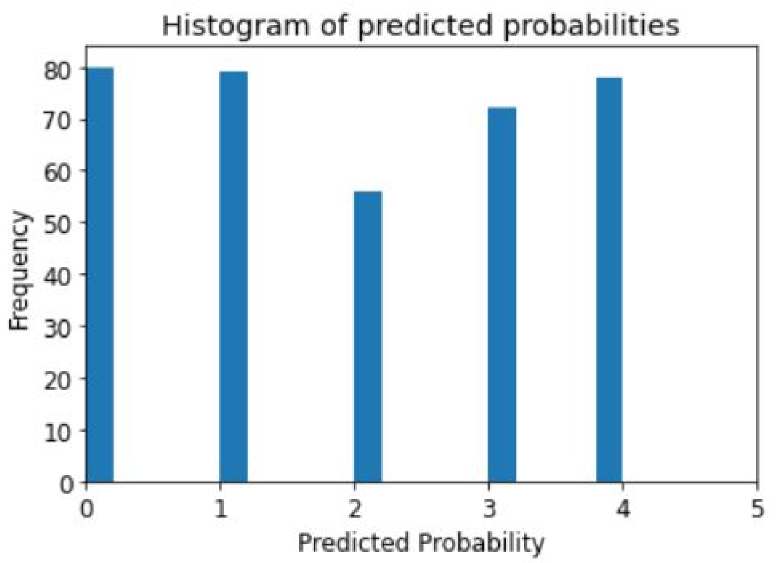


Figure 4.10: Histogram of predicted emotion probabilities

| Predicted-emotion | afraid | calm | happy | neutral | sensitive |
|---|---|---|---|---|---|
| Actual-emotion | | | | | |
| afraid | 69 | 3 | 1 | 0 | 0 |
| calm | 1 | 66 | 0 | 2 | 2 |
| happy | 2 | 0 | 76 | 1 | 0 |
| neutral | 1 | 0 | 1 | 43 | 12 |
| sensitive | 0 | 7 | 0 | 14 | 64 |

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| afraid | 0.95 | 0.95 | 0.95 | 73 |
| calm | 0.87 | 0.93 | 0.90 | 71 |
| happy | 0.97 | 0.96 | 0.97 | 79 |
| neutral | 0.72 | 0.75 | 0.74 | 57 |
| sensitive | 0.82 | 0.75 | 0.79 | 85 |
| accuracy | | | 0.87 | 365 |
| macro avg | 0.87 | 0.87 | 0.87 | 365 |
| weighted avg | 0.87 | 0.87 | 0.87 | 365 |

Out[52]: 0.8712328767123287

Figure 4.11: Classification Report and Confusion Matrix for the Random Forest

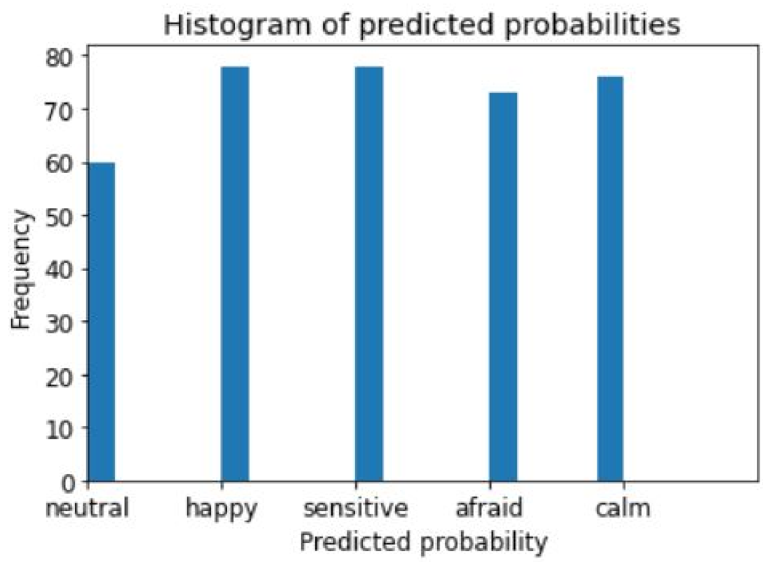


Figure 4.12: Histogram of predicted emotion probabilities

The classification algorithms are applied to different datasets based on the test-case created. Four different data-sets were used and applied MLP, kNN and Random Forest classification algorithms and evaluated the statistical metrics of each test-case.

- This table provides accuracy measures of respective algorithms for dataset 01 which is created from female participant.

| Algorithm | SVM | kNN | Random Forest |
|---|---|---|---|
| Accuracy Measure | 38.25% | 66.33% | 74.28% |
| Precision | 0.38 | 0.66 | 0.74 |
| Recall | 0.38 | 0.66 | 0.73 |
| F1 Score | 0.38 | 0.66 | 0.73 |

Figure 4.13: Accuracy measure for data-set 01

- This table provides accuracy measures of respective algorithms for dataset 02 which is created from male participant.

| Algorithm | SVM | kNN | Random Forest |
|---|---|---|---|
| Accuracy Measure | 39.95% | 65.78% | 73.21% |
| Precision | 0.41 | 0.65 | 0.73 |
| Recall | 0.39 | 0.65 | 0.73 |
| F1 Score | 0.39 | 0.65 | 0.73 |

Figure 4.14: Accuracy measure for data-set 02

- This table provides accuracy measures of respective algorithms for dataset 03 which is created from two test subjects including both female and male participants.

| Algorithm | SVM | kNN | Random Forest |
|---|---|---|---|
| Accuracy Measure | 53.78% | 75.34% | 80.43% |
| Precision | 0.53 | 0.75 | 0.81 |
| Recall | 0.56 | 0.75 | 0.81 |
| F1 Score | 0.53 | 0.75 | 0.81 |

Figure 4.15: Accuracy measure for data-set 03

- This table provides accuracy measures of respective algorithms for dataset 03 which is created from five test subjects including both female and male participants.

| Algorithm | SVM | kNN | Random Forest |
|---|---|---|---|
| Accuracy Measure | 48.78% | 65.21% | 71.25% |
| Precision | 0.46 | 0.63 | 0.71 |
| Recall | 0.47 | 0.66 | 0.72 |
| F1 Score | 0.46 | 0.65 | 0.71 |

Figure 4.16: Accuracy measure for data-set 04

After analyzing the prediction accuracy of each classification algorithm, the Random Forest classification algorithm selected as the best option to proceed with mental state classification.

## 4.3 Analysis of Work

The real-time brain signal acquisition and processing of noisy signals is a considerable and challenging task involved in this research. In the context of emotion detection, this study employed with a new data acquisition method. As depicted in the below figure, the EEG-based mental state detection is carried out using different feature extraction methods and machine learning algorithms. This method is identified as an intelligent method that can take decisions to predict overall emotion of a person by considering real-time stream of EEG data.

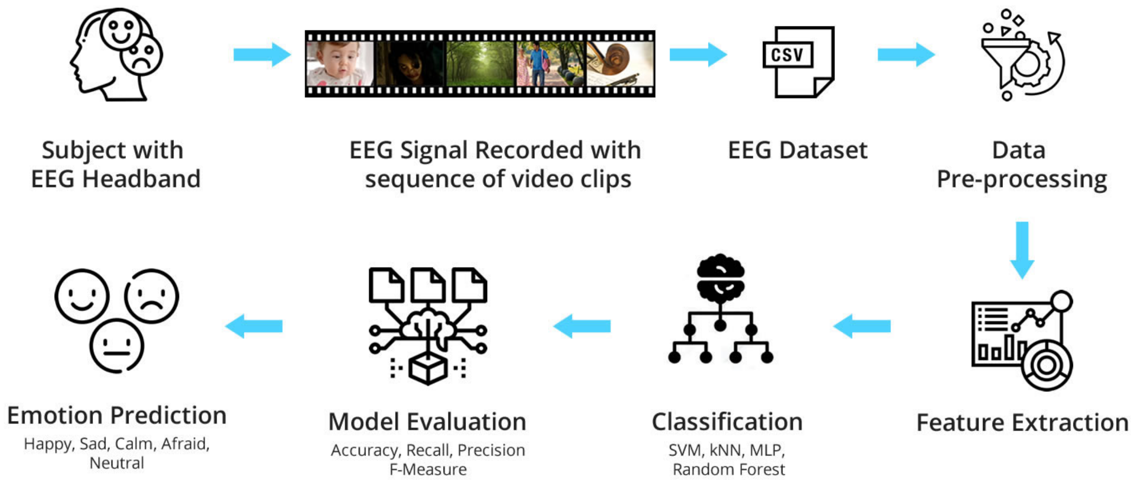


Figure 4.17: Flow of the Methodology

This model can be further developed to other emotional states such as anger, stress, etc. Moreover, this data acquisition method can be enhanced to invoke those emotions by adding a few more video clips related to those emotional states. The accuracy of the classification model can improve by involving more test subjects as well by using different data pre-processing, feature extraction methods. Further, this data set will be exposed to the public data repositories where other researchers can be useful for their research studies. This model can be further developed for many applications such as measuring attention level and based on that users can use it for tracking their concentration level or meditation progress. In addition to that, this model can be used as a user experience testing tool which capable to provide a quantitative measure of user experience of a particular application, website, or even an arrangement of a store. This can provide whether the users are happy with their entire user journey or not, based on that product owners can improve their products.

# Chapter 5

# CONCLUSION

This project presents a novel approach to recognize the mental state of humans in real-time using a wearable EEG device and proved the possibility of applying this system as BCI or adopt as a context-aware application. A data-driven methodology is occupied to predict the mental state and update it in real-time. Set of features are obtained by applying a short-term windowing technique which captured from five signals (alpha, beta, gamma, theta, delta) from EEG sensors to categorize five different mental states: textithappy, textitsad, textitcalm, textitafraid and textitneutral. Although the Muse 2 device is integrated with few electrodes the acquired dataset was sufficient to develop the classification model which can detect several mental states. A set of feature selection methods and classifications models were applied to accomplish an acceptable level of accuracy and performance on the captured dataset for train the model and live streaming data. The developed classification method can identify complex patterns of brain activity and detect mental state accordingly. The random forest classifier produced 87.12% of prediction accuracy from the multiple feature set and classifier models. Further real-time mental state recognition web application, Mood was developed by integrating the classification model which returns the current mental state of the person. Based on the mental state, the application provides some mindfulness activities which users can follow. Based on the user feedback the accuracy of the recommendations can be improved and this recommendation service exposed accurate recommendations for the researchers, mindfulness app developers, or the people who are interested in a similar domain. Furthermore, this study focused on some more optimization in the real-time application as future works and some of the enhancements on the Mood application which users can get a better insight into how their mental states change over a particular period. In addition to that improve the accuracy of the recommendations by collecting user feedback.

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# APPENDICES

# Appendix A

# Brain Location

Below figure shows how the EEG devices capture the EEG signals via different sensors, located in the areas of the brain.

- MindWave - FP1
- EPOC - AF3, AF4, FC5, FC6, F7, F3, F4, F8, O2, O1, T7, P7, T8, T8
- Muse - TP9, TP10, FP1, FP2
- Insight - AF3, AF4

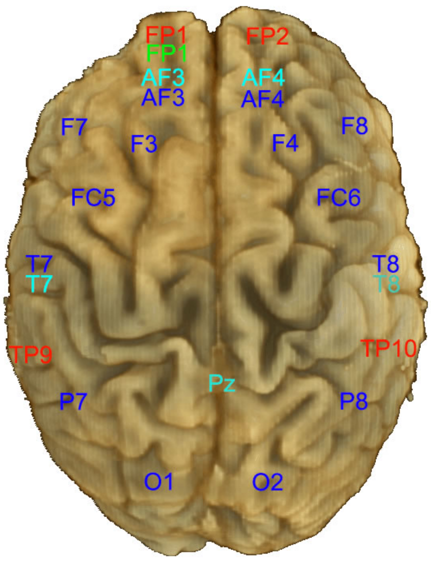


Figure A.1: Sensor Location in the Brain [23]

# Appendix B

# EEG Data Description

This section described about the data provided by the Muse devices sensors and importance of those data values [24].

- *Accelerometer*

  provides three pieces of data and three-axis accelerometer data packet

- *AlphaAbsolute*

  Derived value. Absolute alpha band powers for each channel.

- *AlphaRelative*

  Derived value. Relative alpha band powers for each channel. Consists of same amount of data as an EEG packet and has the same channel mapping. Values range [0;1].

- *BetaAbsolute*

  Derived value. Absolute beta band powers for each channel.

- *BetaRelative*

  Derived value. Relative beta band powers for each channel. Consists of same amount of data as an EEG packet and has the same channel mapping. Values range [0;1].

- *GammaAbsolute*

  Derived value. Absolute gamma band powers for each channel.

- *GammaRelative*

  Derived value. Relative band powers for each channel. Consists of same amount of data as an EEG packet and has the same channel mapping. Values range [0;1].

- *DeltaAbsolute*

  Derived value. Absolute delta band powers for each channel.

- *DeltaRelative*

  Derived value. Relative delta band powers for each channel. Consists of same amount of data as an EEG packet and has the same channel mapping. Values range [0;1].

- *ThetaAbsolute*

  Derived value. Absolute theta band powers for each channel.

- *ThetaRelative*

  Derived value. Relative band powers for each channel. Consists of same amount of data as an EEG packet and has the same channel mapping. Values range [0;1].

- *DRLREF*

  Raw data from REF and DRL sensors. This provides two pieces of data. Units in microvolts.

- *Battery*

  Related to battery. This gives three pieces of data.

- *droppedaccelerometer*

  Packet indicates in for n dropped samples of the accelerometer type. Size of the values array = 1.

- *droppedeeg*

  Packet indicates in for n dropped samples of the eeg type. Size of the values array = 1.

- *EEG*

  Raw EEG samples. Values in this packet correspond to EEG data read from the different sensor locations on the headband. Units in microvolts

- *Gyro*

  provides three pieces of data and 3-axis gyro data packet

- *ISGOOD*

  Derived value. ”Is Good” imply whether or not the last 1 second of raw EEG data on each channel was good or not. Muscle movement or Eye blinks can interfere with EEG data and to report that the data is not good by using ”IS Good”. This is emitted every 1/10 of a second to represent the rolling window of the last second of EEG data. This is only useful for real time EEG analysis.

- *AUXLEFT*

  Left auxiliary

- $AUXRIGHT$

  Right auxiliary

- $EEG1$

  TP9 - Left ear

- $EEG2$

  AF7 - Left forehead

- $EEG3$

  AF8 - Right forehead

- $EEG4$

  TP10 - Right ear

# Appendix C

# Mood Web Application - User Interfaces

The below figure shows the Login page of the Mood web application which users can access the Mood application by providing correct login credentials.

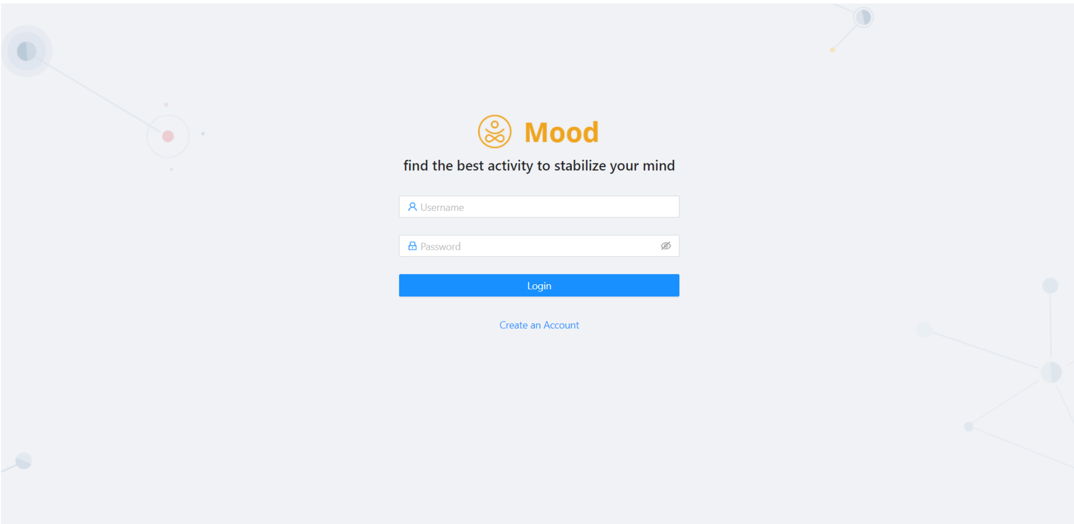


Figure C.1: Login Page

The Figure C.2 show the create account page which enables anyone to create an account in Mood application and get interact with it.

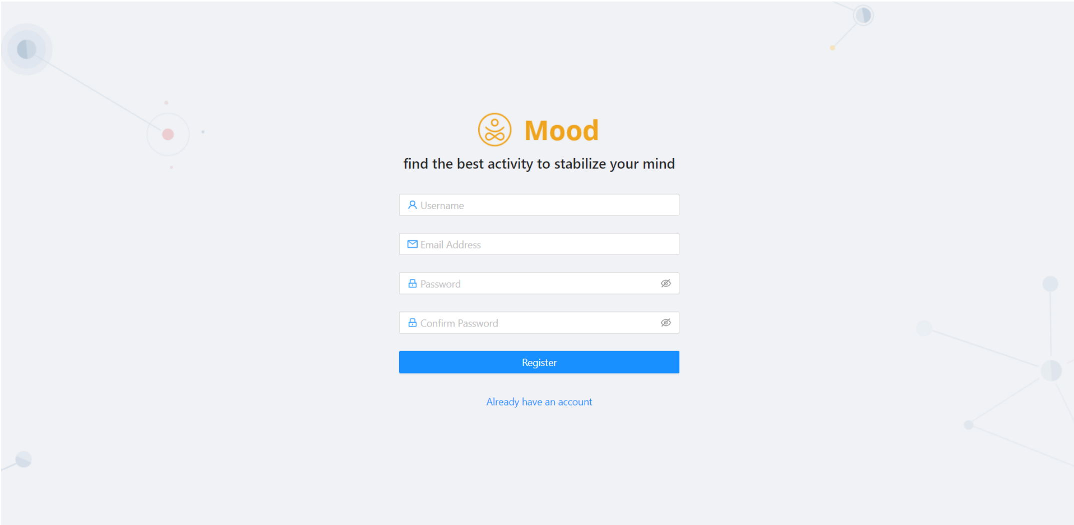


Figure C.2: Create Account Page

The below figure shows the landing page of the Mood web application once the user logged as normal user.

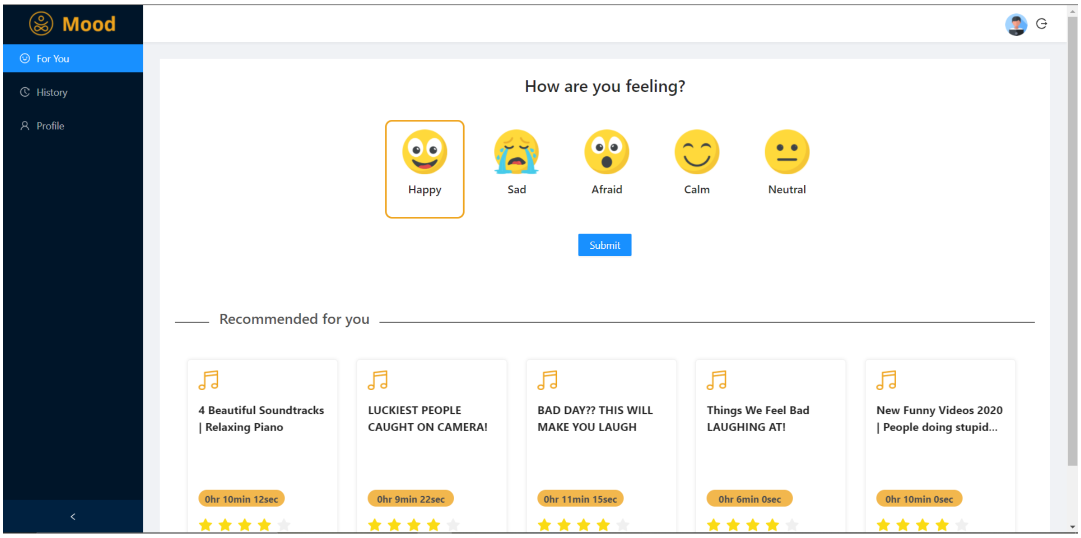


Figure C.3: Landing Page - Normal User

The below figure shows once user click on the recommendation card and able to add feedback, ratings to the media.

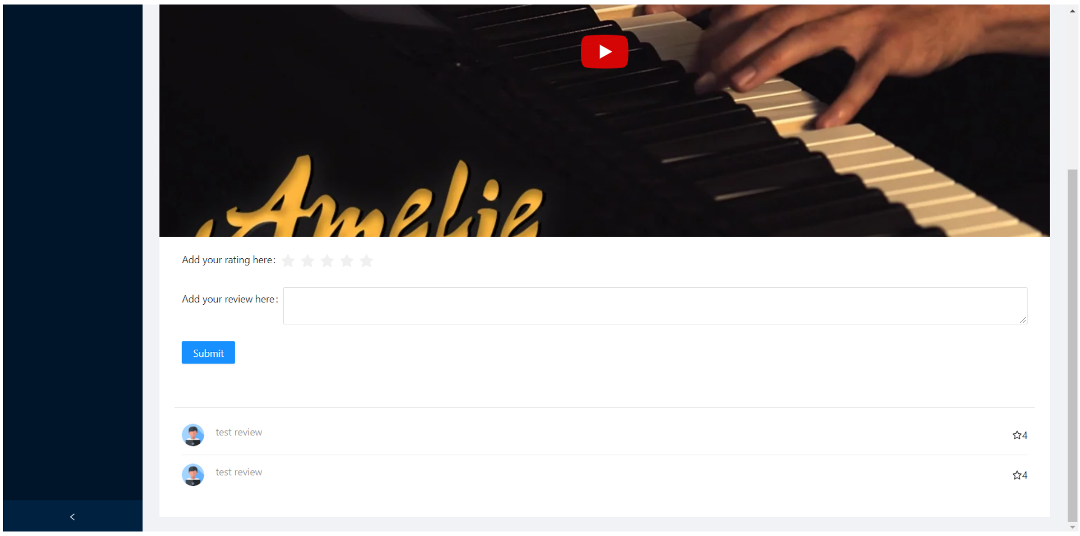


Figure C.4: Media Details Page

The below figure shows once user navigate to the history tab and it contains total interactions, views and feedback provided as a summary, further the chart represent the logged Moods in a particular time period and the table contains the information related to recently followed medias.

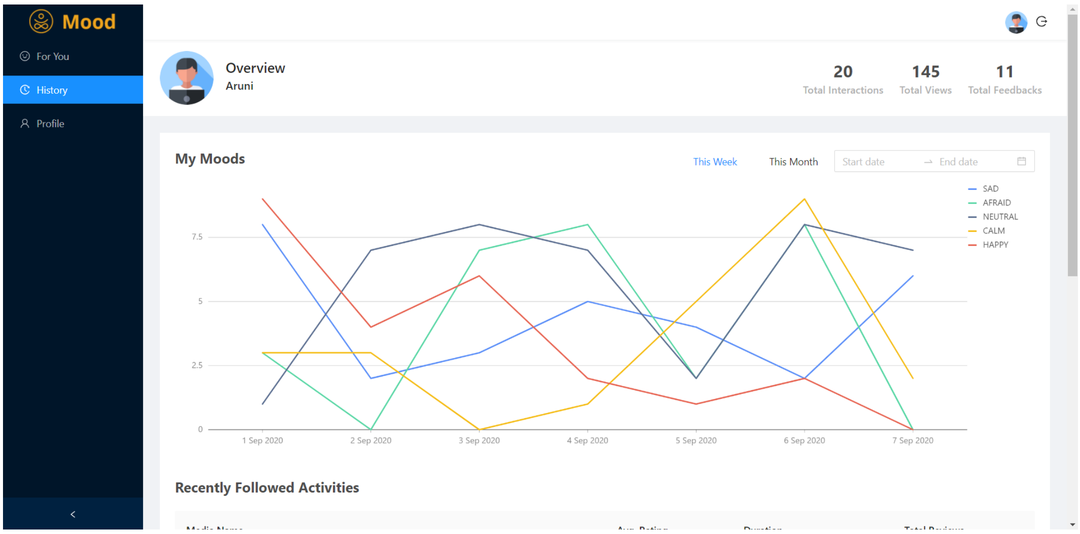


Figure C.5: Summary Details Page - Normal User

The below figure shows once user click on the profile tab in both user and admin portals which allows user to change their password.

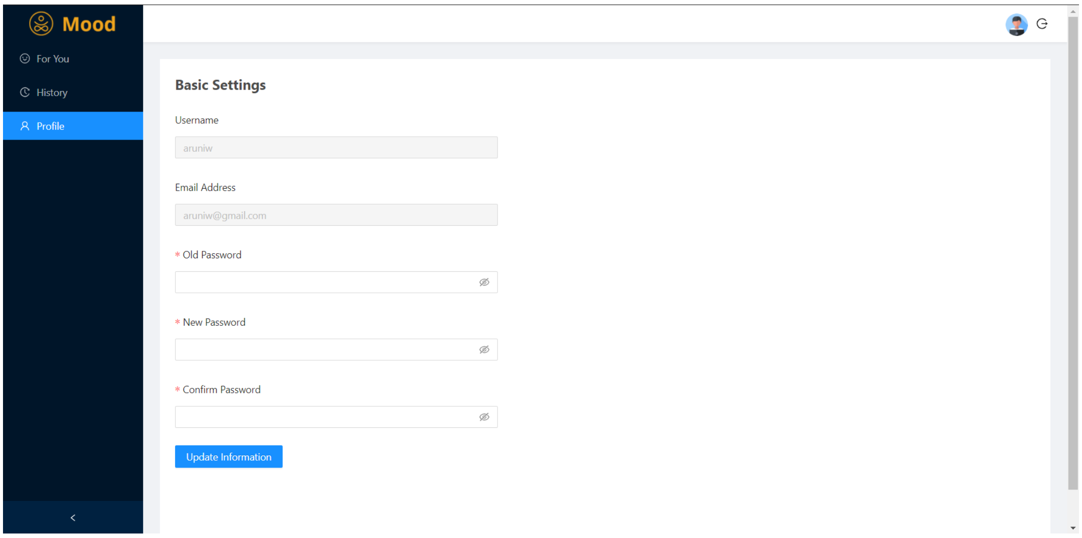


Figure C.6: Profile Page - Admin User

The below figure shows the interface which allows admin user to upload media to the system.

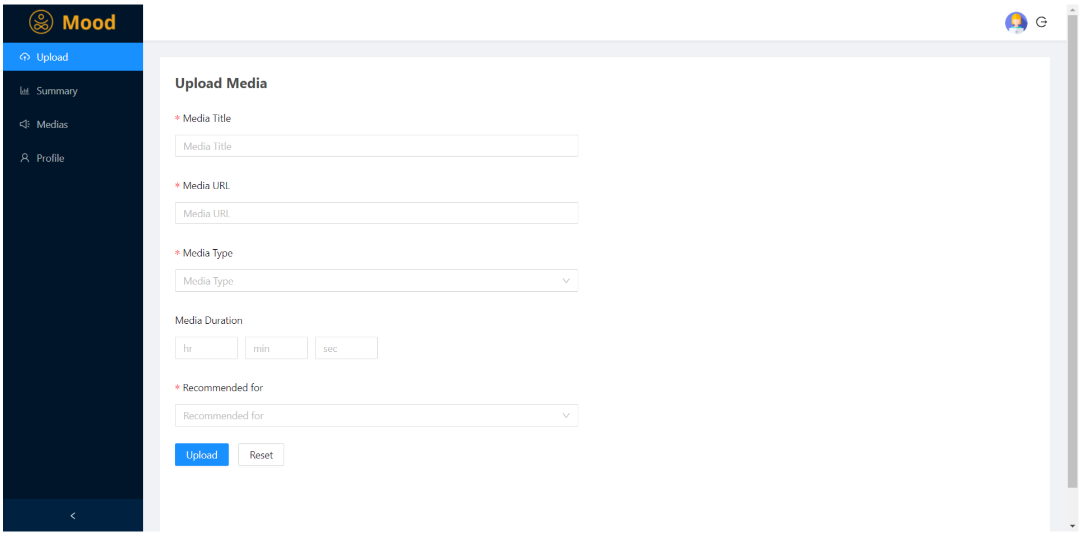


Figure C.7: Media Upload Page - Admin User

The below figure shows the interface which list all the medias added to the system with relevant information such as avg.ratings, total views, review counts. Further admin user can remove any media which are not interacted by the users.

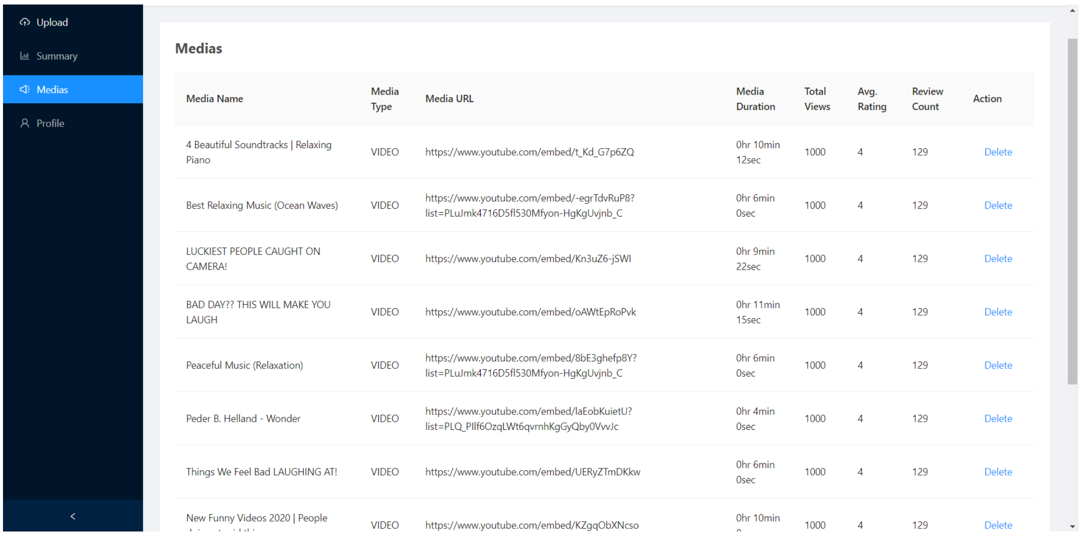


Figure C.8: Media List Page - Admin User

The below figure shows two charts that represent the summary of interactions and feedback provided by the user in a particular date range or this month.

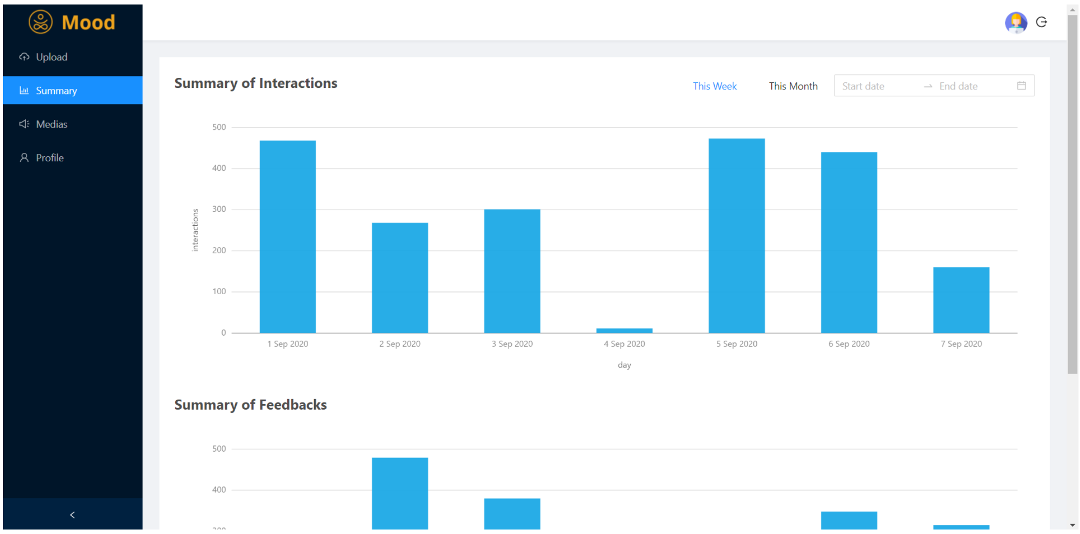


Figure C.9: Summary Detials Page - Admin User

# Appendix D

# Wearable EEG Devices

Below figures shows some of the wearable, VR devices used to enhance the meditation and well-being experience. The following devices are clearly analyzed and identified their drawbacks in the context of features, technology and tried to resolve them via this developed solution.

Figure D.1: Spire Wearable Device [36]

Spire is designed by Stanford University's Calming Technologies Lab that can measure the breathing patterns, counting steps and notifies the tension levels of the user via a mobile application. Figure D.2 depicts the Being wearable device. The Zensorium developed this mindfulness tracker and able to differentiate good stress by tracking the sleep cycles, heart rate and blood pressure. It also capable to mapping user's emotions such as stressed, calm and excitement by analyzing the variability of the heart rate.

Figure D.2: Being Wearable Device [36]

WellBe is capable of monitoring heart rate levels and matches specific interactions and moments throughout the day. Its eco-friendly composition makes the users wear and keep them comfortable 24x7. It offers guided meditations, breathing exercises, and a positive playlist and set of mentoring programs.

Figure D.3: WellBe Wearable Device [36]

EMOTIV Insight is five channels mobile EEG devices capable of providing fully optimized, clean, and robust signals at any time. These EMOTIV devices are only developed for research applications and personal usage only.


Figure D.4: EMOTIV Insight EEG-Based Wearable Device [37]

Neuroon open sleep mask is known as Lucidcatcher which decides what you need to do in a dream, which employed with EEG signals along with guided meditation. It applies various stimuli like sounds, lights, an insignificant amount of electric currents to keep the lucid state.


Figure D.5: EEG-based Neuroon sleep mask [37]

# Appendix E

# Data Acquisition using Muse Device

This section describes how the Muse 2 headband is configured to collect EEG data with the aid of Muse Lab desktop application and Muse Direct mobile application. Muse Direct is only available in the Apple apps store which collects the EEG data stream and visualize them using different graphs. Muse Direct app consists of rich user interfaces that connect with the Muse device via Bluetooth. The following screen is involved with establishing a connection between the device and the mobile application.

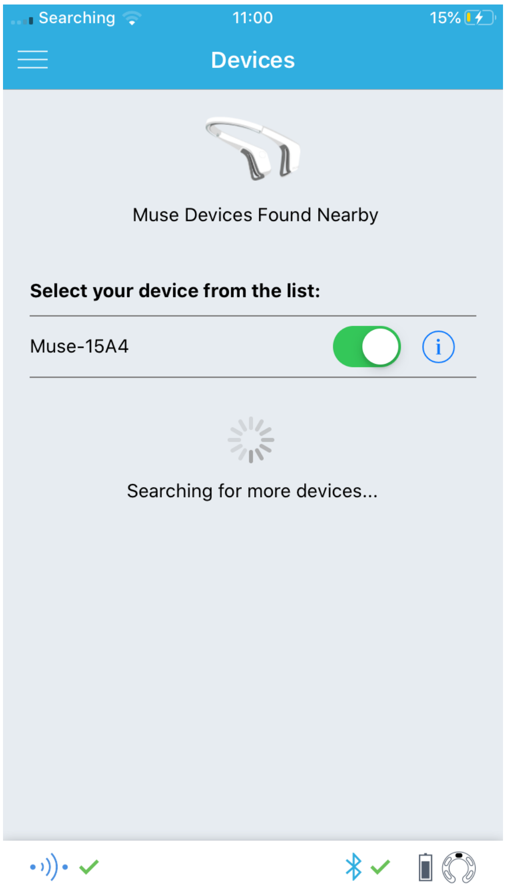


Figure E.1: List the Muse Devices Nearby

This streaming page is used to enable OSC streaming by keeping the Muse Lab and the Muse Direct in the same network by specifying the IP address and port number. It is required to toggle the Enable OSC streaming button and at the same time, the user can add an OSC prefix as well. The following figure shows how to enable OSC streaming in Muse Direct application.

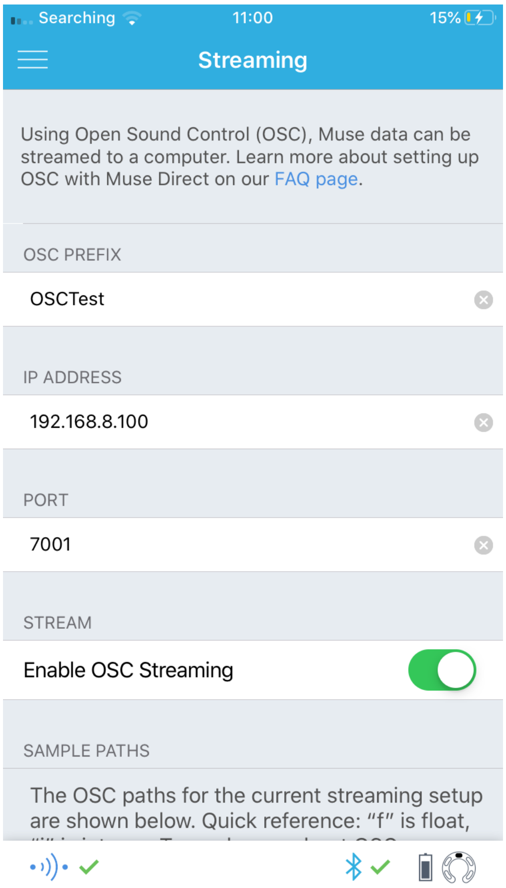


Figure E.2: Enabling OSC streaming

The following figure shows how the Muse Direct app visualizes the EEG data coming from different sensors. As shown in the figure, EEG data is coming from four Electrodes, AF7, AF8, TP9. TP10 and signals are measured in microvolts. Horseshoe icon which appeared in the bottom left corner indicates how the sensors are contacted with the body. If it indicates solid colored five ovals, the sensors are connected properly with your body. If it shows outline ovals that indicates there is a poor connection to the body.

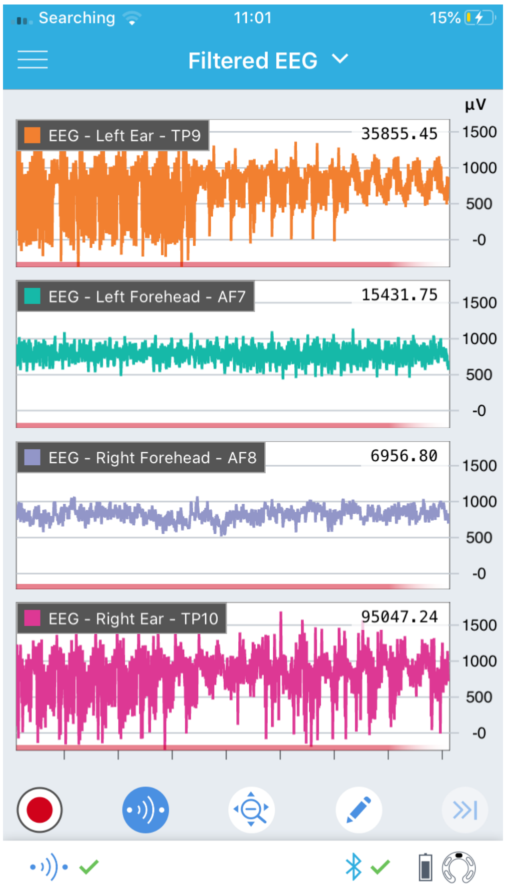


Figure E.3: Visualization of real-time EEG data

Muse Lab is used to visualize the EEG data, enable recording, OSC streaming, annotating, and filtering the data. Muse Direct and Muse Lab should be configured in the same network and incoming port is opened to capture data from Muse Direct. Users are allowed to see the incoming message as shown in the figure E.4. Outgoing UDP port is opened as shown in figure E.5, which allow the user to follow the incoming message to the intended location, in this study that stream of incoming messages is forwarded to Java application.

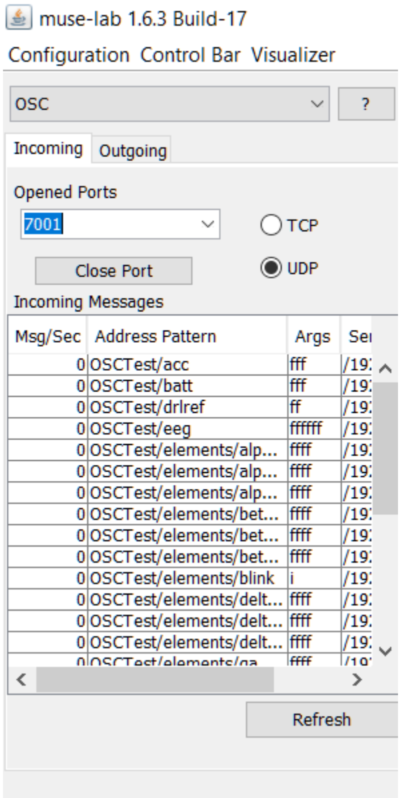


Figure E.4: Configure MuseLab to enable incoming data from Muse Device

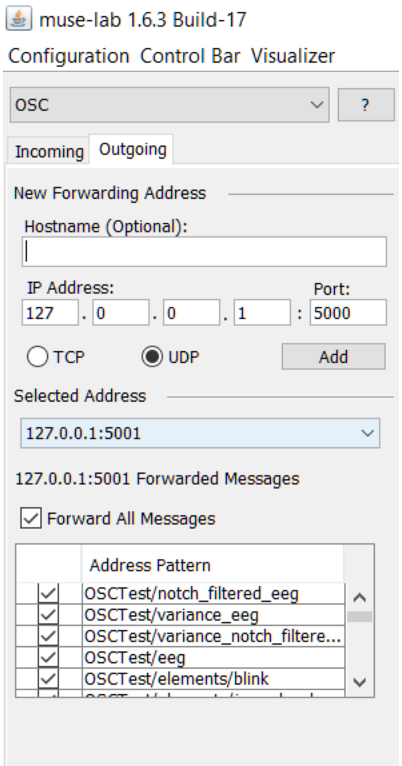


Figure E.5: Configure MuseLab to enable incoming data from Muse Device