HUMAN STRESS ANALYSIS BETWEEN NORMAL AND BIPOLAR DISORDER PATIENTS BY USING NEURAL NETWORKS BASED ON EEG SIGNALS

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Abstract

Stress is a common factor in our daily lives and has a significant impact on our mental and physical well-being. It is a known fact that individuals with bipolar disorder are more susceptible to stress and its effects. In this study, a neural network was used to analyze the difference in stress levels between normal individuals and individuals with bipolar disorder using EEG signals. The EEG signals were collected and processed, and the results were fed into a neural network for analysis. The study found that there was a significant difference in stress levels between normal individuals and those with bipolar disorder. The results showed that individuals with bipolar disorder had higher levels of stress compared to normal individuals. This study provides valuable insights into the physiological differences between normal and bipolar individuals under stress and can be useful in developing new diagnostic and therapeutic techniques. The findings of this study also highlight the importance of early detection and effective management of stress in individuals with bipolar disorder.

Keywords— Artificial Neural Network, EEG Signals, Stress, Bipolar Disorder, Normal Patient

1. Introduction

Bipolar disorder (previously known as manic-depressive disease or manic depression) is a mental condition characterized by remarkable changes in mood, energy, activity levels, focus, and capacity to carry out daily duties. Bipolar disorder is classified into three categories. All three categories cause noticeable shifts in mood, energy, and activity levels. These emotions vary from excessively "up," exhilarated, irritated, or energetic behavior (known as manic episodes) to extremely "down," sad, apathetic, or hopeless conduct (known as depressive episodes) (known as depressive episodes). Hypomanic episodes are less intense manic episodes. When a person's symptoms of bipolar illness do not fall into one of the three categories given above, this is referred to as "other specified and unspecified bipolar and associated disorders." Bipolar disorder is usually diagnosed in late adolescence or early adulthood. Bipolar symptoms might arise in youngsters on occasion. Although symptoms may change over time, bipolar illness often needs lifetime therapy. Following a treatment plan can assist patients in managing their symptoms and improving their quality of life [1].

A mental disorder is any of several issues that affect a person's mood, thinking, behavior, and overall functioning. Some common mental illnesses include depression, anxiety disorders, bipolar disorder, schizophrenia, eating disorders, and obsessive-compulsive disorder. Mental illnesses can be brought on by a combination of biological, environmental, and psychological factors, and their symptoms can range from mild to severe. Mental health conditions can be treated with therapy, medication, lifestyle changes, or a combination of these approaches. It is critical to keep in mind that mental illnesses are medical conditions that can be effectively treated and that seeking therapy is a sign of strength and bravery.

A person's mental wellness is more than the absence of mental disease. It denotes a condition of well-being in which you feel well and perform well in the world. The World Health Organization [2] defines good mental health as the ability to cope with life's regular stresses [3], work successfully, realize your potential, and contribute to the community. If you have good mental health, you may experience feelings such as happiness, love, joy, and compassion, and you may be usually content with your life. You may also feel as though you are part of a community and are contributing to society. You may also experience sensations of spiritual well-being, meaning or purpose, and tranquility [4].

Normal mental health is characterized as a level of well-being in which a person can successfully manage daily problems, pursue employment, and give back to their community. It is described as having the capacity to act in ways that are compatible with one's personal values and aspirations, as well as the capacity to forge strong relationships with other people. When a person's mental health is in good shape, they can control their emotions, thoughts, and actions in a flexible and adaptable way. They also feel fulfilled and like their lives have meaning.

Bipolar disorder is a mental health condition characterized by dramatic changes in mood, energy, and activity. Sometimes people refer to it as a manic-depressive illness. In those with bipolar disorder, mania is characterized by feelings of elation, increased energy and activity levels, racing thoughts, and a diminished need for sleep. They might also experience depression, which is characterized by feelings of hopelessness, fatigue, and despondency. A person with bipolar disorder may experience severe effects on all aspects of daily life, including relationships, employment, and general functioning. Although the exact cause of bipolar disorder is unknown, a combination of genetic, physiological, and environmental variables is likely to be responsible. Treatment for bipolar disorder frequently consists of a combination of medication, psychotherapy, and lifestyle changes. Bipolar patients must have a proper diagnosis and treatment plan from a mental health professional because, if untreated, the disorder can worsen and have serious consequences, including hospitalization, suicide, and difficulties carrying out daily tasks. However, many people with bipolar disorder may be able to successfully manage their symptoms and lead fulfilling lives with the correct therapy.

Although the term "normal" patient does not have a specific medical meaning, it is commonly used to describe someone who does not have a recognized mental health issue and is capable of performing daily tasks with little to no difficulty. A regular person does not experience such extreme and protracted mood changes. But it's important to keep in mind that everyone has mood swings and other emotional ups and downs, and there is no universally accepted definition of what is "normal." Bipolar illness's manic or hypomanic episodes can be extremely distressing and interfere with day-to-day activities, leading to damaged interpersonal connections, decreased productivity, and, in severe cases, hospitalization.

The comparison of stress levels in normal persons and those with bipolar illness, in particular, can give useful information. The MLP [5] approach in MATLAB will be used to assess and identify the variations in stress levels between normal persons and those with bipolar disorder using neural networks based on EEG recordings. The dataset we are utilizing comes from two people, one with a mental illness and one who is well. EEG signals offer non-invasive brain activity monitoring, while neural networks offer a powerful tool for data processing and classification. This study aims to shed light on the effects of stress on individuals with bipolar illness and advance our understanding of the underlying physiological mechanisms by comparing the EEG signals of normal and bipolar disorder patients under stress. By contrasting the EEG signals of healthy individuals and those with the bipolar disease under stress, this study aims to shed light on the effects of stress on people with bipolar illness and deepen our understanding of the underlying physiological mechanisms.

2. Literature Review

For the classification problem, many different algorithms have been created, including Support Vector Machine (SVM) [6], Logistic Regression [7], K-Nearest Neighbors [8], and others. Despite this, the resurgence of deep neural networks and the introduction of Multi-layer perceptron (MLP) [5] exceed those techniques. By leveraging the deep learning neural network design, MLP has significantly helped to solve extremely difficult recognition tasks. MLP can train on its own without assistance thanks to deep learning neural networks, and the model can be improved as fresh data becomes available. A Multilayer Perceptron (MLP) is a type of artificial neural network that is composed of multiple layers of interconnected nodes, or artificial neurons. It is a supervised learning algorithm that can be used for a variety of tasks, such as image classification, speech recognition, and natural language processing. MLPs have been widely used for a variety of applications and be highly effective in many cases. However, they can be challenging to train and can require a large number of computational resources. Additionally, they are not well-suited to certain types of tasks, such as image segmentation and object detection, where a more complex network architecture is needed.

According to a study [9] in 2020, the research paper aims to investigate the use of electroencephalogram (EEG) signals in the classification of cognitive states.

Cognitive states refer to different mental states an individual experiences during different activities. EEG signals reflect the brain's electrical activity and can provide insights into different cognitive states. The experiment was carried out to obtain EEG data from subjects while performing various activities. The participants were invited to relax for a few minutes with their eyes closed in a quiet environment and a comfortable chair to obtain a baseline EEG signal. The participants were then asked to complete several tasks, including an eyes-open resting state, an eyes-closed resting state, a math exam, and a memory recall task. The participants were requested to sit motionless with their eyes open and not execute any specific task during the eyes-open resting state. The participants were asked to sit motionless with their eyes closed and not do any specific task during their eyes-closed resting state. During the math test, participants were required to solve a series of simple arithmetic problems. During the memory recall test, participants were instructed to recollect as many words as they could from a list that had previously been shown to them. The EEG signals were collected with 32-channel EEG equipment and electrodes inserted on the scalp following the worldwide 10-20 method. The signals were recorded at a 500Hz sample rate and pre-processed to remove artifacts like eye blinks, muscle movements, and other noise. The pre-processing stage comprised removing artifacts from the EEG signals and ensuring they were clean and ready for analysis. Following that, the feature extraction process extracted various properties from the EEG signals, such as power spectral density, average power, and maximum power in different frequency bands. The classification stage was then carried out, in which machine learning techniques were utilized to categorize the cognitive states based on the extracted attributes. Various techniques, such as decision trees, support vector machines, and k-nearest neighbors were utilized and compared to identify the optimal algorithm for the classification problem. The experiment's findings demonstrated that EEG signals could be utilized to classify various cognitive states reliably. The results also show that several machine learning methods may be employed for classification, with the optimum approach depending on the unique data and application. Overall, the study found that EEG signals provide helpful information about various cognitive states and can be used to design systems for monitoring and improving cognitive function. This has significant ramifications for domains like psychology, neurology, and education, as well as applications like brain-computer interfaces, mental health, and military training.

Another study [10] found in 2022, the research aims to use EEG signals and multi-channel data fusion to diagnose depression in patients. The authors want to create an effective technique for EEG-based depression diagnosis by combining data from numerous EEG channels and using clipping augmentation and a convolutional neural network (CNN). The protocol for the experiment included data gathering from EEG signals of depressed and healthy people. The EEG data were collected while the individuals rested with their eyes closed. The multi-channel data fusion approach was used to extract features from the EEG signals, and the clipping augmentation technique was applied to the feature matrix to boost the robustness of the CNN. The research methodology included pre-processing, feature extraction, and classification. Filtering, downsampling, and artifact removal were among the pre-processing stages. The authors used the common spatial pattern (CSP) approach with clipping augmentation to extract features from EEG signals. The features were then fed into a CNN for categorization. The authors evaluated the method's performance using the receiver operating characteristic (ROC) curve. According to the study's findings, the proposed method outperformed the typical single-channel EEG method in terms of accuracy. The scientists concluded that using multi-channel data fusion and clipping augmentation with CNN to diagnose depression from EEG signals is successful. The study offers a new method for detecting depression based on EEG data. It emphasizes the potential of wearable technology in boosting health and wellness through reliable and long-term monitoring. The research shows that combining multi-channel data fusion and clipping augmentation with a convolutional neural network can effectively detect depression using EEG signals. The findings confirm wearable technology's potential to promote health and wellness by providing reliable and long-term monitoring.

In 2020, this research [11] aims to solve the problem of adequately detecting depression using Electroencephalography (EEG) data. Clinical depression is a serious neurological condition, and EEG signals are considered the best diagnostic instrument. However, the complexity and variety of EEG signals in depressed people make diagnosis difficult. The protocol for the experiment comprised recording EEG data from the right and left hemispheres of the brain while the patients were resting with their eyes closed. The data was collected using a typical EEG recording setup. The research methodology was divided into three stages: pre-processing, feature extraction, and classification. The noise in the EEG signals was removed and the signals were normalized during the pre-processing stage. A

Convolution Neural Network (CNN) and Long Short Term Memory (LSTM) were utilized in the feature extraction stage to extract significant features from the EEG signals. The CNN learned the local properties of the EEG signals, whereas the LSTM learned the patterns in the EEG signal sequence. The retrieved features were input into fully connected layers, which performed the classification during the classification stage. The research showed that the designed deep learning model had a high accuracy of 99.07% and 98.84% for the right and left hemispheres EEG signals, respectively, when tested using the random splitting technique. The study's results showed that the proposed deep learning model could be used to detect clinical depression automatically. In conclusion, the study proposes a novel method for successfully diagnosing clinical depression using EEG signals based on a deep learning model that combines CNN and LSTM. The difficulties created by the complexity and variability of EEG signals from depressed people were successfully addressed by integrating CNN and LSTM into the deep learning model.

Another research [12] in 2017 was to collect EEG data from unspoken phrases such as 'Yes' and 'No' in English ('Haan' and 'Na' in Hindi), which are commonly employed in practical BCI applications. They take into account the replies of 5 individuals to 20 'Yes/No' questions in each language. The investigation is based on EEG thinking patterns related to semantic meanings. They correctly classify various silent words. They also discover that, within tolerable limitations, common word-specific patterns of brain activity exist across languages. They use four different types of classifiers: Support Vector Machine (SVM), Random Forest, AdaBoost (AB), and Artificial Neural Networks (ANN). They choose the optimum hyperparameters by doing a grid search across plausible sets of values and training repeatedly. They utilized the Electrical Geodesics, Inc. (EGI) Clinical Geodesic EEG System 400, a 32-channel EEG headset that comes with a Net Amps 400 amplifier and Net Station 5 for review and acquisition, to capture EEG data. The sampling rate of the gadget is 250 Hz. The majority of the recordings concentrated on Broca's and Geshwind-areas Wernicke's (left cortical hemisphere), which are critical for language processing. They also investigate prefrontal brain areas, which are important for decision-making. F7, T7, P7, P3, and C3 for language classification (henceforth referred to as L sensors), and Fp1, FpZ, Fp2, F3, Fz, F4 for decision making are the sensors of interest in this work (D sensors). In addition, the entire set of 11 sensors (L+D sensors) is investigated. All of the subjects were multilingual, with natural Hindi competence and complete functioning English ability. Five volunteers aged 19 to 22 were considered and consented to participate in this investigation. To get data between 0-40 Hz, raw data from the EGI Geodesic headset was filtered using the Net Station Digital 60/50 Hz notch filter. The data was segmented so that only values occurring within the 10-second reaction period were extracted. This time frame guaranteed precise and efficient categorization. The PyEEG software was used for further processing. The experimental findings show that utilizing ANN, the best accuracy is 85.20% for decision classification and 92.18% for language classification. The total categorization accuracy of bilingual speech is 75.38%. A network of this type might be used in a real-world multilingual context for BCI applications. This paper describes a unique approach for obtaining high-accuracy predictions for unspoken speech and language categorization using EEG. It employs data from bilinguals to develop a classification model that captures bilingual decision-making and language understanding. It also supports previous research on choice and language processing in various brain areas by employing suitable sensors and getting highly normalized values of alpha, beta, and gamma bands via a rolling mean technique.

In 2021, they conducted an emotion-induction experiment for the Dep and HC groups, who reacted to face-in-the-crowd task stimuli of six human facial emotions in this study [13]. They employed both positive and negative emotional stimuli. Differential entropy (DE) and the genetic algorithm (GA) were utilized for feature extraction and selection, respectively, while SVM was used for classification. The experiment's goal was to use spatial information to build an effective EEG-based detection approach for depression categorization. The Dep group consisted of 16 right-handed diagnosed outpatients with depression recruited from SMHC (male/female = 6/10, 37.75 14.19 years old, 12.06 2.91 years of schooling). 14 right-handed healthy subjects (male/female = 4/10, 40.86 12.29 years old, 11.54 3.75 years of schooling) with no personal history of neurological or mental disease were included in the HC group. Before the studies, all subjects were interviewed and the Hamilton rating scale for depression (HAMD, Dep: 24.5 7.40, HC: 7.27 6.94) was administered. The individuals completed the self-rating anxiety scale (SAS, Dep: 61.3 9.74, HC: 35.5 5.13) and the self-rating depression scale (SDS, Dep: 0.89 0.08, HC: 0.48 0.09). The face-in-the-crowd task stimuli were six human faces chosen from the Ekman emotion database. Without hair, spectacles, beards, or other facial adornments, there were three sorts of expressions (positive, negative, and neutral). The experiment was divided into 4 blocks, each with 144 trials (2 positive and 2 negative target blocks). The participants were shown 72 positive, 36 negative, and 36 neutral stimuli during the positive blocks, and 72 negatives, 36 positive, and 36 neutral stimuli during the negative blocks. In this work, wavelet packet decomposition was used to extract delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-80 Hz) waves as well as wideband EEG (EEGW). We recorded and preprocessed the EEG data using the face-in-the-crowd task stimuli. We chose the baseline EEG to be 200 ms before the stimulus onset and the task EEG to be 1000 ms after the stimulus. With the two EEG data, we examined the TCSP performance. To detect patients with depression, we developed an improved EEG-based feature classification approach based on frequency information filtering, temporal information feature extraction, and spatial information feature selection. The classification performance increased dramatically, demonstrating that the TCSP can improve spatial differences before feature extraction. Correlation studies will be used in a future study to achieve more thorough data.

3. Protocol of Experiment

An EEG can be performed as an outpatient procedure or as part of a hospital stay. Procedures may differ based on your situation and the procedures of your healthcare practitioner. Discuss what you will encounter throughout the test with your healthcare practitioner [14]. The experiment consisted of four phases, as seen in Figure 1.

Figure 1. Protocol of experiment

Data Collection: Data collection will be the protocol's first stage. Both those with bipolar disorder and a control group without the condition will have their EEGs recorded. The recordings will be acquired through various techniques, including enlisting volunteers for EEG research and gaining access to public databases of EEG recordings. The EEG signals will be recorded using a conventional EEG headset while the subjects are at rest with their eyes open and closed. The EEG data is gathered using three EEG electrodes, one for each of the positive, negative, and ground terminals. Because the signal is measured in microvolts, it must be amplified using an amplifier circuit [15].

Table 1. The duration of each experiment

Activity	Time (Minute)
Eyes Opened	1
Eyes Closed	1
Happy	1
Calm	1
Fear	1
Sad	1
Math Questions	4

Eyes Open (Resting state): The EEG signals will be recorded when the individuals are at rest and their eyes are open following data collection. The participants will be told to keep still, keep their eyes open, and concentrate on a certain area of the room. This protocol will last one minute and aims to record EEG signals while the participants are awake and alert. When the eyes were closed, relative delta reduced exclusively at occipital sites, whereas relative theta decreased at parietal and occipital locations. These findings revealed significant changes in EEG development between eyes-open and eyes-closed resting situations, emphasizing the need for more investigation [16].

Eyes Closed (Resting state): The EEG signals will then be recorded when the individuals are at rest with their eyes closed. Participants will be given instructions to sit still and close their eyes. This protocol will last one minute, aiming to record participants' EEG signals while they are relaxed. The eyes-closed (EC) resting state in young adults and children is one of low EEG arousal, with the transition to eyes-open (EO) largely including a rise in arousal. This arousal approach was employed to interpret EC/EO disparities in young and old persons [17].

Emotional States: Four different emotional states, happy, calm, fear and sad will be displayed by participants during this phase. Each emotional state will be displayed for one minute, with participants instructed to express their emotions as accurately as possible. Emotional changes can induce variances in electroencephalography (EEG) signals, which reflect distinct emotional states and are difficult to conceal. Human-computer interface, medical diagnosis, military, and other areas have all made extensive use of EEG-based emotion identification [18].

Math Test: EEG signals will be recorded as participants complete an arithmetic test as the protocol's last phase. Participants will be required to execute mental calculations and problem-solving exercises as part of the test, which will be difficult to pass. This protocol will last 4 minutes and aim to obtain EEG signals while the participants are engaged in cognitive effort and engagement. The use of event-related potentials (ERPs) and frequency analysis to investigate processes involved in arithmetic methods allows researchers to learn how participants solve different types of problems by distinguishing arithmetic techniques based on their electrophysiological signatures [19].

4. Raw Signals Analysis

Raw signal analysis is the study of unprocessed data and deducing information from the patterns of the waves caused by the patient's brain to deduce information about the functioning of the brain, such as the detection of seizures or sleep stages. The capacity to gather and analyze sensitive information delivered by various signals is referred to as signal analysis [20]. To interpret the encrypted information, this specialist intercepts these signals and analyses the information using cryptanalysis [20]. A high-level security career [21] is defined by a Signal Analysis definition.

The analysis done here will be comparing 2 male adults, the first one is presumably normal as in not suffering from any apparent mental health issues and is capable of performing day-to-day activities with little to no difficulty, while the other is clinically diagnosed with bipolar disorder.

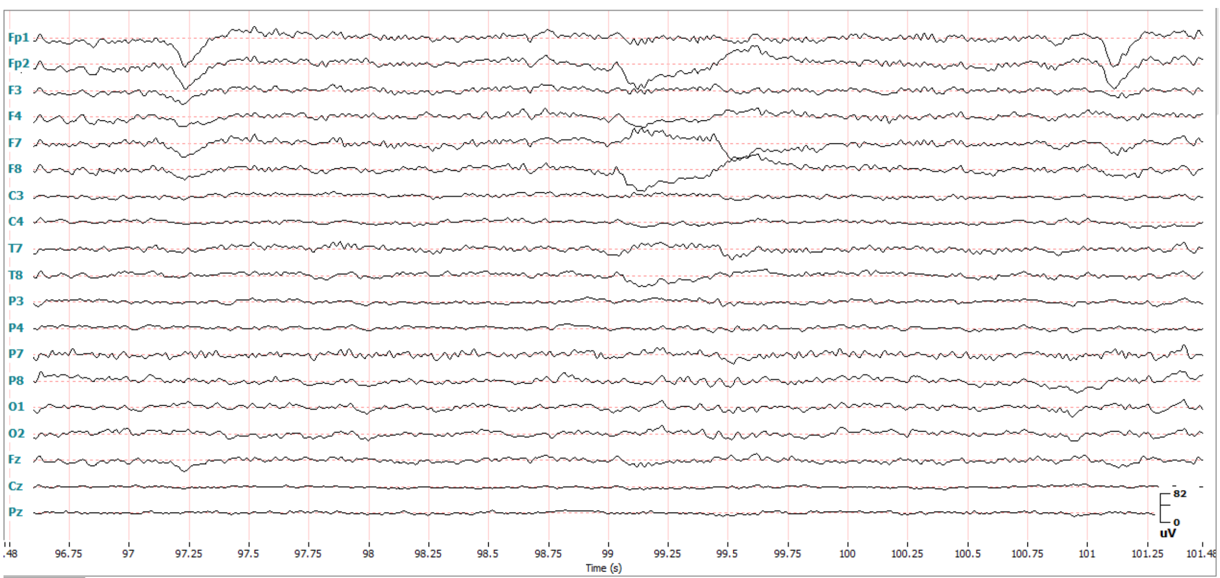

Figure 2. EEG waves of the normal patient while performing arithmetic questions

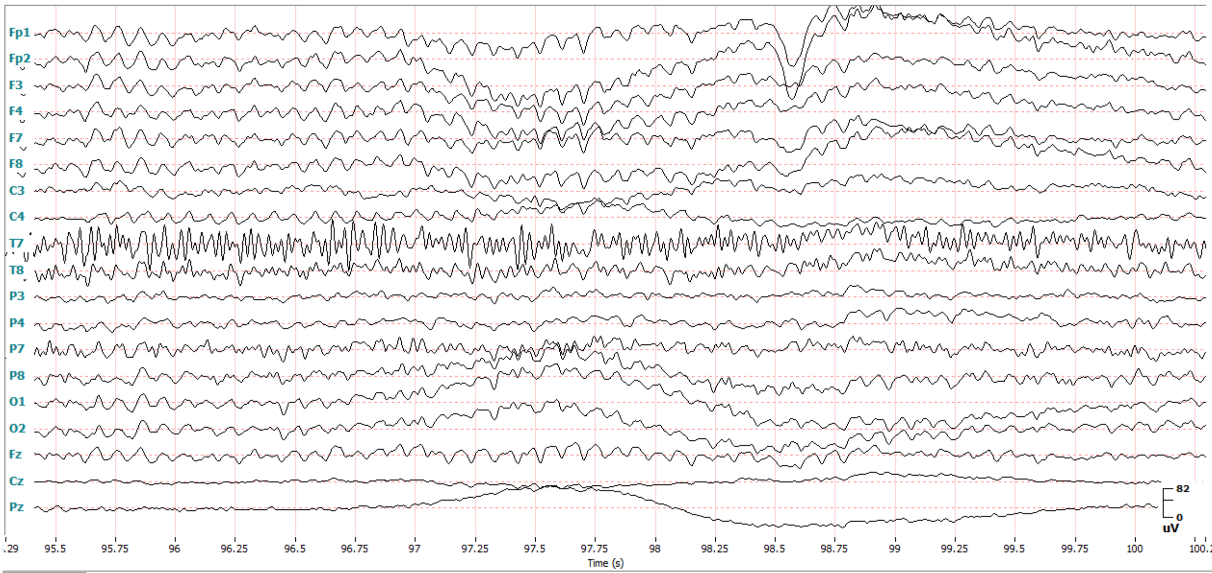

Figure 3. EEG waves of the bipolar subject while performing arithmetic questions

As we can see here the brains waves of a normal patient while performing arithmetic questions is obviously under strain from calculating which is an intensive brain task and the waves can be categorized as beta waves to mildly high beta waves; however, in contrast for the bipolar patient there is much messier and the waves have less frequency, and if we look closer at the ‘t7’ node the most amount of activity is exerted there, this is presumed as the ‘t7’ node is located on the frontal lobe which is responsible for higher-level activities such problem-solving.

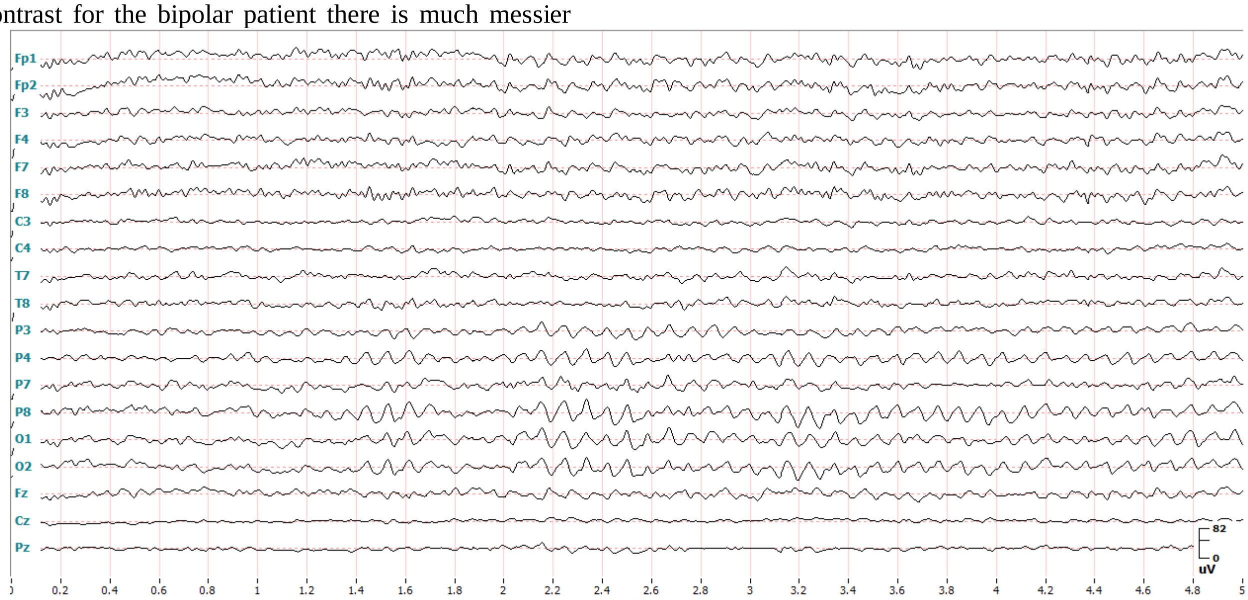

Figure 4. EEG waves of the normal patient while resting with eyes closed

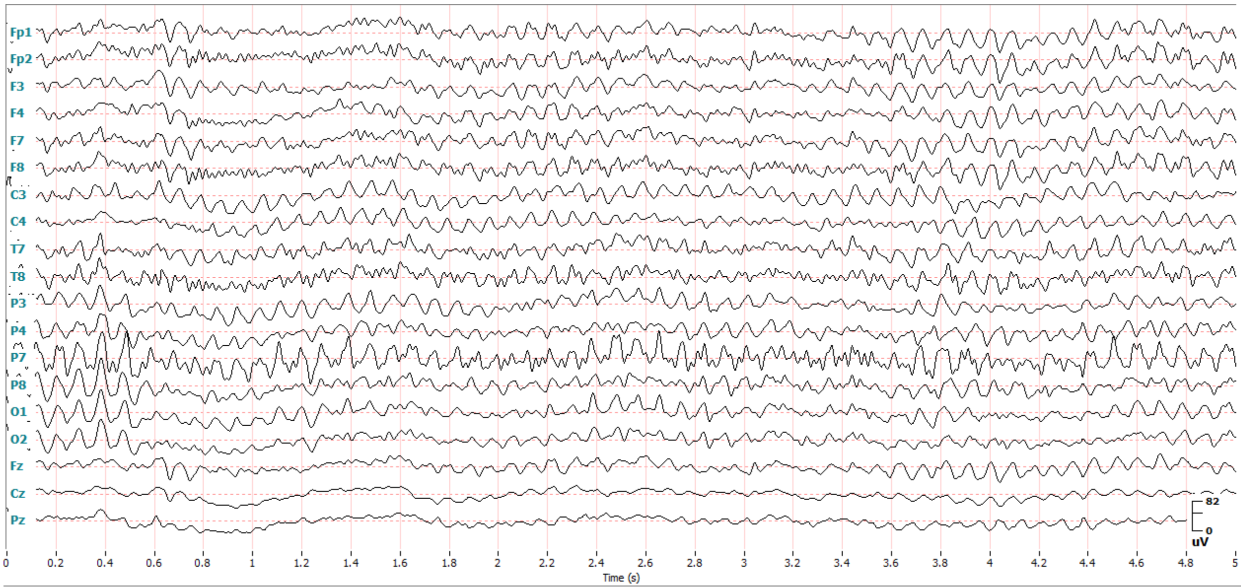

Figure 5. EEG waves of the bipolar patient while resting with eyes closed

Even when assigned a simple task such as relaxing and closing their eyes we can see that the normal patient has calm brain waves in the alpha to low beta waves range as there is no intensive brain task assigned the subject is simply relaxing; however, the bipolar patient even with a simple task still has a much higher brain activity than usual as the amplitude of the waves is higher although the frequency is fairly similar.

In comparison, every single given task had noticeably higher brain activity and noticeably messier waves with the bipolar subject than what the normal subject had. The comparison is to The four emotions (calm, fear, sad, and happy) two eye states (open and closed), and arithmetic questions test. The subjects had similar comparisons as all tests had the bipolar subject have higher than average brain activity, especially at the t7 node. While the normal subject has a less messy brain wave signal, it can be seen that in general, the normal patient did have on average higher frequencies

5. Research Methodology

Signal processing is a branch of electrical engineering that studies, modifies, and synthesizes signals such as sound, pictures, and scientific measurements. However, in this study, we are conducting research on Brain Signal Processing utilizing an Electroencephalogram (EEG), which is defined as electrical activity generated by the firing of neurons inside the human brain and often recorded at the brain scalp. To analyze the brain signals we need to do Pre-processing, Feature Extraction, and Classification of the dataset on brain signals.

To continue we collected datasets of brain signals from two patients. The first one was normal without any mental disorder and the second one was a mental disorder diagnosed with bipolar disorder during the protocol of the experiment as explained before in the protocol experiment part. Then when we load the dataset into MATLAB, we found that the dataset was not balanced and we decided to clean it to get a good training of the dataset as seen in figure 6 and figure 7. We are explaining how we used the Neural Network technique to analyze those datasets using MLP in MATLAB.

To analyze EEG data in MATLAB using a Multi-layer Perceptron (MLP), follow the procedures below:

1. Preprocess the EEG signals to extract relevant features. This may include filtering, segmentation, and feature extraction techniques.
2. Split the EEG signals into training (Happy, Calm, Fear, Sad) and testing(EO, EC, Math_Questions) sets.
3. Define the architecture of the MLP network, including the number of layers, the number of neurons in each layer, and the activation functions for each layer.
4. Train the MLP network using the training set and a suitable optimization algorithm, such as gradient descent or stochastic gradient descent.
5. Evaluate the performance of the trained MLP network on the testing set by computing metrics such as accuracy, precision, recall, and F1-score.
6. Use the trained MLP network to predict the label of unseen EEG signals.

Pre-processing is the process of removing extraneous signals from a dataset so that it may be utilized for classification later. And there may be some issues with the data signals, such as artifacts in EEG (electroencephalogram) records produced by numerous reasons such as line interference, EOG (electrooculogram), and ECG (electrocardiogram). These noise sources make interpreting the EEG and collecting clinical information more challenging. As a result, appropriate filters must be designed to reduce such artifacts in EEG recordings. As a result, we are utilizing an Ellipord filter to filter the noise before processing.

Feature Extraction is a dimensionality reduction procedure that reduces an initial collection of raw data to more manageable groupings for processing. Windowing the signal, applying the DFT, obtaining the log of the magnitude, and then warping the frequencies on a Mel scale, followed by using the inverse DCT are the essential steps in the MFCC or Mel-frequency cepstral coefficients (MFCCs) feature extraction approach. Aside from that, we employ Kernel Density Estimation (KDE), Fisher's discriminant ratio (FDR), and main component analysis (PCA).

The classification approach uses independent variable (feature) values as input to determine which class an independent variable belongs to. A classifier contains several parameters that must be trained using a training dataset. A trained classifier may recognize new instances in an unseen testing dataset by modeling the relationship between classes and relevant characteristics. Classifiers such as Multi-Layer Perceptron (MLP), Support Vector Machine (SVM), ANFIS, Nave Bayes (NB), K-Nearest Neighbour, and Multi-Layer Perceptron (MLP) are used in this project to classify our data signal. MLP is a non-linear neural network-based approach with three successive layers: input, hidden, and output, where the hidden layer sends input data to the output layer. However, due to an insufficient or excessive number of neurons, the MLP model might produce over-fitting.

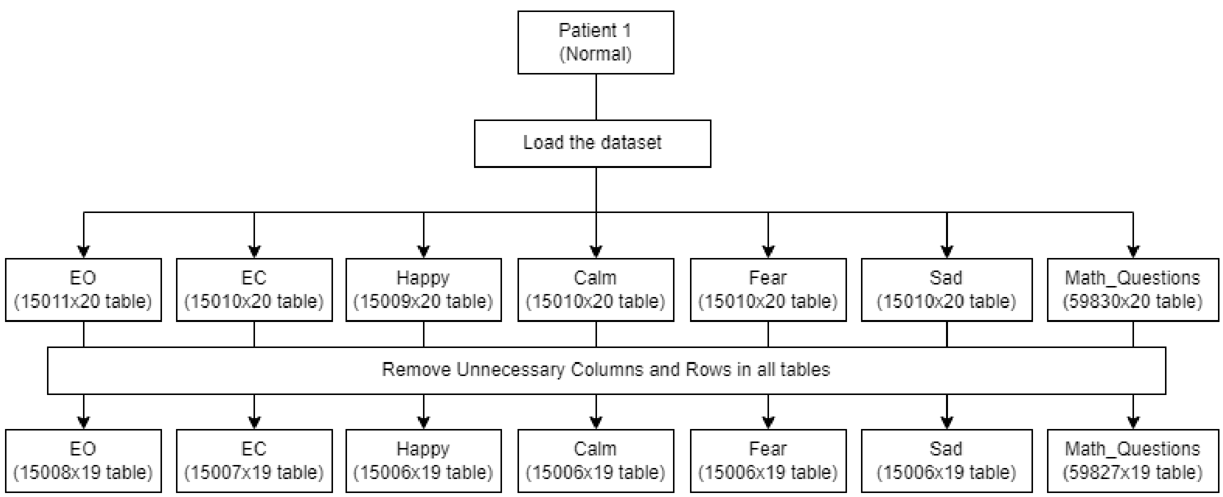

Figure 6. Cleaning Data Signals for Patient 1

Figure 6 and figure 7 show that after importing the dataset, each dataset had 20 columns, but we reduced them to 19 each since we eliminated the date column. Furthermore, looking at the rows, we can see that there are modifications since we eliminated the rows with null values as well as certain rows on some of the emotion data (Calm, Fear, Sad) to make all four balanced as they are the data that will be trained later.

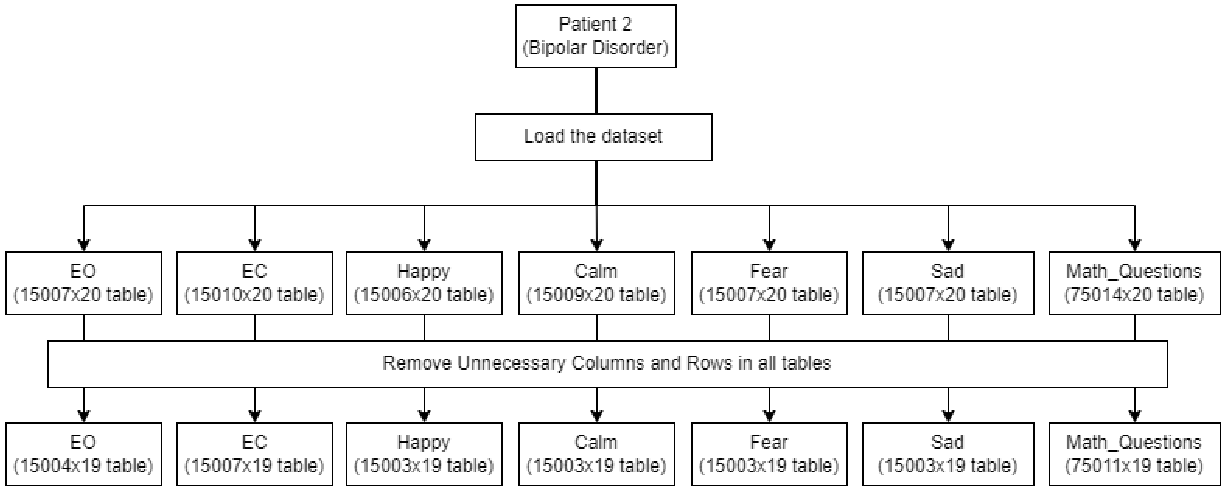

Figure 7. Cleaning Data Signals for Patient 2

6. Results and Findings

A Multi-layer Perceptron (MLP) is a sort of artificial neural network that is commonly employed in the processing of EEG signals. MLP is trained on EEG data in this context to identify distinct mental states or detect anomalies in brain activity. The outputs of an MLP model in EEG signal analysis can be utilized for medical diagnosis and treatment, monitoring brain activity during various activities, and brain function research. These outcomes might be expressed as accuracy, sensitivity, specificity, or other performance indicators. The results of MLP-based EEG signal analysis can be utilized to make more informed decisions and enhance patient outcomes. We analyzed the dataset by training the emotional data and then we choose the Alpha [22] and Beta [22] band waves to test the Eyes Opened(EO), Eyes Closed(EC), and Arithmetic test(Math_Questions) activities. From the analysis of the Alpha and Beta band waves of the two patients, we displayed three graphs on each band wave. Those three graphs are, Eyes Opened, Eyes Closed, and Arithmetic Test. The y-axis of the graphs represents the emotional state, which is Happy, Calm, Fear, and Sad. We are going to use Valence and Arousal to determine the emotion in the graphs, if both are positives it means the patient is happy, if both are negatives it means the patient is sad, if Valence is negative and Arousal is positive it means the patient has fear, and lastly if Valence is positive and Arousal is negative it means the patient is calm.

To continue with our analysis, we have achieved 100% accuracy for the Alpha band wave in patient 1. The graphs below depict the various graphs on Eyes Opened (EO), Eyes Closed (EC), and Arithmetic exam (Math Questions) based on Valence (V) and Arousal (A).

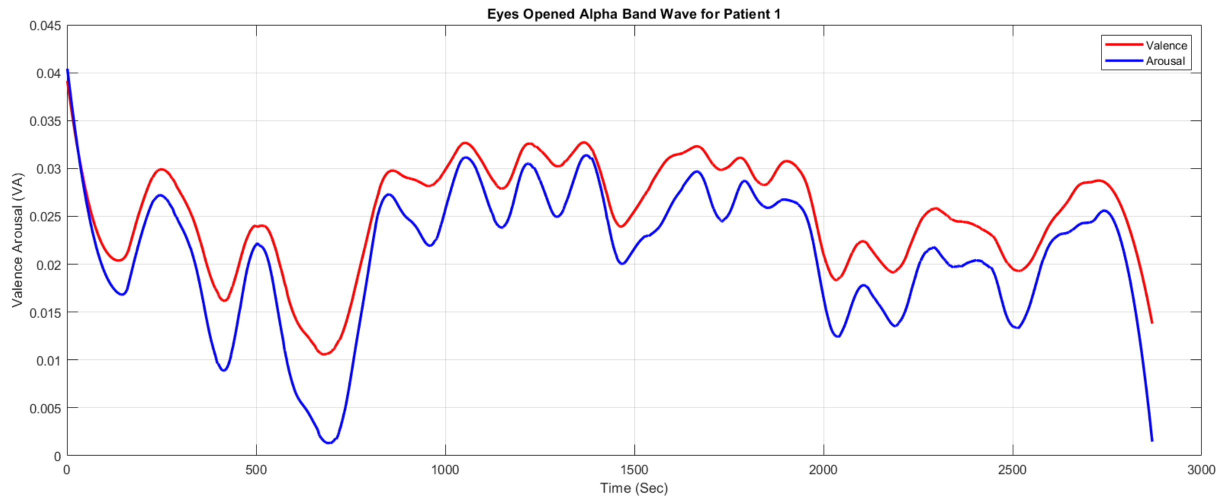

Figure 8. Eyes Opened Alpha Band Wave for Patient 1

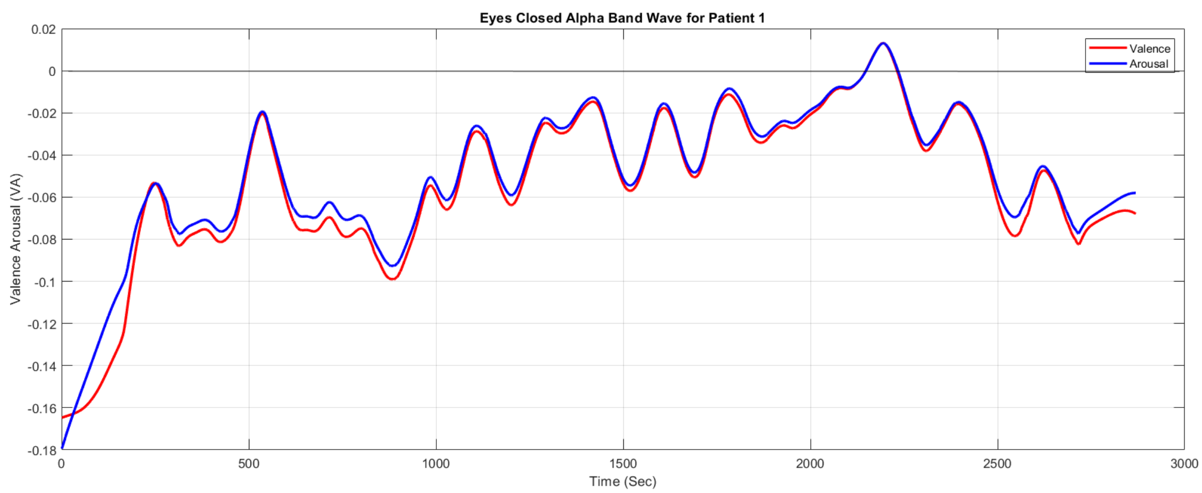

Figure 9. Eyes Closed Alpha Band Wave for Patient 1

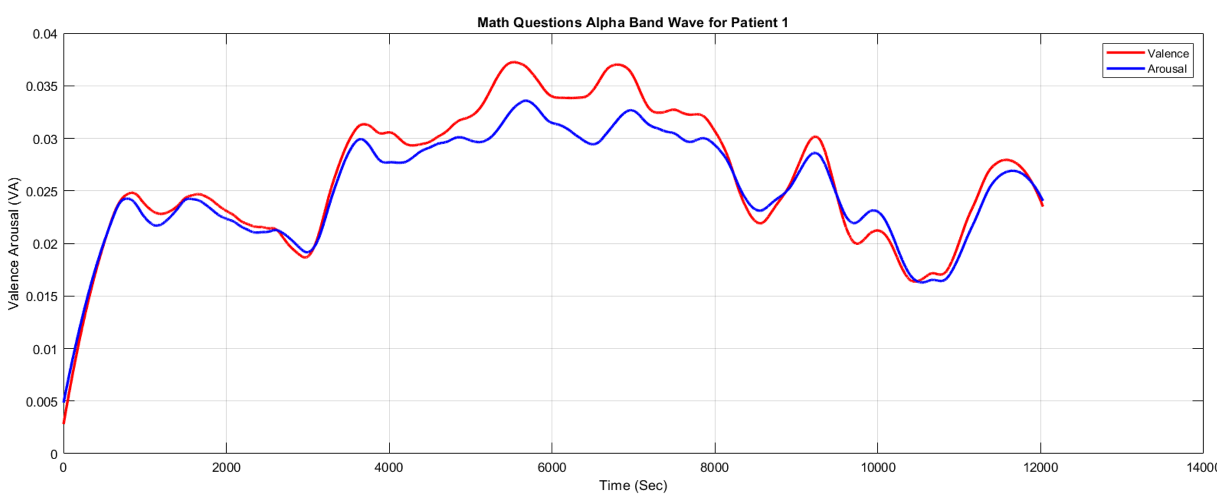

Figure 10. Arithmetic Test Alpha Band Wave for Patient 1

Based on the graphs above we can see that patient 1 emotional state is normal and happy with Eyes Opened (Figure 8) and Arithmetic Test (Figure 10), however, that turns into a sad emotion with Eyes Closed (Figure 9). Patient 1 remained stable and positive throughout the data collection and he was not stressed or uncomfortable, but he gave feedback that during the first test which is Eyes Opened his eyes were tearing up while focusing on opening the eyes. With that, we can say that is the reason why he was emotionally sad during the second test which is Eyes Closed because of the eyes tearing up during test 1. These results also suggest that patient 1 is functioning well and has a positive emotional state during Eyes Opened and Arithmetic Test but he had a negative emotional state during Eyes Closed. All of those results are based on the Valence and Arousal graphs in the Alpha band wave, which are both positive for happy emotion and negative for negative emotion.

In patient 2, we achieved 100% accuracy with the Alpha band wave. The graphs below exhibit several graphs on Eyes Opened (EO), Eyes Closed (EC), and Arithmetic tests (Math Questions) based on Valence (V) and Arousal (A).

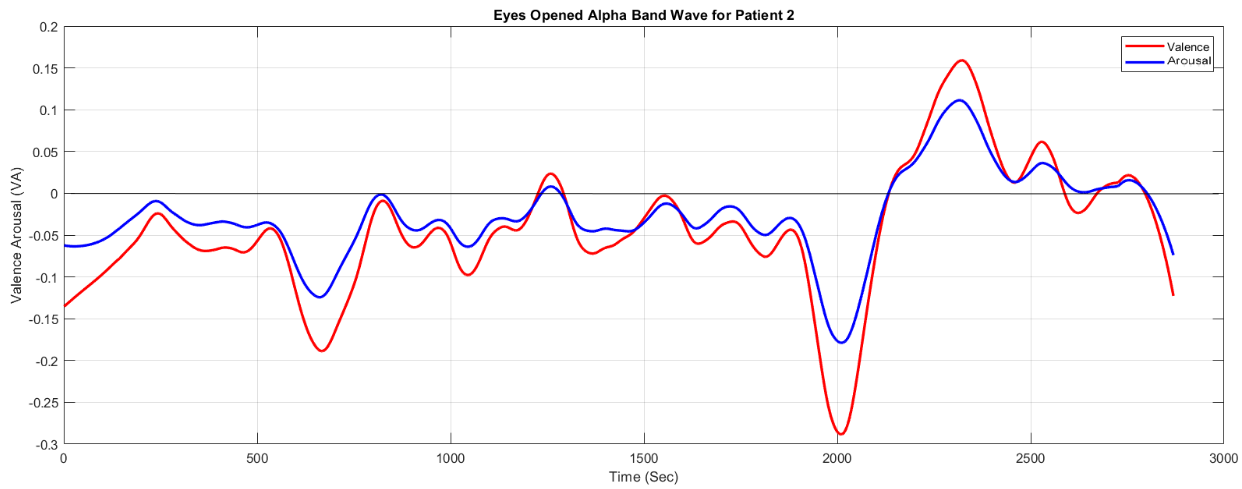

Figure 11. Eyes Opened Alpha Band Wave for Patient 2

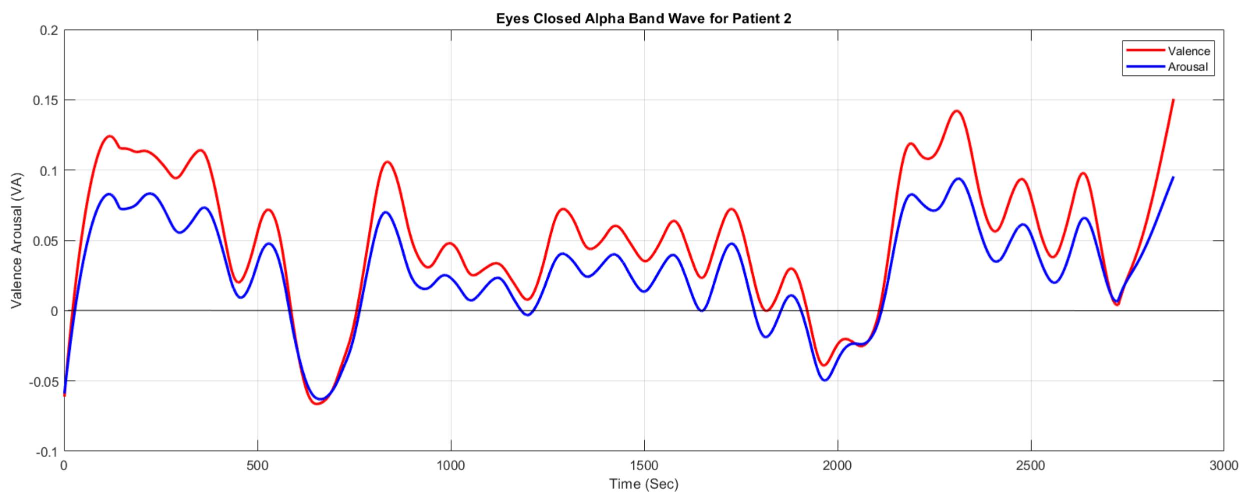

Figure 12. Eyes Closed Alpha Band Wave for Patient 2

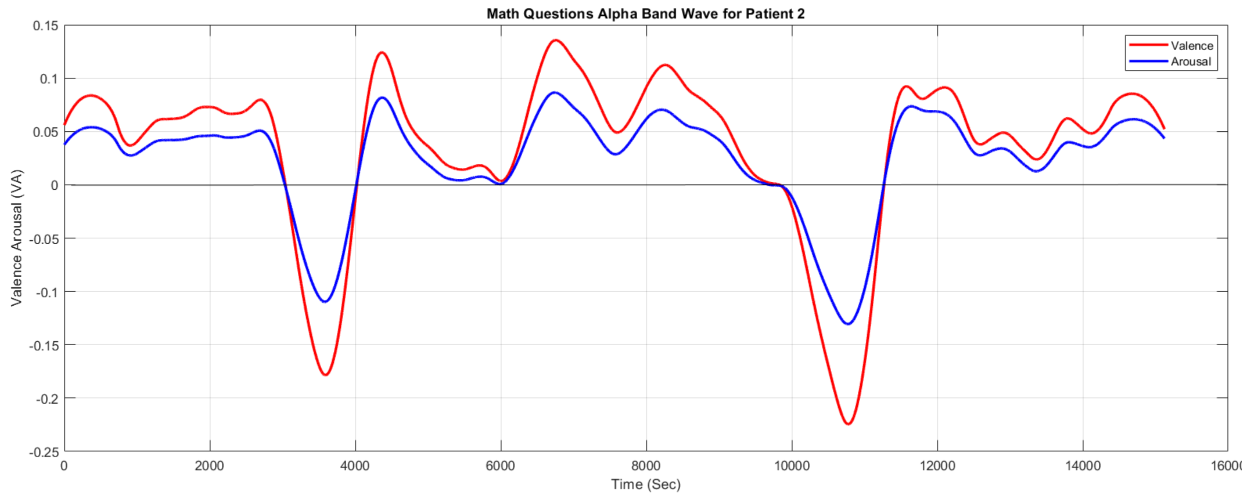

Figure 13. Arithmetic Test Alpha Band Wave for Patient 2

According to the graphs above, patient 2's emotional state is sad at the beginning of Eyes Opened (Figure 11) and has fear at the end of this stage. During Eyes Closed (Figure 12) the emotional state changes over time. It was not stable, starting with sadness, then going to happiness and going to fear and returning to sadness, and so on. At the end of the Arithmetic Test (Figure 13), the emotion was stable at the start and at the end which indicates a happy emotional state, but in the middle, the emotion was not stable and shows multiple emotions stated which are sad, fear, happy, and calm. These results also suggest that patient 2 is not functioning well and has positive and negative emotional states during the 3 experimental tests based on the Valence and Arousal which are both positives and sometimes negatives and most of the area in the three graphs in the Alpha band wave.

With the Beta band wave, we achieved 100% accuracy in patient 1. Several graphs on Eyes Opened (EO), Eyes Closed (EC), and Arithmetic tests (Math Questions) based on Valence (V) and Arousal (A) are shown below.

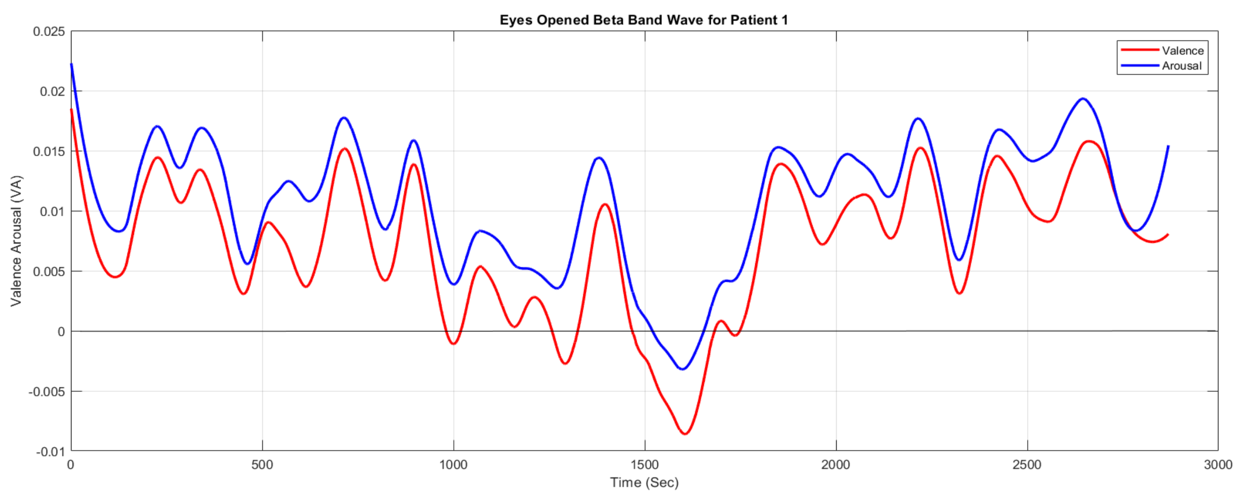

Figure 14. Eyes Opened Beta Band Wave for Patient 1

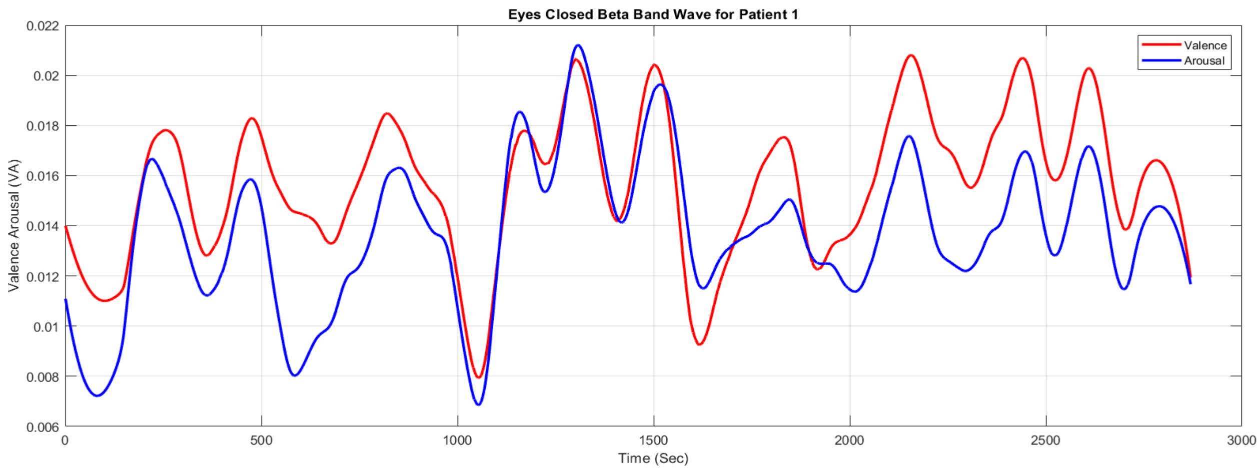

Figure 15. Eyes Closed Beta Band Wave for Patient 1

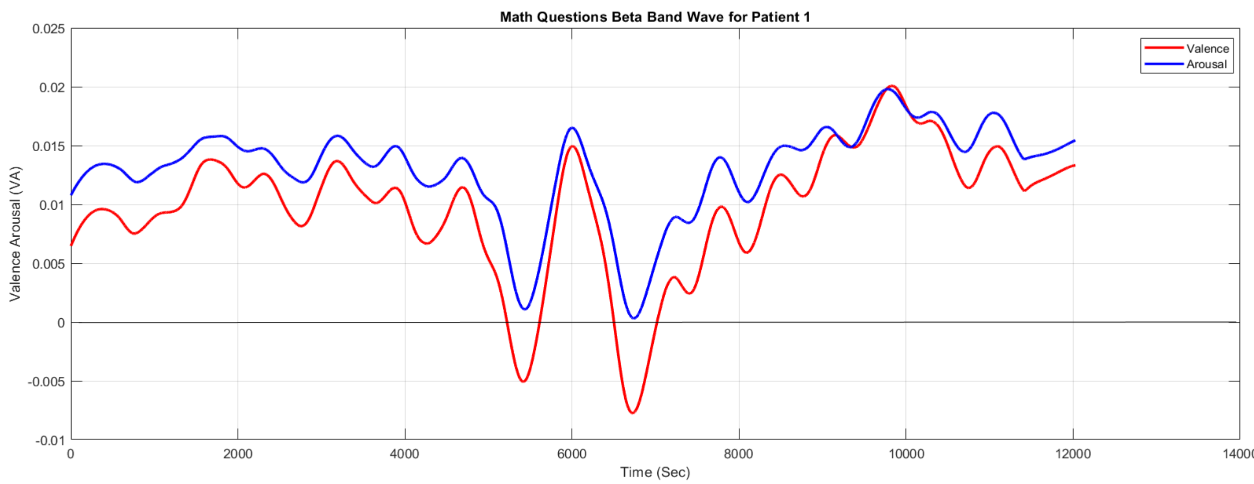

Figure 16. Arithmetic Test Beta Band Wave for Patient 1

According to the graphs above, patient 1 emotional state is normal and happy with Eyes Closed in Figure 15. During Eyes Opened (Figure 14) the emotional state changes starting with happy then going to calm in the middle of the experiment and then going back to happy at the end. And that situation happened again during the Arithmetic test as we can see in Figure 16. Patient 1 stayed calm and optimistic throughout the data collection, and he was neither worried nor uncomfortable. Based on the Valence and Arousal, which are both positives for Eyes Closed and both changing to Valence positive and Arousal negative in the middle of the experiment for Eyes Opened and Arithmetic Test, the majority of the area in the three graphs in the Beta band wave suggest that the patient is functioning well and has a positive emotional state.

In patient 2, we got 100% accuracy using the Beta band wave. Several graphs based on Valence (V) and Arousal (A) are provided below for Eyes Opened (EO), Eyes Closed (EC), and Arithmetic exams (Math Questions).

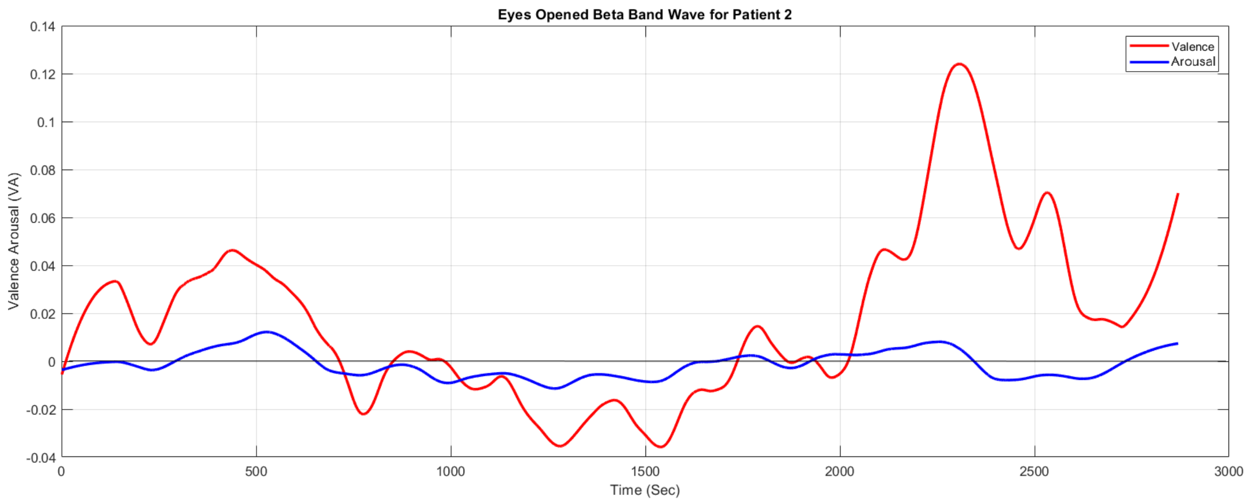

Figure 17. Eyes Opened Beta Band Wave for Patient 2

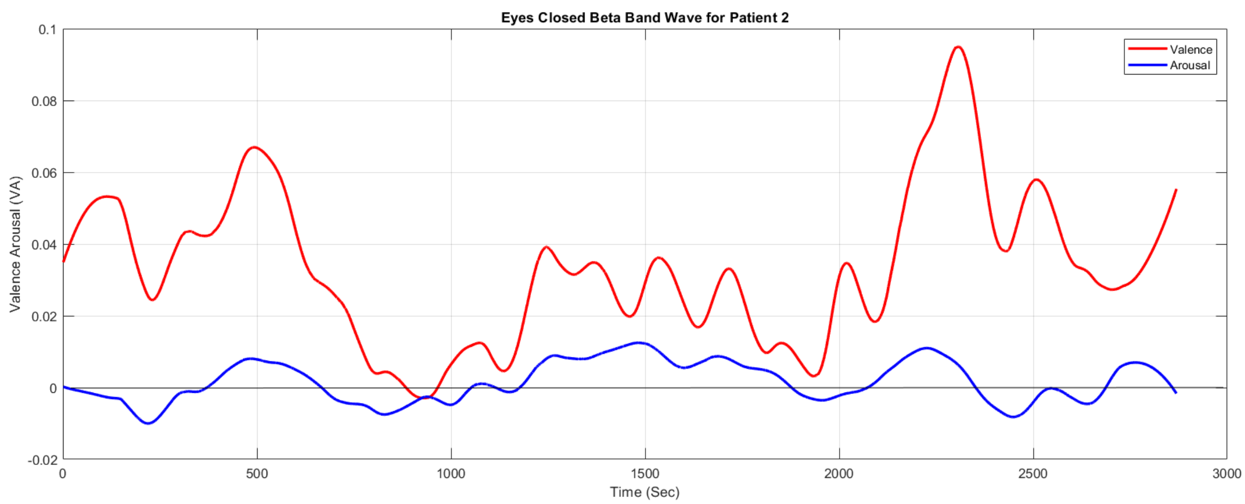

Figure 18. Eyes Closed Beta Band Wave for Patient 2

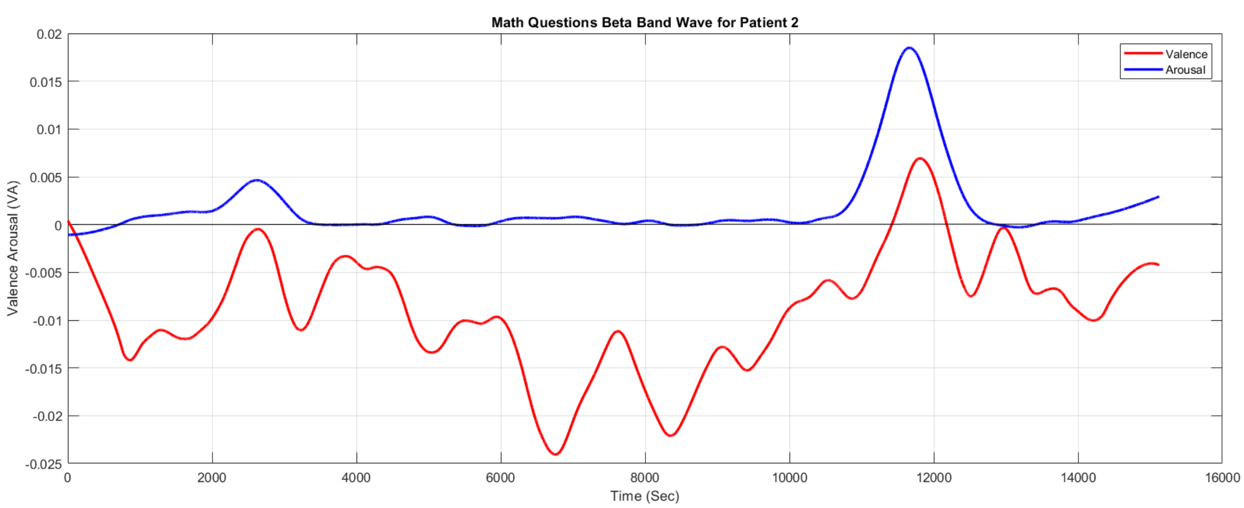

Figure 19. Arithmetic Test Beta Band Wave for Patient 2

According to the graphs above, patient 2 emotional state changes start with calm then going to sad in the middle of the experiment, and then went back to calm at the end of Eyes Opened (Figure 17). During Eyes Closed (Figure 18), the emotional state is calm and, in the middle, we can see it changes to being happy for a little time. At the end of the Arithmetic Test (Figure 19), the emotion was fear in process. These findings also indicate that patient 2 is not functioning well and has both positive and negative emotional states but mostly the negative emotional states dominate during the three experimental tests, as measured by Valence and Arousal, with the majority of the area in the three graphs falling within the Beta band wave.

7. Conclusion

In conclusion, EEG data analysis is an effective technique for measuring brain activity. This investigation examines EEG data to measure brain activity and identify the patient's emotional state, whether it is joyful, calm, fearful, or sad, and whether it is normal or atypical. The data was pre-processed, features extracted with MFCCs, and classification performed with an MLP neural network. The findings were displayed in three graphs: one for Eyes Closed, one for Eyes Opened, and one for Arithmetic Test tested in two separate band waves, Alpha and Beta. The graphs demonstrated that the patient's emotional condition remained constant and positive throughout the recording, whereas the patient's emotional state changed during the recording, indicating a mental illness. The use of EEG data to categorize normal and bipolar disorder patients using MLP is an exciting new method in neuroscience and psychiatry. The MLP algorithm can efficiently evaluate the complex patterns contained in EEG signals and distinguish between bipolar disorder patients and healthy persons. However, the outcomes of these studies differ, and further study is needed to establish the findings' dependability and generalizability. Furthermore, boosting the performance of the MLP algorithm through the application of more sophisticated approaches may result in higher accuracy in patient categorization. The comparison of our two patients by analyzing the MLP results in the two Alpha and Beta band waves revealed that for the Alpha band wave, patient 1 was happy during the Eyes Opened and Arithmetic Test experiments and sad during the Eyes Closed experiment due to the eyes tearing up during the Eyes Closed experiment. However, in all of the studies, patient 2's emotional state was unstable and changed often. Moving on to the Beta band wave, we can see that patient 1 is still happy based on the three graphs, and the emotional state may shift to calm at times, but that is still a positive emotion. In contrast, the patient's two mood states moved dramatically in all three graphs, from pleased to terror and fear to calm. Overall, the combination of EEG signals and MLP has the potential to improve the diagnosis and treatment of bipolar disease, but further research is needed to fully fulfill this potential. As a result, we may infer that patient 1's emotional state remained normal and positive throughout the studies, indicating that he or she has good mental health, but patient 2's emotional state varies all the time due to bipolar disorder.

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