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GROUP PROJECT REPORT

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

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Introduction

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.

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 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.

Literature review

Research Paper 1

“EEG Based Classification of Long-Term Stress Using Psychological Labeling”

The objective

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 Protocol of the Experiment

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.

Methodology

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.

Findings

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.

Conclusion

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.

Research Paper 2

"EEG diagnosis of depression based on multi-channel data fusion and clipping augmentation and convolutional neural network."

The objective

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 of the Experiment

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.

Methodology

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.

Findings

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.

Conclusion

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.

Research Paper 3

“EEG-based deep learning model for the automatic detection of clinical depression”

The objective

This research 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 of experiment

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.

Methodology

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.

Findings

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.

Conclusion

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.

Protocol of Experiment

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.

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.

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.

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.

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.

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 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.

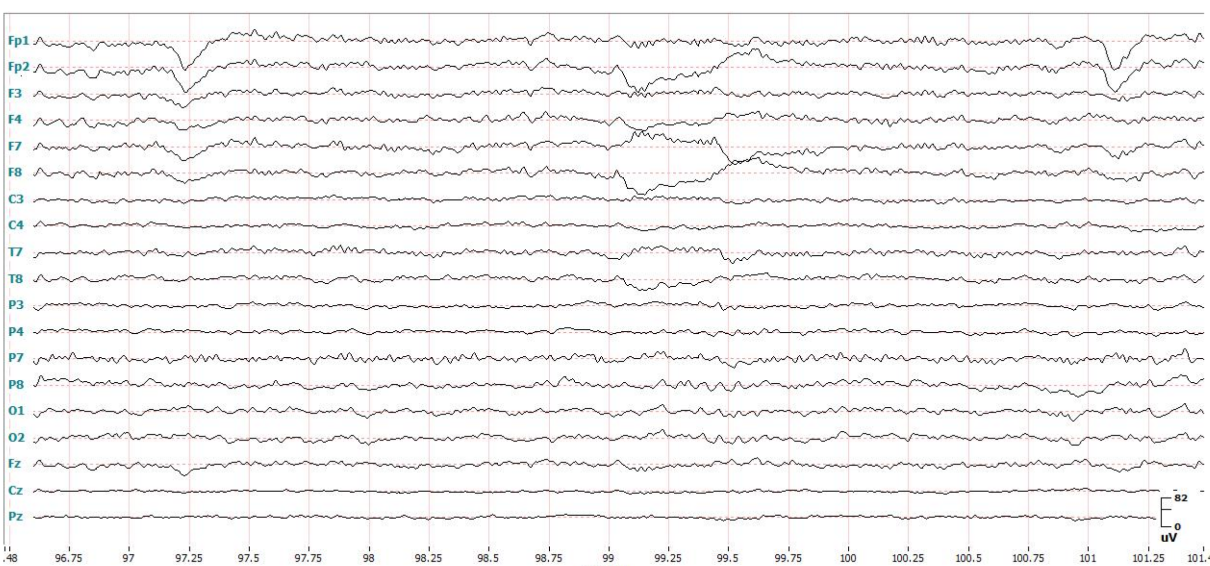

Figure 2: EEG waves of the normal patient while performing arithmetic questions

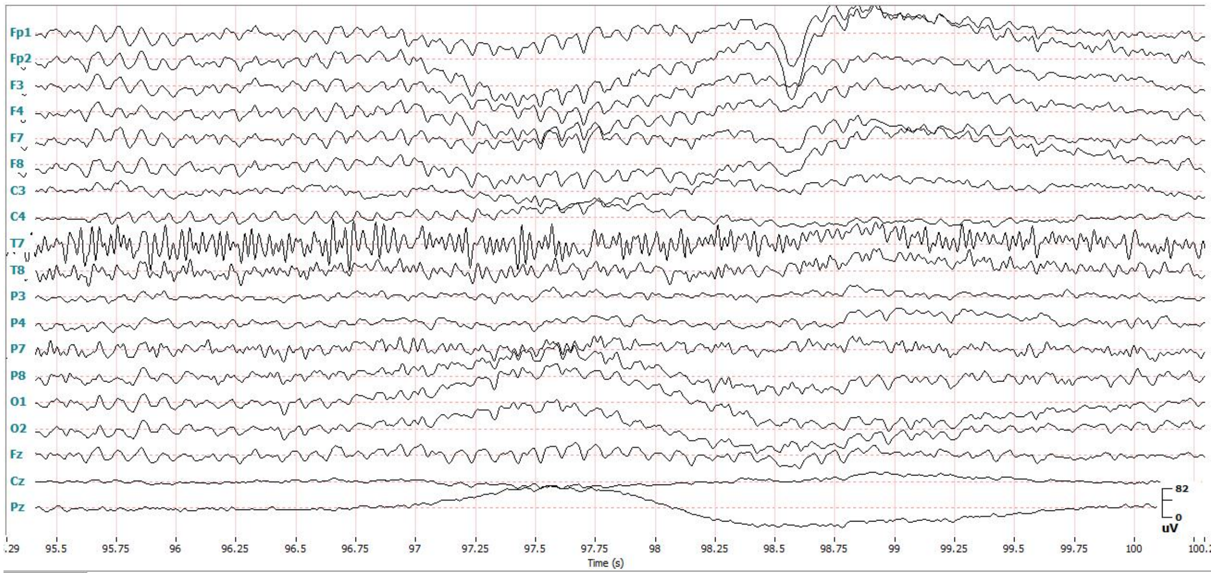

Figure 3: EEG waves of the bipolar subject while performing arithmetic questions

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 in 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.

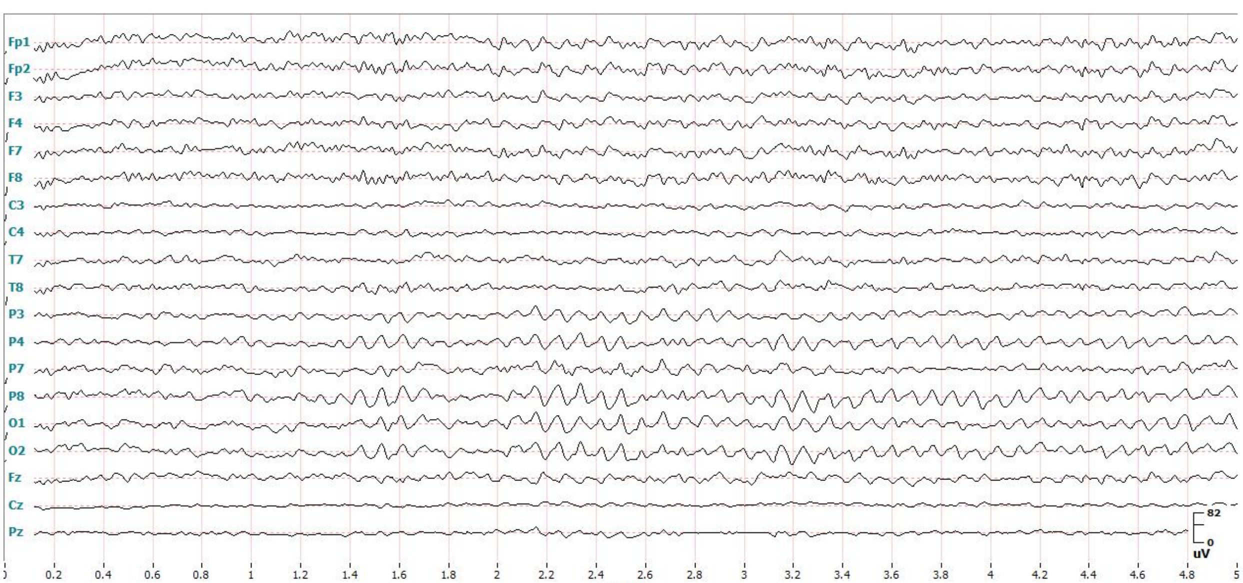

Figure 4: EEG waves of the normal patient while resting with eyes closed.

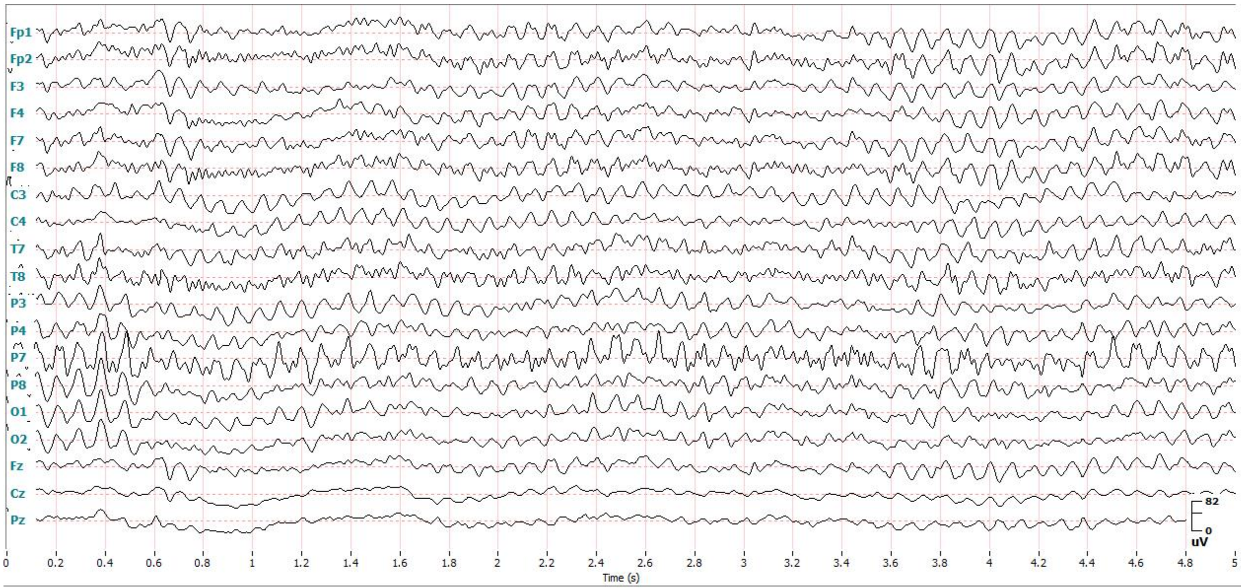

Figure 5: EEG waves of the bipolar patient while resting with eyes closed.

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 had 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.

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. In order 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 in order 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 prior to 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.

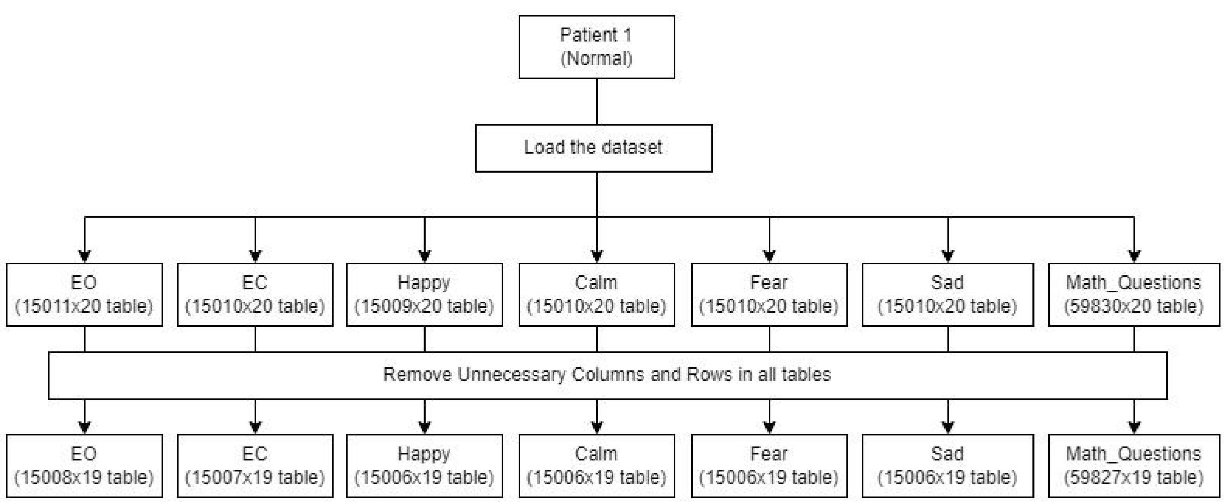

Figure 6: Analyze EEG Signals for Patient 1

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) in order to make all four balanced as they are the data that will be trained later.

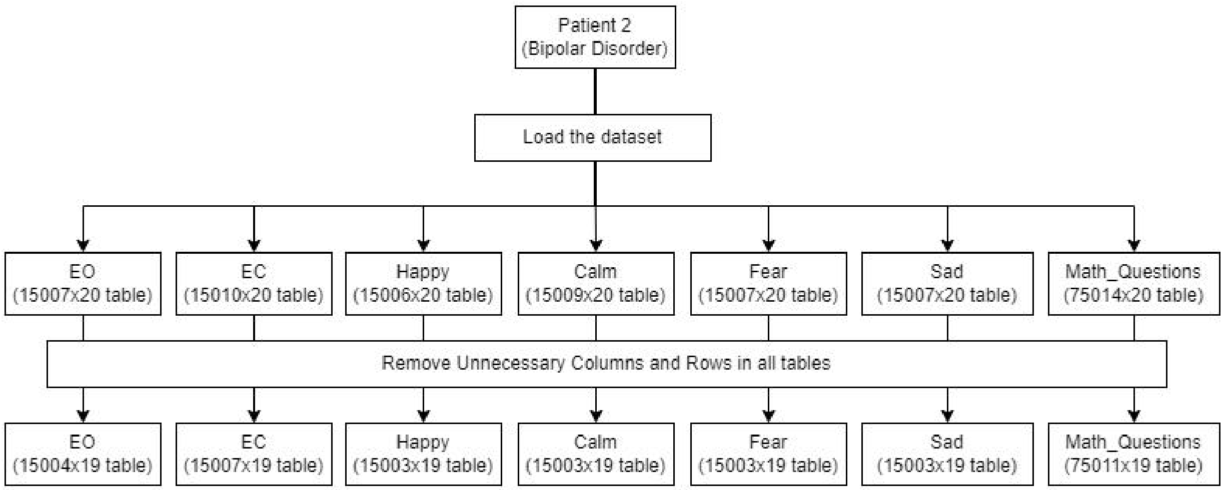

Figure 7: Analyze EEG Signals for Patient 2

Results & 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 and Beta 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).

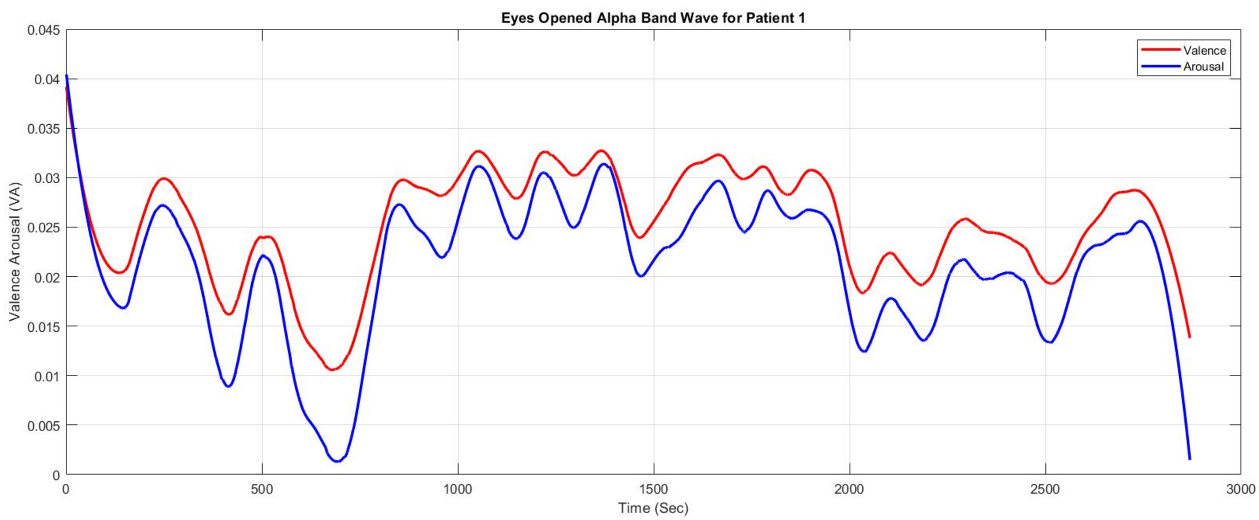

Figure 8: Eyes Opened Alpha Band Wave for Patient 1

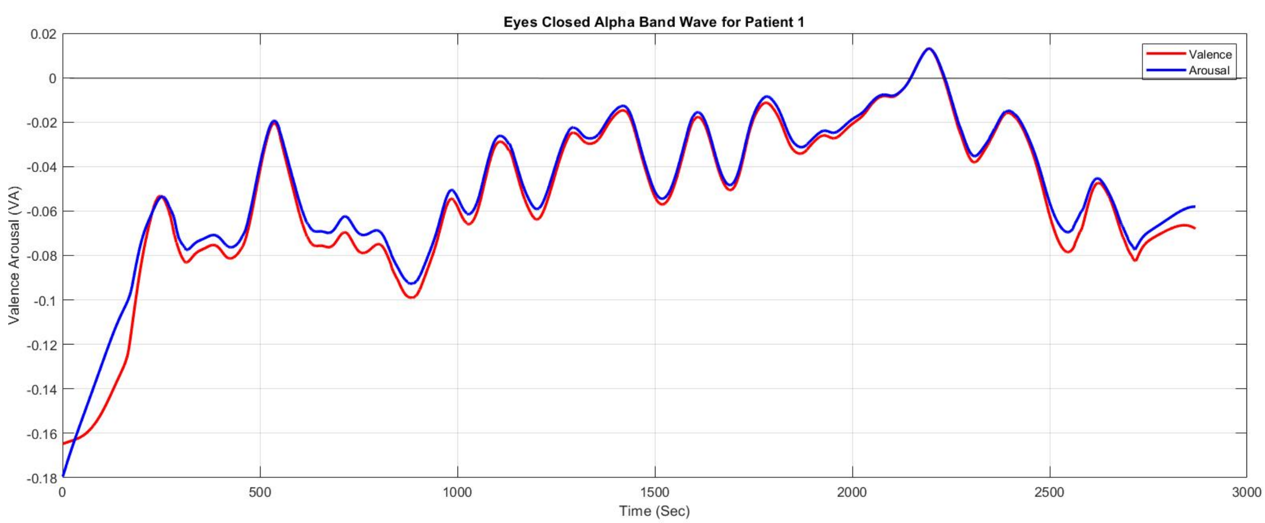

Figure 9: Eyes Closed Alpha Band Wave for Patient 1

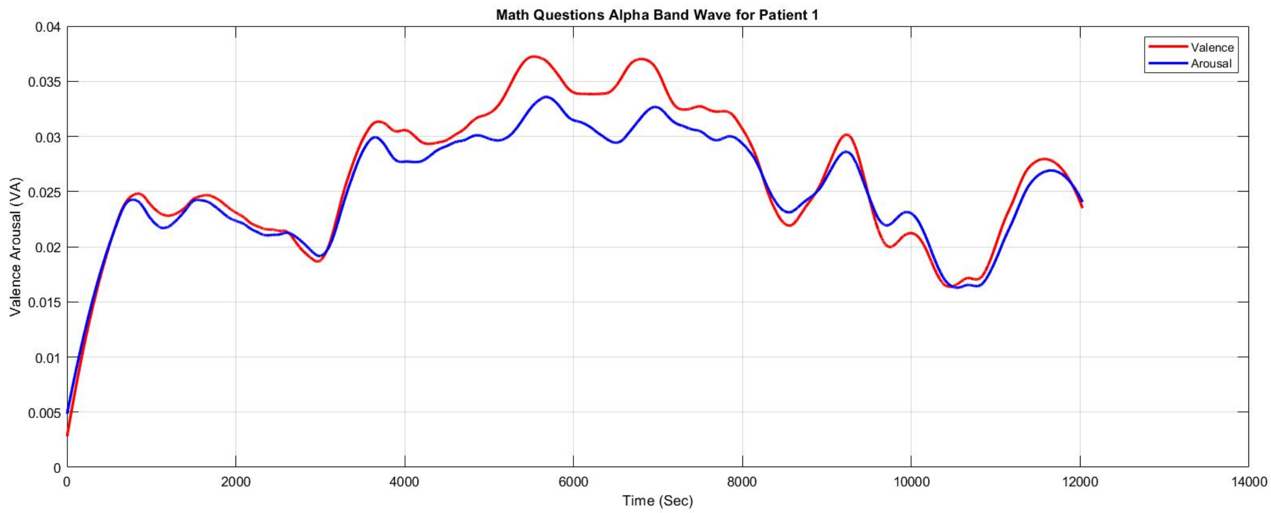

Figure 10: Arithmetic Test Alpha Band Wave for Patient 1

Based on the graphs above we can see that patient 1 emotional state is normal and happy for Eyes Opened (Figure 8) and Arithmetic Test (Figure 10), however, that turns into a sad emotion on Eyes Closed (Figure 9). Patient 1 remained stable and positive throughout the duration of 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).

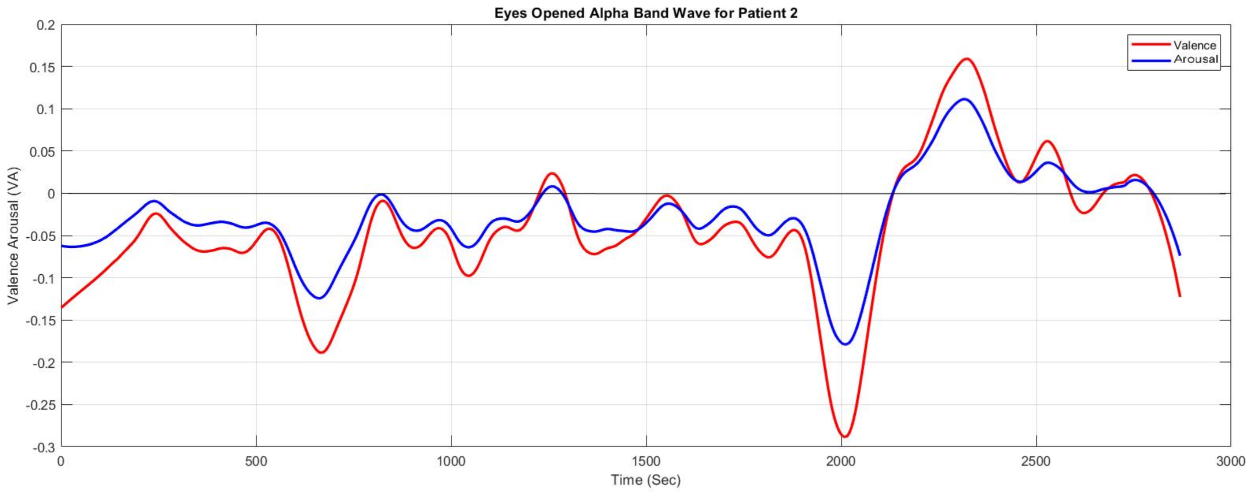

Figure 11: Eyes Opened Alpha Band Wave for Patient 2

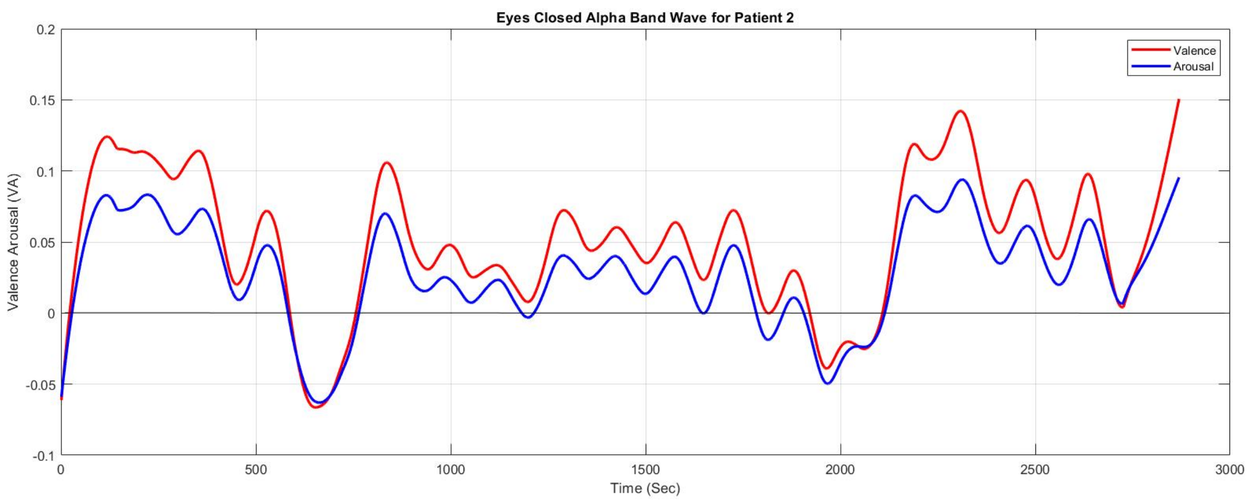

Figure 12: Eyes Closed Alpha Band Wave for Patient 2

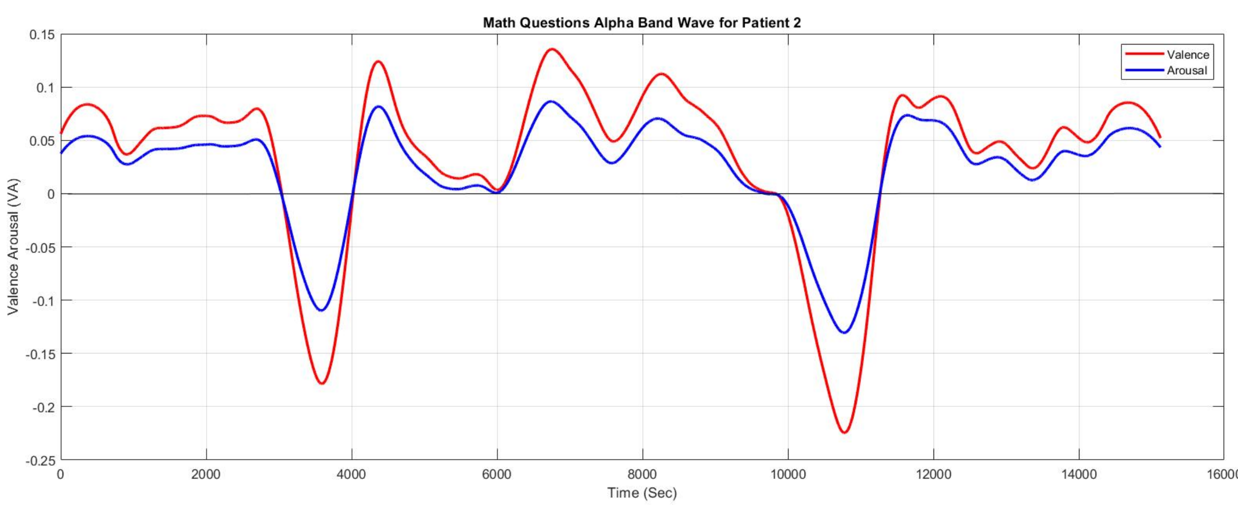

Figure 13: Arithmetic Test Alpha Band Wave for Patient 2

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 back 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.

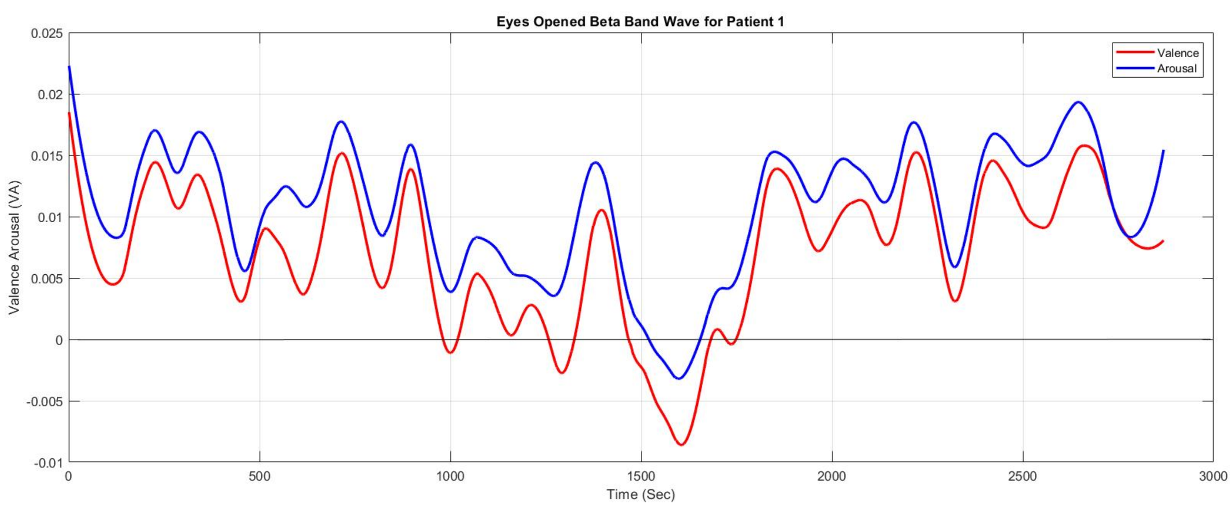

Figure 14: Eyes Opened Beta Band Wave for Patient 1

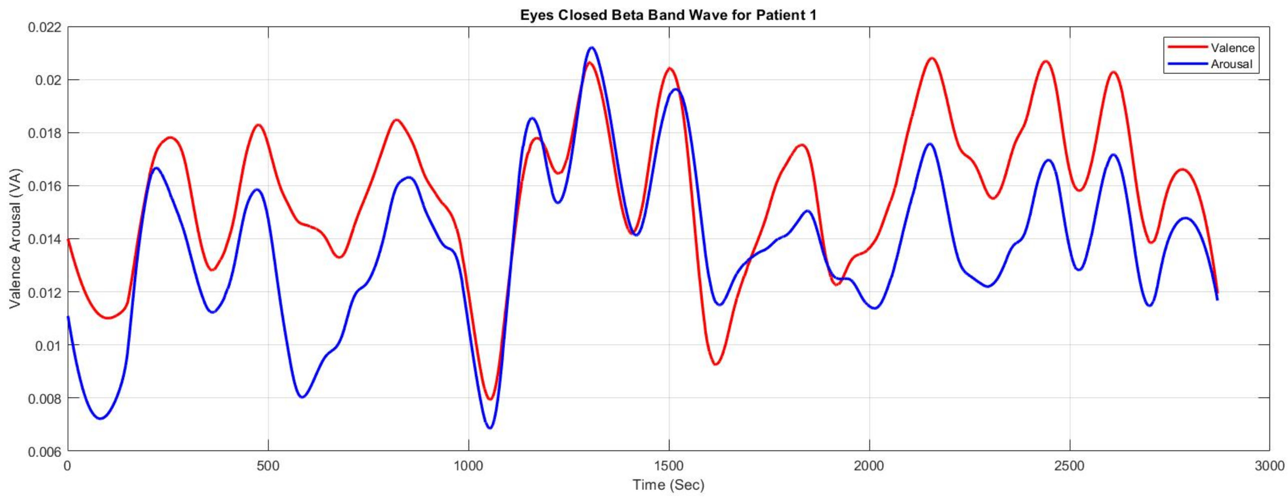

Figure 15: Eyes Closed Beta Band Wave for Patient 1

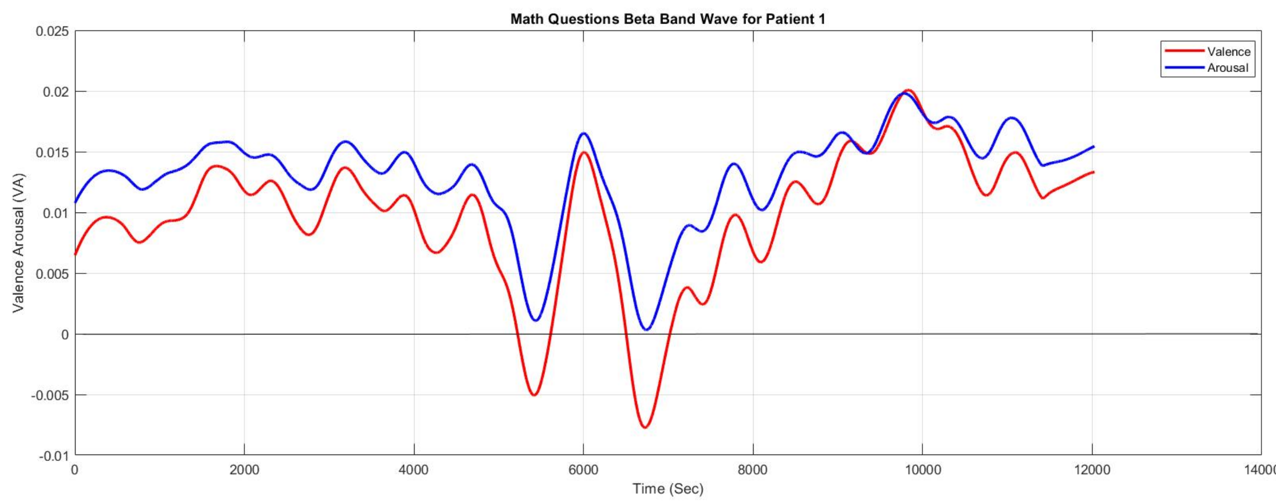

Figure 16: Arithmetic Test Beta Band Wave for Patient 1

According to the graphs above, patient 1 emotional state is normal and happy for 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).

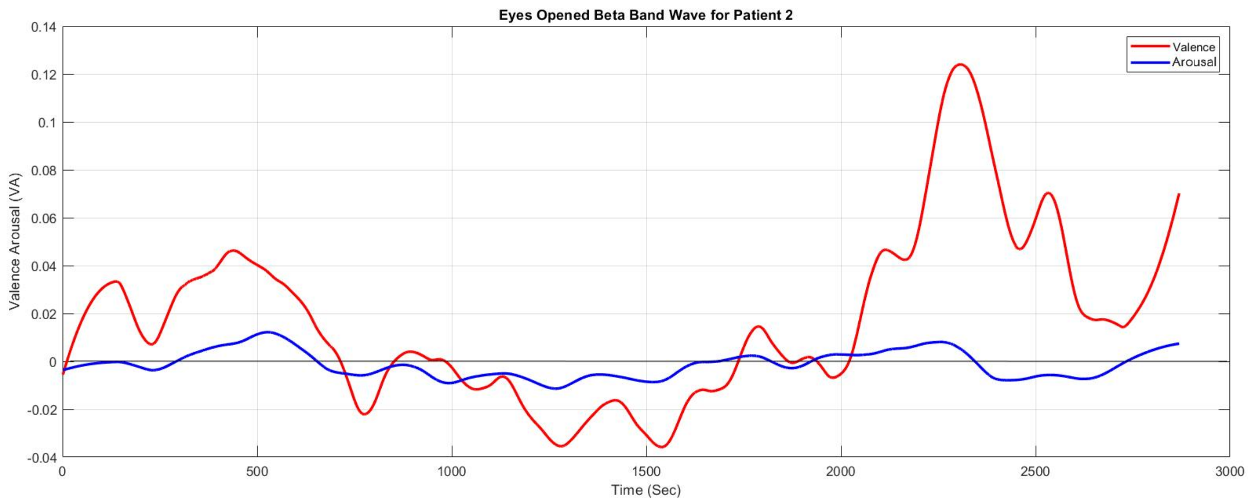

Figure 17: Eyes Opened Beta Band Wave for Patient 2

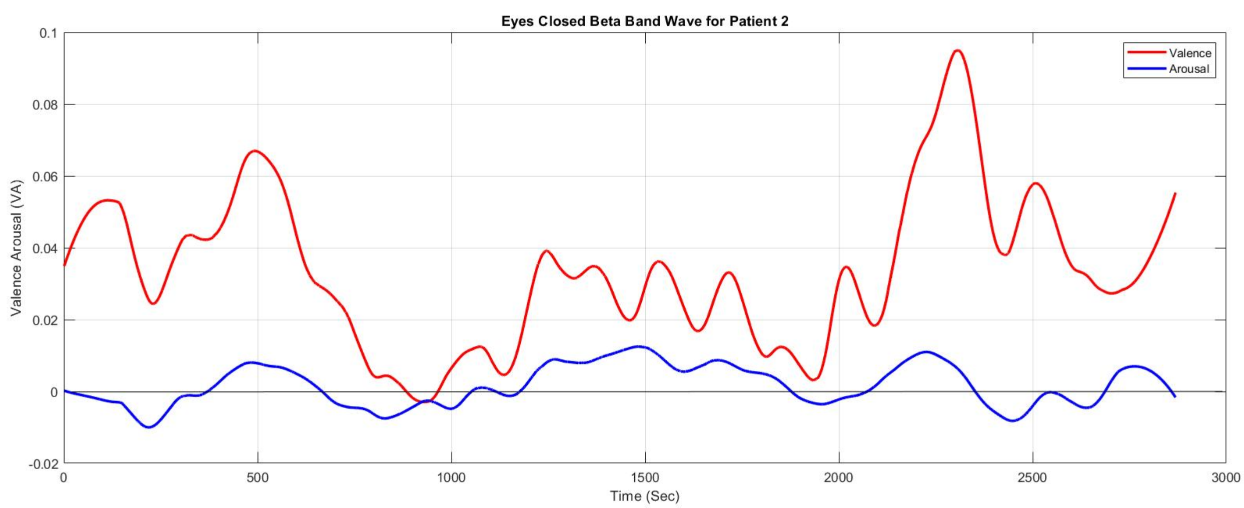

Figure 18: Eyes Closed Beta Band Wave for Patient 2

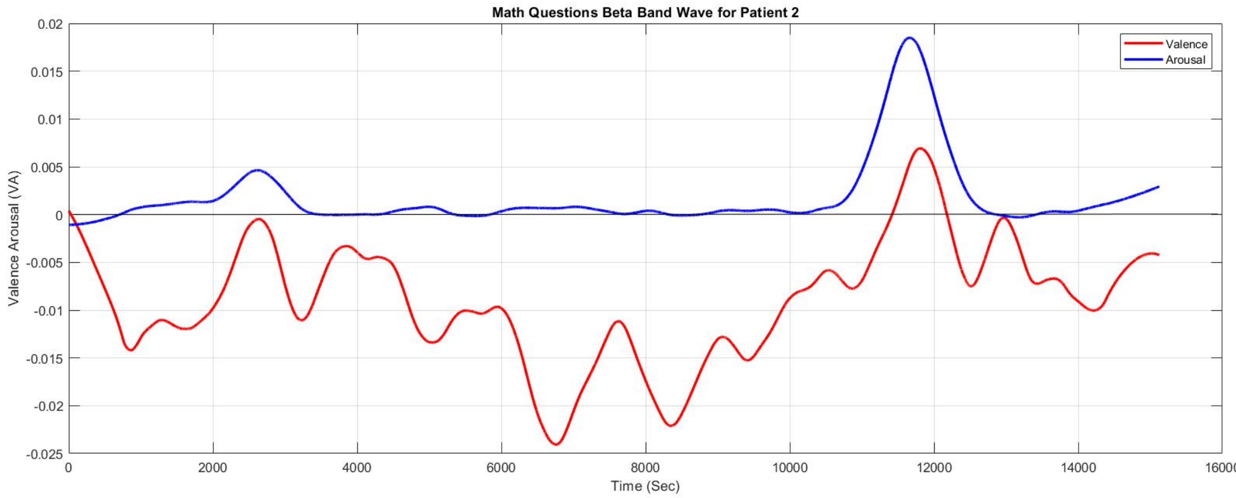

Figure 19: Arithmetic Test Beta Band Wave for Patient 2

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 going 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 be 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.

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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