Voting Classifier based Model for Mental Stress Detection and Classification Using EEG Signal

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Abstract – As stated by WHO, stress is a major problem of human beings also has a large effect on physical and mental health. This research presents one of the most basic methods for detecting stress using EEG data processing. Currents spreading through the skull of a person are created by the electrical activity of neurons in the form of voltage changes and magnetic fields, and these currents reach the scalp's surface. Voltage changes at the scalp are getting measure and this form of signals is called the EEG. These captured EEG signals got processed for obtaining useful information to identify various mental diseases. This evolved system is used to classify the characteristics of FFT and to detect whether the individual is nervous, by using the feature extraction and voting classifier. This research presents a simple and effective approach for estimating the PSD for spectrum monitoring using the Welch periodogram.. As characteristic for stress detection, the α, β, θ, & γ waves are the most appropriate characteristic. From the experiment result, we have revealed that the proposed model based on the voting classifier provides the highest 88% accuracy in comparison to a baseline model.
Keywords - Mental Stress, EEG Signal, Feature Extraction, FFT (Fast Fourier Transform), Welch periodogram, Voting Classifier.

1. Introduction

The human body's response to demand for change is seen as stress [1]. In healthy people, there is a balance between parasympathetic & sympathetic arms of the autonomous nervous system. When a dangerous condition is experienced, a fight/flight response is invoked. There is no danger to life from everyday stress; however, fight or flight response should also be used. Stress leads to a persistent feeling of energy efficiency and depression.

During routine work, stress induces inefficiency and makes it a social cause. Chronic stress can adversely affect the anxiety and bipolar diseases of people. Our physical health may also be affected by mental stress. According to the latest study in 2016/2017, 526,000 workers suffered from stress, depression, or anxiety (new or long-term). Mental health care has become a demand. People want successful approaches to mental health [2]. Conventional counseling requires that a person be able to speak frankly and those who need counseling will not consider it. In these circumstances, it is essential to study brain activity and the state of the brain with electroencephalogram (EEG) signals.

The human body responds to psychosocial or physical conditions which are subjected to mental stress. It affects people worldwide regardless of age, gender or occupation. It is due to growing work issues, pressure & demanding daily activities faced every day [3]. The level of mental stress is a key parameter that affects physical well-being, cognition, emotions, & work effectiveness. It's important to test to cure it with increasing adversities in modern standards of living that cause abnormal mental stress. As neurofeedback for clinical and personal assessments, a regular personal stress profile can be used [4]. At the present, the main cause of most medical conditions is mental stress. These comprise strokes, heart attacks, depression, nervousness, PTSD (Post-Traumatic Stress Disorders) & immunological disorders. Stress can also affect the activity and structure of the brain. Early detection of stress is also important to avoid disease and to decrease the risk of brain damage also other health issues.

Meditation is a type of mental exercise and has become a common activity in the United States. Regular meditation practices are recorded to cause changes in mental state and resting patterns of electroencephalograms that continue after the period of active practice. In regions that are regularly practiced during this mental exercise, we assumed that regular meditation should also result in major improvements to the cortical structure [5].

The EEG stress detection technology is used in the proposed method. EEG is one of the most accurate sources of electrical activity in the brain. The voltage changes in the brain EEG neurons are used to calculate the voltage variation caused by the ionic current. Epilepsy is most commonly diagnosed with coma, sleep disorders, encephalopathy, and EEG death of the brain. EEG is used for identifying a stroke, a focal brain disorder, and tumors as a first-line method. EEG hardware costs are much less than other techniques. Besides, EEG will track the long-term sleep stage or epilepsy near the bed of the patient's bio signals; this is why EEG is most preferred. Compared to other techniques, EEG is more advantageous because it is a convenient tool for research in physiology. If the subject performs the behavior, or it can be used as a wearable sensor out of the EEG laboratory. During various phases of life, EEG may detect brain changes without distracting a patient, e.g., EEG Sleep Analysis [6].

The remainder of the study is summarized below: Section-2 summaries related works; Section-3 introduces a thorough summary of a proposed methodology; Section-4 provides detailed simulation results achieved, & Section-5 concludes the paper.

2. Literature Review

The current study [7] is based on the classification of baseline (relax) and stress detection using EEG sub-band power ratio as features. To classify power ratio features to stress detection, a support-vector-machine (SVM) classifier with different kernel function values and a k-nearest-neighbor (K-NN) classifier with many neighbors with holdout and a ten-fold cross validation approach was used. Different performance criteria have been used to evaluate classifier performance. It can be seen that Euclidean distance K-NN with numerous neighbors improves efficiency in both validation methodologies and anterior frontal channel (Fp1) on the left side of the brain, with a nitty-nine pt. forty-two percentages accuracy. The performance of mental cognitive effort, that is, mental serial subtraction, is assessed using a publicly available mental arithmetic dataset, causes stress in this case.

This paper [8] examines the efficacy of electroencephalography (EEG) detection of multiple stress types and the effectiveness of different methods of stress relief. Average intra-subject classification accuracy of 85.6 percent on stress vs. rest, 71.2% on two stress and rest levels, and 58.4% on three stress and rest levels were obtained by 10-fold cross-validation results. The findings were highly promising to use EEG to detect stress level & chosen features to reveal that Beta brain waves (13HZ to 30HZ) and prefrontal relative gamma power are most discriminatory. 5 various stress reduction techniques were tested & the most efficient way of hugging a pillow was found to reduce stress level detected with EEG. These findings demonstrate promise for future studies to identify and reduce stress in real-time by using EEG to alleviate stress and relieve stress.

This paper [9] examines the application of IoT technologies in the healthcare sector with the cloud to assess the physical and mental activity of the brain using an EEG headset. The goal is to incorporate the concept of a brain race for the diagnosis and assessment of mental status as a new transition from an evaluation of entertainment and brain activity in various scenarios.

In this study [10] the researchers examine the use of EEG for predicting people's stress levels without manual intervention & recording through brain computer interface (BCI). The efficiency of SVM and K-NN Machine learning algorithms is evaluated. A training set target class is allocated by a stress value derived from the PSS-fourteen questionnaire response. They achieve a maximum average classification accuracy of seventy-four pt. forty-three percentages using the K-NN method. They notice that band power ratios of different bands are correlated to the stress level of subjects from measured EEG signals in the front part of the brain.

The study & meditation application, which has been developed and suggested, can be used to meditate and decrease stress levels using EEG to get brainwave signals. FFT was utilized in this evolved method for feature extraction and KNN was used for classifying features and detecting whether or not people were stressed. As the features were most appropriate for stress detection & mediation applications, theta waves, delta waves, beta waves, & alpha waves where the best value for K is equal to 3 in KNN classification and have eighteen percentage accuracy [11].

[12] The essence of this paper is to establish a method of stress detection and an indicator of stress levels to measure human brain stress using the EEG signal. Signals coming from the human brain frontal lobe are used for stress measurement. The brain waves of the thirty subjects are recorded when five mathematically complex issues are resolved. They suppose that the subjects undergo five different levels of stress: relaxed, stressed less, stressed moderately, stressed higher, and stressed alarmingly, to solve these problems. Data is processed and features are extracted after the recorded EEG. They develop a feed-forward neural network to identify stress in the brain of humans. We are preparing a new set of questions for study, comprising simple and complicated numerical questions. During this question set, they record EEG data from a subject. From the processed EEG data of the object, they extract six feature values. These data are supplied to the feed neural network. The neural network estimates the stress level and in the 'stress indicator' circuit the expected stress level is indicated.

3. Research Methodology

3.1. Problem Statement

Stress is a condition that causes a person to have negative thoughts and feelings. The same condition is not evocative or stressful for all people, because when stressed, people do not feel the same negative thoughts or feelings. The wearable devices off-the-shelf today provide us with high-quality data standards. However, for high-quality data acquisition, such conditions must be fulfilled. By the directions of the machine the electrodes should be properly placed, wristbands should be adjusted and body movements restricted. Otherwise, noise, poorly worn devices, and body movement are polluted by signals. Any signal processing methods have to be used to remove the noise. Each problem provides researchers with several options. To provide an example, if a subject wears the device loosely, and data cannot be obtained for certain periods, the researcher may choose to ignore or interpolate the data during this time. For stress detection, KNN was an efficient method in the existing work but it has some limitations. it was not so high for accurate classification of the mental stress so it was not good for early prediction. In higher dimensional space, the cost to calculate distance becomes expensive and hence impacts the performance. KNN is sensitive to outliers and missing values.

3.2. Proposed Methodology

The purpose of this paper is to use as the auxiliary classifier a more efficient voting classifier based on the KNN & RF classification to increase the accuracy of the current model based on the KNN classification for a greater number of datasets. The objective of this essay is to identify stress in individuals, to find out what characteristics can enable us to achieve the results needed, and to decide which classifier provides the best results for stress determination, Determining the stress level, taking adequate measures to better a person overcome stress. A computer-sided diagnostic tool that helps people to diagnose stress and to take proactive action to minimize stress and its effects may be designed from the proposed system. FFT & EEG classification has been included in the proposed system. The proposed voting classifier model could classify stress into various levels.

Based on the KNN and RF classifiers, this paper suggested a voting classifier. Firstly, we have an input dataset in the form of signals then apply Fast Fourier Transform to generate all waves from these signals. After using FFT, the PSD vector value is obtained by generating the PSD vector value of all waves. Finally, a voting classifier was used to detect mental stress.

3.2.1. FFT (Fast Fourier Transform)

FFT algorithm usually serves to estimate or reverse the DFT (Discrete Fourier Transform) in any sequence. The FFT transforms each N frame of Time domain signal into a kind of Frequency domain [13] with a speech voice signal. The FFT is called the computationally efficient implementation of the DFT method, described in a set of N samples $[x_n]$ as follows:

$X_k = \sum_{n=0}^{N-1} x_n e^{-(j\pi kn/N)},\ k = 0,1,2,\ldots,N-1,\ldots$ (1)

Where $[x_k]$ is a complex integer referred to as an absolute value (frequency magnitude or modulus)

$[x_k]$ is the resultant sequence which is defined as follows: +ve frequencies zero $\leq f < \left(\frac{1}{2}\right) F_s$ correspond to the values zero $\leq n \leq \left(\frac{1}{2}\right) N - 1$, likewise -ve frequencies $-\left(\frac{1}{2}\right) F_s < f <$ zero correspond to $\left(\frac{1}{2}\right) N + 1 \leq n \leq N - 1$. F_s is the sampling rate. The results obtained are based on the frequency spectrum of speech signals [14].

3.2.2. PSD Vector Generation

The power spectral density function shows the intensity of fluctuations (energy) as frequency function. In other words, it illustrates the significant frequency fluctuations as well as the frequency's weaknesses. The PSD unit consists of energy by frequency (width) which you can get through the integration of PSD in a particular frequency range. PSD is computed directly using the method named FFT or calculating autocorrelation function and then transformed. The pyplot. psd function is used to plot PSD. In this work, the PSD vector has determined the Welch periodogram for group 1 and group 2. The Welch algorithm [15] is a non-parametric way of estimating PSD which making the frequency spectrum smoother than the raw FFT flow. Consider that the FFT is computed during the signal duration. The 'x' vector is also divided into NFFT segments in the Welch average periodogram method for evaluation of PSD (say, P_{xx}). Each segment is windowed with the function window and detrended by function detrend.

3.2.3. Voting Classifier

A Voting Classifier is a Machine Learning algorithm that learns on an ensemble of different samples and focuses on the highest likelihood of the chosen class as the output. This simply summaries the voting classifier results and forecasts the performance category based on the biggest majority. Instead of creating separate models for each of them, we create a single model that trains and forecasts performance based on the performance groups' cumulative voting majority. In our proposed projects, we offer random forest and K-NN (usually of varied varieties) as well as fundamental statistics (such as the average).

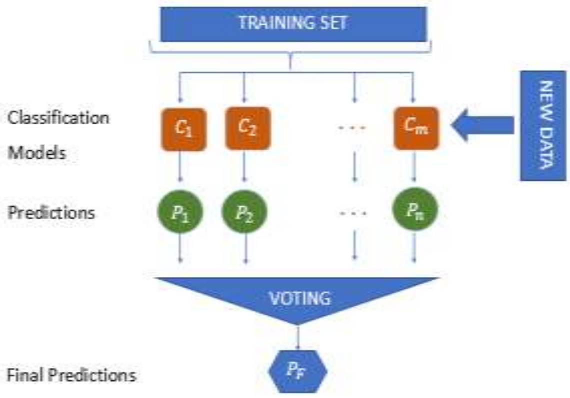

Figure 1. Voting Classifier Architecture

3.2.4. Random Forest (RF)

Leo Breiman from California University first suggested the random forest in 2001. It consists of a large number of basic classifiers (decision trees) that are fully independent of each other. A test sample for this classification will be determined depends upon voting outcomes of every single classification and class label for this sample [16].

The key steps to building up the random forest classifier are as follows:

1. Specifies a proper value for a variable named "M," which is no. of elements of every feature subset.
2. Select a new feature subset hk is chosen at random from the complete feature set based on the M value. Another subset in a succession of h1...hk is independent of hk.
3. Train the data set with a feature subset for each training set group to build a decision tree. Each and every classifier can be h (X, hk) (where X represents inputs).
4. Select new hk also repeat the above process until feature subsets have been traveled. A random forest classifier is done.

3.2.5. K-Nearest Neighbor (K-NN)

KNN method is a non-parametric method used in mathematical applications since the beginning of the 1970s. The basic theory behind KNN is that set of k samples are found nearest to unknown samples in the calibration dataset (for example, depends upon distance functions). The average response variables are calculated from these k samples by measuring the label of unknown samples (that is, class attributes of KNN). As a consequence, k plays a significant role in the efficiency of KNN for this classifier. This means that KNN is the primary tuning parameter [17].

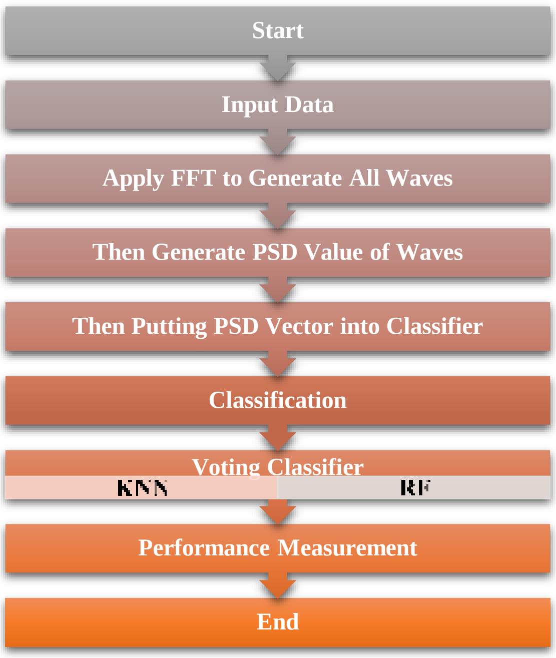

Figure 2. Proposed Model

4. Observations and Discussion

In this suggested study, Jupyter notebook was used to explore with Python programming. The data set was utilized for electroencephalogram signal waves such as delta wave, beta wave, gamma wave, alpha wave, and theta wave. The suggested voting classifier's efficiency is simulated using experimental settings, and the test results are provided below.

In the present study, the experiment has been conducted in two groups. There are 72 files in these groups. In the first group, 36 files execute. And in the second group, the remaining 36 files are also executed. While Performance conduction, we are applying Fast Fourier transform (FFT) for executing both groups. After that, we are generating delta, beta, gamma, alpha, and theta waves for these groups, then generating all waves we are finding the PSD vector (Power Spectral Density) of both groups. And then we are using a voting classifier with the use of K=3 which provides computational performance.

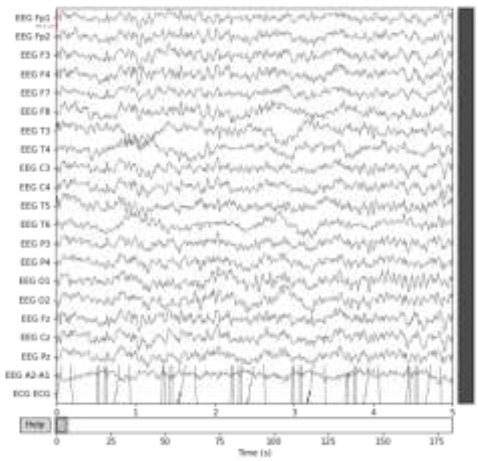

Figure 3. Plot of raw sample of 1st group

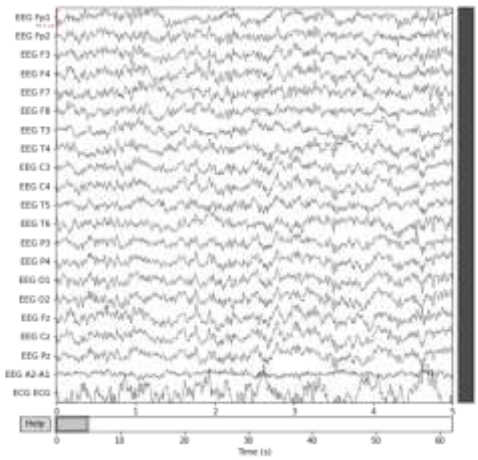

Figure 4. Plot of raw sample of 2nd group

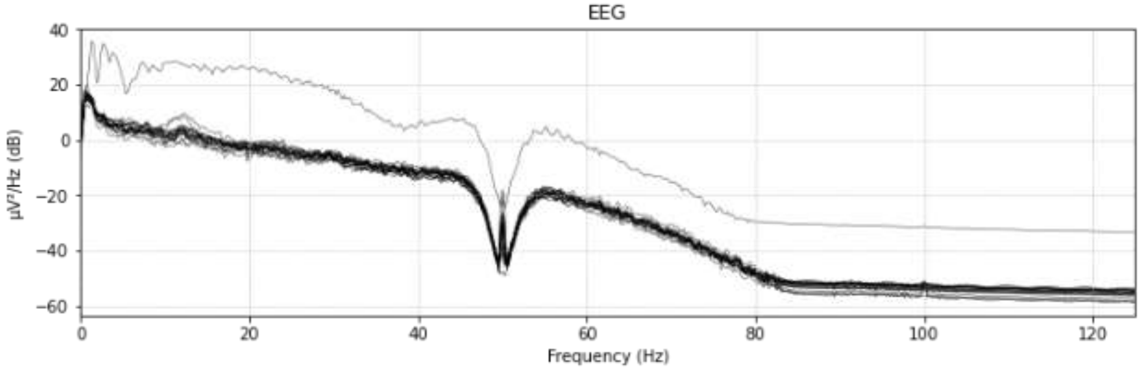

Figure 5. PSD Plot of raw sample of 1st group

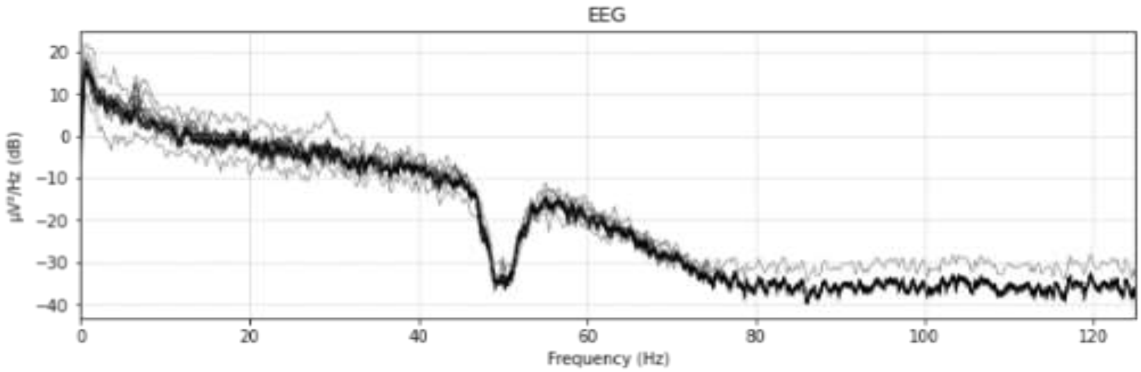

Figure 6. PSD Plot of raw sample of 2nd group

4.1. Wave Signal Information

α (alpha), β (beta), γ (gamma), θ (theta), & δ (delta) are the parameters for this analysis. The δ-wave can calculate the depth of the sleep, and its frequency (one to four Hz). The δ-wave can be identifying the slow-wave sleep using electroencephalogram, in slow-wave sleep brain waves are very slow so this is called dreamless sleep, and Dreams occurred very often. Nightmares occur during this sleep, but we are unable to remember them. The following rates are decreasing during this sleep BP, respiratory rate, and BMR. The θ-wave can be used to know the functions of the brain, which means that the difficult task of the brain and it is associated with the weakness level. The frequency is about (four to seven Hz), The θ-wave is connected with all-around brain processing such as memory conceal and cognitive workload, it is also calculating the tired level of humans. α denotes our mind-released state, and it records the relaxation of the brain whenever we closed our eyes, we turn into a calm state at that time the α-wave take over, and it is related to shyness and attention, the frequency of the α-wave is (seven to twelve Hz). The β-waves with frequencies of (twelve to thirty Hz). It can detect body motions such as limb movement forelimb hindlimb, which rises in β when we observe physical movements of others. Human brains copy limb motions, demonstrating the mirror neuron system. The γ-waves, typically the γ-frequency is (> thirty Hz to forty Hz). The γ-waves can give information about our sensory inputs. These waves are comparable to rapid eye movement sleep. At some point during this procedure, all of the cases were used to assess, and the remaining instances were used to train the classifier [18].

4.2. Screenshots of the Results

```
# # Define EEG bands
    eeg_bands = {'Delta': (0, 4),
                 'Theta': (4, 8),
                 'Alpha': (8, 12),
                 'Beta': (12, 30),
                 'Gamma': (30, 45)}
```

Figure 7. EEG bands for 1st group

```
# # Define EEG bands
    eeg_bands = {'Delta': (0, 4),
                 'Theta': (4, 8),
                 'Alpha': (8, 12),
                 'Beta': (12, 30),
                 'Gamma': (30, 45)}
```

Figure 8. EEG bands for 2nd group

Figures 7, 8 are the representation of EEG bands after applying the Fast Fourier Transform (FFT) for the 1st and 2nd groups. It shows values of EEG bands that are Theta, Delta, Beta, Alpha & Gamma.

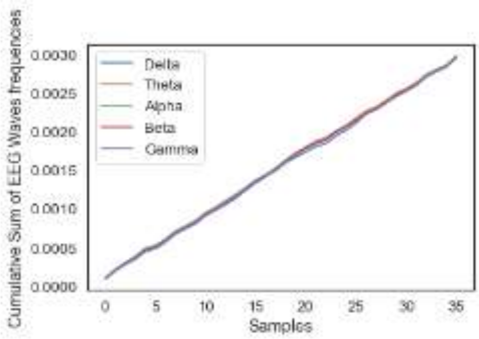

Figure 9. Graph plot of 1st group for all EEG waves

Figure 9 represent a line graph between cumulative sum of EEG waves frequencies and samples of data frame group 1

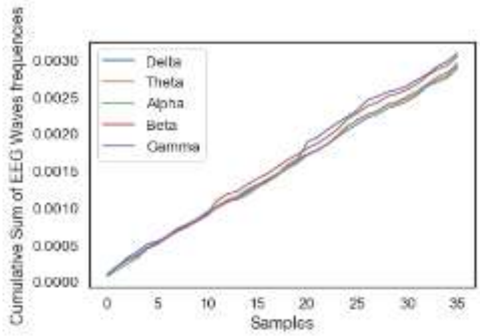

Figure 10. Graph plot of 2nd group for all EEG waves

Figure 10 represent a line graph between cumulative sum of EEG waves frequencies and samples of data frame group 2

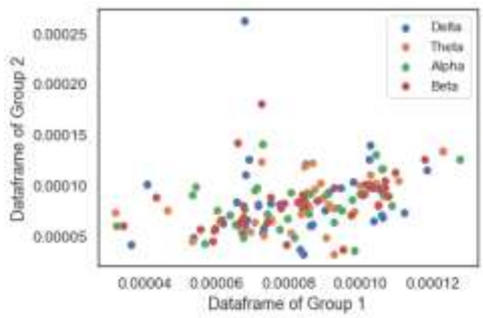

Figure 11. Scatter plot for both groups after removing gamma waves

Figure 11 shows a scatter plot between both data frame groups (first and second) after deleting the γ waves, which have no effect on the correctness of our model.

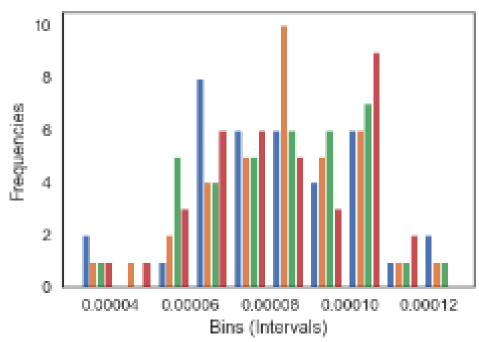

Figure 12. Histogram of 1st group

Figure 12 represent the histogram between frequencies and bins (intervals) of data frame group 1.

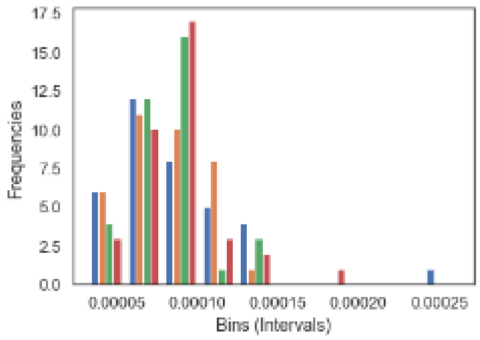

Figure 13. Histogram of 2nd group

Figure 13 represent the histogram between frequencies and bins (intervals) of data frame group 2.

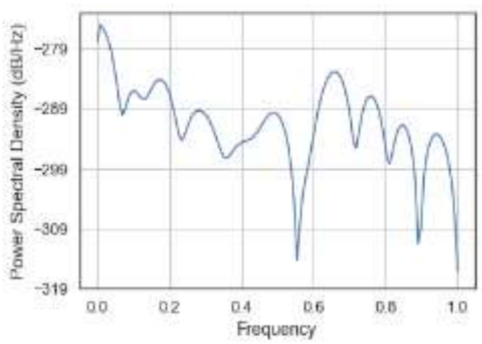

Figure 14. PSD plot of PSD vector of 1st group

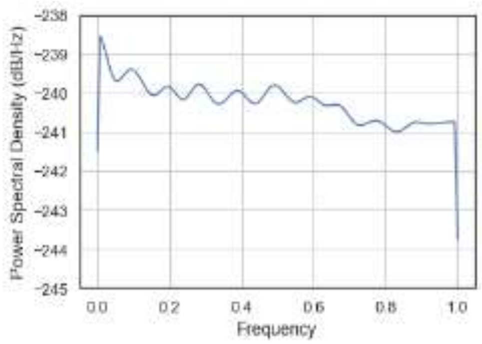

Figure 15. PSD plot of PSD vector of 2nd group

The findings produced by both techniques on the gathered EEG signal dataset are tabulated in Table 1. We selected Mean Square Error (MSE) and accuracy as evaluation measures since these approaches are commonly employed in the assessment of mental stress categorization. This table compares existing KNN and proposed voting classifiers in terms of MSE and accuracy. In contrast to the present KNN classifier (shown in figure 17), the suggested technique improves accuracy by 8% and reduces MSE.

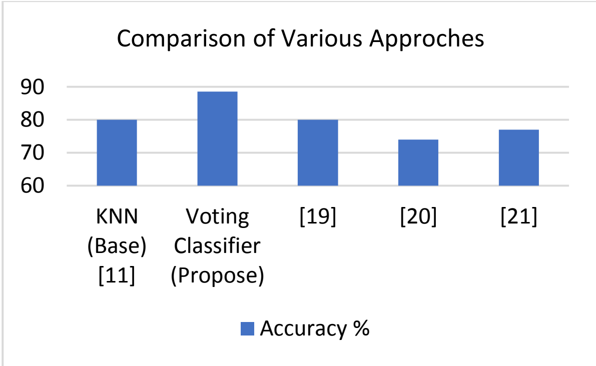

Figure 16. Comparison of various approaches according to their accuracy

Table 1. Comparison Table of Test Results

Methods	MSE	Accuracy
KNN (Base) [11]	19.95%	80.04%
Voting Classifier (Propose)	11.41%	88.58%

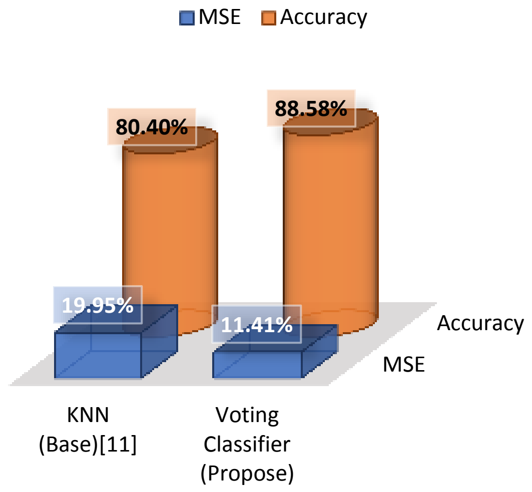

Figure 17. Comparison Graph between base and propose model for MSE and Accuracy

5. Conclusion

The work presents in this paper proposed a method to detect and classify stress using EEG signals. It is based on the features extracted from the EEG waves (α, β, γ, θ, & δ). A voting classifier model is used in the proposed method to successfully detect stress at different levels. FFT is used to the EEG data to create periodogram waves, which are then utilized to construct the PSD vector. The PSD vector is sent into the suggested supplementary voting classifier. The voting classifier used in the experiment is based on KNN and RF. Experimental results have found that the proposed voting classifier model is better than the previous KNN classifier model in terms of accuracy and MSE. It has achieved 88.58% accuracy and 11.42% mean squared error. The main contribution of the paper is the use of voting classifier to detect and classify stress.

Advantages; In future work, we can use other biomedical signals such as ECG, EMG etc. to detect the stress using the same methodology. Moreover, intervention and sensitivity analysis methods on EEG signals can also be added to determine the stress level.

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