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Depression Diagnosis Based on KNN Algorithm and EEG Signals

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Abstract

This work aims to diagnose depression and isolate healthy people from depressed patients based on EEG brain signals via the k-nearest neighbor algorithm (KNN) and using 10-fold cross-validation. Five regular frequency bands (Gamma, Beta, Alpha, Theta, and Delta) were utilized from the signals. Band power and median band frequency were extracted by Welch's periodogram method as features. After classification, the highest accuracy gained by using frequency features in the left hemisphere was from the Alpha and Beta waves which resulted in 100% output ($p<0.05$), and as for the right hemisphere highest accuracy was for the Gamma, alpha, and Beta oscillators, which also resulted in 100% ($P<0.05$). the lowest accuracy was assigned to the Delta band. In general, combining the two hemispheres boosted the accuracy.

Keywords: Depression, KNN algorithm, Electroencephalography, Band Power

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1. Introduction

Depression is a prevalent mental disease that impacts more than 264 million people around the world according to the World Health Organization. It is defined by constant sorrow and a lack of enthusiasm or pleasure in previously appealing or pleasant activities. Furthermore, it may provide disturbance for sleep and appetite; tiredness and poor concentration are common. Depression is the foremost reason for inability globally and adds greatly to the global burden of illness. The results of depression can be long-lasting and can extremely alter a person's ability to function and maintain a fulfilling lifestyle [1].

Electroencephalography (EEG) is a non-invasive electrophysiological monitoring approach to record the electrical activities of the brain. EEG measures and records the brain's natural electrical activities from various electrodes on the scalp during a period of time [2]. Puthankattil et al. (2012) [3] analysed 30 patients which consisted of 5-minute EEG recording in resting-state condition for each subject. in this project, relative wavelet energy (RWE) and artificial feedForward neural network are used to identify the EEG signals of normal and depression cases, to classify the signals into appropriate detail levels and approximation level an eight-level multiresolution decomposition method of discrete wavelet transform (DWT) is applied. subsequently, relative wavelet energy (RWE) and wavelet entropies (WE) based upon the Shannon entropy were obtained from each level of the decomposition. Mumtaz et al. (2017) [4] studied five-minute recordings of 33 major depression disorder cases and 30 normal subjects. a suggested machine learning (ML) scheme was examined. They were utilizing linear features of EEG particularly the power of frequency bands and EEG alpha interhemispheric asymmetry as input characteristics to the offered ML scheme to distinguish between the major depression disorder cases and normal subjects. Logistic regression, SVM, and Naïve Bayesian algorithms were used. Hinrikus et al. (2009) [5] proposed a study to analyse the sensitivity of various EEG indicators to identify the depressed patients. Thirty-minute recordings of 18 normal and 18 depressed women were examined and introduced a unique spectral asymmetry index (SASI) which is based upon the stability among the powers of two specific EEG frequency bands selected lower and higher of the EEG spectrum maximum and eliminating the middle frequency from the estimations. Acharya et al. (2015) [6] examined 30 patients (15 normal and 15 depressed), the study presented the latest efforts on Computer-Aided Diagnosis (CAD) of depression utilizing EEG signals with a focus on applying nonlinear techniques to obtain the EEG signal characteristics for CAD of depression and ultimately detect depression. Hanshu Cai et al. (2018) [7] presented a study with 121 healthy cases and 92 depressed subjects. The EEG signals of all subjects under resting state were gathered. After diagnosing, 270 nonlinear and linear characteristics were obtained. Four classification techniques SVM, K-Nearest Neighbour, Classification Trees, and ANN were used to identify the depressed patients from the normal group.

The purpose of this paper is to collect data from the brain signals of healthy and depressed cases. Each recording includes 5 minutes of duration in a resting state with eyes open and closed. For the extraction of features, we used Welch's periodogram method. twenty frequency band powers and medians (Beta, Theta, Alpha, Gamma, and Delta) in both the right and left hemispheres were used as inputs to the KNN classifier using 10-fold cross-validation to avert overfitting. Figure 1 demonstrates the block diagram of the proposed method.

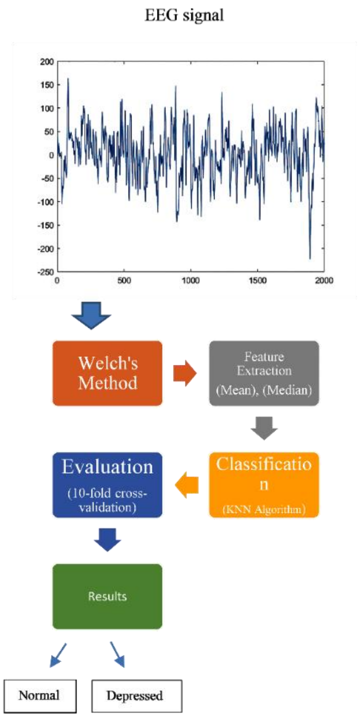

Fig. 1. Block diagram of the proposed method

2. Method

A) Data

Alireza Azizi et al. [8] provided the data which is used in this study. EEG signals contain data recorded from 40 (20 normal and 20 depressed) subjects between the ages of 20 to 50. Data contains a sampling rate of 256 Hz; to eliminate disruptive interferences Notch filter was implemented. With a bipolar montage, EEG was recorded. The span of each EEG recording is 5 minutes in a resting state, with both eyes closed and open, each selected data includes 1500 samples. These signals are recorded by four electrodes in T3-FP1 and T4-FP4 sections. Eye moving and blinking as well as muscle artifacts were discarded visually. A sample of EEG signals from both normal and depressed patients are shown in Figures 2 and 3.

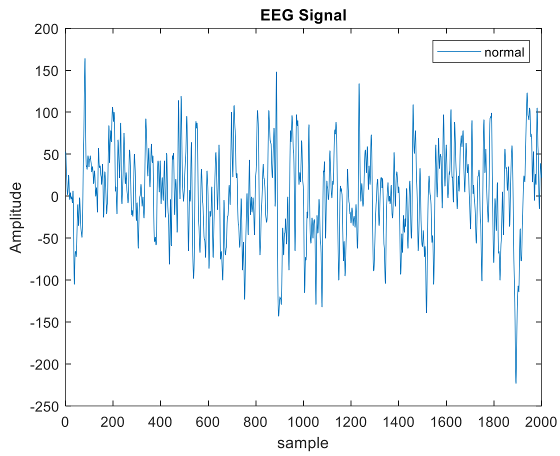

Fig. 2. EEG signal from a Normal patient

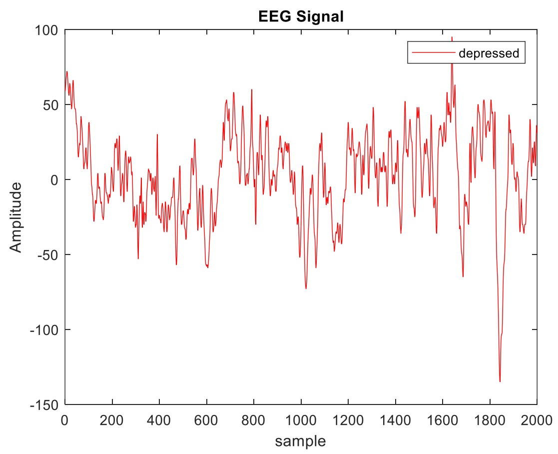

Fig. 3. EEG signal from a Depressed patient

B) Feature Extraction

The EEG signal has five main frequency bands: delta wave (0.5-4 Hz), theta wave (4–8 Hz), alpha wave (8–14 Hz), beta wave (14–30 Hz), and gamma (30–50 Hz). The splitting of the frequency waves is a standard technique to obtain data from signals. First, Welch's Periodogram method is used for estimating the power spectrum density to measure average band powers in various frequencies [9]. This approach was utilized for each band, hamming window and fifty percent overlap were used as parameters. Welch's method [10] for computing power spectral is accomplished by cutting the time signal into consecutive segments, creating the periodogram for each section, and averaging. Denote the m th windowed, zero-padded frame from the signal x by:

$$x_{m(n)} \triangleq w(n)x(n+mR), \quad n = 0,1,\dots,M-1, \quad m = 0,1,\dots,K-1 \tag{1}$$

The periodogram of the m th block is given by:

$$P_{x_m,M}(w_k) = \frac{1}{M}\left|FFT_{N,k}(x_m)\right|^2 \triangleq \frac{1}{M}\left|\sum_{n=0}^{N-1} x_m(n)e^{-\frac{j2\pi nk}{N}}\right|^2 \tag{2}$$

The Welch estimate of the power spectral density is given by:

$$S_x^{\widehat{W}(w_k)} \triangleq \frac{1}{K}\sum_{m=0}^{K-1} P_{x_m,M}(w_k) \tag{3}$$

Using the most common frequency bands, including theta (4–8 Hz), delta (0.5-4 Hz), alpha (8–13 Hz), gamma (30–50 Hz), and beta (13–30 Hz) to extract median band frequency. Welch's method was performed to approximate power spectrum density to measure median frequency in various frequencies for each band (median was calculated in the indexed frequency).

C) Classification

The purpose of the classification is to accurately separate the signals based on the selected features, the selected features were used as inputs to the classifier. Signals are classified into normal and depressed groups. In this article, we used the K-nearest neighbor (KNN) algorithm for classification.

The k-nearest neighbors algorithm (KNN) is a non-parametric method that is used for classification. It operates by determining the lengths then chooses the most frequent and nearest label [11]. The k closest training examples in the feature space are the inputs. By a majority vote of its neighbors, an object is classified, and it gets attributed to the group most common among its k nearest neighbors. [12]-[13]. Euclidean distance is usually used as a distance metric. The Hamming distance or overlap metric may be used for discrete variables, such as for text classification [14]. A case is classified by a majority vote of its neighbors, with the case being assigned to the class most common amongst its K nearest neighbors measured by a distance function [15].

$$Euclidean\ Distance = \sqrt{\sum_{i=1}^{k}(x_i - y_i)^2} \tag{4}$$

$$Hamming\ distance = D_H = \sum_{i=1}^{k}|x_i - y_i|\ x = y \to D = 0\ x \neq y \to D = 1 \tag{5}$$

D) Evaluation

In order to prevent overfitting 10-fold cross-validation is employed. Cross-validation is a method to assess predictive models by dividing the first sample into a training set to train the model, and a test set to estimate it [16]. From the confusion matrix, sensitivity and Accuracy were obtained. Specificity (SP) is calculated as the number of correct negative predictions is divided by the total number of negatives, Sensitivity (SN) is measured as the number of correct positive predictions divided by the entire number of positives [17].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

$$Specificity = \frac{TN}{TN+FP} \tag{7}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{8}$$

3. Results

In this paper, the p-value is calculated to make sure that the two groups are independent. Overall, the p-value is a measure of the probability that an observed difference could have happened just by random chance. The lower the p-value, the higher the statistical importance of the observed difference [18]. If the p-value is lower than 0.05 it indicates that there is a significant distinction between the two classes.

A) Frequency results

Table 1 illustrates the p-values of different band powers in both right and left hemispheres respectively. According to the results, delta band power in the left hemisphere shows notable discrimination between the two groups compared to the right hemisphere. The other four also represent a remarkable difference between the normal and abnormal subjects in both hemispheres. Table 2 presents p-values of median frequency in different bands. Based on the information, all frequency bands show a significant difference between the groups in both hemispheres($p<0.05$). while generally, delta band power shows the worst distinction in the right hemisphere. The best results are from gamma, Bata, and alpha waves in right and left hemispheres.

B) Classification results

The results of the classification for band power in the right and left hemispheres are presented in Tables 3 and 4 respectively. The combining of the two hemispheres boosted the accuracy (Table 5). The highest accuracy was obtained from beta, alpha, and gamma oscillations which resulted in 100%. Tables 6 and 7 illustrate the results of classification for median frequency in both right and left hemispheres for all bands. Furthermore, after the combination of the two hemispheres the results improved (Table 8). The highest accuracy was achieved from beta and alpha bands and the lowest was for the delta band. A boxplot is a method that is used to diagrammatically describe groups of numerical data through their quartiles. It shows the second and third quartiles, and a vertical line inside to show the median value [19]-[20].

Figures 4 and 5 indicates the boxplot of the alpha band power which shows the discrimination between the normal and abnormal classes in left and right hemispheres respectively. Figures 6 to 9 also demonstrate the differences of the two classes (normal, depressed) in the both hemispheres of beta and gamma band powers respectively. As it can be seen the interquartile range of the depressed class is much smaller than the normal in all frequency bands, the interquartile range is the gap between the upper and lower quartiles [21]. Also, the middle number (median) of the data set in the depressed group is lesser than the non-depressed in all the graphs.

4. Discussion

This study aimed to determine the relations between depression and the brain's frequency bands. As it can be observed from the results the accuracy and p-values of alpha and beta waves are higher whether in the right or the left hemisphere compared to other bands, and according to Figures 4-7, they can distinguish between the two groups more efficiently, although the results demonstrated that there is a small difference between the delta waves of depressed and healthy cases. Furthermore, the results revealed that the depressed group's activity in the right hemisphere is higher, in contrast to the opposite hemisphere. In a similar study, Henriques et al. (1991) [22] gathered and studied the EEG signals of (with closed eyes) 13 normal subjects and 15 depressed cases when eyes were closed. Their study demonstrated that the activity in the left hemisphere in the depressed group is notably lower than in a healthy person. According to Figures 4 and 5, the alpha power band in the right hemisphere can discriminate between the two groups better compared to the left hemisphere. In a recent paper, P.F. Lee et al. (2015) [23] studied 8 individuals (4 patients with depression and 4 normal cases) and discovered in their study that alpha waves in the depression group were lower compared to the non-depressed group when eyes were both opened and closed. Zaika et al. (2002) [24] gathered EEG signals from 86 normal subjects and 53 unhealthy cases. Their paper confirmed that subjects with depression have a lower alpha and beta energy, in comparison with the non-depressed group.

5. Conclusion

In this study,1500 samples of 40 EEG signals (20 healthy and 20 depressed) were analyzed. KNN classification algorithm, using 10-fold cross-validation has been utilized to classify the two groups. According to the results, the highest accuracy was obtained from the Alpha and Beta oscillators in both hemispheres, which resulted in 100%. In the right hemisphere, the Gamma band also showed some high accuracy (100%).The combination of the two hemispheres improved the classification results. In conclusion, there is a strong connection between the power of Alpha and Beta waves with depression; thus the two bands can play a significant role in the discovery of depression compared to the other bands and can more productively distinguish between depressed and normal classes.

Table.1.
P-Values of different band powers

Frequency bands	*Right hemisphere*	*Left hemisphere*
Delta	0.9247	9.7212e-04
Theta	0.0205	3.6357e-17
Alpha	2.5248e-16	1.9089e-19
Beta	5.7364e-28	2.0917e-24
Gamma	2.6668e-23	5.9918e-17

Table.2.
P-values of median frequency in different bands

Frequency bands	*Right hemisphere*	*Left hemisphere*
Delta	0.8513	3.3027e-07
Theta	0.0052	2.561e-16
Alpha	7.5425e-18	1.0471e-17
Beta	1.3956e-24	2.3281e-24
Gamma	3.1027e-19	6.9169e-11

Table.3.
Result of classification for band power (right hemisphere)

Frequency bands/feature	*accuracy*	*Specificity*	*sensitivity*
Delta	***77%***	***80%***	***75%***
Theta	***87%***	***90%***	***85%***
Alpha	***100%***	***100%***	***100%***
Beta	***100%***	***100%***	***100%***
Gamma	***100%***	***100%***	***100%***

Table.4.
Result of classification for band power (left hemisphere)

Frequency bands/feature	*accuracy*	*Specificity*	*sensitivity*
Delta	90%	95%	85%
Theta	100%	100%	100%
Alpha	100%	100%	100%
Beta	100%	100%	100%
Gamma	97%	95%	95%

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Table.5.
Result of classification for band power (both hemispheres)

Frequency bands/feature	***accuracy***	***Specificity***	***sensitivity***
Delta	85%	100%	70%
Theta	97%	100%	95%
Alpha	100%	100%	100%
Beta	100%	100%	100%
Gamma	100%	100%	100%

Table.6.
Result of classification for median frequency for each band (right hemisphere)

Frequency bands/feature	***accuracy***	***Specificity***	***sensitivity***
Delta	65%	75%	50%
Theta	90%	100%	85%
Alpha	100%	100%	100%
Beta	100%	100%	100%
Gamma	100%	100%	100%

Table.7.
Result of classification for median frequency for each band (left hemisphere)

Frequency bands/feature	***accuracy***	***Specificity***	***sensitivity***
Delta	92%	90%	85%
Theta	100%	100%	100%
Alpha	100%	100%	100%
Beta	100%	100%	100%
Gamma	97%	100%	95%

Table.8.
Result of classification for median frequency for each band (both hemispheres)

Frequency bands/feature	***accuracy***	***Specificity***	***sensitivity***
Delta	87%	100%	75%
Theta	95%	100%	90%
Alpha	100%	100%	100%
Beta	100%	100%	100%
Gamma	97%	100%	95%

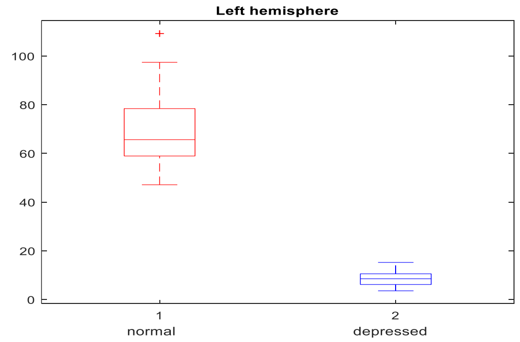

Fig. 4. Boxplot of alpha band power in the left hemisphere

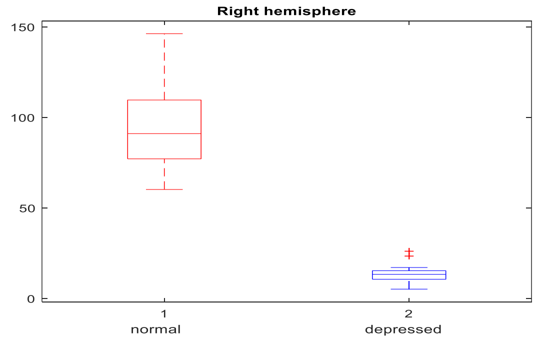

Fig. 5. Boxplot of alpha band power in the right hemisphere

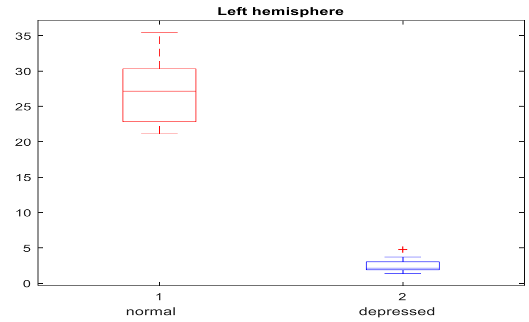

Fig. 6. Boxplot of beta band power in the left hemisphere

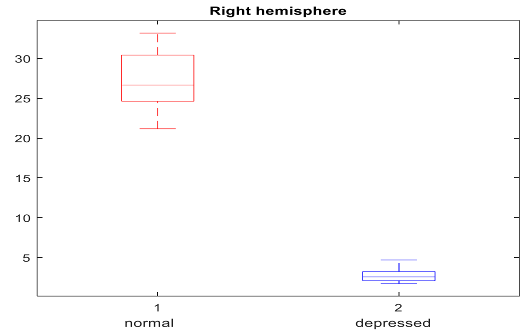

Fig. 7. Boxplot of beta band power in the right hemisphere

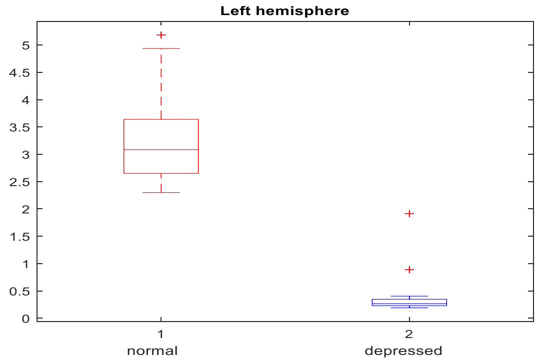

Fig. 8. Boxplot of gamma band power in the left hemisphere

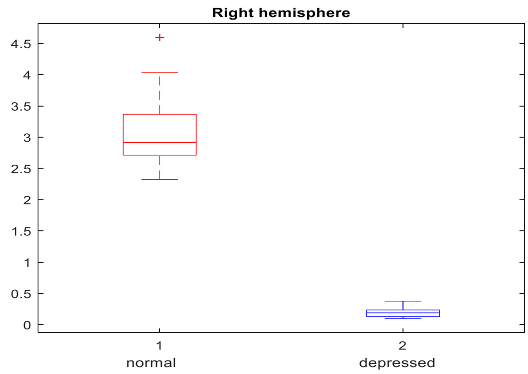

Fig. 9. Boxplot of gamma band power in the right hemisphere

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