IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 27 February 2023, accepted 23 March 2023, date of publication 29 March 2023, date of current version 1 May 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3262930

RESEARCH ARTICLE

Computer Aided Detection of Major Depressive Disorder (MDD) Using Electroencephalogram Signals

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This research work was funded by Institutional Fund Projects under grant no. (IFPIP: 1117-611-1443). The authors gratefully acknowledge technical and financial support provided by the Ministry of Education and King Abdulaziz University, DSR, Jeddah, Saudi Arabia.

ABSTRACT MDD or depression is psychiatric disorder which affects many of people globally. Due to the nonexistence of any available laboratory tests, poor identification of depression is a key contributing factor. In this study, a framework is developed in order detect depression with minimal number of channels to increase the portability as well as with high accuracy. In this study, two dataset has been considered i.e. Public and Private dataset. Different regions of brain as well as feature has been selected to find out the minimal number of channels and features so that higher accuracy is also achieved. According to the study, depression has different impacts on each hemisphere of the temporal and parietal regions of the brain. Depression also has an impact on Detrended Fluctuation Analysis. The study results in a model made up of 4 channels with high accuracy of 91.74% which is portable, faster and cheaper. Thus, model can act as an assistive tool for diagnosis of depression. The study confirms that depression affects the temporal area of the brain since using the same set of features and classifiers in both the public and private datasets and utilising only temporal channel EEG data provided quite high accuracy in detection of MDD. The fact that using features delta, alpha, beta paired asymmetry and DFA from only temporal channel (T8 and T9) provided high accuracy of 89.24%(Public Dataset) and 82.68%(Private Dataset) supports the claim that the temporal lobe of the brain is impacted by depression.

INDEX TERMS Major depressive disorder (MDD), band power, detrended fluctuation analysis (DFA), temporal region.

I. INTRODUCTION

Major Depressive Disorder (MDD) is psychological problem which negatively effects the individual's actions. There around 350 million people suffering from MDD. Presently there is no laboratory test to detect MDD. Detection of MDD is based on standardized questionnaire which differs from individual to individual's perspective. This leads wrong diagnosis of MDD.

Electroencephalogram (EEG) signal reflects the electrical activity of the brain. Any change in the state in the mind of an individual is reflected in the EEG signal. Thus EEG signal could act a standardized measure by which we could accurately detect depression in objective manner [1].

In the present state of the art there has been a number of research in this area. The accuracy of a model in detection of MDD using EEG signal is dependent on number of factors like gender, sample size, age, number channels, racial characteristics, etc. Gender acts as an important covariate in the study as it has been found that characteristics of male depression patient EEG signal is different from the characteristics of female depression patient's EEG signal [2].

Positive values of Spectral Asymmetry Index (SASI) prevail for patients with depressive disorder, negative values for healthy subjects. SASI was found to be correlated with HAM-D scores [3]. It was found that Spectral Asymmetry

The associate editor coordinating the review of this manuscript and approving it for publication was Md. Kafiul Islam.

(SA) values were found to be positive for depression patients and negative for healthy subject [4].

It has been found in female subjects that, SASI values were found to be significantly higher for depression patient than for control group (p = 3.577e–05), while Detrended Fluctuation Analysis (DFA) values are significantly lower for depressive group (p = 0.033). SASI has superior discrimination ability with classification accuracy of 76.5%, while the classification accuracy of DFA was 70.6%. Linear combination of SASI and DFA resulted in 91.2% classification accuracy [5]. Using Higuchi's Fractal Dimension (HFD) and SASI accuracy of 94% and 88% was achieved respectively. In both SASI and HFD, maximum discrimination capability was in parietal region [6].

It has been found that right hemisphere showed higher accuracy in detection of depression [7], [8]. The study also shows the effectiveness of nonlinear feature as well as ANN, LS-SVM and CNN-LSTM for detection of depression [9], [10], [11], [12].

If the number of EEG channels is high, it decreases the portability and increases the cost of the framework. Thus, it is always better to have lesser number of channels as well higher accuracy. Thus few researched has been done with lesser number of channels. EEG recording was done use only 3 channels Fp1, Fpz and Fp2. Band Power, features of EEG power spectrum (Max frequency, Mean frequency and Centroid frequency) and three non-linear features: Renyi entropy, Correlation dimension and C0 complexity were extracted and SVM was applied which provided accuracy of 83.07% [13]. From the same dataset authors extracted 16 linear and non-linear features All these features, one at time were checked in KNN, SVM, ANN and Deep Belief Network (DBN). Highest accuracy 78.24% was obtained using Deep Belief Network (DBN) along with absolute power of beta wave [14].

Thus, the significance of theta band as well as higher frequency band in detection of depression has been found [15].

In many studies, was observed that depression affected more in the temporal region [16]. Presence of Alpha peak characteristics in Frontal Brain Asymmetry (FBA) was observed in person having depression or history of depression [17]. Combination of linear and nonlinear feature along with LR provided very high accuracy of 92% [18]. The study also reconfirms the fact that depression affects higher frequency bands [19].

The objective in the study is to decrease the number of EEG channels to the minimal as well as finding the most significant feature for detection of depression. Thus the model would help in the development of the portable device with higher accuracy.

II. MATERIAL AND METHODS

The flowchart of the entire study is shown in Fig 1 where the EEG signal is first loaded in the system for analysis. The EEG data is divided into smaller 2 sec epochs to create a larger dataset. Then the noise removal was done using i) Filter ii) Re-referencing to Common Average Referencing (CAR) iii) Removing eye blinks using Independent Component Analysis (ICA) iv) Removing the epochs having noise v) Visual analysis. Delta, alpha, beta paired asymmetry and DFA features are extracted. Further features are normalized using Min-max algorithm.

The features are then input into the SVM for training and testing the models selected. 100 iterations of 10 CV has been applied in each sub.

The removal of artefacts is done. The study can be divided into 3 sub models

i) Model based on 6 channels (T7, T8, P7, P8, F7, F8) based on previous study [26].

ii) Model based on 4 channels (T7, T8, P7, P8) based on previous study [26].

iii) Model based on 19 channels and one feature: In this model, DFA is extracted from all 19 channels. DFA was found to be one of the most significant features based on the previous study [26]

In the Public dataset, the study was done on the basis of 19 channels and the study on Private dataset was based on 128 channels. Hence for comparative analysis and reconfirmation of the result some amount of approximation was required to be done as the electrode in the exact location mapping of Private dataset was not available on the Public dataset. The mapping of the channel and feature selected using ReliefF in the Private dataset to that of the Public dataset was done as follows:

Note: As per Modified Combinatorial Nomenclature (MCN) T3 and T4 is replaced by T7 and T8 [38].

The sampling frequency in Public dataset was 256Hz. So, the gamma power band values cannot be extracted from the signal. So, the features related to Gamma 1 and Gamma

FIGURE 1. Flowchart of the Study containing 3 sub models.

TABLE 1. Mapping of the features of the private dataset to that of public dataset.

Rank	Channel Location	Feature in Private Dataset [27]	Mapping of Channel in Public Dataset[26]
1	TP7, TP8	Paired Gamma2 Asymmetry	None
2	TP7, TP8	Paired Gamma1 Asymmetry	None
3	T7	DFA	T7
4	TP7	DFA	T7, P7
5	T8	DFA	T8
6	TP7, TP8	Paired Beta Asymmetry	(T7,T8)(P7,P8)
7	TP8	DFA	T8,P8
8	FT7	DFA	F7,T7
9	FT8	DFA	F8,T8
10	T8, T7	Paired betas	(T8,T7)
11	FT8, FT7	Paired Delta asymmetry	(F8,F7) (T8,T7)
12	TP8, TP7	Paired Alpha Asymmetry	(T8,T7) (P8,P7)
13		Gamma1 Asymmetry	None
14	T8, T7	Paired Alpha Asymmetry	(T8,T7)
15	TP8, TP7	Paired Delta Asymmetry	(T8,T7) (P8,P7)

Note: As per Modified Combinatorial Nomenclature (MCN) T3 and T4 is replaced by T7 and T8 [38].

2 band power has been dropped in the Public dataset as shown in Table 1.

In another study Comparison of Performance of Public Dataset and Private Dataset using only Temporal Channel EEG Data has been done. Analysis was carried out on the features selected from the temporal only. The features used in the study are delta, alpha, beta paired asymmetry and DFA from temporal channel (T7 and T8).

The feature was extracted from channel T7 and T8 because it was the only channel pair which was available in the temporal region of both the dataset. Hence, T7 and T8 channels were selected in order to provide common channel for reference in both Public Dataset and Private dataset. Table 2 shows the common features which were used in both Public dataset and Private dataset for the comparative analysis.

The Figure 2 shows the flow chart of comparison of performance of Public Dataset and Private Dataset using only temporal channel EEG Data. First the EEG data of both Public

TABLE 2. Common features used in both Public dataset and Private dataset for the comparative analysis.

Sl. no	Channel Location of Private and Public Dataset	Feature used in the Private and Public Dataset
1	T7	DFA
2	T8	DFA
3	T8, T7	Paired Beta Asymmetry
4	T8, T7	Paired Delta asymmetry
5	T8, T7	Paired Alpha Asymmetry

dataset as well as Private dataset is loaded and artifacts are removed. The signals are further epoch into 2 seconds data. T7 and T8 channels for each of the Public as well as Private dataset are selected. Delta, alpha, beta paired asymmetry and DFA are extracted from T7 and T8 channel for analysis. Further features are normalized using Min-max algorithm. Extracted features are inputted into the SVM classifier separately for Public and Private dataset. Further the computation of accuracy, sensitivity and specificity for each of the dataset is computed. 100 iterations of 10 CV has been applied in the model for both Public and Private Dataset.

FIGURE 2. Flowchart of comparison of performance of public dataset and private dataset using only temporal channel EEG Data.

A. SUBJECTS

In this study two dataset is considered for the analysis.

i) Public Dataset: It is an open access dataset consisting of 34 (17female+17male, avg. age=40.3+12.9yrs) MDD and 30(9female+21male, avg. age=38.3+15.6yrs) normal subjects. EEG data of 4 MDD patient was rejected due to corruption from large number of artifacts. The study was approved by ethical committee of Hospital Universitii Sans Malaysia (HUSM) [26].

ii) Private Dataset: The data set consisted of eyes closed EEG data of 24 MDD (average age = 35+5.9 yrs) patients and 20 normal subjects (average age = 36 +4.2 yrs). The data set consisted only of male subjects. The study was approved by ethical committee of Central Institute of Psychiatry (CIP), Ranchi, Jharkhand, India [25].

B. DATA ACQUISITION

In public dataset, 19 channels EEG data were obtained, each with a linked ear reference as shown in Fig 5 [21].The data was recorded using 19 electro-gel sensors based EEG cap. Then further signals were amplified using Brain Master Discovery (Make: Brain Master, Model: Discovery 24e, Manufacturer: Brainmaster Technologies Inc.).

The recording was done in eyes closed resting state condition for 5 minutes. 256 Hertz was set as sampling frequency. The location of 19 channels were mainly divided into six lobes: frontal lobe (F7, F3, F4, Fz), central lobe (C3, C4), temporal lobe (T3, T4, T5, T6), occipital lobe (O1, O2), parietal lobe (P3, P4), pre-frontal lobe (Fp1, Fp2) as shown in Fig 1. Fig 1 shows the 6 different region of the brain.

In the private dataset, 15 minutes eyes closed EEG data was recorded using 128 channels EEG India. The EEG data was recorded using EB Neuro BE Plus LTM in accordance with the 10-5 system using 128 channels.

In the study, there are no relative parameter taken into consideration which could affect the resulting performance in diagnose. The patient as well as the control group that has been studied are all as age and sex matched in both private and public dataset [25], [26]. The groups taken into consideration for the study are free from the effect of any drug so that there is no effect in the relative performance.

Fig 3 shows the EEG data depression patient. Visually it is impossible to differentiate the EEG data between depression patient and normal subjects.

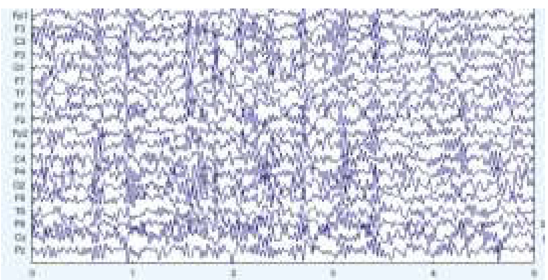

FIGURE 3. Depression patient's 19 channel EEG of Public dataset Here X-axis is for time (in seconds) and Y-axis is for the channel name [26].

C. PRE-PROCESSING

All EEG data are affected by artifacts. It is necessary to remove these artifacts so that the classifier works efficiently. In this study, the methodology adopted in cleaning the EEG data are discussed as follows:

i) First the EEG data is recorded in eyes closed (EC) condition in resting position using international standard 10/20 (Public Dataset) or 10/5 (Private Dataset).

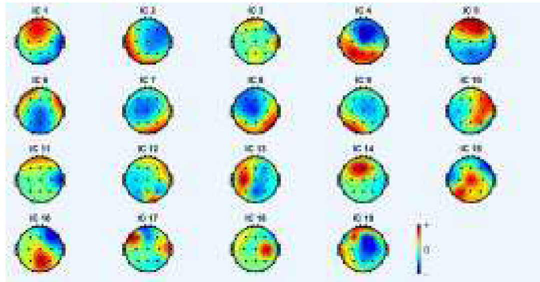

FIGURE 4. Depression patient's ICA for 19 channel EEG data of Public dataset where IC1 and IC5 represent eyeblinks [26].

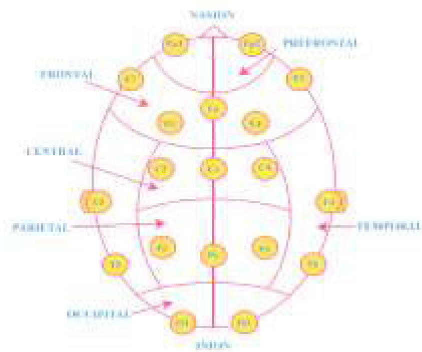

FIGURE 5. View of regions of the head and channel location.

ii) Sampling frequency of 256 Hz (Public Dataset)/ 512 Hz (Private Dataset) is used.

iii) All the signals were High Pass Filtered with 0.5 Hz cut-off and Low Pass Filtered with 32 Hz cut-off frequency (Public Dataset) or Low Pass Filtered with 250 Hz cut-off frequency (Private Dataset).

iv) 50 Hz notch filter was used to remove line noise.

v) Re-referencing of signals to Common Average Reference (CAR) is done to remove the background noise.

vi) Independent Component Analysis (ICA) is applied for noise removal. Fig 4 shows the ICA components.

vii) Optional: Noise removal using epoched data. Signals are segmented into 2 second epoch data then the peak amplitude of each of the 2 sec epoch data is measured. The epoch data having peak amplitude higher than 3-standard deviation was rejected and considered as noise [19].

Finally, after running through all 5 steps, the final cleaned data is obtained on which the analysis is further carried out. Fig 4 shows 19 channels EEG signal of Depression patient containing noise.

D. FEATURE

Features can be extracted from the signals using linear or nonlinear approaches. Linear approaches can be divided into time domain and frequency domain features. Time domain features includes EEG features in simplest way i.e. mean, variance, standard deviation, kurtosis, peak, amplitude and so on. Frequency domain features includes Delta, Theta, Alpha, Beta band power, their corresponding asymmetry, ratio between frequency band and so on. The foundation of nonlinear EEG analysis is the mathematical theory of dynamical nonlinear systems. Thus it is expected that nonlinear features would be more efficiently be able to capture the chaotic behaviour of EEG signal. Nonlinear features include Higuchi's Fractal Dimension (HFD), Approximate Entropy (ApEn), Lyapunov Exponent (LE), Correlation Dimension (CD), Detrended Fluctuation Analysis (DFA) and so on [18]. It has found in the studies that both linear and nonlinear features are equally good in detection of MDD. References [21], [23], [24]

The feature used in the study is both linear and nonlinear and selected based on the previous study [25]. Linear features used in the study in Paired Asymmetry for Delta, Theta, Alpha and Beta power which was found to be an important feature for detection of MDD [26]

'The nonlinear feature used in the study is Detrended Fluctuation Analysis (DFA). Many studies has found DFA as an important for detection of MDD [25], [26].

The EEG is used to extract the three frequency bands: beta, theta and delta. The Fast Fourier Transform (FFT) applied on EEG data for delta(0.5-4Hz), theta (4–8 Hz) and beta (13–30 Hz) bands using infinite impulse response (IIR) 4th order Butterworth band-pass filters. To compute the power spectrum of the EEG signal, the Welch periodogram was used. The signal is separated into small pieces in this approach, and each segment has a 50% overlap. Each band's signal power is determined by averaging all modified periodogram [27], [28].

Three EEG band was considered i.e. delta, theta, alpha and beta power based on the findings in [25] where it was found using ReliefF(feature selection technique) that delta, theta and beta asymmetry as well DFA were found to be more important than the other extracted features The Higher band i.e. Gamma band couldn't be considered as the sampling frequency for the public data was only 256 Hertz. Also in previous study it has been found that paired asymmetry is a significant feature in detection of depression [29].

i) Paired Asymmetry

Paired asymmetry was calculated as for delta, alpha and beta power as

$$\text{PairedAsymm} = \log(\text{TPowR}) - \log(\text{TPowL}) \tag{1}$$

where TPowR is power of right electrode which can be any of F8, T8 and P8. TPowL is each pairs corresponding left electrode's theta power. Thus paired theta asymmetry is calculated as the difference of log power between the paired electrodes.

The paired electrodes includes:

F8-F7, T8-T7, P8-P7 where band power are computed for each delta (0.5 to 4 Hz), alpha (8 to 13 Hz) and beta (13 to 30 Hz) for the respective channels.

ii) DFA-Nonlinear feature: It was proposed by Peng et al. in 1994 [30]. DFA is used in showing the spread of long-range correlation in a signal. It is computed directly in time domain [31]. It is computed as follows:

First the signal is integrated with m samples. The fully integrated signal is then split into equal length (m) box [32], [33]. The trend of each of the box is represented in least square line that is fitted to each box. ym(k) represents the y co-ordinate of the straight line. The integrated time series y(k) is detrended by deducting each boxes local trend ym(k). The root mean square fluctuation F(m) is computed as

$$F(m) = \sqrt{}(1/N \sum \_(k = 1)\text{^}m[y(k) - y\_m(k)]\text{^}2) \tag{2}$$

The computation of F(m) is repeated over all box sizes to find the relationship between average fluctuation and box size (m). Generally, F(m) increases as the box size increases. Presence of power law scaling (fractal) is indicated by linear relationship on a log graph. Scaling component (α) characterizes the fluctuation which is computed as slope of line relating F(m) versus log m.

Value of $\alpha > 0.5$ and $\alpha < 1$ represents constant long range power law correlation.

To bring the feature to a common scale, normalization is done. All feature extracted are normalized using Min-Max normalization so that the classifier could work more efficiently and correctly.

E. CLASSIFIER: SUPPORT VECTOR MACHINE (SVM)

It was developed by Cortes and Vapnik in 1995 [34], [35]. SVM has the ability to classify both linear and non-linear data. SVM finds the best separating Maximal Marginal Hyperplane (MMH) i.e. largest margin which separates both class separating hyperplane. If the data set is non-linearly separable in lower dimension, it is transformed to the higher dimension space by using kernel function and then further classification is done. Some of the kernel function includes polynomial kernel, Sigmoid kernel, Gaussian Radial basis kernel.

SVM are generally highly accurate. SVM always finds a global solution and never gets stuck in local minima. It can model complex nonlinear boundaries for classification. It is less prone to overfitting as the classification is dependent on the support vectors and MMH. It has the capability to work with large number of predictor variables. It can very well handle irrelevant, correlated and redundant predictors very well. It is less effected by outliers

In SVM, slow training and testing due to the computation time required for the nonlinear transformation and kernel mapping. In SVM, the major issue is there in deciding on the kernel to be used and its parameter values for providing optimal result. More efficient method is required to implement multiclass classification for SVM [32].

Gaussian Kernel: It is also known as Gaussian Radial Basis function kernel. It is represented as:

$$\phi(\text{X\_i, X\_j}) = \text{e\^{}}(-\|\_i - X\_j\|\text{\^{}}2/(2\sigma\text{\^{}}2)) \tag{3}$$

where σ is the standard deviation.

In our study, SVM with Gaussian Kernel has been used. There are two features, which are explained as follows.

F. FEATURE MATRIX

It is formed of r-rows and c-columns, where r rows represent the number of EEG data and c columns represent number of features extracted from EEG data. In this study both linear and non-linear features are used. Linear features include 3 features for each delta, alpha and beta paired Asymmetry. So it comes up 9 ($3 \times 3 = 9$) linear features.

For non-linear feature, 19 features for DFA is used. So it comes up 19 ($19 \times 1 = 19$) linear features.

Thus total number of EEG feature = 9 linear Features + 19 non-linear features = 28 features

Total number of epoch (2 seconds) EEG data =8,572

G. ANALYSIS OF ALGORITHM

1) TRAINING

The dataset contains total 60 tuples. The tuples used for training the classifier for classifying the accurately is known as training data. In this study, the dataset is partitioned into 70:30 ratio. The 70% i.e $0.7 \times 8{,}572 = 6000$ samples are used for training the classifier.

2) TESTING

The tuples used for testing the classifier for verifying the accuracy of classifier is called testing data. In this study 30% i.e. $0.3 \times 8{,}572=2572$ samples are used for testing the classifier.

III. RESULTS

Statistical Analysis: All the features i.e. DFA (T7, T8, P7, P8) and Paired Delta Asymmetry, Paired Theta Asymmetry, Paired Alpha Asymmetry and Paired Beta Asymmetry for significance for channel pair (T8 and T7), and (P7 and P8) was found to be statistically significant at $p<0.001$ [34], [35], [36]. The result reconfirms the fact that depression affects both hemisphere of the brain differently and DFA and Paired Delta Asymmetry, Paired Theta Asymmetry, Paired Alpha Asymmetry and Paired Beta Asymmetry are significant features for detection of depression.

Note: In this Section, analysis using t-test was done using MATLAB.

Results for detection of depression using temporal, parietal and frontal channel EEG data applied to Public dataset:

It can be analysed from the table 3 that a high classification accuracy 93.88% using paired asymmetry and DFA from only six channel (T7, T8, P7, P8, F7 and F8).

Comparable accuracy of 91.74% is achieved by the model using only four channels (T7, T8, P7 and P8).

Very high accuracy of 84.09% is achieved by using only DFA from all 19 channels. Fig 6 shows the comparison of the accuracy of all the three models in which highest classification accuracy is 93.88% achieved using paired asymmetry and DFA from only six channel (T7, T8, P7, P8, F7 and F8).

TABLE 3. Test for significance using t-test for DFA(T7, T8, P7, P8), paired delta asymmetry, paired theta asymmetry, paired alpha asymmetry and paired beta asymmetry for channel pair (T8 and T7) and (P7 and P8).

Channel	Feature	h (h=1 i.e. null hypothesis is rejected=1 i.e. null hypothesis is rejected)	p-value
T7	DFA (Temporal)	1	2.02E-32
T8	DFA (Temporal)	1	8.93E-08
P7	DFA (Parietal)	1	2.37E-42
P8	DFA (Parietal)	1	4.42E-138
T8, T7	Paired Delta Asymmetry (Temporal)	1	2.02E-18
P8, P7	Paired Delta Asymmetry (Parietal)	1	3.59E-44
T8, T7	Paired Theta Asymmetry (Temporal)	1	3.59E-48
P8, P7	Paired Theta Asymmetry (Parietal)	1	8.63E-03
T8, T7	Paired Alpha Asymmetry (Temporal)	1	2.21E-17
P8, P7	Paired Alpha Asymmetry (Parietal)	1	1.29E-37
T8, T7	Paired Beta Asymmetry (Temporal)	1	2.54E-42
P8, P7	Paired Beta Asymmetry (Parietal)	1	6.23E-102

Results for comparison of performance of Public dataset and Private dataset using only Temporal Channel EEG Data:

It can be analysed from the table 5 that a high accuracy of 89.24% is achieved for the Public dataset and accuracy of 82.68% is achieved in Private dataset using same set of features and the same classifier (SVM) using only 2 channels T7 and T8 using delta, alpha, beta paired asymmetry and DFA as feature and SVM as classifier. The accuracy achieved in public dataset is found to be higher by 6.56% than that achieved in the Private dataset. Fig 7 shows the different accuracy achieved by each of the datasets.

TABLE 4. Comparison of accuracy, sensitivity and specificity of 3 models.

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)
Model based on 6 channels	93.88	93.84	93.93
Model based on 4 channels	91.74	91.78	91.7
Model based on 19 channels and one feature (DFA)	84.09	84.73	83.42

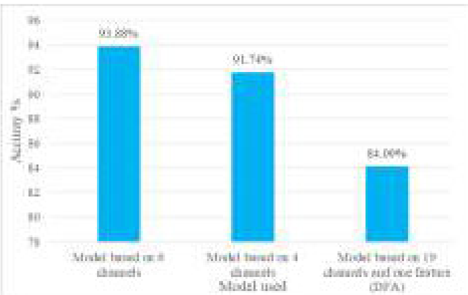

FIGURE 6. Comparison of Accuracy of all three models in Public dataset.

TABLE 5. Comparison of accuracy, sensitivity and specificity of Public and Private Dataset using on 2 channels t7 and t8.

Dataset Used	Accuracy (%)	Sensitivity (%)	Specificity (%)
Public dataset	89.24	88.94	89.55
Private dataset	82.68	86.18	74.53

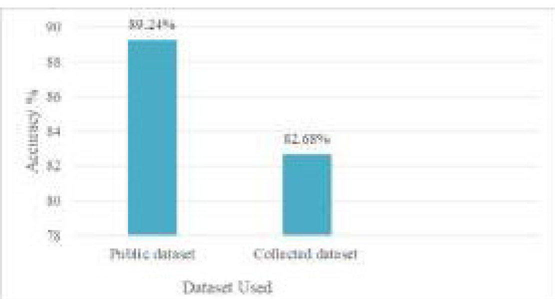

FIGURE 7. Comparison of Accuracy for the Public and Private Dataset using channel T7 and T8 along with delta, alpha, beta paired asymmetry and DFA as feature and SVM as classifier.

IV. DISCUSSION

The study confirms the fact that DFA is significant feature for detection of depression because using a single feature from 19 channel a very high accuracy of 84.09% is obtained. This strongly confirms the fact that that DFA is affected by depression.

The study also that depression affects the temporal and parietal region of the brain as observed from the study from the model based on 4 channels (T7, T8, P7, P8) applied on the temporal and parietal region which provided a very high accuracy of 91.74%. Highest classification accuracy of 93.88% is achieved when using most of the features In this study, the features selected are the paired asymmetry from temporal and parietal region in model using 4 channel which provides a classification accuracy of 91.74%. Thus, the study confirms the facts that depression affects each of the hemisphere of temporal and parietal region of the brain differently as reported.

From Fig 6, it is observed that by dropping of 2 channels makes the accuracy drop by only 2.14 %. Thus, the model based on 4 channels can be considered for computer aided

TABLE 6. Comparison between Public and Collected dataset.

	Public Dataset [26]	Private Dataset [25]
Subjects	34 depression patients and 30 normal subjects. The group of 34 depression patients consists of 17 male and 17 female patients with average age of 40.3±12.9y. The normal subjects consisted of age matched 21 males and 9 females with the average age of 38.3±15.6y.	24 MDD (average age = 35±5.9y) patients and 20 normal subjects (average age = 36 ±4.2y). All Males
Region	Hospital Universitii Sains Malaysia (HUSM), Malaysia.	Central Institute of Psychiatry (CIP), Ranchi, India
Number of Channels	19 Channels	128 Channels
Sampling Frequency	256Hz	512Hz
Demographic Information	Not Available. Only EEG data available	Available
Recording time	Resting state 5 minutes eyes closed (EC)	Resting state 15 minutes eyes closed (EC)
Filtering	HPF through 0.5Hz and LPF through 32Hz	HPF through 0.5Hz and LPF through 250 Hz

diagnosis. The use of 4 channels would make the system more portable, faster and cheaper.

Fig 7 shows the comparison of accuracy of Public and Private Dataset. The difference of 6.56% in the accuracy between the dataset could mainly be contributed due to the difference in the gender of the population. The public dataset consisted of both male and female subjects whereas the Private dataset consisted of only male subjects.

The study confirms the fact that the model works quite well in both the dataset. High accuracy of 89.24% and 82.68% is achieved for Public dataset and Private dataset respectively using two channels (T7 and T8), delta, alpha, beta paired asymmetry and DFA as feature and SVM as classifier. The study confirms the fact in both the dataset that depression affects the temporal region of the brain as well as both hemispheres differently with respect to paired delta, alpha and beta power asymmetry. The study also confirms the fact that DFA gets affected during depression.

Table 6 shows the comparison between the two dataset used. The major limitation of Public Dataset i.e. low sampling frequency and absence of detailed information of the patient severity of depression i.e. HAM-D score and depression rating, etc [26]. The limitation of Public Dataset is overcome in Private data set with higher sampling frequency of 512 Hz which allows analysis of gamma band power also. Severity scaling information i.e. HAM-D and severity rating is also available in Private Dataset which makes it possible for the researcher to also identify the severity of depression of the patient [25].

Limitation of the study i.e. larger size of the dataset should be studied to generalize the results. Analysis of more number of features should be done along with new classifiers and different feature selection technique could also be used in order to achieve higher accuracy from the model [38].

V. CONCLUSION

The study confirms the fact that depression affects the temporal and parietal region of the brain and depression, depression effects hemisphere of the temporal and parietal regions of the brain differently and depression also affects DFA. The study results in a model made up of 4 channels with high accuracy of 91.74% which is portable, faster and cheaper. Thus, model can act as an adjunct tool for detection of depression. The study of comparison of performance of Public dataset and Private dataset using only temporal channel EEG data reconfirms the finding that depression affects the temporal region of the brain by both Public and Private dataset using the same set of feature and classifier. The fact that using features delta, alpha, beta paired asymmetry and DFA from only temporal channel (T8 and T9) provided high accuracy of 89.24% and 82.68% supports the claim that depression affects the temporal region of the brain.

COMPLIANCE WITH ETHICAL STANDARDS

Conflict of Interests: The authors have no conflict of interests regarding the publication of this paper.

Ethical Approval: This article does not contain any studies with human participants performed by any of the authors

ACKNOWLEDGMENT

The authors would like to thank Mumtaz et al. for the dataset contribution [24].

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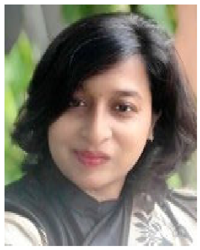

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