Original Article

Detection of Schizophrenia from EEG Signals using Dual Tree Complex Wavelet Transform and Machine Learning Algorithms

Fahmida Ahmed Antara[1], A S M Shamsul Arefin[1*], Md. Tamjid Rayhan[1] and Sabbir Ahmed Chowdhury[2]

[1] Department of Biomedical Physics and Technology, University of Dhaka, Dhaka - 1000, Bangladesh

[2] Institute of Education and Research, University of Dhaka, Dhaka - 1000, Bangladesh

* Corresponding Author email: arefin.bmpt@du.ac.bd

Abstract

This research was conducted with the aim to detect schizophrenia automatically from EEG signals using machine learning algorithms. The 16 electrode EEG data were collected from the online repository where 43 schizophrenic and 39 healthy persons' dataset is available. By applying Low Pass Filter and Total Variation Denoising method, raw EEG signals were denoised and were decomposed into beta, alpha, theta and delta waves by using Dual Tree Complex Wavelet Transform. To apply machine learning algorithms, five features: mean, median, standard deviation, energy and kurtosis were considered for all the four wave bands. With Linear Support Vector Machine and Random Forest classifier machine learning algorithms, 12 out of 16 channels were classified with test accuracy above 95% and F1 score above 90%. Among them, 7 channels were predicted with 100% test accuracy. This research thus has the potential to detect schizophrenia unsupervised and within a noticeably short period of time giving the opportunity to real time monitoring of patients. Hence, people living in remote areas or deprived of adequate healthcare professionals can be benefitted through the outcome of this research.

Keywords: *Wavelet Transform, EEG, LPF-TVD, Schizophrenia, Machine Learning.*

Introduction

A neurological disorder associated with abnormal social behavior, dementia, hallucinations, predicting imagination into reality is known as Schizophrenia. People with schizophrenia have a tendency to believe in something which does not exist, sometimes they hear or see things which is in their imaginations. Disorganized communication, meaningless word, social withdrawal etc. are also symptoms of schizophrenia [1]. If it is not detected and treated in early stage, patients may lead to have suicidal thoughts and it could be fatal.

Several studies have been conducted about detecting schizophrenia in prodromal stage. Electroencephalography (EEG) is an effective measure from which abnormalities in different lobe of brain can be detected. Some researchers at the School of Medicine in University of California, San Diego have found from EEG studies that people with schizophrenia do not respond with reoccurring sounds [2]. State of the art computational studies have recommended that schizophrenia patients have changes in functional connectivity [3], detectable changes in different frequency band waves such as beta, alpha, delta or theta waves [4]. Based on these changes, EEG recordings have become a strong tool in modern technology to detect schizophrenia automatically using some artificial intelligence.

Shim *et al.* extracted both sensor-level and source-level features from EEG signals to classify schizophrenia [5]. The EEG was performed during an auditory oddball task done by a group of schizophrenic patients and normal persons. Here, due to the use of both sensor-level and source-level features, the performance was found better (88.24%) than that of sensor-level features only (80.88%). Moreover, the sensor-level features were mostly originated in the frontal area while the source-level features were mostly found from the temporal area, which coincide well with the pathological region of cognitive processing in patients with schizophrenia [5].

In another study by Squarcina *et al.*, a model was developed which was based on biological quantities recorded from EEG [6]. Here, spatiotemporal images of event-related potentials were recorded from three different auditory oddball stimuli to the patients. Using multivariate pattern analysis, a machine learning technique was applied to classify schizophrenia patients and healthy controls. 80.48% accuracy was achieved by support vector machine and Gaussian processes classifier and the Receiver Operator Characteristics (ROC) analysis secured an Area under the Curve (AUC) of 0.87 [6].

A recent study by Krishnan *et al.* represented multivariate analysis of electroencephalogram to detect schizophrenia [7]. Here, the EEG signal was decomposed into intrinsic mode functions and the randomness of the signal was measured in terms of five entropy such as approximate entropy, sample entropy, permutation entropy, spectral entropy and singular value decomposition entropy. The data were collected from an online repository and total 95 features were created. The highest accuracy obtained from several classifiers was about 93% and the classifier was Support Vector Machine based on Radial Basis Function (SVM-RBF) [7].

Deep Learning algorithm was used in a schizophrenia research by Oh *et al.* [8]. A deep convolutional neural network is trained with 873 structural MRI dataset and it shows different classification performance for different group of patients. For instance, the AUC is found to be 0.97 when MR images are selected randomly. However, the value is degraded to 0.71 with a new dataset of younger patients and a shorter duration of illness [8].

Depending on the techniques for processing EEG data, decomposition, statistical analysis and deployment of the Machine Learning (ML) algorithms; the detection accuracy varies over a wide range [9]. Numerous analyses have been performed in this regard but to detect schizophrenia more accurately and reliably, there is a scope to develop a new method which is the goal of this research work.

Methodology

Secondary raw EEG dataset from online repository for both schizophrenic patient and healthy people went through the same processes. Time-frequency analysis was chosen over other methods for data preprocessing due to the characteristics of EEG signals. The unwanted signals were removed from each channel using Low Pass Filter and Total Variation Denoising (LPF-TVD) technique. In order to extract features, the signals were required to be segmented into beta, alpha, theta and delta wave which were performed using Dual Tree Complex Wavelet Transform (DTCWT) function. Features were extracted in a manner to avoid over-fitting as the dataset was very small. Machine learning based classifiers were deployed to classify schizophrenic EEG from normal EEG. Fig. 1 describes the block diagram of the overall methodology.

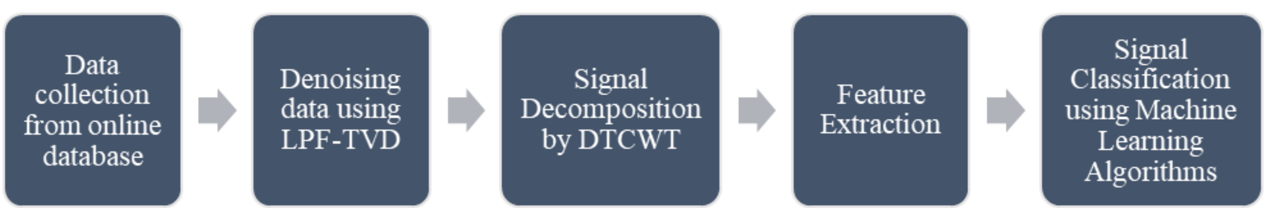

Figure 1. Block diagram of the methodology.

MATLAB 2015b software was used for performing the task of noise removal, signal segmentation and feature extraction and the rest of the works were performed in Python 3.8.8.

Data Source

For this research work amid COVID-19 pandemic, secondary data were collected from the Laboratory for Neurophysiology and Neuro-Computer Interfaces, Lomonosov Moscow State University [10]. There were 39 healthy adolescents in one group while another group had 43 adolescents with symptoms of schizophrenia. Data were collected from 16 channels for each patient. Each channel has 7680 samples and sampling rate was 128 Hz. Hence, 7680 samples were referred to 1 minute record. The recordings were collected from 16 electrodes which were placed on scalp according to 10-20 rules. 16 channels were referred as F7, F3, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2 respectively.

Signal Denoising using LPF-TVD method

Linear Time Invariant (LTI) filtering method has been playing a strong role in the removal of noise from data. EEG signals has specific frequency band. LTI filtering method is one of the most suitable methods to denoise EEG signals. A method proposed by Selesnick *et al.* that combines LTI filtering, specifically Low Pass Filter (LPF) and Total Variation Denoising (TVD) which is used to cancel noise from EEG signal in the proposed system [11]. EEG signals may contain high frequency pass artifact for which LPF would be an appropriate measure. Moreover, a noisy signal having sparse derivative can be treated with TVD method. A noisy signal with low frequency pass component and sparse derivative can be represented by the following mathematical expression:

$$y(n) = f(n) + x(n) + w(n) \; where, n = 0,1,2 \ldots\ldots\ldots\ldots\ldots..N-1]$$

Where, the former portion i.e., $f(n) + x(n)$ represents the denoised signal. In addition, N is the number of samples in EEG signal of each channel. Here, f(n) is a low pass signal, x(n) is a signal of sparse derivative and w (n) is Gaussian White Noise.

Here, estimation of f, $\hat{f} = LPF(y - \hat{x})$ where, Estimate of $x = \hat{x}$ and$f = \hat{f}$.

These imply that, $f = LPF(y - \hat{x})$

The raw EEG signals are treated with low pass filter by choosing a cut-off frequency. In the proposed method, cut-off frequency was chosen to be 20 Hz as the sampling frequency was 128 Hz. To carry out the simulation, the filter length is considered as 1. After passing through LPF, the filtered signal is then subjected for total variation denoising.

Total variation denoising is performed by formulating l1 norm of derivative of signal x(n). The optimization problem can be expressed as follows:

$$\underset{x}{\arg min} \{\frac{1}{2} \|y - x\|_2^2 + \lambda \|D_x\|_1\} \quad (1)$$

Here, λ determines the regularization factor. As approximation of derivative is the first-order difference; thus, minimization of $\|D_x\|_1$ is done in (1). Its solution can be written as:

$$tvd(y, \lambda) = \underset{x}{\arg min} \{\frac{1}{2} \|y - x\|_2^2 + \lambda \|D_x\|_1\} \quad (2)$$

To solve the equation (2), several algorithms have been studied [12-13], however, in the proposed system the "majorization-minimization" (MM) approach [14] was applied to develop the algorithm. The algorithm of MM approach substitutes a complex minimization problem with a sequence of simpler ones [14]. To minimize a function f(x), the MM procedure produces a sequence x_k according to the following equation,

$$x_{k+1} = \underset{x}{\arg min} \, G_k(x) \quad (3)$$

Here, k represents the iteration index and k > 0.

The function $G_k(x)$ indicates any convex majorizer of f(x). This function coincides with f(x) at x_k, i.e., Gk (x_k) =f(x_k).

Assuming the initial value of x_k as x_o, equation (3) generates a sequence x_k that converges to the minimizer of f(x) [14].

$$\text{Here, } \frac{1}{2} x^T \Lambda_k^{-1} x + \frac{1}{2} \|x_k\|_1 \geq \|x\|_1 \quad (4)$$

Where, $\Lambda_k = diag(|x_k|)$

In equation (4), a majorizer for l_1 is used.

When, $x = x_k$, the left side of equation (4) is a majorizer of $\|x\|_1$.

The value of λ is tuned until an accepted signal is found. For the research, the value was found to be 500 while the number of iterations is 50. The LPF-TVD method proved a suitable way for denoising different types of bio-signals i.e., ECG or EEG [15-16].

Signal Decomposition by DTCWT

Due to the non-stationary nature of EEG signals, the frequency spectrum of Fast Fourier Transform varies with the variation of Fourier co-efficient during decomposition [17]. However, the wavelet coefficients found from discrete wavelet transform are used to distinguish features of pathological EEG signals from those of healthy EEG signals [18]. The DWT method generates wavelet from input signal by scaling and shifting the mother function. The resulted two sub-bands are called approximation coefficients (low frequency components) and detailed coefficients (high frequency components). The approximation components are then further decomposed into another low frequency and high frequency components and so on.

DTCWT is an extended version of DWT. It is a two-dimensional wavelet transform that can be represented by following equations [19]:

$$\psi(t) = \psi_h(t) + j\psi_g(t) \tag{5}$$

$$\phi(t) = \phi_h(t) + j\phi_g(t) \tag{6}$$

Where, ψ(t) represents complex wavelet and ϕ(t) represents scaling function which are obtained from Hilbert transform [20].

In the proposed system, 4-level decomposition is performed to generate beta, alpha, theta and delta sub-bands of EEG signals. The block diagram of decomposition is shown in the Fig. 2.

Feature Extraction

In some recent studies [21-22], it is observed to use a smaller number of features extracted from EEG sub bands to classify anomalies. Ben *et al.* used mean, median and standard deviation as selected features to classify epileptic seizure from EEG [22]. To avoid over-fitting due to the small size of the dataset, the dataset for this study was subjected to be classified with five statistical features only. Obtaining sub bands from previous section, statistical analyses, like mean, median, standard deviation, energy, kurtosis of each sub bands were performed to calculate the class of EEG. The features extracted for channel F3 is shown in Table 1.

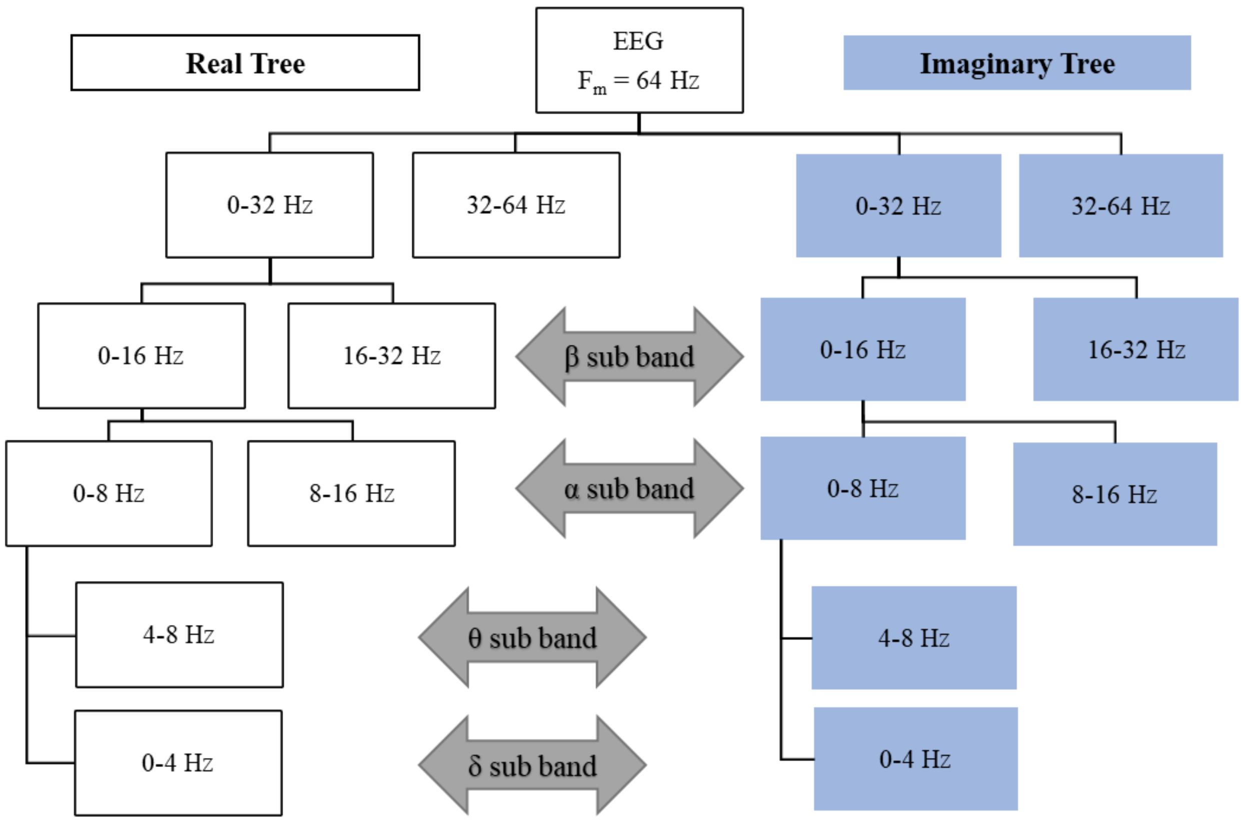

Figure 2. 4-Level Decomposition of a signal using DTCWT.

Table 1. All features calculated for channel F3.

Sub-bands	**Features**	**Correlation value**	**Sub-bands**	**Features**	**Correlation value**
	Mean	0.329		Mean	0.356
	Median	0.584		Median	0.327
Beta wave	Standard deviation	0.349	**Theta wave**	Standard deviation	0.317
	Energy	0.367		Energy	0.530
	Kurtosis	0.764		Kurtosis	0.855

Alpha wave	Mean	0.555	**Delta wave**	Mean	0.365
	Median	0.311		Median	0.375
	Standard deviation	0.301		Standard deviation	0.360
	Energy	0.458		Energy	0.488
	Kurtosis	0.755		Kurtosis	0.947

Classification with Machine Learning Algorithm

There is a total of 20 features for each channel. Though features are extracted for 16 channels of 82 subjects, the feature table of F3 channel for a subject is shown in Table 2.

Table 2. Features of different EEG sub-bands for channel F3.

Sub-band	Mean (μV)	Median (μV)	Standard Deviation (μV)	Energy	Kurtosis
Beta	-6.87E-09	0.23	39.12	0.42	10.93
Alpha	2.12E-08	-0.19	62.99	1.09	6.33
Theta	-5.69E-08	0.30	89.58	2.20	4.98
Delta	-5.00E-08	2.14	93.58	2.40	6.20

In Table 2, the value of Kurtosis in beta wave implies that there are some outliers present in data. However, as the other three waves having value almost close to mesokurtic value, this feature is taken into account to calculate efficiency.

The whole dataset (82×20) for 16 channels was split into training set and test set in order to test the model with unseen data. The split was performed in the following way:

- Training set: 75% data of the dataset (61 samples)
- Test set: 25% data of the dataset (21 samples)

Considering the size of the dataset, Random Forest and Support Vector Machine algorithms were used in this work for classification purpose because of the following reasons:

i) Support vector machine and random forest classifiers perform faster than any other classifiers for small dataset.

ii) Neural network is mostly suitable for large dataset and they can deal best with complex model. Therefore, these were not implemented in the proposed system.

iii) In case of SVM, using different types of kernels, several discriminant hyperplanes can be obtained which leads to better accuracy for classifying anomalies in EEG [23].

The performance of classifier models was evaluated in terms of precision, sensitivity, F1 score, confusion matrix, and validated further by plotting the ROC and AUC.

Results and Observations

Outcome of LPF-TVD

The analysis was performed for 30 seconds data; hence, the output is shown for 3840 samples. The cut off frequency of LPF is 20 Hz and filter order is 1. For TVD, number of iteration and regularization constant are chosen empirically 50 and 500 respectively. Besides observing the outputs of raw EEG and denoised EEG, the signal-to noise ratio (SNR) was calculated to be 6.104 and 8.95 for pathological and healthy EEG raw signal respectively while these were 7.63 and 12.03 for denoised signals.

The raw EEG obtained from frontal lobe (F7 channel) along with the denoised signal in time domain for a schizophrenic patient and a healthy subject are shown in Fig. 4 and Fig. 5 respectively.

Outcome of DTCWT

Using four level dual tree complex wavelet transform, EEG signal of each channel was subdivided into beta, alpha, theta and delta wave respectively. The coefficients of these waves were then used for statistical analysis. The waveshapes found from decomposition are shown in the Fig. 6.

Evaluations of classifier models

Linear SVM and random forest classifier models were developed to perform classification for each channel. Table 3 contains the performance metrics according to the best fitted classifier models for each channel according to test accuracy.

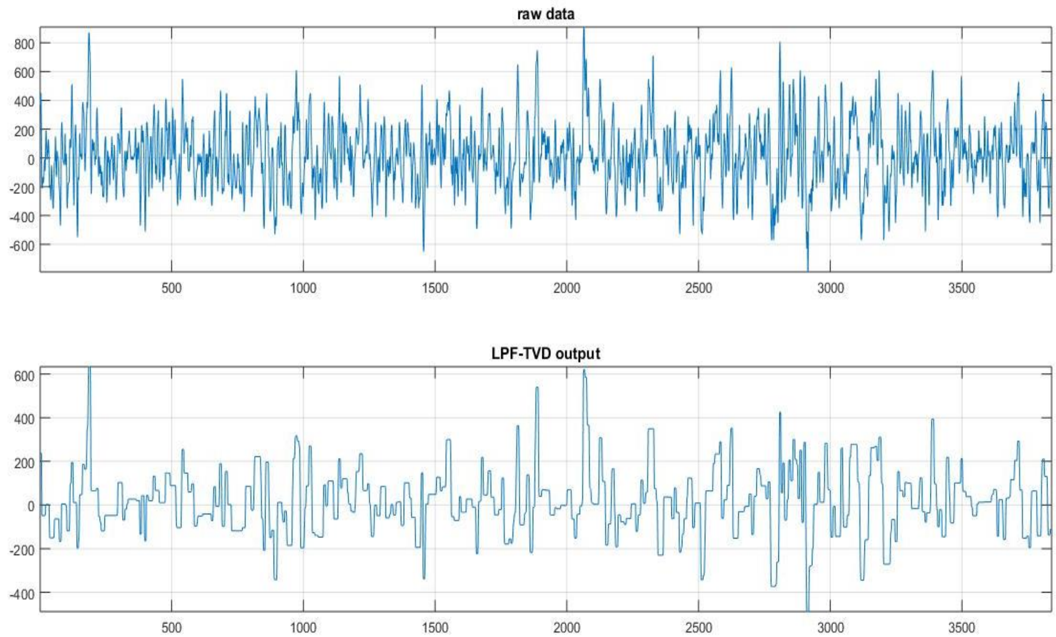

Figure 4. Raw EEG signal in time domain (top) and denoised EEG signal in time domain (bottom) of a schizophrenic patient (Channel- F7).

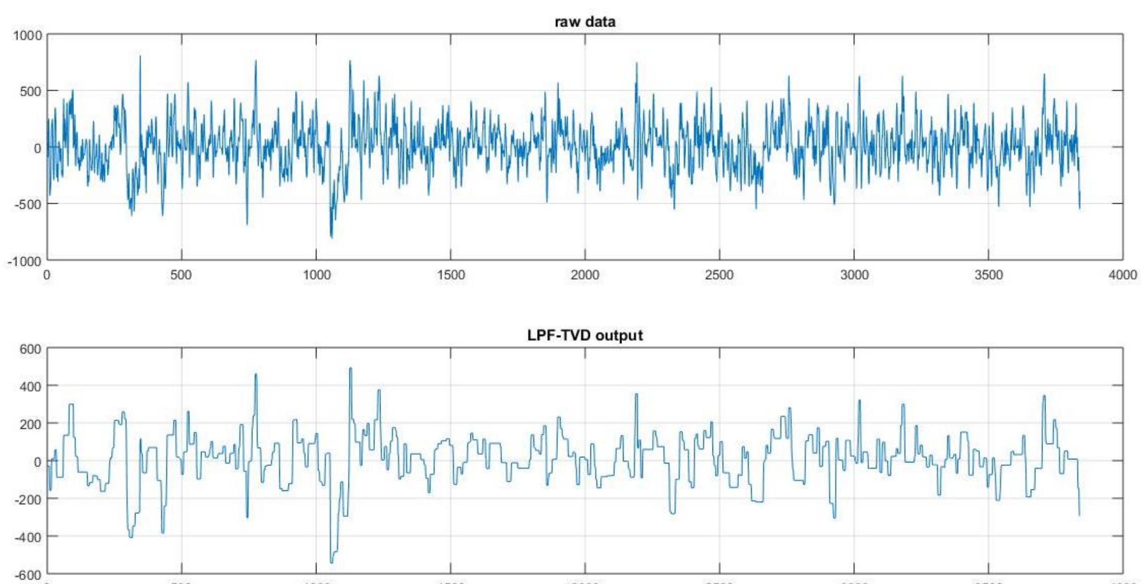

Figure 5. Raw EEG signal in time domain (top) and denoised EEG signal in time domain (bottom) of a healthy subject (Channel- F7).

For F7 channel, linear support vector machine and random forest classifier showed 100% training accuracy and 95.24% test accuracy which is highest among all. Both classifiers showed better sensitivity for schizophrenic patient though random forest classifier shows 100% precision in case of healthy people detection while linear SVM shows 92%.

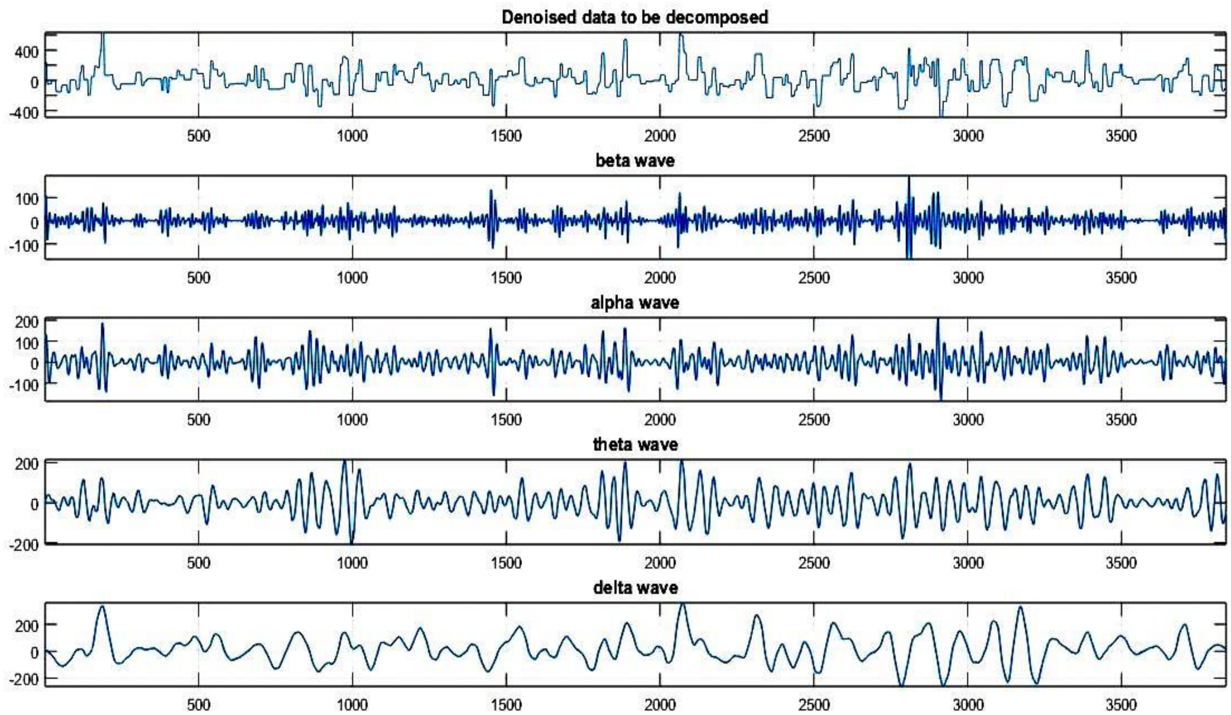

Figure 6. Decomposed EEG signal of a Schizophrenic patient (Channel-F7).

For F3 channel, linear support vector machine and random forest classifier showed 100% training accuracy and test accuracy. Both classifiers showed 100% sensitivity and precision for schizophrenic patient as well as for healthy person.

Both LSVM and Random Forest classifier performed 90.48% test accuracy for F4 channel. Here, Precision, F1 score and sensitivity of a schizophrenia patient were found to be 0.88, 0.85 and 0.88 respectively while they were 0.92 in case of healthy people.

The linear SVM showed 100% training accuracy and 90.48% test accuracy for F8. However, random forest classifier has 80.95% test accuracy with a poorer precision, sensitivity and F1 score compared to LSVM.

For T3 channel, LSVM showed 95.24% test accuracy, 0.89 precision, 1 sensitivity and 0.94 F1 score in case of schizophrenic patient. A lesser percentage was found in all sections while the channel was classified with random forest classifier.

In case of C3 and Cz channel, both LSVM and RF showed 100% accuracy in all cases for schizophrenic as well as healthy specimen.

Table 3. Performance metrics of each channel in terms of test accuracy.

Channel No.	Classifier Name	Test accuracy (%)	Precision		Sensitivity		F1 score	
			Schizophrenic	Healthy	Schizophrenic	Healthy	Schizophrenic	Healthy
F7	LSVM	95.24	0.88	0.92	1	0.94	0.96	0.92
	RF	95.24	0.88	0.92	1	0.94	0.96	0.92
F3	LSVM	100	1	1	1	1	1	1
	RF	100	1	1	1	1	1	1
F4	LSVM	90.48	0.88	0.92	0.85	0.92	0.88	0.92
	RF	90.48	0.88	0.92	0.85	0.92	0.88	0.92
F8	LSVM	90.48	0.80	1	1	0.85	0.89	0.92
	RF	80.95	0.67	1	1	0.69	0.80	0.82
T3	LSVM	95.24	0.89	1	1	0.92	0.94	0.96
	RF	85.71	0.73	1	1	0.77	0.84	0.87
C3	LSVM	100	1	1	1	1	1	1
	RF	100	1	1	1	1	1	1
Cz	LSVM	100	1	1	1	1	1	1
	RF	100	1	1	1	1	1	1
C4	LSVM	95.24	0.89	1	1	0.92	0.94	0.96
	RF	90.48	0.8	1	1	0.85	0.89	0.92
T4	LSVM	76.19	0.64	0.9	0.88	0.69	0.74	0.78
	RF	85.71	0.73	1	1	0.77	0.84	0.87
T5	LSVM	95.24	1	0.93	0.88	1	0.93	0.96
	RF	90.48	0.8	1	1	0.85	0.89	0.92
P3	LSVM	100	1	1	1	1	1	1
	RF	100	1	1	1	1	1	1
Pz	LSVM	100	1	1	1	1	1	1
	RF	100	1	1	1	1	1	1
P4	LSVM	90.48	0.8	1	1	0.85	0.89	0.92
	RF	90.48	0.8	1	1	0.85	0.89	0.92
T6	LSVM	90.48	0.8	1	1	0.85	0.89	0.92
	RF	90.48	0.8	1	1	0.85	0.89	0.92
O1	LSVM	95.24	0.89	1	0.92	0.85	0.94	0.96
	RF	100	1	1	1	1	1	1
O2	LSVM	95.24	0.89	1	0.92	0.85	0.94	0.96
	RF	100	1	1	1	1	1	1

For C4 channel, test accuracy of this channel was slightly poor compared to other channels. The highest test accuracy obtained by LSVM model which is 95.24%. The precision of this model to detect schizophrenia was 0.89 while it was 1 for healthy people. In the scenario of sensitivity, opposite phenomena can be observed. While analyzing with random forest classifier, comparatively poorer performance was observed in all cases.

In case of T4 channel, it was demonstrated that test accuracy was poor compared to any other channels though most of the classifiers had 100% training accuracy. Highest test accuracy was obtained from random forest classifier (85.71%). It classified healthy people precisely but the precision falls to 0.73 in detection of schizophrenia. Opposite happened while measuring sensitivity.

For T5 channel, higher test accuracy was obtained from linear SVM. It classified schizophrenia precisely but the precision fell to 0.93 in detection of healthy people. Opposite happened while measuring sensitivity.

It was observed from P3 channel that both classifiers had 100% training and test accuracy, 100% precision, sensitivity and F1 score for both pathologic and healthy subjects.

Linear support vector machine and random forest classifier showed 100% training accuracy and test accuracy for Pz channel. Both classifiers showed 100% sensitivity and precision for schizophrenic patient as well as for healthy people.

In case of P4 and T6 channel, linear SVM and random forest classifiers showed 100% training accuracy and test accuracy was same for them too (90.48%). Both classifiers showed 80% precision in detecting schizophrenia while sensitivity was 100% in this case.

Random forest classifier showed 100% training and test accuracy, 100% precision, sensitivity and F1 score for both pathologic and healthy subjects in case of O1 and O2 channel. On the contrary, linear SVM classified schizophrenic patient with 95.24% test accuracy from the EEG recorded by O1 and O2 channels.

It can be inferred that ML classifiers gave the best performances for Channel F3, C3, Cz, P3, Pz, O1 and O2 in distinguishing schizophrenia from EEG with 100% test accuracy. T4 channel showed the poorest performance. It can be also illustrated from Table 3 that except for the channels F8, T4, P4 and T6, all the channels had test accuracy more than 95% with F1 scores more than 90% for schizophrenia and normal EEG. The F1 score showed an effective analysis for all channels as no channel gave value less than 80%, neither in case of schizophrenia nor in case of healthy people.

The confusion matrix for F3 channel which is one of the best performed channels classified by both LSVM and RF is shown in Fig. 7 as an example. Likewise, the confusion matrix for T4 channel which is the worst performed channels classified by LSVM and RF is shown in Fig. 8.

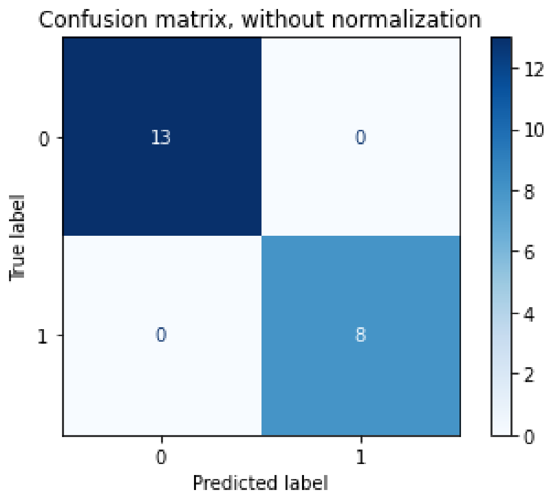

Figure 7. Confusion matrix of linear SVM and RF for channel-F3 (Actual).

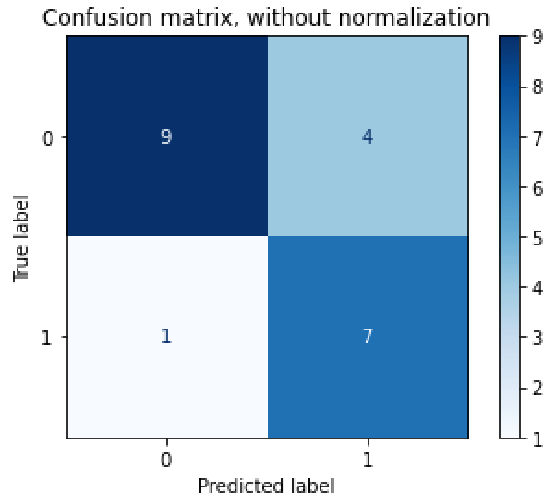

Figure 8. Confusion matrix of linear SVM for channel-T4 (Actual).

The confusion matrix of Fig. 7 illustrates that linear SVM predicted the schizophrenic patient and healthy people 100% accurately. There is no misclassification. Therefore, among 21 test data, there are 8 people who have schizophrenia and 13 normal people who are detected accordingly. Fig. 8 illustrates that LSVM predicted the specimen as 31% schizophrenic and 69% healthy people. Therefore, among 21 test data, it misclassified 4 healthy people as schizophrenia patient and 1 schizophrenic patient as healthy people. The ROC curve for F3 channel for linear SVM is shown in Fig. 9 as an example. Similarly, The ROC curve for T4 channel for LSVM is shown in Fig. 10. Both the ROCs conform the confusion matrices.

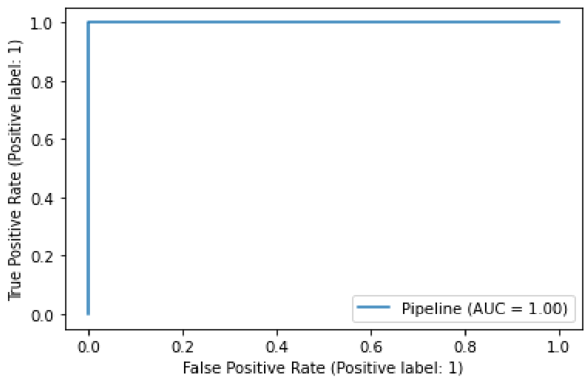

Figure 9. ROC curve for LSVM (Channel-F3)

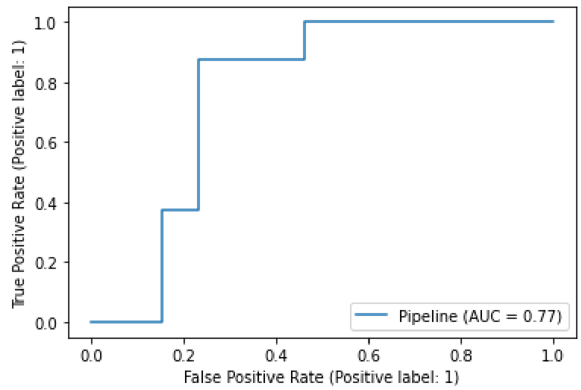

Figure 10. ROC curve for LSVM model (Channel-T4).

The LPF-TVD method was used to denoise the raw EEG signal which improved SNR in the denoised signals. Initially, it was a challenge to remove sparse derivative noise and high frequency noise from recorded EEG. However, tuning the parameters of LPF and TVD, an appropriate model was established. The artifacts due to EMG, EOG etc. may disturb EEG [24]. These noises were removed with LP filter in LPF-TVD method. The filter order was chosen to 1 and the cut off frequency is 20 Hz. As already discussed, that EEG is a non-stationary signal and that is why it may contain sparse noise. The TVD method truncated those sparse data from EEG. As a consequence, a smoother EEG was found after processing it with LPF-TVD method. For Fig. 4, the SNR was found to be 6.104 for raw signal and 7.63 for denoised signal. In case of healthy people, the SNR of noisy signal was obtained to be 8.95 while after treating with LPF-TVD, it was increased to 12.03. The higher the SNR, the better the performance of LPF-TVD method in removing noise from signal [25]. Therefore, it can be implied that almost 25% - 35% SNR was improved due to the application of LPF-TVD method.

Among the several wavelet transform methods, DTCWT exhibits some superiorities. For instance, continuous and discrete wavelet transform are suffered from shift variance problem. The DWT method generates wavelet from input signal by scaling and shifting the mother function. As a result, it offers higher degree shift invariance and better selectivity. Considering these advantages of dual tree complex wavelet transform, the filtered EEG signal was decomposed by DTCWT. The coefficients obtained from the two trees of level 2, 3 and 4 were plotted to get the waveform of beta, alpha, theta and delta respectively. Applying DTCWT for segmentation of EEG in MATLAB 2015b software was slightly time consuming. However, the process was much faster in MATLAB 2021 versions.

Obtaining coefficients from beta, alpha, theta and delta sub-bands, features were calculated. The features used for classification were mean, median, standard deviation, energy and kurtosis. Before applying these features into machine learning algorithm, the whole dataset (82 x 20) was split into training set and test set. 25% data was set as testing set that is, 21 patients were subjected to prediction. All of 16 channels underwent the process of classification. For each channel, linear SVM and Random Forest classifier models were developed.

Linear SVM model classified 9 channels with accuracy and F1 score more than 90%. While considering test accuracy ≥ 95%, F7, F3, C3, CZ, P3 and Pz channels were classified accurately by LSVM. Except channel F7, rest 5 channels were classified 100% accurately by LSVM. In addition, for these 5 channels, precision and recall were also 100%. While the confusion matrix and ROC is observed for F7 channel, linear SVM predicted the schizophrenic patient 100% accurately while it misclassified one healthy person as a schizophrenic one. Besides, it classified 12 healthy people correctly among 13 people which is shown in normalized confusion matrix as 0.92 or 92%. However, in case of F3, C3, CZ, P3 and Pz channels, no misclassification was occurred by the LSVM model. On the other hand, Random Forest classifier was able to identify schizophrenia most accurately from 11 channels among 16 with almost 91% test accuracy. For more than 95% test accuracy and 90% F1 scores, this model could predict accurately for 8 channels which were F7, F3, C3, CZ, P3, Pz, O1 and O2. Among them, it classified 7 channels except F7 with 100% accuracy, precision, recall and F1 score.

While comparing the performances among the channels, it has been observed that the classifier models could classify the data with 100% accuracy from electrodes on parietal, temporal and central lobes into schizophrenic and healthy controls. The precision, sensitivity, F1 score and test accuracy of channel F3, T3, C3, Cz, P3, Pz, O1 and O2 were found to be 100%. Fig. 11 illustrates the 12 channels as marked black which have test accuracy more than 95% and F1 scores more than 90%, while the checkered channels (T6, T4, F8 and P4) demonstrate poor schizophrenia detections.

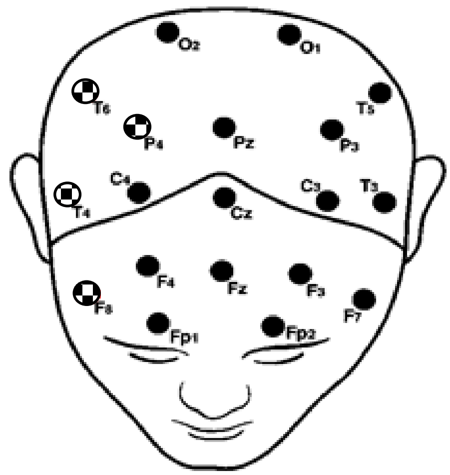

Figure 11. Summary of ML classifiers on EEG channels. Worst performances were obtained in channels T6, T4, F8 and P4.

According to Fig. 11, the 4 electrodes on right hemisphere have the poorer performances. The test accuracy of these channels was less than 90%. Moreover, the highest F1 score of these channels was found 0.92 for healthy subjects while it was 0.89 for schizophrenic ones. Though the precision for healthy subjects of these channels were 1, the value falls to 0.8 or less in case of schizophrenia. The left hemisphere of cerebral cortex is more active for language and handedness. While any person is diagnosed with schizophrenia, his/her behavior, thoughts etc. get affected due to structural and functional change in brain. This may cause reduction of lateralization of language to the left hemisphere of brain. Besides, with the progress of the disease, the anomalies in left-hemisphere might be dominant. Therefore, the classifiers were able to identify schizophrenia from the electrodes of left hemisphere more accurately than some electrodes of the right hemisphere.

Discussion

Schizophrenia is a complex mental disorder which can be diagnosed manually by interviewing the patient. To some extent, this process is not 100% effective. Moreover, it is time consuming and sometimes the patient may not want to cooperate the healthcare instructor. Regarding these situations, many researchers are trying to develop computer-based tools that can easily detect schizophrenia automatically from fMRI, SPET, PET or EEG.

In this study, a proposal was made based on detecting schizophrenia from EEG using DTCWT and ML algorithms. By implementing the proposed method, the problems with manual diagnosis mentioned above can be solved. As schizophrenia can be detected unsupervised with this method within a very short period of time, real time monitoring is also possible. Consequently, people living in rural areas or deprived of adequate healthcare professionals can be benefitted through the outcome of this research.

The EEG sub-bands were extracted using DTCWT. As the proposed method consists of real and imaginary trees, the problem of shift variance found in another wavelet transform was overcome here. The coefficients found from the segmentation are used for features calculations. Five distinguishable features for each sub-band i.e., mean, median, standard deviation, energy and kurtosis were selected for further process. The proposed method to work, EEG signals need to be denoised initially. The EEG signals were free from low frequency and sparse noise due to the application of LPF-TVD filtering. However, discontinuities or spikes in EEG signals sometimes spreads out over the entire frequency range which causes the removal of peaks despite of its being in the range of cut-off frequency due to the application of TVD. As a consequence, it may introduce minor artifacts in the signal.

Implementation of linear SVM and Random Forest Classifier classified schizophrenia from healthy control. Based on the test accuracy, precision, sensitivity, F1 score, confusion matrix, ROC and AUC; the classifiers accurately detected schizophrenia from EEG Channels F7, F3, F4, T3, C3, Cz, C4, T5, P3, Pz, O1 and O2 with test accuracy more than 95%. However, the dataset was relatively small to reap the greater benefits using ML algorithm. Additionally, numbers of features were kept small to avoid over-fitting due to small dataset. More statistical features can be implemented in future while real-time large dataset will be used to detect schizophrenia. Furthermore, the proposed method is applicable for binary classification only. Based on the findings, the logical sequence of this research will be to collect primary data in clinical setup so that the model can be employed to larger dataset and tested for better output.

References

1. Heaton, R. K., Gladsjo, J. A., Palmer, B. W., Kuck, J., Marcotte, T. D., & Jeste, D. V., *Stability and course of neuropsychological deficits in schizophrenia*. Archives of general psychiatry, 58(1): 24–32, 2001. https://doi.org/10.1001/archpsyc.58.1.24.

2. EEG Test to Help Understand and Treat Schizophrenia, UC San Diego Health. [https://health.ucsd.edu/news/releases/pages/2014-10-29-eeg-to-understand-treat-schizophrenia.aspx]. Accessed on April 15, 2021

3. Koenig, T., Lehmann, D., Saito, N., Kuginuki, T., Kinoshita, T., & Koukkou, M., *Decreased functional connectivity of EEG theta-frequency activity in first-episode, neuroleptic-naïve patients with schizophrenia: preliminary results*. Schizophrenia research, 50(1-2): 55–60, 2001. https://doi.org/10.1016/s0920-9964(00)00154-7.

4. Geya, A., *Forecasting Generalized Epileptic Seizures from the EEG Signal by Wavelet Analysis and Dynamic Unsupervised Fuzzy Clustering*. IEEE Transactions of Medical Engineering, 45(10): 1205–1216, 1998.

5. Shim, M., Hwang, H. J., Kim, D. W., Lee, S. H., & Im, C. H., *Machine-learning-based diagnosis of schizophrenia using combined sensor-level and source-level EEG features*. Schizophrenia research, 176(2-3): 314–319, 2016. https://doi.org/10.1016/j.schres.2016.05.007.

6. Squarcina, L., *Classification of first-episode psychosis in a large cohort of patients using support vector machine and multiple kernel learning techniques,* Neuroimage, 145: 238–245, 2017.

7. Krishnan, P., *et al.*, *Schizophrenia detection using Multivariate Empirical Mode Decomposition and Entropy Measures from Multichannel EEG signal.* Biocybernetics and Biomedical Engineering, 40(3): 1124-1139, 2020. https://doi.org/10.1016/j.bbe.2020.05.008.

8. Oh, J., Oh, B. L., Lee, K. U., Chae, J. H., & Yun, K., *Identifying Schizophrenia Using Structural MRI With a Deep Learning Algorithm.* Frontiers in psychiatry, 11: 16, 2020. https://doi.org/10.3389/fpsyt.2020.00016.

9. Wang, B. *et al.*, *Comparison of different classification methods for EEG-based brain computer interfaces: A case study.* International Conference on Information and Automation. pp. 1416-1421, 2009. https://doi.org/10.1109/ICINFA.2009.5205138.

10. EEG of healthy adolescents and adolescents with symptoms of schizophrenia. Laboratory for Neurophysiology and Neuro-Computer Interfaces, Lomonosov Moscow State University. [http://brain.bio.msu.ru/eeg_schizophrenia.htm]. Accessed on January 10, 2021.

11. Selesnick, I.W. *et al.*, *Simultaneous low-pass filtering and total variation denoising.* IEEE Transactions on Signal Processing, vol. 62, no. 5, pp. 1109– 1124, 2014.

12. Combettes, L. *et al.*, *Proximal thresholding algorithm for minimization over orthonormal bases.* SIAM J. on Optimization, 18(4):1351–1376, 2008.

13. Esser, E., *et al.*, *A general framework for a class of first order primal-dual algorithms for convex optimization in imaging science.* SIAM J. Imag. Sci., 3(4):1015–1046, 2010.

14. Figueiredo, M., *et al., Majorization minimization algorithms for wavelet-based image restoration.* IEEE Trans. Image Process, 16(12):2980–2991, 2007.

15. Ray, S.,*et al., Approximation of ECG Signals using Chebyshev Polynomials.* International Conference on Inventive Research in Computing Applications (ICIRCA), 2018.

16. John, T. N., *et al., Analysis of long range dependence in the EEG signals of Alzheimer patients*. Cognitive Neurodynamics, p-17, 2018.

17. Zhu, J., *et al., Classification of EEG Signals Using Wavelet Coefficients and an ANN*. 10th Pan Pacific Workshop on Brain Electric and Magnetic Topography, Sydney, Australia. 1994.

18. Chen, D., *et al., A high-performance seizure detection algorithm based on Discrete Wavelet Transform (DWT) and EEG*. PLoS ONE 12(3 e0173138), 2017.

19. Selesnick, W. I., *et al., The dual-tree complex wavelet transform.* IEEE Signal Process Mag, 22(6): 123–151, 2005.

20. Figueiredo, M., *Majorization minimization algorithms for wavelet-based image restoration*. IEEE Trans. Image Process, 16(12):2980–2991, 2007.

21. Omerhodzic, I., Avdakovic, S., Nuhanovic, A., Dizdarevic, K., & Rotim, K., *Energy Distribution of EEG Signal Components by Wavelet Transform.* In (Ed.), Wavelet Transforms and Their Recent Applications in Biology and Geoscience. IntechOpen, 2012. https://doi.org/10.5772/37914.

22. Ben, S. I., *et al., EEG epileptic seizure detection and classification based on dual-tree complex wavelet transform and machine learning algorithms*. Journal of Biomedical Research, 34(3): 151-161, 2020.

23. Bruno, A., *et al., Automatic EEG Processing for the Early Diagnosis of Traumatic Brain Injury*. Procedia Computer Science, Volume 96, Pages 703-712, ISSN 1877-0509, 2016.

24. Kumar, A., *et al., Low Frequency Noise Remove from EEG Signal*. International Journal of Recent Technology and Engineering, (IJRTE) ISSN: 2277-3878, Volume-9 Issue-1, 2020.

25. Tripathi, P., *Artefact Removal from EEG Signals using Total Variation De-noising.* International Journal of Innovative Technology and Exploring Engineering (IJITEE), ISSN: 2278-3075, Volume-9, 2020.