International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 04 Issue: 06 | June -2020 ISSN: 2582-3930

DETECTION OF EPILEPTIC SEIZURE BASED ON EEG SIGNALS USING ENSEMBLE AND LSTM APPROACH

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Abstract
Epileptic seizures are a neurological disorder which consists of immoderate and activities recurring at particular period in the brain. Clinically, diagnosing by skilful clinicians according to EEG, which is time consumption even for doctors. Therefore, the paper proposes a detection program by the major phases for performance of epileptic seizure detection and follows signal preprocessing, feature extraction and classification. EEG signals are divided into certain time and frequency features are drawn out away from one and all epoch. On the layout to assess the proposed method in which experiments are carried on publicly obtainable EEG dataset (CHB-MIT). The proposed scheme benefit from the EEG signals for enhancement by PCA and extracted discriminative feature used to name the onsets of seizure. Ensemble classifiers are used to make additional accurate solutions than single model would. The LSTM model makes use of a broad field of features extracted preceded the classification, as well as time-frequency features. The experimental outcome shows that the task of the method is competitive also performs better than some other futuristic of seizure detection on standard EEG dataset.
Keywords*: Seizure detection, multi-domain feature, principle component analysis, Ensemble classifier, long-short term memory.*

1. Introduction

Epilepsy is known to be nervous disorder diseases. To identify epilepsy, most famous testing tool as EEG signal are used, because of its painless, non-intrusive tool for examining multiplex manners and for supervising separate physiological circumstances of the brain. EEG is referred to be graphical data for proceeding activities of the brain between different electrodes. In this aspect, signal enhancements like principal component analysis are used largely for decreasing the proportionality and signal are enhanced by the application such as common spatial patterns which are explored less in number on detection. There are small group of factors that exert influence on a behaviors which involved in the feature area and the availability of imbalanced labels as well as an efficient method are the main concept to design an accurate feature extraction technique as well as quality of feature set make a role on classification. LSTM networks entrenched on detection of seizure and its algorithms are enlarged by utilizing EEG datasets.

The contributions of the recommended methods are,

I. Feature extraction based on time as well as frequency domain features.

II. The output is classified by LSTM and Ensemble classifier.

2. Related work

Recently so many researchers aimed on feature extraction namely statistical, wavelet as well as fractal dimension for detection from EEG datasets and then be fused with various classifiers such as bi-spectral phase concurrence index (BSPCI) [1], artificial neural network [9], and Q-Tuned wavelet transform [3]. In EEG database, the benefits of the wavelet transform are outlined in [2] to decompose EEG signal into five frequency wavelets and to achieve overall sensitivity of 91.03%. To developed a patient-non-specific method [6] for seizure detection depending on Undecimated Wavelet Transform and also for the mean values of parameters. It established for similar accuracies in detection by making use of ELM classifier [4] with set up of nonlinear features namely entropy as well as Hurst exponent. Basing on the above mentioned observation, for EEG, the paper explored a latest feature extraction method that use multi- domain for extracting multiple channel EEG datasets and also combined with RF classifier [8]. EEG datasets are used to focus on varies algorithm for detection by an automated soft computing system. It evaluated the performance of three ensemble methods, namely, bagging [5], boosting [10], and random subspace ensembles [7].The paper is sorted in order as: in Section II explained about the methodology used which deals with signal preprocessing, feature extraction and classification methods. Section III provided experimental results. Section IV, Conclusion of this paper.

3. Methodology

In this paper, EEG data's are examined by wavelet remodel to decompose the signal to produce five functional EEG bands, delta (0-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-60 Hz). Then features were taken out over both signal decomposed as well as raw data.

3.1. Dataset

The dataset in this work taken from database recorded in CHB-MIT which has be made up of brains scalp activities from different subjects with varies seizures. Thus all the signals are recorded of sampling rate and resolution of 16-bit in 23 patients which has males and females aged in-between of 3 to 26 years old and placed in order of 10-20 placement system. In entire dataset consists of 18 channels across all 23 cases including: F1-F7, F7-T3, T3-P6, P6-O2, FP1-F3, F3-C3, C3-P3, P3-O1, FP1-F4, F4-C7, C7-P6, P6-O2, FP2-F7, F7-T5, T5-P7, P7-O2, FZ-CZ and CZ-PZ. The proposed diagram is illustrated on Figure 1. More information about the specific EEG dataset is shown in Table 1.

3.2. Signal Enhancement

In this paper, the data dimensionality are reduced using PCA method and then CSP approach are used to have a largely variance in many classes. Instinctively, PCA are acted as the direct execution on CSP in which the main motive to transform a signal into separate one class of variance signals which are maximized and minimized via.

3.3. Feature Extraction

This process is set up for decreasing the dimension and for improves accuracy. Thus, features are categorized in two separate methods namely time and feature domain features and they are explained on subheading:

3.3.1. Time domain features

These extractions are stepped on two major parts. One as statistical features and other as correlation coefficients. A statistical feature in every channel adds up kurtosis and skewness. Correlation coefficients which calculate Eigen values on this work.

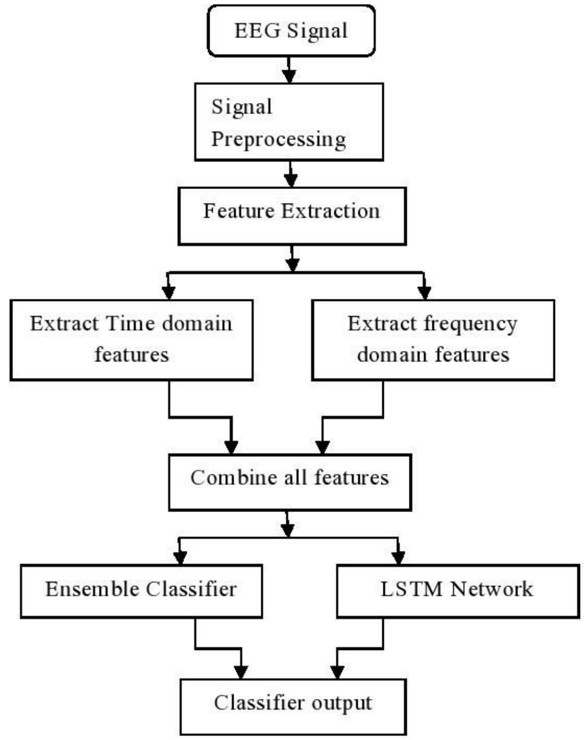

Figure 1: Block diagram of proposed approach.

3.3.2. Frequency domain features

Not only time domain features are used for detection purpose due the EEG dataset has non stationary properties. Therefore, frequency domains are used for extracting the synchronization character of entire amplitude from each epoch data for performing wavelet transform algorithm.

3.4 Classification based on Ensemble and LSTM

3.4.1 Ensemble Classifier

Many weak classifier are combined on their particular results as it help to improve the working performance on weaken classifiers to enrich this three major methods are used, namely bagging, boosting and gradient boosting.

Bagging: The bootstrap aggregating- N train samples are selected to sample the trained data signal on individual dataset are replacement from the original dataset for prediction of test sample in most common voting process in the bootstrap sampling technique and accuracy are improved.

AdaBoost algorithm: The trained signals in each classifier are constructed for measuring weight of the each sample. During this the sample classifier, correct and misclassifies are decreased and increased respectively. Finally, adaboost ensemble method is used to combining the separate classifiers based on their specific accuracies

Table 1:
CHB-MIT EEG signal dataset are sorted out. Gender: Male (M) Female (F)

Case	Gender	Age	Number of event	Duration (hr)
1	M	12	9	43
2	F	9	3	36
3	F	16	8	39
4	M	13	5	23
5	F	18	6	40
6	M	5.5	10	66
7	F	22.5	3	67
8	M	11.5	5	21
9	M	20	4	67
10	F	7	7	50
11	M	17	3	34
12	F	22	2	20
13	M	19	27	33
14	M	14	8	26
15	F	14	20	40
16	M	4	10	19
17	M	21	3	21
18	F	10	6	35
19	F	18	3	29
20	F	8	8	27
21	M	15	4	32
22	M	5	3	31
23	F	3	7	26
24	-	-	17	21
Total			181	

3.4.2 LSTM (Long Short-Term Memory) Network

For seizure prediction the Multi-task learning are framed based on Long Short-Term memory (LSTM) network. This framework is used for prediction as well as latency regression concomitantly. Main reason for approaching this deep learning method is that required few amount of samples are taken to train number of parameters and for testing the various layers of units in datasets. This method increase the prediction results in two major layers selected for classification method. LSTM are explored on combined features of both time and frequency domain features among cross correlation.

4. Results

This Work assesses the detection of entire seizure events for further medical operation purpose. Fast diagnosis gives an addition advantage on better curing of epilepsy diseases. The results in Figure 2 show signal frequency decomposition to five functional EEG Bands namely, delta, theta, alpha, beta and gamma.

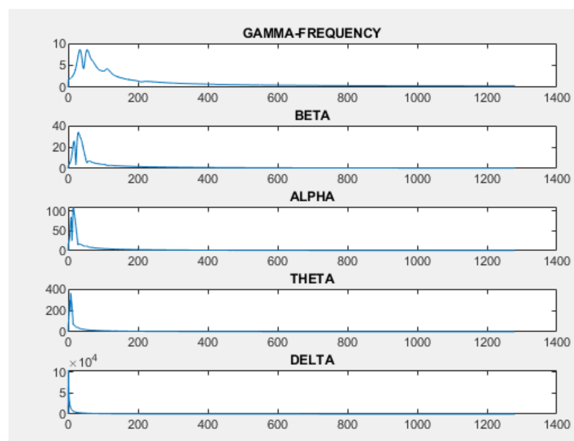

Figure 2: Wavelet decomposition

Figure 3 shows EEG signal are basically in non-stationary natures. Therefore, for examining the both time and frequency in wavelet transform and number of decomposition levels.

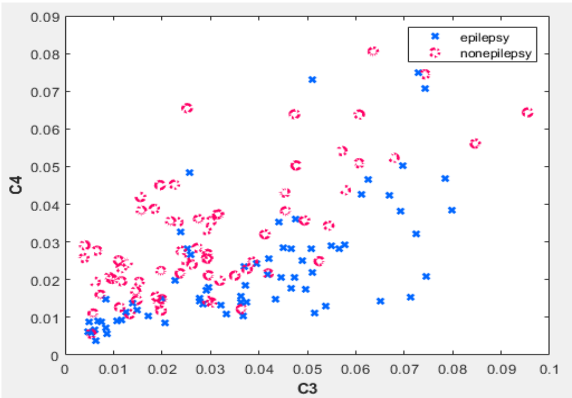

Figure 3: Wavelet transform extraction

PCA are used as a signal enhancement process and reduce dimensionality of EEG signals as well as SNR (Figure 4).

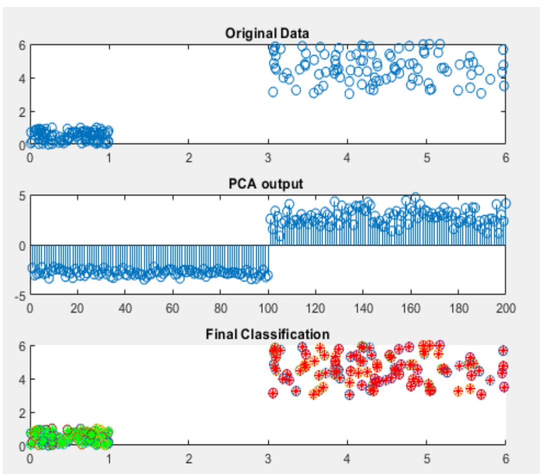

Figure 4: Principle Component Analysis (PCA).

Every sample in the time series are taken and plotted in the excursion for one channel, at which the data has higher variance in one channel than other in Figure 5.

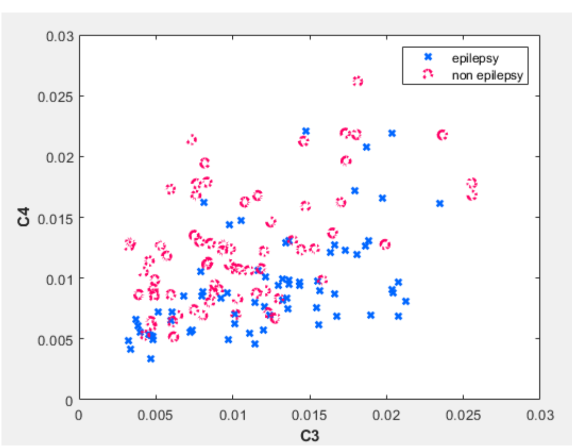

Figure 5: Common Spatial Pattern (CSP)

Kurtosis and Skewness features are statistical measure used to explain the distribution of observed data around the mean. Figure 6 shows the data becomes more symmetrical as its value approaches zero

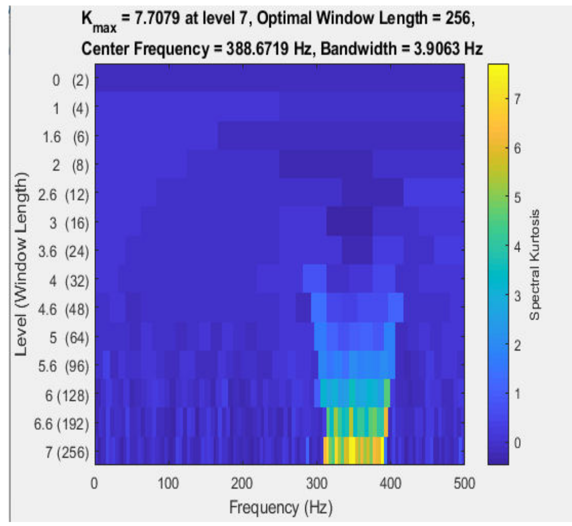

Figure 6: Kurtosis and skewness features

In Figure 7, Ensemble learning for EEG signal classification is effective, though different ensemble methods in Figure 7.a shows a adaboost ensemble classifier makes a new prediction by adding up of weight multiply with have more power of influence the final decision., in Figure 7.b shows a gradient boosting to make a new classification by adding up of all samples and in Figure 7.c displays a bagging function which have a training features of random subset of data.

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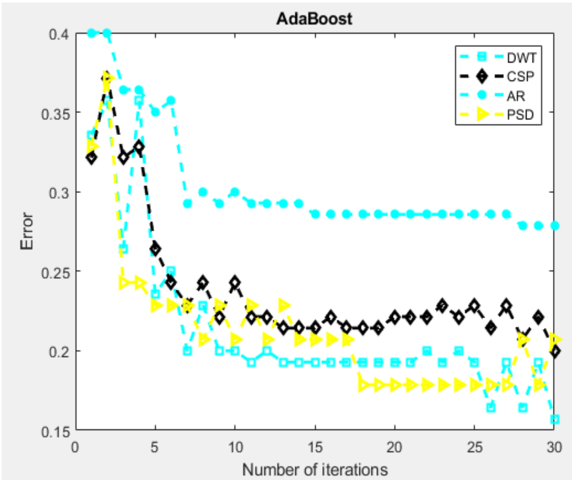

Figure 7.a: Adaboost Ensemble method

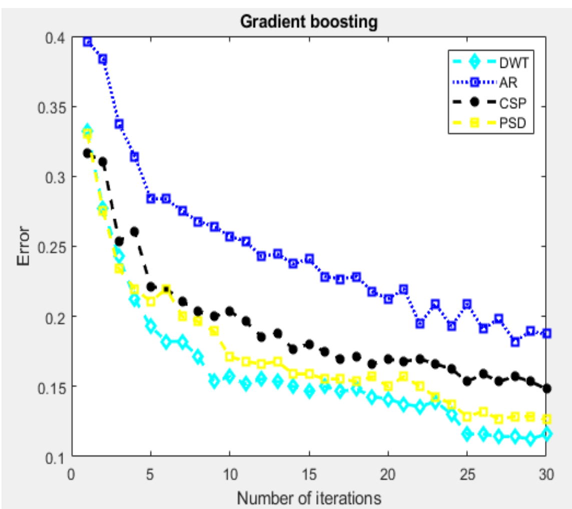

Figure 7.b: Gradient boosting Ensemble Classifier

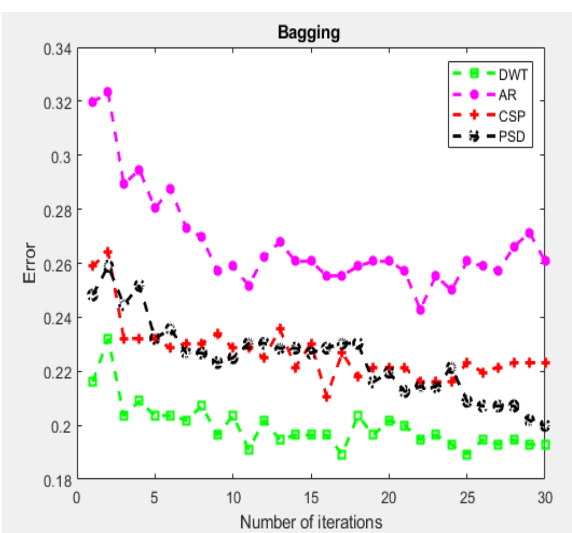

Figure 7.C: Bagging Ensemble Method

LSTM networks are entrenched in epileptic seizure forecast in Figure 8 the output by LSTM and Ensemble classifiers are combined. Lastly, on this paper the parameters are compared with present and previous papers based on same datasets. As it has been summarized in Table 2.

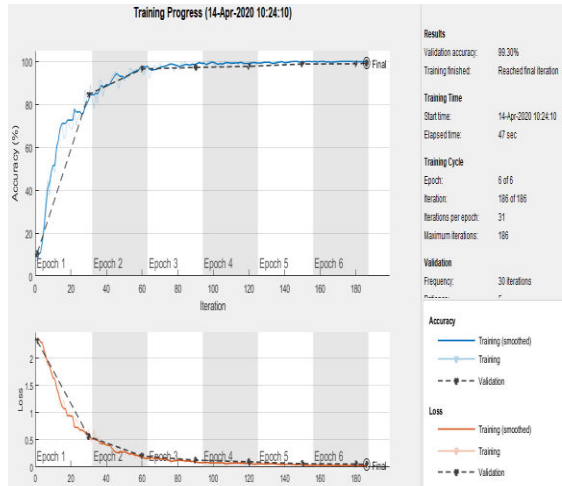

Figure 8: LSTM Network.

Table 2: Subject-to-subject classification results for dataset.

PATIENT ID	CLASSIFICATION PERFORMANCE MEASURE (%)		
	Sensitivity	**Specificity**	**Accuracy**
Id 01	91.23	98.43	99.23
Id 02	98.43	99.83	99.59
Id 03	92.63	99.26	99.20
Id 04	94.63	96.43	99.76
Id 05	99.57	98.97	99.61
Overall	98.63	98.48	99.44

5. Conclusion

This paper introduced ensemble and deep learning approach for detection of epileptic seizure based on EEG signal. We proposed framework are filled with signal decompose followed by features of time and frequency domain and finally classified by ensemble and LSTM.

A new method, LSTM is referred as a multi-task learning method is used to improve accuracies. For the better performances, the proposed method used to improve the accuracy, specificity, sensitivity. The obtained results are the comparison of best classifier with other pervious literature in terms of classification accuracy despite working on raw EEG signals.

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