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Deep learning method to reduce time complexity to analyses the brain wave signals

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Abstract –

Human brain continuously generates electrical signals or impulses. When there is change occur in electrically functioning of brain, temporary change in behaviour can be seen, this alteration of behaviour is known as seizure. If seizure happened very commonly or repeatedly that will define as epileptic. This epileptic seizure can be identified by multiple artificial methods but in most of the methods time complexity is a major concern and to reduce the time complexity, huge amount of data sets are needed. In this article we discuss Frequency Band Based Epileptic Seizure Detection method. In this to improve performance and time reduction, very tiny signals of brain wave are analyzed.

Keywords: electrical signals, seizure, Epileptic Seizure Detection, time complexity.

1. Introduction

Epileptic seizure is a transient event of signs or manifestations because of anomalous excessive or synchronous neuronal movement in the brain. Electroencephalogram (EEG) signals plays significant role in finding disorders like epilepsy. These signals are used to record the operation by the electric device electros which placed on the scalp of the brain. Different types of brain disorders can be examined by these signals. Epilepsy is the one of the most common disorders found out nearly among 50 million people around the world. This neurological disorder causes sudden seizure and it is a tedious task for the doctors to find out manually.

Various detection methods have been proposed by the researchers by the use of automated systems in machine learning and deep learning classification methods. K-nearest neighbor, naïve bayes, random forest, support vector machine, decision tree, etc. are the machine learning classification methods that applied in previous studies. In these methods, plenty of data is required for training process. It takes longer time for running and correcting the errors. The process of large amount of data takes huge time to improve the performance and predictions. Features are extracted manually in machine learning approach and the human intelligence is required to analyze the results. It is a tedious task to evaluate the performance of all algorithms in machine learning and choosing the best one with better accuracy. Hence development of new features canbe done by the deep learning algorithms automatically, and produce the results directly. There are different categories of unstructured data such as images, texts, signals, etc. can be handled by the deep learning methods. It automatically learns the data, and extracts the features quickly. When the correct data is given to solve the particular problem, it performs repetitively more routines, and gives the best results in minimal time. It detects the labeling problem of training. Signal recognition performed precisely by deep learning methodsby finding most significant learning techniques by finding most significant features and difference between them. In the earlier methods long signal was partitioned into smaller and high peak features was extracted for classification with machine learning. That will also be used here with additional frequency band analysis with deep learning all peak signal values i.e. feature selection is performed for epilepsy detection. In this article, Frequency Band Based Epileptic Seizure Detection (FBESD) is discussed to detect epileptic seizure based on the frequency band of peak signal sequence after horizontal and vertical segmentation is discover theminute differences by analyzing the frequency band of EEG signals at the alpha, beta, theta and delta level because at gamma level abnormality can be easily found out on the high peak signal range above 30 Hz. This feature selection method and frequency band analysis increases the efficiency of detection with reduced time complexity.

2. Related Works

The apparent discrepancy for seizure detection is marginal for EEG signal classification, making it difficult to detect epileptic seizures [1]. As a result, information on EEG feature extraction using the time-frequency wavelet transform [2]. Yong Zhang et al., [3] suggested an auto regressive (AR) method with sample entropy and the extracted features were fed into support vector machine for classification. Further improvement will have to be made on class imbalancing. Farhan Riaz et al., [5] proposed feature extraction method called Empirical mode decomposition (EMI) and gathered output as Intrinsic mode functions (IMF). Finally, the extracted features are classified using Support Vector Machine (SVM). Further improvements have to be made by extracting another different set of features. In [5], the D&F method was used to create a bridge between EEG data and an epileptic seizure detection model, resulting in a neural mass model. Machine Learning (ML) research in epileptic seizures, on the other hand, is showing an interest in both feature extraction and classification. With a sensitivity of 73 percent and a specificity of 67 percent, the KNN classifier was used to predict epileptic seizures. [6] Naive Bayes (NB) performed worse than KNN, Support Vector Machine (SVM), and Back propagation [7].

Sunil kumar et al., [8] performed comparison between features which were extracted by code-convertor with measurement of City-Block Distance (CBD) and Euclidean Distance (ED). In order to find out the risk level of detection of epilepsy, they used the features like sharp waves, peaks, etc. The output was evaluated with performance Index (PI) and Quality Value (QV). Asrul Adam et al., [9] used angle modulated simulated kalman filter (AMSKF) for selecting the best features from the combined existing features and Neural Network with random weights (NNRW) method is used for classification. Sasweta pattnaik et al., [10] used Discrete Wavelet Transform (DWT) for feature extraction and the extracted features were fed into Artificial Neural Network (ANN).

Yizhang Jiang et al., [11] proposed TL-SSL-TSK, S-TL-SSL-TSK and A- TL-SSL-TSK models which produced efficient classification but most expensive which needs to be reduced. Ozan kocadagli and Reza langari [12] developed reliable frame work with the dimensionality reduction fed into ANN and decomposition was made by DWT. Further improvement will be needed on this experiment with the help of neurologist.

Asrul Adam et al., [13] improved their work with eye event based applications. Feature weight learning (FWL) combined with optimization methods and extracted features put into four best models like Dumpala, Acir, Liu and Dingle. They concluded with Dingle displayed best accuracy as 74% among four models. Badaruddin Muhammad et al., [14] used BSKF (Binary Simulated Kalman Filter) and AMSKF (Angle Modulated

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Simulated Kalman Filter) methods and found out BSKF results were more accurate thanthe AMSKF in feature selection process of peak area of EEG signal.

3. Methodology

The electroencephalogram (EEG) is a unique noninvasive and moderately reasonable method used to screen the condition of the brain. The input EEG signal is directly fed into the deep learning algorithms like Auto Encoder, Stacked Auto Encoder, CNN, LSTM and BiLSTM to classify whether the signal is normal or abnormal. The same input EEG signal is segmented as Horizontal and vertical segmentation with high and low peak values and its extracted features were classified using machine learning algorithms.

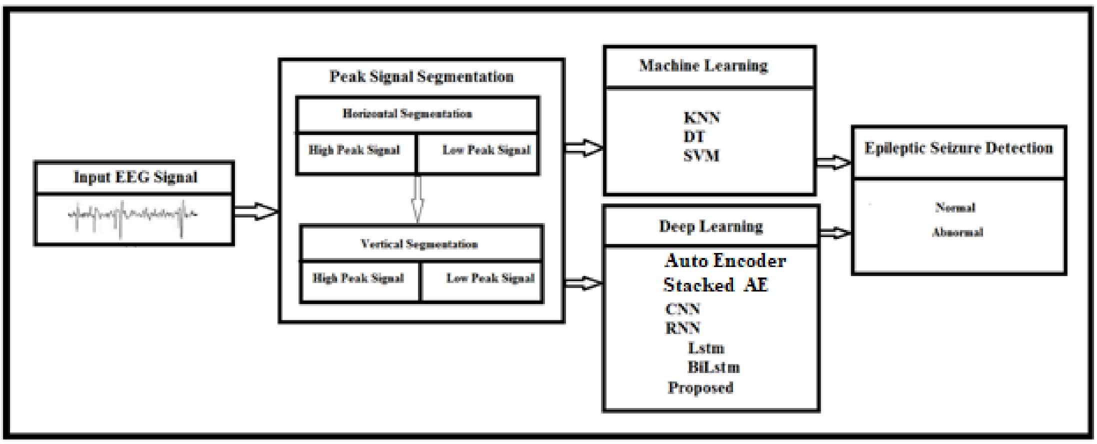

Fig.1. Overall Architecture

The overall Architecture is shown in figure 1, the features Selection is performed on the peak area of the signal and it is fed as an input to Auto Encoder, Stacker Auto Encoder, CNN, LSTM and BiLSTM methods and the BiLSTM performs better so it is chosen for the Frequency Based Epileptic Seizure Detection (FBESD) method is included as the segmented peak signal sequence values are further classified by Deep Learning algorithms with the help of frequency band range of EEG signals with features selection from the EEG signal.

3.1 Horizontal Segmentation

After the horizontal segmentation, high and low peak values are selected based on the adaptive thresholdvalue. The values above the threshold up to the maximum values are high peak values and likewise the low peak values are also selected. The use of this process long signal is breakdown into smaller divisions for deeper scrutiny.

3.2 Vertical Segmentation

After that the signal is divided into four vertical segments and it contains one feature each and it is collected using entropy for machine learning classification.

3.3 Frequency Band Based

Hence the above is further split based on the frequency of the given signal. The frequency range of 4-8 is Theta, 8-13 is Alpha, 13-30 is Beta and 30 and above is Gamma respectively.

The following figure 2 depicts the block diagram of the FBESD method. It clearly shows how the EEG signal is fed into the deep learning algorithm that includes signal sequence values after segmentation.

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In this FBESD methodology, depiction of brain electrical processing contains different frequencies and shape of the signal waves of EEG are alpha (Awake), beta (Drugs), theta (sleep) and delta (Deep Sleep) which is used to find the abnormality in it. These four categories of EEG signals frequencies are used to discover the abnormality more clearly. These optimized values of signals are fed as an input for further classification which will improve the efficiency by analyze small variations of the signals of the epilepsy detection and the prediction accuracy rate with minimum timing.

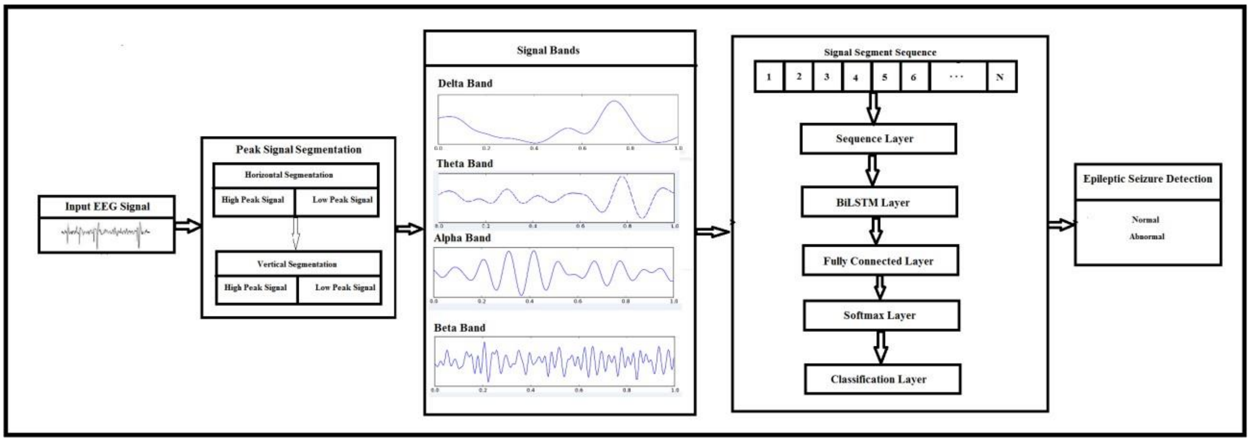

Fig.2. Block diagram of FBESD method

4. Result

The test investigation is done with the Bonn University Dataset where the EEG time series were collected. The dataset contains 200 segments of normal and 300 segments of abnormal subjects of five healthy and five epileptic patients' signals. Normal dataset cases were named as A and B with eyes open and closed respectively. Abnormal dataset cases were named as C and D which were recorded before surgery. At time of epileptic seizure, recordings were named as E. Table-1 shows the result of Deep learning algorithms for the datasets taken. Here EEG signals fed directly as raw signals. The result shows that BiLSTM gives better results than other algorithms, thus it is applied for FBESD method. The following Table-1 shows Recognition Accuracy and F-Measure of CNN, LSTM, BiLSTM and FBESD method with error rate.

Table 1. Overall Performance of CNN, LSTM, BiLSTM and FBESD

Measurement	CNN	LSTM	BiLSTM	FBESD
RA %	96.01	96.50	96.90	**97.88**
FM %	97.71	98.12	98.20	**99.01**
ER	0.037	0.035	0.031	**0.026**

5. Conclusion

Epilepsy is one of the most widely recognized neurological conditions and one of the most un-comprehended disorders. The seizures that portray epilepsy are every now and again unannounced and influence a victim's personal life, just as expanding the danger of injury and

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causes death sometimes. The finding of epilepsy is normally made by a nervous system specialist yet can be hard to be made in the beginning phases. We have discussed about the physiological signs identified with seizure just as how to utilize these signs to monitor and identify seizures. The experimental result demonstrates the effectiveness of the FBESD approach with highest RA performance.

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