Seizure and Non-Seizure EEG Signals Detection Using 1-D Convolutional Neural Network Architecture of Deep Learning Algorithm

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***Abstract*—In this paper, seizure activities of EEG signals have been detected exploiting 1-D convolutional neural network architecture of deep learning algorithm. In past some years, many algorithms have been developed for seizure detection. Traditional method of seizure detection includes manual feature selection and classifier separately. In recent years, convolutional neural network architecture of deep learning gets very much popularity in place of traditional method.Though, very few works of convolutional neural network are found in literature for one dimensional signal classification. However, one dimensional EEG and ECG signal classifications are necessary to detect and investigate diseases like seizure activity, sleep apnea or arrhythmia and so on. The proposed method of one dimensional EEG signal classification for epileptic seizure detection involves the smallest and simplest 1-D convolutional neural network architecture for automated feature selection. The projected architecture is implemented to detect several kinds of seizure and non-seizure EEG signals and found achieving greater accuracy and sensitivity in comparison to that acquired by state-of-the-art methods involving manual feature selection and the identical EEG dataset.**

***Keywords*—Electroencephalogram (EEG), epilepsy, seizure, 1-D convolutional neural network (CNN)**

I. Introduction

There are many types of seizures. Seizure types depend on where and how they begin in the brain. Mostly they sustain from 30 seconds to two minutes. It is an emergency situation if any person is attacked by seizure and the duration is more than five minutes. Seizures are more common disease. Seizures can happen for many reasons. Among the reasons, some are person experiencing head injury, brain infection, stroke, fever and many other health problems. But still, when a person is attacked by seizure, cause cannot be defined accurately [1].

Many processes or algorithms have been used to detect seizure. As we see in traditional methods, features have to be extracted from the EEG signal. Normal Inverse Gaussian (NIG) statistical modeling parameters or higher order statistics (HOS) have been used as features for EEG signal. These features have been analyzed in Empirical Mode Decomposition (EMD) domain or in Discrete Wavelet Transform (DWT) domain. However, no specific IMF or time-frequency band has been mentioned in these works and thus increased the size of feature set and computational burden. Then classifier like SVM or ANN hve been used to detect the seizure from the normal EEG signal. These are actually lengthy process as well as time consuming method [2], [3], [4]. So, we have been motivated in this work to use Convolutinal Neural Network (CNN) scheme for detection and classification of seizure and non-seizure 1D EEG signal which will replace the above mentioned lengthy and time consuming methods with automatic feature selections.

In recent years, the deep learning with CNN architecture for automatic feature selection is gathering popularity in signal processing. This method involves fast computation as the manual feature and classification step are not done here. EEG signal has the feature of low frequency signal for long time period and the feature of high frequency for small time period. There is a kind of hierarchy among these features of EEG signal. Deep learning is also known as hierarchical learning which encodes hierarchy of features. So for EEG signal classification, we are proposing deep learning based method.

The paper is arranged as follows: we have presented in section II method description; in section III results & analysis which includes dataset description, goodness of features, performance assessment & comparison of proposed and existing methods; and in section IV conclusions.

II. Method Description

The sequence of EEG signal ranges up to 60 Hz [5]. 60 Hz above of an EEG signal are noise. The noise of EEG signal has been removed by passing the signal over a 6th order Butterworth filter. The cutoff frequency of the low pass filter has been selected 60 Hz.

In this paper, we have used convolution neural network method. This method is replacing the traditional & manually selecting feature extraction and classification steps.

CNN model automatically reads the pattern of EEG signal from the data and performs classification. On the other hand in traditional approach, at first features are extracted, major features are separated and then a classifier is used for classification. Full traditional approach is a manual process. But through CNN, the scheme is fully automated.

A CNN has three layers. One input layer, one output layer and multiple hidden layers. The CNN architecture consists of convolutional layers, maxpooling layers and fully connected layers. In these layers, unknown number of mathematical

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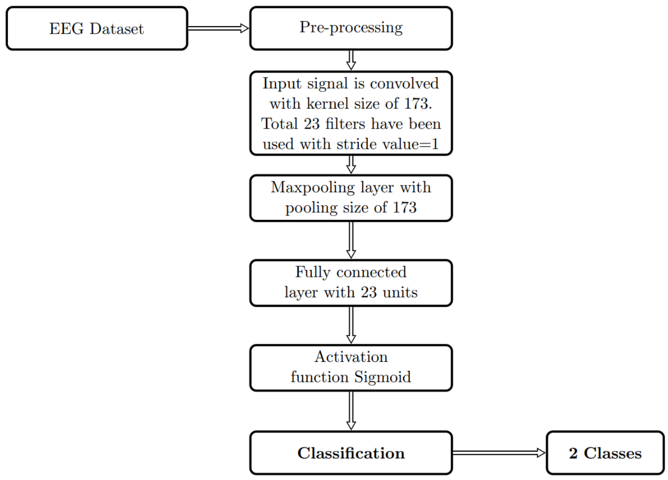

Fig. 1: The Proposed Model Architecture

operations are being performed.

CNN model is based on convolutional process. The considered data signals are seizure and the non-seizure EEG signals. Each time two different data-class has been considered for analysis of this work. The input signal is convolved with the selected kernel size 173. Total 23 numbers of filters has been considered in each analysis of 2 classes. The kernel size of 173 and 23 number of filters have been selected because the sampling rate of EEG signal is 173.61. The length of input signal is 4097 as the sampling rate is 173.61 and the each set data segments are of 23.6 seconds. After each convolution operation, the output data contains the feature map of the input signal. Here, stride is selected at 1.

Down sampling operation is performed in max pooling layer. Performing max pooling layer on the output of the convolutional layer reduces the dimension of the output neuron. Through this layer, maximum value has been selected from the output feature maps.Max pooling size is set in this work equal to the kernel size that is 173. So, this down sampling operation consequently reduces the computational intensity. After that, the output from max pooling is flattened out and the output is applied as the input for the fully connected layer (FC). FC layers are 1D vector. FC layer see the output of the previous layer.At first, fully connected layers are set to 23 which is equal to the number of filters. In the next step, FC layers are set to 2. It actually works as the classifier. This layer determines the features correlating to a particular class.

Two activation functions have been used in this paper. One is sigmoid and another is softmax. These are non linear functions. Activation functions are used as a decision maker as activation function activates or fires a neuron from the output of fully connected layer. Activation function sigmoid is used which thresholds at zero. Thus, it keeps the volume unchanged. This layer increases the nonlinear properties of the model. The methodology used in this paper is presented in Fig 1.

III. Results and Analysis

A. Dataset Description

For analyzing, we have used the EEG signal data from Bonn university seizure database [6] and proposed CNN for epileptic seizure detection. Dataset description are as follows:

Recorded data has been collected by placing 10-20 electrodes which is an internally recognized standard system. In the database, there are five data sets. The notations for five data sets are declared as A to E. The EEG signals of each set has been recorded by 128 amplifier system. The data available in each set are 100 single channels EEG segments with duration of 23.6 seconds. Set A consists of those EEG data segments which have been recorded at relaxed with awaken state and eyes open. Set B consists of those EEG data segments which have been recorded at relaxed with awaken state and eyes closed. Both A and B sets data are of five healthy volunteers. The EEG signal segment in set C, D & E have been taken from 5 seizure patients. Sets C, D and E have been taken from EEG archive of pre-surgical diagnosis. EEG signal segments in D set have been recorded from the epileptogenic zone during seizure-free intervals. On the other hand, EEG signal segments in C set have been recorded from hippocampal formation of opposite hemisphere of the brain during seizure-free intervals. E set is found solely with the recording of those EEG signal segments of the patients undergoing epilepsy .

The data acquiring process of EEG signal involves sampling rate of 173.61 Hz and 12 bit analogue-to-digital converter. From the visual examination of continuous multichannel EEG recordings, the band pass filter of 0.5340 Hz (12 dB/oct) has been used to remove the desired segments.

In this investigation, we have used all the five datasets from A to E of Bonn university seizure database. The CNN has been done using keras neural network library. We have run the code to differentiate between 2 classes of EEG signals: A-E, B-E, C-E, D-E, ABCD-E & A-C. Figure II-VI show the raw EEG signals of the above mentioned pairs which are required to be classified. It is well-understood from the figures that without extracting appropriate features, it is very difficult to differentiate the classes from the raw EEG signals.

Training set and the testing set are not definitely defined. For binary classification, randomly fifty percent of the total segments are selected for training purpose and the rest fifty percent are selected for testing purpose. Ensuring the performance of the adopted methodology and the system for each binary classification, the methodology has been run for 10-times randomly for cross checking. As a result, this step ensures the unbiased performance of the adopted methodology as the each time randomly different sets of training and testing sets have been automatically selected. Standard deviation has been calculated for each binary classification which shows the deviation of the ten sets of results.

B. Goodness of Features

The features extracted by CNN architecture have been exploited to understand the features quality by Geometrical Separability Index (GSI) and Bhattachariya Distance (BD)

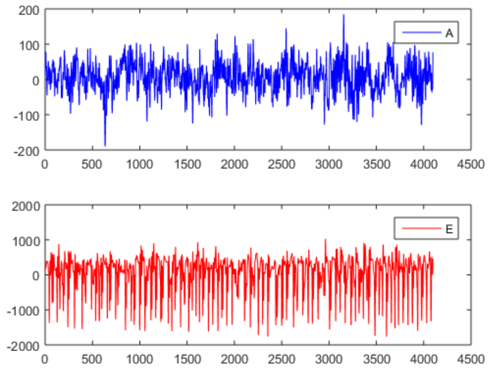

Fig. 2: Time Domain Plot of A and E Classes of EEG Signals

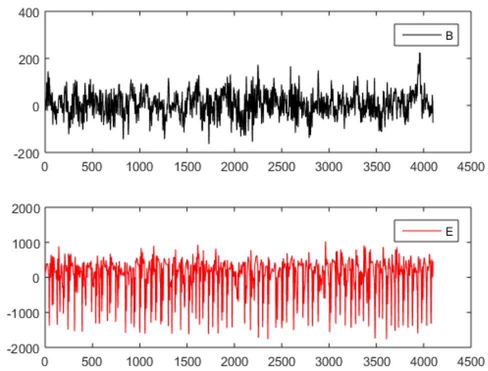

Fig. 3: Time Domain Plot of B and E Classes of EEG Signals

value [4]. GSI and BD values are two measures of inter-class distance and intra-class compactness; respectively. To which extent two classes can be distinct together in the neighboring sense is indicated by GSI value. The 0 GSI value directs two class as inseparable while the GSI value greater than 0.5 estimates two classes as detachable.
Intra-class compactness of clusters is shown by BD value. The smaller BD value postulates more compactness of the features in similar class. The GSI and BD values for mentioned all five

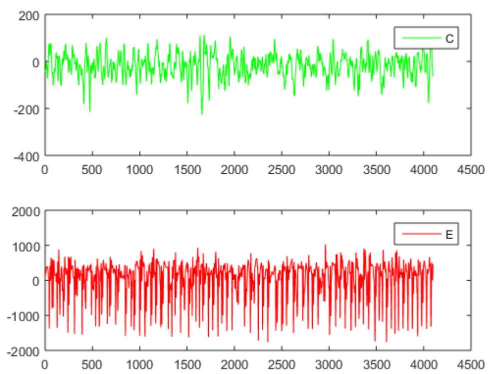

Fig. 4: Time Domain Plot of C and E Classes of EEG Signals

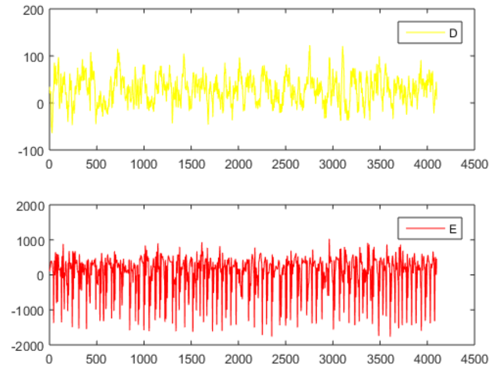

Fig. 5: Time Domain Plot of D and E Classes of EEG Signals

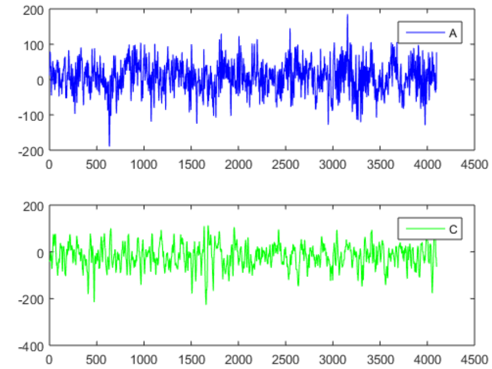

Fig. 6: Time Domain Plot of A and C Classes of EEG Signals

TABLE I: GSI VALUES OF THE PROPOSED SCHEME

Class	A	B	C	D	E
A	0.04	0.90	0.81	0.90	0.93
B	0.90	0.33	0.96	0.95	0.50
C	0.81	0.96	0.4	0.98	0.98
D	0.90	0.95	0.98	0.36	0.95
E	0.93	0.50	0.98	0.95	0.42

TABLE II: BD VALUES OF THE PROPOSED SCHEME

A	B	C	D	E
0.0193	0.0389	0.0487	0.0951	0.0583

classes in the dataset are shown in Table I and Table II.

C. *Performance Assessment*

To evaluate the performance of the proposed model, accuracy with standard deviation and sensitivity has been calculated. Accuracy with standard deviation and sensitivity results for binary classificatinons are stated in Table III, Table IV, Table V , Table VI, Table VII & Table VIIII. The following equations have been used for the analysis of the output result

TABLE III: PERFORMANCE RESULT FOR CLASS A-E

Methods	**Sensitivity% for A%**	**Sensitivity% for E**	**Accuracy% ± Avg STD**
Scheme of ref [3] using HOS parameters	76.6	99.3	87.9
Scheme of ref [2] using NIG parameters	97.5	94	95.75
Proposed CNN structure for classes A-E	98.80	100	99.4±0.52

of proposed model [7]:

$$\text{Sensitivity}_i = \frac{TP_i}{TP_i + FN_i} \times 100\% \tag{1}$$

$$\text{Accuracy}_i = \frac{TP_i + TN_i}{TP_i + TN_i + FP_i + FN_i} \times 100\% \tag{2}$$

All these are calculated in percentage. In the above equation TP stands for true positive, TN stands for true negative, FP stands for false positive and FN stands for false negative.

D. Comparison of Proposed and Existing Methodology

The methodology used in this paper is very simple CNN architecture . Accuracy result for A-E through the proposed methodology is 99.4% which is an improved result from the EMD based methodology in scheme of reference [3]. Accuracy result for D-E is 99.4% which is higher than the accuracy found through EMD based methodology in scheme of reference [3]. The sensitivity & the standard deviations are presented in Table III to Table VIII.

In some paper, it has been found that dual-tree complex wavelet transform has been used with features obtained from five sub-bands gamma, beta, alpha, theta and delta. And after that separately SVM classifier has to be used for classification [2].

The absorbed methodology in this paper used only single layer of max pooling layer and two layers of fully connected layer. So, definitely the time for running the code gets reduced as well as the complexity of CNN architecture has also been reduced. If we see other works on CNN methodology, it is found that complex CNN architecture are adopted like three or four convolutional layer, three or four FC layer etc [8]. These architectures are time consuming as the computational time and complexity of these architectures are higher than the proposed methodology.

In this paper, the binary classification has been performed for A-C & B-E class. The scheme of reference [2] and the scheme of reference [3] have not been used for the binary classification of A-C & B-E class. But in this paper, all the binary classification has been performed from class A to class E with a better accuracy result.

It is experimented that steps in proposed CNN architecture can differentiate two classes of seizure with minimal time and also replacing the EMD based analysis and wavelet transformation based analysis with better experimental result.

IV. CONCLUSION

We have explored the proposed method for 1-D signal. The computational complexity has been very much reduced through the proposed method of CNN architecture and the accuracy is found satisfactory. So it can be a preferable methodology for seizure classification.

TABLE IV: PERFORMANCE RESULT FOR CLASS B-E

Methods	**Sensitivity% for B**	**Sensitivity% for E**	**Accuracy% ± Avg STD**
Proposed CNN structure for classes B-E	99.60	99.80	99.7 ±0.48

TABLE V: PERFORMANCE RESULT FOR CLASS C-E

Methods	**Sensitivity% for C**	**Sensitivity% for E**	**Accuracy% ± Avg STD**
Scheme of ref [2] using NIG parameters	97.88	95.44	96.66
Proposed CNN structure for classes C-E	98.60	99.80	98.5 ±0.42

TABLE VI: PERFORMANCE RESULT FOR CLASS D-E

Methods	**Sensitivity% for D**	**Sensitivity% for E**	**Accuracy% ± Avg STD**
Scheme of ref [3] using HOS parameters	66.1	88.8	77.4
Scheme of ref [2] using NIG parameters	95.38	96.63	96
Proposed CNN structure for classes D-E	99.20	99.60	99.4 ±0.52

TABLE VII: PERFORMANCE RESULT FOR CLASS A-C

Methods	**Sensitivity% for A**	**Sensitivity% for D**	**Accuracy% ± Avg STD**
Proposed CNN structure for classes A-C	97.60	99.37	98.5 ±0.53

TABLE VIII: PERFORMANCE RESULT FOR CLASS ABCD-E

Methods	**Sensitivity% for ABCD**	**Sensitivity% for E**	**Accuracy% ± Avg STD**
Scheme of ref [3] using HOS parameters	58.8	98.1	90.2
Scheme of ref [2] using NIG parameters	97.13	94.41	94.95
Proposed CNN structure for classes ABCD-E	99.80	98.34	99 ± 0.33

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