Feature Extraction and Enhanced Convolutional Neural Network (ECNN) for Detection and Diagnosis of Seizure using EEG Signals

N. Sharmila Banu, S. Suganya

Abstract: ***Seizure detection in non-stationary electroencephalography (EEG) is perplexing and difficult task. The human examination for detecting the seizure activities in EEG signals is liable to errors. Apart from the errors, it is a time driven task and also the detection is not precise. In order to detect epileptic seizures more precisely various automatic systems have been emerged to assist neurophysiologists by researchers in various attempts. There are various limitations such as time-consuming, technical artifact issues, result variation with respect to reader expertise level, abnormalities identification. Enhanced Convolutional Neural Network (ECNN) is a technique proposed to mitigate the above mentioned limitations and to categorize more accurate epileptic seizures results. A novel automatic method to sense epileptic seizures using feature extraction and detection is proposed in this research. Linear filter is helpful in reducing the noise along with artifacts when the EEG signals are preprocessed. The noise can be still removed by applying Least Mean Square algorithm. In this proposed research the features are extracted via analytic time frequency with Cascaded wavelet transform and fractal dimension (FD) in order to detect epileptic seizures. Lastly, to analyze the EEG signal for better classification performance of the given dataset, ECNN is adopted. During this research to classify normal, preictal, and seizure classes, a 13-layer deep ECNN algorithm is implemented. This research has special characteristics such that the model yields promising classification accuracy. The experimental result demonstrates that the proposed ECNN is superior in terms of higher sensitivity, specificity, accuracy and lower time complexity rather than the existing methods.***

Key words: cascaded wavelet transform, epileptic seizures, EEG signalenhanced convolutional neural network, feature extraction, linear filter, fractal dimension.

I. INTRODUCTION

Electroencephalogram (EEG) signals play a vital role in diagnosing the neurological disorders such as epileptic seizures and the neurophysiologists also essentially depend on this EEG signals. Nearly 1% of the entire world's population suffers with epilepsy which has been considered as major neurological disorder [1]. The frequently occurring spikes are used to characterize the EEG signal which is the beginning of epileptic seizures. Epileptic seizures can be classified into two types. They include focal epileptic and another one is generic epileptic seizure.

Revised Manuscript Received on October 30, 2019.
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The seizure that affects the cerebral hemisphere is said to be a focal epileptic seizure, which shows the symptoms in corresponding parts which in turn affects the mental health The later one deals with the entire brain which leads to unconsciousness exhibiting bilateral motor symptoms. Both the types of epileptic seizures can affect any people irrespective of age.

EEG recording of the patients who suffers from epilepsy exhibits two classifications of unusual activity. One among them is inter-ictal, unusual EEG signals, which are recorded between seizures and the other is ictal, the activity that is recorded during an attack of epileptic seizures or epilepsy. The main difference is that an inter-ictal activity observed in EEG recording indicates transient waveforms in the form of variable spikes, spike trains, crisp waves or spike wave complexes whereas ictal activity in EEG signals consists of polymorphic waveforms of differential amplitude and frequency. In earlier days representation based on Fourier transform and parametric methods are used. Variations in frequency sub bands due to epileptic seizure existing in EEG are given as δ(0.4-4 Hz), θ(4-8 Hz),α(8-12 Hz),and β(12-30 Hz).Generally Conventional frequency based methods are suitable for decomposing EEG signals due to non stationary and multicomponent signals in EEG. The better performance is observed in time–frequency based methods compared with conventional frequency based methods. Various methods are presented to mitigate the artifacts for epilepsy patients from scalp EEG recordings to facilitate seizure diagnosis or detection [3].This work concentrates on stationary wavelet transform and spectral band enclosing the seizure activities (i.e., 0.5-29 Hz), that are taken into account. The most frequently appeared artifacts in real EEG recordings are identified by simulating the different artifact templates. Three sets of artificial data that includes completely simulated, semi-simulated, and actual data are utilized by the algorithm for the purpose of evaluation of artifact removal performance and seizure detection performance. Once the artifacts are eliminated, then it is easy to differentiate seizures from non-seizures for which the EEG features are accountable. As a result, there will be a reduction in false alarms in seizure detection. The wavelet transform (WT) is used in feature extraction method by which the usual signals and epileptic seizure signals obtained from the EEG signals of individuals showing signs of epilepsy and those obtained from healthy individuals [4] [5] are classified by selecting the least number of features. The detail coefficient and approximation coefficients from the EEG signals are generated by selecting the minimum number of features in WT. By using statistical methods 40 initial features are acquired from the generated wavelet co-efficient which inculcates frequency distributions and the amounts of variableness in frequency distributions.

Classification process plays a vital role in classifying the normal and abnormal electrical discharge in the brain[6]. Multi-level Local Patterns (MLP) for best average classification accuracy over the given datasets is described with new discriminant feature [7]. Empirical mode decomposition is deployed to disintegrate non-static EEG signals into intrinsic mode functions (IMFs). The sample value of the signal is compared with the local neighbourhood to compute the Multi-level local patterns for each IMFs. By computation of histograms of MLPs, a feature set is formed. The Nearest Neighbour (NN) classifier is employed to identify the category of the EEG signal by utilizing the scores computed from matching of histogram features of MLPs

This research work deliberates on classification of epileptic seizure on the EEG signal which is the challenging task. The accuracy of seizure detection is not achieved significantly though several researches and methodologies are introduced. The main drawbacks of time consumption and inaccurate epileptic seizure detection of EEG signals are mitigated by means of the proposed ECNN technique with the added feature of feature extraction and pre-processing methods. The main contribution of this research is preprocessing, feature extraction using cascaded wavelet transform and fractal dimension (FD) method and classification of epileptic seizure and seizure free signals in EEG recordings. The proposed method provides more accurate results using effective algorithms for the given dataset.

II.LITERATURE REVIEW

In [8], Adeli et al (2010) investigated about the EEG signal which measures the electrical impulses within the brain which has been utilized in both invasive and non-invasive manner in order to analyse cognitive processes, the brain's physiology, various neurological ailments etc. Moreover, it is employed in various non-clinical areas such as Brain Computer Interaction (BCI) Applications device control, Training and education, Gaming and Entertainment. EEG is the primary tool for neurologists and clinical specialists to diagnose various disorders such as epilepsy sleep disorders, schizophrenia, identification of spikes, prediction of seizures, and localization of the seizure focus, monitoring consciousness, coma and brain death. Also it is used to locate damaged regions after head injury, stroke and tumour; testing afferent pathways; monitoring degree of anaesthesia, etc. EEG signal is ambiguous for the parts inside view of brain.

In [9], presents Hilbert-Huang Transform (HHT) for denoising the EEG signal. For non-stationary time series, EMD is introduced for decomposition. The reconstruction of the original signal is accomplished by the sum of the decomposed intrinsic mode functions (IMF).Sometime IMFs may contain mostly noise components due to the corruption of signal by wideband additive noise. The challenge lies in identifying which IMFs have informative oscillations or information free noise components. This challenged is eradicated by using hierarchical clustering based on instantaneous frequencies (IF) of the IMFs obtained by the HHT used for denoising the signal efficiently.

In [10], Kher et al (2016) suggested the method in which adaptive filter is utilized in removing the artifacts contained in EEG signal. Two reference inputs such as recorded noisy EEG and clean EEG are used separately in this method. The three kinds of EOG artifacts, such as horizontal eye movement, vertical eye movement and eye blinks have gotten recorded for five subjects, for noisy EEG signals. The adaptive filter is used to produce an output which matches the reference input based on a least mean square (LMS) algorithm

In [11], Selvathi et al (2017) utilizes wavelet transform and Support Vector Machine (SVM) classifier for efficient detection of seizure presence in EEG signal. Discrete Wavelet Transform is used to disintegrate seven levels of EEG signal so that delta, alpha, theta, beta and gamma sub bands are obtained. Alpha wave is considered to possess highest amplitude in the range of 100µv which helps in identifying the seizures. Thereby the statistical features are extracted from alpha band and SVM classifier is used for final classification of EEG signal. It is applicable for two sets of EEG signal, which include 1) Normal EEG dataset; 2) seizure dataset during the time of seizure. In this work 76% of LUTs and 20% of registers are utilized. The overall power analysed for the implementation of this technical work is 0.017W and classification accuracy is achieved at 95.6%.

In [12], Finotello et al (2015) investigated the problem of sleep identification from EEG data by the application of features based on fractal dimension. The numerous applications of EEG aids in promoting novel methodologies for the extraction of synthesized and valuable features from the EEG signals. The two novel indices along with the features based on fractal dimension, add useful information to standard EEG features and pointedly boost the sleep detection performance.

In [13], Park et al (2018) suggested a new technique based on deep convolutional network for detecting the epileptic seizures. This paper suits for multi-channel EEG signals and 1D and 2D convolutional layers is used for spatio-temporal correlation, which is a feature observed in epileptic seizure detection. In which 1D and 2D convolutional layer is used for temporal evolution of the EEG signal of every channel and spatial relationships between EEG channels respectively. The datasets for the EEG experiment are obtained from CHB-MIT EEG Scalp database and SNUH-HYU EEG database, which include the recordings of long-term EEG monitoring at Seoul National University Hospital and Children's Hospital located in Boston. The different duration is considered for the EEG segments. Low Pass filter is applied to the EEG signals with the aim of examining the impact of artifact reduction on epileptic seizure detection. This model achieves 90.5% prediction accuracy for SNUH-HYU EEG database.

In [14], Antoniades et al (2017) presents from intracranial EEG data along with intracranial EEG data along with clinical insight by deliberating deep learning for epileptic patients to include automated generation of feature. Hierarchical Process is utilized for automatic learning the meaningful features in a subject independent fashion. Expert clinicians elucidates Interictal Epileptiform Discharge (IEDs) in which the convolved filters in the deepest layers is used to understand the different types in it. This method aids in evaluating the treatment of a patient by utilizing the morphology of the IEDs.

International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-9 Issue-1, October, 2019

III. PROPOSED METHODOLOGY

In the proposed methodology, the categorization of more accurate epileptic seizures is accomplished with the help of Enhanced Convolutional Neural Network (ECNN). In this research feature extraction and detection method is used to identify epileptic seizures thereby producing a novel automatic approach. The digitized EEG signals are preprocessed by means of a linear filter to eliminate the noise and artifacts. Furthermore left over noise is eliminated by means of Least Mean Square. The Cascaded wavelet transform and fractal dimension (FD) is used in the proposed work to detect epileptic seizures by extraction features via analytic time frequency. In order to classify the given dataset the EEG signals in a better manner, ECNN is employed finally. For the classification involving normal, preictal, and seizure detection 13-layer deep ECNN algorithm is realized.

The accuracy of classification using the proposed system is the exemplary characteristics. The block diagram of the newly introduced system is illustrated in Fig 1

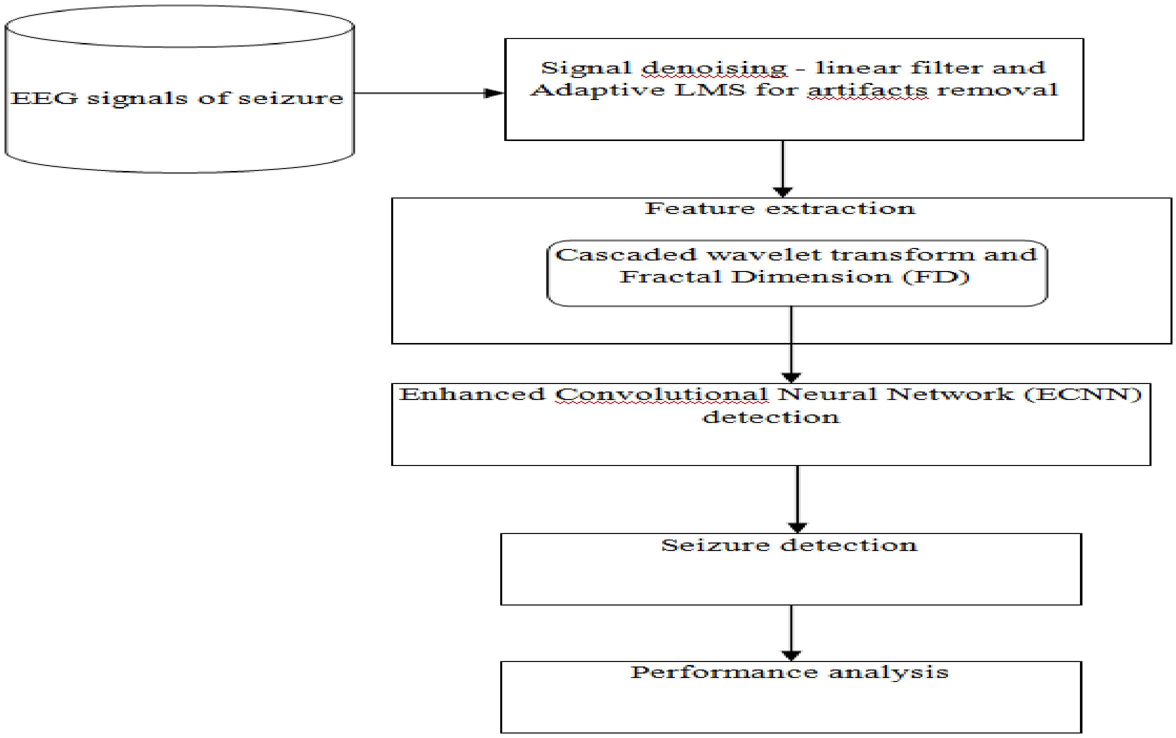

Fig 1 Block diagram of the proposed system

A. Denoising EEG Signal and Artifact Removal

The role of EEG signal plays a vital role in detecting the epileptic seizure, hence denoising these signals for correct analysis and diagnosis is mandatory. For the purpose of linear filtering of EEG signal, linear filter is utilized and Adaptive LMS for artifacts removal for the given data.

If the mask is centred at (x,y) which indicates that the coefficient w(0,0) intersects with signal value f(x,y), when the computation of sum of products takes place. Consider EEG signal f of size MxN with a filter mask of size mxn is expressed by the equation used for linear filtering

$$g(x,y) = \sum_{s=-q}^{q} \sum_{t=-r}^{r} w(s,t) f(x+s, y+t) \qquad (1)$$

where x and y are two signal values for the given EEG signal. It is just the mean of the signals present in the vicinity of the filter mask [15]. The quality of the signal is improved by reducing the noise efficiently.

The EEG signal complicates the underlying processes by means of artifacts presence such as eye blinks etc. These are considered as a noise source which in turn makes EEG analysing more complicated still and thereby loss of clinical information. These artifacts removal plays a vital role since it may effect on the tasks of detection and acquisition of features from the EEG signal. The eye blinking, muscle activity, line noise etc. may cause contamination, due to which large amount of data may often be discarded. Artifacts may resemble almost any kind of EEG pattern which in turn can have a critical effect on the outcomes, ultimately resulting in erroneous inferences when included in automatic analysis.

The artifacts are considered as important factor during analysis of EEG, whether visual or quantitative, hence care must be taken while dealing with it. Thus, the careful handling of artifacts reports reliable EEG data processing and validated. Sometime valuable information is present in artifacts themselves. Adaptive Least Mean Square (ALMS) is a technique which focuses on artifact minimization, identification and removal a part of artifact processing. By which it gives a better way to understand the basic electrical impulses within the brain and achieving the right deductions by segregating artifacts from the EEG data.

Here adaptive filter is used to generate a signal similar to the artifacts present in the signal to be filtered [16] by adapting the coefficients of the linear filter and thereby the frequency response.

The filter coefficients are determined using adaptive LMS process which inculcates cost minimization function. The squared error between its output and a primary signal is reduced by adjusting the adaptive filter coefficients.

Optimization theory forms the base for the adaptive filters. Based on the selected features of the signals being analyzed [17], LMS property can be modified. The algorithm that uses the steepest distance is as expressed below

$$L(n+1) = l(n) - \mu \nabla J(L(n)) \quad (2)$$

Where $\nabla J(L(n))$=$-2s_{dx} + 2q_x l(n) s_{dx}$ and $q_x L(n)$ are the instantaneous estimates and are defined with reduced in mean square

$$L(n+1) = l(n) + 2\mu E(n) x(n) \quad (3)$$

Where $Y(n) = L^T(n) x(n), e(n) = d(n) - y(n) \quad (4)$

Equations 3 and 4 are the necessary outputs obtained from ALMS algorithm where y (n) refers to the filter output and E (n) stands for the error over the EEG signal. In this work, $d(n)$ is the primary signal and e(n) is minimized adaptive artifacts for the EEG signal. Thus it is used to reduce the artifacts effectively for the given dataset. The organization of adaptive filter is illustrated in Fig 2.

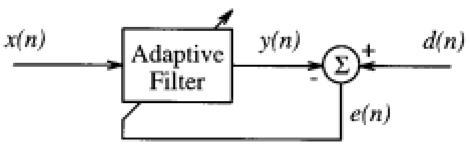

Fig 2 Structure of adaptive filter

Whenever d (n) and y (n) values are equal this indicates zero error. This filter could be utilized combined with several other applications concentrating on artifacts removal. Various parameters are associated with LMS adaptive filter have a significant role in minimizing the errors. Adaptive LMS algorithm is slightly varied to provide more accurate results in seizure or seizure free detection for the given dataset by reducing the artifacts

B. Feature Extraction Using Cascaded Wavelet Transform and Fractal Dimension for Epileptic Seizures Detection

Cascaded wavelet transform play a vital role in this research for improved epileptic seizures detection of the EEG signals. In order to classify seizure or seizure free signals on the given dataset, number of suited features are extracted. Cascaded WT is helpful in disintegrating these features, with transients and steady-state components of time vibrations, into various frequency sub-bands employing continuous wavelet transform function [18]. The coefficients are computed using a mother wavelet wl, maximum scale $a$to change the time segment into x^i frequency sub-bands using

$$C^i = cascadedWT(x^i, a, wl) \quad (5)$$

where$C$is a $a \times b$matrix. Where a is maximum scale level and $b$is time. The spike and wave features are extracted by the cascaded WT, while simultaneously extracting the time and frequency characteristics of a signal. In this work, the epileptic seizures on the given dataset are accomplished by analytic time–frequency (t-f) with cascaded WT .

Three equal-sized windows are chosen in time domain where as in frequency domain five sub-bands are obtained by partitioning and it presents a sample analogous t-f applied for feature extraction process [19].The frequency sub bands that are expressed depending on medical information on EEG, include 0–2.5 Hz, 2.5–5.5, 5.5–10.5, 10.5– 21.5, and 21.5–43.5 Hz. Sometime certain features are anticipated to be seen in specific frequency bands for the EEG segments, which are included in the dataset. Expert neurologist suggests the size of the time windows and it is within the range of windows selected. Each feature f(i,j) is computed as,

$$f(i,j) = \int^{ti} \int^{wi} (t,w) dwdt \quad (6)$$

Where t_i refers to the i^{th} time window and w_j stands for the j^{th} frequency band. The integral part is calculated as

$$f(i,j) = \sum_{t \epsilon ti} \sum_{w \epsilon wj} (t,w) \quad (7)$$

The fractional energy of the signal in a particular frequency band and time window is given by each one of its feature owing to depict the spread of the signal's energy over the t-f plane. The feature set may contain adequate information associated with the non-static characteristics of the EEG signal. A cascaded WT preserves the importantfeatures for distinguishing the kind of EEG records [20] by reducing the original signals into a few parameters. Higher temporal resolution is the main advantages which may contain both the frequency and the positional information (location in time). The filtered results of each decomposed band yield significant values. Therefore, the more informative features are extracted from EEG signal.

$$Q_a = \sum_{j \in Z} a(j) f(2-j), \quad f \in lp(R) \quad (8)$$

$where Q_a$ is the cascade operator and the linear operator on Lp thus the Qa is redefined for cascaded wavelet transform as follows

$$Q_a = \sum_{j \in Z} a(2k+j) \overline{b(j)} + C^i \forall k \in Z \quad (9)$$

Where a and b are cascaded convergence for sequence Z and analytic t-f cascaded WT can be rewritten as follows to provide more informative features from EEG signal

$$W(f(\mu, s, Q_a)) =< f, \varphi_{\mu,s} >= \int_{-\propto}^{\propto} f(t) \frac{1}{\sqrt{s}} \varphi\left(\frac{t-\mu}{s}\right) du \frac{ds}{s^2} \quad (10)$$

The important feature information and vice versa may be discarded once the important features are extracted by analyzing the EEG signals and vice versa. Hence, in the cascaded WT technique can eradicate such deficiency and extract effective features.

Algorithm 1: Cascaded WT
Input: EEG signals
Output: extracted informative features from EEG signals

Step 1: Read the input I=[x1, x2,….xn] EEG signals

Step 2: Apply analytic t-f with cascaded WT using (9) and (10)

Step 3: Extract the necessary features based on higher coefficients

Step 4: End

FRACTAL DIMENSION (FD)

Fractal dimension is one in which the statistical measure of complication exhibited by objects or a quantity, which is self-identical over various regions of time interval or space is obtained. For a better speed and classification accuracy the fractal dimension technique is the most suitable method. A sliding window of size s is used in this research is used to estimate part of the sample within the window by a time step. The fractal dimensions were merged into feature vectors [21]. Time step of one second is utilized for testing the dissimilar window sizes. The pair wise differences of the fractal dimensions are calculated once the estimation of the fractal dimensions of the samples from selected electrodes are done which are used in analysing the identification from EEG data. The fractal dimension yields a complication which defines the measure of curve length variations based on the scale k utilized as a measurementunit.

Higuchi's standard methodology is used for the estimation of the fractal dimension D of an EEG signal which consist of the following steps. It is also used for the accurate fractal dimension calculation of the time series and also detects the periodic components mixed with fractal signals.

1. For every sample i belonging to the EEG segment Sj , absolute differences existing between the values Sj(i) and Sj (i+k) (i.e. samples at distance k) are measured, taking k = 1, . . . , k_{lin}
2. These absolute differences are then multiplied by a normalization coefficient taking the number of samples present for every value of k into account.
3. For every k, L(k) is computed by adding the values obtained along every sample of the EEG segment and then dividing by k.
4. As per definition, if L(k) value is proportional to k −D, and so the curve is fractal with dimension D. In case of verification of this condition for k = 1, . . . ,k_{lin}, then log(k) and log(L(k)) exhibit a linear correlation. Especially, from the log(L(k)) vs. log(k) curve, called in as `k below, D can be computedusing ordinary least squares to be the linear coefficient of the regression line
5. k_{lin} is selected as the maximum k for which L(k) is proportional to k^{-D}

$$FD(t(lk)) = \sum_{n=i}^{N} \left| \frac{\Delta x(n)\Delta^2 y(n) - \Delta^2 x(n)\Delta y(n)}{[(\Delta x(n))^2+(\Delta y(n))^2]^{3/2}} \right| \quad (11)$$

where N refers to the number of points of the curve k. $\Delta x(n) = x(n) - x(n-1)$,$\Delta^2 x(n) = \Delta x(n) - \Delta x(n-1)$,$\Delta y(n) = y(n) - y(n-1)$, $\Delta^2 y(n) = \Delta y(n) - \Delta y(n-1)$. The above equation is used for more accurate seizure detection from the extracted synthetic and informative features from EEG signals.

C. Enhanced Convolutional Neural Network (ECNN) for Classification

In this research, classification of seizure or seizure free for the given EEG signal is accomplished by ECNN. EEG signal is given as input to the network and confidence of each signal is obtained as output.Basically CNN comprises of an input and an output layer, in addition to the numerous hidden layers. Convolution layers, pooling layers and entire connected layers are the various layers of CNN hidden layer. Convolutional layer performs convolution operation of the input and the convoluted output is transferred to the next subsequent layer.This will follow the response given by an individual neuron to optical stimuli. Convolution networks comprises local or global pooling layers which merge the outputs of neuron clusters in onelayer into one single neuron in the next layer. Mean pooling makes use of the average value from every cluster of neurons in the layer before it. Each neuron in one layer communicates witheach neuron present in another layer by means of fully connected layers. The basic principle of CNN is similar to that of traditional multi-layer perceptron neural network [22].The proposed ECNN comprises input layer, convolutional layer, sub-sampling layer and classification layer. This proposed method has apparentbenefits for the analysis of high-dimensional data. It employs a parameter sharing approach by which the number of parameters are reduced and controlled by convolutional layers. The architecture diagram of ECNN is shown in Fig 3.

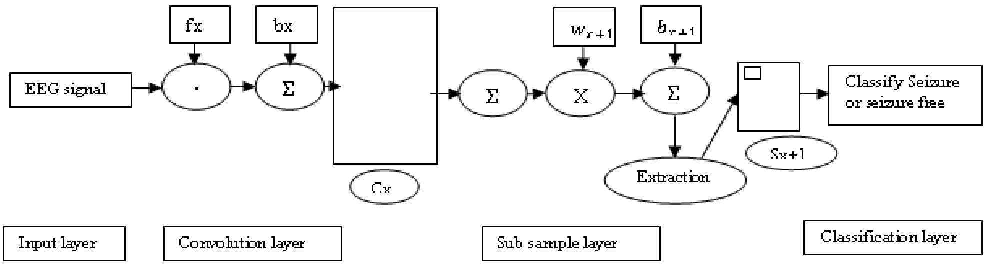

Fig 3 Architecture diagram of ECNN

The transformationof the data into one combined format to transfer the data into next layer precisely once the input layer receives EEG signals from training samples. The initial parameters like the scale of the local receptive fields and various filters are defined in this layer.

Convolution layer (Cx) convolutes the input data and several layers known as feature map comprising convolution calculation results from the previous layers are created.

The main purpose is the extraction ofcore features and reduction of the network's computational complexity.The output equation of the convolution calculation is as follows:

$$x_j^l = f(\sum_{i\in mj} x_i^{l-1} * k_{ij}^l + b_j^l) \qquad (12)$$

$$\mathrm{f(x)}\frac{1}{1+e^{-x}} \qquad (13)$$

Where x refers to the output value of the convolution layer, k stands for the kernel (or known as the filter), l indicates the number of output layer that is determined by the number of kernels, i stands for the stride of the kernel movementin each step of computation, mj indicates the jth feature map generated by various kernels, b stands for the bias and f refers to an activation function generally defined to be a sigmoid function given in equation (12). Sharing of same weights and bias is done for neuron of the same feature map, although every output neuron has different receptive fields. In this way, training parameters are greatly decreased.

An activation function is employed after every convolutional layer. Activation function is one which is used to map an output to a set of inputs which makes the network structure to be non-linear. The initial connection weights are set to the entire given feature values. A new input pattern is then applied and the output is computed as

$$y(n) = f(\sum_{i=1}^{i=N} w_i(n)x_i(n) \qquad (14)$$

$$\text{Where } f(x) = \begin{cases} +1 & if x \geq 0 \\ -1 & if x < 0 \end{cases} \qquad (15)$$

Where n is the iteration index

Connection weights are updated according to

$$w_i(n+1) = w_i(n) + \eta(d(n) - y(n)x_i(n),$$

$$i = 1,2,..n \qquad (16)$$

Where η is the gain factor

Then apply standard deviation

$$\sigma = \sqrt{\frac{1}{n} f_i(x_i - \overline{x})^2} \qquad (17)$$

These weighted features are given into proposed ECNN network and obtained more accurate classification results. Every feature map from the previous convolution layer is sub-sampled in this layer. From the Fig 2, $Sx + 1$is summing the informative features. The sub-sample method is the calculation of the weighted summation or considering the maximum value in an n × n area of each feature map. The output of sub-sample layer is as given:

$$x_i^l = f(b_j^l downsample(x_i^{l-1})) + b_j^l \qquad (18)$$

Where xl refers to the output value resulting of the lth sub-sample layer, down-sample indicates the sub-sample function, βstands for the bias of the sub-sample function, f and b indicates the activation function and the bias correspondingly. The numbers of training parameters, filters noises are mitigated by the sub-sample layer and over-fitting is avoided in the network.

Classification Layer: The size of output feature maps continuously decreases once the data has crossed several convolution layers and sub-sample layers. The only one neuron becomes a feature vector for every feature map in the classification layer. The vector is fully connected with a classifier. The segmentation of EEG data is performed by a given time window and series of plot EEG signals is obtained.

The time window parameter ranges from 0.5 s to 10 s (0.5, 1, 2, 5, and 10 s). When the size of the time window is less than or equal to 1 s, segmentation of EEG happens without overlapping or data are segmented each second with overlapping with earlier segments, e.g., a 9-s overlap for a 10-s segment.

CNN model is trained such that each of the segments completely within seizure states are helpful inmodelling the seizure class. Random selection of segments that are 8 times longer compared to the seizure period is done from inter-ictal states and defined as per the isolation from the seizure state by more than 1 hour, to model non-seizure class during CNN learning.

It is classified as either seizure or non-seizure by the trained CNN for each 0.5 s for the 0.5-s segment and every second for the rest of the segments. The CNN classificationperformance is enumerated by seizure/ non-seizure labels using CNN which are allocated by epileptologists. Seizure states are the true positive and true negative rates which inculcates segments that include a seizure period. Non-seizure states are the rest of the seizure periods. The classification performance is evaluated either in leave-one-out testing or pairwise testing. During the testing phase EEG data is trained and tested from the last remaining subject. In case of pairwise testing single subject's data is considered for construction and testing from each subject individually.

Steps in ECNN

Procedure epileptic seizure or seizure free

For all input signal, depicting EEG signal ∈ EEG dataset do

Convert the input into sub layers

Detect EEG seizure features

Extract more informative features using ECNN

Perform training and testing process for given dataset

Copy predefined EEG signal label for each signal as per the input dataset

Classify more accurate epileptic seizure or seizure free results

IV.EXPERIMENTAL RESULTS

In this research,existing methods of SVM, CNN and proposed ECNN algorithms are used for the evaluation of the performance metrics. Various metricssuch as sensitivity, specificity, accuracy and time complexity are taken into account. For obtaining the results five sets (represented as A–E) with each one having 100 single channel EEG segments of 23.6-sec duration are considered.Let us consider muscle activity or eye movements in which selection of segments is done and split out from continuous multichannel EEG recordings once the artifacts are visually inspected. The two set of segments A, B obtained from surface EEG recordings, which were acquired from five healthy personsemploying a standardized electrode placement approach [24].The states A and B are the awake conditions with eyes open and eyes closed correspondingly.

The pre surgical diagnosis of EEG archive is termed as sets C, D, and E. Five patients were selected in a manner such that an entire seizure control once the resection of one of the hippocampal creations is realised. Segments present in set D were recorded from within the epileptogenic area and set C from the hippocampal formation of the opposite hemisphere of the brain. Sets C and D refers seizure independent intervals and E confined to the activityof seizure. In this, the segments were chosen from all the recording sites depictingictal activity.

The recording of all the EEG signals is accomplished with the help of the same 128- channel amplifier system, utilizing an average common reference [avoiding electrodes with pathological activity (C, D, and E) or strong eye movement artifacts (A and B)].The continuous writing of data is done after 12 bit analog-to-digital conversion onto the disk of a data acquisition computer system at a sampling rate of 173.61 Hz and the Band Pass Filter is set to 0.53–40 Hz ~12 dB/oct.

Sensitivity

Sensitivity is also known as the true positive rate, the recall, or probability of detection in few fields of measurements and it states that ratio of actual positives, which are rightlydetected as such (e.g., the percentage of illpersons who are rightlyfound to have the condition)

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (19)$$

Where TP is True Positive, FN is False Negative

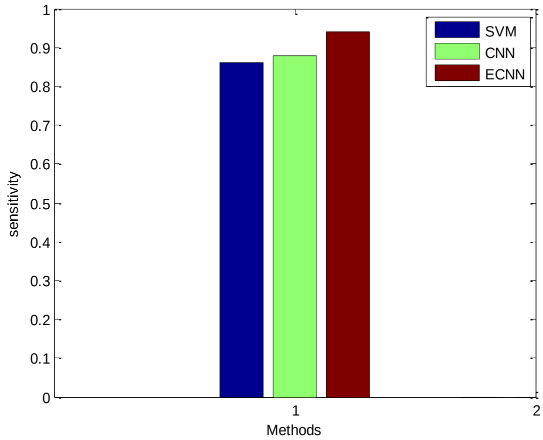

Fig 4 Sensitivity comparison

Fig 4 shows the sensitivity comparison of proposed with existing methods in which methods are compared with sensitivity value. The existing SVM and CNN algorithms exhibits lower sensitivity whereas proposed ECNN algorithm provides higher sensitivity for the given EEG signal dataset. The classification performance by classifying accurate results in epileptic seizure is thereby improved comparatively.

Specificity

Specificity (also known as the true negative rate)refers to the measure of the proportion of the original negatives, which are rightlydetected as such (e.g., the percentage of healthy people who are rightlydetectedto be not affected by the condition).

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (20)$$

Where TN is True Negative and FP is False Positive

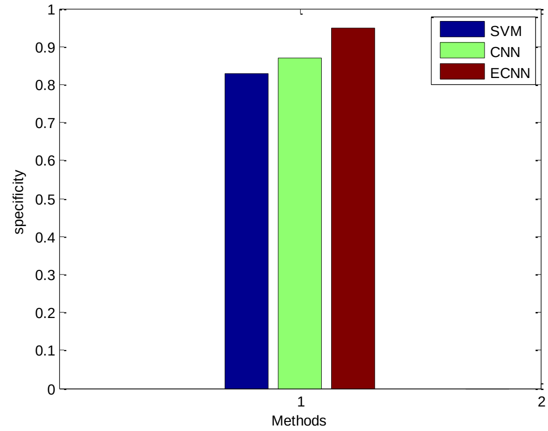

Fig 5Specificity comparison

Fig 5 indicates the specificity comparison of methods Vs. percentage of specificity. ECNN algorithm delivers higher specificity for the given EEG signal dataset when compared with SVM and CNN algorithms.The classification performance by classifying accurate results in epileptic seizure is thereby improved comparatively.

Accuracy

Accuracy is defined to be the overall correctness exhibited by the model and is computed to be the total real classification parameters $(T_p + T_n)$ which is segregated by the sum of the classification parameters $(T_p + T_n + F_p + F_n)$. The accuracy is computed as like :

$$\text{Accuracy} = \frac{T_p+T_n}{(T_p+T_n+F_p+F_n)} \quad (21)$$

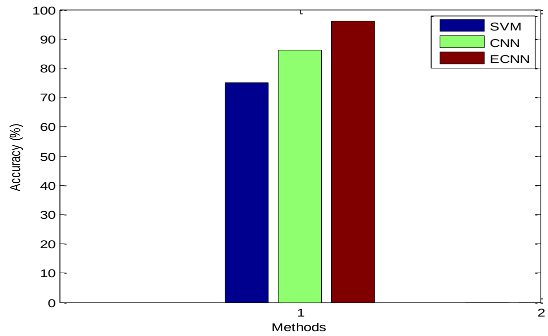

Fig 6 Accuracy comparison

Fig 6 shows the accuracy comparison of proposed with existing methods in which methods are compared with accuracy value.

The existing SVM and CNN algorithms exhibits lesser accuracy while the novel ECNN algorithm yields superior accuracy for the EEG signal dataset provided. The classification performance by classifying accurate results in epileptic seizure is thereby improved comparatively

Time complexity

The system produces better performance when the proposed algorithm executes in less time consumption.

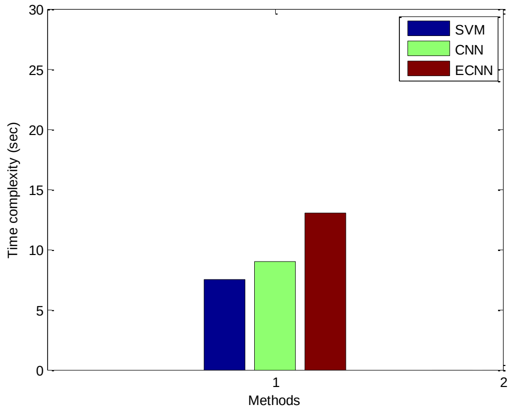

Fig 7 Time complexitycomparison

Fig 7 shows the time complexity comparison of proposed with existing methods in which methods are compared with sensitivity value. The existing SVM and CNN algorithms exhibits lower time complexity while the novel ECNN algorithm provides higher time complexity for the EEG signal datasetgiven. The classification performance by classifying accurate results in epileptic seizure is thereby improved comparatively

V.CONCLUSION AND FUTURE WORK

Seizure detection in non-stationary electroencephalography (EEG) is perplexing and difficult task. Enhanced Convolutional Neural Network (ECNN) is technique proposed to categorize more accurate epileptic seizures results. A novel automatic method to sense epileptic seizures using feature extraction and detection is proposed in this research. Linear filter is utilized for reducing the noise and artifacts when the EEG signals are preprocessed. The noise can be still removed by applying Least Mean Square algorithm. In this proposed research the features are extracted via analytic time frequency with Cascaded wavelet transform and fractal dimension (FD) in order to detect epileptic seizures. Lastly, to analyze the EEG signal for better classification performance of the given dataset, ECNN is adopted. To classify normal, preictal, and seizure classes, a 13-layer deep ECNN algorithm is implemented. This research has special characteristics such that the model yields promising classification accuracy. The experimental result demonstrates that the proposed ECNN is superior in terms of higher sensitivity, specificity, accuracy and lower time complexity rather than the existing methods

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