A Survey On Approaches For Epileptic Seizure Detection And Prediction

Renuka Mohan Khati, Rajesh Ingle

Abstract: Epileptic seizure is a neurological disorder. Currently, approximately 50 million people are affected by epileptic seizures. Detection of epileptic seizure is very difficult as they vary from patient to patient. The electroencephalography (EEG) capture brain activity, these EEG signals are required to be analyzed by neurologists in order to detect seizures. Traditionally, neurologists perform visual inspection to detect the presence of epileptic seizures which is time taking. But accurate diagnosis is required to be done within time so that appropriate therapies can be initiated and the further complications can be reduced. Hence an automatic approach is required for the detection and prediction of epileptic seizures. Seizure prediction is important because if seizures are predicted at an early state, then they can be suppressed using electric stimulations. We first start with the different algorithms or approaches used to detect and predict seizures, followed by comparison study of different approaches used for seizure diagnosis, our proposed approach, and finally the conclusion.

Index Terms: Deep learning, Epileptic seizure, feature extraction, ictal, machine learning, prediction, preictal, detection.

1 INTRODUCTION

Approximately 75% of the seizure patients cannot even meet the expenses of the epilepsy diagnosis [1]. In a year approximately 2.4 million people are diagnosed with epileptic seizures [4]. To overcome these problems, some automated approach is required which can detect and predict seizures in less amount of time. Although there are several challenges in proposing an automated approach such as: availability of small datasets, the characteristics of epileptic patients vary from patients to patients, data may contain some noise that may affect the prediction result [1]. The visual inspection method to diagnose epileptic seizures is time consuming and moreover in developing countries, neurologists may not be available immediately [5]. Seizure detection and prediction methods involve mainly 2 stages: feature extraction and EEG signal classification [2]. EEG signals record the electrical activity of brain using electrodes placed on the patient's scalp [3]. EEG signals play a very important role in detection of epileptic seizures, as it shows the variations in the voltage between electrodes [14]. An accurate detection of epileptic seizure is required so that anti-epileptic therapies can be initiated at proper time. Fig. 1 shows the different approaches used for the detection and prediction of epileptic seizures. Deep learning techniques are considered as more robust technique over other approaches [5]. It performs automatic feature extraction that captures robust details of the input EEG signal and thus gives effective results. Fig. 2, Fig. 3, Fig. 4 shows healthy, Preictal and ictal EEG signals respectively.

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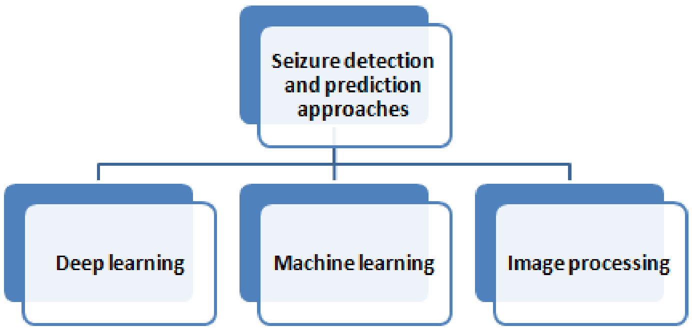

***Fig. 1**. Epileptic seizure detection and prediction approaches*

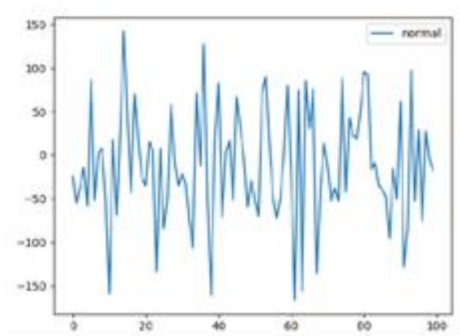

***Fig. 2**. Healthy EEG signal*

2 EPILEPTIC SEIZURE DETECTION AND PREDICTION APPROACHES:

2.1 Machine learning:

The goal of the work by [8] was to construct a function that takes the feature vector of the EEG signal as an input and maps it to seizure or non seizure class. Since the classification task was not linear, RBF kernel was used for the non linear classification. The seizure feature vectors formed 2 clusters: one represented seizure and other represented non seizure class. Spectral, spatial, temporal features were extracted. Binary classification into seizure or non seizure classes was performed using SVM classifier. Leave one out cross validation was also used. The detector with EEG data had a mean latency of 4.2 seconds, but addition of ECG data improved the performance and the latency resulted into 2.7 seconds.

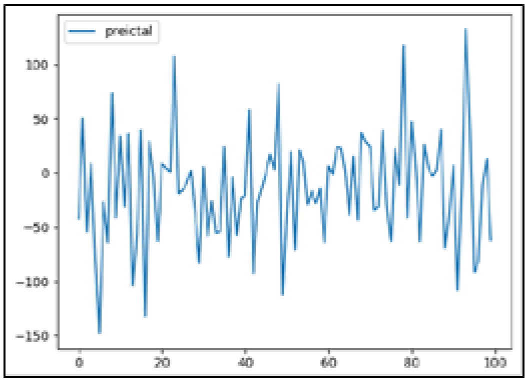

Fig. 3. *Preictal EEG signal*

Wavelet decomposition was performed in the approach proposed by [10], EEG waveforms morphology, and their spatial localization features were extracted. Binary classification was performed with seizure and non seizure class. SVM classifier was used in the approach. From each EEG channel of EEG signal, features were extracted. These features were combined together to form a feature vector. This feature vector was further used to classify an EEG signal as seizure of non seizure using the SVM classifier. In the approach proposed by [11], time domain features, frequency domain features, brain connectivity along with graph features were extracted. LSTM classifier was used for the classification task. Speech signal processing techniques can be used for the detection of epileptic seizures. An approach proposed by [17] uses MFCC based features that provides a great accuracy when used along with XGBoost. Bonn university database was used to perform multiclass classification using XGBoost. Since both speech and EEG signals are time series based, MFCC features are used by some approaches for seizure detection also. It was observed that XGBoost provides better accuracy results than that of the SVM classifier and accuracy was greater for the MFCC based features input data than the classifiers using MFCC dataThe anticipation time and true positive prediction rate of a model is largely dependent upon the EEG signal preprocessing. A methodology proposed by [18] provides reliable way of data preprocessing and reduction of features. Preprocessing was performed in two stages: first stage, surrogate channel was obtained from multichannel EEG signal. In second stage, to increase the Signal to noise ratio, empirical mode decomposition has been applied as a preprocessing technique to the surrogate channel. CHB-MIT dataset was used for binary classification using time and frequency domain feature like spectral and statistical moments. k-nearest neighbor, naive Bayes, and Support Vector Machines classifiers were used in the approach. SVM performed better in the case of sensitivity and hence was used for the classification task. Using the proposed approach, the prediction was performed before 23.6 minutes thereby giving time to the patients to undergo medication. The main goal of the work was to predict the seizure state.

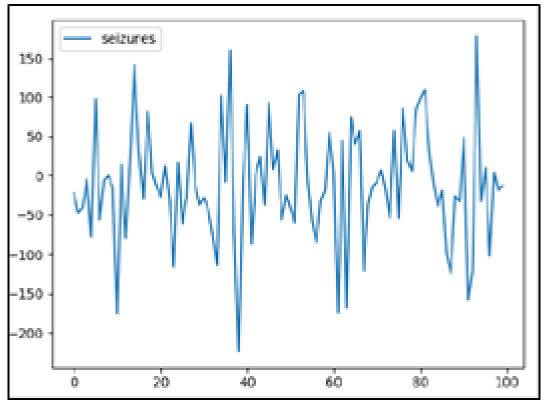

Fig. 4. *Ictal (seizure) EEG signal*

In the proposed approach by [20], extraction of 52 features (time, frequency, time-frequency features) was performed using EEG signal data. Feature selection was performed using RelieF feature selection algorithm that selected best 15 features out of 52. Binary and multiclass classification was performed using 10 classification models. Bonn university database was used for the work. For error correction, 10 fold cross validation was performed. It was observed that using 15 features and 10 fold cross validation, QDA and RF were the best models for 3 class classification, whereas SVM linear and with RBF kernel was the best for 5 class classification. In the approach proposed by [21], multiclass classification of EEG signals was performed for classes “pre-ictal”, “ictal”, “inter-ictal” using artificial neural network. Feature extraction was performed after preprocessing and the features were ranked for the dimensionality reduction. Artificial neural network was used in the approach. For feature ranking, fisher scoring technique was used and the accuracy obtained was: 96.9%. Entropy was found to be the most distinguishable feature. Potential features extraction was the main challenge of this approach. The accuracy of classification of epileptic seizure depends upon the features extracted and selected features for model training. In the method proposed by [22], feature selection was performed using t test, bhattacharya, Wilcoxon, ROC. Out of 12 features, 8 features were used to train the model. Following features were extracted: time, frequency, time-frequency, non linear domain. It was observed that band power is the best feature. Extraction of robust features is very important for accurate classification. In the methodology proposed by [23] they have introduced a unique set of features capable of performing the classification of EEG signals into epileptic and non epileptic classes using the linear SVM kernel. Bonn university database was used by them. Training and testing data split criterion was: 60% and 40% respectively. Zero-crossing, mean absolute value, RMS, Waveform length Features were extracted from the EEG signal. 95% accuracy was obtained. It was observed that ensemble of time domain features provides higher accuracy then single individual feature. Kmeans clustering can be used to divide the data into clusters. In the approach proposed by [25], features were extracted from each cluster. Bonn university database was used in the approach. Features extracted were: mean, median, standard deviation, maximum, minimum, minimum first quartile, third quartile, IQR, skewness, kurtosis. SVM, naïve bayes, logistic regression classifiers were used for the classification of EEG signals. WEKA tool was used to perform the analysis. 10 Fold cross validation technique was also used. Using SVM classification model 100% accuracy was obtained across epileptic and non epileptic seizure classification. In the method proposed by [26], epileptic seizure detection was performed using reduced set of features. Features were extracted such as expect activity measurement coefficient, higuchi fractal dimension. Performance measures used were: accuracy, precision and Jaccard coefficient. KNN classifier was used to perform classification.

2.2 Deep learning:

Machine learning methods cannot accommodate multichannel EEG data effectively [2]. Seizure detection can be performed effectively using deep learning approaches. Convolutional neural network (CNN) can extract the robust features from EEG signal to provide more accurate classification results. Using CNN, manual feature extraction is not required, since automatic features extraction is performed. CHB MIT dataset has been used in the proposed approach by [1] for performing binary classification using the multichannel EEG signals into seizure and non seizure class by making use of CNN. The deep learning model proposed by them was inspired by the winning architecture in computer vision [12]. They have used a CNN model that extracts temporal, spatial and spectral features of an EEG signal. The system was tested for both cross patient and patient specific EEG data. Correlation maps were generated that can relate to the output in the form of images. Also, brain mapping images were produced that can be used by the clinicians for the diagnosis purpose. Overall accuracy achieved for cross patient and patient specific data was obtained as 98.05% and 99.65% respectively. It was observed that CNN needs huge training and is not easy to interpret. Moreover, due to the availability of small dataset, cropped training dataset was used to increase the size of dataset. It is very difficult to use multichannel EEG data in a machine learning approach. 3D CNN can be used effectively given a multichannel EEG signal input. In the methodology proposed by [2] they have claimed it as first approach to use 3D kernel CNN for the detection of epileptic seizures using EEG signals. Automatic features extraction was performed using CNN. For each channel, a 2D image was constructed and then using these 2D images, 3D images were generated. 3D kernel was responsible to characterize different stages of epilepsy namely: inter-ictal, pre-ictal, ictal. The conversion of EEG signal into 3D array was performed such that it keeps most of the information of EEG signal. Dropout and 10 fold cross validation strategy were used to get better accuracy. It was observed that the overall accuracy obtained using 3D CNN model was better than the accuracy obtained by 2D CNN model. Fig. 6 shows accuracy, false negative rate, false positive rate result obtained by [2]. It was observed that multichannel 3D CNN provide better accuracy results. Fig. 5 shows the accuracy, false negative rate and false positive rate for approach proposed by [2].

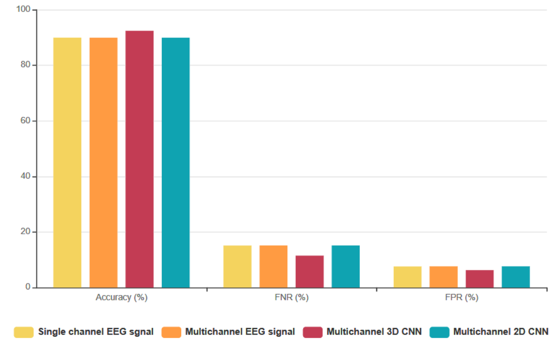

***Fig. 5**. Accuracy, false negative rate and false positive rate analysis for approach proposed by [2]*

Convolutional neural network and artificial neural network are used in the methodology proposed by [24] for seizure detection. Time, frequency, time-frequency domain features were extracted in this approach. Dominant features were provided as an input to the artificial neural network, whereas raw EEG signals were provided to the convolutional neural network. It was observed that convolutional neural network provides better accuracy results than that of artificial neural network. Fig. 6 shows the accuracy, specificity, sensitivity and f1 score values obtained by [24]. It was observed that ANN has obtained better sensitivity and f1 score, whereas CNN provided better specificity, accuracy. Bonn university database has been used in the approach proposed by [4] for multiclass classification with classes namely normal, Preictal and seizure. Automatic feature extraction using 13 layers CNN architecture was performed along with 10 fold cross validation. They have claimed their approach as the first approach using deep CNN for epilepsy detection. EEG signals have variations over the same class for inter and intra patient data. The proposed approach by [5] can locate the brain's seizure occurring area. They have extracted spectral, temporal and spatial features from the multichannel EEG signals for the binary classification: seizure and non seizure class. They have used CHB MIT dataset for their work. The multichannel EEG signal was firstly converted into a 2D image. For preserving the distance between the electrodes in the 3D plane, they have used Polar projection method. Cubic interpolation was used to interpolate the values of the electrode projection. The CNN is used for automatic robust feature detection task. The CNN is connected to the recurrent network. The output of CNN is then given to recurrent network into one of the functional blocks. Leave one out cross validation was used in their approach. It was observed that image representation has clinical benefits.

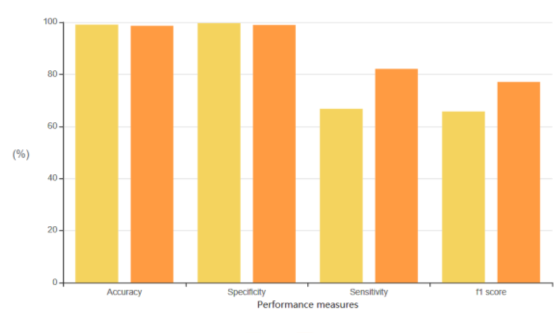

***Fig. 6**. Accuracy, specificity, sensitivity, f1 score values analysis for approach proposed by [24]*

Generation of feature representation using divergence encoded spectrograms was performed by [6]. Robust features at temporal and spatial resolution were extracted from EEG signal. Binary classification was performed into seizure, non seizure class. Their methodology consists of two main modules: divergence encoded spectrograms generation and dense feature learning. To train their CNN model, they required EEG data in the form of a 3D structure, for this purpose they used divergence encoded spectrograms. The second module, dense feature learning is responsible for the generation of the divergence encoded spectrograms. Their proposed CNN architecture has 2 sub-networks. One of the sub-network is a Deep convolutional network (DCN). In the DCN, multiple convolution layers are interconnected together and generate feature representation using divergence encoded spectrogram data. The second sub-network is a classification network. They have claimed this work as the first approach that uses the features learnt by DCN model to learn probabilistic distribution for the class prediction. In the approach proposed by [9], for the removal of high frequency noise, data preprocessing was performed on the EEG signals, by making use of butterworth bandpass filter. The EEG data was segmented to generate windows. Long time - duration window segment gave higher accuracy. Leave one out cross validation was used in the proposed approach. Channel restricted CNN was used in the proposed methodology. The challenges were: unbalanced data, good classification accuracy considering the artifacts involved. Image based classification was performed in the approach proposed by [13], the EEG signal short segments were generated and then were converted into images. These images were used to classify a signal as epileptic or non epileptic EEG signal. Leave one out cross validation was also performed. In the methodology proposed by [15], the EEG signal was converted into matrix format, also called as image like representation in order to maintain important information. The CNN model was trained using these as input. The main focus of the work by [28] was to use latest and effective machine learning techniques and hardware for the detection of epileptic seizures. CHB MIT dataset was used to perform classification using max pooling CNN. 50% dropout was used to reduce the overfitting. The architecture consisted of 1-3 convolutional and max pooling layers followed by 1-3 fully connected layers. Filtering and downsampling was performed as preprocessing steps. They have used 3 model approaches: Generalized model, patient-specific model, hybrid Model. The proposed system is able to detect 184 seizure onset with an average latency of 1.47 seconds. 2 fold is the novelty of this work. The complete system is implemented into an embedded SoC. It was observed that, average accuracy obtained using the frequency domain signal was higher as compared to time domain signals. For CNN frequency domain signals provide higher accuracy than that of time domain signals. Time domain, frequency domain were extracted in the approach proposed by [14]. Fig. 7 and Fig. 8 shows the accuracy obtained in 3 experiments using time domain and frequency domain EEG signals for Freiburg database and CHB MIT database respectively. It was observed that frequency domain EEG signal provide better accuracy results.

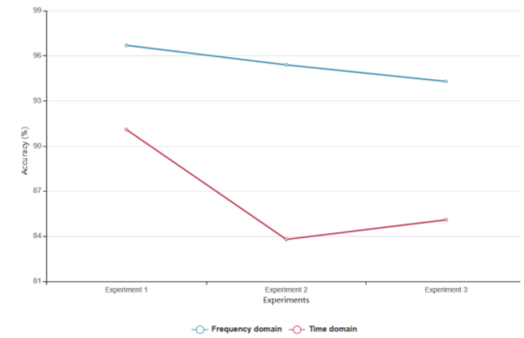

Fig. 7. *Analysis of accuracy obtained time and frequency domain EEG signals for Freiburg database using 3 experiments proposed by [14]*

Seizure detection can be performed from videos also, [27] have trained their model such that it gives generalized to different seizure types. They have used CNN to map the input of patient's epilepsy recording to the probability of presence of seizure as the output. The network they have used is shallow but the performance is good and it is fast as well. They have achieved realtime performance from video yielding an AUC 78.33%. Further the lightweight design makes it compatible for the hardware of mobile devices. Interictal epileptoform discharges can be used for the classification of epileptic and non epileptic EEG signals. In the approach proposed by [3], EEG signals were classified on the basis of the interictal epileptoform discharges. The proposed methodology comprises of 3 modules: preprocessing, CNN level classification, EEG level classification. Waveform level classification used CNN and EEG level classification was performed using SVM classifier. Based on the p value, 20 best features were selected from the output CNN. They obtained 83.86% mean 4 fold classification accuracy. Since the dataset used in the approach was not standard, performance comparison was not possible. In the approach proposed by [19], frequency domain features were used to train the model. For a signal 10 seconds window was used because the smallest time frame in which seizure occurred in the dataset was 10 seconds. The model learnt EEG signal patterns for seizure and non seizure EEG signals. 10 fold cross validation was performed. The F-measure accuracy achieved was 95%. Frequency based features extraction was performed, so that the time domain data can be converted into meaningful features. CHB-MIT dataset was used for binary classification using deep neural network

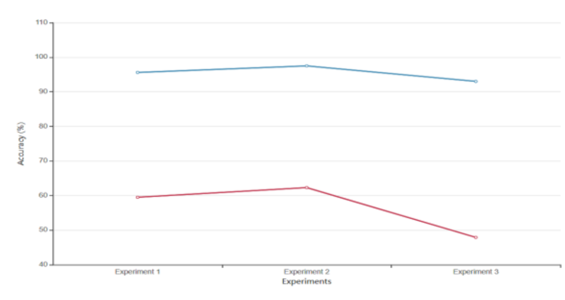

Fig. 8. *Analysis of accuracy obtained using time and frequency domain EEG signals for CHB MIT using 3 experiments proposed by [14]*

2.3 Image processing:

Image processing techniques can be used to detect the epileptic seizures activities by applying classification techniques on brain map representations of EEG. In the approach proposed by [16], independent component analysis was used to extract independent components and then brain maps were formed using those independent components.
Two features were extracted: closed neighbourhood gradient pattern, combined texture pattern. After comparing the results with the results of other approaches that have used image processing, it was found that the proposed methodology gives better results and provide assistance to the neurologists such that they can visualize brain maps to locate seizures. For each channel of multichannel EEG signal, 2D images were generated by [2]. Then 3D images were generated by making use of these 2D images. 3D kernel was used to classify the different stages of epilepsy. An approach was proposed by [5] in which, the multichannel EEG signals were first converted into 2D images. For preserving the electrode's distance, in the 3D plane, polar projection method was used. For the interpolation of the values of the electrode projection, cubic interpolation was also used. An approach was proposed by [13] in which, image based detection of epileptic seizure was performed. The EEG signals were further divided into segments and then a plot image was generated. These images were used to classify a signal as epileptic or non epileptic EEG signal. Binary classification was performed for seizure and non seizure classes. Leave one out cross validation was also performed. In the methodology proposed by [15], they have used input images for the classification of EEG signals. For the conversion of EEG signals into image shape, wavelet and fourier transform was used in the approach. They have proposed a patient specific seizure prediction method. They have used 30 seconds window on EEG signal to extract both time and frequency features and short term frequency transform is applied on the window. Afterwards, standardization was performed on the short term fourier transform components and over the complete frequency range. In this methodology, the EEG signal was converted into matrix format, also called as image like representation in order to maintain important information. Fig. 9 shows the accuracy obtained using CNN classifier by various proposed approaches. It was observed that "[28]" provided the highest accuracy result of 100%.

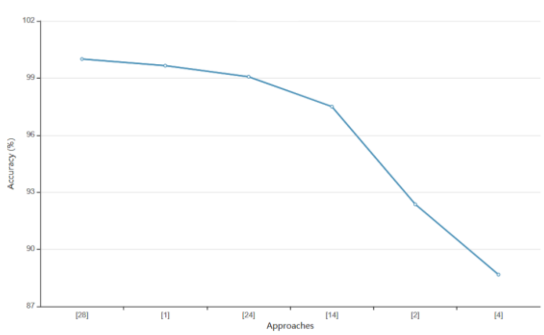

***Fig. 9**. Accuracy obtained using CNN classifier by different proposed approaches*

Fig. 10 shows the classifier accuracy obtained using SVM classifier by various proposed approaches. It was observed that "[25]" achieved the maximum accuracy of 100% using SVM classifier.

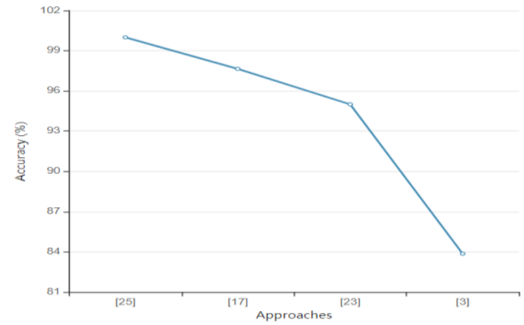

***Fig. 10**. Obtained using SVM classifier by different proposed approaches*

Fig. 11 shows the accuracy results obtained by other classifiers like XGBoost, ANN and KNN. It was observed that XGBoost provides better classification accuracy of 99.5%.

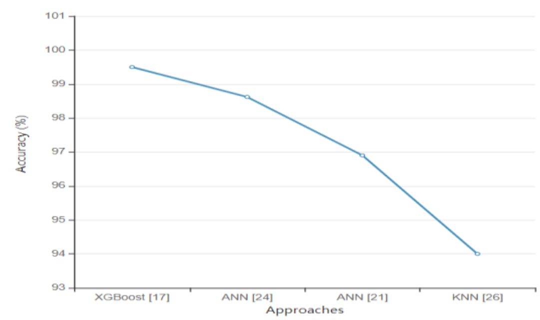

***Fig. 11**. Accuracy obtained using other classifiers (XGBoost, ANN, KNN) by different proposed approaches*

Fig. 12 shows the accuracy obtained by different approaches using two datasets: Bonn university and CHB MIT databases.

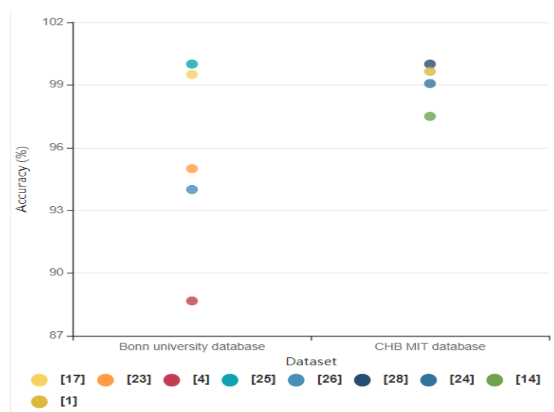

***Fig. 12**. Accuracy obtained by different approaches using Bonn university and CHB MIT benchmark databases*

Fig. 13 shows the sensitivity and specificity values obtained by different approaches.

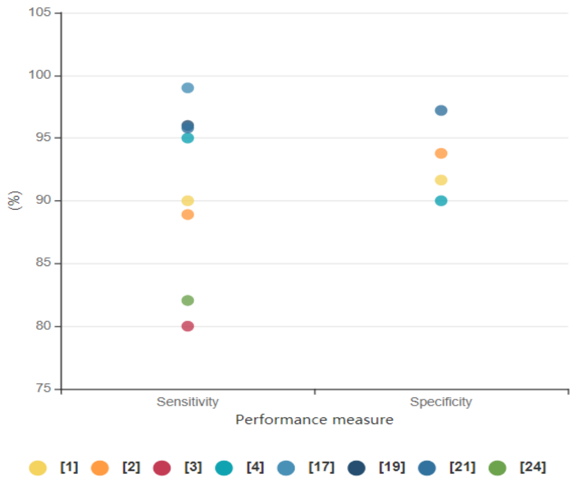

***Fig. 13.** Sensitivity and specificity values obtained by different approaches*

TABLE 1
COMPARISON OF DIFFERENT APPROACHES USED FOR SEIZURE DETECTION AND PREDICTION

Authors	Features	Classifier	Accuracy	Novelty
[1]	Temporal and spectral	CNN	Cross patient: 98.05% Patient specific: 99.65%	Inspired with the winning architecture in computer vision.
[2]	Spectral, temporal	3D CNN	92.37%	First approach to use 3D kernel CNN using EEG signals for detection of epileptic seizures.
[3]	Interictal epileptoform discharges	CNN, SVM	83.86%	Classification based on interictal epileptoform discharges
[4]	Automatic feature extraction	CNN	88.67%	First approach using deep CNN for epilepsy detection.
[5]	Spectral, temporal, spatial	RCNN	-	Locating the brain's seizure occurring area
[6]	Frequency, temporal and spatial features	DCN	-	First approach, that uses deep CNN model foe seizure classification
[8]	Spectral, spatial, temporal	SVM	-	Detection latency of 2.7 seconds
[9]	Automatic feature extraction	Channel restricted CNN	-	Good classification accuracy considering the artifacts involved
[10]	EEG waveforms morphology, and their spatial localization	SVM	-	Designed to work on a variety of seizure types
[11]	time domain, frequency domain, brain connectivity, graph features	LSTM	-	5 seconds long EEG segment was analyzed.
[13]	Spectro-temporal features	CNN	-	Seizures can be detected by visualizing the plot images
[14]	Time domain, frequency domain	CNN	Freiburg database: 96.7% CHB-MIT: 97.5%	Frequency domain signals provide higher accuracy than time domain signals
[15]	Time and frequency	CNN	-	Using convolutional neural network with minimum feature engineering.
[16]	Closed neighbourhood gradient pattern, combined texture pattern	Least square support vector machine	-	Visualization of brain maps to locate seizures
[17]	MFCC based features	XGBoost	99.5%	XGBoost classifier using MFCC-based features can obtain high accuracy
[18]	Time and frequency domain	SVM	-	prediction was performed before 23,6 minutes
[19]	Frequency domain	deep neural network	-	Extracted spectral domain Features, proposed multilayer perceptrons structure
[20]	Time domain, frequency domain, time-frequency domain	Knn, nb, per, lda, qda, mlp, dt, rf, svm, svm2	-	Study of different feature extraction and classification methods
[21]	Mean, Maximum, Minimum, Variance, Standard deviation, Skewness, Kurtosis, Entropy	ANN	96.9%	Performance of three different feature ranking techniques is investigated on computed features
[22]	Time, frequency, time-frequency, non linear domain	-	-	8 features were Selected out of 12
[23]	Zero crossing, mean absolute value, RMS, Waveform length	Linear SVM	95%	Ensemble of time domain features dominates over a single, individual feature.
[24]	Time, frequency, time - frequency	CNN	99.07%	CNN requiring no feature extraction is slightly better than ANN
[25]	Mean, median, standard deviation, maximum, minimum, minimum first quartile, third quartile, IQR, skewness, kurtosis	SVM	100%	K-means clustering approach for detection of seizures
[26]	Activity measurement coefficient, higuchi fractal dimension	KNN	94%	Epileptic seizure detection using reduced set of features
[27]	Automatic feature extraction	CNN		Seizure detection from video input data.
[28]	Automatic feature extraction	Max pooling CNN	100 %	2 fold, complete system is implemented into a embedded SoC

2.4 Proposed Approach

In proposed methodology, ensemble technique is used for classification. It was observed that frequency domain EEG signals provide better results [14]. Also multichannel 3D CNN provide good classification accuracy for seizure diagnosis [2]. The frequency domain EEG signals are provided as input to the 3D CNN classifier. The 3D CNN performs classification and the predicted results are provided to a majority voter. The majority result is selected as the final classification result.

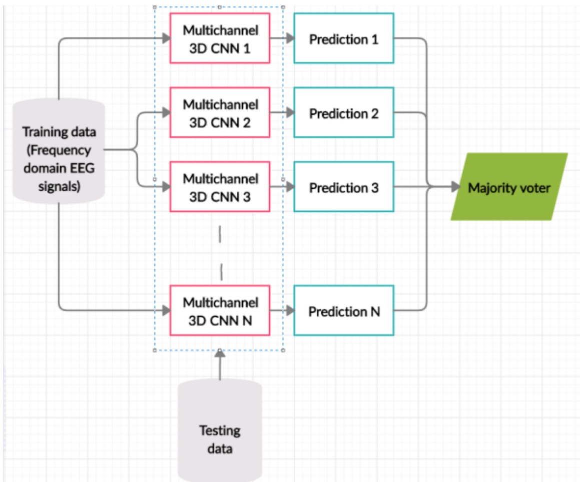

***Fig. 14**. Proposed methodology : Ensemble technique*

Although, the proposed approach is costly as it is making use of N number of multichannel 3D CNN. But combining the power of such N number of multichannel 3D CNN may provide better accuracy results. In medical domain, accuracy cannot be compromised over computation cost. Fig. 14 shows the proposed approach.

3 CONCLUSION

Deep learning techniques provide a way of extracting robust features and generate feature maps using kernels. It provides good accuracy results and accuracy is very important in case of health domain. Machine learning methods also provide great accuracy and thus are used widely for the detection and prediction of epileptic seizures. But there is a limitation in using machine learning techniques. Machine learning techniques cannot accommodate multichannel EEG signal data effectively. Hence deep learning is an effective approach. With detection, prediction of seizure is equally important as if it gets predicted at early stage, then suitable therapies can be done to reduce the seizure risk. An automated approach for seizure detection and prediction will eliminate the expensive scans that are required for the diagnosis of epileptic seizures and the diagnosis time will also get reduced. This system will help patients in developing countries where the neurologists might not be available immediately.

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