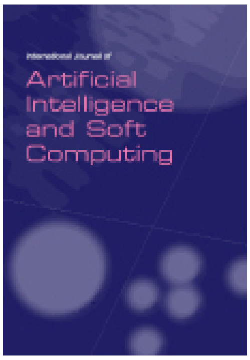

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An efficient hybrid approach for the prediction of epilepsy using CNN with LSTM

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Abstract: Epileptic seizures are a severe neurological disorder with significant implications for public health. Epileptic seizure is one of the neurological disorders which affect either children in the age group of 10–20 years old or adults in the age group of 65–70 years old. It affects brain cells. Electroencephalogram (EEG) is the best tool for the recording of brain electrical activity. Epileptic seizures can be studied in four stages known as preictal, ictal, postictal, and interictal. This paper presents a literature review for the prediction of epilepsy using various machine learning-based approaches. This paper also presents the comparative analysis of various computational-based techniques used to predict epilepsy. This paper proposes a hybrid approach for the prediction of epilepsy using convolutional neural network and long-short-term memory. Here, the proposed model achieved an accuracy of 98%, precision of 98.21%, recall of 92.02%, F1-score of 95.01%, specificity of 99.56%, MCC of 93.84%, TPR of 92.02%, FPR of 0.44% and AUC is 100%. IT is also observed that the proposed model performed better in comparison to other approaches.

Keywords: epileptic seizure; convolutional neural network; CNN; long-short-term memory; LSTM; deep learning; support vector machine; SVM.

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1 Introduction

Neurological disorders are diseases of the central and peripheral nervous systems. The opinion to the world health organisation, disorders include epilepsy, Alzheimer's disease, Parkinson's disease, dementia, shingles, and strokes are neurological diseases that can greatly influence the brain, the spinal cord, and the nerves that join them. Nearly 27% of the people in the world hurts from some neurological disorder (de Souza et al., 2018). Epilepsy is a chronic, severe, and divesting neurological illness. Nearly 1–2% of the world population is suffering from epilepsy and amongst them, nearly 30–40% suffers from medication–refractory epilepsy. Research evidence proves that epileptic seizures can be predicted as patients feel 'auras' before epileptic seizures. Since these are the four states of seizure but we are interested in only two states that interictal and preictal. Ictal and postictal states are discarded because they are out of our discussion. It focused on the classification between interictal and preictal states. Thus, a particular seizure prediction job becomes a classification problem (Mirowski et al., 2008). Treatment of epileptic patients can be done with drugs or surgical procedures earlier prediction benefits the epileptic patient, in the sense they can protect themselves before the severe injury or attack by taking appropriate medicine and improving their condition. Epileptic seizures can be categorised into four different states: preictal state (before the seizure), ictal state (during the seizure), postictal state (after the seizure), and interictal state (between the seizure) (Usman et al., 2017).

Only half of the epileptic patients who go through surgery keep themselves free from an epileptic seizure. And the remaining patients who are experiencing uncertain and unpredictable seizures during per day routine can experience a very terrific attack. It is observed that the treatment of epileptic seizures cannot be done completely. Several researchers are trying to investigate the techniques such that seizures can be predicted before their onset (Eberlein et al., 2018). Since it is very difficult to capture brain electric activity, therefore several researchers have tried ECG signals, the reason is that medical proofs that heart rate pattern changes before an epileptic seizure (Hoyos-Osorio et al., 2016). An electroencephalogram (EEG) is used to record brain electrical activity (signals). One of the German neurologists first use an EEG to capture the electrical activity of the human brain (Osman and Alzahrani, 2018). In the past 30 years, even the best technique for seizure prediction cannot give good sensitivity (can predict seizure) and specificity (ignoring false alarm) (Freestone et al., 2017). Every year, approximately two million new epileptic patient accounts and maximum 70% of epileptic patients can improve their health condition by the anti-epileptic drugs (AEDs) and other 30% are not controllable. Some symptoms of seizure include loss of recognition or consciousness, trouble in movement, poor ability of perception, and loss of other reasoning ability. Epileptic patients are confined from riding or driving any vehicles and cannot get sincere or good employment because of uncontrolled seizures. It is observed that epileptic disease can be experienced by either child in the age group between 10–20 years old or people in the age group between 65–70 years old. EEG is considered the most effective and powerful tool for recording brain electric activity. Without EEG it is very difficult to record the electrical signal of the brain. If a preictal state is found out among the main interictal state true alarm is raised (Daoud and Bayoumi, 2019). Electrodes are placed on the scalp of the patient to record EEG. This way electroactivity of the brain can be captured (Lasefr et al., 2017).

It is observed in Sharma et al. (2015) that the brain wave samples differ in the preictal and interictal states. That is why the seizure prediction technique uses the Bivariate feature instead of univariate features. Seizure prediction methods are specific for the specific patient because there are fluctuations in the seizure type and seizure location among the patient. So different EEG signals are observed among the patients. The authors used a supervised machine learning technique that focuses on the two important stages which are feature extraction and classification between the two states that are preictal and interictal. Among all other classifiers, the support vector machine (SVM) achieved great accuracy in the sense of specificity and sensitivity. Some previous research mentioned that deep learning algorithms have attained outstanding results in classification issues. For the forecasting of an epileptic seizure, multi-layer perceptron and convolutional neural network (CNN) were used on the extracted feature of the EEG data. Because of the importance of prior and precise forecasting of an epileptic seizure, authors developed a new automated framework that combines feature extraction and classification. The authors developed a deep learning-based algorithm that automatically extracts the important features without any pre-processing. Multi-layer perceptron and deep CNN were used to extract features. Deep CNN combined with recurrent neural network to do the classification process. Sharma et al. (2015) used a new term synchrony measure and established a connection between EEG signals captured from different sections of the brain the development of the classification methods of the epileptic seizure.

2 Related work

From the past few decades to now, researchers have proposed their views in the field of neurological disorders especially epilepsy disease. They proposed several methods for the prediction of epileptic seizures so that an important step was taken to improve the quality of the patient's life. Some of the proposed methods or techniques are given below:

Panichev et al. (2015) proposed a technique that forecasts the seizure based on the specific patient. Here, patient-specific epileptic seizure prediction is done. This method used intracranial EEG signals for the prediction of epileptic seizures in humans and dogs. Prediction of seizure in human, SVM, showed the best result for time window $T_w = 60$ sec ($AUC = 0.9349$); Prediction of seizure in the dog, SVM, showed the best result for time window $T_w = 30$ sec ($AUC = 0.9432$). The above past works motivated us to try a different approach. Fujiwara et al. (2015) proposed a method based on the heart rate variability (HRV) for the forecasting of an epileptic seizure. This method had good sensitivity and a false-positive rate of 91% and about 0.7 times per hour respectively. Asadi-Pooya and Bahrami (2019) examined the extent of loss of responsiveness in individuals with psychogenic non-epileptic seizures as well as described the physical changes of individuals that may be correlated with that kind of a phenomenon. Patients with psychogenic non-epileptic seizures will often experience loss of responsiveness, which is directly correlated with seizure-related injuries. Raghu et al. (2019a) demonstrated an EEG matrix determinant as an important component for epileptic seizure identification. Eleven non-epileptic communities, as well as epileptic EEG identification issues, were written to analyse functional brain activity in various epileptic states. This test showed the highest grading accuracy of 99.45% (using Bonn University dataset) as well as 97.56% (using RMCH dataset). Rosas-Romero et al. (2019) implementation of functional near-infrared spectroscopy (fNIRS) to the identification of epileptic seizures yields findings that are preferable to all those dependent on EEG and indicate that the deep learning method to this issue is effective given the existence of fNIRS recordings. Costa et al. (2019) illustrated the feasibility of utilising lipid-based nanosystems to treat epilepsy and anxiety by pointing out the intranasal route as well as toxicological issues linked to the requirement to test the condition based on mucociliary clearance. Hussein et al. (2019) illustrated the medical utility of the seizure detection method obtaining excellent results in terms of seizure detection accuracy across cutting edge approaches. The seizure detection strategy can help to diagnose epileptic seizures reliably and robustly in optimal or real-life conditions.

Raghu et al. (2019b) presented an improved method for seizure identification using a new efficient and robust feature called sigmoid entropy, generated from discrete wavelet transformations. The sigmoid entropy in each sub-band was calculated from the wavelet coefficients as well as categorised using a cross-validated nonlinear SVM. Al Ghayab et al. (2019) presented a novel method that integrates the frequency domain data with the information gain technique for detecting epileptic seizures from EEG data. This process contains four major phases as well as has the strongest capability of detecting epileptic seizures in the EEG data. Wei et al. (2019) represented an attractive approach for pre-processing the actual EEG data into an appropriate form to retain temporal and spatial detail. A workable mechanism LRCN was suggested to develop a predictive epileptic seizure model, which could categorise epileptic key stages as well as establish an initial warning. It was suggested that the post-processing technique forecast the seizures in various timeframes. To assess the results, the segments-evaluation or the event-evaluation were processed. A comparison was performed with the common data throughout this article, with multiple techniques. Overall, the LRCN system gives an improvement in sensitivity and specificity of around 5 to 9%. Tzimourta et al. (2019) proposed a randomised controlled automated seizure detection technique depending on the discrete wavelet transform. A five-level transformation is implemented in every EEG section, as well as the wavelet coefficients extract five characteristics. The extracted vector is employed to train or even distinguish among ictal as well as interictal features in a random forest classifier. The outcomes of classification are impressive, achieving accuracy over 95% and supporting the robustness of this system.

Leong et al. (2019) identified which patients from psychogenic non-epileptic seizures and epileptic seizures diagnostic classes exhibit specific personality styles, as well as whether they could be used in medical practice to effectively test for PNES. Epilepsy has a lesser openness especially in comparison to psychogenic seizures. Openness is also smaller in people with epilepsy compared with the overall population. The results are stable and statistically important. Wu et al. (2020) proposed an automated epileptic seizure detection method, combining CEEMD and XGBoost, called CEEMD-XGBoost. The decomposition approach CEEMD was used to separate raw EEG signals into a series of intrinsic mode functions as well as residues, which is designed to efficiently reduce the impact of mode mixing. The multi-domain functions were retrieved from input signals and the decomposed components and subsequently sorted accordingly to the extracted features' significant scores. Eventually, XGBoost was implemented to establish the model for the diagnosis of epileptic seizures. Zazzaro et al. (2019) discussed how to evaluate the EEG signal employing data mining strategies and procedures with the primary goal of detecting a seizure within EEG signals immediately. They designed and created a multifunctional and extensible tool called training builder for the extraction of features from time-series data. Vidyaratne and Iftekharuddin (2017) integrated the wavelet decomposition method along with the directed transfer function method to introduce a new wavelet-based directed transfer function (WDTF) approach for the identification of patient-specific seizures. This approach had obtained 99.4% accuracy. The WDTF approach is capable of improving the effects of seizure identification in long-term EEG health records with focal epilepsy. Wang et al. (2018) presented a novel real-time, patient-specific automatic identification of epileptic seizure occurrence, using scalp as well as intracranial EEG. The proposed new method receives harmonic fractal characteristics based on numerous resolutions or even self-similarity from the EEG for reliable seizure onset detection. To obtain better frequency resolutions without repetitive calculations, a quick wavelet decomposition process, known as HWPT, is calculated dependent on the Fourier transform. The developed system is successful in detecting seizure onset with 96% sensitivity, 0.1 for each hour median false detection rate, with a mean latency of 1.89 seconds along with 99.8% accuracy.

Hassan and Subasi (2016) proposed a specific EEG lead-dependent automated seizure screening process for epilepsy. This employs a new method for signal processing, called CEEMDAN. They incorporate a machine learning algorithm based on ensemble learning known as LPBoost for the first time for the classification of epileptic seizures. Usman et al. (2017) suggested a model that would give an effective way for pre-processing or even extraction of features. They used EMD for pre-processing with derived time domain and frequency domain characteristics to develop a prediction model. The proposed method identifies the beginning of the preictal state, which is the condition that begins several minutes before the onset of the seizure, with a 92.23% true positive rate along with an average prediction period of 23.6 minutes on the 22 subjects scalp EEG CHB-MIT. In women with epilepsy, throughout pregnancy, the seizure magnitude may be significantly impacted by variables like variations in ASD metabolism, alteration in hormone levels. New-onset seizures were unusual throughout childbirth. Many patients with first-time epileptic seizures throughout childbirth have had epileptic seizures after birth, which suggests a first epileptic presentation (Ma et al., 2020). Tsiouris et al. (2018) proposed a new approach based on long-short-term memory (LSTM) that offers a substantial improvement in the efficiency of seizure prediction. They used LSTM networks in EEG signals for epileptic seizure prediction. A two-layer LSTM network is chosen to test predictive seizure output employing four distinct preictal window lengths, varying from 15 min to 2 h. The new approach based on LSTM offers a substantial improvement in the efficiency of seizure prediction. Rincon et al. (2020) established a model-based classification system to diagnose epileptic seizures that are used to process EEG signals. The fundamental aim was to develop an EEG filtration system that would improve the epileptic signal waveform. Using the curve fitting method, the filtered signal was fitted into a quadratic linear-parabolic configuration. In this method, 92% sensitivity and 94.1% accuracy were achieved. Kiral-Kornek et al. (2018) proposed a method based on the intracranial electroencephalography (iEEG) data, and data of ten patients were brought from the seizure advisory system and observed that the system obtained average sensitivity of 69%.

3 Computational intelligence technique

This paper proposed an ensemble deep learning-based approach for the prediction of epilepsy. Here, a brief introduction of CNN and LSTM is given.

3.1 Convolutional neural network

A CNN also known as shift-invariant in machine learning is a category of deep neural networks, used to analyse visual imagery. CNN is mostly used in the field of NLP, image and video recognition, and medical image analysis. CNN was initially developed in the neural network image processing community. A CNN involves two operations named convolution and pooling as feature extractors. The output of this sequence of operations is connected to a fully connected layer same as a multi-layer perceptron. There are two kinds of pooling used such as max-pooling and average-pooling. The CNN is also applied to text in natural language processing. When we use CNN for text instead of images, then we use the 1-dimensional array to represent the text. Mostly in the NLP task, CNN is used in sentence classification. To perform text classification, each sentence or document is represented as a matrix. Each row of the matrix shows one token, typically a word. We can say that each row is a vector and represents a word. Typically, these vectors are word embeddings like Word2Vec and Glove, word embedding is the low dimensional representations of vectors but they could also be one-hot vectors that index the word into a vocabulary. In the NLP task, we use filters over full rows of the matrix (words) so the width of filters and the width of the input matrix are the same (Kalchbrenner et al., 2014).

3.2 Long-short-term memory

LSTM is another model that is used for sequential information and proposed by Hochreiter and Schmidhuber (1997). LSTM is an RNN architecture that remembers values over arbitrary intervals. It is used to solve the problem of vanishing gradient problem. It can learn long-term dependencies. RNN has only two gates that are input gate and the output gate from the last hidden state at observation time t and beside the hidden state, there is no information about the past to remember. LSTM's allow RNN's to remember their inputs over a long period. That is why LSTM uses its memory to accumulate information over a long period. This memory cell is known as a gated cell, where the gated means that the cell represents whether or not to store or delete information, based on the information importance (Hochreiter and Schmidhuber, 1997).

4 Material and methods

4.1 Dataset description

The dataset used in this paper is taken from the Kaggle website in the contest of epileptic seizure prediction. This dataset is publicly available on the Kaggle website. The main dataset contains five different folders, where each folder is having 100 files, each file representing a single subject per person. And it is noted that for 23.6 seconds the brain activity is being recorded this information is contained in each file. 4,097 data points sample the parallel time series. Each data represents the EEG recording value of persons at a different time. So we can conclude that, since we have 500 different files it means we have 500 different people and each has 4,097 data points representing the value of EEG recording for 23.5 seconds.

Now, we split and rearrange 4,097 data points into 23 chunks where each chunk has 500 files. Each chunk contains 178 data points for one second, and each data point representing the value of EEG recording at a different time. So we have 23 * 500 = 11,500 rows and each row contains 178 data points for one second that represents 178 columns, and the last column is named as 'class' which has binary values that are yes or no. Yes represents an individual who has an epileptic seizure and no represents an individual who did not have an epileptic seizure.

4.2 Performance measure

To evaluate the performance and comparative analysis of various computational intelligence techniques, it is needed to calculate the various parameters involved in the performance measure. There are various parameters involved in the performance measure. Some of them are as follows:

- Accuracy: In the numerator, we have correct predictions as true positive and true negative and in the denominator, we have all the predictions made by the model. It is very important in the classification problem and defines as the ratio of the number of correct predictions made by the model over the total prediction made (Zhu et al., 2010).

  It is calculated mathematically as follows:

  $$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

- Precision: It is a measure that describes the ratio of true positive and summation of positive predictions made by the model (Sokolova et al., 2006; Sahin and Subasi, 2015).

  It is calculated mathematically as follows:

  $$Precision = \frac{TP}{TP + FP}$$

- Recall: It is also called sensitivity. It is a measure that describes the ratio of true positive concerning all positive data points (Sahin and Subasi, 2015).

It is calculated mathematically as follows:

$$Recall = \frac{TP}{TP + FN}$$

- Specificity: It is exactly the opposite of the recall. It is a measure that describes the proportion of true negative concerning all negative data points (Zhu et al., 2010).

  It is calculated mathematically as follows:

$$Specificity = \frac{TN}{TN + FP}$$

- F-measure: It is also called the F-score. It is the Harmonic mean of the precision and recall. It is denoted by *F* (Goutte and Gaussier, 2005).

$$F = \frac{2 * Precision * Recall}{Precision + Recal}$$

- MCC: It stands for Matthews correlation coefficient. It can be directly calculated by using the below formula with the help of a confusion matrix (Boughorbel et al., 2017).

$$MCC = \frac{TP * TN - FP * FN}{\sqrt{(TP + FP) * (TP + FN) * (TN + FP) * (TN + FN)}}$$

- True positive rate: Its formula is the same as that of the sensitivity. It is defined as the ratio of positive data points that are correctly examined as positive concerning all positive data points (Benbadis, 2005).

$$True\ positive\ rate = \frac{TP}{FN + TP}$$

- False positive rate: Its formula is the same as that of the specificity. It is defined as the ratio of negative data points that are inaccurately examined as positive for all negative data points (Benbadis, 2005).

$$False\ positive\ rate = \frac{FP}{FP + TN}$$

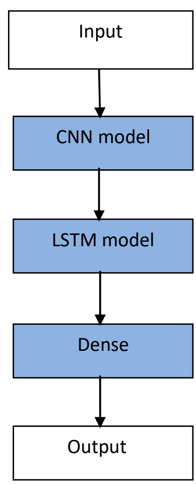
- AUC ROC: A ROC diagram is a visual curve that shows a binary classifier system's monitoring capability as its threshold for discrimination is changed. The receiver operating characteristic curve is formed by calculating the true positive rate over numerous thresholds points versus the false positive rate. ROC results give capabilities for selecting potentially efficient models as well as discarding inadequate models regardless of the cost scenario or class distribution (Narkhede, 2018; Davis and Goadrich, 2006).

4.3 Proposed method

The CNN has given the state of result in the task like image classification, speech recognition, and many natural language tasks. CNN can extract better feature representation from unstructured data than the traditional machine learning algorithms. Also, it has proven to be efficient. On the other hand, recurrent neural networks have given a state of result in a task, which uses sequential data, for example, machine translation, speech to text, etc. Thus use of 1DCNN as a feature extraction followed by LSTM model for interpreting the features across time steps and finally using the fully connected network for the classification. The EEG data is one-dimensional time-series data, Therefore the application of tree-based algorithms, fully connected networks did not work very well. This work explored the state of art sequential modelling method for tackling the task. From the comparative analysis, it is concluded that a combination of convolutional and recurrent networks working well for the task. CNN has given the state of result in the task like image classification, speech recognition, and many natural language tasks. CNN can extract better feature representation from unstructured data than the traditional machine learning algorithms. Also, it has proven to be an efficient feature extraction method. The CNN allows the sparse interaction of input neurons to the output neurons. CNN uses a convolution operation to accomplish this task.

$$s(t) = (x * w)(t)$$

Figure 1 Proposed ensemble approach (see online version for colours)



Typically a smaller kernel than the feature size will make sparse interaction mentioned above. The sparse interaction allows us to store lesser hyperparameters as compared with the fully connected network and hence memory and time-efficient. In our initial attempt to tackle the problem, we explored 1DCNN-based network, but due to the shallow param sharing over time, the 1DCNN model alone could achieve a good result and hence we shifted our attention to use recurrent networks. A recurrent neural network has given the state of result in a task that uses sequential data, for example, machine translation, speech to text, etc. The recurrent neural network uses a different approach to share parameters with the time as compared with the 1DCNN network. The recurrent network uses a recurrence relation to share the parameters between the hidden layers.

$$s(t) = f\left((t-1), \theta\right)$$

The recurrent recurrence relation allows the network to model variable-length sequences. The Valina recurrent network suffers from exploding gradient problem, therefore many variants of the recurrent network were proposed finally memory-based recurrent networks such as LSTM and GRU achieved a state of result in sequence modelling, in this paper the LSTM networks are used. As per our exploration, the result of LSTM was not very promising and thus we thought of taking advantage of feature extraction of convolution network and then using the recurrent model extract more meaningful information and hence finally using a fully connected model for the classification. The proposed ensemble approach is shown in Figure 1.

5 Results and comparative analysis

In this paper, for the comparative analysis nine machine learning models such as logistic regression, SVM, K-nearest neighbour (KNN), Gaussian Naïve Bayes, artificial neural network (ANN), CNN, LSTM and hybrid model of CNN and LSTM are used. Here, it is observed that the hybrid model (CNN + LSTM) gives better result in comparison to the other approaches, see Table 2 and Figures 2–7.

Figure 2 ROC for the classification using logistic regression (see online version for colours)

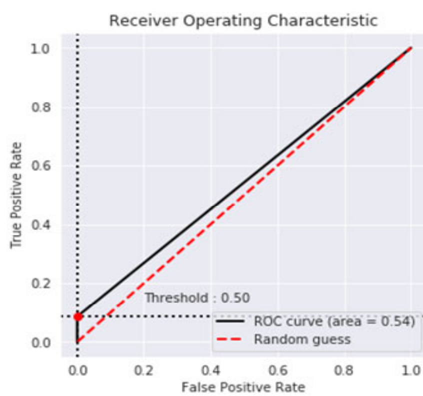


Figure 3 ROC for the classification using SVM (see online version for colours)

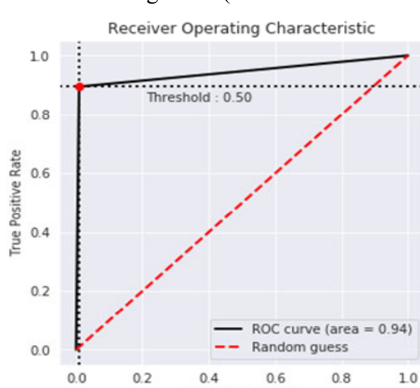


Figure 4 ROC for the classification using KNN (see online version for colours)

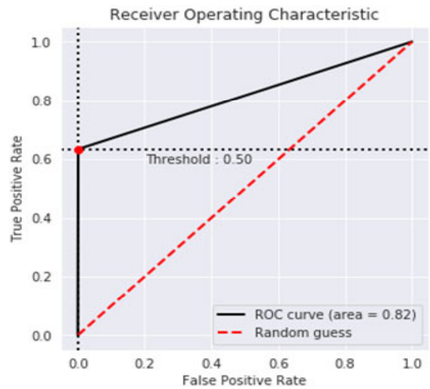


Figure 5 ROC for the classification using CNN (see online version for colours)

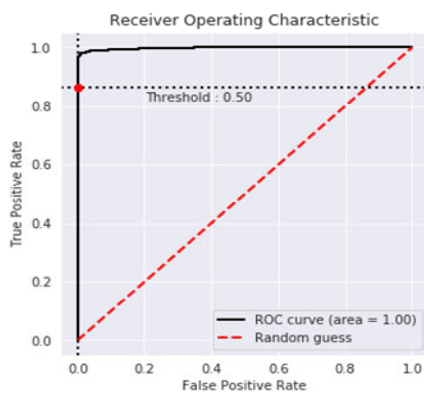
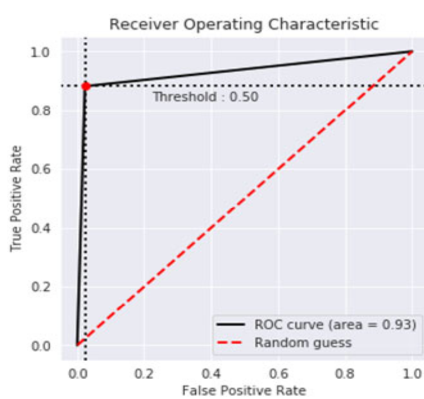


Figure 6 ROC for the classification using Gaussian Naïve Bayes (see online version for colours)



Here, it is observed that the proposed approach an ensemble of CNN and LSTM are achieved an accuracy of 98%, precision of 98.21%, recall of 92.02%, F1-score of 95.01%, specificity of 99.56%, MCC of 93.84%, TPR of 92.02%, FPR of 0.44% and

AUC is 100%. IT is also observed that the proposed model performed better in comparison to other approaches.

Figure 7 ROC for the classification using LSTM (see online version for colours)

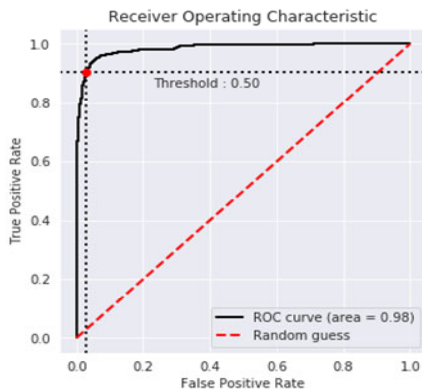


Figure 8 ROC for the classification using ANN (see online version for colours)

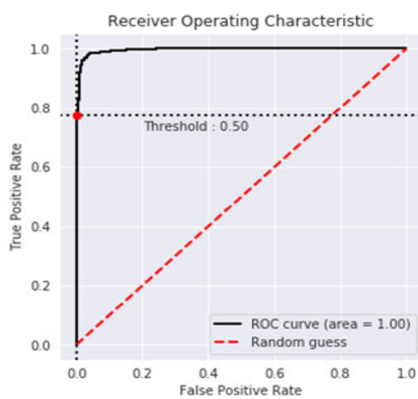


Figure 9 ROC for the classification using CNN + LSTM (see online version for colours)

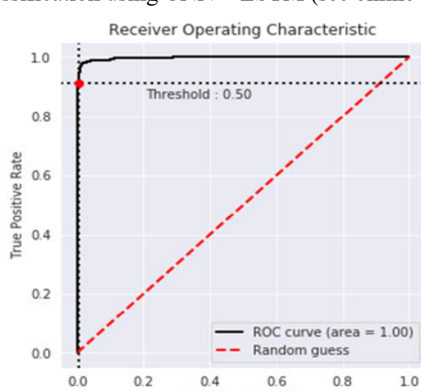


Table 1 Comparative analysis of various machine learning algorithms

Performance	*Logistic regression*	*SVM*	*K-nearest neighbours*	*Gaussian Naïve Bayes*	*ANN*	*CNN*	*LSTM*	*CNN + LSTM (proposed approach)*
Accuracy	81.09%	97.13%	92.35%	95.74%	94.96%	97.22%	95.78%	*98%*
Precision	100%	96.38%	99.34%	90.91%	98.91%	99.76%	89.40%	*98.21%*
Recall	8.61%	89.50%	63.45%	88.24%	76.47%	86.76%	90.34%	*92.02%*
F1-score	15.85%	92.81%	77.44%	89.56%	86.25%	92.81%	89.87%	*95.01%*
Specificity	100%	99.12%	99.89%	97.70%	99.78%	99.95%	97.20%	*99.56%*
MCC	26.37%	91.12%	75.76%	86.89%	84.26%	91.44%	87.20%	*93.84%*
TPR	8.61%	89.50%	63.45%	88.24%	76.47%	86.76%	90.34%	*92.02%*
FPR	0.00%	0.88%	0.11%	2.30%	0.22%	0.05%	2.80%	*0.44%*
AUC	54%	94%	82%	93%	100%	100%	98%	*100%*

6 Conclusions

The prediction of epilepsy at an early stage is a most important and challenging problem. Epileptic seizures are severe neurological disorders with significant implications for public health. Epileptic seizure is one of the. It affects brain cells. EEG is the best tool for the recording of brain electrical activity. This paper presented a literature review for the prediction of epilepsy using various machine learning-based approaches. This paper also presented the comparative analysis of various computational-based techniques used to predict epilepsy. This paper proposed a hybrid approach for the prediction of epilepsy using CNN and LSTM. Here, the proposed model achieved an accuracy of 98%, precision of 98.21%, recall of 92.02%, F1-score of 95.01%, specificity of 99.56%, MCC of 93.84%, TPR of 92.02%, FPR of 0.44% and AUC is 100%. IT is also observed that the proposed model performed better in comparison to other approaches.

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