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PAPER

A hybrid 1D CNN-BiLSTM model for epileptic seizure detection using multichannel EEG feature fusion

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Keywords: bidirectional long short-term memory (Bi-LSTM), convolutional neural network(CNN), epilepsy, electroencephalogram (EEG), seizure detection

Abstract

Epilepsy, a chronic non-communicable disease is characterized by repeated unprovoked seizures, which are transient episodes of abnormal electrical activity in the brain. While Electroencephalography (EEG) is considered as the gold standard for diagnosis in current clinical practice, manual inspection of EEG is time consuming and biased. This paper presents a novel hybrid 1D CNN-Bi LSTM feature fusion model for automatically detecting seizures. The proposed model leverages spatial features extracted by one dimensional convolutional neural network and temporal features extracted by bi directional long short-term memory network. Ictal and inter ictal data is first acquired from the long multichannel EEG record. The acquired data is segmented and labelled using small fixed windows. Signal features are then extracted from the segments concurrently by the parallel combination of CNN and Bi-LSTM. The spatial and temporal features thus captured are then fused to enhance classification accuracy of model. The approach is validated using benchmark CHB-MIT dataset and 5-fold cross validation which resulted in an average accuracy of 95.90%, with precision 94.78%, F1 score 95.95%. Notably model achieved average sensitivity of 97.18% with false positivity rate at 0.05/hr. The significantly lower false positivity and false negativity rates indicate that the proposed model is a promising tool for detecting seizures in epilepsy patients. The employed parallel path network benefits from memory function of Bi-LSTM and strong feature extraction capabilities of CNN. Moreover, eliminating the need for any domain transformation or additional preprocessing steps, model effectively reduces complexity and enhances efficiency, making it suitable for use by clinicians during the epilepsy diagnostic process.

1. Introduction

An epileptic seizure is the occurrence of sudden and uncontrolled electrical activity in the brain, which leads to unusual behaviour and sensations, sometimes loss of awareness. According to the World Health Organization (WHO), approximately 50 million people across the world are diagnosed with epilepsy, and approximately 80% of them are living in developing countries. Of this, approximately 8 million people have epilepsy who are living in India. Studies show that compared to the general population, risk of an epileptic patient for Sudden Unexpected Death in Epilepsy [SUDEP] is approximately 24-fold [1]. It accounts for 0.5% or higher of the global disease burden, a time-based measure which combines lost years due to premature mortality and the years lived in less-thanoptimal health. Epilepsy has a significant impact in economy in terms of health care needs, lost work productivity and premature death. To date, the condition has primarily been managed with anti-epileptic medications and surgery. There are no anticonvulsant treatments available today that can fully treat and cure epilepsy [2]. However, timely identification of seizures and effective interventions can mitigate the detrimental consequences of epilepsy [3].

Electroencephalography (EEG), a non-invasive electrophysiological technique that records electrical

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activity from the brain, is a commonly used diagnostic tool for epilepsy. Even though EEG is considered the most accurate and promising test in diagnosing epilepsy, the signal often contains large fluctuations due to the functional behaviours of the brain. Hence finding and marking traces through the visual analysis by human experts is always challenging. Also, inadequate training and human errors resulting from the cumbersome process of visually inspecting EEG may lead to misinterpretation and inaccurate diagnosis. Therefore, the necessity of a rapid accurate and effective system for the processing of long-term EEG recordings has become inevitable to reduce the misinterpretations, which would certainly reduce the workload of epileptologists and improve the quality of life of epileptic patients [4].

In the past few years, many studies have been conducted and a number of techniques have been developed to detect seizures, given the impact of this problem. Traditional machine learning methods use manual feature extraction techniques by dividing the signal into different sub-bands or components in either time, frequency, or wavelet-based domain. These hand-crafted features form the input to the model. Akut extracted and processed EEG signal features using wavelet transform [5], whereas Yang *et al.* [6] used short time Fourier transform (STFT) for the feature extraction. For instance, after extracting features using discrete wavelet transform (DWT) and K-means method, Orhan *et al.* used multilayer perceptron (MLP) for classification [7]. Similarly, after extracting features from wavelet decomposition coefficients, Jareda *et al.* explored Support Vector Machine (SVM) and K-Nearest Neighbour (KNN) classifiers for realisation of their EEG based seizure classification technique [8]. In another research [9], discrete wavelet transform has been used for feature extraction and SVM with radial basis function was used for training and classification. They showed that the gray wolf optimizer SVM approach can enhance the diagnosis of epilepsy. In another method [10] proposed by Chakraborty *et al.* two entropy-based methods such as Multiscale Dispersion Entropy (MDE) and Refined Composite Multiscale Dispersion Entropy (RCMDE) were explored for extracting the statistical features. SVM is used for feature classification. Before inputting to SVM they employed ANOVA for selecting the significant features. On top of that, Wang *et al.* used symlet wavelets to decompose the signal into different frequency bands. Statistical features extracted from 5 sub bands were used for three class classification of EEG signals using gradient boosting machine technique [11]. Additionally, principal component analysis was employed for reducing the dimensionality of features in the model. However, because of the non-stationary nature of EEG signals and artifacts during the acquisition time, statistical components change across subjects and these domain-based methods are susceptible to variations in seizure pattern. Also, these algorithms do not eliminate requirement of manual feature selection and hence it is required to have expertise in signal processing and data mining to develop an accurate seizure detection model using traditional machine learning methods [12].

Kukker *et al.* proposed a reinforcement learning based seizure classification method [13, 14] eatures were extracted using Hilbert Huang transform. In their proposed fuzzy-Q learning approach genetic algorithm was also employed for optimisation of the model. Meanwhile, EEG signal features were created from fuzzy lattices in the form of Kinetic Energy from which highest seven lattices were utilised to train the classifier [14]. Reinforcement learning algorithms exhibit good classifier performance, albeit choosing right learning rate and domain expertise is critical for the effectiveness of the model.

In recent studies, deep learning techniques are explored more in seizure detection or prediction tasks. It is found from studies that automated extraction of features prior to classification significantly enhances performance than manually extracting and inputting signals to the classifier. For instance, Hossain *et al.* developed a two-dimensional CNN model to extract spatial and temporal EEG signal characteristics. They have attained an accuracy of 98.05% with their 9 layered network [15]. In Acharya *et al.*'s work [16], a deep convolutional neural network model consisting of 13 layers for automatic seizure detection was developed. They have achieved an average accuracy of 88.7% with a specificity of 90% and a sensitivity of 95% [16]. Khan *et al.* proposed a three-class model with CNN architecture of 6 convolutional layers for classifying the wavelet transformed input to pre-ictal, ictal and inter-ictal classes [17]. The output resulted in an average FPR of 0.142/h. Similarly, Zhou *et al.* proposed a patient specific seizure detection system using CNN [18]. On top of that Jana *et al.* proposed a two-dimensional CNN architecture for automatic feature extraction and classification of seizures. By using a channel selection algorithm they reduced the number of channels from 32 to 6 which effectively reduced the complexity of the model [19]. CNN with stacked auto-encoders was used in Li *et al.*'s seizure classification and detection task [20]. In the same vein researchers explored different CNN architectures in their seizure detection algorithms [21–24 . The CNN based method however, is unable to remember past time series patterns, making it difficult to directly learn the most significant and representative features from time series of 1D EEG signals. It also has difficulties in extracting the global relevance of the data even if it has good feature capturing ability for noisy and non-stationary signals [25].

Studies have shown that recurrent neural network (RNN) architecture acquires the temporal features of sequential data more efficiently and can learn long term dependencies thus remembering information from the past [26, 27]. Long Short-Term Memory

(LSTM) is an RNN architecture [28] commonly used to deal with time series data such as EEG. It considers the long-term dependencies of data ignoring the local spatial information [29]. Shekokar *et al.* proposed a 3-layer LSTM network for seizure detection model [30]. In the same concern, Singh *et al.* used spectral feature-based LSTM network in their epileptic seizure detection model [31]. By using FFT they derived spectral power and mean spectrum amplitude features for 23 channel EEG signals. Whereas Duan *et al.* proposed bidirectional gated recurrent unit to predict seizures effectively [32]. In the same concern an RNN classifier is presented by Najafi *et al.* for the classification of focal and generalised epilepsy [33]. They utilised Pearson's rank correlation coefficient in selecting discriminative features that are extracted after the discrete wavelet transformation of signals. These studies have utilised temporal dependencies of LSTM networks in their seizure classification tasks to achieve good performance. Given the efficacy of CNN and LSTM in processing EEG signals, few researchers utilised stacked serial CNN and RNN structures to extract the temporal and spatial features [34, 35]. However, information may be lost in the middle layers of neural network with this kind of stacking, resulting in poor classification performance [36].

In our study we combined the capabilities of CNN and LSTM to form a spatio-temporal feature fusion network as a parallel feature fusion model (CNN-BiLSTM) for the efficient classification of epileptic EEG signals. With no preprocessing steps the model gives a very positive result for seizure detection. The organizational structure of this paper is: section 1 reviews previous works on seizure detection, section 2 describes the materials and methods including the dataset, preprocessing, model architecture and evaluation indicators. The results and discussions are included in section 3 and section 4 describes conclusion.

2. Materials and methods

2.1. EEG dataset

A multichannel EEG dataset from open source CHB-MIT database collected by Children's Hospital Boston is used in this study [37–39]. It is a collection of scalp EEG recordings from 22 paediatric patients (5 males in the age range of 3–22 and 17 females of 1.5–19 age. 24th case is unknown and chb 21 is recorded 1.5 years after the record of chb01. See table 1 for details) with refractory epilepsy. The dataset contains 664.edf files which includes a total of 976.55 h of EEG signals among which 198 seizures were recorded. All the signals were collected using international 10–20 system of electrode position sampled at 256 Hz, 16-bit resolution. 18 or more channels were used in each record. For the uniformity in analysis only channels which are common in all the cases is used in the study. The channels include 'FP1-F7', 'F7-T7', 'T7-P7', 'P7-O1', 'FP1-F3', 'F3-C3', 'C3-P3', 'P3-O1', 'FP2-F4', 'F4-C4','C4-P4', 'P4-O2', 'FP2-F8', 'F8-T8', 'T8-P8', 'P8-O2', 'FZ-CZ', 'CZ-PZ'.

Table 1. Details of the CHB MIT dataset used in the study.

Patient Id	Sex	Age	Number of seizures	Number of channels	Seizure duration (s)
Chb01	F	11	7	23	499
Chb02	M	11	3	23	175
Chb03	F	12	7	23	409
Chb04	M	22	4	23	382
Chb05	F	7	5	23	563
Chb06	F	1.5	9	23	147
Chb07	F	14.5	3	23	328
Chb08	M	3.5	5	23	924
Chb09	F	10	4	23	280
Chb10	M	3	7	23	454
Chb11	F	12	3	23	809
Chb12	F	2	21	18	1515
Chb13	F	3	12	23	547
Chb14	F	9	8	18	117
Chb15	M	16	20	18	2012
Chb17	F	12	3	18	296
Chb18	F	18	6	18	323
Chb19	F	19	3	23	239
Chb20	F	6	8	23	302
Chb21	F	13	4	23	303
Chb22	F	9	3	23	207
Chb23	F	6	7	23	431

2.2. Methodology

The proposed model works in two phases. In the first phase dataset undergoes segmentation and normalisation to acquire ictal and interictal segments from long EEG records of each patient. Seizure onset and offset times are annotated by the domain experts in the database. Based on the annotation, ictal and interictal signals are first identified. Ictal segments are defined as the signals during seizure and interictal segments are defined as the signal between two seizures. Successive seizures with time difference greater than 30 min are considered as separate events, otherwise they are taken as single seizure event. Additionally, patients who have seizures lasting lesser than 15 s are excluded from the seizure detection task. Interictal segments are extracted at intervals of atleast one hour apart from preceding ictal segments.

Considering that the deep learning models require large dataset for its robust performance, we applied data augmentation technique during extraction of EEG segments from continous EEG records. Moreover, a major challenge with seizure datasets is significant class imbalance with much reduced number of ictal segments compared to interictal segments. To adress this challenge, overlapping sliding window technique with an 80% overlap for ictal and 0% overlap for interictal signals is employed. Raw EEG signals are slided horizontally in the direction of time series

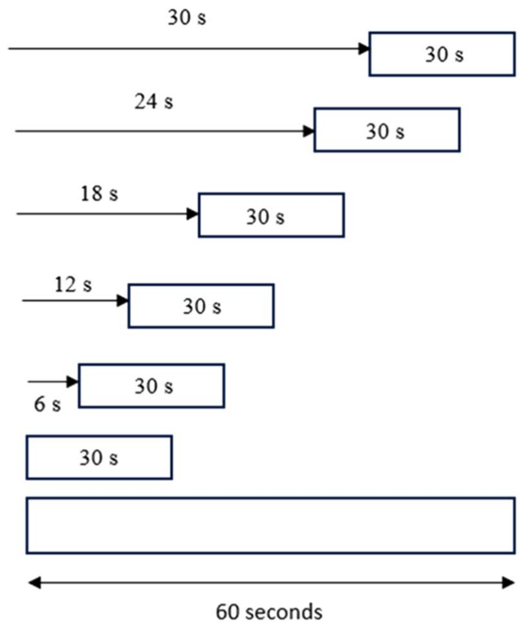

Figure 1. Windowing process - Sliding window technique used in the model for a 60 s segment is shown. A window with a length of 30 s slides over EEG ictal data with a step size of 6 s.

with a step time of 6 s as shown in figure 1. Window size is fixed at 30 s in each slide. This technique effectively expanded original dataset while preserving original distribution of features. The final dataset consisted of 21 instances, resulted in total of 2344 datapoints/samples including both ictal and interictal segments. Each of thus extracted raw EEG signal is standardised using z score normalisation to reduce feature variances and to accelerate the convergence of the model.

In the second phase, normalised segments for the selected 18 channels are fed into the proposed model for epileptic seizure detection. The framework combines two deep learning architectures: convolutional neural network (CNN) and bi directional long short-term memory network (Bi-LSTM) in two pathways (pathway 1 & 2) as shown in figure 2. The CNN component is responsible for extracting spatial features from the input EEG signals, while Bi-LSTM captures temporal features.

In pathway 1 as shown in figure 3, two convolutional layers are used for spatial feature extraction. Each convolutional layer is activated by ReLU activation function to introduce non linearities into the model. The first convolution layer comprises 16 filters with kernel size of 3 and stride of 1, while second convolutional layer comprises 32 filters with the same kernal size and stride. These layers are followed by pooling layers to reduce dimensionality of feature maps. Size and stride of pooling layer is set to 2. Max pooling used in conv 1 extracts the most prominent features within local regions however retains all spatial features. Global average pooling in CNN2 computes the average activation of learned features to have a global representation of entire feature map. Leveraging different pooling layers benefits from capturing local and global representations of the data, enhancing generalization ability and computational efficiency of the model. Batch normalization layer is used then to reduce overfitting and to stabilize the training process. Finally, a dense layer with 32 number of neurons, activated by ReLU function is used after flattening the feature maps, to extract the hierarchical features from input signal. Dropout rate of 0.25 is also used in pathway 1 (convolution block) to increase the training stability of the model.

Convolution process in this paper is given by

$$a_{i,j,c} = \sum\nolimits_{m=1}^{3} X_{l,c}.W_{m,c,i} + b_i \tag{1}$$

where l = j+m-1. X represents the input datapoints, W is the convolutional kernel weights, b represents the bias and a is the output activations. i is the number of filters, j the number of sampling points per channel and c is the number of channels.

LSTM networks have the ability to capture long term dependencies and store the network's temporal state. A bidirectional LSTM is employed in pathway 2 as in figure 4. Two LSTM layers with 64 and 32 number of units for each is employed to capture temporal information in both positive and negative directions. The data is fed into the Bi-LSTM block simultaneously with the CNN block leveraging the parallel processing capability of the model. Mathematically LSTM can be defined as

$$i_t = \sigma(W_i).[h_{t-1}X_t] + b_i \tag{2}$$

$$f_t = \sigma(W_f.[h_{t-1}X_t] + b_f \tag{3}$$

$$\acute{c}_t = \tanh\,(W_c.[h_{t-1}X_t] + b_c) \tag{4}$$

$$c_t = f_t.c_{t-1} + i_t.\acute{c}_t \tag{5}$$

$$o_t = \sigma(W_O.[h_{t-1}, X_t] + b_o \tag{6}$$

$$h_t = O_t.\tanh\,(c_t) \tag{7}$$

where i_t represents the input gate which decides how much new information is to be added to the cell state. f_t represents the forget gate that determines which information is to be forgotten from the previous node. C_t represents the cell state at time t and $\acute{c}_t$ represents new information, referred as candidate cell state. h_t represents hidden state at time step t. This state retains the relevant information from input sequence and serves the memory function. o_t is the output gate of the LSTM. The bidirectional LSTM layer concatenates the forward and backward hidden states. W_i, W_f, W_c, W_o are the weight matrices b_i, b_f, b_c, b_o are corresponding biases and σ represent sigmoid activation function [40].

Flatten layer is used to reshape the output feature maps obtained from Bi-LSTM which is then further passed to fully connected layer with 10 neurons activated by ReLU function. As in pathway 1, batch normalization layer is used to increase the training stability.

Afterward, the spatio-temporal features thus obtained from CNN and Bi-LSTM are concatenated to

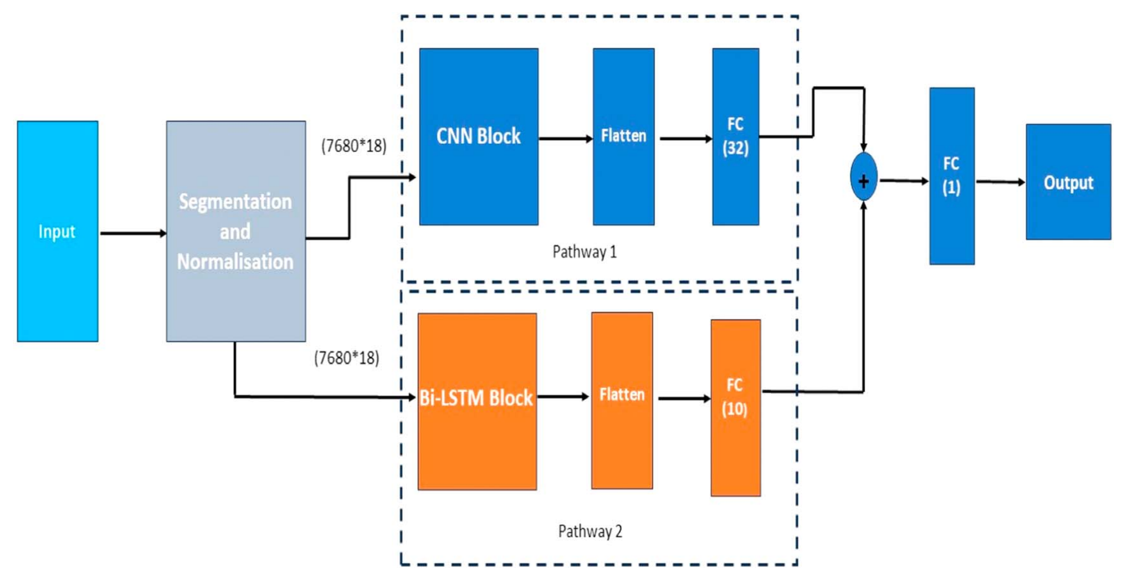

Figure 2. Overview of the proposed hybrid CNN-BiLSTM seizure detection model.

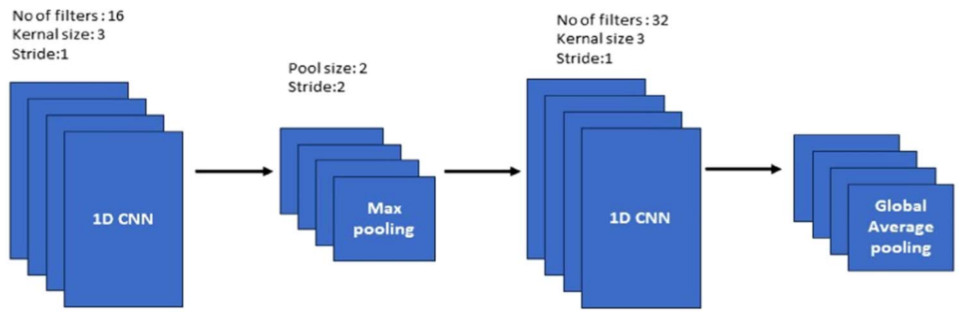

Figure 3. Details of convolutional block used in pathway 1.

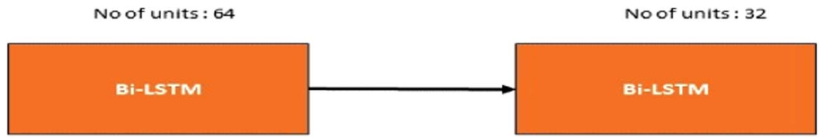

Figure 4. Details of Bi-LSTM Block used in pathway 2.

form a complete sequence. Finally, these fused features are input into fully connected layer with single neuron and sigmoid activation function, transforming the neuronal output to a bounded range between 0 and 1.

The CNN-BiLSTM parallel combination ensures that both architectures have its own path in capturing important spatial and temporal information. Without intersecting or affecting each other, they concurrently extract features thereby avoiding possible loss of information as seen in serial architectures. All parameters used in our model were chosen empirically through experimentation to avoid overfitting and to reduce complexity of the model.

2.3. Evaluation indices

The performance of the model is evaluated using accuracy, precision, sensitivity, specificity, f1 score as defined below.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{10}$$

$$Specificity = \frac{TN}{TN + FP} \tag{11}$$

$$F1Score = \frac{2}{\frac{1}{precision} + \frac{1}{recall}} \tag{12}$$

where TP is true positive (number of samples correctly classified as positive), TN is true negative (number of samples correctly classified as negative), FP is false positive (number of samples incorrectly classified as positive), and FN is false negative (number of samples incorrectly classified as negative) for the given number of n samples. In general, accuracy is the overall correctness of the model whereas precision focus on accuracy of positive predictions. While sensitivity measures the ability of model to capture positive cases, f1 score provides balance between precision and recall (sensitivity). Receiver operating characteristics curve (ROC) and precision recall curve is also plotted to further evaluate the performance of model.

3. Results and discussion

Our model is implemented in python 3.10 using Google Collaboratory notebook Tesla T4 GPU. We combined CNN and Bi-LSTM architectures to obtain a hybrid model leveraging spatial and temporal features of EEG. Unlike previous methods that combine these methods serially, we used a parallel architecture to give input simultaneously to CNN and Bi-LSTM, allowing extraction of different aspects of EEG signals concurrently. In serial architectures where one block is used after another, there may occur information loss as the layer may not capture complete information from the signal, before passing it to the next layer. Parallel processing ensures that no information is lost during feature extraction through independent access of blocks. After normalisation and segmentation of input, fixed length EEG segments are directly fed to CNN and Bi-LSTM blocks. The algorithm does not involve any domain transformation steps or other preprocessing techniques which increases model complexity. We applied 5-fold stratified cross validation method to increase the reliability of the results and to obtain a better error estimation. Each fold of the model is trained and evaluated independently with 100 epochs and batch size of 32. Training and testing instances in a single fold remained distinct from those used in other folds and in each fold the performance metrics are estimated independently. Average of these k matrices determines overall performance of the model.

Performance learning curves such as accuracy, ROC, precision recall for every five folds is depicted from figures 5(a)–(c) respectively. We obtained an average accuracy of 95.90 for the 5 folds as shown with false positivity rate of 0.05/h**.** The ROC Curve (figure 5(b)) plotted between sensitivity and false positivity rate provides a comprehensive evaluation of classifier performance on attaining balance between true positive and false positive classifications. Closer the ROC curve to the upper left corner, the higher the overall performance of the model. The area under the curve (AUC) is an aggregate measure of model's performance to discriminate between seizure and non-seizure classes. The higher AUC score obtained in every folds indicates that the model has higher probability to distinguish between two classes present in target samples. Furthermore, the AUC of precision recall curve depicted in figure 5(c) represent that model could identify groups of signals with seizure more readily at low false positive rate and low false negative rates.We obtained average precision of 94.78%, average sensitivity of 97.18% with average specificity as 94.62%, average f1 score of 95.95% and a false positivity rate of 0.05/hr.

Our model is trained using binary cross entropy loss function and optimised using Adam optimiser with learning rate of 0.001. The optimisation curve (loss curve) for each of the k folds is shown in figure 5(d). For every folds, curve exibited a consistent trend of steady decrease, indicating that the model is learning effectively as well as errror between predicted labels and true labels decreasing over epochs.

The performance comparison of classifiers between papers is challenging as there is no standard rule for the system development. However we compared our results with similar CNN-LSTM models and summarised in table 2. Approach proposed by Shahbai *et al.* employed frequency domain transformation for the signal during preprocessing step. They have used a very short 10 s window of EEG signal for STFT 2D representation and utilised 2D CNN—LSTM [41] to extract the spectral spatial and temporal features. Addition of domain transformation and two dimensional CNN and LSTM layers adds complexity to the model. On evaluating the model using CHBMIT dataset they achieved high sensitivity of 98.21, but with FPR of 0.13/h.

Although researchers used a different dataset for their model [42–45, 49, they explored CNN and LSTM architectures in implementation. Additionally, these studies utilised common evaluation metrics which enables a meaningful comparison with our results. Though the model proposed by Sakim *et al.* [42] achieved sensitivity of 78.2%, specificity was not competative, meaning that the model outputs more false alarms [42]. The 1DCNN-RNN model proposed by Roy *et al.* yielded an accuracy of 82.27%, however significant overfitting issues are pointed out in the paper [43]. On comparing our results with similiar models as shown in in table 2, it is observed that our model achieved higher performance in terms of accuracy and sensitivity [44, 45. Liang *et al.* and Bhattacharya carried out their experiments using CHBMIT dataset [46, 48]. Obviously results obtained by Liang [45] and Bhattacharya [48] with 84% and 97.74% sensitivity at FPR 0.2/h respectively, are much better than others, however, model proposed in these studies are highly complex with increased number of 2DCNN and LSTM layers. CNN-LSTM architecture in Hussain *et al.*'s work combined 6 channel data into a feature vector to form input to CNN [48]. The reliable and most discriminative spatial features with epileptic seizure that are captured by CNN are then fed to LSTM. However the serial architecture of CNN-LSTM may have

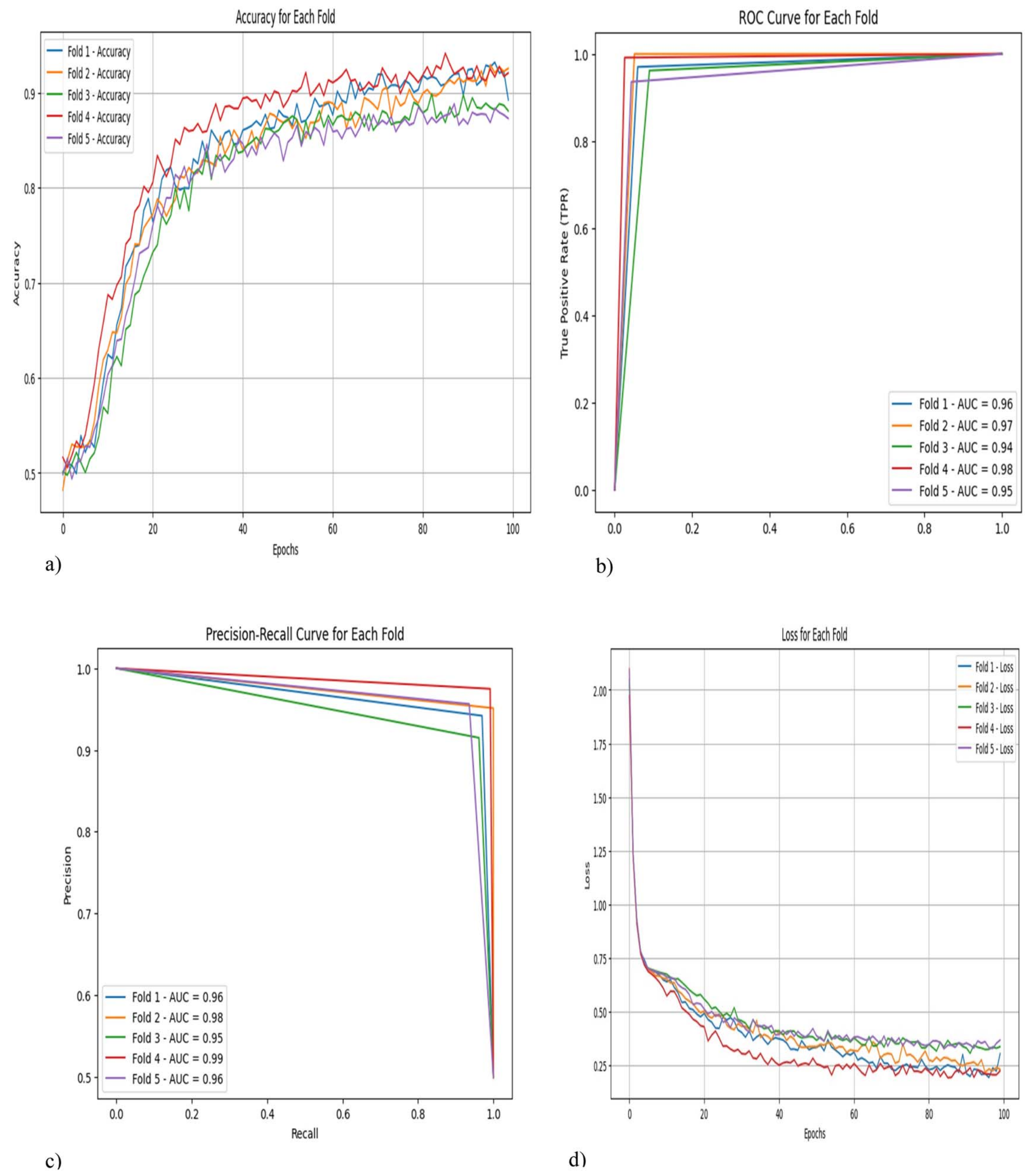

Figure 5. CNN-BiLSTM model learning curves for 5 folds using CHB MIT dataset. (a) Accuracy curve for each fold (b) ROC curve for each fold (c) Precision recall curve for each fold (d) Loss curve for each fold.

Table 2. Comparison of our results with other works.

Work	Dataset	Model	Acc	Precision	Sen	Spec	F1 score	FPR
[41]	CHB -MIT	2DCNN-LSTM	N/A	N/A	98.2	N/A	N/A	0.13
[42]	TUSZ	CNN-LSTM	N/A	N/A	78.2	N/A	N/A	0.629
[43]	TUH	CNN-RNN	82.27	N/A	N/A	N/A	N/A	N/A
[44]	TUH	CNN-LSTM	N/A	N/A	30.83	N/A	N/A	N/A
[45]	Clinical	CNN-LSTM	92	N/A	88	N/A	N/A	N/A
[46]	CHB -MIT	CNN-LSTM	99	N/A	84	99	N/A	0.2
[47]	SNUH-HYU & CHB-MIT	1DCNN-2DCNN	83.2	N/A	79.2	88.0	N/A	N/A
[48]	CHB-MIT	CNN-LSTM	N/A	N/A	97.74	N/A	N/A	0.2373
[49]	Freiburg	CNN-LSTM	93.99	N/A	94.36	94.13	N/A	N/A
This model	**CHB -MIT**	**1DCNN-BiLSTM**	**95.90**	**94.78**	**97.18**	**94.62**	**95.95**	**0.05**

significant information loss, which may lead to inaccurate results. Park *et al.* have used two datasets in their 1D-2D CNN seizure detection model (SNUH-HYU & CHB-MIT).

The feature maps generated by 1D convolutions for each channel is concatenated to perform 2D convolution. They have identified the spatio temporal correlation using 10,20,30 s of EEG segments from both datasets. The model yielded accuracy of 83.2% but at sensitivity of only 79.2% [47]. In addition, most of the above mentioned studies are patient specific which cannot be generalised to new unseen data. Our proposed model is not patient specific and fits well to new unseen data with low false positivity rate of 0.05/hr, that it can be generalised to use.

4. Conclusion

In this paper a novel hybrid 1D CNN-BiLSTM method is proposed for seizure detection from multichannel EEG signals. The method can be utilised as an effective tool to reduce the workload of epileptologists and also to improve the quality of life of epileptic patients.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://physionet.org/content/chbmit/1.0.0/.

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