This article has been accepted for publication in IEEE Journal of Biomedical and Health Informatics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/JBHI.2023.3265983

A Hybrid Deep Learning Approach for Epileptic Seizure Detection in EEG signals

Ijaz Ahmad, *Student Member*, *IEEE*, Xin Wang, *Student Member*, *IEEE*, Danish Javeed, *Student Member*, *IEEE*, Prabhat Kumar, *Member*, *IEEE*, Oluwarotimi Williams Samuel*, *Senior Member*, *IEEE* and Shixiong Chen*, *Member*, *IEEE*

***Abstract*—Early detection and proper treatment of epilepsy is essential and meaningful to those who suffer from this disease. The adoption of deep learning (DL) techniques for automated epileptic seizure detection using electroencephalography (EEG) signals has shown great potential in making the most appropriate and fast medical decisions. However, DL algorithms have high computational complexity and suffer low accuracy with imbalanced medical data in multi seizure-classification task. Motivated from the aforementioned challenges, we present a simple and effective hybrid DL approach for epileptic seizure detection in EEG signals. Specifically, first we use a K-means Synthetic minority oversampling technique (SMOTE) to balance the sampling data. Second, we integrate a 1D Convolutional Neural Network (CNN) with a Bidirectional Long Short-Term Memory (BiLSTM) network based on Truncated Backpropagation Through Time (TBPTT) to efficiently extract spatial and temporal sequence information while reducing computational complexity. Finally, the proposed DL architecture uses softmax and sigmoid classifiers at the classification layer to perform multi and binary seizure-classification tasks. In addition, the 10-fold cross-validation technique is performed to show the significance of the proposed DL approach. Experimental results using the publicly available UCI epileptic seizure recognition data set shows better performance in terms of precision, sensitivity, specificity, and F1-score over some baseline DL algorithms and recent state-of-the-art techniques.**

***Index Terms*—Convolutional Neural Network, Epileptic seizure, Electroencephalographic, Electroencephalography (EEG).**

This work was supported in part by the National Key R&D Program of China (2022YFE0197500), National Natural Science Foundation of China (81927804, 62101538), Science and Technology Planning Project of Shenzhen (JSGG20210713091808027, JSGG20211029095801002), China Postdoctoral Science Foundation (2022M710968). (The first two authors contributed equally to this work.) (Corresponding authors: Shixiong Chen; Oluwarotimi Williams Samuel.).

I. Ahmad, X. Wang, O. W. Samuel and S. Chen are with the CAS Key Laboratory of Human-Machine Intelligence Synergy Systems, Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences, Shenzhen, Guangdong 518055, China.(Email: ijaz@siat.ac.cn, wangxin@siat.ac.cn, samuel@siat.ac.cn, sx.chen@siat.ac.cn).

I.Ahmad and X. Wang are with the Shenzhen College of Advanced Technology, University of Chinese Academy of Sciences, Shenzhen, Guangdong 518055, China.

I. Ahmad, X. Wang and S. Chen are also with the Guangdong-Hong Kong-Macao Joint Laboratory of Human-Machine Intelligence-Synergy Systems, Shenzhen, Guangdong 518055, China.

O. W. Samuel is also with the School of Computing and Engineering, University of Derby, Derby, UK, DE22 3AW. (Email: o.samuel@derby.ac.uk).

Danish Javeed is with the Software College, Northeastern University, Shenyang 110169, China. (Email: 2027016@stu.neu.edu.cn).

Prabhat Kumar is with the Department of Software Engineering, LUT School of Engineering Science, LUT University, 53850 Lappeenranta, Finland (Email: prabhat.kumar@lut.fi).

I. Introduction

Epilepsy is a non-communicable neurological disorder disease that is typically associated with abrupt attacks [1]. Over 50 million people of various ages have been diagnosed with epilepsy worldwide [2]. Epileptic seizures are characterized by rapid and abnormal changes in the brain's electrical activity and the worst case, often trigger the whole body to become unresponsive [3]. Though developed anti-epileptic medicines have some therapeutic effects but they may result in body damage or even death in some cases [4]. According to previous research [5], electroencephalography (EEG) recordings monitor the electrical activity of the brain by implanting electrodes either outside the skull (extracranial recording) or inside the skull (intracranial recording), providing data that can be used for epilepsy seizure identification.

Furthermore, the scalp EEG data from multiple input channels with high temporal resolution from the brain can be collected using distributed continuous sensing [6]. The epileptic records are typically divided into four separate stages of brain activity: interictal, preictal, ictal, and postictal in seizure prediction research. This enormous amount of data can reveal the synchronized activity of neurons in many brain regions. As a result, epileptic seizure detection utilizing multi-channel scalp EEG data has received significant attention in the neuro-information technology field in recent years. Generally, neurology specialists conduct visual examinations of patients in clinics for the diagnosis of epilepsy. Furthermore, neurologists usually spend a lot of time and effort analyzing long-term EEG records for signs of epilepsy [7]. However, the majority of current EEG automatic seizure detection techniques perform poorly in real-time, particularly in terms of specificity and sensitivity, making them ineffective for application in clinical practice. The improved automated computer-aided system is urgently required for clinical practice to support neurologists with the 1D entity and accurately detect epileptic seizures. In this way, the amount of time spent by the neurologist analyzing long-term EEG recordings can be substantially minimized, while accurate detection would be realized [8]. Previous studies in [8], [9] used different machine and deep learning (ML/DL) models to extract significant and unique features from EEG biomedical signals. In contrast, DL classifiers, i.e., Convolutional Neural Network (CNN) and bidirectional long short-term memory (BiLSTM), are recently in trend and have proven to have the capability of excellent automated feature extraction and classification of EEG epileptic seizures. For

TABLE I: Related studies in seizure detection based on deep learning methods.

Publication	Dataset	Methods	Achievement
[14]	CHB-MIT	1D CNN, RNN	Performed 97.05%, 97.10% accuracy.
[16]	TUH EEG data	1D CNN	Achieved 79.9% accuracy.
[20]	Freiburg	BiLSTM	The proposed model has high accuracy (98%) for binary classification.
[23]	CHB-MIT	GRU	The proposed approaches accurately classified seizure and non-seizure classes performed 98% accuracy).
[25]	CHB-MIT	1D CNN, BiLSTM	The models performed 96% and 95% accuracy.
[18]	Freiburg	1D CNN	Accurately classified the epilepsy segments (ictal, preictal).
[28]	CHB-MIT	BiLSTM	The models performed 98% accuracy.
[26]	CHB-MIT	Hybrid 1D CNN-LSTM	Achieved 96% accuracy.

instance, the CNN collects translation-invariant characteristics from the signal, and the BiLSTM provides a superior prediction on time-sequential data employing memory cell elements to improve the epileptic seizure classification performance [10]. Thus, hybrid DL models have shown more effectiveness and superiority to classify epileptic seizures accurately. However, most of these classifiers have high computational complexity and suffer low accuracy with imbalanced medical data in multi seizure classification task (to distinguish between preictal and completely linked states) [11], [12]. Thus, the critical task is to find out epileptic seizures from EEG recordings by implementing imbalance classification information that possesses a higher duration of ictal than interictal, which directly influences the classification performance of the model. In this work, we propose a hybrid DL approach that combines 1D CNN and BiLSTM to efficiently extract spatial and temporal sequence information from the epileptic seizure dataset. At the same time, this is the first EEG study that uses K-means SMOTE and hybrid DL models with 10-fold cross-validation for the automated classification of binary and five EEG classes. Furthermore, to lower the computational complexity of the proposed approach, we trained our model using Truncated Backpropagation Through Time (TBPTT) mechanism.

A. Contribution

The following are the main contributions of this paper.

- A novel hybrid DL approach that combines 1D CNN with BiLSTM model to automatically extract spatial and temporal sequence information from the epileptic seizure dataset is proposed. The proposed approach uses softmax and sigmoid classifiers at the classification layer to perform multi and binary seizure classification tasks.
- The K-means SMOTE technique is used especially for binary EEG data to address the oversampling issue of long-term EEG samples.
- We employ the Truncated Backpropagation Through Time (TBPTT) mechanism to train the proposed model. To the best of our knowledge, this study is the first to integrate deep learning with the TBPTT algorithm for epileptic seizure detection in EEG signals.
- To evaluate the classification performance of the proposed 1D CNN-BiLSTM model in terms of accuracy, sensitivity, precision, specificity, and f1-score, 1D CNN-LSTM, 1D CNN-GRU, and the other current ML/DL models have been tested on the same publicly available UCI epileptic seizure recognition data set.

The structure of the remaining article is as follows. In Section II, we review the recent epileptic seizure detection techniques with their limitations. In Section III, we introduce the proposed framework, its functional components and the proposed algorithm. Then, in Section IV, we have discussed the experimental results. Finally, in Section V, the conclusion and future work are highlighted.

II. Related Work

Recently, various machine learning (ML) models, including the Random Forest (RF), Support Vector Machine (SVM) and K-Nearest Neighbor (K-NN) were used for epileptic seizure detection using different EEG signal datasets [10], [13], [14]. In [13], an Artificial neural network (ANN) approach with cost function for EEG epileptic seizure detection is designed. The authors achieved a high accuracy with an f1-score of 86%. This investigation study addresses the imbalance dataset issue using the CHB-MIT dataset. In [14], the authors implemented a hybrid model of support vector machine, and extended neighbour network (ENN) reported accuracy up to 97.7%. ML models can classify the EEG data, detect seizures and identify 1D meaningful patterns without compromising their overall performance. However, handling imbalanced EEG data is a significant challenge for ML models and requires high time complexity (sec). Furthermore, the extraction of the distinctive and meaningful features of EEG signals is conducted manually, which directly influences the model's classification performance [15]. To address such limitations of the ML models, DL techniques have been extensively used in different fields, such as detecting psychological disorders and diseases [16].

In particular, the CNN extracts a distinctive and rich set of meaningful features by applying different filters in the convolutional layers [17]. The 1D CNN architecture is the best choice for processing brain EEG signals because it is a straightforward structure requiring fewer parameters. It is faster than 2D CNN architecture and efficient in achieving

This article has been accepted for publication in IEEE Journal of Biomedical and Health Informatics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/JBHI.2023.3265983

high accuracy. Therefore, 1D CNN can diagnose epileptic seizures [11], [18], [19]. However, CNN cannot remember previous time series of patterns, making it difficult to learn the most important attributes of EEG data presented in time series form [20]. Thus, CNN faces difficulty reconstructing the relationship between epileptic seizure outcomes and the raw EEG. Recurrent neural networks (RNNs) can memorize past information since they are trained on prior outputs.

RNNs are the most competitive models for processing biomedical EEG signal data. Furthermore, they have been widely used to overcome the aforementioned challenges and have yielded promising results. To address the limitations of RNNs, such as their lack of long-term memory and vanishing gradient, the BiLSTM model has been used in [21]. In [22] study used a 2-layer BiLSTM model with a SoftMax function for analyzing the data and achieved an accuracy of 90%. While the authors of [23] established a 3-layer LSTM architectural approach for detection and achieved excellent results. In [24], the authors proposed a hybrid model of GRU with BiLSTM. The proposed work of [25] used ten alternative RNN architectures, each with 31 layers, which provided the most accurate results as the RNN model tends to help process the sequential data and reduce the vanishing gradient problem.

Moreover, in [26], the authors applied various pre-processing schemes and implemented a hybrid CNN-LSTM model that comprises 13 layers and got an average accuracy of 96.65 % applied time frequency-domain signals for the binary classification. The hybrid CNN-LSTM in epileptic seizure detection has made some progress; however, there are still some limitations. During model training, the unidirectional LSTM only learns past signal sequences. The BiLSTM improves recognition by integrating previous and future information. To further improve the classification performance of the EEG signal, the authors in [12] proposed a 1D CNN-LSTM hybrid model for automatic feature extraction of the EEG signals and classification of epileptic seizures. In [27], time series EEG data were subjected to various pre-processing schemes before feeding to their proposed CNN-LSTM model with 13 layers. The authors achieved efficient outcomes. Moreover, the comparative study on [28] indicated that BiLSTM has excellent classification performance compared to LSTM and GRU. Table. I presents the recent literature based on deep learning methods in seizure detection.

III. Proposed Framework for Epileptic Seizure Detection in EEG signals

In this section, we have discussed the main components and proposed algorithm. This includes oversampling technique, ID CNN, BiLSTM, proposed 1D CNN-BiLSTM and its training using TBPTT mechanism. The proposed framework and its working are shown in Fig. 1. The notation used in the proposed framework is mentioned in Table II. The components are described in the below subsections.

A. Oversampling Technique (K-means SMOTE)

In this research, most of the EEG data consists of non-epileptic seizure samples, which are highly imbalanced, including 2300 samples of epileptic seizure and 9200 samples of non-epileptic seizure. For accurate EEG classification, the data must be balanced. To balance the EEG dataset, K-means SMOTE is used in the present study, which resamples the imbalanced data within the region or boundary and overcomes the issue of traditional SMOTE. In this study, the hyper-parameter K-means for the SMOTE is 5. The mathematical equations and summary of the K-means SMOTE are as follows:

TABLE II: Notation Table.

Notation	Description
h_t	Input gate
f_t	Forget gate
o_t	Output gate
σ	Sigmoid function
$f(x)$	Nonlinear function
$tanh$	Hidden states of the LSTM model
x_t	Input of the timestamp
c_t	Cell state at time stemp (t)
$Ht^{forward}$	Forward gate of the BiLSTM model
$Ht^{backward}$	Backward gate of the BiLSTM model
ht^{Bilstm}	Both gates of BiLSTM layer
W^*, U^*	Weight metrics of the respective gates
b^*	Bias
X_n^m	m_{th} feature map of the n^{th} layer
c_b^i	b^{th} neurons of the i-feature map
k	Window size

$$Sparsity(j) = \frac{\bar{D}^m}{S_{minority}} \tag{1}$$

Where $\bar{D}^m$ represents the Euclidean distances within j^{th} cluster. While $S_{minority}$ explain the minority sample of the cluster. The imbalance division can be calculated as

$$Imbalance = \frac{S_{minority}}{S_{majority}} \tag{2}$$

While the weight of the minority samples ratio can be calculated as

$$Weight = \frac{Sparsity(j)}{\sum_{j=1} Sparsity(j)} \tag{3}$$

The objective of the weight is to determine the sample in the cluster. Finally, the SMOTE algorithm generates the cluster of synthetic samples $(Imbalance > 1)$ by,

$$\bar{y} = y + \lambda(y_{kn} - y) \tag{4}$$

Where y shows the random minority sample, y_{kn} presents the random sample selected by K-nearest neighbours of y, while λ shows the random values $0 < \lambda < 1$. After the balanced samples, the data is fed into the proposed 1D CNN for autonomous feature extraction. Furthermore, Algorithm 1 represents the whole process of the K-means SMOTE technique using unbalanced EEG data.

B. 1D CNN

To extract the most relevant and effective features from data of one-dimensional time series, the 1D CNN performed 1D convolutional operations to implement various filters. As shown in Fig. 2, the arrow represented the 1D feature of the

This article has been accepted for publication in IEEE Journal of Biomedical and Health Informatics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/JBHI.2023.3265983

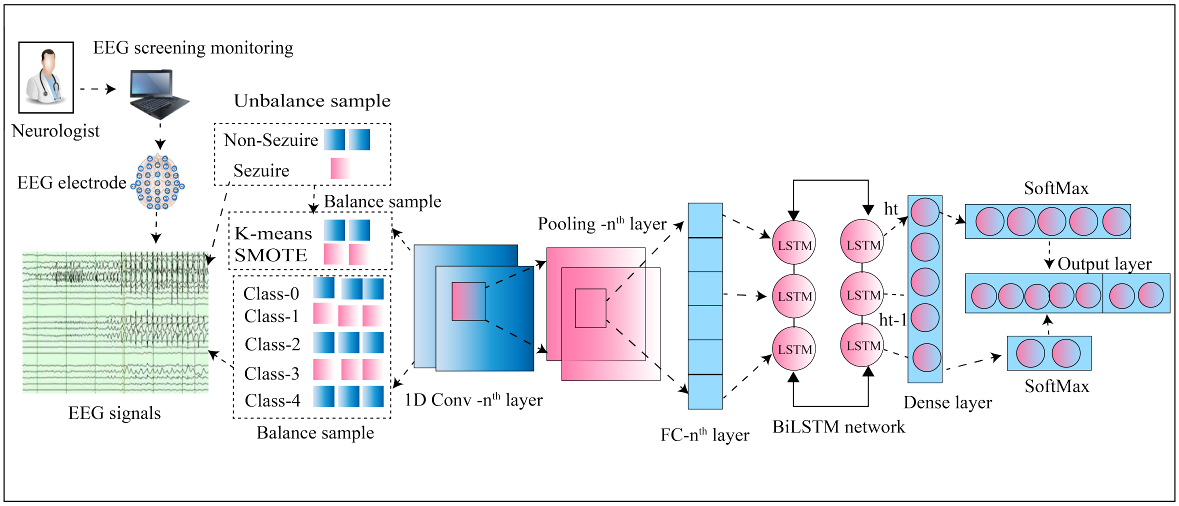


Fig. 1: A block diagram of the proposed model for EEG epileptic seizure detection.

Algorithm 1 K-means SMOTE

Input: S_{maj},S_{min},K

Output: K_{Smote}

Function:(S_{maj},S_{min},K)
Y_{ksmote}= [ ]

for i =1 to Length of S_{min} **do**
  n = $K_{nn}(Y_i, S_{min}, K)$
  R=[S_{maj}/100]
  while $R >= 0$ **do**
    while Y_{knn} = Select random(n) **do**

      Y_{ksmote} =$Y_i + rand(0, 1) \times \|Y_{knn} - Y_i\|$

      R = $R - 1$
      Return=K_{Smote}
    end while

raw EEG signal. The feature maps and convolutional filters of the 1D CNN allowed it to match the 1D feature of the raw data of the EEG signal. However, the specifications of the 1D convolution process were given in more depth in the following sections. To extract high-dimensional features that are essential for epileptic seizure detection tasks, it is important to increase the number of convolutional layers (CLs) in the CNN architecture.

C. BiLSTM

The BiLSTM uses two distinct RNNs to avoid the RNN's exploding gradient issues. Additionally, the BiLSTM layer evaluates the EEG data in both directions, forward and backward, extracting both short-term and long-term dependencies (complex temporal feature), enabling it to precisely identify the irregular EEG patterns that may signify an approaching seizure. Then, categorization is done using the BiLSTM layer's output. The block diagram of the BiLSTM model is described

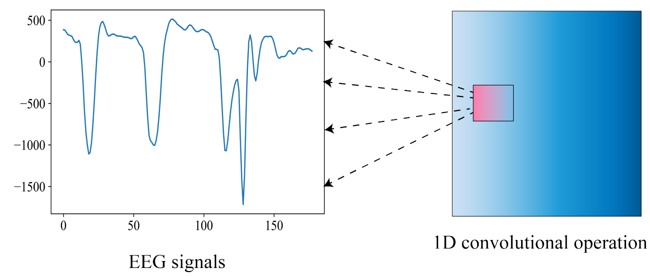


Fig. 2: Conceptualization operational process of 1D convolution.

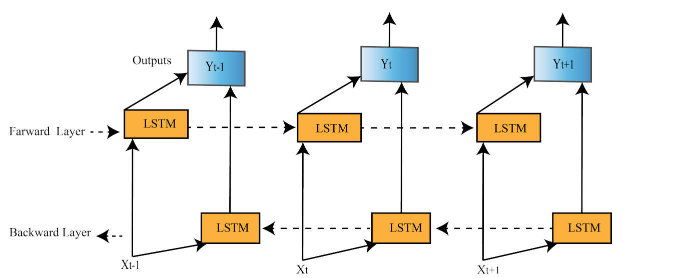


Fig. 3: The typical block structure of the BiLSTM model.

in Fig. 3. The mathematical expression of the basic LSTM units is explained as follows:

$$h_t = f(W_h.x_t + U_t.h_{t-1} + b_h) \tag{5}$$

$$f_t = \sigma(W_f.x_t + U_f.h_{t-1} + b_f) \tag{6}$$

$$i_t = \sigma(W_i.x_t + U_i.h_{t-1} + b_i) \tag{7}$$

$$o_t = \sigma(W_o.x_t + U_o.h_{t-1} + b_o) \tag{8}$$

$$C_t = f_t * ct - 1 + i_t \tanh(W_c.x_t + U_c.h_{t-1} + b_c) \tag{9}$$

$$h_t = f(W_h.x_t + U_t.h_{t-1} + b_h) \tag{10}$$

$$h_t = o_t \times \tanh(C_t) \tag{11}$$

This article has been accepted for publication in IEEE Journal of Biomedical and Health Informatics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/JBHI.2023.3265983

where x_t shows the input, W^*, U^* presents weights matrices, b^* is the bias, $f(x)$ describes the nonlinear function. The regular hidden state is denoted by $\tanh$ and h_t. Technically, BiLSTM has two separate LSTM units, one in the forward direction and the other in the backward direction. The concatenation of two hidden states is h_t, and its formulation is as follows:

$$h_t^{bilstm} = h_t^{forward} \oplus h_t^{backward} \tag{12}$$

Moreover, BiLSTM has an advantage over LSTM and GRU models. BiLSTM integrates previous and future information about EEG epileptic seizures, improving the EEG classification performance, while other ML/DL models lack both information.

D. 1D CNN-BiLSTM

The proposed model (1D CNN-BiLSTM) comprised the input layer, three convolutional layers, two BiLSTM layers, three fully connected layers, and the output (soft-max) layer. Initially, the 1D EEG signal is introduced directly to process the input for the 1D CNN-BiLSTM, where the shape is 178 x 1. To extract the meaningful features from the EEG raw signal data, the input is given to the first convolutional layer (Conv Layer1), where the size of the convolutional Layer1 is 64. Moreover, each convolutional kernel shape and the stride were 3 x 1 and 2. Rectified Linear Units (ReLUs) were implemented as ReLU activation layers to optimize the proposed models with gradient-based methods. The 1D convolutional layer (CLs), along with ReLU activation, are calculated as

$$X_n^m = \sigma(\sum_{j=1}^{N-1} Conv1D(K_{i,m}^{n-1} + a_m^n) \tag{13}$$

X_n^m shows the m^{th} feature map of the n^{th} layer; while $Conv1D$ represents the operation of one-dimensional convolution operation $K_{i,m}^{n-1}$ possess the i, j feature map of the $n-1^{th}$ layer. Moreover, a_n^m represents the n^{th} layer of the m feature map. while σ shows the ReLU activation function, can be express as follows:

$$\sigma(Y) = \begin{cases} Y, & \text{if } Y > 0 \\ 0, & \text{if } Y \leq 0 \end{cases} \tag{14}$$

After the convolution and activation function, the output contains 64 feature that is mapped with an overall dimension of (176 x 1) followed by a max-pooling layer. The size and stride were both 2 after this layer, the one-dimensional (1D) substantially decreases the training parameters for the 1D CNN-BiLSTM and speeds up the training process. The max-pooling is calculated as

$$C_i^b = \max(c_b^i = b \leq b < b + k) \tag{15}$$

Where c_b^i shows the b^{th} neurons of the i-feature map after the operation of max-pooling. While k shows the window size. Afterwards, the feature maps were 64, and the size (88 ×1) is obtained due to the pooling process while two convolutional layers were applied to extract high dimension features that might be used to assist the classification process Meanwhile,

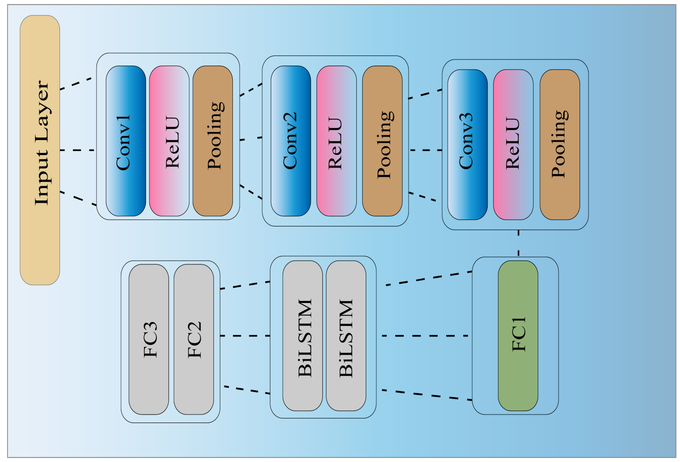


Fig. 4: The detailed structure of the proposed 1D CNN-BiLSTM model.

convolution layer 2 with the shape of (3 × 1) had 128 kernels, while in convolution layer 3, there were 512 kernels in the same shape. Additionally, the number of additional parameters of the convolution layer 3 and convolution layer 2 is the same as convolution layer 1. Initially, the map fed into 1D CLs, got the feature maps 1024, consisting of the 82 × 1 size, then passes through an FC layer including 256 neurons. Moreover, the dropout is applied with a fully connected (FC) layer output. To better fit the input of BiLSTM layers, fully connected layer1 concatenate with the output layer of the convolution layers, which decreases the size of feature maps, and the dropout could change the overfitting issues to some extent. It is possible to overcome the long-term dependence and vanishing gradient problem in the conventional RNN by feeding the output features into the BiLSTM layer after they pass through the fully connected Layer 1. While bidirectional input runs in two directions: backwards to forward and forward to backward, they can also work together to keep prior information secure and improve the ability to extract useful features from EEG data in a time series of peak-to-peak phases. Besides, 64 and 32 neurons were included in BiLSTM Layers 1 and 2 as shown in Fig. 4. After the feature extraction process of the BiLSTM layers, the output is passed through two fully connected layers (FC Layers 2 and FC Layers 3) for further processing with 128 and 64 neurons, respectively. Finally, the SoftMax activation layer is added with 1D CNN-BiLSTM to improve the network's results.

Further, we employed the BPTT for training the proposed model. The transition function for a given epileptic seizure detection system with state D, input Z and parameters $\wp$ is as follows:

$$D_{t+1} = F(Z_{t+1}, D_t, \wp) \tag{16}$$

The objective is to find a $\wp$ that minimizes total loss Lo_T with respect to the desired outputs P_t.

$$Lo_T = \sum_{t=1}^{T} lo_t = \sum_{t=1}^{T} lo(D_t, P_t) \tag{17}$$

This article has been accepted for publication in IEEE Journal of Biomedical and Health Informatics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/JBHI.2023.3265983

Algorithm 2 Hybrid 1D CNN-BiLSTM Model

Input: EEG Dataset=*ED*
Output: $ES \leftarrow 0$,$NS \leftarrow 1\, NS \leftarrow 2$ and so on
1D CNN layer = C ; BiLSTM layers =D ; epochs= e; k-Folds = k;
for k :=1 to 10 **do**
  for epochs :=1 to e **do**
    if select.layer[C] = 1D CNN **then**
      Initialize F and W:
      Calculate the features from the convolution layers ;
    else
      Create a feature vector (FV).
    end if
    if select.layers [D] = BiLSTM **then**
      Arbitrarily create the F and W;
      for each timestamp t; **do**
        Compute f_t, i_t, o_t and h_t;
        $f_t = \sigma(W_f.x_t + U_f.h_{t-1} + b_f)$
        $i_t = \sigma(W_i.x_t + U_i.h_{t-1} + b_i)$
        $o_t = \sigma(W_o.x_t + U_o.h_{t-1} + b_o)$
        Compute the h_t vector;
        $h_t = o_t * \tanh(c_t)$
        $h_t^{bilstm} = h_t^{forward} \oplus h_t^{backward}$
      end for
    else
    end if
  end for
end for
while True **do**
  Calculate the result of 1D CNN-BiLSTM;
  Generate output;
  Return output
end while=0

While in the 1D CNN-BiLSTM case, the $D_t = (o_t, h_t)$, where the o_t represents the output layer's activation function (AF), while hidden layers AF is denoted by the h_t. At this stage, the transition functions are as follows:

$$h_{t+1} = \tanh(W_d(D_{t+1}) + W_h h_t + b) \tag{18}$$

$$o_{t+1} = W_o h_(t+1) \tag{19}$$

$$lo_{t+1} = lo(o_{t+1}, P_{t+1}) \tag{20}$$

We have the parameters $\wp = (W_d, W_h, b)$. The objective is to calculate the $\Phi Lo_T/\phi\wp$. The TBPTT is responsible for this whole computation. Such a process to avoid delay in the training process. Now with the truncation length $Lo < T$, the gradient terms becomes $\phi lo_{t+1}\frac{\phi F}{\phi D}(Z_{t+1}, D_t, \wp)$ every Lo time steps, namely

$$\phi \hat{lo}_t := \begin{cases} \frac{\phi lo}{\phi D}(D_t, P_t) \\ \phi lo_{t+1}\frac{\phi F}{\phi D}(Z_{t+1}, D_t, \wp) \end{cases} \tag{21}$$

Referring to the proposed 1D CNN-BiLSTM model in Fig. 4, the pseudo-code for epileptic seizure detection is shown in Algorithms 2.

IV. Experimental Results and Discussion

In this section, we present the experimental setup, dataset information, performance metrics and a through analysis of the proposed framework. Table III shows a comprehensive description of the hardware and software specifications employed for the implementation of the proposed framework. Moreover, the description of the parameters used in the proposed framework is shown in Table IV.

TABLE III: Experimental setup.

Computing resource	Description
CPU	7th Generation, Core-i6 and 2.80 GHz processor
GPU	NVIDIA GeForce 1060 ,6 GB.
O.S.	64-bit, Window.
RAM	8 GB.
Languages	Python 3.8
Libraries	Tensor Flow, Pandas, Keras, NumPy and Scikitlearn

A. Data set description

The original data set of epileptic seizures is a publicly available dataset on Kaggle, namely UCI epileptic seizure recognition data set, which includes five health conditions [29]. The dataset is structured as follows: This includes five folders of the 100 files, and every file measures the brainwave measurement time to 23.6 seconds. The dataset includes 11,500 samples, or 23 x 500 (23 chunks* 500 in each folder), including 178 features. The dataset is divided into five classes: binary (y = 0, 1) and five classes (y = 0,1,2,3,4), which are organized as follows:

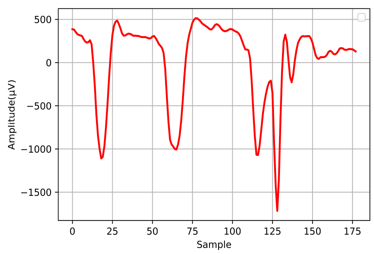
- Class-0 (Epileptic seizure): EEG data of seizure activity is in the class label 'S'.
- Class-1 (1^{st} normal): The signal of the patient before seizure activity and tumour located 'NS'.
- Class-2 (2^{nd} normal): Healthy brain EEG recorded data is in the class label 'H.B.'
- Class-3 (3^{rd} normal): Eyes closed were in the class label 'EC.'
- Class-4 (4^{th} normal): Eyes opened were in the class label 'EO.'

In the experimental analysis, we performed the binary and multi-classification tasks. For binary, the target variable of the EEG dataset was transformed as class 0: S, seizure (ictal) and class 1: NS, non-seizures (preictal), while classes 1 to 4 for multi-classification, there is no need to transform the targets. Fig. 5 depicts various raw EEG signal data types from a representative subject in five different health states. It is easy to distinguish the raw EEG signal waveform between epileptic seizures and health conditions, but the difference can hardly be observed between the various normal conditions of the raw EEG signal. Furthermore, the analysis and diagnosis by neurologists in all five classes are very important. Consequently, the systematic evaluation of the proposed model performance, both binary and five-class recognition problems of epileptic seizure detection, were addressed. Table V presents the full description of the UCI epileptic seizure recognition data set. After the preparation of the dataset, the next step is the data pre-processing, and it is fed into the model for further processing. Finally, the classification is performed using the proposed 1D CNN-BiLSTM approach.

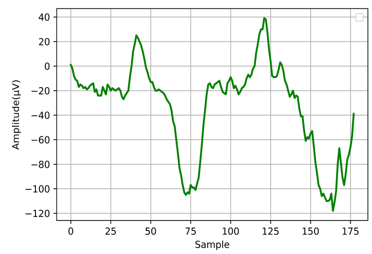
This article has been accepted for publication in IEEE Journal of Biomedical and Health Informatics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/JBHI.2023.3265983

TABLE IV: Description of the hyperparameters employed by the proposed method.

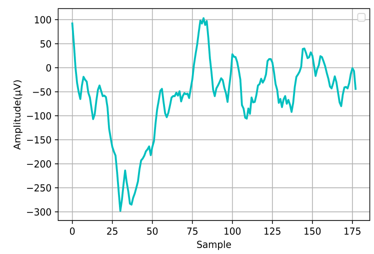
Proposed Model	Layer	Shape of layer	Size	Stride	Kernel	Activation Function	Other parameters
1D CNN-BiLSTM	Conv Layer 1	3 × 1	178 ×1	2	64	ReLU	(Batch-size= 100), (epochs= 100), (Optimizer= Adam), (learning rate = 0.001)
	Max-pooling layer	-	88×1	2	64	-	
	Conv_ Layer2	3 × 1	-	2	128	ReLU	
	Conv_ Layer3	3 × 1	-	2	256	ReLU	
	FC_layer1	-	82 × 1	-	512	-	
	BiLSTM layer	-	-	-	64	-	
	BiLSTM layer	-	-	-	32	-	
	FC_layer2	-	-	-	128	-	
	FC_layer3	-	-	-	64	-	
	Output_layer	-	-	-		SoftMax	



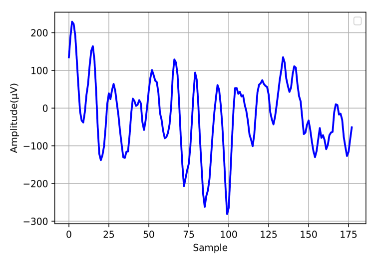
(a) Epileptic seizure



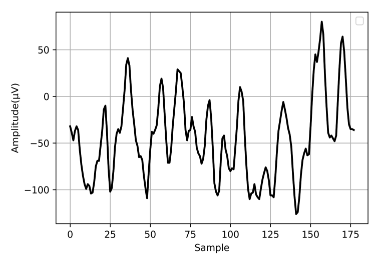
(b) 1st normal condition(tumor located)



(c) 2nd normal condition(healty brain)



(d) 3rd normal condition(Eye closed)



(e) 4th normal condition(Eye opened)

Fig. 5: Representation of EEG signals for seizures and non-seizure conditions in the time-domain (a-e).

TABLE V: Description of the UCI epileptic seizure recognition data set.

Class (target)	Class Description	Class labels	No. of samples	Binary classification	Multi-classification
0	Epileptic seizure.	S	2300	2300	2300
1	1st-normal condition (Before seizure, signal of the patient).	NS	2300		2300
2	2nd-normal condition (Healthy brain EEG recorded data).	HB	2300		2300
3	3rd-normal condition (Eyes closed have no seizure).	EC	2300	9200	2300
4	4th-normal condition (Eyes opened have no-seizure).	EO	2300		2300

B. Performance metrics

The evaluation indicators below are computed to assess how well the proposed framework performs in correctly differentiating seizures from non-seizures using EEG records. To calculate these metrics, the following parameters are used:

- True Positive (TP): Positive (Seizure) samples which are predicted as positive.
- True Negative (TN): Negative (Non-seizure) samples that are predicted as negative.
- False Positive (FP): Negative samples, which are predicted as positive.
- False Negative (FN): Positive samples, which are predicted as negative.

The following is the mathematical representation of accuracy (AC), sensitivity (SE), specificity (SP), precision (PR), and Matthews's correlation coefficient (MCC). For a better indication of the classifier's performance, we used F1-score (F1). These metrics are usually adopted for evaluating the detection of an epileptic seizure. $AC = \frac{TP+TN}{TP+TN+FP+FN}$, $PR = \frac{TP}{TP+FP}$, $SE = \frac{TP}{TP+FN}$, $SP = \frac{TN}{FP+TN}$, $F1 = \frac{2*PR*SE}{PR+SE}$, $MCC = \frac{TP+TN}{\sqrt{2}(TP)+FP+2(FN)*2(TN+FP)}$. We have also used a few more evaluation metrics in addition to the above-mentioned. For example, False Detection Rate (FDR: the ratio of PPV and NPV), the False Omission Rate (FOR: the ratio of negative samples for which the condition of positive is true), the False Positive Rate (FPR: shows the proportion of incorrectly classified negative and total negative samples), and the False Negative Rate (FNR: presents the ratio of the positive samples that are incorrectly classified). $FDR = \frac{FP}{FP+TP}$, $FOR = \frac{FN}{FN+TN}$, $FPR = \frac{FP}{FP+TN}$, $FNR = \frac{FN}{FN+TP}$. In

This article has been accepted for publication in IEEE Journal of Biomedical and Health Informatics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/JBHI.2023.3265983

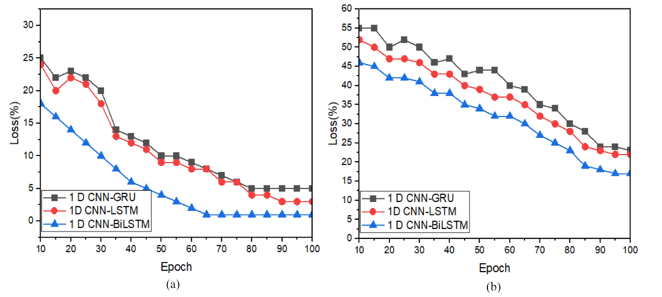


Fig. 6: Comparison of fitness value under (a) binary classification, (b) multi-classification.

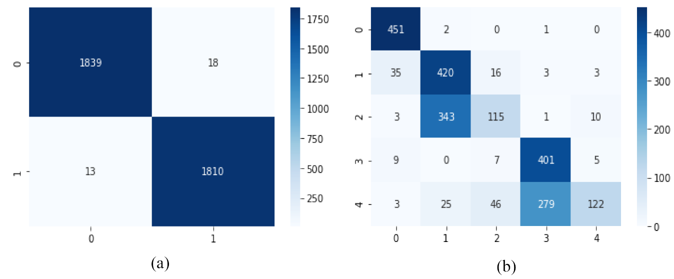


Fig. 7: Confusion matrix of the proposed 1D CNN-BiLSTM model under (a) binary, (b) multi-classification.

this paper, the analysis is carried out on the same experimental dataset using 10-fold cross-validation. In 10-fold cross-validation, the EEG signal is randomly distributed into ten portions, and eight of the ten portions were used to train the proposed model. One portion is used for validation and one for testing.

C. Analysis based on fitness value

Fig. 6 represents the fitness value analysis of the binary and multi-classification tasks. The best k-fold is 10. When the epoch is 5 to 10, the proposed model loss (%) is 20 % in the binary classification task. When the epoch increases to 100, the loss of the proposed model gradually decreases by 4 % as compared to the 1D CNN-LSTM and 1D CNN-GRU models. In the five classification task, when the epoch is 10, the proposed model loss is 40 %, after 50 to 100 epochs the proposed model loss drops to 25 % to 20 %. Therefore, the proposed algorithm has a fast convergence rate as compared to the 1D CNN-LSTM and 1D CNN-GRU models. This is due to the TBPTT approach that we have used to train our proposed DL model.

D. Confusion matrix

A confusion matrix can measure the classification performance of the algorithms. Fig. 7 shows the normalized confusion metrics of the proposed algorithm. It indicates that the proposed 1D CNN-BiLSTM is superior based on the classification performance of binary and the five classification tasks of an epileptic seizure. As can be observed in Fig. 7(a) and Fig. 7(b), the proposed DL technique successfully classified the majority of instances in the dataset correctly for both the binary and the multi-class classification task.

E. Models efficiency in terms of computational time

In this subsection, we analyze the proposed model's computational time (testing time) and then perform a comparison with the existing models. Because the training is mostly conducted offline, the model training process's computation time is not considered. Besides, the testing procedure is regarded as an essential metric since it would represent the model's efficiency and overall performance in terms of computational time. Fig. 8(a) and Fig. 8(b) shows the time taken by the proposed 1D CNN-BiLSTM model in binary and five-class recognition tasks of epileptic seizure detection.

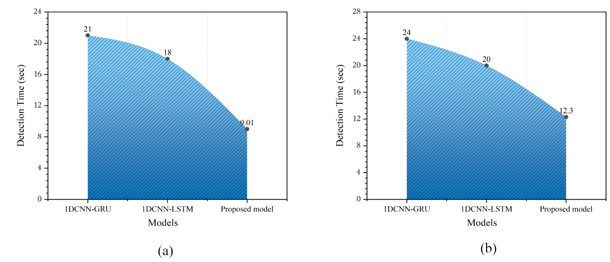


Fig. 8: The speed efficiency under (a) binary, (b) multi-class.

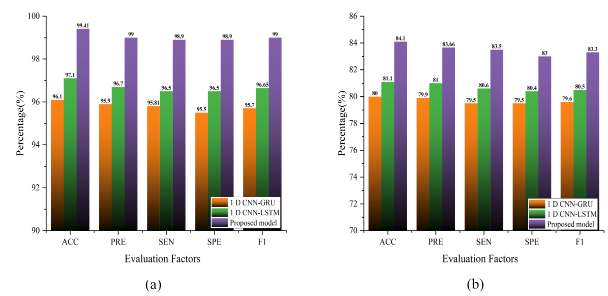


Fig. 9: Comparison with other baseline techniques using (a) binary classification, (b) multi-classification.

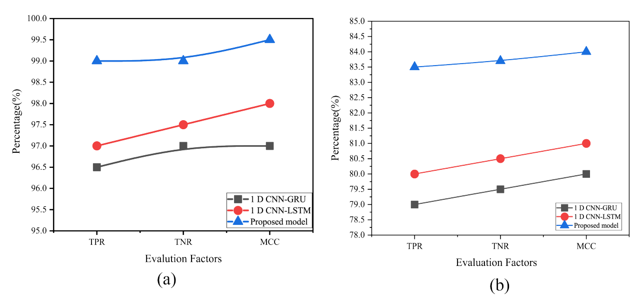


Fig. 10: TPR, TNR, and MCC under (a) binary, (b) multi-classification.

F. Comparison with baseline approaches

The empirical analysis is conducted and compared with some baseline approaches, such as the 1D CNN-LSTM and 1D CNN-GRU models of binary and multi-class EEG classification tasks. All the configurations and parameters of the proposed models are given in the Table. IV for each task.

TABLE VI: Comparison with baseline techniques with a 10-fold cross-validation strategy under binary classification task.

Performance metrics	Models	1	2	3	4	5	6	7	8	9	10
AC (%)	1D CNN-GRU	95.39	95.41	95.50	95.44	95.60	95.57	95.80	96.05	96.03	96.10
	1D CNN-LSTM	96.40	96.33	96.55	96.53	96.60	96.57	96.66	96.66	96.80	97.10
	Proposed Model	**98.40**	**98.61**	**99.05**	**99.13**	**99.10**	**99.16**	**99.20**	**99.30**	**99.27**	**99.41**
PR (%)	1D CNN-GRU	95.10	95.12	95.25	95.22	95.30	95.30	95.40	95.50	95.49	95.55
	1D CNN-LSTM	96.12	96.13	96.25	96.24	96.30	96.30	96.33	96.33	96.40	96.50
	Proposed Model	**98.20**	**98.30**	**98.50**	**98.52**	**98.60**	**98.56**	**98.80**	**98.86**	**98.80**	**98.99**
SE (%)	1D CNN-GRU	95.00	95.06	95.12	95.13	95.15	95.16	95.20	95.25	95.25	95.26
	1D CNN-LSTM	96.05	96.06	96.12	96.12	96.15	96.15	96.16	96.22	96.20	96.25
	Proposed Model	**98.10**	**98.15**	**98.30**	**98.26**	**98.30**	**98.30**	**98.40**	**98.40**	**98.50**	**98.80**
SP (%)	1D CNN-GRU	95.00	95.03	95.06	95.10	95.12	95.30	95.10	95.25	95.25	95.12
	1D CNN-LSTM	96.00	96.03	96.06	96.10	96.12	96.13	96.14	96.13	96.13	96.20
	Proposed Model	**98.00**	**98.06**	**98.14**	**98.13**	**98.15**	**98.17**	**98.19**	**98.20**	**98.25**	**98.40**
F1 (%)	1D CNN-GRU	95.20	95.10	95.11	95.24	95.10	95.15	95.15	95.12	95.14	95.20
	1D CNN-LSTM	96.10	96.08	96.20	96.12	96.15	96.14	96.20	96.20	96.16	96.21
	Proposed Model	**98.12**	**98.10**	**98.15**	**98.20**	**98.15**	**98.20**	**98.25**	**98.30**	**98.30**	**98.37**

TABLE VII: Comparison with baseline techniques with a 10-fold cross-validation strategy under multi-classification task.

Performance metrics	Models	1	2	3	4	5	6	7	8	9	10
AC (%)	1D CNN-GRU	79.13	79.10	79.25	79.30	79.40	79.57	79.80	79.90	79.93	80.00
	1D CNN-LSTM	80.10	80.13	80.10	80.20	80.50	80.45	80.60	80.71	80.80	81.10
	Proposed Model	**83.05**	**83.13**	**83.20**	**83.24**	**83.55**	**83.51**	**83.70**	**83.71**	**83.75**	**84.10**
PR (%)	1D CNN-GRU	78.80	78.77	78.86	78.88	78.90	78.99	79.00	79.10	79.15	79.20
	1D CNN-LSTM	79.33	79.36	79.32	79.40	79.43	79.50	79.55	79.90	80.10	80.13
	Proposed Model	**82.20**	**82.30**	**82.28**	**82.52**	**82.55**	**82.56**	**82.80**	**82.86**	**82.80**	**83.00**
SE (%)	1D CNN-GRU	78.30	78.27	78.37	78.40	78.45	78.50	78.60	78.80	78.85	78.90
	1D CNN-LSTM	78.80	78.85	78.90	78.90	78.99	79.00	79.05	79.16	79.26	79.40
	Proposed Model	**82.00**	**82.10**	**82.12**	**82.14**	**82.20**	**82.30**	**82.34**	**82.42**	**82.50**	**82.52**
SP (%)	1D CNN-GRU	78.20	78.24	78.25	78.30	78.32	78.34	78.36	78.40	78.50	78.89
	1D CNN-LSTM	78.70	78.76	78.78	78.76	78.80	78.90	78.96	78.98	79.10	79.10
	Proposed Model	**81.80**	**81.90**	**81.90**	**82.00**	**82.05**	**82.14**	**82.20**	**82.30**	**82.30**	**82.40**
F1 (%)	1D CNN-GRU	78.25	78.30	78.33	78.35	78.37	78.45	78.50	79.60	78.70	78.85
	1D CNN-LSTM	78.75	78.80	78.86	78.80	78.85	78.95	79.00	78.90	79.16	79.20
	Proposed Model	**81.2**	**82.02**	**82.04**	**82.04**	**82.15**	**81.24**	**82.20**	**82.28**	**82.40**	**82.50**

TABLE VIII: A comparative study of the proposed model with recent works on UCI- Epileptic data.

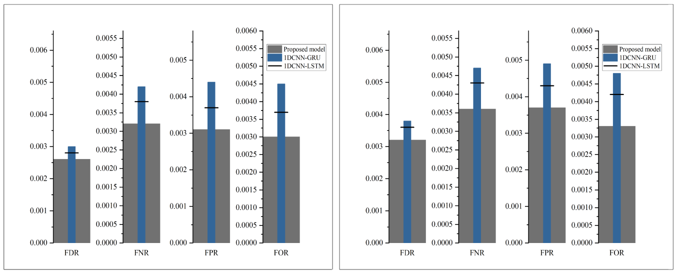
Examination type	References	Dataset	Methods	Metrics/Methods	Pre-processing	AC (%)	SE (%)	SP (%)
Binary classification	[30]	UCI-Epileptic	1D CNN-LSTM	Training (90%)	N/A	99	98	97.70
	[31]	UCI-Epileptic	CNN	Training (80%)	N/A	98	96	96
	[32]	UCI-Epileptic	RF, SVM, KNN	Training (80%)	N/A	97.05, 97.05, 97	96, 96, 95	95.10, 95.20, 94
	Proposed work	**UCI-Epileptic**	**1D CNN-BiLSTM+TBPTT**	**10-fold cross validation**	**K-means SMOTE + Normalization**	**99.41**	**98.99**	**98.80**
Multi- classifications	[30]	UCI-Epileptic	1D CNN-LSTM	Training (70%)	N/A	82	81.50	80.60
	[33]	UCI-Epileptic	RBNN	Training (70%)	N/A	78	76.9	75.9
	Proposed work	**UCI-Epileptic**	**1D CNN-BiLSTM+TBPTT**	**10-fold cross validation**	Normalization	**84.10**	**82.52**	**82.40**

TABLE IX: A comparative study of the proposed model with recent works on EEG seizure dataset.

References	Dataset	Methods	Examination type	Metrics/Methods	AC (%)	SE (%)	SP (%)
[34]	CHB-MIT	CNN	2-class	Training (80%)	92.8	93	93
[35]	CHB-MIT	LRCNN	2-class	Training (70%)	91.05	93	93
[36]	TUH EEG data	RNN, CNN	2-class	Training (80%)	97, 96	96.80 ,96	95, 95
[37]	Bonn	LNDP + ANN	2, 3-class	Training (80%)	98.88, 98.22	97, 96.60	96.30, 95
[38]	Bonn	SVM	2, 3-class	Training (80%)	98, 93.8	97, 93	95, 92
Proposed work	**UCI-Epileptic**	**1D CNN-BiLSTM+TBPTT**	**2, 5-class**	**10-fold cross validation**	**99.41, 84.10**	**98.99, 82.52**	**98.80, 82.40**

Various metrics, such as AC, PR, SE, SP, and F1, are taken into consideration. Table. VI and Table.VII and Fig. 9 (a) and Fig. 9 (b) indicate the value of the proposed model performance compared to other seizure detection methods. For the binary EEG task, the results obtained by the proposed (1D CNN-BiLSTM) model are 99.41%, 98.99%, 98.80%, 98.40% and 98.37% while for the multi-EEG classification task, 84.10%, 83%, 82.52%, 82.40% and 82.50% using 10-fold cross-validation. However, the classification performance of 1D CNN-LSTM and 1D CNN-GRU has not performed well on both EEG classification tasks. The comparative analysis of the True-Positive Rate (TPR), True-Negative Rate (TNR), and MCC of the proposed 1D CNN-BiLSTM model, along with 1D CNN-LSTM and 1D CNN-GRU for the binary and multi-classification tasks is presented in Fig. 10(a) and 10(b) respectively. Moreover, Fig. 11 shows that the proposed (1D CNN-BiLSTM) model outperforms other models by reducing FDR, FNR, FPR and FOR. For instance, the proposed model has achieved FDR (0.0026%), FPR (0.0031%), FOR (0.0026%), and FNR (0.0032%) for binary classification and FDR (0.0032%), FPR (0.0035%), FOR (0.0033%), and FNR (0.0036%) for five class recognition tasks of epileptic seizure

This article has been accepted for publication in IEEE Journal of Biomedical and Health Informatics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/JBHI.2023.3265983



(a) (b)

Fig. 11: FDR, FNR, FPR, FOR of the proposed model under (a) binary, (b) multi-classification.

detection. Thus, the summary of the results shows that the proposed 1D CNN-BiLSTM model is effective and efficient in recognizing different EEG class states compared to other methods.

G. *Comparison with state-of-the-art approaches*

Furthermore, to test the effectiveness of the proposed model on binary and five EEG class tasks. The experimental results are compared with the recent existing literature, as shown in Table VIII, using the same UCI epileptic seizure recognition data set. Moreover, we checked the efficiency, reliability and classification of the proposed algorithms compared with recent spectral baseline methods with well-known EEG data sets, as shown in Table IX. The proposed method successfully detected seizure and non-seizure classes in EEG epileptic seizure detection. In addition, the testing time for the proposed model is less i.e. 9.01 and 12.30 sec, compared to other competitor models. On the other hand, the proposed hybrid model, especially BiLSTM with 1D CNN, has advantages over 1D CNN-LSTM and 1D CNN-GRU, because BiLSTM can potentially process the EEG signals in both forward and backward directions, which is better suited for detecting the onset and offset of seizures in the recordings. Moreover, the BiLSTM model handles long-term dependencies, effectively reducing false positives and can handle long-term dependencies. However, the proposed model has some limitations. Initially, the performance of the 1D CNN-BiLSTM model is highly dependent on the choice of hyper-parameters, such as the number of filters in the CNN layer, the number of units in the LSTM layer and the learning rate of the optimizer tuning these hyperparameters can be time-consuming but thanks to the power of GPU, we can overcome this limitation.

V. Conclusion

This research proposed a novel hybrid seizure detection approach consisting of 1D CNN and Truncated Backpropagation Through Time (TBPTT) based Bidirectional Long short-term Memory (BiLSTM) network for epileptic seizure detection. In this work, first, the long-term EEG sample is balanced using a novel K-means SMOTE technique before the training process. Second, the most powerful capabilities of the 1D CNN were used to extract discriminative EEG signal features. Third, the BiLSTM network is fused with 1D CNN to remember a sequence of EEG signals and solve the RNN's vanishing gradient problem to accelerate the training process. The efficiency of the proposed model is demonstrated through experiments carried out, including binary- and multi-classification applied to a well-known UCI epileptic seizure recognition data set. The results of the experiments indicated that the proposed approach was substantially better in terms of accuracy, precision, sensitivity, specificity, and F1-Score on both binary and five-class EEG epileptic seizure detection tasks. Additionally, we compared the proposed algorithm with sibling hybrid deep learning models, including 1D CNN-LSTM, 1D CNN-GRU and other existing ML/DL algorithms, on different k-fold cross-validation to show the effectiveness, accuracy and superiority of the algorithm for automatic epileptic seizure detection. Future studies include testing the proposed algorithms on other EEG datasets with federated and transfer learning models.

References

[1] E. Chouery, C. Mehawej, S. Sabbagh, J. Bleik, and A. Megarbane, "Early infantile epileptic encephalopathy related to necap1: Clinical delineation of the disease and review," *European Journal of Neurology*, vol. 29, no. 8, pp. 2486–2492, 2022.

[2] G. Das, S. Biswas, S. Dubey, D. Lahiri, B. K. Ray, A. Pandit, S. P. Saha, and A. Biswas, "Perception about etiology of epilepsy and help-seeking behavior in patients with epilepsy," *International Journal of Epilepsy*, vol. 7, no. 01, pp. 22–28, 2021.

[3] C. Dhasarathan, M. K. Hasan, S. Islam, S. Abdullah, U. A. Mokhtar, A. R. Javed, and S. Goundar, "Covid-19 health data analysis and personal data preserving: A homomorphic privacy enforcement approach," *Computer Communications*, vol. 199, pp. 87–97, 2023.

[4] M. Fakhoury, R. H. M. A. Ahmad, E. D. Al-Chaer, and N. B. Lawand, "Behavioral tests for assessing pain and nociception: Relationship with the brain reward system," *The Brain Reward System*, pp. 169–179, 2021.

[5] A. P. Ostendorf, S. M. Ahrens, F. A. Lado, S. T. Arnold, S. Bai, M. K. B. Owen, K. E. Chapman, D. F. Clarke, M. Eisner, N. B. Fountain *et al.*, "United states epilepsy center characteristics: a data analysis from the national association of epilepsy centers," *Neurology*, vol. 98, no. 5, pp. e449–e458, 2022.

[6] K. Burelo, G. Ramantani, G. Indiveri, and J. Sarnthein, "A neuromorphic spiking neural network detects epileptic high frequency oscillations in the scalp eeg," *Scientific Reports*, vol. 12, no. 1, p. 1798, 2022.

[7] G. Wiegand, N. Japaridze, K. Gröning, U. Stephani, and N. E. Kadish, "Eeg-findings during long-term treatment with everolimus in tsc-associated and therapy-resistant epilepsies in children," *Seizure*, vol. 103, pp. 101–107, 2022.

[8] C. da Silva Lourenço, M. C. Tjepkema-Cloostermans, and M. J. van Putten, "Machine learning for detection of interictal epileptiform discharges," *Clinical neurophysiology*, vol. 132, no. 7, pp. 1433–1443, 2021.

[9] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, and H. Adeli, "Deep convolutional neural network for the automated detection and diagnosis of seizure using eeg signals," *Computers in biology and medicine*, vol. 100, pp. 270–278, 2018.

[10] J. Zhao, X. Mao, and L. Chen, "Speech emotion recognition using deep 1d & 2d cnn lstm networks," *Biomedical signal processing and control*, vol. 47, pp. 312–323, 2019.

[11] Ö. Yıldırım, U. B. Baloglu, and U. R. Acharya, "A deep convolutional neural network model for automated identification of abnormal eeg signals," *Neural Computing and Applications*, vol. 32, pp. 15 857–15 868, 2020.

[12] N. Jiwani, K. Gupta, M. H. U. Sharif, N. Adhikari, and N. Afreen, "A lstm-cnn model for epileptic seizures detection using eeg signal," in *2022 2nd International Conference on Emerging Smart Technologies and Applications (eSmarTA)*. IEEE, 2022, pp. 1–5.

[13] J. Birjandtalab, V. N. Jarmale, M. Nourani, and J. Harvey, "Imbalance learning using neural networks for seizure detection," in *2018 IEEE Biomedical Circuits and Systems Conference (BioCAS)*. IEEE, 2018, pp. 1–4.

[14] M.-P. Hosseini, D. Pompili, K. Elisevich, and H. Soltanian-Zadeh, "Random ensemble learning for eeg classification," *Artificial intelligence in medicine*, vol. 84, pp. 146–158, 2018.

[15] T. Wadhera, "Brain network topology unraveling epilepsy and asd association: Automated eeg-based diagnostic model," *Expert Systems with Applications*, vol. 186, p. 115762, 2021.

[16] N. K. C. Pratiwi, I. Wijayanto, and Y. N. Fu'adah, "Performance analysis of an automated epilepsy seizure detection using eeg signals based on 1d-cnn approach," in *Proceedings of the 2nd International Conference on Electronics, Biomedical Engineering, and Health Informatics*. Springer, 2022, pp. 265–277.

[17] X. Tian, Z. Deng, W. Ying, K.-S. Choi, D. Wu, B. Qin, J. Wang, H. Shen, and S. Wang, "Deep multi-view feature learning for eeg-based epileptic seizure detection," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 10, pp. 1962–1972, 2019.

[18] F. Radenović, G. Tolias, and O. Chum, "Fine-tuning cnn image retrieval with no human annotation," *IEEE transactions on pattern analysis and machine intelligence*, vol. 41, no. 7, pp. 1655–1668, 2018.

[19] L. Sui, X. Zhao, Q. Zhao, T. Tanaka, and J. Cao, "Localization of epileptic foci by using convolutional neural network based on ieeg," in *Artificial Intelligence Applications and Innovations: 15th IFIP WG 12.5 International Conference, AIAI 2019, Hersonissos, Crete, Greece, May 24–26, 2019, Proceedings 15*. Springer, 2019, pp. 331–339.

[20] C. Park, G. Choi, J. Kim, S. Kim, T.-J. Kim, K. Min, K.-Y. Jung, and J. Chong, "Epileptic seizure detection for multi-channel eeg with deep convolutional neural network," in *2018 International Conference on Electronics, Information, and Communication (ICEIC)*. IEEE, 2018, pp. 1–5.

[21] M. Geng, W. Zhou, G. Liu, C. Li, and Y. Zhang, "Epileptic seizure detection based on stockwell transform and bidirectional long short-term memory," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 3, pp. 573–580, 2020.

[22] W. Kong, Z. Y. Dong, Y. Jia, D. J. Hill, Y. Xu, and Y. Zhang, "Short-term residential load forecasting based on lstm recurrent neural network," *IEEE transactions on smart grid*, vol. 10, no. 1, pp. 841–851, 2017.

[23] G. Liu, L. Tian, and W. Zhou, "Patient-independent seizure detection based on channel-perturbation convolutional neural network and bidirectional long short-term memory," *International Journal of Neural Systems*, vol. 32, no. 06, p. 2150051, 2022.

[24] S. Garg *et al.*, "A novel convolution bi-directional gated recurrent unit neural network for emotion recognition in multichannel electroencephalogram signals," *Technology and Health Care*, no. Preprint, pp. 1–20, 2022.

[25] J. He, J. Cui, G. Zhang, M. Xue, D. Chu, and Y. Zhao, "Spatial–temporal seizure detection with graph attention network and bi-directional lstm architecture," *Biomedical Signal Processing and Control*, vol. 78, p. 103908, 2022.

[26] M. N. A. Tawhid, S. Siuly, and T. Li, "A convolutional long short-term memory-based neural network for epilepsy detection from eeg," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1–11, 2022.

[27] M. Woodbright, B. Verma, and A. Haidar, "Autonomous deep feature extraction based method for epileptic eeg brain seizure classification," *Neurocomputing*, vol. 444, pp. 30–37, 2021.

[28] M. Geng, W. Zhou, G. Liu, C. Li, and Y. Zhang, "Epileptic seizure detection based on stockwell transform and bidirectional long short-term memory," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 3, pp. 573–580, 2020.

[29] U.M.L, "Repository, epileptic seizure recognition data set," https://archive.ics.uci.edu/ml/datasets/Epileptic +Seizure+Recognition, May 2022.

[30] G. Xu, T. Ren, Y. Chen, and W. Che, "A one-dimensional cnn-lstm model for epileptic seizure recognition using eeg signal analysis," *Frontiers in neuroscience*, vol. 14, p. 578126, 2020.

[31] M. Woodbright, B. Verma, and A. Haidar, "Autonomous deep feature extraction based method for epileptic eeg brain seizure classification," *Neurocomputing*, vol. 444, pp. 30–37, 2021.

[32] K. M. Almustafa, "Classification of epileptic seizure dataset using different machine learning algorithms," *Informatics in Medicine Unlocked*, vol. 21, p. 100444, 2020.

[33] A. H. Osman and A. A. Alzahrani, "New approach for automated epileptic disease diagnosis using an integrated self-organization map and radial basis function neural network algorithm," *IEEE Access*, vol. 7, pp. 4741–4747, 2018.

[34] S. M. Usman, S. Khalid, and Z. Bashir, "Epileptic seizure prediction using scalp electroencephalogram signals," *Biocybernetics and Biomedical Engineering*, vol. 41, no. 1, pp. 211–220, 2021.

[35] X. Wei, L. Zhou, Z. Zhang, Z. Chen, and Y. Zhou, "Early prediction of epileptic seizures using a long-term recurrent convolutional network," *Journal of neuroscience methods*, vol. 327, p. 108395, 2019.

[36] T. Liu, N. D. Truong, A. Nikpour, L. Zhou, and O. Kavehei, "Epileptic seizure classification with symmetric and hybrid bilinear models," *IEEE journal of biomedical and health informatics*, vol. 24, no. 10, pp. 2844–2851, 2020.

[37] A. K. Jaiswal and H. Banka, "Local pattern transformation based feature extraction techniques for classification of epileptic eeg signals," *Biomedical Signal Processing and Control*, vol. 34, pp. 81–92, 2017.

[38] H.-S. Chiang, M.-Y. Chen, and Y.-J. Huang, "Wavelet-based eeg processing for epilepsy detection using fuzzy entropy and associative petri net," *IEEE Access*, vol. 7, pp. 103 255–103 262, 2019.

Ijaz Ahmad is currently pursuing Ph.D. degree in pattern recognition and intelligence system from Shenzhen Institute of Advanced Technology (SIAT), Chinese Academy of Sciences (CAS) under the ANSO Scholarship for young scientists. He got his M.E degree in Computer Applied Technology from Changchun University of Science and Technology, China, under the prestigious fellowship of the Ministry of Education funded by the Government of China in 2020. He has many research contributions in the area of pattern recognition, applied machine intelligence, biomedical signal processing, biomedical imaging, clinical decision support systems and the Internet of Things(IoT). He has authored or co-authored over 20+ publications in high-ranked journals and conferences. He is also an IEEE Student Member.

Xin Wang (Student Member, IEEE) received his B.E. degree and Msc from Wuhan University of Science and Technology and University of Chinese Academy of Sciences, China, in 2017 and 2020 respectively. He is currently a Ph.D. candidate in Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences. His research interests include biomedical signal processing and audiometry technology.

Danish Javeed is currently pursuing the Ph.D. degree in Software Engineering, specializing in Information Security with the Software College, Northeastern University, China under the prestigious fellowship of Ministry of Education funded by the Government of China. He got his M.E degree in Computer Applied Technology from Changchun University of Science and Technology, China, under the same fellowship in 2020. He is also working on various research projects with researchers from LUT School of Engineering Science, LUT University, Lappeenranta, Finland. He has many research contributions in the area of Deep Learning, Cybersecurity, Intrusion Detection and Prevention System, the Internet of Things, Software-defined Networking and Edge Computing. He has authored or coauthored over 10+ publications in high-ranked journals and conferences. He is also an IEEE Student Member.

Prabhat Kumar received his Ph.D. degree in Information Technology, National Institute of Technology Raipur, Raipur, India, under the prestigious fellowship of Ministry of Human Resource and Development (MHRD) funded by the Government of India in 2022. Thereafter, he worked with Indian Institute of Technology Hyderabad, India as a Post-Doctoral Researcher under project "Development of Indian Telecommunication Security Assurance Requirements for IoT devices". He is currently working as Post-Doctoral Researcher with the Department of Software Engineering, LUT School of Engineering Science, LUT University, Lappeenranta, Finland. He has many research contributions in the area of Machine Learning, Deep Learning, Federated Learning, Big Data Analytics, Cybersecurity, Blockchain, Cloud Computing, Internet of Things and Software Defined Networking. He has authored or coauthored over 35+ publications in high-ranked journals and conferences, including 13+ IEEE TRANSACTIONS paper. One of his Ph.D. publication was recognized as a top cited article by WILEY in 2020-21. He is IEEE Consumer Technology Society (CTSoc) Technical Committee member in Machine learning, Deep learning, and AI in Consumer Electronics. He has served as a program co-Chair, and a Technical Program Committee member for major conferences, including IEEE ICCE and ACM CCS. He is also an IEEE Member.

Oluwarotimi Williams Samuel (Senior Member, IEEE) obtained a Ph.D. degree in Pattern Recognition and Intelligent Systems from the University of Chinese Academy of Sciences, Beijing, courtesy of the CAS-TWAS President's Fellowship with excellent dissertation honor and graduate awards. Before that, he received his bachelor's and master's degree in Computer Science with first-class honors and distinction, respectively. He is currently a Senior Lecturer and Lead Investigator with the School of Computing and Engineering, University of Derby, United Kingdom. His research focuses on developing cutting-edge solutions to core problems in Cyber-physical Systems (Rehabilitation robotics, Clinical decision support systems, Human-machine interfaces, etc.) and he is the principal/co-investigator of various reputable national and international research grants. He has a track record of 100+ articles in reputable peer-reviewed international journals and IEEE conference proceedings with several "Top Cited/Influential Papers" courtesy of Web of Science, ESI-Index, and IOP Science. Besides, his scholarly contributions have earned him 15+ academic awards and honors, including "IEEE Best Paper Awards", "IEEE Outstanding Young Investigator Research Visit Award", "Merit Award for Outstanding Execution of Youth Innovation Project", and a nomination for the "2022 STEM for Britain Award" among others. He has chaired, co-chaired, and served/serving as a Technical Programme Committee Member of various IEEE international conferences. Additionally, he is an Associate Editor of Frontiers in Big Data and an ELSP International Open Science Platform (ELSP-IOSP) Advisory Board Member.

Shixiong Chen (IEEE Member) received his bachelor's and master's degrees from Tsinghua University (China) in 2005 and 2007, respectively. He got his Ph.D. degree from Arizona State University (USA) in May 2012. He is currently a professor with the Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences. He has been awarded Shenzhen high-level Overseas talents, pilot talents of Shenzhen Nanshan District, Shenzhen high-level professional talents, Zhuliyuehua outstanding teacher award of the University of Chinese Academy of Sciences. He is the primary investigator of multiple national/governmental research grants and has authored over 100 papers in peer-reviewed journals, such as IEEE Transactions on Biomedical Engineering, Journal of Neural Engineering, and IEEE Journal of Biomedical and Health Informatics. His research interests include the acquisition and processing of biomedical signals, rehabilitation of hearing and swallowing disorders, and medical device instrumentation.