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Detection of Epileptic Seizures through DCNN–Bi-LSTM on EEG Signals

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Abstract

Epileptic seizure detection is a critical task in neurological diagnosis, where timely identification can significantly improve patient outcomes. This work presents a hybrid deep learning model that combines Convolutional Neural Networks (CNN) with Bidirectional Long Short-Term Memory (Bi-LSTM) networks for analyzing EEG signals. The CNN component captures spatial characteristics of brain activity, while the Bi-LSTM layer models temporal dependencies in both forward and backward directions. The proposed model is evaluated using the Bonn EEG dataset, achieving an accuracy of 96.09%. The results indicate that the hybrid approach performs better than conventional machine learning techniques such as Support Vector Machines and Random Forests, making it suitable for automated seizure detection systems.
Keywords: Epilepsy detection, Electroencephalography, Long Short-Term Memory.

INTRODUCTION

Epilepsy is neurological condition marked by recurrent seizures resulting from irregular electrical activity in the brain. Although medical technologies have advanced considerably, accurate diagnosis remains a challenge, with reported misdiagnosis rates reaching up to 30%, potentially leading to serious health consequences.

EEG is a non-invasive technique used to monitor brain activity. However, traditional analysis methods and basic machine learning approaches often fail to capture both spatial and temporal patterns present in EEG signals. To address this issue, deep learning methods have been widely adopted. In particular, combining Convolutional Neural Networks (CNN) with Bidirectional Long Short-Term Memory (Bi-LSTM) provides an effective solution. CNN helps in extracting spatial features from EEG data, while Bi- LSTM captures temporal dependencies by processing sequences in both directions. In this work, a hybrid CNN–Bi-LSTM model is used for automatic seizure detection. This combination improves the model's ability to learn complex patterns, resulting in better detection performance and supporting clinical decision-making.

LITERATURE SURVEY

Early studies on seizure detection mainly used machine learning techniques such as SVM combined with entropy and wavelet-based features, achieving moderate performance [1], [2]. With the advancement of deep learning, CNN-based models have been introduced to automatically learn features directly from raw EEG signals, reducing the need for manual preprocessing [3]. Further improvements were achieved by incorporating temporal models such as Bi-LSTM, which enhanced the ability to capture sequential patterns in EEG data [4], [5]. Hybrid architectures combining CNN and LSTM have shown better performance by learning both spatial and temporal information simultaneously [6], [7]. Additionally, advanced approaches integrating signal transformation techniques and deep networks have demonstrated improved classification accuracy in seizure detection tasks [8].

Beyond CNN–LSTM approaches, alternative deep architectures have been explored. O'Shea and colleagues [9] presented a fully convolutional network for neonatal related seizure detection using raw multi-channel EEG, showing parity with classical SVM-based methods but with full automation. Talathi [10] investigated gated RNNs (GRUs) for early seizure detection, achieving near-perfect accuracy and rapid detection within seconds of seizure onset. Notably, hybrid CNN-SVM models with mutual information-based feature selection was proposed by Hassan *et al.* [11], yielding high classification performance across both Bonn and CHB-MIT datasets. Further work in seizure prediction and detection expanded the repertoire of model architectures and datasets. Golmohammadi *et al.* [12] introduced a recurrent convolutional network for detection using large clinical EEG databases like TUH, illustrating the necessity of integrating both spatial and temporal contexts.

Asif *et al.* [13] created SeizureNet, employing multi-spectral feature embeddings to classify seizure types, but noted challenges in generalization across EEG datasets. Contemporary deep learning trend reviews have been compiled by Acharya *et al.* [14], illustrating the field's evolution and challenges systematically. Newer methods have also explored advanced signal representations and network designs. Qin *et al.* [15] combined improved variational mode decomposition with deep forest models for EEG classification, while Sarwat and Chahal [16] developed a CNN–LSTM system that achieved exceptionally high accuracy. Chen *et al.* [17] applied feature fusion and CNN for EEG related seizure detection with high accuracy. In addition, recent hybrid models integrating dual-stream networks have been proposed by richhariya and Tanveer [18] using PCA, ICA, and DWT preprocessing methods in combination with CNN–LSTM pipelines, holding promise for future multimodal approaches [22].

METHODOLOGY

A CNN

CNN is used to extract important spatial features from EEG signals, which helps in identifying abnormal brain activity. The core operation of a CNN is the convolution, which applies learnable filters over the input signal to produce feature maps.

The convolution operation is expressed as:

$$y_{i,j}^{(k)} = f\left(\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} x_{i+m,j+n} \cdot w_{m,n}^{(k)} + b^{(k)}\right) \quad (1)$$

Where $y_{i,j}^{(k)}$ represents the output feature map at position (i,j) for the k^{th} filter, x is the input, $w^{(k)}$ denotes the kernel weights of the k^{th} filter of size $M \times N$, $b^{(k)}$ is the bias term, and $f(\cdot)$ is the non-linear activation function such as ReLU.

Subsequent to convolution, pooling layers are applied to decrease the dimensionality while preserving important features. A common pooling function is max pooling, which is written as:

$$y_{i,j} = \max_{(m,n)\in R} x_{i+m,j+n} \quad (2)$$

where R denotes the local receptive field. This operation ensures translation invariance and decreases computational complexity. Finally, the features are passed through fully connected layers and a softmax classifier for prediction. The softmax function is expressed as:

$$P(y = c \mid z) = \frac{e^{z_c}}{\sum_{j=1}^{C} e^{z_j}} \quad (3)$$

where $P(y = c \mid z)$ represents the probability of the input belonging to class c, z is the feature vector, and C is the count of classes.

Bidirectional Long Short-Term Memory (Bi-LSTM)

Bi-LSTMs extend traditional recurrent architectures by incorporating two LSTM layers that process the input sequence in both forward and backward directions. The equations governing the operations of an Bi-LSTM cell are:

Forget gate:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (4)$$

Input gate and candidate state:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$
$$\tilde{C}_t = \tanh(W_C[h_{t-1}, x_t] + b_C) \quad (5)$$

Cell state update:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (6)$$

Output gate and hidden state:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$
$$h_t = o_t \odot \tanh(C_t) \quad (7)$$

Bi-LSTM is a type of recurrent neural network that processes input sequences in both forward and backward directions. This allows the model to capture temporal dependencies more effectively by considering both past and future information. The network uses gating mechanisms to control how information is stored and updated, enabling stable learning over long sequences. By combining outputs from both directions, Bi-LSTM provides a more comprehensive representation of EEG signals, making it suitable for detecting seizure patterns.

Proposed Methodology

The Bonn University EEG dataset was considered in the study. Signals were pre-processed using filters, segmented into windows, and normalized. Features were extracted by CNN and temporal patterns were modeled by LSTM, followed by softmax classification. The model was trained and evaluated. The results were compared with the SVM and RF classifiers.

The following are the phases in the proposed methodology:

Step 1: Dataset Preparation

The EEG dataset is divided into training and testing sets, where each segment is labeled as seizure or non-seizure based on expert annotations.

Step 2: Pre-processing

The signals are processed using band-pass filtering to remove noise and notch filtering to eliminate power-line interference. The data is then segmented into smaller windows and normalized to ensure consistency.

Step 3: Feature Extraction with CNN

A CNN model is used to automatically learn spatial and frequency-related patterns from the EEG signals, reducing the need for manual feature engineering.

Step 4: Temporal Modelling with LSTM

The extracted features are passed to a Bi-LSTM network, which captures temporal relationships by analyzing sequences in both forward and backward directions.

Step 5: Classification Layer

The output from the Bi-LSTM layer is fed into dense layers, followed by a softmax function to classify the signals into seizure and non-seizure categories.

Step 6: Model Training

The model is trained using the Adam optimizer along with categorical cross-entropy loss. Dropout is applied to minimize overfitting.

Step 7: Performance Evaluation

The performance of the model is evaluated using metrics such as accuracy, precision, recall, F1-score, and AUC. The results are compared with traditional models like SVM and Random Forest.

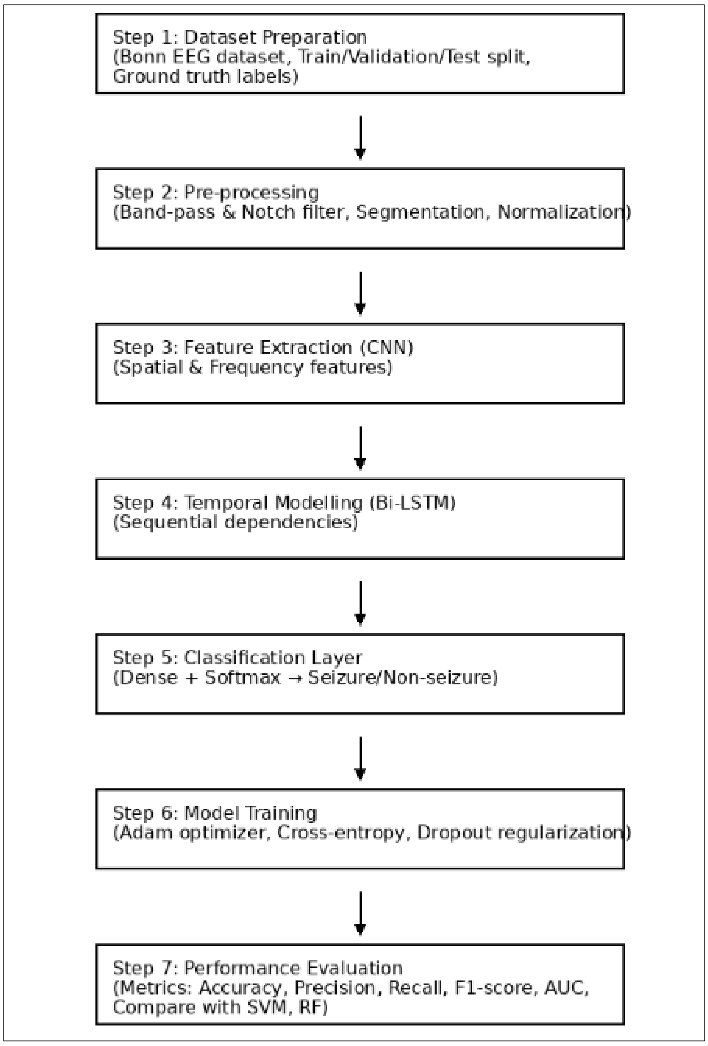

Fig. 1: Flow of Proposed CNN-BiLSTM seizure detection model

RESULT ANALYSIS

Bonn University EEG dataset

The Bonn University EEG dataset is widely used for evaluating seizure detection models due to its structured design and reliability. It consists of single-channel EEG recordings sampled at 173.61 Hz, where each segment contains 4097 data points corresponding to 23.6 seconds. The dataset is divided into five subsets labeled A to E, with each subset containing 100 segments. Subsets A and B represent normal brain activity from healthy individuals, while subsets C and D contain seizure-free recordings from epilepsy patients. Subset E includes EEG signals recorded during seizure activity. This clear categorization makes the dataset suitable for classifying normal, interictal, and ictal conditions [21].

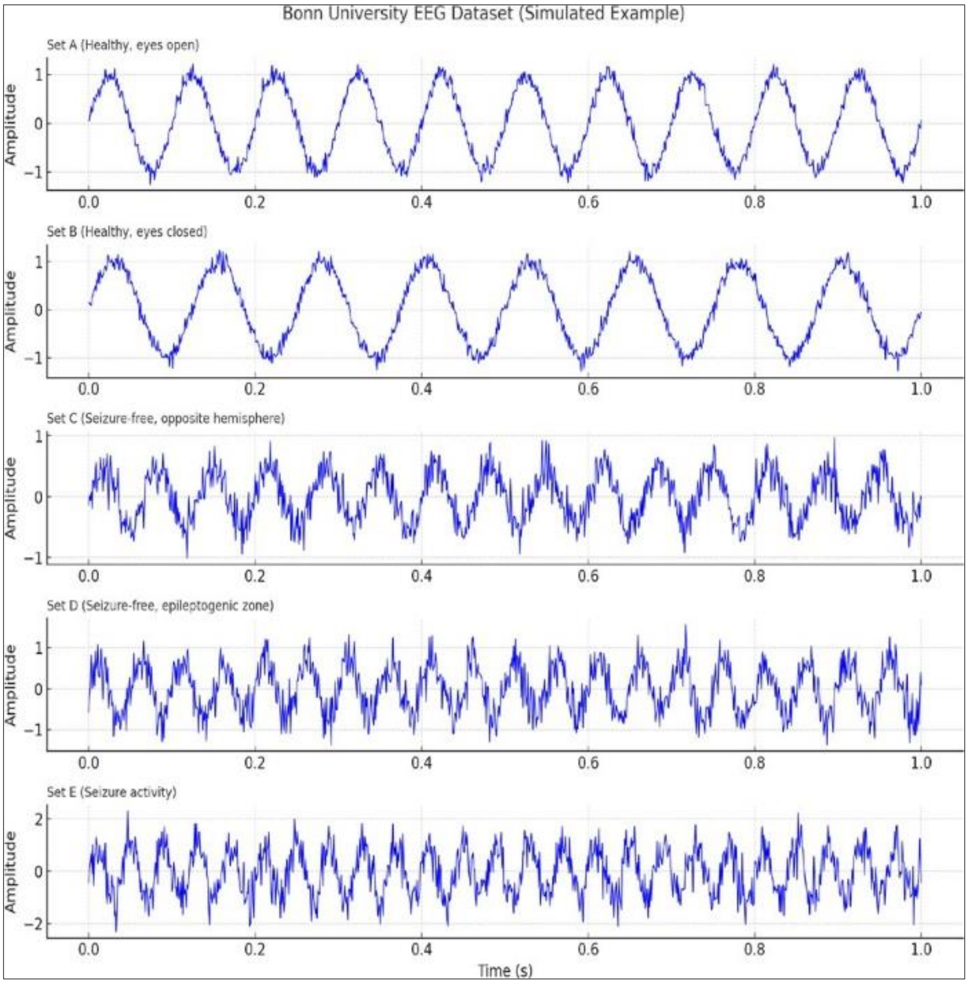

Fig. 2: Bonn EEG Dataset, subsets A – E

Experimental Analysis

The performance of different models on the EEG dataset is summarized in Table 1 and illustrated in Fig. 2. It is observed that traditional machine learning approaches provide baseline performance, with SVM achieving an accuracy of 68.91% and Random Forest achieving 89.91%. However, these models are limited in capturing complex spatial and temporal patterns in EEG signals.

In contrast, deep learning models show significantly better performance. The CNN–LSTM model achieved an accuracy of 96.00%, while the proposed CNN–BiLSTM model slightly improved the performance to 96.09%. Furthermore, the CNN–BiLSTM model achieved higher precision (96.39%), recall (96.09%), and F1-score (96.09%), indicating better classification effectiveness.

The improved results highlight the advantage of Bi-LSTM in capturing both past and future temporal dependencies, leading to more accurate seizure detection compared to conventional LSTM-based models.

Table I: Performance comparison of models on Bonn EEG DATASET

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	68.91	73.41	68.91	65.93
Random Forest	89.91	89.93	89.91	89.91
CNN-LSTM	96.00	96.17	96.00	96.01
CNN-BiLSTM (Proposed)	96.09	96.39	96.09	96.09

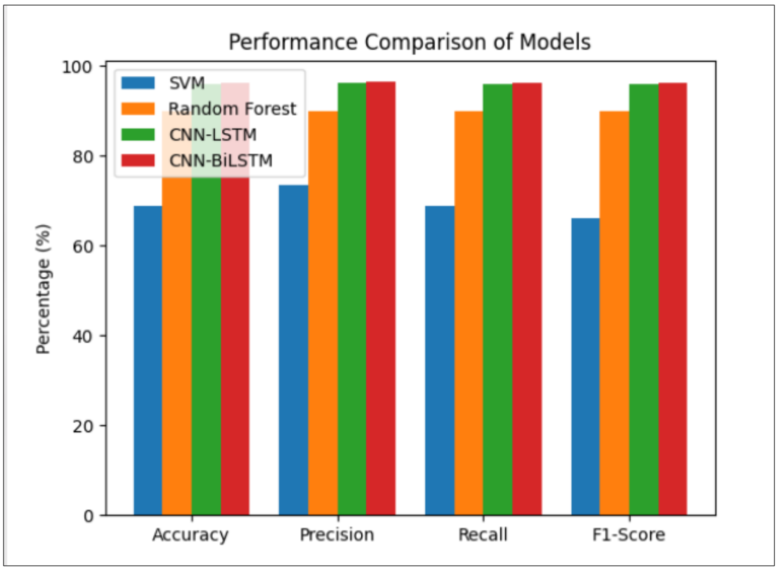

Fig. 3: Performance comparison of different models

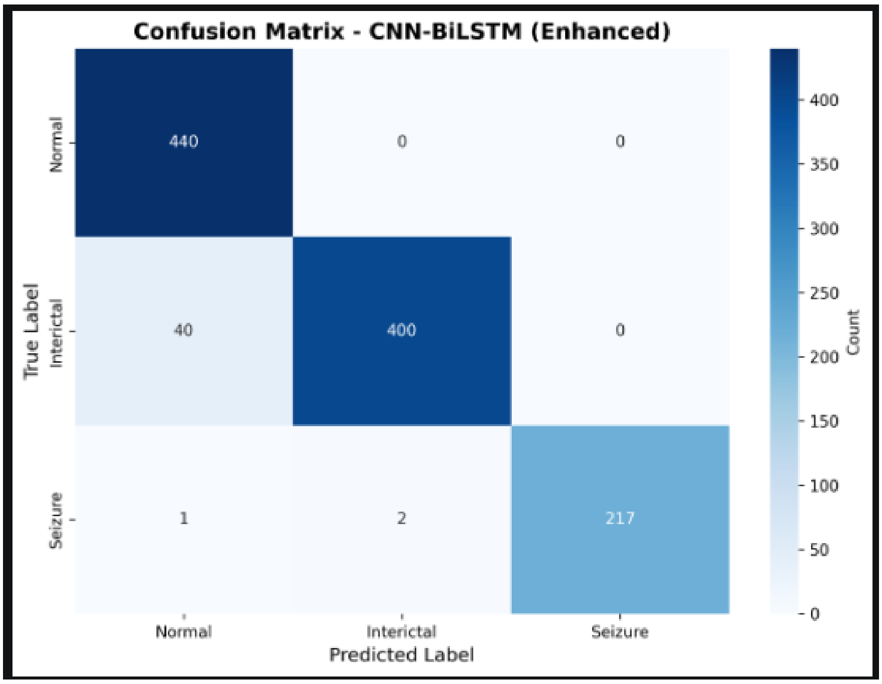

Fig. 4: Confusion matrix of proposed CNN-Bi-LSTM model

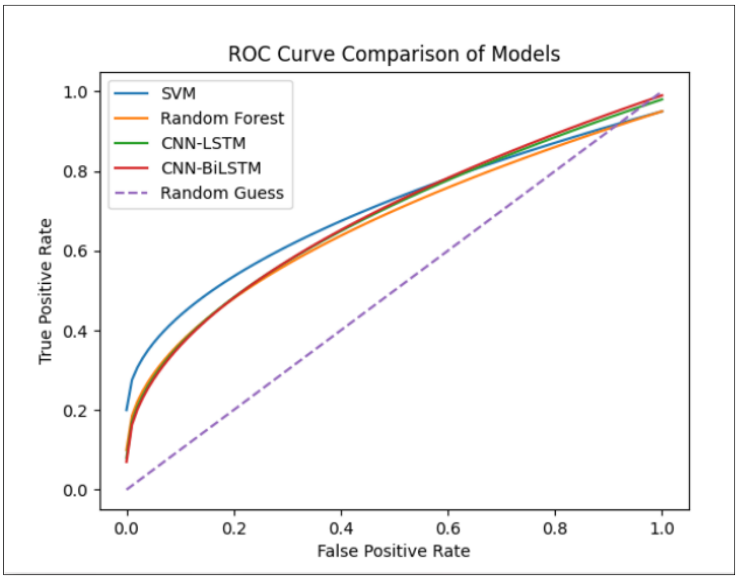

Fig. 5: ROC–AUC comparison of models

CONCLUSION

This study presents a CNN–BiLSTM framework for automated epilepsy seizure detection. While SVM and Random Forest provided baseline results, deep learning models performed significantly better. The CNN captured spatial features, and the Bi-LSTM modeled temporal relationships, improving overall classification performance.

The proposed model achieved the highest accuracy and balanced predictions, as reflected in the confusion matrix. These results suggest that the approach is effective for reliable seizure detection and may support early diagnosis.

Future work will focus on validation using larger datasets and incorporating multimodal data, such as EEG and MRI, to further enhance model robustness.

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