An Optimized Hybrid CNN-LSTM Model for Epileptic Seizure Detection and Prediction

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ABSTRACT

Timely detection and prediction of epileptic seizures are critical for enabling rapid clinical intervention. Conventional Electroencephalogram (EEG) analysis, however, is labor-intensive and prone to inaccuracies, highlighting the need for automated solutions. This study proposes an optimized hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) model that enhances seizure detection by integrating spatial feature extraction (CNN) with temporal pattern recognition (LSTM). The model was trained and validated using the publicly available CHB-MIT EEG dataset, with performance further improved through hyperparameter optimization and feature selection. Experimental results show that the hybrid model achieves an accuracy of 98.5%, outperforming standalone CNN (95.8%) and LSTM (94.2%) models. Moreover, the proposed hybrid model achieves a False Positive Rate (FPR) of only 1.06%,

surpassing the individual CNN (5.32%) and LSTM (4.26%) models. These findings demonstrate the potential of the proposed hybrid model in real-time monitoring epileptic episodes application.

Keywords-epileptic seizure detection; CNN; LSTM; Electroencephalogram (EEG); DL; prediction; hybrid model

I. INTRODUCTION

Electroencephalography (EEG) is the standard technique for identifying the characteristic brain wave patterns associated with seizures and epilepsy. Epilepsy is a chronic neurological condition, affecting an estimated 50 million people worldwide, which is caused by excessive neural synchronization that results in convulsions [1]. The condition poses a significant risk of injury or death, particularly for individuals engaged in activities such as driving or operating machinery. This underscores the urgent need for reliable seizure prediction systems, especially since traditional approaches often prove insufficient [2]. Convolutional Neural Networks (CNNs) have largely replaced traditional manual feature extraction in EEG analysis, while advanced Deep Learning (DL) approaches have shown superior performance in medical datasets compared to previous models [3]. However, the implementation of such techniques can be computationally expensive and complex [4]. The pursuit of improved predictive performance has led to the evaluation of novel biomimetic DL networks against established Machine Learning (ML) models [5] to enable the early and accurate detection of epileptic seizures, which is critical for administering proper therapy and mitigating brain damage [6]. To address the complexity of multichannel EEG signals, current approaches have explored methods like dynamic functional connectivity Neural Networks (NNs) [7], identifying functional connections within the brain and generating connectivity graphs by extracting non-Euclidean characteristics and incorporating specialized loss functions. In a different approach, Approximation Entropy (ApEn) derived from wavelet transformations has been used to automatically identify seizure episodes in continuous EEG monitoring [8]. Hybrid architectures, such as those employing both a Bidirectional Long Short-Term Memory (Bi-LSTM) and a CNN, have also been proposed to predict epileptic seizures, where deep Bi-LSTM layers are integrated into a densely coupled feed-forward structure [9, 10]. Researchers have also explored dynamical systems for predicting brain events in multichannel EEG recordings, using biomarkers like critical slowing down characteristics in conjunction with a long-term NN-based filter [11]. For instance, authors in [12] integrated DL algorithms with EEGs to create a user-facing seizure warning interface. Accordingly, authors in [13] developed a unique seizure warning model that emphasizes temporal dependencies and global spatial interactions to learn generalized characteristics from the data. Authors in [14] used a multistage methodology that integrates CNNs with traditional ML-based outlier identification to reduce the false-positive predictions. Additionally, authors in [15] used an NN-based classifier architecture that has been designed specifically to detect seizures in pediatric cases. ML models using techniques like Random Forest (RF) for feature extraction have also been explored, alongside the application of the Support Vector Machine (SVM) [16]. Research has also extended beyond EEG to differentiate epileptic episodes using Surface Electromyography (sEMG) signals, where features from various muscle sensors were selected and categorized with an Artificial Neural Network (ANN) classifier [17]. Further efforts to improve diagnostic precision have combined ensemble learning with NNs, and lightweight decision tree models have been described for categorizing seizure events from brain waves [18].

While the above mentioned studies showcase diverse and innovative strategies, significant gaps remain, especially since many existing DL models do not adequately capture both spatial and temporal EEG characteristics, which limits their accuracy and reliability. This paper addresses these shortcomings by proposing an optimized hybrid CNN-LSTM model designed to improve the accuracy and efficiency of seizure prediction by cohesively integrating spatial and temporal information extraction. By demonstrating superior performance and resilience compared to current state-of-the-art methodologies, this work presents an innovative DL solution that advances the potential for real-time epilepsy monitoring.

II. PROPOSED METHOD

This work proposes an optimized hybrid CNN-LSTM model, a type of architecture known for its effectiveness in various application areas requiring complex pattern recognition, such as healthcare monitoring, optimization, and ethnicity classification [19-21].

A. Dataset

The CHB-MIT Scalp EEG database [22] is a widely used public dataset for research in epileptic seizure detection. This dataset contains scalp EEG recordings from 23 subjects, including 22 pediatric patients between the ages of 1.5 and 22 years who experienced intractable seizures. The EEG recordings were captured using the international 10-20 electrode system across 23 channels. The signals were sampled at a frequency of 256 Hz with a 16-bit resolution. In total, the collection comprises 664 EEG recordings, of which 198 have been annotated by experts to mark the precise start and offset times of seizure events. To facilitate a comprehensive evaluation of our proposed model, a detailed breakdown of the EEG recordings used is provided in Table I. The dataset was partitioned into two parts, 80% (531 recordings) for training and 20% (133 recordings) for testing.

B. Preprocessing

The preprocessing phase comprises several steps. Firstly, a bandpass filter is implemented between 0.5-60 Hz to reduce noise and artifacts of raw EEG data, therefore removing undesirable frequency components that may disrupt categorization. The data is then normalized using z-score normalization, which standardizes each channel by subtracting the mean and dividing by the standard deviation, to provide consistent amplitude scaling across EEG channels. After normalization, the continuous EEG recordings were segmented into non-overlapping fixed-length windows of 5 seconds. As the EEG signals were sampled at 256 Hz, each segment contained 1,280 samples. Each segment retains significant geographical and temporal attributes, enabling the CNN and LSTM layers to discern meaningful patterns. The preprocessed EEG segments are then transformed into a suitable format for input into the hybrid model.

C. Proposed Architecture

Figure 1 illustrates the workflow of CNN-LSTM model for the identification of epileptic seizures, while Figure 2 illustrates the model architecture. After the EEG data collection from the CHB-MIT dataset and the preprocessing phase, the data are passed to the CNN layers. CNN layers apply convolutional filters to EEG data to extract key spatial features such as sharp spikes, rhythmic discharges, and amplitude fluctuations, which are distinctive indicators of epileptic seizures. These are followed by pooling layers, which reduce the dimensionality of the extracted features while retaining essential information, thus enhancing computing efficiency and mitigating overfitting.

TABLE I. CHB-MIT DATASET SPECIFICATIONS

Parameter	Value
Dataset name	CHB-MIT Scalp EEG Database
Source	PhysioNet
Total subjects	23 (22 patients + 1 healthy subject)
Total EEG channels	23 per patient
Sampling rate	256 Hz
Total EEG records	664 (198 Seizure and 466 Non-Seizure)
Data format	EDF
Duration per segment	1-2 hours per record
Preprocessing steps	Bandpass Filtering (0.5–60 Hz), Normalization

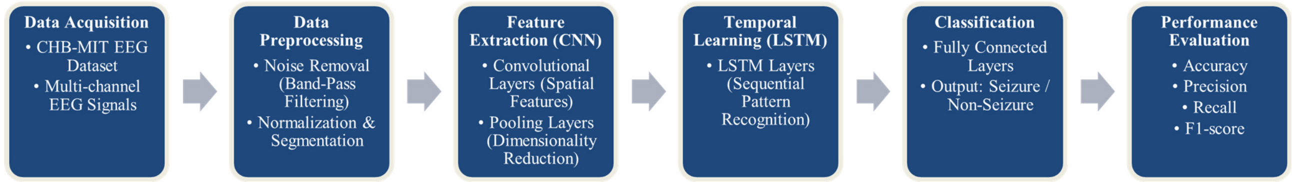

Fig. 1. Proposed model workflow.

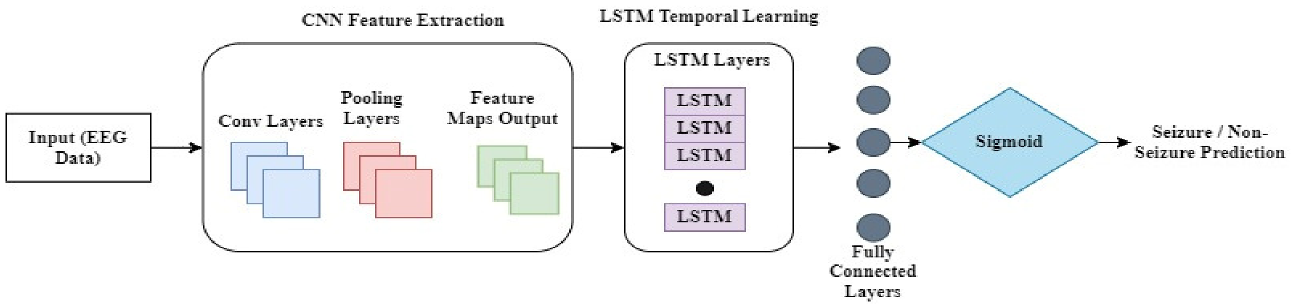

Fig. 2. Proposed model architecture.

The convolution operation is defined in (1):

$$Z_{i,j,k} = \sum_m \sum_n X_{i+m,j+n} \cdot W_{m,n,k} + b_k \quad (1)$$

where $Z_{i,j,k}$ is the output feature map, $X_{i+m,j+n}$ is the input EEG data, $W_{m,n,k}$ is the convolution kernel (filter), and b_k is the bias term. ReLU increases non-linearity by substituting negative values with zero, hence enhancing model learning efficiency as shown in (2):

$$f(Z) = \max(0, Z) \quad (2)$$

The extracted spatial features are then passed to the LSTM component, which captures temporal dependencies within the EEG signal. As seizures typically develop progressively, LSTM networks are well-suited for identifying sequential patterns indicative of seizure onset. Table II indicates the LSTM equations used for EEG-based seizure identification. The final layers of the model consist of fully connected dense layers, which integrate the spatial and temporal features and apply an activation function to perform classification. The output layer generates a binary prediction, either seizure or non-seizure, based on the patterns learned by the CNN–LSTM architecture.

TABLE II. LSTM EQUATIONS FOR TEMPORAL LEARNING IN EEG-BASED SEIZURE DETECTION

Temporal Learning Stage LSTM	Equations	Description
Forget Gate	$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f$ (3)	Removes extraneous historical EEG characteristics from memory.
Input Gate	$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i$ (4) $\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C$ (5)	Uses significant new EEG characteristics in memory.
Cell State Update & Output Gate	$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$ (6) $o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o$ (7) $h_t = o_i \cdot \tanh(C_t)$ (8)	Changes long-term memory to reflect seizure patterns. Produces the ultimate hidden state for seizure classification.

To maximize model performance and ensure robustness, hyperparameter tuning was performed to determine the optimal configuration of key parameters, thereby enhancing classification accuracy. To reduce the risk of overfitting, regularization techniques such as dropout were employed, randomly deactivating subsets of neurons during training to promote the learning of generalizable features. Additionally, feature selection methods were applied to identify the most informative EEG attributes, improving both computational efficiency and the reliability of the model's classifications. Table III lists several specifications for the proposed model.

TABLE III. SPECIFICATIONS OF THE CNN-LSTM MODEL

Parameter	Value
Number of CNN layers	3
Kernel size (CNN)	3 × 3
Pooling type	Max Pooling
Pooling size	2 × 2
Activation function (CNN)	ReLU
Number of LSTM layers	2
LSTM units per layer	128
Activation function (LSTM)	Sigmoid & Tanh
Batch size	64
Optimizer	Adam
Learning rate	0.001
Loss function	Categorical Cross-Entropy
Dropout rate	0.3
Training epochs	50
Regularization	L2 Regularization

III. RESULTS AND DISCUSSION

Figure 3 illustrates the accuracy progression of the CNN–LSTM model over 50 training epochs. By epoch 10, the model reaches an accuracy of 85.2%, showing steady improvement as training continues. At epoch 30, accuracy increases to 95.3%, indicating effective learning. The model achieves peak accuracy of 98.5% by epoch 50, reflecting strong generalization and robust seizure pattern recognition over time.

Figure 4 compares the classification performance of the CNN–LSTM model against standalone CNN and LSTM models using key performance metrics. The hybrid model outperforms both, achieving an accuracy of 98.5%, a recall of 98.7%, and an F1-score of 98.5%, with the high recall reflecting the model's ability to minimize false negatives, ensuring more seizures are correctly detected. The improved accuracy reduces false alarms, and the balanced F1-score underscores the model's strong overall classification performance, enhancing its reliability.

Figure 5 presents the False Positive Rate (FPR) comparison across models. The CNN–LSTM model achieves the lowest FPR at 6.8%, compared to 8.2% for CNN and 9.5% for LSTM. A reduced FPR is essential in seizure detection systems to avoid misclassifying normal brain activity as seizure events, thereby improving system dependability. This enhancement makes the hybrid model highly effective for real-time seizure identification and prediction.

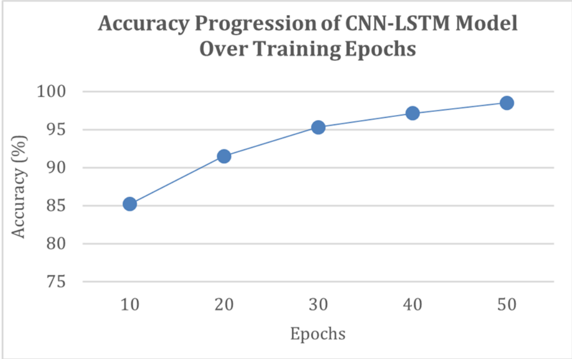

Fig. 3. Impact of training duration on CNN-LSTM model accuracy.

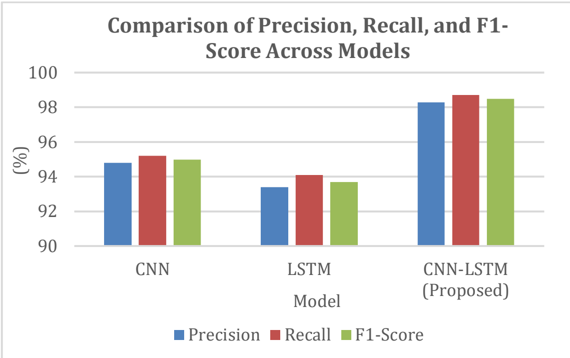

Fig. 4. Metrics of the hybrid model against the standalone CNN and LSTM model.

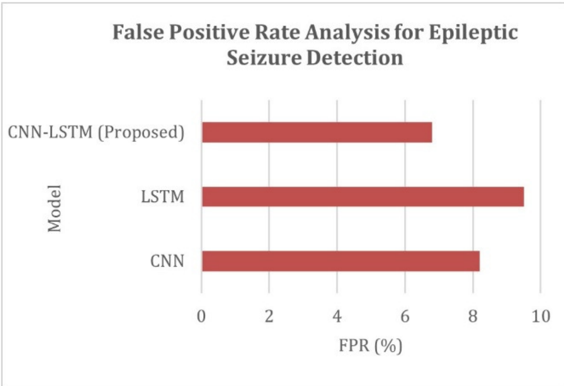

Fig. 5. FRP comparison among CNN-LSTM, CNN, and LSTM.

Figure 6 shows the obtained confusion matrix of the proposed CNN-LSTM model for seizure classification. The model correctly identified 38 seizure instances (true positives) and 93 non-seizure instances (true negatives). Only one seizure instance was misclassified (false negative), and one non-seizure instance was incorrectly classified as a seizure (false positive).

Table IV compares the accuracy of various ML models used for epileptic seizure detection against the proposed model.

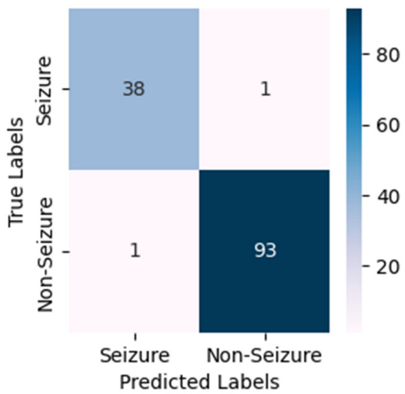

Fig. 6. Confusion matrix of the proposed hybrid CNN-LSTM.

TABLE IV. PERFORMANCE COMPARISON OF DIFFERENT ML MODELS

Model	Accuracy (%)
Random forest classifier [2]	95
SVM [16]	82
ANN [17]	96
Decision tree [18]	91.17
CNN-LSTM (proposed)	98.5

The CNN-LSTM model demonstrates superior predictive performance compared to prior approaches. Despite its advantages, the model has certain limitations, including high computational demands and a reliance on large, labeled EEG datasets. Real-time deployment in resource-constrained environments may also face latency issues. Future research will focus on optimizing the model for edge computing, reducing computational complexity, and enhancing real-time performance.

IV. CONCLUSION

This research presents a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) trained on the CHB-MIT Electroencephalogram (EEG) dataset for detection and prediction of epileptic seizures. The proposed model achieved a superior accuracy of 98.5% compared to independent CNN (95.8%) and LSTM (94.2%) models. It also outperformed traditional methods by offering higher accuracy, fewer false positives, and improved computational efficiency. The results affirm that the hybrid model provides a reliable solution for seizure monitoring, supporting timely intervention and improved patient safety. Nevertheless, challenges remain, including computational complexity and reliance on large, labeled datasets. Future research will focus on optimizing the architecture for edge computing, integrating explainable AI (XAI) to enhance interpretability, and expanding dataset diversity to improve generalizability. In conclusion, the CNN–LSTM model represents a robust and practical Deep Learning (DL) approach for automated seizure detection, offering valuable support for clinicians in epilepsy management.

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