

EEG-Based Epileptic Seizure Detection Using a Hybrid CNN-LSTM Deep Learning Framework

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Abstract: Epilepsy is a neurological disorder that affects millions of people worldwide. It causes repeated seizures due to abnormal electrical activity in the brain. Early and accurate seizure detection is important for proper diagnosis and treatment. Electroencephalography (EEG) is a non-invasive technique which is used to record brain signals and widely used for seizure analysis. However, manual analysis of EEG signals is difficult and time-consuming. In this study, a hybrid CNN-LSTM deep learning model is proposed for automatic epileptic seizure detection using EEG signals. The Epileptic Seizure Recognition dataset containing 11,500 samples was used for training and testing the model. Before training, the EEG data were normalized and prepared for deep learning analysis. The CNN layers were used to extract the important features from EEG signals, while the LSTM layer was used to learn patterns over time. The proposed model achieved an accuracy of 98.43% with high precision, recall, F1-score, and AUC values. The results show that the CNN-LSTM model could accurately classify seizure and non-seizure EEG signals. This study demonstrates that deep learning can be an effective tool for automatic seizure detection and can support future real-time healthcare and monitoring systems.

Keywords: EEG Signals, Epileptic Seizure Detection, Deep Learning, CNN-LSTM, Neural Networks, Classification

1. Introduction

Epilepsy is one of the most common neurological disorders which is affecting millions of people worldwide. It is characterized by repeated seizures caused by abnormal electrical activity in the brain. These seizures can affect a person's movement, behaviour, awareness, and overall quality of life. Early and accurate seizure detection is important for proper diagnosis, treatment planning, and patient safety [1]. Traditionally, neurologists analyse Electroencephalography (EEG) recordings to identify seizure activity. EEG is a non-invasive technique that records electrical signals generated by the brain. Although EEG is widely used in clinical practice, manual analysis of EEG recordings is time-consuming, difficult, and depends heavily on the experience of medical experts. Therefore, there is a growing need for automated systems that can assist healthcare professionals in detecting seizures accurately and efficiently [6].

1.1 Background and Motivation

The increasing availability of EEG recordings has created opportunities for developing automated seizure detection systems. Traditional seizure diagnosis relies on expert interpretation of EEG signals, which can be time consuming and prone to human error, especially when dealing with large volumes of data. As the number of epilepsy patients continues to grow, there is a need for intelligent systems that can assist neurologists in making faster and more accurate diagnoses. Recent advances in Artificial Intelligence and Deep Learning have shown promising results



in medical signal analysis. Deep learning models can automatically learn meaningful patterns from EEG data without requiring manual feature engineering. Among these models, Convolutional Neural Networks (CNNs) are effective in extracting important features from EEG signals, while Long Short-Term Memory (LSTM) networks can capture temporal dependencies in sequential data.

The motivation of this research is to develop an efficient and accurate seizure detection framework by combining CNN and LSTM architectures. The proposed hybrid CNN-LSTM model aims to improve classification performance and support automated EEG analysis for clinical applications [2][3].

1.2 EEG for Seizure Detection

EEG is one of the most effective tools for monitoring brain activity and detecting neurological disorders. It records electrical signals from different regions of the brain using electrodes placed on the scalp. EEG signals contain valuable information that can help identify abnormal brain activity associated with epileptic seizures [12]. EEG-based seizure detection has gained significant attention because EEG is non-invasive, relatively low cost, and capable of capturing real-time brain activity. However, EEG signals are often complex, noisy, and difficult to interpret manually. Automated analysis techniques can help overcome these challenges and improve diagnostic accuracy [14].

1.3. Deep Learning for EEG Signal Analysis

Recent advances in Artificial Intelligence (AI) and Deep Learning have shown promising results in biomedical signal processing. Deep learning models can automatically learn important patterns from raw data without requiring manual feature extraction. This makes them highly suitable for EEG signal analysis [1][3]. Convolutional Neural Networks (CNNs) are effective in extracting important spatial features from EEG signals, while Long Short-Term Memory (LSTM) networks are capable of learning temporal patterns and dependencies in sequential data. By combining CNN and LSTM models, it is possible to capture both spatial and temporal information from EEG signals, leading to improved seizure detection performance [2][10].

1.4 Research Objective

The main objective of this study is to develop a hybrid CNN-LSTM deep learning model for automatic epileptic seizure detection using EEG signals. The proposed model aims to improve classification accuracy by combining the feature extraction capability of CNN layers with the temporal learning capability of LSTM layers [2]. The Epileptic Seizure Recognition dataset is used to evaluate the performance of the proposed model. The effectiveness of the framework is measured using accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC metrics. Experimental results show that the proposed CNN-LSTM model achieves an accuracy of 98.43%, demonstrating the effectiveness of deep learning techniques for EEG-based seizure detection.

2. LITERATURE REVIEW

2.1 Previous Approaches

Authors (Year)	Title	Techniques Used	Key Focus/Contributions
Ahmed et al. (2024)	Psychiatric Disorder Detection	DL	EEG-based disorder classification
Soltani-Nejad et al. (2025)	Schizophrenia Diagnosis	Hybrid DNN	Temporal & functional features
Liu et al. (2025)	Mental Health Monitoring	DL	Robust EEG analysis
Naregalkar et al. (2025)	Depression Detection	ML	EEG-based de-pression analysis

Elnaggar et al. (2025)	Depression Detection (Review)	Review	Survey of EEG methods
Uyanik et al. (2025)	EEG Disorder Detection (Review)	AI, DL	Over-view of EEG-AI systems
Nadella et al. (2025)	Real-Time Mental Monitoring	Unsupervised DL	Real-time EEG monitoring
Yadulla et al. (2025)	EEG Mental Health (Review)	Unsupervised DL	Review of monitoring methods
Ural (2025)	Psychiatric Pre-Diagnosis	Ensemble DL	Non-invasive diagnosis
Modi et al. (2025)	Mental Stress Detection	Hybrid DL	Stress detection using EEG
Ange-lakis et al.(2024)	EEG Model Comparison	DL	Performance comparison
Vicchiatti et al. (2023)	Alzheimer's Classification	ML	EEG-based AD detection
Fouad & Labib (2023)	Alz-heimer's Detection	ML, ResNet	Central lobe EEG analysis
Latifoğlu et al. (2025)	Dementia Classification	ANN	AD & FTD classification
Bi et al. (2025)	Alz-heimer's EEG Review	Review	Summary of EEG methods

2.2 Research Gap

Most of existing studies rely on either CNN or LSTM models individually. However, standalone models often fail to capture both spatial and temporal EEG characteristics simultaneously. Therefore, a hybrid CNN-LSTM framework is proposed to improve seizure detection performance.

3. PROPOSED METHODOLOGY

3.1 Dataset description

The dataset contains 11,500 EEG samples with 178 EEG features and one target class. The Epileptic Seizure Recognition Dataset was obtained from the UCI Machine Learning Repository and is publicly available through Kaggle. The dataset contains 11,500 EEG samples with 178 EEG features and one target class. The dataset was used for training and evaluating the proposed CNN LSTM Model.

Figure 1 shows the architecture of the proposed CNN-LSTM model. The CNN layers extract important EEG features, while the LSTM layer learns temporal patterns. The final dense layer performs binary classification of seizure and non-seizure signals.

3.2 Data preprocessing

Before training the model, EEG signals were normalized and reshaped for deep learning processing. Noise and irrelevant signal variations were reduced using normalization techniques. The dataset labels were converted into binary classes:

0 = Non-Seizure

1=Seizure

3.4 Proposed CNN-LSTM Architecture

Dataset Shape: (11500, 180)
Model: "sequential_12"

Layer (type)	Output Shape	Param #
conv1d_23 (Conv1D)	(None, 176, 64)	256
max_pooling1d_23 (MaxPooling1D)	(None, 88, 64)	0
conv1d_24 (Conv1D)	(None, 86, 128)	24,704
max_pooling1d_24 (MaxPooling1D)	(None, 43, 128)	0
lstm_12 (LSTM)	(None, 64)	49,408
dense_24 (Dense)	(None, 64)	4,160
dropout_12 (Dropout)	(None, 64)	0
dense_25 (Dense)	(None, 1)	65

Total params: 78,593 (307.00 KB)
Trainable params: 78,593 (307.00 KB)

Figure 1 shows the architecture of the proposed CNN-LSTM model. The CNN layers extract important EEG features, while the LSTM layer learns temporal patterns. The final dense layer performs binary classification of seizure and non-seizure-signals.

Layer	Purpose
Conv1D	Feature extraction
MaxPooling	Dimensionality reduction
Conv1D	Deep feature learning
LSTM	Temporal pattern learning
Dense	Classification
Dropout	Prevent overfitting

Layer Type	Output Shape	Parameters
Conv1D	(176,64)	256
MaxPooling1D	(88,64)	0
Conv1D	(86,128)	24,704
MaxPooling1D	(43,128)	0
LSTM	(64)	49,408
Dense	(64)	4,160
Dropout	(64)	0
Dense	(1)	65

Total Parameters: 78,593

3.5 working diagram:

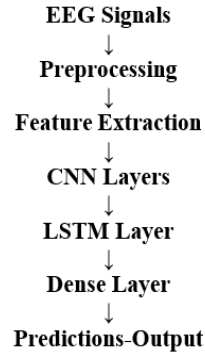


Figure 2. Illustrates the complete workflow of the proposed system, starting from EEG signal pre-processing and ending with seizure classification.

4. EXPERIMENTAL RESULTS, ANALYSIS AND DISCUSSION

4.1 Training Configuration

The model was trained using TensorFlow/Keras framework.

Optimizer: Adam, Loss Function: Binary Cross entropy, Epochs: 40, Batch Size: 32 Evaluation Metrics: Accuracy, Precision, Recall, F1-Score

Hardware: Google Colab

Software: Python 3.10, TensorFlow 2.x, Keras, NumPy, Pandas, Scikit-Learn, Matplotlib

Parameter	Value
Optimizer	Adam
Learning Rate	0.0005
Batch Size	32
Epochs	40
Validation Split	20%
Dropout Rate	0.3
Activation Function	ReLU
Output Activation	Sigmoid

4.2 Model Accuracy Figure3

Training and Validation Accuracy of the Pro-posed CNN-LSTM Model . The first Conv1D layer contains 64 filters and ex tracts local EEG features. The second Conv1D layer contains 128 filters for higher-level feature extraction. The LSTM layer with 64 units cap-tures temporal dependencies in EEG signals. Dropout with rate 0.3 prevents overfitting. The fi-nal sigmoid layer performs binary classification

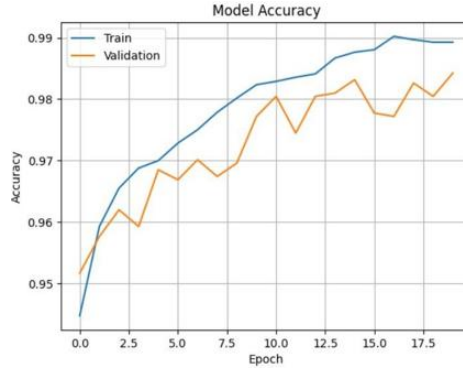


Figure 3

Shows the training and validation accuracy during model training. Both curves increase steadily, indicating successful learning and good generalization. The proposed CNN-LSTM model achieved a test accuracy of 98.43%, demonstrating strong capability in distinguishing seizure and non-seizure EEG signals.

Accuracy=98.43%,

Precision=97%,

Recall=95%,

F1-score = 96%

4.3 Classification Report:

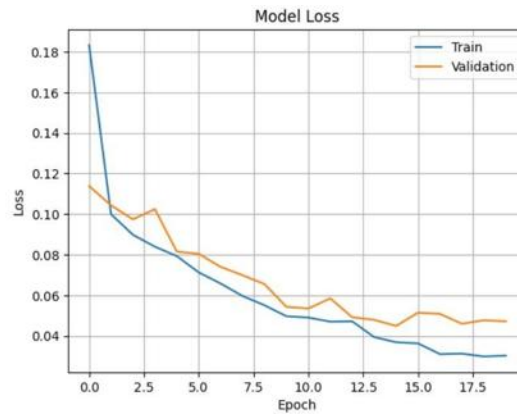


Figure 4. presents the training and validation loss curves. The loss decreases gradually over epochs, showing effective optimization.

Class	Precision	Re-call	F1-Score
Non-Seizure	0.99	0.99	0.99
Seizure	0.97	0.95	0.96

4.4 Confusion matrix Analysis Figure 5

Confusion Matrix of the Proposed CNN-LSTM Model. The confusion matrix shows that the model correctly classified 1827 non-seizure samples and 437 seizure samples, with very few mis-classifications.

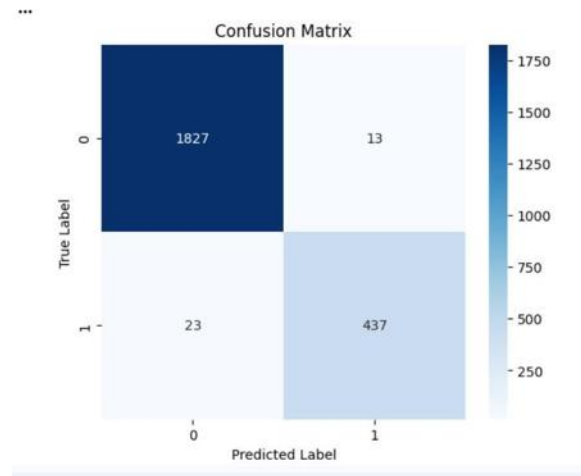


Figure 5

Actual	Predicted Non-Seizure	PredictedSeizure
Non-Seizure	1827	13
Seizure	23	437

4.5 ROC curve analysis Figure 6.

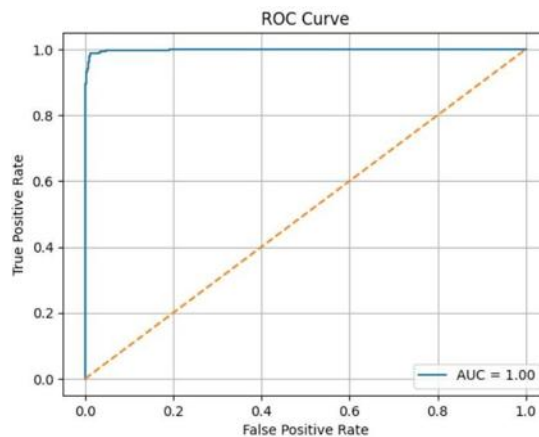


Figure 6.

ROC Curve of the Proposed CNN-LSTM Model.

The ROC curve achieved an AUC score close to 1.0, indicating excellent classification capability and high sensitivity of the proposed model.

4.6 Training and Validation Curves

Accuracy Graph: Training and validation accuracy steadily increased during training, showing stable convergence without severe overfitting.

Loss Graph: Training and validation loss gradually decreased across epochs, demonstrating effective learning behaviour.

4.7 Discussion

The dataset used in this study is publicly available through the UCI Machine Learning Repository and Kaggle platform. The implementation of the proposed CNN-LSTM model was developed using Python, TensorFlow, and Keras on Google Colab. The proposed CNN-LSTM model achieved an accuracy of 98.43%, outperforming traditional machine learning methods such as SVM and standalone CNN models. The convolutional layers successfully extracted spatial EEG patterns while the LSTM layer captured temporal dependencies. The low false-positive and false-negative rates demonstrate the robustness of the proposed framework.

5. COMPARISON TABLE

Performance Comparison of Different Models on the Same Dataset

Model	Accuracy
SVM	89%
CNN	94%
LSTM	96%
Proposed CNN-LSTM	98.43%

6. CONCLUSION AND FUTURE WORK

This paper proposed a hybrid CNN-LSTM deep learning framework for EEG-based epileptic seizure detection. Experimental evaluation on the Epileptic Seizure Recognition dataset achieved 98.43% classification accuracy. The proposed framework effectively captured both spatial and temporal EEG characteristics and demonstrated superior performance for seizure classification tasks. Future work will focus on real-time deployment and explainable AI integration. Future work will focus on real-time EEG monitoring, multi-class seizure classification, explainable AI techniques, IoT-based healthcare systems, wearable EEG devices, and transfer learning approaches.

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