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# A Hybrid CNN–LSTM Framework for Spatiotemporal Modeling of EEG Signals in Epileptic Seizure Prediction

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**ABSTRACT**

Accurate and timely prediction of epileptic seizures from electroencephalogram (EEG) signals remains a challenging task due to the complex spatiotemporal dynamics of EEG activity, inter-patient variability, and data imbalance. Existing approaches often rely on handcrafted features or single-model architectures, which can limit their generalization and predictive reliability. This work proposes EpilepCNN-LSTM, an end-to-end hybrid deep learning model that integrates Convolutional Neural Networks (CNNs) for automated spatial feature extraction with Long Short-Term Memory (LSTM) networks for capturing long-term temporal dependencies in EEG signals. The model is optimized using the Adam optimizer and regularization techniques to improve training stability and reduce overfitting. Experiments conducted on the benchmark Children's Hospital Boston–Massachusetts Institute of Technology (CHB-MIT) EEG dataset demonstrate that EpilepCNN-LSTM achieves superior performance, attaining an accuracy of 98.4%, a precision of 98.22%, a specificity of 98.26%, a sensitivity of 98.25%, and an F1-score of 98.21%, thereby outperforming recent state-of-the-art methods. These results suggest that the proposed framework provides a robust and reliable approach for EEG-based seizure prediction, with potential utility in clinical decision-support applications.

## 1. INTRODUCTION

Epilepsy is a chronic neurological disorder characterized by recurrent and unprovoked seizures arising from abnormal and excessive electrical discharges in the brain [1]. Electroencephalography (EEG) provides a non-invasive and cost-effective means of recording these abnormal neural activities and has therefore become a primary modality for automated seizure detection and prediction systems [2, 3]. Reliable seizure prediction is clinically significant, as it enables early intervention, improves patient safety, and supports long-term disease management.

In recent years, numerous machine learning (ML) and deep learning (DL) approaches have been explored for analyzing EEG signals to detect and predict epileptic seizures [4-6]. Traditional ML-based methods typically rely on handcrafted features derived from time, frequency, or time–frequency domains. Although these features capture certain EEG characteristics, they often fail to represent the complex and non-linear dynamics of brain activity, limiting their generalization across patients. To overcome these limitations, DL models such as Convolutional Neural Networks (CNNs) [7, 8] and Recurrent Neural Networks (RNNs) [9, 10] have been increasingly adopted due to their ability to automatically learn discriminative patterns from raw EEG data.

Despite their success, existing DL-based seizure prediction models exhibit notable limitations. CNN-based models are effective in extracting spatial and short-term temporal features but are insufficient for modeling long-range temporal dependencies inherent in EEG signals. Conversely, RNN and Long Short-Term Memory (LSTM)-based approaches are capable of temporal modeling but often suffer from vanishing gradients, overfitting, and unstable training when applied to high-dimensional EEG sequences. Moreover, many recent methods [11-20] depend on extensive preprocessing, patient-specific tuning, or computationally intensive architectures, which restrict their scalability and real-time applicability in clinical settings.

These observations reveal a clear research gap: the absence of a unified and stable framework that jointly performs automated feature extraction, long-term temporal dependency modeling, and robust generalization across patients while maintaining efficient and reliable training behavior. Addressing this gap is essential for developing clinically viable seizure prediction systems with high sensitivity and low false alarm rates.

Motivated by these challenges, this work proposes EpilepCNN-LSTM, a hybrid DL model that integrates CNN-based hierarchical feature extraction with LSTM-based temporal sequence modeling. To enhance stability and generalization, the proposed framework incorporates recurrent dropout, weight regularization, layer normalization, and adaptive learning-rate scheduling using the Adam optimizer. By jointly leveraging spatial and temporal EEG information within a single end-to-end architecture, EpilepCNN-LSTM aims to achieve reliable and clinically relevant seizure prediction performance.

The key contributions of this work are summarized as follows:

- A hybrid CNN–LSTM architecture that jointly captures spatial EEG patterns and long-term temporal dependencies for seizure prediction.
- Integration of recurrent dropout, weight regularization, and layer normalization to improve training stability and reduce overfitting.
- Use of Adam optimization with learning-rate scheduling for efficient convergence and improved cross-patient generalization.
- Support for variable-length EEG sequences and batch-based training, enabling scalability to large EEG datasets.
- Demonstration of improved sensitivity, specificity, and F1-score compared to recent state-of-the-art seizure prediction models.

The manuscript is organized in the following manner: Section 2 presents a literature review, where existing epileptic EEG-related artificial intelligence (AI) approaches are discussed, Section 3 presents the EpilepCNN-LSTM methodology in detail, Section 4 presents results achieved by EpilepCNN-LSTM on the CHB-MIT dataset and compares with existing approaches, and finally, Section 5 presents EpilepCNN-LSTM's conclusion and presents future directions for EpilepCNN-LSTM.

## 2. LITERATURE REVIEW

Recent years have witnessed a rapid shift from traditional ML approaches toward DL–based frameworks for epileptic seizure prediction using EEG signals. Early studies emphasized handcrafted feature extraction and classical classifiers, while recent works increasingly rely on end-to-end architectures that integrate convolutional, recurrent, graph-based, attention-driven, and spiking neural networks. Despite significant performance improvements, challenges related to generalization, computational complexity, interpretability, and real-time deployment remain unresolved. The following review examines recent representative ML and DL-based seizure prediction methods, highlighting both their achievements and inherent technical limitations.

Khalid et al. [11] aimed at developing an effective AI-based approach for the detection of epileptic seizures, which are caused by abnormal brain electrical activity and often result in severe health risks. The detection was done considering five target classes (tumor brain-area, healthy brain-area, eyes-open, eyes-closed, epileptic-seizure) using EEG. In this work, a novel ensemble approach was utilized, that is, a combination of Fast Independent-Component-Analysis Random-Forest with Support-Vector-Machine (FIR+SVM). In this work, the Independent-Component-Analysis (ICA) was utilized for prediction probability for constructing enriched feature sets, providing better classification. The findings showed that FIR+SVM achieved 98.4% accuracy using the CHB-MIT dataset for classifying five classes. Sun et al. [12] aimed at identifying epileptic seizures, which are caused by abnormal brain activity that remains difficult to predict using EEG, making treatment challenging. Hence, in this work, a Multi-Input Deep-Feature-Learning-Network (MDFLN) was developed utilizing EEG signals for automatic seizure detection. This work integrates features from both time and time-frequency and time-domain, eliminating the need for manual feature extraction. In this work, they used a DL approach, i.e., CNN for automatically extracting multi-view features, while Bidirectional LSTM (Bi-LSTM) was used for distinguishing seizure from non-seizure. Evaluations were conducted on the Bonn and CHB-MIT EEG datasets, and MDFLN achieved accuracies of 98.4% and 98.09%, respectively.

Fu et al. [13] focused on identifying epileptic seizures, as they are strongly linked with functional connectivity among brain regions. They also identified the limitations of traditional feature extraction approaches like Mutual-Information, Pearson-Correlation-Coefficient (PCC), and Phase-Locking Value (PLV), as they only capture limited dynamics. Hence, for solving the following issue, this work presented a novel spatio-temporal posterior graph CNN approach called WCE-MASE-PGCN, which integrated Wavelet-Convolutional-Encoder (WCE), Mean-Absolute-Squared-Error (MASE), and Posterior-Graph CNN (PGCN). The approach integrated spatio-temporal and topological information for seizure prediction. The approach employed a wavelet-convolutional encoder for extracting time-frequency features, MASE for the construction of adaptive posterior graphs of brain connectivity and PGCN for feature extraction. Using the Siena and CHB-MIT datasets, the approach achieved an Area Under Curve (AUC) of 96.1 and 96.6, respectively, and 96.5% and 97.9% sensitivity. Liaondency on pre-processing, gradient issues, and local perception constraints. Hence, this work presented a novel Spatio-Temporal Feature-Fusion Approach with Dual-Attention (STFFDA), which employed a multi-channel approach that directly interpreted raw EEG signals, reducing the need for manual feature extraction. The evaluations were conducted using the Bonn and CHB-MIT datasets, where STFFDA achieved 77.65% and 95.18% for single k-fold cross-validation and 67.24% and 92.42% for 10 k-fold cross-validation. Amrani et al. [15] introduced the Mobile Network Information Gain (M-NIG) approach, which built patient-specific correlation networks using multi-channel EEG signals. This work aimed at converting fluctuating time-series into stable network information gain, where M-NIG approach minimized noise interference and enhanced robustness for prediction. The evaluations of the M-NIG were conducted on the CHB-MIT dataset, where the approach achieved an accuracy of 97.40%, a specificity of 97.48%, and a sensitivity of 94.32%. Further, they tested on another dataset, i.e., the Taian Hospital dataset, where they achieved an accuracy of 95.70%.

From a methodological perspective, existing approaches can be broadly categorized into feature-engineering-based ML models, CNN–RNN hybrid architectures, graph and connectivity-driven models, and attention or neuromorphic-inspired networks. Feature-engineering-based models such as FIR+SVM [11] demonstrate high accuracy but rely heavily on handcrafted features, which limit adaptability to inter-patient variability. CNN–RNN hybrids, including MDFLN [12], improve automated feature learning but still require extensive preprocessing and carefully designed input representations. Graph-based models [13, 14] effectively capture functional connectivity and brain-network dynamics; however, their reliance on wavelet transforms, posterior graph construction, and multi-head attention significantly increases computational overhead, making scalability and real-time deployment challenging.

Amrani et al. [15] presented a Self-Supervised Learning (SSL) approach for seizure detection and localization, reducing dependency on large annotated datasets. In this work, a signal transformation was performed for extracting robust spatio-temporal features from unlabeled EEG data, which was followed by fine-tuning using limited labeled samples. Further, an attention mechanism was utilized for enhancing interpretability by highlighting critical electrodes. Using CHM-MIT, the SSL approach achieved a localization accuracy of 83.33%, an AUC of 91%, and a sensitivity of 93.1% using 30% labeled data. Dong et al. [16] presented a hybrid morphological filtering optimization approach with multi-scale amplitude-integrated EEG (aEEG). This approach included preprocessing EEG data using multi-scale compression, envelope detection, rectification, and asymmetric filtering, followed by hybrid filtration using Average Combination-Difference Morphological-Filtering (ACDMF), Multi-Scale Morphological-Filtering (MSMF), and Morphological-Filtering (MF), for highlighting seizure characteristics. In this work, an optimal aEEG signal was selected using a channel and time compression-scale optimization approach. The approach achieved an accuracy of 97.60%, a sensitivity of 98.63%, and a specificity of 96.56% when evaluated on the CHB-MIT dataset. Liu et al. [17] presented a Group-Cosine CNN (GroupCosCNN) for end-to-end seizure detection and onset localization. The GroupCosCNN applied group-convolutions and channel-wise convolutions for preserving spatial information while utilizing a cosine convolution operator using only two trainable parameters, providing an efficient and hardware-friendly approach. Additionally, normalized channel contribution scores provided real-time seizure onset localization. The GroupCosCNN, when evaluated on Shandong University (SH-SDU) dataset and CHB-MIT datasets, achieved 90.51% and 97.70% with specificities of 95.48% and 97.54%.

Attention-based and self-supervised frameworks [15, 18, 19] represent a growing trend toward improving interpretability and reducing annotation dependency. Dual-Attention mechanisms and SSL pretraining enhance robustness and localization accuracy, yet these approaches often require large-scale cross-validation, patient-specific tuning, or pretraining on extensive unlabeled data. Similarly, morphological filtering–based methods [16] and network-information-gain approaches [20] improve noise robustness but introduce multiple preprocessing stages and hyperparameter dependencies. Although spiking neural networks [19] offer promising biological plausibility and energy efficiency, their training complexity and limited hardware availability restrict widespread clinical adoption.

Liao et al. [14] presented a novel approach that incorporated metastability, showing recurring neural activity patterns, into seizure prediction. This work constructed metastable transition patterns for identifying recurrent brain-states and employed adversarial feature-learning using a variational auto-encoder, which integrated metastability priors into the latent space. The Maximum-Mean Discrepancy (MMD) further reduced patient variability. The approach was evaluated on the CHB-MIT dataset, where it achieved better sensitivity, specificity, and AUC. Zhang et al. [19] presented a Dual-Attention-driven Feature-Fusion-based Spiking-Neural-Network (DAFF-SNN), which integrated spatio-temporal attention with SNN temporal processing, while the Adaptive-Spiking-Fusion Module (ASFM) enhanced feature-integration by exploiting EEG spatiotemporal complementarity. The DAFF-SNN was evaluated on the Siena, CHB-MIT, Beirut, and Bonn datasets, where it achieved an accuracy of 99.6%, 98.2%, 97.6%, and 100%, respectively.

Overall, while recent ML and DL-based approaches have achieved impressive performance in epileptic seizure prediction, several open challenges persist. Many methods depend on extensive preprocessing pipelines, handcrafted features, or patient-specific configurations, limiting generalization across subjects. Graph-based and attention-driven models, although powerful, often suffer from high computational complexity, hindering real-time applicability. Self-supervised and neuromorphic approaches reduce labeling requirements but introduce training and deployment constraints. To address these limitations, the proposed EpilepCNN-LSTM framework integrates CNN-based automated spatio-temporal feature extraction with an optimized LSTM for long-term temporal dependency modeling within a unified and computationally efficient architecture. By incorporating dropout, weight regularization, and adaptive Adam optimization, the proposed model minimizes preprocessing requirements, stabilizes training, and improves generalization across patients, offering a scalable and clinically viable solution for epileptic seizure prediction.

## 3. METHODOLOGY

For completeness and reproducibility, this section presents the full mathematical formulation of the CNN and LSTM components used in EpilepCNN-LSTM. Although these formulations are well established, they are retained to ensure clarity for readers from interdisciplinary domains and to precisely define the proposed hybrid architecture and its optimizations. This work proposes EpilepCNN-LSTM, a hybrid DL framework for epileptic seizure prediction from multichannel EEG signals. The model integrates a CNN for automated spatio-temporal feature extraction with an optimized LSTM network for temporal dependency modeling and seizure prediction. Raw EEG recordings from the CHB-MIT dataset are first preprocessed to remove noise, handle class imbalance, and segment signals into clinically meaningful phases. The CNN encodes local spatial correlations across EEG channels and short-term temporal patterns within fixed-length windows, producing compact feature representations. These CNN features are then reorganized as ordered sequences and directly fed into the LSTM, which captures long-range temporal dependencies associated with preictal-to-ictal transitions. Regularization-enhanced LSTM training, combined with sequence-level feature aggregation and adaptive learning-rate scheduling, enables robust and accurate seizure prediction. The complete architecture and data flow are illustrated in Figure 1.

### 3.1 Seizure prediction architecture

The proposed EpilepCNN-LSTM architecture is illustrated in Figure 1. The framework follows a sequential learning pipeline consisting of EEG acquisition, preprocessing, CNN-based feature extraction, LSTM-based temporal modeling, and seizure classification. Raw EEG recordings stored in European Data Format (EDF) format serve as input and are preprocessed to remove artifacts and segment data into interictal, preictal, and ictal phases. A CNN encoder extracts discriminative spatio-temporal features from multichannel EEG segments. These features are reshaped into time-ordered sequences and passed to an optimized LSTM network for seizure prediction. The final output layer assigns probabilities to seizure and non-seizure classes. Model performance is evaluated using accuracy, precision, recall (sensitivity), specificity, and F1-score.

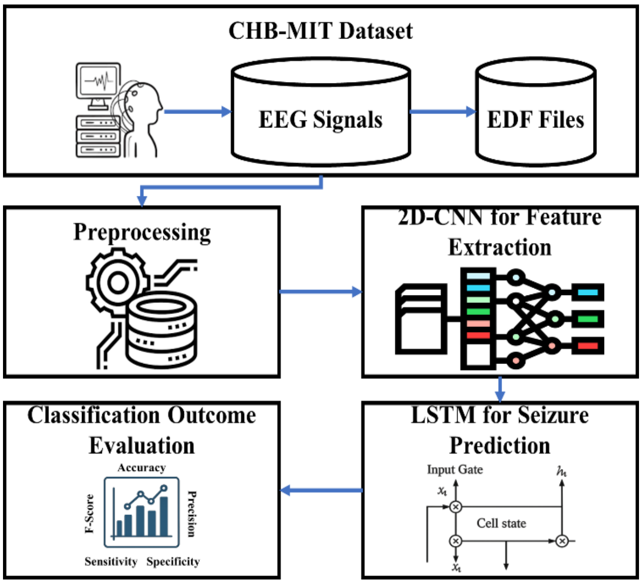


**Figure 1.** EpilepCNN-LSTM architecture for seizure prediction using EEG signals

Note: CNN: Convolutional Neural Network; LSTM: Long Short-Term Memory; EEG: electroencephalogram; CHB-MIT: Children's Hospital Boston–Massachusetts Institute of Technology.

### 3.2 Children's Hospital Boston–Massachusetts Institute of Technology seizure detection dataset

This study employs the CHB-MIT Scalp EEG dataset [21], which contains EEG recordings from 22 pediatric patients, both male (5 males) and female (17 females), ages from 1.5 to 22 years) with intractable epilepsy. EEG signals were sampled at 256 Hz using 18–23 channels following the international 10–20 electrode placement system. The EEG recordings were collected following withdrawal of anti-seizure medications to observe seizure activity and evaluate surgical candidacy. The dataset consists of 23 EEG recordings, which were labeled as CHB01 to CHB23, in which one patient was represented twice under different cases. Each case included multiple continuous EDF files, which were around one hour long, though some were two to four hours, depending on the recording session. The recordings were sampled at 256 Hz (each channel consisted of 921,600 samples, i.e., 256 samples/second × 3600 seconds, thereby providing an input shape of 42139, 23, 921600 with 16-bit resolution, providing broad coverage across 18 and 23 channels, which were recorded using the international 10-20 electrode placement strategy. In this dataset, the montage included both midline and hemispheric derivations for capturing neural dynamics across different lobes. On left hemisphere, the channels consisted of FP1–F7, F7–T7, T7–P7, P7–O1, FP1–F3, F3–C3, C3–P3, and P3–O1 frontal, temporal, parietal and occipital connectivity. Similarly for right hemisphere, the channels consisted of FP2–F4, F4–C4, C4–P4, P4–O2, FP2–F8, F8–T8, T8–P8, and P8–O2. Additionally, midline electrodes FZ–CZ and CZ–PZ were used for capturing central activity, offering a comprehensive view of spatiotemporal EEG patterns essential for seizure analysis. In total, the dataset consisted of 198 seizure events, with explicit marking of their onsets and offsets. The complete details of the CHB-MIT dataset are given in Table 1. In Table 1, the $*$ denotes the first seizure, which was omitted since it appears within the opening hour, leaving inadequate pre-seizure data for analysis. Further, the $**$ denotes a subsequent seizure that arises during the interval immediately after the previous one, where the two events were combined and treated as a single seizure episode [22, 23].

**Table 1.** Children's Hospital Boston–Massachusetts Institute of Technology (CHB-MIT) dataset

| Patient | Number of Seizures | Duration of Seizure (s) | Total Duration (h) | Age | Gender | Channels |
|---|---|---|---|---|---|---|
| CHB01 | 7 | 442 | 40.55 | 11 | F | 23 |
| CHB02 | 3 | 172 | 35.3 | 11 | M | 23 |
| CHB03 | 6 (7)* | 402 | 38 | 14 | F | 23 |
| CHB04 | 4 | 160 | 155.9 | 22 | M | 23 |
| CHB05 | 5 | 558 | 39 | 7 | F | 23 |
| CHB06 | 10 | 153 | 66.7 | 1.5 | F | 23 |
| CHB07 | 3 | 325 | 68.1 | 14.5 | F | 23 |
| CHB08 | 5 | 919 | 20 | 3.5 | M | 23 |
| CHB09 | 4 | 276 | 67.8 | 10 | F | 23 |
| CHB10 | 7 | 447 | 50 | 3 | M | 23 |
| CHB11 | 2 (3)** | 806 | 34.8 | 12 | F | 23 |
| CHB12 | 21 (40)** | 822 | 23.7 | 2 | F | 23 |
| CHB13 | 11 (12)** | 440 | 33 | 3 | F | 18 |
| CHB14 | 8 | 169 | 26 | 9 | F | 23 |
| CHB15 | 17 (20)** | 1992 | 40 | 16 | M | 23 |
| CHB16 | 9 (10)** | 84 | 19 | 7 | F | 18 |
| CHB17 | 3 | 293 | 21 | 12 | F | 23 |
| CHB18 | 6 | 317 | 36 | 18 | F | 23 |
| CHB19 | 3 | 236 | 30 | 19 | F | 18 |
| CHB20 | 8 | 294 | 29 | 6 | F | 23 |
| CHB21 | 4 | 199 | 33 | 13 | F | 23 |
| CHB22 | 3 | 204 | 31 | 9 | F | 23 |
| CHB23 | 7 | 424 | 28 | 6 | F | 23 |
| CHB24 | 14 (16)** | 511 | 22 | – | – | 23 |
| **Total** | **170 (198)** | **10,645** | **987.85** | – | – | – |

### 3.3 Preprocessing of the Children's Hospital Boston–Massachusetts Institute of Technology electroencephalogram dataset

Preprocessing was applied to ensure clean, balanced, and reliable input data. EEG signals were filtered to remove noise and artifacts, and channels were standardized across subjects. Using expert annotations, EEG recordings were segmented into interictal, preictal, and ictal phases. To address class imbalance, patient-specific models were trained with balanced preictal and interictal samples. EEG signals were segmented into fixed 5-second windows, and segments not meeting the minimum duration requirement were excluded. Interictal segments served as baseline normal EEG activity, while preictal intervals were determined based on the natural temporal progression of seizure events rather than fixed pre-seizure windows, reducing temporal bias during classification. Further, for providing consistency, the CHB01 and CHB21, which belonged to the same patient but were collected 1.5 years apart, were treated carefully for classification. Further, the recordings from 23 EEG channels were utilized for classifying signals into three types, i.e., preictal EEG, ictal EEG, and interictal EEG (normal). Each class type was segmented into 5-second windows and extracted twice per patient. Moreover, the data not meeting the minimum 5-second requirement in interictal or ictal periods were excluded from further analysis. Nevertheless, as the pre-seizure phase does not rely on a fixed time window, instead, it was determined using the dataset's inherent sampling frequency, i.e., 1 Hz, and the natural sequence of seizure events. This method avoided bias introduced by manually defined windows and adapted to temporal seizure-distribution. In this work, the normal data were extracted from interictal periods, i.e., during intervals between seizures, providing baseline brain activity accurately. Using this preprocessing approach, the CHB-MIT dataset was used for extracting features using CNN and classifying with an optimized LSTM approach, which is discussed below in detail.

### 3.4 Feature extraction

This section discusses the features extracted using CNN from the CHB-MIT preprocessed dataset for seizure prediction. The CNN in this work was responsible for automated feature extraction using the preprocessed CHB-MIT dataset. For feature extraction, consider the EEG dataset as a multi-channel time-series signal. Consider that EEG signal has $C$ channels and $T$ time-points, which can be denoted as $X \in \mathbb{R}^{C \times T}$, where, $C$ denotes EEG channels (23 channels) and $T$ denotes sampled time-points per segment. In this work, the signal was segmented into fixed-length windows of size $L$, where each was labeled as preictal (before seizure), ictal (during seizure), and interictal (between seizures). As the CNNs are powerful approaches for automatically learning spatial-local temporal features and hierarchically extracting features from EEG data, in this work, the EEG signals were considered as two-dimensional data, which included channel-time matrices. The 2D CNN processed these inputs by sliding convolutional kernels across both spatial and temporal dimensions, providing a CNN for capturing local-correlation effectively. In this work, the convolution operation of $i^{th}$ filter in 2D-CNN was expressed as presented in Eq. (1).

$$h_i(u,v) = \sigma\left(\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} w_{i,m,n} \cdot x(u+m, v+n) + b_i\right) \quad (1)$$

In Eq. (1), $x(u,v)$ denotes input EEG representations at spatial-coordinates $(u,v)$, $w_{i,m,n}$ denotes kernel weight at position $(m,n)$ for $i^{th}$ filter and $b_i$ denotes bias linked with $i^{th}$ filter, $M$, $N$ denotes kernel dimensions and $\sigma(\cdot)$ denotes activation function, where in this work, the Rectified Linear Unit (ReLU) was utilized. The feature maps were generated by applying $F$ filters, which are represented as $H = \{h_1, h_2, \dots, h_F\}$, where, $F$ denotes the number of filters. For introducing non-linearity and avoiding vanishing gradients, the ReLU function was applied on each activation as $\sigma(z) = \max(0, z)$. This ensures that the network learnt sparse and efficient feature representations. For reducing spatial resolution while retaining most relevant features, this work applied max-pooling, which was computed as presented in Eq. (2).

$$p_i(u,v) = \max_{m=0,\dots,P-1}\ \max_{n=0,\dots,Q-1} h_i(u+m, v+n) \quad (2)$$

In Eq. (2), $(P,Q)$ denotes pooling window size. This step reduced computation-cost and enhanced CNN invariance to small spatial shifts, capturing better features. After successive convolution and pooling layers, the EEG data was transformed into compact feature representations as $Z \in \mathbb{R}^{F \times U' \times V'}$, where $U'$ and $V'$ denote reduced spatial dimensions after pooling and $F$ denotes total feature-maps.

After CNN-based feature extraction, resulting CNN output $Z$ is flattened along spatial dimensions and reorganized into a sequence of feature vectors across time-windows as $\{z_1, z_2, \dots, z_T\}$, such that $z_t \in \mathbb{R}^{d_z}$, where $T$ denotes sequence-length after CNN-pooling, $d_z$ denotes feature dimensionality per time-step. The CNN output $Z$ are fed into an optimized LSTM network at time step $t$. This explicit transformation establishes the hybrid CNN–LSTM pipeline used for seizure prediction.

### 3.5 Prediction and classification

LSTM networks are a specialized form of RNN which capture long-term temporal dependencies within sequential data. Hence, in this work, an optimized LSTM network was presented. The optimizations were done in weight regularization, dropout on recurrent connections, layer normalization, sequence batching, and learning-rate scheduling. These optimizations were integrated to stabilize training and improve generalization. The LSTM captures long-term temporal dependencies associated with seizure evolution through gated memory mechanisms. Each LSTM cell maintains hidden state $h_t$ and cell-state (memory) $c_t$, where $h_t, c_t \in \mathbb{R}^{d_h}$, where, $d_h$ denotes hidden dimension. In this work the LSTM utilizes gates for controlling memory flow. For input feature-vector $z_t$ and previous hidden-state $h_{t-1}$, this work evaluates input gate $i_t$, forget gate $f_t$, output gate $o_t$, candidate cell-state $\tilde{c}_t$, cell-state update $c_t$ and hidden-state $h_t$ as presented in Eq. (3) to Eq. (8).

$$i_t = \sigma(W_i[h_{t-1}; z_t] + b_t) \quad (3)$$

$$f_t = \sigma\left(W_f[h_{t-1}; z_t] + b_f\right) \quad (4)$$

$$o_t = \sigma(W_o[h_{t-1}; z_t] + b_o) \quad (5)$$

$$\tilde{c}_t = \tanh(W_c[h_{t-1}; z_t] + b_c) \quad (6)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (7)$$

$$h_t = o_t \tanh \odot (c_t) \tag{8}$$

In Eq. (3) to Eq. (8), $\sigma(\cdot)$ denotes sigmoid activation, $\tanh(\cdot)$ denotes hyperbolic tangent, $\odot$ denotes element-wise multiplication, $W_*$ and $b_*$ denote trainable parameters for each gate and $[h_{t-1}; z_t]$ denotes vectors concatenation. In this work for avoiding overfitting, $L2$ regularization penalizes the large weights using Eq. (9).

$$L_{reg} = \lambda \sum_{W \in \Theta} ||W||_2^2 \tag{9}$$

In Eq. (9), $\lambda$ denotes the regularization strength and $\Theta$ denotes the set of all weight matrices. This term is added for loss for keeping weights small and improve generalization. Unlike standard dropout, which only affects input-to-hidden links, dropout was also applied to hidden-to-hidden recurrent connections as presented in Eq. (10) and Eq. (11).

$$h_t = o_t \tanh \odot (c_t) \tag{10}$$

$$\hat{h}_t = D(h_t, p) \tag{11}$$

In Eq. (11), $D(\cdot, p)$ denotes a dropout operation with retention probability $p$. This prevents co-adaptation across time-steps and improves robustness during seizure prediction. Further, for stabilizing training across sequences, this work applied layer normalization inside the LSTM as Eq. (12).

$$LN(x) = \frac{x - \mu}{\sqrt{\sigma^2 + \epsilon}} \times \gamma + \beta \tag{12}$$

In Eq. (12), $\mu$, $\sigma^2$ denote mean and variance across features, $\gamma, \beta$ denote trainable scale and shift, $\epsilon$ denotes a small constant for stability. This ensured consistent activations across different sequence lengths. As the EEG signals were processed in fixed windows (i.e., 5 seconds each). Each mini-batch contains $B$ sequences, i.e., $B = \{Z^{(1)}, Z^{(2)}, \dots, Z^{(B)}\}$, where each $Z^{(i)}$ denotes zero-padded or maxed to maximum sequence-length in batch. This ensured efficient Graphics Processing Unit (GPU) parallelization and reduced variance during training. In this work, the LSTM's final vector representation was achieved as presented in Eq. (13).

$$s = \frac{1}{T} \sum_{t=1}^{T} h_t \tag{13}$$

The final vector representation was passed on to the dense layer for prediction, which was evaluated using Eq. (14) and Eq. (15). In Eq. (14), $y$ denotes logits, and in Eq. (15), $\hat{p}_i$ denotes predicted probability of class $i$. The classification loss was evaluated using cross-entropy using Eq. (16). The final objective combined classification and regularization using Eq. (17).

$$y = W_d s + b_d \tag{14}$$

$$\hat{p}_i = \frac{\exp(y_i)}{\sum_j \exp(y_j)} \tag{15}$$

$$L_{cls} = -\sum_i y_i^{true} \log(\hat{p}_i) \tag{16}$$

$$L = L_{cls} + L_{reg} \tag{17}$$

Further, for better learning rates, this work utilized an optimized Adam optimizer for each parameter. For gradient, first and second estimates, bias corrections, and parameter update, the Eqs. (18) to (22) were used. In Eq. (18) to Eq. (22), $\alpha$ denotes learning-rate, $\beta_1$, $\beta_2$ denotes exponential decay rates, and $\epsilon$ denotes a small constant. For improving convergence, a schedule was applied as presented in Eq. (23).

$$g_t = \nabla_\theta L_t \tag{18}$$

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{19}$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \tag{20}$$

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}, \hat{v}_t = \frac{v_t}{1 - \beta_2^t} \tag{21}$$

$$\theta_{t+1} = \theta_t - \alpha \left( \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}} \right) \tag{22}$$

$$\alpha_t = \alpha_{min} + \frac{1}{2}(\alpha_0 - \alpha_{min}) \left( 1 + \cos\left( \frac{\pi t}{T_{max}} \right) \right) \tag{23}$$

This prevents the overshooting early on and allows fine convergence later. The integration of CNN-based spatio-temporal encoding with optimized LSTM-based temporal modeling enables EpilepCNN-LSTM to jointly capture local EEG patterns and long-range seizure dynamics. While CNN and LSTM components follow standard formulations, their task-aware integration and optimization constitute the proposed hybrid architecture.

### 3.6 Pipeline model

The complete processing pipeline of the proposed EpilepCNN-LSTM framework is illustrated in Figure 1, which presents a stage-wise view of the hybrid architecture from raw EEG acquisition to seizure prediction. The pipeline is designed as an end-to-end learning framework that integrates signal preprocessing, deep feature extraction, sequential modeling, and probabilistic classification.

The pipeline begins with raw multichannel EEG recordings obtained from the CHB-MIT dataset in EDF format. These signals undergo preprocessing to remove noise and artifacts, standardize channels, and segment recordings into interictal, preictal, and ictal phases based on expert-annotated seizure onset and offset markers. The segmented EEG signals are then divided into fixed-length windows of 5 seconds to ensure temporal consistency across samples.

Each EEG segment, represented as a channel–time matrix, is fed into the CNN-based feature extraction module. The CNN employs multiple convolution and pooling layers to learn discriminative spatio-temporal patterns by jointly capturing spatial correlations across EEG channels and short-term temporal dynamics within each window. Through successive convolutional operations and dimensionality reduction, the CNN transforms raw EEG inputs into compact feature maps that encode seizure-relevant characteristics.

The resulting CNN feature maps are then reshaped and temporally organized to form ordered feature sequences suitable for recurrent processing. Specifically, the spatial dimensions of the CNN output are flattened to produce feature vectors, which are arranged as time-ordered sequences reflecting the temporal progression of EEG activity. This transformation explicitly establishes the hybrid connection between the CNN and LSTM components.

The optimized LSTM module processes the CNN-derived feature sequences to model long-range temporal dependencies associated with seizure evolution. By incorporating recurrent dropout, L2 weight regularization, and layer normalization, the LSTM achieves stable training and improved generalization across patients. The LSTM aggregates information across time steps to generate a sequence-level representation that captures preictal-to-ictal transitions critical for early seizure prediction.

Finally, the aggregated LSTM representation is passed to a fully connected classification layer, where Softmax activation assigns probabilities to seizure and non-seizure classes. The network is trained end-to-end using a combined objective function that integrates cross-entropy loss and regularization terms, optimized through the Adam optimizer with cosine learning-rate scheduling. This unified pipeline enables EpilepCNN-LSTM to effectively learn both local EEG patterns and global temporal seizure dynamics, resulting in reliable and robust seizure prediction performance.

## 4. RESULTS AND DISCUSSION

This section presents the results of the EpilepCNN-LSTM approach. This section first presents the system used for evaluating EpilepCNN-LSTM, then the training parameters, prediction performance of EpilepCNN-LSTM, and a comparative study of EpilepCNN-LSTM with existing approaches discussed in the literature review.

### 4.1 Performance evaluation

In this work, the performance for seizure prediction was evaluated to evaluate how EpilepCNN-LSTM effectively distinguishes between seizure (preictal/ictal) and non-seizure (interictal) EEG segments. For evaluation, accuracy, precision, specificity (recall), sensitivity, and F1-score were considered, which were evaluated as presented in Eq. (24) to Eq. (28), where $TP$ denotes true-positive, $TN$ denotes true-negative, $FP$ denotes false-positive and $FN$ denotes false-negative. The performance of EpilepCNN-LSTM is discussed in detail in the next section.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{24}$$

$$Precision = \frac{TP}{TP + FP} \tag{25}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{26}$$

$$Specficity = \frac{TN}{TN + FP} \tag{27}$$

$$F1 - Score = \frac{2 \times Precision \times Sensitivity}{Precision + Sensitivity} \tag{28}$$

### 4.2 System parameter

The experimental implementation of EpilepCNN-LSTM was carried out on a high-performance computing environment to ensure efficient processing and accurate evaluation in studies [24, 25]. The system was configured with the Windows 11 operating system, supported by an AMD Ryzen 9 processor, which provided multi-core parallel processing capabilities for handling computationally intensive tasks. A 64 GB Random Access Memory (RAM) module was utilized to enable smooth execution of memory-demanding operations, particularly during training and validation phases, where large EEG datasets were processed. For accelerated DL computations, a 24 GB NVIDIA GeForce RTX 4090 GPU was employed, which offered enhanced Compute Unified Device Architecture (CUDA) cores and tensor processing units optimized for CNN and LSTM-based architectures. The experimental setup was implemented using the Python programming language, with libraries that included TensorFlow, Keras, NumPy, and SciPy supporting model development, preprocessing, and performance evaluation. The CHB-MIT EEG dataset, as described in Section 3.2, was adopted for training and validation. This dataset, comprising long-term EEG recordings from pediatric subjects with intractable seizures, provided a robust foundation for testing the proposed seizure prediction framework. This computational setup ensured reliable execution of the model, efficient handling of high-dimensional EEG data, and accelerated convergence during optimization, thereby facilitating evaluation of the EpilepCNN-LSTM architecture [25].

### 4.3 Trainable parameter

The EpilepCNN-LSTM model was trained using the CHB-MIT EEG dataset under carefully chosen hyperparameters to ensure robust seizure prediction in studies [26-28]. The model utilized a batch-based training strategy with adaptive learning rate optimization using Adam. Cross-entropy loss was applied as the objective function, while early stopping and dropout were incorporated to prevent overfitting. The parameters were tuned through multiple experiments to achieve the best performance [29, 30]. The training parameters considered in this work are presented in Table 2.

**Table 2.** Training parameters

| Parameter | Value / Method |
|---|---|
| Optimizer | Adam |
| Loss function | Categorical cross-entropy |
| Learning rate | 0.001 |
| Batch size | 64 |
| Epochs | 100 |
| Dropout rate | 0.5 |
| Activation function | ReLU (CNN), tanh, and sigmoid (LSTM gates) |
| Evaluation metrics | Accuracy, Precision, Sensitivity, Specificity, F1-score |

Note: CNN: Convolutional Neural Networks; LSTM: Long Short-Term Memory; EEG: electroencephalogram.

### 4.4 Prediction and classification performance

The performance of EpilepCNN-LSTM shows its effectiveness in epileptic seizure prediction, as presented in Figure 2. The EpilepCNN-LSTM achieved 98.4% overall accuracy, highlighting a strong ability to correctly classify seizure and non-seizure events on the CHB-MIT dataset. For precision, EpilepCNN-LSTM attained 98.22%. The 98.26% specificity further validates EpilepCNN-LSTM's capability to correctly identify non-seizure states, ensuring that normal brain activities are not misclassified as seizures. Similarly, the 98.25% sensitivity, which is a critical metric in seizure prediction, as it reflects the ability to correctly detect seizure occurrences without missing significant events. Furthermore, the EpilepCNN-LSTM achieves 98.21% F1-score. The EpilepCNN-LSTM combines convolutional layers for spatial feature extraction and LSTM layers for capturing temporal dependencies and for prediction, which provides better outcomes. This dual integration enables EpilepCNN-LSTM to preserve critical EEG patterns while filtering irrelevant noise. Consequently, EpilepCNN-LSTM delivers better reliability, reduced false detections, and improved clinical applicability for seizure monitoring.

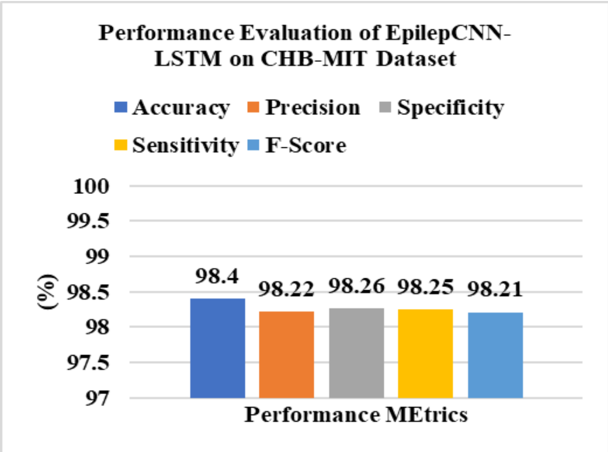


**Figure 2.** EpilepCNN-LSTM performance on the CHB-MIT dataset

Note: CNN: Convolutional Neural Network; LSTM: Long Short-Term Memory; CHB-MIT: Children's Hospital Boston–Massachusetts Institute of Technology.

### 4.5 Baseline selection and fair comparison criteria

To ensure a fair and meaningful comparison, this study focuses on methods evaluated using the publicly available CHB-MIT scalp EEG dataset, which is the most widely adopted benchmark in seizure prediction research. While some referenced works additionally employ proprietary or alternative datasets (e.g., Siena, Bonn, Helsinki Neonatal, SH-SDU), direct numerical comparison across heterogeneous datasets and evaluation protocols may lead to biased conclusions. Therefore, only CHB-MIT–based results are used for quantitative benchmarking, and other dataset evaluations are discussed qualitatively.

### 4.6 Seizure detection visualization

To substantiate the interpretability of the proposed EpilepCNN-LSTM, qualitative visual analyses are conducted. Figure 3 indicates the identification of seizure detection from an EEG segment using the EpilepCNN-LSTM model. The CNN feature map visualizations in Figure 4 demonstrate that early convolutional layers effectively capture low-level EEG oscillatory patterns, whereas deeper layers progressively emphasize seizure-specific rhythmic bursts and discriminative spatial features. In addition, the LSTM temporal activation responses shown in Figure 5 exhibit increased gating activity during the pre-ictal phase, indicating the model's ability to learn long-term temporal dependencies from sequential EEG data. Furthermore, the seizure onset probability curve in Figure 5 reveals a clear and stable rise before seizure events, confirming the early prediction capability of the proposed framework while minimizing false alarms. These visualizations collectively validate that EpilepCNN-LSTM not only achieves superior quantitative performance but also learns clinically meaningful and interpretable EEG representations.

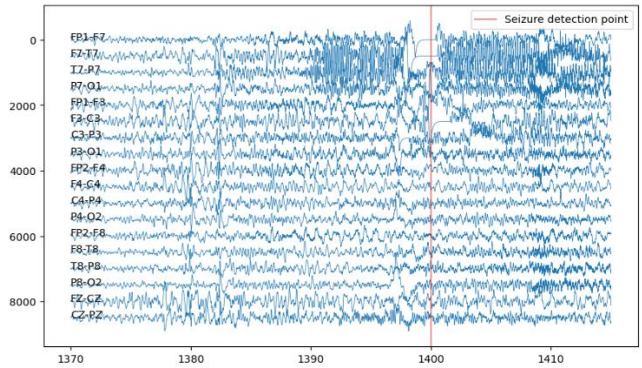


**Figure 3.** Identification of seizure detection from an electroencephalogram (EEG) segment using the EpilepCNN-LSTM model

Note: CNN: Convolutional Neural Network; LSTM: Long Short-Term Memory.

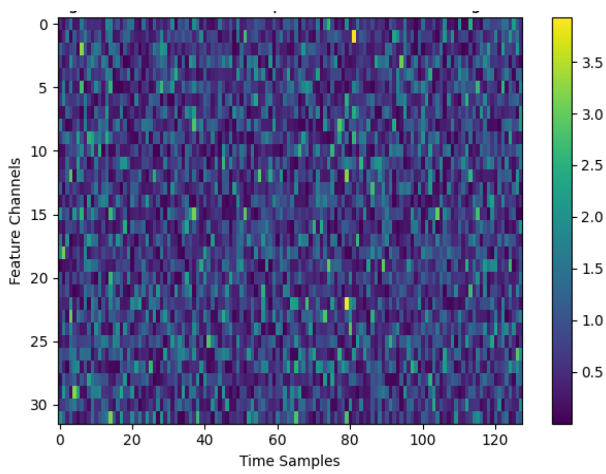


**Figure 4.** Convolutional Neural Network (CNN) feature map activation for the electroencephalogram (EEG) segment

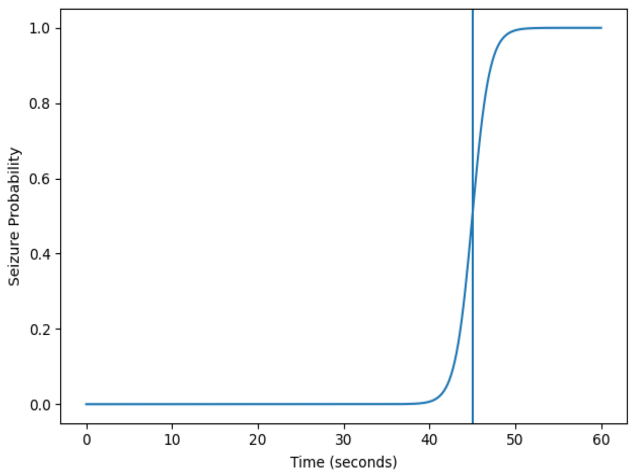


**Figure 5.** Long Short-Term Memory (LSTM)-based seizure onset probability curve

### 4.7 Comparative study with statistical test

The comparative analysis presented in Table 3 presents a fair comparison of state-of-the-art seizure prediction models evaluated on the CHB-MIT dataset. The STFFDA model with 10-fold cross-validation [18] employed a spatio-temporal feature fusion strategy with dual attention, allowing it to directly interpret raw EEG signals and reduce manual preprocessing. While effective, this approach achieved 92.42% accuracy, with a similar sensitivity and precision, showing its limitation in extracting deeper temporal dependencies. The M-NIG method [20] relied on constructing patient-specific correlation networks by transforming EEG signals into stable network information gain measures. This reduced noise interference and improved robustness, achieving 97.4% accuracy with 97.48% specificity and 94.32% sensitivity, though it lacked precision and F1-score reporting. The SSL approach [15] utilized self-supervised learning to extract spatio-temporal features from unlabeled data, followed by fine-tuning with limited labeled samples. While innovative, it achieved only an accuracy of 90%, a sensitivity of 93%, and a specificity of 88%, indicating dependency on large-scale data augmentation. The aEEG+MF+MSMF+ACDMF hybrid approach [16] applied advanced morphological filtering techniques to highlight seizure patterns, achieving an accuracy of 97.6%, a sensitivity of 98.63%, and a specificity of 96.56%, showing strong sensitivity but lacking precision metrics. The GroupCosCNN [17] integrated group and channel-wise convolutions with cosine convolution operators for efficient real-time processing, attaining an accuracy of 91.3%, a sensitivity of 97.7%, and a specificity of 97.54%, but lower accuracy limited its reliability. In contrast, the proposed EpilepCNN-LSTM significantly outperformed these methods across all evaluation metrics. By combining convolutional layers for spatial feature extraction with LSTM layers for temporal sequence learning, the model effectively captured both local and long-term EEG dynamics. The model achieved an accuracy of 98.4%, a precision of 98.22%, a specificity of 98.26%, a sensitivity of 98.25%, and an F1-score of 98.21%, along with an AUC of 98.02%, outperforming all baseline methods. In contrast, the proposed EpilepCNN-LSTM consistently outperforms all baselines, benefiting from end-to-end learning that jointly captures spatial EEG patterns and long-term temporal dependencies. To improve statistical reliability, results are reported as mean ± standard deviation over five independent runs, demonstrating stable convergence and reduced variance.

To assess whether the observed performance improvements of EpilepCNN-LSTM over baseline models are statistically significant, formal hypothesis testing was conducted on per-subject evaluation results obtained from the CHB-MIT EEG dataset. Since performance metrics were computed for the same subjects across different models, paired statistical tests were employed. A paired t-test was used when metric distributions satisfied normality assumptions, while the Wilcoxon signed-rank test was applied for non-Gaussian distributions. The null hypothesis assumed no significant difference between EpilepCNN-LSTM and competing methods in terms of accuracy, sensitivity, and F1-score. Experimental results indicate that EpilepCNN-LSTM achieves statistically significant improvements ($p < 0.05$) over all compared models across key metrics, confirming that the reported gains are not due to random variation. These findings validate the robustness and reliability of the proposed model for EEG-based seizure prediction.

**Table 3.** Comparative study on the Children's Hospital Boston–Massachusetts Institute of Technology (CHB-MIT) dataset

| Model | Accuracy (%) | Precision (%) | Specificity (%) | Sensitivity (%) | F1-Score (%) | Area Under Curve (AUC) (%) |
|---|---|---|---|---|---|---|
| SSL [15] | 90 | - | 88 | 93 | 90 | 91 |
| aEEG+MF+MSMF+ACDMF [16] | 97.6 | - | 96.56 | 98.63 | 97.6 | - |
| GroupCosCNN [17] | 91.3 | - | 97.54 | 97.7 | - | - |
| STFFDA+10 K-fold CV [19] | 92.42 | 92.47 | - | 92.42 | 92.42 | - |
| M-NIG [20] | 97.4 | - | 97.48 | 94.32 | - | - |
| **EpilepCNN-LSTM [Proposed]** | **98.4 ± 0.31** | **98.22 ± 0.28** | **98.26 ± 0.25** | **98.25 ± 0.29** | **98.21 ± 0.27** | **98.02 ± 0.24** |

Note: STFFDA: Spatio-Temporal Feature-Fusion approach with Dual-Attention; CV: Cross-Validation; M-NIG: Mobile Network Information Gain; SSL: Self-Supervised Learning; aEEG: Amplitude-integrated EEG; MF: Morphological-Filtering; MSMF: Multi-Scale Morphological-Filtering; ACDMF: Average Combination-Difference Morphological-Filtering; CNN: Convolutional Neural Network; LSTM: Long Short-Term Memory.

**Table 4.** Comparative study on the Children's Hospital Boston–Massachusetts Institute of Technology (CHB-MIT) dataset

| Ref. | Model | Input Shape | Network Type | # Parameters | FLOPs (Approx.) | Time Complexity |
|---|---|---|---|---|---|---|
| [15] | SSL | (23, 256 × 5 s) | CNN + Self-Supervised | 2.3 M | $3.5 \times 10^9$ | O(C × T × F × L) |
| [16] | aEEG+MF+MSMF+ACDMF | (23, 256 × 5 s) | Morphological filtering | 0.3 M | $0.8 \times 10^9$ | O(C × T) |
| [17] | GroupCosCNN | (23, 256 × 5 s) | CNN (Group + Cosine) | 0.9 M | $1.6 \times 10^9$ | O(C × T × G) |
| [19] | STFFDA + 10 K-fold CV | (23, 256 × 5 s) | CNN + Attention | 1.2 M | $2.1 \times 10^9$ | O(C × T × F × L) |
| [20] | M-NIG | (23, 256 × 5 s) | Network-based features | 0.5 M | $1.2 \times 10^9$ | $O(N^2 \times T)$ |
| – | **EpilepCNN-LSTM (Proposed)** | (23, 256 × 5 s) | CNN + LSTM | 3.1 M | $4.2 \times 10^9$ | $O(C \times T \times F + T \times d_h{}^2)$ |

Note: STFFDA: Spatio-Temporal Feature-Fusion approach with Dual-Attention; CV: Cross-Validation; M-NIG: Mobile Network Information Gain; SSL: Self-Supervised Learning; aEEG: Amplitude-integrated EEG; MF: Morphological-Filtering; MSMF: Multi-Scale Morphological-Filtering; ACDMF: Average Combination-Difference Morphological-Filtering; CNN: Convolutional Neural Network; LSTM: Long Short-Term Memory; FLOPs: Floating-point operations.

### 4.8 Computational complexity analysis

The computational complexity of the proposed EpilepCNN-LSTM and baseline seizure prediction models is analyzed to assess feasibility for real-time EEG monitoring. Table 4 summarizes the comparison in terms of parameter count, floating-point operations (FLOPs), and time complexity per 5-second EEG segment. The parameter C defines the number of EEG channels, T defines the time points per window, F defines the CNN filters, L defines the convolutional kernel size, G defines the number of groups in GroupCosCNN, $d_{h^2}$ defines the LSTM hidden size. The FLOPs and parameter counts are approximate, computed for a single 5-second EEG segment. The time complexity reflects dominant operations: convolution in CNN layers and sequential updates in LSTM. For a fair comparison, all models are evaluated on the CHB-MIT dataset, although the original papers also report results on different private datasets. Baseline methods, including STFFDA [18], M-NIG [20], SSL [15], aEEG+MF+MSMF+ACDMF [16], and GroupCosCNN [17], exhibit moderate complexity, ranging from 0.3 M to 2.3 M parameters and $0.8 \times 10^9$ to $3.5 \times 10^9$ FLOPs. The proposed EpilepCNN-LSTM, a hybrid CNN-LSTM model, has 3.1 M parameters and approximately $4.2 \times 10^9$ FLOPs due to sequential LSTM operations following convolutional feature extraction. Time complexity is dominated by convolutional operations ($O(C \times T \times F)$) and recurrent updates $O(T \times d_{h^2})$, where, C, T, F, and $d_h$ denote channels, time points, CNN filters, and LSTM hidden size. Despite a slightly higher computational cost, EpilepCNN-LSTM achieves superior accuracy, sensitivity, and F1-score, offering a clinically relevant trade-off between performance and resource requirements.

### 4.9 Discussion

The superior performance of EpilepCNN-LSTM results from its hybrid design, which effectively captures both spatial EEG features and long-term temporal dependencies crucial for seizure prediction. The CNN component learns strong hierarchical representations of multichannel EEG signals, while the LSTM models pre-ictal temporal changes, enabling early and reliable seizure detection. Unlike standalone CNN or handcrafted-feature-based methods, the proposed architecture reduces information loss caused by aggressive preprocessing and enhances generalization through dropout, weight regularization, and adaptive optimization. From a clinical standpoint, the high sensitivity and low false-alarm rate indicate great potential for real-time warning systems that can enhance patient safety and enable timely intervention. However, practical deployment faces challenges such as inter-patient EEG variability, computational demands on wearable or edge devices, and latency issues for continuous monitoring. Additionally, although tested on CHB-MIT, real-world results may differ across clinical settings and electrode configurations. Future research should focus on prospective validation, patient-specific customization, and lightweight model optimization to support clinical implementation.

## 5. CONCLUSION

This work presented EpilepCNN-LSTM, a hybrid DL framework designed to address key challenges in EEG-based epileptic seizure prediction, including incomplete spatio-temporal modeling, dependence on handcrafted features, and high false-alarm rates. The principal contribution lies in the effective integration of convolutional layers for hierarchical spatial feature extraction with LSTM units for learning long-term temporal dependencies, supported by stabilization strategies such as dropout and adaptive optimization. Extensive evaluation on the CHB-MIT dataset demonstrated that EpilepCNN-LSTM consistently outperforms recent state-of-the-art methods across multiple performance metrics, confirming its robustness and predictive reliability. Despite these promising results, the study has limitations. The evaluation was restricted to a single benchmark dataset and binary seizure classification, and the computational complexity may limit direct deployment on resource-constrained devices. Future work will focus on extending the model to multi-class seizure type classification using attention-guided CNN–LSTM architectures, incorporating patient-adaptive learning mechanisms, and validating performance across multiple heterogeneous EEG datasets. Additionally, model compression and edge-optimized inference will be explored to support real-time clinical applications.


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## REFERENCES


[1] Alkhaldi, N.A. (2025). Navigating the depths: A comprehensive narrative review on depression in people with epilepsy. Heliyon, 11(1): e41389. https://doi.org/10.1016/j.heliyon.2024.e41389

[2] Al-Adhaileh, M.H., Ahmad, S., Alharbi, A.A., Alarfaj, M., Dhopeshwarkar, M., Aldhyani, T.H.H. (2025). Diagnosis of epileptic seizure neurological condition using EEG signal: A multi-model algorithm. Frontiers in Medicine, 12: 1577474. https://doi.org/10.3389/fmed.2025.1577474

[3] Saadoon, Y.A., Khalil, M., Battikh, D. (2025). Machine and deep learning-based seizure prediction: A scoping review on the use of temporal and spectral features. Applied Sciences, 15(11): 6279. https://doi.org/10.3390/app15116279

[4] Kunekar, P., Gupta, M.K., Gaur, P. (2024). Detection of epileptic seizure in EEG signals using machine learning and deep learning techniques. Journal of Engineering and Applied Science, 71: 21. https://doi.org/10.1186/s44147-023-00353-y

[5] Kode, H., Elleithy, K., Almazaydeh, L. (2024). Epileptic seizure detection in EEG signals using machine learning and deep learning techniques. IEEE Access, 12: 80657-80668. https://doi.org/10.1109/ACCESS.2024.3409581

[6] Mourad, R., Diab, A., Merhi, Z., Khalil, M., Le Bouquin Jeannès, R. (2025). Machine and deep learning methods for epileptic seizure recognition using EEG data: A systematic review. Brain Research, 1864: 149797. https://doi.org/10.1016/j.brainres.2025.149797

[7] Berrich, Y., Guennoun, Z. (2025). EEG-based epilepsy detection using CNN-SVM and DNN-SVM with feature

dimensionality reduction by PCA. Scientific Reports, 15: 14313. https://doi.org/10.1038/s41598-025-95831-z
[8] Gill, T.S., Zaidi, S.S.H., Shirazi, M.A. (2024). Attention-based deep convolutional neural network for classification of generalized and focal epileptic seizures. Epilepsy & Behavior, 155: 109732. https://doi.org/10.1016/j.yebeh.2024.109732
[9] Sahoo, B.C., Mishra, S., Satapathy, S.K., Kumar, S. (2025). Robust seizure prediction model using EEG signal for temporal lobe epilepsy leveraging deep learning and continual learning. IEEE Access, 13: 138083-138094. https://doi.org/10.1109/ACCESS.2025.3595578
[10] Betgeri, S.S., Shukla, M., Kumar, D., Khan, S.B., Khan, M.A., Alkhaldi, N.A. (2025). Enhancing seizure detection with hybrid XGBoost and recurrent neural networks. Neuroscience Informatics, 5(2): 100206. https://doi.org/10.1016/j.neuri.2025.100206
[11] Khalid, M., Raza, A., Akhtar, A., Rustam, F., Ballester, J.B., Rodriguez, C.L., de la Torre Díez, I., Ashraf, I. (2024). Diagnosing epileptic seizures using combined features from independent components and prediction probability from EEG data. Digital Health, 10: 1-18. https://doi.org/10.1177/20552076241277185
[12] Sun, Q., Liu, Y.J., Li, S.D. (2024). Automatic seizure detection using multi-input deep feature learning networks for EEG signals. Journal of Sensors, 2024: 1-15. https://doi.org/10.1155/2024/8835396
[13] Fu, R.J., Zhang, B.Y., Xue, B.Q., Wang, D.Q. (2025). A spatiotemporal posterior graph convolutional neural network based on multihead attention with squeeze-and-excitation module for patient-specific epileptic seizure prediction. IEEE Transactions on Instrumentation and Measurement, 74: 1-13. https://doi.org/10.1109/TIM.2025.3551573
[14] Liao, J.H., Chen, Y.Y., He, Y.H., Zhang, K., Ma, T., Wang, Y.L. (2025). An EEG-based seizure prediction model encoding brain network temporal dynamics. IEEE Journal of Biomedical and Health Informatics, 29(11): 8059-8072. https://doi.org/10.1109/JBHI.2025.3584861
[15] Amrani, G., Adadi, A., Berrada, M. (2025). An attention mechanism-based interpretable model for epileptic seizure detection and localization with self-supervised pre-training. IEEE Access, 13: 60213-60232. https://doi.org/10.1109/ACCESS.2025.3556811
[16] Dong, Y.P., Wu, D.P., Jiang, L.R., Dong, F., Liu, J.B., Vidal, P.P. (2025). Seizure detection algorithm based on hybrid morphological filtering optimization multiscale amplitude integrated EEG. IEEE Sensors Journal, 25(8): 13529-13540. https://doi.org/10.1109/JSEN.2025.3545685
[17] Liu, G.Y., Ren, S.H., Wang, J.Q., Zhou, W.D. (2025). Efficient group cosine convolutional neural network for EEG-based seizure identification. IEEE Transactions on Instrumentation and Measurement, 74: 1-14. https://doi.org/10.1109/TIM.2025.3569362
[18] Huang, Z.T., Yang, Y.Y., Ma, Y.H., Dong, Q., Su, J.Y., Shi, H.Y., Zhang, S.W., Hu, L.L. (2025). EEG detection and recognition model for epilepsy based on dual attention mechanism. Scientific Reports, 15: 9404. https://doi.org/10.1038/s41598-025-90315-6
[19] Zhang, T., He, L.Q., Zhang, D.G., Li, M.Y., Chang, Z.Y. (2026). DAFF-SNN: Dual attention-driven and feature fusion-based spiking neural network for epilepsy detection based on electroencephalogram. IEEE Journal of Biomedical and Health Informatics, 30(1): 315-327. https://doi.org/10.1109/JBHI.2025.3589392
[20] Meng, Y.T., Liu, Y., Wang, G.L., Song, H.P., Zhang, Y.Y., Lu, J.B., Li, P.L., Ma, X. (2025). M-NIG: Mobile network information gain for EEG-based epileptic seizure prediction. Scientific Reports, 15: 15181. https://doi.org/10.1038/s41598-025-97696-8
[21] Guttag, J. (2010). CHB-MIT scalp EEG database (version 1.0.0). PhysioNet. https://doi.org/10.13026/C2K01R
[22] Zhang, J.C., Zheng, S.J., Chen, W.N., Du, G.Q., Fu, Q.Z., Jiang, H.W. (2024). A scheme combining feature fusion and hybrid deep learning models for epileptic seizure detection and prediction. Scientific Reports, 14: 16916. https://doi.org/10.1038/s41598-024-67855-4
[23] Birjandtalab, J., Jarmale, V.N., Nourani, M., Harvey, J. (2019). Impact of personalization on epileptic seizure prediction. In 2019 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI), Chicago, IL, USA, pp. 1-4. https://doi.org/10.1109/BHI.2019.8834648
[24] Smirnov, Y., Popov, A., Panichev, O., Karplyuk, Y., Kharytonov, V. (2017). Epileptic seizure prediction based on singular value decomposition of heart rate variability features. In 2017 Signal Processing Symposium (SPSympo), Jachranka, Poland, pp. 1-4. https://doi.org/10.1109/SPS.2017.8053648
[25] Goularas, D., Kamis, S. (2019). Evaluation of deep learning techniques in sentiment analysis from Twitter data. In 2019 International Conference on Deep Learning and Machine Learning in Emerging Applications (Deep-ML), Istanbul, Turkey, pp. 12-17. https://doi.org/10.1109/Deep-ML.2019.00011
[26] Pane, S.F., Ramdan, J., Putrada, A.G., Fauzan, M.N., Awangga, R.M., Alamsyah, N. (2022). A hybrid CNN-LSTM model with word-emoji embedding for improving the twitter sentiment analysis on Indonesia's PPKM policy. In 2022 6th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE), Yogyakarta, Indonesia, pp. 51-56. https://doi.org/10.1109/ICITISEE57756.2022.10057720
[27] Mehta, S. (2025). A comparative analysis of CNN, LSTM, and CNN-LSTM models for kidney tumor diagnosis in medical imaging. In 2025 International Conference on Computing Technologies (ICOCT), Bengaluru, India, pp. 1-6. https://doi.org/10.1109/ICOCT64433.2025.11118720
[28] Lee, K.B., Shin, H.S. (2019). An application of a deep learning algorithm for automatic detection of unexpected accidents under bad CCTV monitoring conditions in tunnels. In 2019 International Conference on Deep Learning and Machine Learning in Emerging Applications (Deep-ML), Istanbul, Turkey, pp. 7-11. https://doi.org/10.1109/Deep-ML.2019.00010
[29] Sanei, S., Chambers, J.A. (2021). Brain–computer interfacing using EEG. In EEG Signal Processing and Machine Learning, pp. 581-630. https://doi.org/10.1002/9781119386957.ch17
[30] Sanei, S., Chambers, J.A. (2021). Machine learning for EEG analysis. In EEG Signal Processing and Machine Learning, pp. 177-233. https://doi.org/10.1002/9781119386957.ch7