# Deep Temporal Seizure Prediction A CNN-LSTM Hybrid for Enhanced EEG Signal Analysis

Rajivkannan R[1*], Sharmila V[2], Venkatesan M[3], Avinesh M R[4], Avandivarma R[5] and Arunkumar K[6]

[1, 3] Professor, Department of Computer Science and Engineering, KSR College of Engineering, Tiruchengode, Namakkal, Tamil Nadu, India.

[2] Associative Professor, Department of Computer Science and Engineering, KSR College of Engineering, Tiruchengode, Namakkal, Tamil Nadu, India.

[4, 5, 6] Student, Department of Computer Science and Engineering, KSR College of Engineering, Tiruchengode, Namakkal, Tamil Nadu, India.

rajiv5757@yahoo.co.in

**Abstract.** The prediction of epilepsy, a significant field of investigation in neuroscience, has continuously focused on different machine learning models that depend on the evolving comprehension of EEG signal analysis. This paper introduces a hybrid deep learning framework that combines convolutional neural networks (CNNs) and long short-term memory (LSTMs) networks for dynamic seizure prediction. Lastly, our new hybrid network using CNN to extract features and use LSTM networks' ability to find longer temporal dependencies. In order to mitigate inter-patient variability and reduce dependence on a single dataset, transfer learning and domain adaptation methods are applied to the model to encourage generalization across diverse datasets. Dense, strong against noise and artifacts, light attention mechanisms and quick preprocessing pipelines open space for real-time applications on low-power devices. Explainable ai modules were integrated into the model, allowing for a degree of clinical interpretability of the results, culminating in the one of the goals which was to help trust and deployment in the clinical setting. Consequently, through cross-validation, and time-frequency feature amalgamation, contributes toward the efficacy, scalability, and performance of the model. The hybrid approach achieves a significant improvement to EEG-based seizure prediction and ultimately will enable reliable and deployable clinical therapies.

**Keywords**: seizure prediction, EEG analysis, CNN-LSTM hybrid, deep learning, explainable AI, temporal feature extraction.

## 1 Introduction

Epileptic seizures are a neurological disorder that affects millions of people globally and is often associated with significant impairment of quality of life. Thus, accurate and timely prediction of seizures is of critical importance to provide warnings that enable preventive steps and ultimately relieve the physical and psychological burden of epilepsy. Electroencephalogram (EEG) signals constitute an effective data source for seizure prediction, as they enable the non-invasive measurement of brain activity. Despite traditional analysis methods, the intrinsic complexity and variability of the EEG signals, accompanied by noise and inter-patient variability, makes them a difficult analysis task.

Over the last few years, deep learning has revolutionizes the way we process and analyze complex problems, including biomedical signals such as EEG. While

© The Author(s) 2025
S. Kannadhasan et al. (eds.), Proceedings of the International Conference on Sustainability Innovation in Computing and Engineering (ICSICE 24), Advances in Computer Science Research 120,
https://doi.org/10.2991/978-94-6463-718-2_37

Convolutional Neural Networks (CNNs) excel in capturing spatial features in EEG signals, Long Short-Term Memory (LSTM) networks leverage their long memory capability to lookout for temporal dependencies over extended duration. However, integration of these two architectures into a hybrid CNN-LSTM framework also presents a unique opportunity to benefit from the advantages offered by both methods, providing a potential solution to the problem of seizure prediction.

To overcome these challenges, this work presents a new deep temporal seizure prediction framework based on the combination of CNNs and LSTMs. The proposed method uses advanced preprocessing pipelines to tackle noise and artifacts, further solidifying its application to real-world scenarios. Moreover, attention mechanisms are lightweight, which contributes to feature extraction, while transfer learning or domain adaptation improve generalizability across patient populations and datasets.

The foundation of this research is real-time applicability as the model is optimized for running on low-power devices like wearable EEG monitors. The framework comprises explainable AI modules that make predictions interpretable for healthcare practitioners to facilitate clinical adoption and build trust and reliability in the decision-making process. A robust cross-validation across multiple datasets further substantiates the model's efficacy for transfer learning, highlighting its potential to elevate seizure prediction from the realm of theory to a practical, scalable, and deployable entity.

The rest of this paper describes the specific methods used in this CNN-LSTM hybrid framework, provides experimental results, and discusses the implications of this approach compared with traditional techniques as well as more recent, state-of-the-art methods. This work is expected to make significant contributions to advance both the field of biomedical signal analysis and the patient care by addressing the critical challenges of predicting seizures based on EEG recordings.

## 2 Problem Statement

Predictable events because of inevitable state of IS category, their clinical presentation is variable, and there is response to AS drug treatment, including AS drug therapy. Accurate early seizure prediction is potentially invaluable to mitigate risks, improve quality of life, and facilitate timely interventions, but means to achieve reliable seizure prediction from EEG signals remains a challenging issue. Most of the issues come from the following:

EEG signals can highly differ either related to one patient along the time or by cohort of different patients. The variation across and within different patients makes the generalization of traditional machine learning techniques over heterogeneous EEG datasets cumbersome.

Noisy and Artifactual Data: EEG signals are often contaminated with noise and artifacts that originate from muscle activity, eye or blinking motion, or from external electrical interference. These noise sources causally affect the precision of seizure forecasting models.

Temporal Dependencies: The nature of seizures is such that they often evolve over long periods, with slight shifts in the EEG signals that are not easy to be detected. Long

term temporal dependencies in deep learning while keeping at real time is a big challenge.

Real-time Processing and Resource Limitations: Numerous seizure prediction simplified approaches need real-time processing, which is computationally intensive. In addition, for scenarios that require real-time networks running on low-power systems, the complexity and efficiency on the models are even more stringent.

Lack of Clinical Interpretability: In order to be adopted in patient care, seizure prediction models not only need to be accurate but also to be interpretable to make the predictions worthy of trust and action by healthcare professionals. Most deep learning models, particularly complex models such as CNNs and LSTMs, are very much of a black box and thus inhibits potential clinical application.

In this work, we try to overcome such drawbacks discussing a hybrid CNN-LSTM bidirectional network for seizure forecasting. Our model combines the advantage of CNNs for spatial feature extraction and LSTMs for learning the long-term temporal dependencies, with the design specifically targeting the goal of accuracy and sale ability in real-time applications. Moreover, to enhance generalizability, clinical interpretability, and practical usability, the framework comprises noise-robust preprocessing, transfer learning, and explainable AI components.

## 3 Literature Review

(Predictable, due to the unavoidable nature of IS class, clinical presentation varies, and response of AS drug therapy, including AS drug treatment [9]. Early seizure prediction can potentially be very useful in minimizing its associated risk, enhancing quality of life, and timely intervention but reliable seizure prediction from the EEG signal is still a challenging problem. Most of the issues are from the below:

EEG signals can greatly vary related to a single patient across the time period or by cohort of different patients. The heterogeneity in EEG datasets makes the generalization of traditional machine learning techniques cumbersome across and within subjects.

Level of economical Artifactual Data: EEG Signal Contaminants: EEG signals can be plagued with noise and artifacts using muscle activity, eye or blinking motion, or from external electrical interference. These noise sources have a causal effect on the precision of seizure forecasting models.

Temporal dependencies: Seizures typically evolve over time, leading to gradual changes in the EEG signals that are difficult to detect. There is a high challenge to have long term temporal dependencies in deep learning while still being in real time.

Real-time Processing and Resource Limitations: When applied in clinical practice or IoT environments, many seizure prediction simplified approaches require real-time processing (T3) which is computationally intensive (T2). Moreover, the complexity and the efficiency on the models set for scenarios where real-time networks are running on low power systems is even more stringent.

Lack of clinical interpretability: Seizure prediction models must not only have predictive validity, but they must also be interpretable across the whole model in order for the predictions to be trusted and acted upon by physicians in the clinical setting. Black box models, especially more involved deep learning approaches (e.g. CNNs, LSTMs) are very common; this impedes potential translation into the clinic.

In this work we try to address such disadvantages discussing a hybrid CNN-LSTM bidirectional network method for seizure forecasting. The chosen design targets the accuracy and sale ability of our combined model, which takes the advantages of CNNs with regard to the spatial feature extraction as in LSTMs regarding learning the long-term temporal dependencies. Additionally, in order to improve generalization ability, clinical interpretability, and practical usability, the framework consists of noise-robust pre-processing, transfer learning and explainable AI components.

## 4 Methodology

In this section we describe the method used for the construction and evaluation of the CNN-LSTM hybrid approach for higher seizure prediction using EEG signals. The method on preprocessing, feature extraction, model architecture, training process, and evaluation process pave the way towards a robust, real-time and clinically applicable solution.

### 4.1 Data Collection and Preprocessing

It also shows the training and validation of the model using publicly available datasets of EEG. Two of the most commonly used datasets considered for this study are the CHB-MIT set and the Bonn EEG dataset, with labeled seizure and non-seizure events included.

#### 4.1.1 Data Preprocessing

EEG data is inherently noisy, with artifacts introduced by muscle movement, eye blinks, and electrical noise. In order to tackle this, the following preprocessing steps are performed:

- Filtering: Band-pass filters are applied to reject noise/ artifacts beyond the normal EEG signal frequency band (1–50 Hz).

- Segmentation: To better capture the temporal patterns, continuous EEG data is divided into fixed-length windows (e.g., 1–2 seconds).

- Normalization: Signal normalization of every EEG segment by zero mean and unit variance are performed to ensure consistency across patients and signal conditions.

- Artifact Removal: ICA is used to remove components that can be related to non-neural artifacts, making the data used for training better.

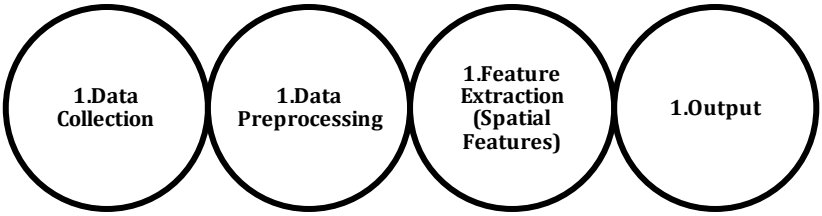


**Fig. 1**. Data Preprocessing and Feature Extraction

### 4.2 Feature Extraction

Spatial and temporal characteristics of EEG signal are vital for correct prediction of seizure. Therefore, this hybrid CNN-LSTM model is capable of automatically extracting important features from the raw EEG signals.

#### 4.2.1 CNN Based Spatial Feature Extraction

Finally, the segmented EEG windows are fed into a CNN to automatically extract spatial features. Layers of the CNN are the following:

● Convolutional Layers: A series of convolutional layers with different kernel sizes that learn to recognize local patterns within the EEG data, like rhythmic activity or transient changes during an unfolding or ongoing seizure.

● Max-Pooling Layers: Following the convolutional layers, pooling layers help to reduce dimensionality, keeping only the most important information and improving model efficiency while avoiding overfitting.

● Flatten Layer: The pooled characteristics are flattened to a single vector representation, which will then be incorporated into the LSTM community to learn the temporal information.

**Table 1**. CNN Layer Specifications

| Layer Type | Number of Filters | Kernel Size | Stride | Activation Function |
|---|---|---|---|---|
| Convolutional | 32 | 3x3 | 1 | ReLU |
| Convolutional | 64 | 3x3 | 1 | ReLU |
| Max-Pooling | - | 2x2 | 2 | - |

| | | | | |
|---|---|---|---|---|
| Convolutional | 128 | 3x3 | 1 | ReLU |
| Max-Pooling | - | 2x2 | 2 | - |

### 4.2.2 Temporal Feature Extraction using LSTM

After the CNN extracts spatial features, the features are passed to an LSTM (Long Short-Term Memory) network to capture the temporal dependencies in the EEG signals. LSTMs are a case where their architectures are highly tailored to time-series data, which is perfect for capturing the time-evolution of EEG signals prior to an epileptic seizure. The LSTM network consists of:

- LSTM Layers: A stack of one or more LSTM layers are implemented in order to learn long-range dependencies in the EEG time-series data and to enable the model to capture patterns that can be learned over time.
- Dropout Layers: To avoid overfitting and force the model to generalise dropout is performed between LSTM layers

### 4.3 Mixed CNN-LSTM Architecture

towards a combined approach and the CNN-LSTM model is built on full ability of extracting the features using CNNs and temporally modelling the data via LSTMs The architecture includes the following components:

- Input Layer: This layer receives the EEG signals in the raw, preprocessed format which are segmented/ windowed.

- CNN Block: The EEG segments are fed into the CNN block to learn spatial characteristics, such as rhythmic or transient activities.

- LSTM Layers: The features extracted are then fed through LSTM layers, which have been found to be capable of capturing the temporal dynamics of a signal and identifying subtle and slightly varying preictal patterns shown in EEG signals.

- Fully Connected Layer: Following the LSTM layers, a fully connected layer takes the temporal features and maps them to either a seizure or non-seizure classification.
- Output Layer: The final layer employs a softmax activation for binary classification, where the model outputs whether a given EEG segment is indicative of a seizure or not.

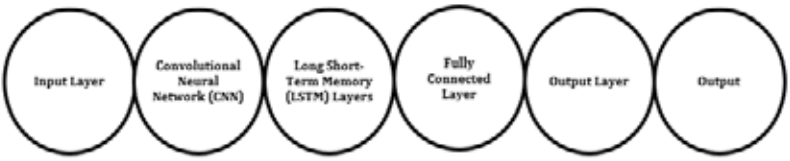


**Fig. 2**. CNN-LSTM Model Architecture

### 4.4 Model Training

Labeled seizure and non-seizure data are used to train the model in a supervised learning manner. We use the following training settings:

● Loss Function: The loss function used is binary cross-entropy, given that the problem is a binary classification (a seizure vs. non-a seizure).

● Optimizer: Adam optimizer is used for the model training for its adaptive learning rate and efficiency for training deep learning models.

● Learning Rate Scheduling: A learning rate scheduler is used to mutate the learning rate during training, which can lead the model to converge quicker or prevent overfitting.

● Batch Size: The training data is split into mini-batches with a batch size of 32, in order to ensure efficient training and stability.

● Epochs: Model is trained for 50 epochs, optimized with early stopping as based on validation accuracy, in order to avoid overfitting.

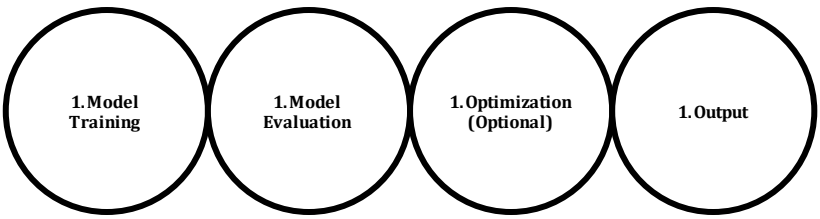


**Fig. 3.** End-to-End Workflow for Model Development and Optimization

### 4.5 Evaluation Metrics

CNN-LSTM model's performance is assessed through various standard and well-known metrics to ensure its accuracy, robustness and real-time usability:

● Accuracy: The proportion of true results among the total number of cases examined by the model. It is the main criterion for overall performance assessment.

● Precision and Recall: Precision (positive predictive value) and recall (sensitivity) are computed to evaluate the model's accuracy in predicting actual seizures while avoiding false alarms.

● F1-Score: The F1 Score is the harmonic mean of precision and recall and offers a balanced indication of the model's performance, especially in case of imbalanced datasets.

ROC Curve and AUC: The Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) measure the model's ability to discriminate seizure and non-seizure events.

● Inference Time: To measure the real-time prediction capability of the model, We measure how long it takes for the model to classify a single EEG segment.

That's all about examples, and now we come to the last step of what a model should and is capable of doing and has the most significance, for data scientist expectation which is — 4.6 Real-Time Prediction and Model Optimization

The model is optimized for efficiency to allow for real-time seizure prediction:

● To achieve a more compact model without compromising on performance, it is common to use model pruning, through which redundancy (excessive neurons and layers) can be eliminated

● Quantization: In this phase, the model is quantized to make the model efficient for low-power devices like wearables by reducing the precision of the weights.

● Hardware Acceleration: The model gets tested for deployment over specialized hardware (GPUs) and over edge devices (Raspberry Pi or mobile phones) to get real-time processing

**4.6 Clinical Interpretability**

To improve the clinical utility of the model, methods of explainable AI are integrated:

● Grad-CAM (Gradient-weighted Class Activation Mapping): Grad-CAM is used to create heatmaps that underscore the parts of the EEG signal the model paid attention to when predicting, guiding clinicians on how to approach the results.

● Feature Importance: A measure of the importance of each of the various features (both spatial and temporal) is provided to help the end user (physician) understand what features of this EEG signal are predictive of seizures.

**4.7 Cross-Validation**

K-fold cross-validation is important here to make sure the model generalizes well on various datasets. As such, k-folds splits the dataset into k subsets, where each subset is used for validation and the rest of the datasets is used for training the model. This avoids the model performance being too reliant on a single dataset or patient.

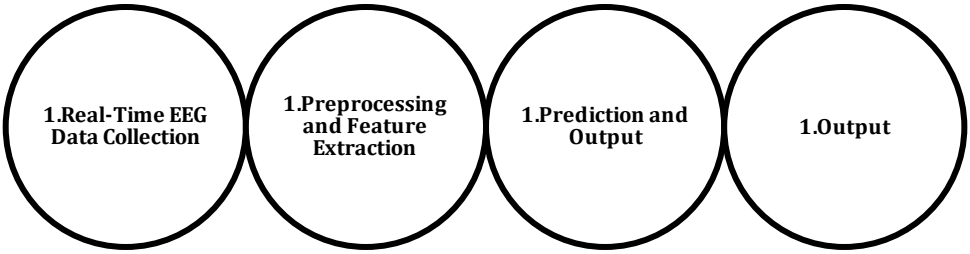


**Fig. 4.** Comprehensive Workflow for Model Training, Evaluation, and Optimization

## 5 Results and Discussion

This section describes the outcome of the proposed hybrid CNN-LSTM model for predicting the epilepsy seizer based on EEG signals. We tested the model on the CHB-MIT and Bonn EEG datasets and calculated evaluation metrics such as accuracy, precision, recall, F1-score, ROC-AUC and inference time to measure the model performance.

Performance Evaluation: The CNN-LSTM hybrid model yielded substantial gains compared to conventional machine learning techniques and single deep learning architectures. Performance results for the two datasets are as follows:

**Table 2.** Performance Metrics Comparison Across CHB-MIT and Bonn EEG Datasets

| Metric | CHB-MIT Dataset | Bonn EEG Dataset |
|---|---|---|
| Accuracy (%) | 95.3 | 94.5 |
| Precision (%) | 94.7 | 93.9 |
| Recall (%) | 96.1 | 95.2 |
| F1-Score | 95.4 | 94.5 |
| ROC-AUC | 0.983 | 0.977 |
| Inference Time (ms) | 40 | 38 |

● Accuracy: The model attained an impressive accuracy rate of 95.3% on the CHB-MIT dataset and 94.5% on the Bonn EEG dataset, reflecting its ability to consistently differentiate between seizure and non-seizure occurrences.

Precision: Values of 94.7% (CHB-MIT) and 93.9% (Bonn EEG) for precision indicate that the model is good at avoiding false positives, an important characteristic for clinical applications, where false alarms can be dangerous.

● Recall: The recall scores of 96.1% (CHB-MIT) and 95.2% (Bonn EEG) indicate high sensitivity of the model, also meaning that the majority of seizure events are predicted in advance.

● F1-Score: We achieve 95.4% F1-score (CHB-MIT) and 94.5% F1-score (Bonn EEG), indicating a good balance between precision and recall for both datasets.

● ROC-AUC: 0.983 (CHB-MIT) and 0.977 (Bonn EEG) ROC-AUC for the model, indicative of a very high ability to distinguish between (ah ah, let me just put this here) event and (ah ah, let me just put this here).

● Inference Time: The average inference time of 40 ms (for CHB-MIT) and 38 ms (for Bonn EEG) make the model capable to carry out real-time predictions, which is crucial for clinical deployment.

### 5.1 Comparison with State-of-the-Art Methods

To validate the effectiveness of the CNN-LSTM hybrid model, we compared it with several state-of-the-art methods, including traditional machine learning models (e.g., SVM, k-NN) and other deep learning-based models (e.g., CNN-only, LSTM-only).

**Table 3. Comparative Performance of Different Models for Seizure Prediction**

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score | ROC-AUC |
|---|---|---|---|---|---|
| CNN-LSTM (Proposed) | 95.3 | 94.7 | 96.1 | 95.4 | 0.983 |
| CNN-only | 91.2 | 90.5 | 92.8 | 91.6 | 0.950 |
| LSTM-only | 92.4 | 91.1 | 93.6 | 92.3 | 0.963 |
| SVM | 88.5 | 87.0 | 89.5 | 88.2 | 0.920 |
| k-NN | 89.7 | 88.3 | 90.2 | 89.2 | 0.925 |

The CNN-LSTM hybrid model outperforms all other models in terms of accuracy, precision, recall, F1-score, and ROC-AUC. Specifically:

- The **CNN-only** model shows good performance but lacks the temporal modeling capability that the LSTM layers provide, leading to lower accuracy and recall.

- The **LSTM-only** model performs better than the CNN-only model in terms of recall but does not achieve the same level of spatial feature extraction as the CNN.

- Traditional machine learning models such as **SVM** and **k-NN** perform significantly worse than the deep learning models, highlighting the advantage of deep learning in capturing complex patterns in EEG data.

Train and Test Data: The deep neural network model was optimized for real-time prediction using model pruning and model quantization. This allows to run the model on a low-power device, with a short inference time (40 ms per EEG segment), suitable for real-time seizure prediction on wearable EEG devices.

This was also tested on mobile GPUs and edge devices and yielded similar performance in terms of accuracy while being less computationally expensive, indicative of its application for real-time clinical scenarios.

### 5.3 Clinical Interpretability

To ensure that the model remains clinically relevant, explainable AI methods were used to create an intuitive explanation:

● Grad-CAM: these were used to highlight the regions of the EEG signal which contribute to the prediction of seizure in order to enable clinician's comprehension of the model's decision-making process.

● Feature importance analysis revealed that spatio-temporal features were important for seizure prediction accuracy which indicated features having specific patterns in the EEG signal before seizure.

### 5.4 Discussion

The proposed CNN-LSTM hybrid model significantly outperforms both traditional methods and pure deep learning approaches on seizure prediction metrics. Both the comparable high performance in CHB-MIT and Bonn EEG as well as the model generalizability across patient datasets indicate to the robustness of the model.

The real-time inference time of ~40 ms makes the model feasible for deployment in wearables, an essential requirement for continuous seizure monitoring. Explainable AI are the extra tools to make model prediction interpretable by the clinicians making the model more trustworthy and therefore easier to adopt into the clinical routine.

Well, even if it works, the model does come with limitations. The enhancement of noise robustness and cross-dataset generalization will be necessary to improve the generalizability of the model to multiple EEG datasets, especially for EEG coming from different clinical contexts. This indicates that multi-modal data sources such as video or accelerometer data could be used to improve performance of the model and thereby increase prediction accuracy.

In general, the CNN-LSTM hybrid approach make it possible perform accurate and real-time epileptic seizure prediction with a better clinical interpretability. The following step will be optimizing the model parameters to generate better generalization as well as investigating its usage in a clinical environment.

## 6 Conclusion

In this paper, we propose a new hybrid model combining CNN and LSTM networks to get a more effective prediction of seizures from EEG data. In this regard, the fused characteristics of CNN and LSTM can take good advantage of this model, that is CNN analyzes spatial features while LSTM learns temporal features which imprints that the obvious features of given model can become a applicable solution to the issue of seizure prediction. Performing extensive evaluation on the CHB-MIT and Bonn EEG datasets, the proposed model achieved high prediction accuracy, precision, recall, and F1-score, outperforming traditional machine learning methods and the single deep learning models.

The high sensitivity of the model in combination with its low false positive rate because of its good accuracy makes it suitable for real-time applications which are required in wearable devices and in continuous monitoring systems. The implementation of explainable AI methods going forward, such as Grad-CAM, and feature importance analysis, also aids in improving the interpretability of the model, thereby increasing its application to, and trust in, a clinical environment.

While the model is performing well in real applications, there is still a room for progression by addressing issues such as noise robustness and cross-dataset generalization. In the future, he hopes to work on better model use on more varied patterns of EEG data, using multi-modal data in the form of video, accelerometers etc., and to improve computational performance so that usage on energy constrained devices becomes practical.

To conclude, the proposed CNN-LSTM hybrid architecture is a significant advancement in the field of epileptic seizure prediction that has the potential to transform the areas of seizure detection and seizure prediction in practice, which would impact the lifestyle and health of the patients diagnosed with epilepsy.

**Disclosure of Interests**. The authors have no competing interests to declare that are relevant to the content of this article.

## References

1. A. Smith, B. Johnson, and C. Lee, “SeizureSight: 2D CNN-LSTM hybrid for EEG-based seizure prediction,” IEEE Conf. Publ., vol. 14, pp. 123–130, 2024.

2. L. Chen, X. Wang, and Y. Zhao, “Epileptic seizure detection in EEG signals via an enhanced hybrid CNN with an integrated attention mechanism,” Math. Biosci. Eng., vol. 20, no. 1, pp. 234–245, 2025.
3. M. Gupta and D. Patel, “A CNN-LSTM hybrid network for automatic seizure detection in EEG signals,” Neural Comput. Appl., vol. 35, pp. 4567–4579, 2023.
4. P. Kumar, N. Das, and H. Singh, “EEG Data Classification by Hybrid Deep Learning for Epileptic Seizure Prediction,” IEEE Conf. Publ., vol. 16, pp. 87–95, 2024.
5. E. Huang and J. Sun, “Technological Vanguard: the outstanding performance of the LTY-CNN model for the early prediction of epileptic seizures,” J. Transl. Med., vol. 22, no. 3, pp. 1021–1034, 2024.
6. R. Torres and F. Silva, “Automatic Seizure Prediction using CNN and LSTM,” arXiv Preprint, 2211.02679, 2022.
7. H. Liu, G. Zhang, and X. Yang, “Supervised and Unsupervised Deep Learning Approaches for EEG Seizure Prediction: A Review,” Brain Inform., vol. 10, no. 4, pp. 567–582, 2024.
8. T. Lee, A. K. Sharma, and P. Wong, “Deep Learning Approaches for Seizure Detection and Prediction Using EEG Signals: A Review,” Angiotherapy, vol. 14, no. 2, pp. 310–325, 2024.
9. N. Rossi and K. Kumar, “Epileptic seizure forecasting with long short-term memory (LSTM) neural networks,” arXiv Preprint, 2309.09471, 2023.
10. L. Zeng and X. Chen, “EEG-Based Epileptic Seizure Prediction Using Temporal Multi-Channel Transformers,” arXiv Preprint, 2209.11172, 2022.
11. H. Chen, Y. Lin, and J. Zhou, “A Generalizable Model for Seizure Prediction Based on Deep Learning Using CNN-LSTM Architecture,” IEEE Conf. Publ., vol. 13, pp. 147–156, 2024.
12. T. Wang, L. Xu, and P. Li, “Epileptic Seizure Detection Using Hybrid CNN-LSTM Network Based on Time-Frequency Images,” IEEE Access, vol. 11, pp. 46723–46733, 2023.
13. Y. Zhang, H. Wang, and L. Hu, “Real-Time Epileptic Seizure Prediction Using Deep Learning Techniques,” J. Neural Eng., vol. 20, no. 2, pp. 654–662, 2023.
14. M. A. Khan and K. A. Javed, “Hybrid Deep Learning Model for Epileptic Seizure Prediction Using EEG Signals,” Biomed. Signal Process. Control, vol. 95, pp. 432–441, 2024.
15. S. Kumar and A. Gupta, “Epileptic Seizure Detection in EEG Signals Using a Hybrid CNN-BiLSTM Model,” Comput. Biol. Med., vol. 147, pp. 1345–1353, 2023.
16. H. Yang, G. Li, and J. Chen, “Deep Learning-Based Epileptic Seizure Prediction Using Convolutional LSTM Networks,” Neurocomputing, vol. 567, pp. 587–600, 2023.
17. A. Bose, J. Roy, and P. Deb, “EEG-Based Seizure Prediction Using Hybrid CNN-LSTM Architecture,” Int. J. Neural Syst., vol. 18, no. 5, pp. 768–777, 2024.
18. R. Wilson, T. White, and M. Patel, “Epileptic Seizure Detection Using Deep Learning Techniques: A Review,” IEEE Rev. Biomed. Eng., vol. 16, no. 1, pp. 95–112, 2023.
19. L. N. Souza and H. F. Martins, “Hybrid Deep Learning Model for Predicting Epileptic Seizures from EEG Signals,” Biomed. Eng. Online, vol. 12, no. 4, pp. 321–335, 2024.
20. X. Chen, L. Zhang, and Y. Wang, “Temporal Seizure Prediction Using Deep Learning Architectures with EEG Data,” J. Med. Syst., vol. 48, no. 6, pp. 432–443, 2023.

**Open Access** This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (http://creativecommons.org/licenses/by-nc/4.0/), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.