

# Deep Learning Models in the Early Prediction of Epileptic Seizures

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## Abstract

Seizure prediction remains an open problem in the field of clinical neuroscience, given its unpredictable nature and the risk profile associated with it. The present study undertakes a comparative assessment of the performance of various architectures of deep learning, including Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), Graph Neural Network (GNN), and Transformer, in predicting epileptic seizures 15 minutes in advance using EEG signals. A standard protocol has been adopted for the experiments, including preprocessing techniques such as filtering, normalization, and segmentation, in addition to feature extraction and balancing, using the CHB-MIT dataset. The performance of the models has been measured using metrics such as accuracy, specificity, reproducibility, F1-score, and area under the receiver operating characteristic curve (AUC).

## 1. Introduction

Epilepsy is a chronic disorder that affects the human nervous system, resulting from abnormal electrical discharges in the cerebral neurons. This condition manifests itself as recurrent, sudden episodes or seizures that are caused by abnormal electrical discharges in the neurons. [1] Epilepsy affects millions of people all over the world, but despite the major advances that have taken place in the development of new medicines and new forms of surgery, 30% of the patients with epilepsy are still living with unstable seizure conditions. This puts them in a dangerous position, affecting their quality of life .[2]

Etiologies of epilepsy involve several factors, including genetic predisposition, traumatic brain injury, neoplasms, congenital malformations, and neurodevelopmental abnormalities, all of which result in abnormalities of normal neural electrical activity. The unpredictable nature of seizures is one of the primary hindrances in the management of the disease, since seizures may arise without prior warnings. Thus, predicting seizures is one of the primary objectives of support systems. [3]

Currently, electroencephalography (EEG) is the most commonly used method for the diagnosis and investigation of epilepsy. This method is accurate and does not involve the invasion of the human brain. Epilepsy is divided into four main phases based on the activity from the electroencephalogram. It is based on electroencephalography (EEG) signals to monitor the brain's electrical activity via small electrodes placed on the scalp. A frequency between 0.5-70 Hz is emitted in epilepsy patients, and the EEG shows four phases.

-Interictal: There is a period of stability between seizures, which may sometimes appear normal, but some cases involve abnormal electrical indicators.

-Preictal: The seizure is immediately preceded and accompanied by subtle changes in electrical signals, making it crucial for early prediction.

-Ictal: The period of the actual seizure, during which electrical activity is very high and its characteristics change over time.

-Postictal: This is followed by the end of the seizure and is characterized by a decrease in the wave speed of brain activity until it returns to its baseline state.

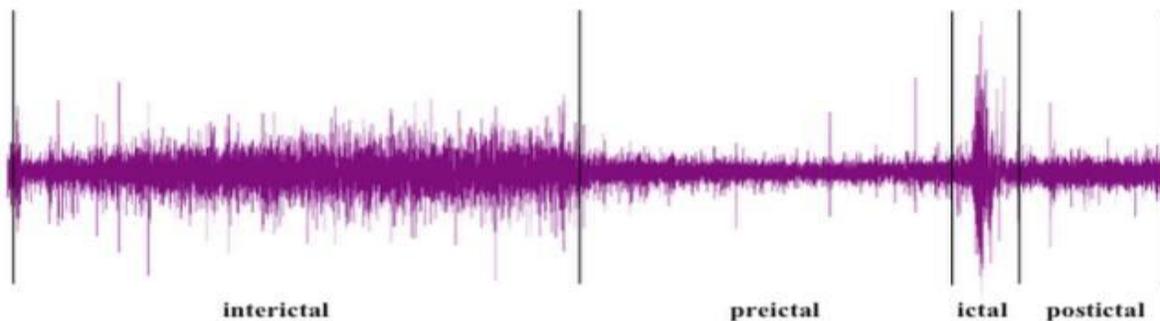


Figure 1: EEG signal segmentation ( Interictal , pre-seizure, seizure, post-seizure)[2]

The preictal phase is a crucial phase for the early prediction of the onset of a seizure, as it contains temporal and physiological changes that take place before the onset of the epileptic seizure, which are used to generate early warnings to prevent injuries [3][4]

Deep learning techniques have demonstrated promising capabilities in the field of medicine, with special attention given to the classification of medical images. The results of the comparative analysis of the capabilities of the convolutional neural networks Alex Net and Google Net suggest that high accuracy of classification may be achieved.[5]

In the last few years, the interest in the application of machine learning (ML) and deep learning (DL) methods to the analysis of the EEG signal and the prediction of the epileptic seizures has increased significantly. Several studies have reported the application of deep network architectures, particularly recurrent networks like long short-term memory (LSTM) networks and bidirectional LSTM networks, due to their powerful capability to deal with the temporal complexity of the signals, thus achieving high performance in the prediction of the seizures when compared to the traditional methods [6][7]

Parallel to this, graph neural networks (GNNs) have been recognized as a novel method for the processing of electroencephalography (EEG) signals in the contemporary literature. Within the GNNs, the EEG channels are represented as nodes, while the spatial and temporal relations are represented as edges in the graph. This provides a precise structural representation of the neural signals. Furthermore, the Transformer models, based on the self-attention mechanism, have been recognized as highly efficient models for the processing of long-range

temporal dependencies due to their potential to process the signals in a parallel manner while providing a comprehensive model of the signals. Therefore, they are recognized as a promising model for the processing of complex time-series signals, such as EEG signals [8][9]

Yet, there still exists a lot of challenges, which act as limitations for the practical performance of the early seizure prediction models. Perhaps the first notable challenge is the unbalanced nature of the EEG dataset, where the pre-epileptic samples were significantly fewer compared to the inter-ictal samples. This unbalanced nature impacts the performance of important metrics, particularly the recall value, which is vital in the field of medicine, as shown in the works of [2][7]

Moreover, while effective in modeling short-term local dependency, such as in long short-term memory networks, there might be some limitations in modeling long-term dependency as well. On the other hand, while the Transformer has been successful in modeling long-range dependency effectively, its inability to model temporal-scale information might be a drawback when considering such a model in isolation. Therefore, a need arises to create a hybrid model that combines the advantages of local time-dependent modeling with long-range dependency modeling in a unified yet efficient way.

With this motivation in consideration, the current study aims to propose an early epileptic seizure prediction framework with the ability to predict epileptic seizure occurrences up to 15 minutes before the actual occurrence by identifying the pre-ictal patterns prior to the ictal phase of an epileptic seizure using EEG signal processing techniques. To evaluate the performance of the proposed approach, the CHB-MIT database is employed, which is publicly available and comprises scalp EEG signals recorded from 24 pediatric patients.

Here, the objectives are to carry out a systematic and comprehensive comparison of various deep learning architectures such as different types of models for handling time-related information (LSTM and Bi-LSTM) and graph structures (GNN) and models based on the use of attention (Transformers).

This study presents a transformer model for prediction epileptic seizure up to 15 minutes before onset. It identifies preictal patterns using EEG signal processing and deep learning, evaluated using the CHB-MIT database. The objectives are: (i) to compare deep learning architectures, including LSTM, Bi-LSTM, GNN, and Transformers, for time-series modeling; and (ii) to introduce a Transformer architecture that combines local temporal information and long-range dependencies. The goal is to improve the accuracy and robustness of early seizure prediction, providing reliable warnings up to 15 minutes prior to seizure ones

## 2. Related Works

Although significant advances have been made in the prediction of epileptic seizures with the help of electroencephalography signals, the studies that have been carried out in the past have a high level of diversity with regard to the databases used, the prediction windows, the deep models that have been implemented, and the ways in which the imbalances have been handled. Such diversity has hindered the comparison of the studies with regard to the performance of the early prediction systems.

In order to clearly illustrate the similarities and differences of the pertinent work in the field of epileptic seizure prediction, the current table attempts to provide an informative synthesis of the key prior works in the field of epileptic seizure prediction, focusing primarily on the types of models developed in each work, the databases used in each case, the prediction horizon of each work, the strategy for mitigating the data imbalance issue in each work, and the key performance metrics of each work.

**Table( 1):** Research literature summary

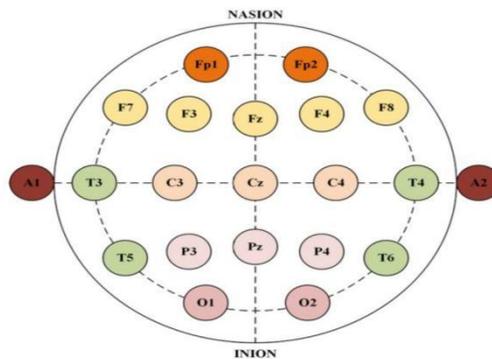
Authors & Year	Proposed Method	Problem Statement	Objective	Enhancements
Kunekar et al. (2024) [10]	LSTM	Due to the difficulty in the accurate automatic detection of a seizure caused by the non-linearity and non-stationarity of EEG signals, as well as the performance of the data set	to improve the accuracy of the epileptic seizure detection, a comparative analysis of the ML and DL approaches is carried out.	Recall=90 F1_score=0.93
Omar & Abd El-Hafeez, (2024) [11]	Models such as Conv1D-LSTM, LSTM, Bi-LSTM, and GRU with the incorporation of feature scaling, PCA, Chi-square feature selection, and dropout.	The differences in seizure recognition performance that may result from improper preprocessing, feature scaling, and model regularization techniques.	to improve the accuracy of recognition of an epileptic seizure by means of an evaluation of deep learning architectures and preprocessing techniques.	True positive rate = 92
Ali esmaeilpour (2024) [2]	STFT CNN	Weakness in prediction accuracy and unreliability	To goal building a robust deep learning model for prediction	Sensitivity =90 FPR=0.94
Zhao et al.(2024) [6]	ResNet with Bi-LSTM (ResBiLSTM)	The accuracy of the automatically detected seizures is difficult to achieve due to the complex spatio-temporal patterns contained in the EEG signals.	To the detection of epileptic seizure can be improved with the joint modeling of spatial and temporal EEG characteristics via the proposed hybrid ResBiLSTM model.	Accuracy =82
Rahmani et al. (2023) [12]	Graph Neural Network based on Meta-Learning that utilizes Graph Convolutional Networks and Graph Attention Networks for analysis of EEG signals.	Issue Limited generalization of seizure detection models across patients, as well as the lack of available patient-specific seizure data.	To derive a patient-specific model of seizure detection and classification that can quickly adapt to new patients using a small set of EEG samples	Accuracy =83 F1-score =83
Muhammad Haseeb aslam (2022) [13]	LSTM	Poor accuracy in early prediction of epileptic seizures and challenges of data imbalance	Building a prediction system based on eeg	Accuracy = 94 Specificity =90
Amar mitiche (2022) [14]	CNN(filter bank common spatial pattern )	Black box problem in deep learning models when predicting	Predict the onset of seizures 30 minutes before the seizure time	Accuracy =90 F1-score =91 Auc=91
Yueyan huang (2021)[3]	CNN	Difficulty in early prediction of epilepsy in children	Designing a model for early pregnancy prediction in children using MRI images and EEG	F1-score=87 Precision =88 Recall=87

Many previous studies have focused on detecting seizures during or shortly before they occur. Therefore, a research gap that has not been adequately addressed is the lack of a model capable of accurately and interpretably predicting early epileptic seizures 15 minutes before they occur, thus providing sufficient warning time

### 3. Methodology

#### a. Dataset

The current research uses CHB-MIT, which is an open public database formed through the joint efforts of Massachusetts Institute of Technology and Boston Children's Hospital. The data consists of EEG recordings of 24 patients in 22 cases of children and adolescents (5 are male and 17 are female). The dataset size is 25GB because each patient has between 20 and 50 EEG recorded files creating a sizable and thorough dataset for analysis . [15]



**Figure(2)** : electrode distribution map of the international 10-20 system for EEG electrode placement [16]

The recordings were made using 23 channels arranged in the 10-20 electrode system, at a sampling rate of 256 Hz and bit resolution of -16 bits. This system provides a clear representation of the electrical activity of the brain. This database contains information about the onset and offset of seizures, which comprises over 180 recorded seizures. This makes it suitable for early prediction and secure segmentation of temporal intervals [17]

#### b. Data Preparation

Raw electroencephalography data in EDF format from the CHB-MIT database was used. For the purpose of ensuring the consistency of the data across subjects, the EEG channels were standardized, and the redundant channels were removed. A set of common EEG channels, which are used across subjects, was also selected for the purpose of the analysis, and the channels was standardized to 15.

#### c. Data Preprocessing

The EEG recordings underwent a series of preprocessing steps that included noise reduction and signal quality improvement before applying time segmentation. The preprocessing steps include removal of DC offset, application of a notch filter to remove electrical interference, and application of a band filter ranging from 1 to 40 Hz. After that, Z-normalization was employed for each channel separately in order to standardize the input and minimize variance across channels, thus stabilizing the subsequent training procedure

**d. Temporal segmentation and labeling strategy:**

These EEG signals were divided into segments of 30 seconds with a 15-second shift. By utilizing the recorded times of seizure onset, the segments were classified as either Pre-ictal or Ictal. Interictal segments were excluded in order to focus the early prediction and increase the model's sensitivity to the pre-seizure phase

**e. Feature Extraction and Dataset Construction**

Each 30-second EEG epoch was transformed into a feature vector by extracting thirty features from each chosen channel, which included statistical, spectral, Hjorth, wavelet, and additional signal descriptors. The features from all channels were then concatenated to form a feature vector for each EEG epoch. Only pre-ictal and ictal segments with labels were used for assembling the final dataset. The feature names were retained for further analysis in feature interpretability.

**f. Splitting Data**

Three data splitting strategies were experimentally tested: random split, strict patient-wise split, and within patient split. The random split approach showed a potential risk of data leakage, and the strict patient-wise split approach imposed rigorous constraints for generalization. Therefore, the within patient split approach was selected as the final evaluation approach, in which the EEG files of each patient were split into 80/20 training and testing sets without any overlap.

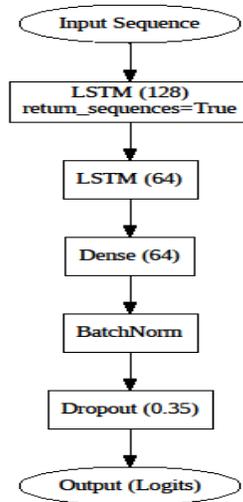
**g. Augmentation procedure**

The technique of data augmentation was used only on the training dataset. This technique is used to reduce class imbalance. Within the ictal intervals, additional overlapping windows are created with a step size of 1 second. The testing dataset is not subjected to any form of augmentation.

**h. Model Architecture**

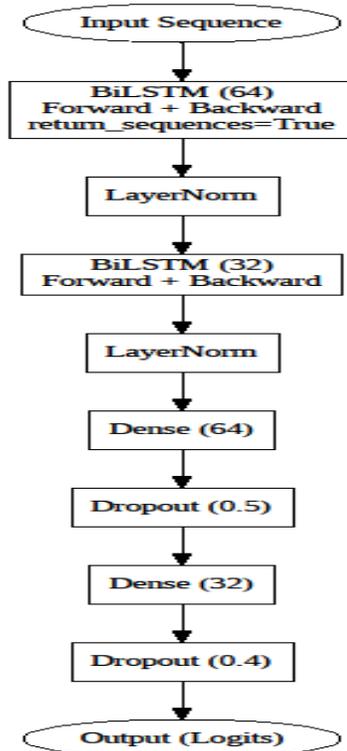
Four deep learning architectures were used to evaluate their potential in early prediction of seizures: Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), Transformer Encoder, Graph Neural Network (GNN), all of which have their own way of addressing the characteristics of EEG signals.

- In the LSTM model, the key feature is that the model has unidirectional sequential processing that can keep track of the progressive evolution of patterns. The LSTM model monitors time-over time changes by analyzing sequential data in one-way style. The stacked LSTM layers are used to achieve them, while saving the first layer for sequential and the second abbreviating it into a static representation. To support the generalization and reduce the percentage of over-processing, using the methods of regulation, such as the normalization of batches, to address the problem of the imbalance of categories and the formation of the final output layer of the predictions of the use of balanced Soft Max.



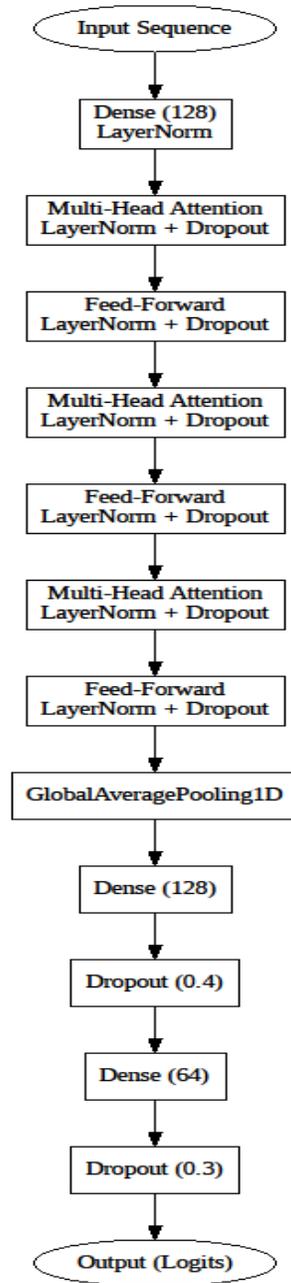
**Figure (3):** the structure of the LSTM model

- The idea is further carried over in the Bi-LSTM model with the addition of directionality. Complexity can negatively impact the performance of the model with less or imbalanced data. It consists of two LSTM two-way Bi-LSTM layers. The first layer monitors the temporal attributes with a full sequence saved, while the second layer is concentrated in a symbolic representation of a fixed length. A normalization for each Bi-LSTM layer is used to achieve balance and stability in training and performance development. To reduce the percentage of over processing, as well as to ensure that data is not leaked in all of the entire chain.



**Figure (4):** the structure of the Bi-LSTM model

- The Transformer Encoder employs a self-attention mechanism to effectively handle temporal sequences in parallel. Compared to other models, the transformer model is effectively monitored by the input sequence using self-attention self-layers. Each of the three stacked encryption blocks that are designed on sub layers have an extension with residual connections, multi-sided focus, and layer normalization, to ensure the formation of prophecies, thus integrating the sequence with the global rate of assembly and operation of intensive layers.



**Figure (5):** the structure of the transformer model

- In the GNN model data input sequence is modeled as a fully interconnected graph with nodes representing time steps and edges defining their relationships. Three convolutional layers stacked with layer normalization and leakage prevention for organization form the structure and contain the prediction records. The graph representation is integrated using a global average for clustering and then exploited through dense layers.

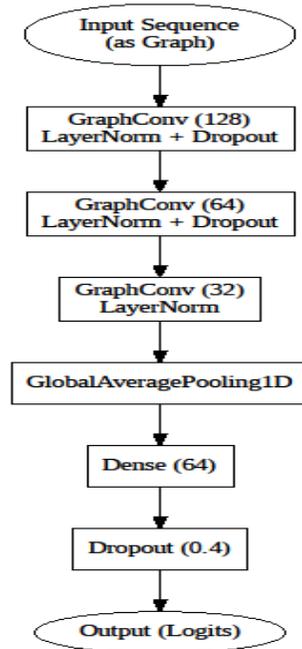


Figure (6): the structure of the GNN model

**i. Training strategy**

Balanced Soft Max loss was employed to correct the imbalance between pre-episode and epileptic categories. The frequency of the categories was extracted from the training set, and then the logarithm of the frequency ratio  $\log(f_1/f_0)$  was generated for the outputs before applying the sigmoid function with a binary loss function. The balancing factor was applied only to the training stages to ensure no leakage, and no other balancing techniques were used. Data augmentation was limited to the training data only to avoid data leakage.

Training was performed using a batch size of 64 with a maximum of 60 training cycles. A dropout ratio between 0.10 and 0.30 was used as a regulatory mechanism. Consequently, the model's performance on an unbalanced test set was evaluated using the AUC, F1-score , Accuracy, precision , recall and specificity

**j. Evaluation Metrics**

1. Accuracy: To gauge the model's overall accuracy.
2. Precision: To lower false alarms and evaluate the accuracy of seizure prediction.
3. Recall: A critical metric in medical applications that assesses the model's capacity to identify real seizures.
4. Specificity: To assess the model's capacity to differentiate between typical circumstances and minimize pointless alerts.

5. F1 score: To strike a balance between recall and precision, particularly when dealing with unbalanced data.
6. AUC: To compare the performance of various models and gauge how well a model can differentiate between seizures and normal conditions.

**k. Explainable Artificial Intelligence (XAI)**

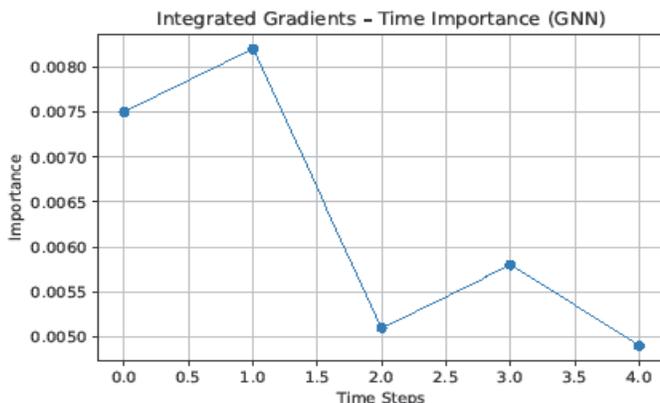
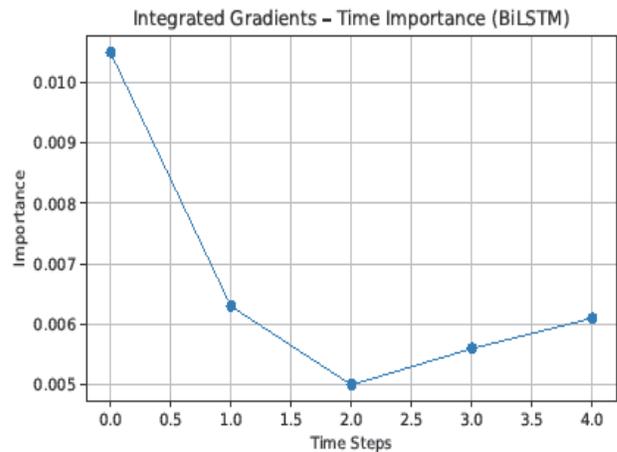
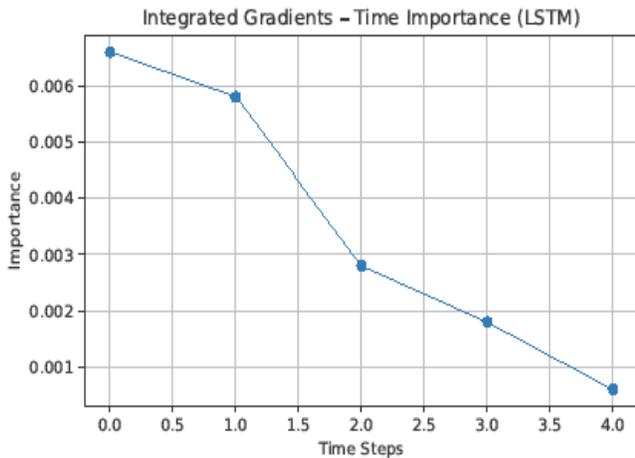
One of the most popular interpretable artificial Intelligence (XAI) techniques is Integrated Gradients, which provides a precise and methodical explanation of how deep learning models make decisions. Its ability to manage the base model without requiring any structural changes while maintaining its original structure is what makes it so effective. Both the feature level and the time-step level of model decisions are interpreted using Integrated Gradients. The most crucial features in the prediction process can be identified by calculating each feature's contribution to the final model output.

greatest influence on decision-making, the method is simultaneously applied to the time dimension to evaluate the importance of each time step within the data sequence.

By identifying the variables that affect the result and when they happen, this combination of feature and time analysis offers a thorough explanation of model behavior. This improves the model's transparency and the accuracy of its

output, especially in delicate applications like seizure prediction and EEG signal analysis.

- Time-step Importance This graph illustrates the each time step in determining the decision for the model.



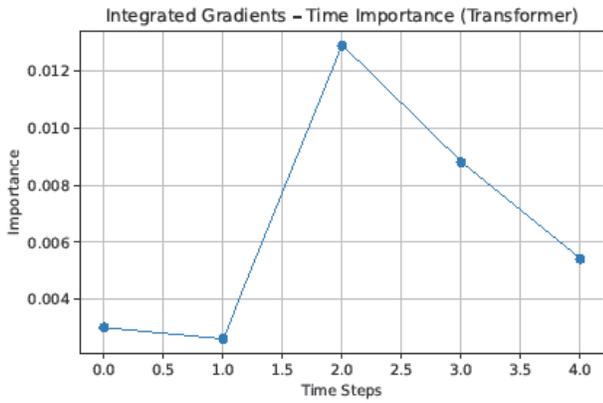
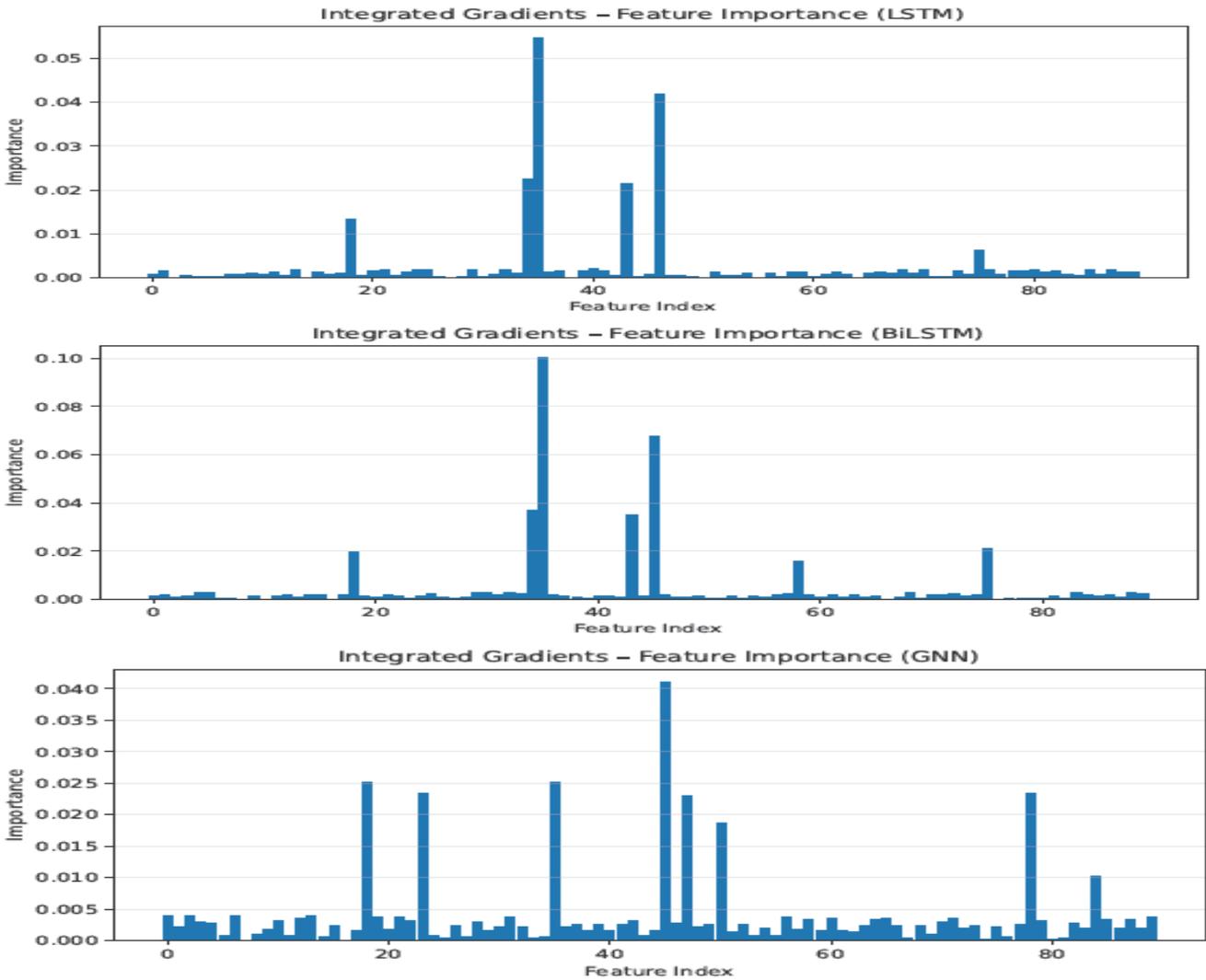


Figure (7): The importance of timelines in deep learning model

- Feature importance

Here charts illustrate the contributions of each feature to the model's decision



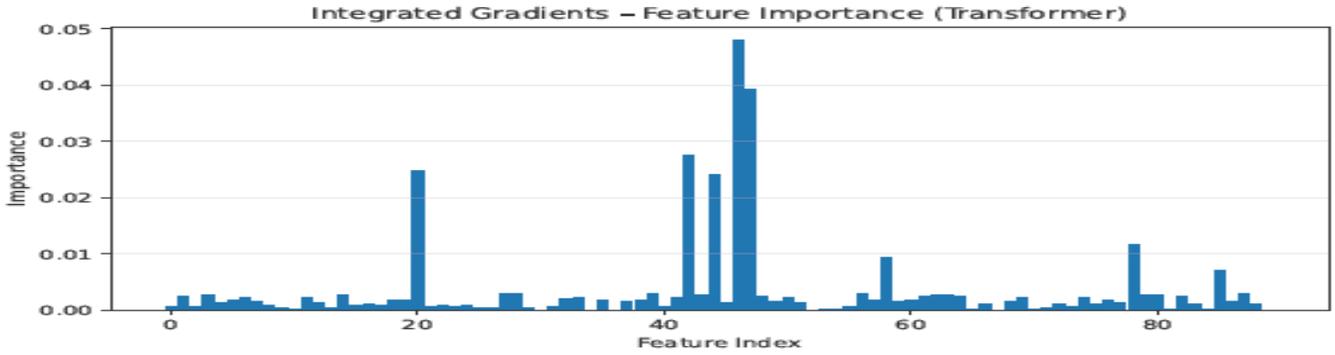


Figure (8): The feature importance in deep learning models

### 7. Results and Discussion

Table (2): shows the comparative performance of the LSTM, BLSTTM, Transformer, and GNN models in

	Lstm	BiLSTM	GN N	Transformer
Accuracy	0.90	0.92	0.92	0.92
PRECISION	0.95	0.94	0.94	0.96
RECALL	0.93	0.95	0.95	0.95
SPECIFICIT Y	0.75	0.75	0.75	0.80
F1_SCORE	0.94	0.95	0.95	0.95
AUC	0.91	0.89	0.89	0.92

predicting early epileptic seizures based on electroencephalography (EEG). All models were evaluated within a standardized framework to ensure fair comparisons and minimize bias in the results. The transformer model achieved the highest accuracy, at 0.92, outperforming the other models. This indicates that combining the two models improved the overall representation of the temporal data. The transformer model demonstrated superior performance with an accuracy of 0.96, indicating a reduction in false alarms. This is a crucial metric in early seizure prediction systems. Regarding recall, the hybrid model achieved 0.95 demonstrating its effectiveness in detecting pre-seizure brain changes, a key

criterion in prediction systems. The specificity was 0.80 the highest among all individual models, indicating a decrease in false alarms while maintaining high sensitivity. This balance between reducing false alarms and early detection is crucial. The hybrid model also achieved an F1 score of 0.95 and an AUC score of 0.92, enhancing its reliability in distinguishing between the pre-seizure and seizure phase

**Table (3):** Comparison between previous study and this study

paper	Data	Model	Evaluate
EEG Based Epileptic Seizure Prediction Using Variants of the Long Short-Term Memory Algorithm (2025) [7]	CHB-MIT Scalp EEG Dataset	Convolution Neural Network (CNN)	Specificity = 90.5% Precision = 88.1% Recall =87.7% F1-score=87.9%
Using Long Short-Term Memory (LSTM) recurrent neural networks to classify unprocessed EEG for seizure prediction (2024)[18]	CHB-MIT Scalp EEG Dataset	LSTM	AUC=0.86
An Interpretable Deep learning Classifier For Epileptic Seizure Prediction Using EEG Data (2022)[14]	CHB-MIT Scalp EEG Dataset	FBCSP	Accuracy =0.90 F1-score =0.91 AUC=0.91
Deep learning models in the early prediction of epileptic seizures	CHB-MIT Scalp EEG Dataset	Transformer	Accuracy =0.92 Specificity =0.80 Precision = 0.96 Recall =0.95 F1-score =0.95 AUC=0.92

This study can be considered an advancement over the existing literature by employing more effective modeling techniques in the context of EEG-based seizure prediction. Unlike previous studies, this one present more promising capacity to identify complex patterns within the data set, which leads to robust performance compared to the existing literature.

## 8. Conclusion

The purpose of this study is to assess the Transformer model's capacity to forecast epileptic seizures up to 15 minutes ahead of time. The Transformers model outperforms the other four deep learning models (LSTM, BILSTM, GNN, And Transformers) in recognizing intricate temporal patterns in EEG signals. Because the model is effective at analyzing big, complicated datasets for every patient, early prediction systems are developed and improved as a result.

## 9. Limitations

- Data Variation: Because there are only 24 patients, the data type may have an impact on generalizability. This restricts the model's suitability for new users.
- Inter-Patient Variation: It is challenging to ensure extremely high accuracy for every patient due to variations in EEG recordings.
- Data Imbalance: Unrealistic measurements, data leakage, and data imbalance are caused by differences between EEG groups

## 10. Future Work

The results of this study open avenues for future research, particularly:

- Dataset enhancement: Using larger datasets that include patients of various ages with varying presentations of symptoms to improve the generalization ability of the model.
- The use of hybrid models: Combining the Transformer with other models or techniques such as Graph Neural Networks or advanced deep learning models such as Attention-based Convolutional Neural Networks to improve the accuracy of the model as well as reduce false positives.
- Application development: Creating a system that can be connected to various devices to send timely alerts to patients.

## 11. References

- [1] T. Kaur *et al.*, "Artificial Intelligence in Epilepsy," May 01, 2021, Wolters Kluwer Medknow Publications. doi: 10.4103/0028-3886.317233.
- [2] A. Esmailpour, S. S. Tabarestani, and A. Niazi, "Deep learning-based seizure prediction using EEG signals: A comparative analysis of classification methods on the CHB-MIT dataset," *Eng. Reports*, vol. 6, no. 11, Nov. 2024, doi: 10.1002/eng2.12918.
- [3] Y. Huang *et al.*, "Early Prediction of Refractory Epilepsy in Children Under Artificial Intelligence Neural Network," *Front. Neurobot.*, vol. 15, Jun. 2021, doi: 10.3389/fnbot.2021.690220.
- [4] X. Lu, A. Wen, L. Sun, H. Wang, Y. Guo, and Y. Ren, "An Epileptic Seizure Prediction Method Based on CBAM-3D CNN-LSTM Model," *IEEE J. Transl. Eng. Heal. Med.*, vol. 11, pp. 417–423, 2023, doi: 10.1109/JTEHM.2023.3290036.
- [5] H. K. Ibrahim, N. Rokbani, A. Wali, and A. M. Alimi, "Deep Networks for Medical Images Classification, a Comparative Study," *2024 IEEE Int. Conf. Artif. Intell. Green Energy, ICAIGE 2024*, 2024, doi: 10.1109/ICAIGE62696.2024.10776632.
- [6] W. Zhao *et al.*, "Residual and bidirectional LSTM for epileptic seizure detection," *Front. Comput. Neurosci.*, vol. 18, 2024, doi: 10.3389/fncom.2024.1415967.
- [7] A. Bajaj and V. Sharma, "EEG-Based Epileptic Seizure Prediction Using Variants of the Long Short Term Memory Algorithm," 2025.
- [8] A. Alasiry, G. A. Sampedro, A. Almadhor, R. A. Juanatas, S. Alsubai, and V. Karovic, "Epileptic

- seizures diagnosis and prognosis from EEG signals using heterogeneous graph neural network,” *PeerJ Comput. Sci.*, vol. 11, 2025, doi: 10.7717/peerj-cs.2765.
- [9] R. Hussein, S. Lee, and R. Ward, “Multi-Channel Vision Transformer for Epileptic Seizure Prediction,” *Biomedicines*, vol. 10, no. 7, Jul. 2022, doi: 10.3390/biomedicines10071551.
- [10] P. Kunekar, M. K. Gupta, and P. Gaur, “Detection of epileptic seizure in EEG signals using machine learning and deep learning techniques,” *J. Eng. Appl. Sci.*, vol. 71, no. 1, Dec. 2024, doi: 10.1186/s44147-023-00353-y.
- [11] A. Omar and T. Abd El-Hafeez, “Optimizing epileptic seizure recognition performance with feature scaling and dropout layers,” *Neural Comput. Appl.*, vol. 36, no. 6, pp. 2835–2852, Feb. 2024, doi: 10.1007/s00521-023-09204-6.
- [12] A. Rahmani, A. Venkitaraman, and P. Frossard, “A Meta-GNN approach to personalized seizure detection and classification,” Mar. 2023, [Online]. Available: <http://arxiv.org/abs/2211.02642>
- [13] M. H. Aslam *et al.*, “Classification of EEG Signals for Prediction of Epileptic Seizures,” *Appl. Sci.*, vol. 12, no. 14, 2022, doi: 10.3390/app12147251.
- [14] I. Jemal, N. Mezghani, L. Abou-Abbas, and A. Mitiche, “An Interpretable Deep Learning Classifier for Epileptic Seizure Prediction Using EEG Data,” *IEEE Access*, vol. 10, pp. 60141–60150, 2022, doi: 10.1109/ACCESS.2022.3176367.
- [15] X. Liu *et al.*, “Epileptic seizure prediction based on EEG using pseudo-three-dimensional CNN,” *Front. Neuroinform.*, vol. 18, 2024, doi: 10.3389/fninf.2024.1354436.
- [16] Z. Wang, L. Shi, H. Wu, J. Luo, X. Kong, and J. Qi, “DistilCLIP-EEG: Enhancing Epileptic Seizure Detection Through Multi-modal Learning and Knowledge Distillation,” Oct. 2025, doi: 10.1109/JBHI.2025.3603022.
- [17] B. Jaishankar, A. M. Ashwini, D. Vidyabharathi, and L. Raja, “A novel epilepsy seizure prediction model using deep learning and classification,” *Healthc. Anal.*, vol. 4, Dec. 2023, doi: 10.1016/j.health.2023.100222.
- [18] J. D. Chambers, M. J. Cook, A. N. Burkitt, and D. B. Grayden, “Using Long Short-Term Memory (LSTM) recurrent neural networks to classify unprocessed EEG for seizure prediction,” *Front. Neurosci.*, vol. 18, 2024, doi: 10.3389/fnins.2024.1472747.