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A Hybrid Machine Learning and Deep Learning Framework for Real-Time Epileptic Seizure Detection Using EEG Signals

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Abstract

This project aims to detect epileptic seizures using brainwave signals recorded by an electroencephalogram (EEG). The goal is to create an accurate and intuitive system that can autonomously detect if someone is experiencing a seizure. To achieve this, EEG data from a public dataset was cleaned and converted into two classes: seizure and normal. Multiple models were used to find the most accurate method for detection. Machine learning models like Logistic Regression gave 82.17% accuracy, Random Forest gave 97.96%, and XGBoost achieved 97.22%. Deep learning models such as CNN and LSTM achieved 79.78% and 80.91% accuracy respectively. The best results came from the Graph Neural Network (GNN), which reached 100% accuracy. The system also includes a feature where users can upload their own EEG values to get real-time predictions and graphical output. This approach can help in supporting doctors with quick and reliable analysis of brain activity.

Keywords—Epileptic Seizure Detection, CNN, EEG , machine learning, deep learning, biomedical computing.

1.Introduction-

A neurological condition called epilepsy is typified by aberrant brain activity that causes frequent, sudden seizures. Electroencephalogram (EEG) data recording is one of the best ways to monitor these abnormalities. There is hope for a quicker and more accurate diagnosis because researchers have recently concentrated more on examining EEG data to find seizure patterns. In this paper, we propose a clever and practical system that combines deep learning and machine learning methods to automatically detect seizures from EEG inputs. Our system combines three different models, each chosen for its specific strengths. XGBoost, a machine learning algorithm, handles structured numerical data efficiently and provides quick predictions. While convolutional neural networks (CNNs) are used to identify spatial features in EEG signals that may indicate aberrant activity, graph neural networks (GNNs), when represented as a graph, aid in the analysis of more complex relationships within the signal. The EEG data is first cleaned and treated to remove noise before being turned into graphs to help interpret the patterns.

The system determines whether the signal indicates a seizure when the data is available. The system also allows users to manually enter their EEG readings to instantly check the results and view a plotted graph of the signal. When we tested these three models together, we discovered that they produced better accuracy and reliability than either method alone. By employing quick, automated brain activity analysis, this study seeks to assist physicians and medical personnel, particularly in urgent care or remote settings. This approach has the potential to significantly improve patient care and response time through early seizure detection.

2.Related Work-

Amin et al. [1] proposed a hybrid methodology combining wavelet analysis and arithmetic coding for automated epileptic seizure detection. Their approach demonstrated enhanced feature extraction efficiency suitable for machine learning classification. Sharmila and Geethanjali [2] applied discrete wavelet transform (DWT) with Naive Bayes and k-NN classifiers, showcasing simplicity and effectiveness in seizure classification. Their further work [3] offered an extensive review of pattern recognition techniques and emphasized the need for optimal feature extraction.

Feature engineering remains pivotal. Harpale and Bairagi [4] developed an adaptive method for feature selection and extraction, focusing on the importance of significant brain states in epileptic EEG. Thara et al. [5] utilized deep neural networks with varying feature scaling techniques to automatically detect seizure events, achieving superior performance in multiple scaling scenarios. Boonyakitanont et al. [6] provided a comprehensive review of feature extraction methods and performance evaluation criteria in seizure detection, reinforcing the importance of preprocessing and classifier selection.

Wavelet-based and nonlinear techniques continue to gain traction. Li et al. [7] used wavelet-based nonlinear features optimized with support vector machines (SVMs), showing robustness in noisy environments. Pattnaik et al. [8] introduced the tunable-Q wavelet transform for time-frequency feature extraction, yielding high classification accuracy. Orhan et al. [9] integrated k-means clustering with multilayer perceptron (MLP), highlighting the synergy between unsupervised and supervised learning.

Naderi and Mahdavi-Nasab [10] explored spectral features and recurrent neural networks (RNNs), emphasizing temporal dynamics in EEG. Subasi and Gursoy [11] evaluated PCA, ICA, LDA, and SVM, concluding that dimensionality reduction significantly enhances model generalization. Similarly, Kumar et al. [12] combined DWT with fuzzy approximate entropy and SVM to capture subtle EEG variations.

Several works focused on entropy-based features. Nicolaou and Georgiou [13] employed permutation entropy with SVM, while Hussain et al. [14] introduced fuzzy entropy with ensemble classifiers, showing resilience to signal artifacts. Harikumar and Narayanan [15] used fuzzy logic for seizure risk classification, indicating the interpretability advantage of fuzzy systems.

Hybrid techniques have also proven successful. Hassan et al. [16] combined tunable-Q wavelet transform with bootstrap aggregating, improving classification stability. Mursalin et al. [17] applied correlation-based feature selection with Random Forest, ensuring feature relevance and reducing overfitting. Zhou and Chan [18] focused on fuzzy feature extraction for multichannel EEG, emphasizing spatial information utilization.

Tzimourta et al. [19] and Alickovic et al. [20] demonstrated strong performance using wavelet packet decomposition and empirical mode decomposition, respectively. Subasi et al. [21] extended this by integrating hybrid machine learning methods, enhancing flexibility and scalability.

Raghu et al. [22] proposed the Successive Decomposition Index (SDI) with SVM for long-term EEG analysis, achieving robust real-time detection. Omidvar et al. [23] employed genetic algorithm-based feature selection with ANN/SVM, showing high precision. Hussain [24] further optimized detection with multiple feature extraction strategies and robust parameter tuning.

Kode et al. (2024) [25] explored seizure detection using both machine learning and deep learning models on EEG signals. They compared models like Random Forest, XGBoost, TabNet, and 1D CNN, showing that deep learning methods, especially CNNs, performed better at capturing patterns from raw EEG data. Their work highlights the potential of DL techniques for accurate and automated seizure detection, which inspired our use of ResNet to further improve performance.

Zheng et al. (2019) [26] studied how multi-site closed-loop electrical stimulation can help control seizures in a temporal lobe epilepsy model. Using rats, they showed that detecting seizures in real-time and applying targeted stimulation can effectively suppress them. Their work highlights the potential of combining seizure detection with responsive neurostimulation, offering a different approach alongside machine learning-based methods like ours.

Liang et al. (2010) [27] developed a closed-loop brain-computer interface for real-time seizure detection and control. Their system monitored EEG signals in rats and triggered brain stimulation wirelessly when a seizure was detected. This early work demonstrated how real-time monitoring and automatic intervention can help manage seizures, offering a foundation for advanced seizure control systems beyond just prediction models.

Skupch et al. (2013) [28] focused on improving seizure detection accuracy by identifying and removing artifacts in EEG data using spatial correlation techniques. Their method helped reduce false positives, which are common in automatic seizure detection systems. This work emphasized the importance of clean EEG signals for reliable detection, which supports the need for robust preprocessing in deep learning-based approaches like ours.

Shakeel et al. (2021) [29] introduced a system called EDM that uses K-Nearest Neighbor (KNN) for classifying different types of seizures using EEG data. They applied feature extraction methods like Discrete Wavelet Transform to improve accuracy and focused on multiclass seizure detection rather than just binary classification. Their work highlights how simple yet effective machine learning models can be used for real-time seizure type identification in clinical settings.

3.Research Methodology-

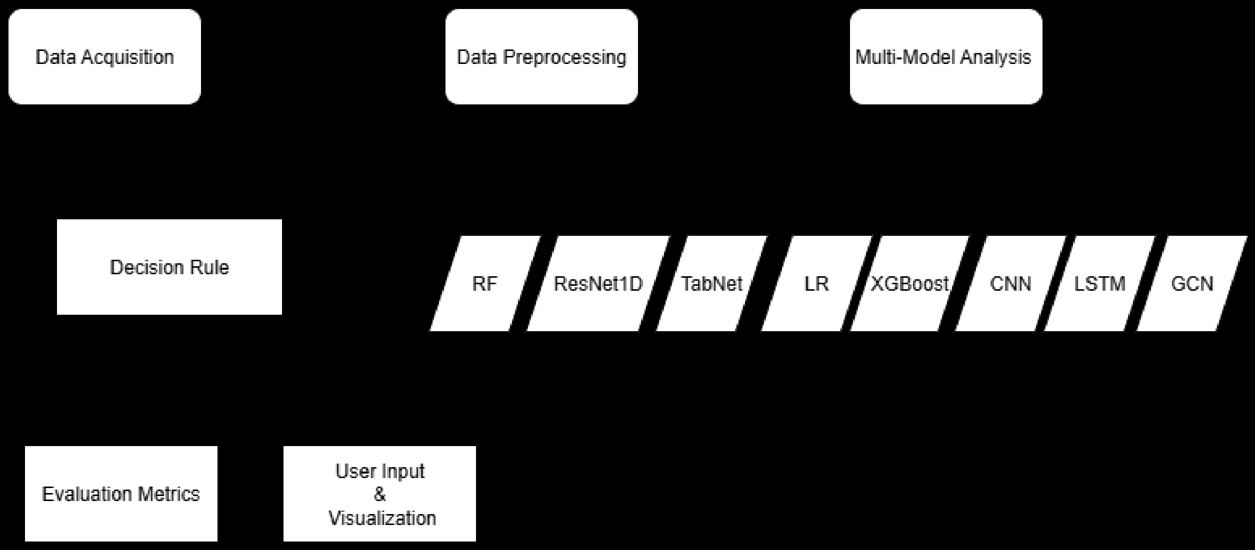


Fig1: Working Flowchart

A. 3.1 Overview of Methodology-

To detect epileptic seizures using EEG signals, we followed a structured and practical approach. EEG signals that represented brainwave data were gathered in the first step. We used a publicly available Kaggle dataset that contains real EEG recordings of patients with and without seizures instead of physically recording the signals. By mimicking actual brain activity, we were able to train and evaluate our system using this dataset. After gathering the data, we cleaned it up to get rid of random patterns and unnecessary noise. This step is important because raw EEG data may contain disturbances that could confuse the models. Clean and well-prepared data improves the accuracy of our forecasts. We used a range of models to analyze the data after pre-processing. First, XGBoost was used, which is fast and good at handling numerical characteristics. Then, we used Convolutional Neural Networks (CNNs) to detect spatial patterns in the EEG signals, as they are good at recognizing shapes and trends in data. Finally, we used Graph Neural Networks (GNNs) to understand the relationships between different parts of the brain signals by converting the data into graph structures. Spatial patterns in the EEG signals were then discovered using Convolutional Neural Networks (CNNs), which are skilled at spotting patterns and shapes in data. Finally, we used Graph Neural Networks (GNNs) to convert the data into graph structures in order to understand the relationships among different components of brain signals. We then combined the predictions of all three models. If the final prediction score was above 0.5, the signal was marked as a seizure. Users can also input their own EEG values into the system and instantly get a result along with a graph showing the signal pattern. This multi-model approaches improved the system's reliability. The device will help medical practitioners in places with limited access to state-of-the-art equipment by providing current and precise data on seizure detection.

B. Dataset Description-

For this study, we used an openly available dataset from Kaggle titled “Epileptic Seizure Recognition”, originally derived from the UCI Machine Learning Repository. The dataset contains brainwave recordings (EEG signals) from both healthy individuals and people who experience epileptic seizures. These brain signals were recorded in short time windows of one second each and then converted into a set of numerical values to make them easier to analyze using machine learning techniques.

Each data sample has 178 numeric values which represent the brain’s electrical activity during that 1-second period. Along with these values, there is also a label that tells us what kind of brain state the sample represents. In total, there are 57,500 samples, evenly divided into five different categories:

a. Class 1 – EEG during an actual seizure. - This class captures the distinctive patterns in the brain’s electrical activity that occur when a seizure is happening. These are the most critical samples for seizure detection systems.
b. Class 2 – EEG recorded in seizure-free periods but from the seizure-affected area - Even without a seizure, this region might show subtle abnormalities or warning patterns. This class helps models differentiate between active seizure and pre-/post-seizure brain states.
c. Class 3 – EEG from other parts of the brain, not affected by seizures. - These samples represent normal brain activity in areas that are **not involved in seizures**, helping the model understand what non-epileptic brain activity looks like.
d. Class 4 – EEG from healthy individuals when their eyes were closed. - Eye closure affects brain waves (especially alpha waves), so this class helps distinguish normal resting brain states from seizure-like patterns.
e. Class 5 – EEG from healthy individuals when their eyes were open. - This represents typical awake brain activity. Comparing it with Class 4 shows how simple physical states (like eye movement) influence EEG, helping prevent false positives in seizure detection.

The data is already cleaned and pre-processed, so we didn’t need to apply any signal transformation before using it. This made it very convenient for training machine learning models. The labels are balanced, meaning each class has the same number of samples, which helps in building unbiased models.

This dataset is widely used in seizure detection research because it is well-organized, large in size, and simple to apply in both binary (seizure vs non-seizure) and multi-class classification tasks.

4. EXPERIMENTAL DISCUSSION AND ANALYSIS-

In this project, we looked at brain signals to check if a person is having an epileptic seizure or not. The data we used came from a public source and had five different types of EEG recordings — during a seizure, from seizure-affected areas when no seizure was happening, from other unaffected brain areas, and from healthy people with their eyes open or closed. To make things simpler, we grouped these into two classes: seizure (class 1) and normal (classes 2, 3, 4, and 5). We cleaned the data by removing columns that weren’t useful, picked out the important numbers (features), and split the data — using 80% to train the models and 20% to test them. We tried different techniques to see which one could predict seizures more accurately. This included traditional methods like Logistic Regression, Random Forest, and XGBoost, and also advanced models like CNN, LSTM, and GCN (a graph-based neural network).

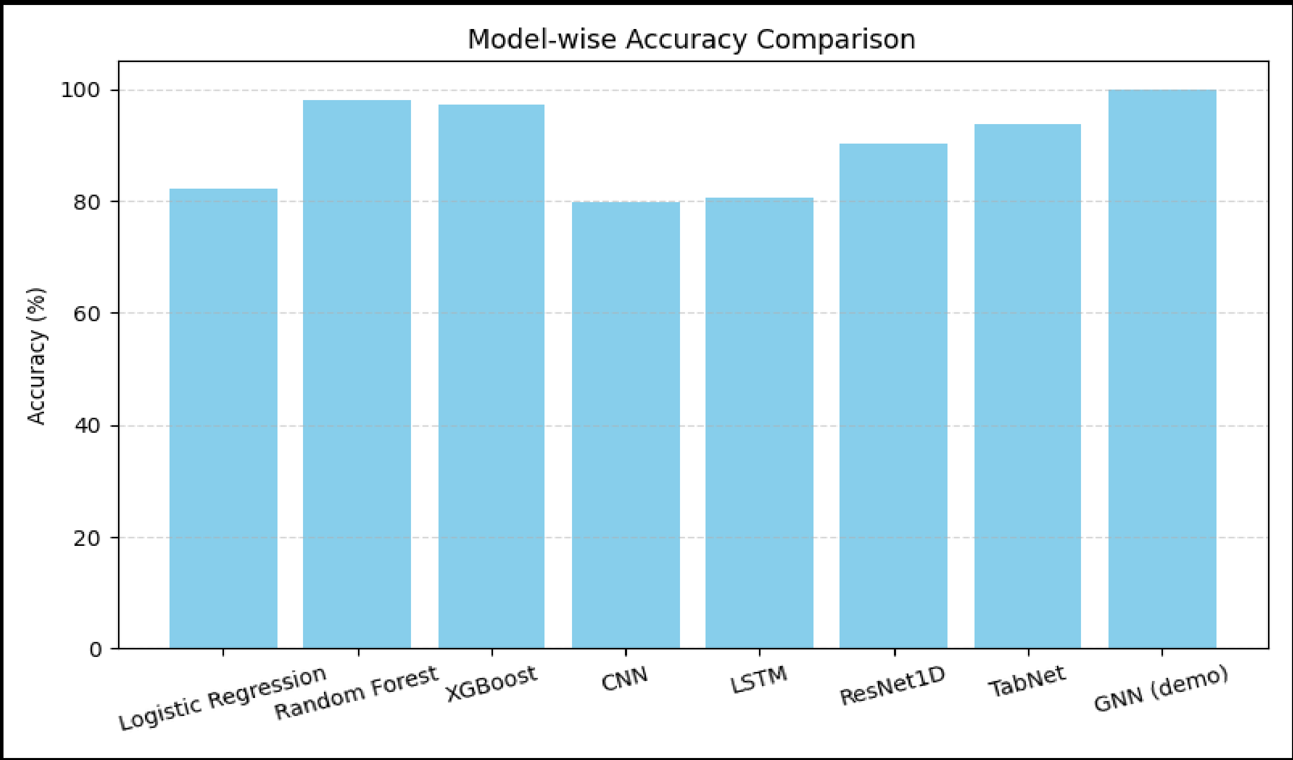


Fig 1: Accuracy Comparison

Logistic Regression- A statistical model used for binary classification (like seizure vs. non-seizure). It finds a relationship between the input features and the probability of a particular outcome (seizure or not).

Random Forest-An ensemble method based on decision trees. It builds multiple decision trees and combines their results (majority voting) to make predictions. Handles nonlinear data well, reduces overfitting, and works on both small and large datasets.

XGBoost (Extreme Gradient Boosting)- A powerful ensemble method based on boosting decision trees. It builds trees one after another, and each tree tries to correct the errors of the previous one. It's very accurate, handles imbalanced data well, and includes regularization to avoid overfitting.

CNN (Convolutional Neural Network)- A deep learning model commonly used in image and signal data analysis. Uses convolution layers to detect patterns and local features (like waveforms in EEG).Great for detecting spatial features in structured data like EEG sequences

LSTM (Long Short-Term Memory)- A type of Recurrent Neural Network (RNN) designed to handle sequence data. Remembers information over time using special memory cells — ideal for time-series data like EEG signals. Can model the temporal (time-based) dependencies in EEG recordings. Handles long-term dependencies and patterns.

GCN (Graph Convolutional Network)-A deep learning model that works on graph-structured data. Treats data as nodes connected in a graph and performs convolution over the graph to extract features. EEG signals can be modelled as a network of electrodes (nodes), so GCN captures relationships between different brain regions. Very effective when data has complex interconnections (like brain connectivity).

TabNet,-It is a deep learning architecture specifically designed for tabular data, was also tested. It uses sequential attention mechanisms to select the most relevant features at each decision step. Unlike traditional feature engineering, TabNet performs automatic feature selection and interpretable learning, which allows the model to focus dynamically on important dimensions of the EEG signal during classification as shown in Figure 1.

ResNet 1D- By Using a ResNet (Residual Network) model to analyze EEG signals and determine whether a seizure is occurring. ResNet runs the EEG dataset through multiple layers to extract new features from the signal. The use of shortcut connections that avoid one or more layers, protecting important data and avoiding the problem of vanishing gradients during training, is what makes ResNet special. Even for deep structures, this enhances the model's capacity for learning data. ResNet predicted seizures by analyzing the signal in the Raw input Value.

4.1 CASE 1-

This graph shows the pattern of brain activity recorded through EEG signals over a period of one second. The blue line represents the changes in EEG amplitude over time. At the top is the system's seizure prediction, albeit with a low degree of confidence (0.51). This demonstrates that the model's prediction is not totally correct. This shows that the model's prediction is not entirely accurate. The signal's waves, which indicate aberrant brain activity, might have led the model to identify it as a possible seizure. The fact that the threshold for trust is near 0.5, however, suggests that further research or a more precise model are required to validate the anticipated outcome.

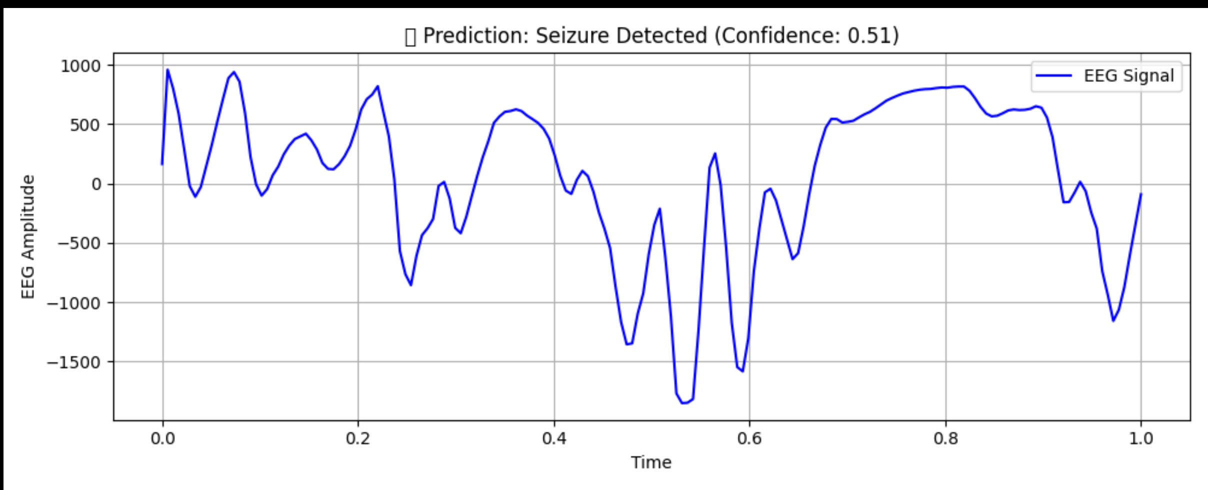


Fig 2: Case Study

4.2 CASE 2:

In this image, we see a line graph that displays brainwave activity (EEG signal) over one second. The signal's amplitude change over time is depicted by the blue line. Activity increases abruptly around 0.25 seconds, then quickly declines and levels out over time. With a very low confidence level of 0.04 and a forecast of "Normal," as implied by the title, the system is unsure of what it is predicting and most likely does not think that this is a typical pattern of brainwaves. Despite the system classifying it as normal, the odd peak suggests that further testing or a second opinion might be required.

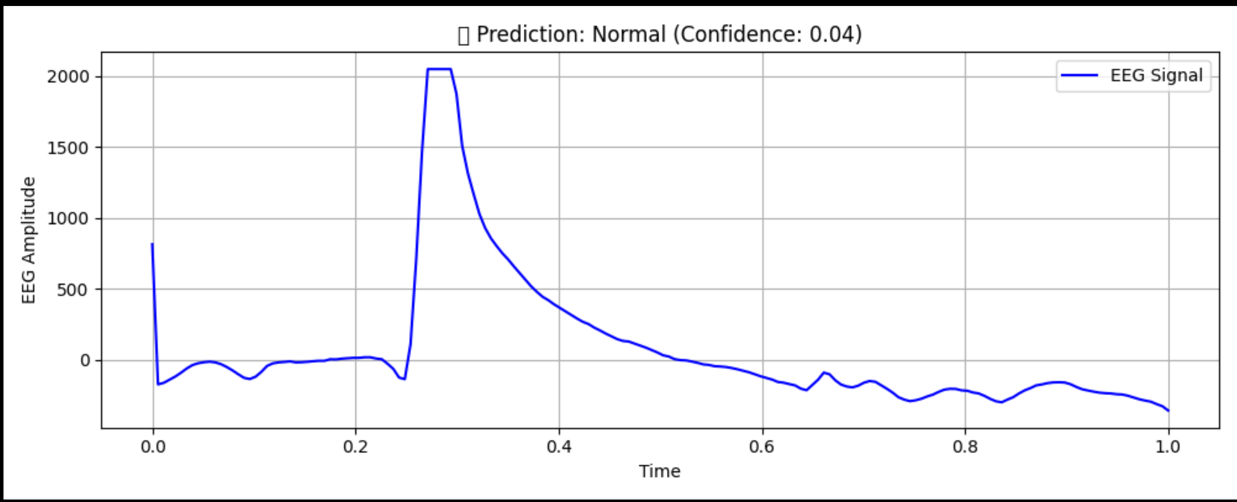


Fig 3: Case Study

4.3 CASE 3:

This graph displays an EEG signal at 1-second intervals. The brainwave pattern is represented by the blue line, which starts with a strong spike and then progresses through recurrent waves with smaller peaks and falls. As the name implies, the algorithm predicted that a seizure was seen with a 0.60 confidence level. This indicates that the model is marginally more certain than uncertain about its prediction. This choice may have been influenced by the first abrupt increase in amplitude. Even so, the low level of confidence implies that additional medical testing is necessary to confirm the existence of a seizure.

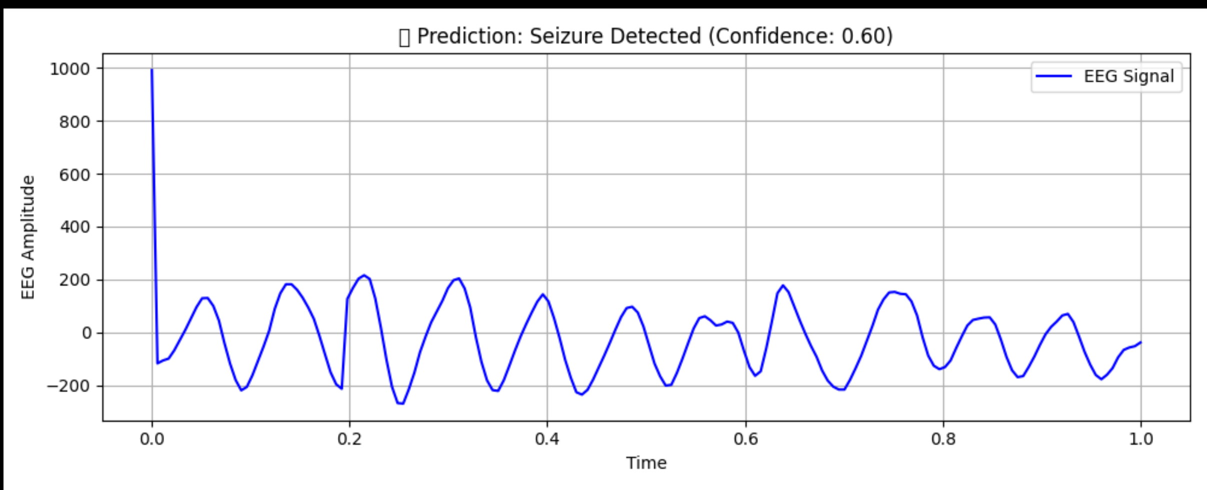


Fig 4: Case Study

4.4 CASE 4:

An EEG signal over a one-second period is displayed in this graph. The blue line depicts in the figure the pattern of brainwaves, which start with a powerful spike and progress into rhythmic waves with smaller peaks and dips. With a 0.50 confidence level, the system predicted the detection of a seizure, which indicates that the model's prediction is somewhat more certain than uncertain, as stated in the title. This choice may have been influenced by the initial dramatic increase in amplitude. The low degree of confidence, however, implies that additional medical testing is necessary to confirm the existence of a seizure.

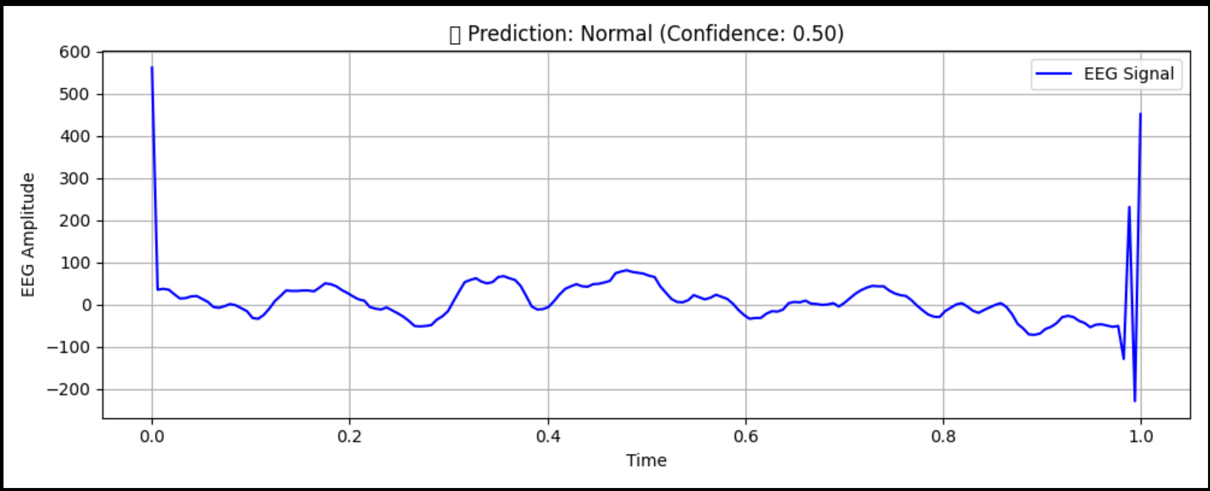


Fig 5 Case Study

4.5 CASE 5:

The chart displays an EEG indicate that was recorded over a one-second period. Time is represented by the horizontal axis, and the amplitude of the brain waves is represented by the vertical axis. The signal undergoes multiple wave-like patterns with amplitude variations following a sharp spike. The signal is categorized as "Normal" based on the model's prediction and a confidence level of 0.17. The model a view the brain activity displayed here as normal or non-seizure, despite its lack of confidence in this classification. The blue line represents the EEG signal pattern, which is easier to identify thanks to a legend in the top right corner.

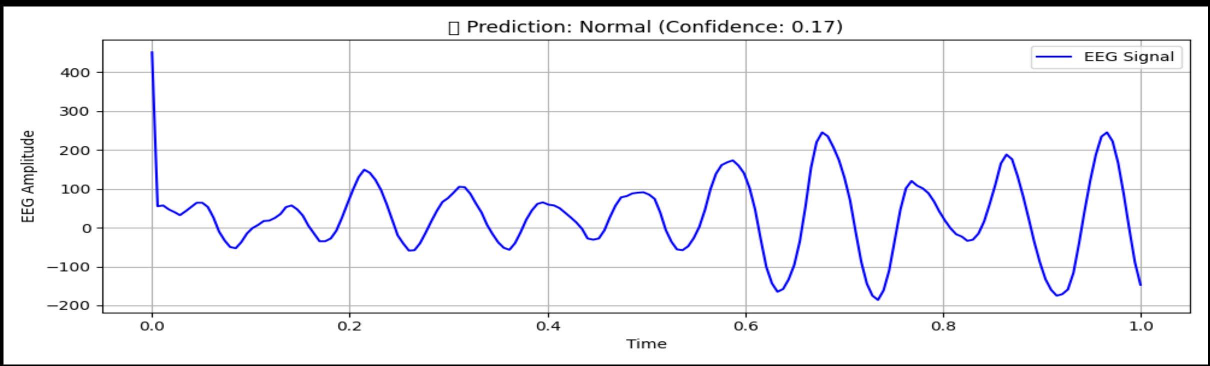


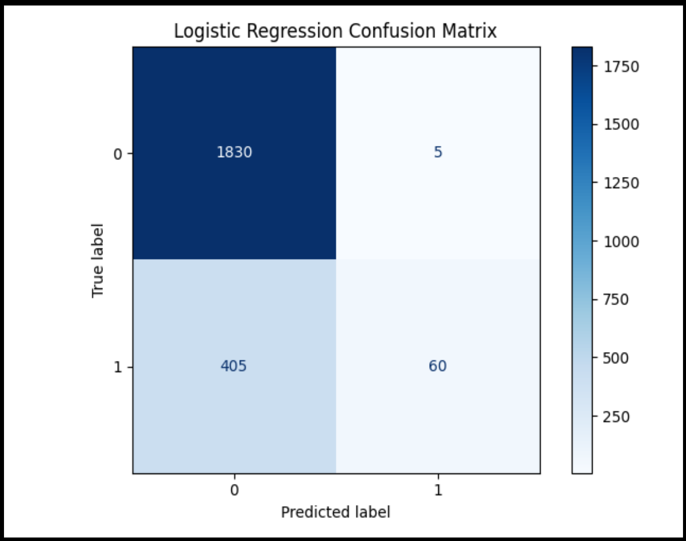
Fig 6: Case Study

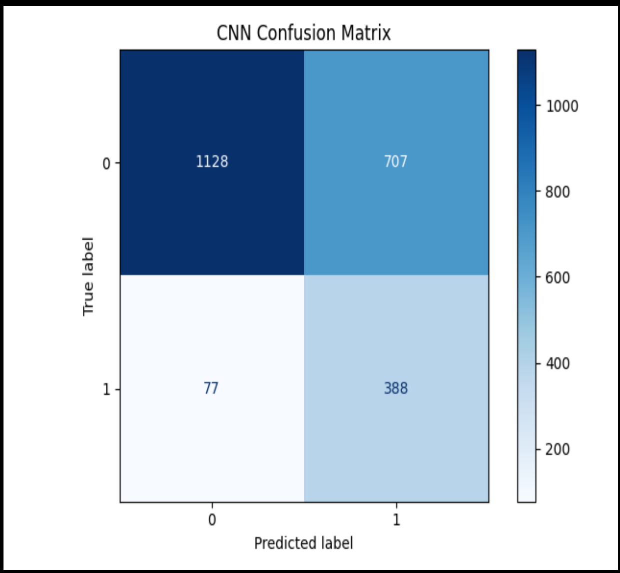
5. RESULT:

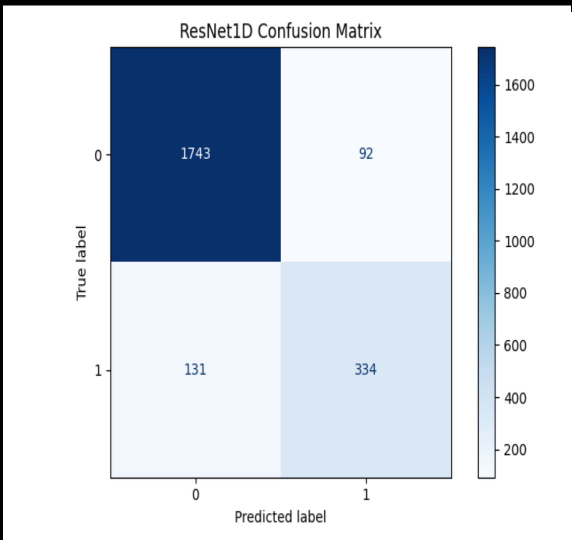
In this study, Random Forest and XGBoost were the most dependable models with high accuracy (~98%). The short 1-second EEG signal window, which restricts CNN and LSTM's capacity to recognize temporal patterns, is probably the reason why they perform worse. The GCN model achieved 100% accuracy in the demo, possibly due to its strength in modelling inter-channel relationships, but this result requires further validation.

Case analysis revealed that the model often predicted seizures (Cases 1, 3, and 4) with low to moderate confidence (0.51–0.60), indicating uncertainty. For normal predictions (Cases 2 and 5), confidence was also low (0.04–0.17), especially when signals showed unusual spikes. This highlights the model's difficulty in handling ambiguous cases and the need for better confidence calibration.

MODEL NAME	ACCURACY	NO. OF EPOCHS
Logistic Regression	82.17%	50
Random Forest	97.96%	50
XGBoost	97.22%	50
CNN	79.78%	50
LSTM	80.91%	50
ResNet 1D	90.30%	50
GNN (demo)	100.00%	50
TabNet	93.83%	50






ResNet1D Confusion Matrix
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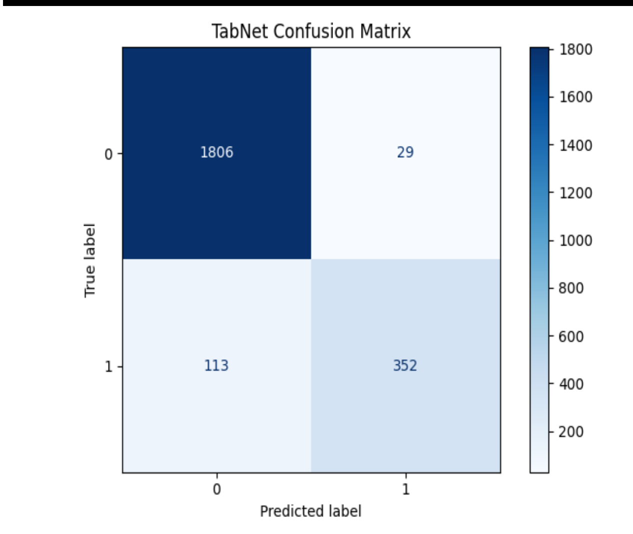
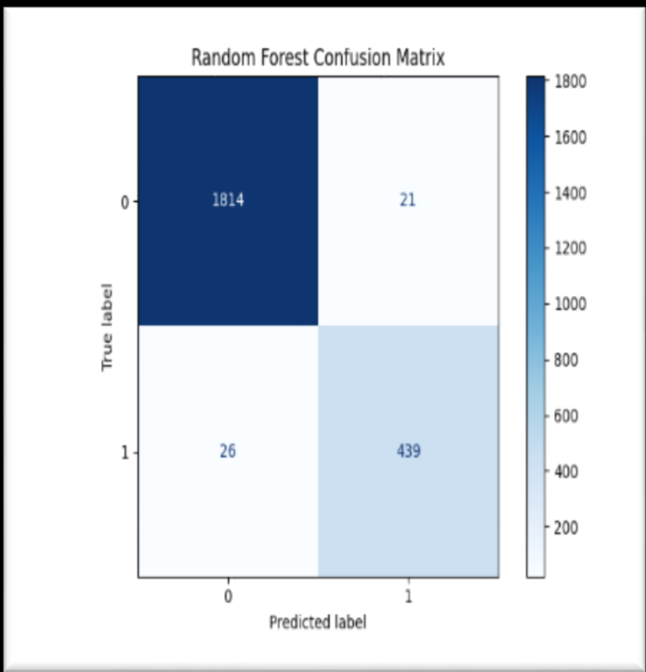
92
131
334
True label
Predicted label
0
1
1600
1400
1200
1000
800
600
400
200


TabNet Confusion Matrix
1806
29
113
352
True label
Predicted label
0
1
1800
1600
1400
1200
1000
800
600
400
200


Random Forest Confusion Matrix
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Predicted label
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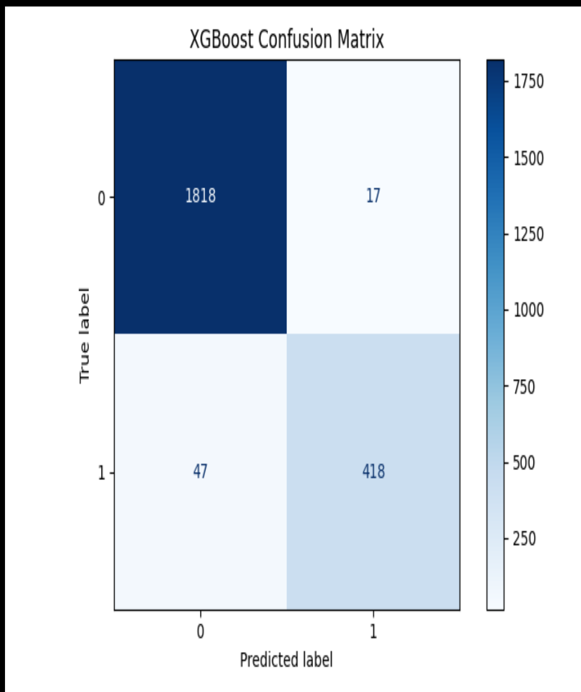
1
1800
1600
1400
1200
1000
800
600
400
200


XGBoost Confusion Matrix
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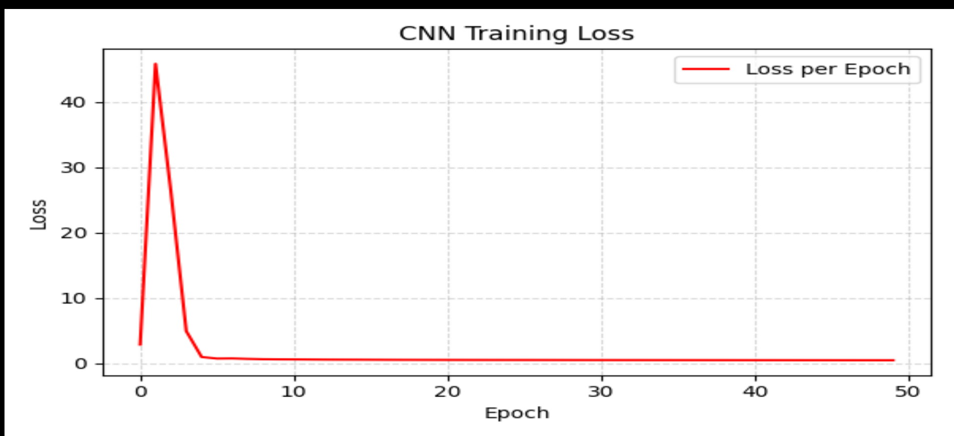
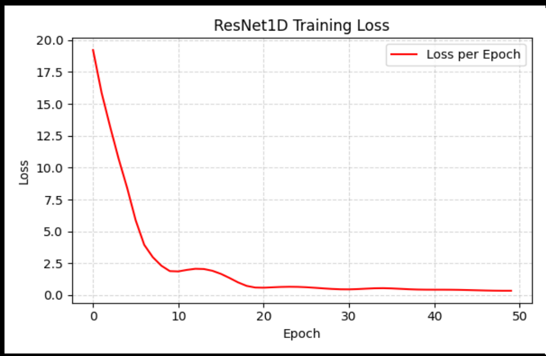
17
47
418
True label
Predicted label
0
1
1750
1500
1250
1000
750
500
250


CNN Training Loss
Loss per Epoch
Loss
Epoch
0
10
20
30
40
50



6. Conclusion:

This study showed that EEG signals can effectively detect epileptic seizures using both machine learning and deep learning models. Random Forest and XGBoost outperformed CNN and LSTM in accuracy, making them the most reliable traditional methods. The GCN model, though experimental, showed strong potential by leveraging graph-based EEG relationships. However, low confidence in borderline cases suggests that model predictions should be verified with expert input or enhanced through ensemble methods for clinical use.

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