SUMMER INTERSHIP PROJECT REPORT

TOPIC

EEG-BASED EPILEPSY SEIZURE DETECTION USING ARTIFICIAL INTELLIGENCE

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INTRODUCTION

Epilepsy, a prevalent neurological disorder affecting approximately 70 million people worldwide, is characterized by sudden and recurrent seizures due to abnormal brain electrical activity. These seizures can lead to severe cognitive, physical, and emotional consequences, making early and accurate diagnosis critical for improving patients' quality of life. Electroencephalography (EEG) remains a cornerstone in epilepsy diagnosis, offering real-time monitoring of brain activity with high temporal resolution. However, the manual analysis of EEG data is challenging due to noise, complexity, and the need for prolonged recording. Recent advancements in artificial intelligence (AI), particularly deep learning, have shown promise in automating the detection and prediction of epileptic seizures from EEG data, potentially overcoming these challenges.

This study aims to explore the integration of advanced deep learning techniques with EEG analysis to enhance the early detection and prediction of epileptic seizures. The research objectives include improving signal processing, developing robust AI models, and addressing challenges related to data quality, interpretability, and ethical concerns. The significance of this research lies in its potential to revolutionize epilepsy diagnosis, providing more accurate and timely interventions. The document is structured to first provide a detailed background, followed by a discussion of the research problem, objectives, and the significance of the study.

LITERATURE REVIEW

Deep learning technology' quick development has had a big impact on medical diagnostics, especially the identification and diagnosis of epileptic episodes. The manual inspection of electroencephalography (EEG) by neurophysiologists has been a crucial technique for monitoring brain electrical activity, but it is time-consuming and prone to human error. Despite these drawbacks, EEG is still the principal technique used to diagnose epilepsy, which affects more than 50 million people globally.

Machine learning and deep learning approaches have been applied recently to improve and automate seizure detection accuracy. Conventional techniques for extracting characteristics and classifying EEG signals have included decision trees and support vector machines (SVMs). Nevertheless, these techniques might not work well with big datasets and frequently call for a high level of signal processing knowledge.

Deep learning models, particularly Convolutional Neural Networks (CNNs), have revolutionized EEG-based seizure detection by automating feature extraction and handling complex, non-stationary EEG signals. Techniques like variable-frequency complex demodulation (VFCD) have further improved signal preprocessing, enhancing the performance of CNNs in detecting seizure-related patterns. These advancements have led to improved classification accuracy and reduced false positives.

However, challenges remain, including the need for large, high-quality datasets, the computational complexity of deep learning models, and the generalizability of these models across diverse patient populations. Additionally, the black-box nature of deep learning models raises concerns about interpretability, which is crucial for clinical trust and acceptance.

In summary, while EEG-based seizure detection has advanced significantly with the integration of deep learning, addressing challenges related to data availability, computational resources, and model interpretability is essential for the broader adoption and effectiveness of AI in epilepsy diagnosis.

DATASET DESCRIPTION

The dataset used for this research project was sourced from Kaggle and consists of comprehensive EEG recordings from 500 individuals, each capturing brain activity for 23.6 seconds. The original dataset is organized into five folders, with each folder containing 100 files corresponding to different subjects. Each recording is sampled into 4097 data points, which were divided into 23 chunks of 178 data points each, resulting in 11,500 rows of data, where each row represents a 1-second interval of EEG activity. The response variable (y) indicates the state of the subjects, categorized into five classes: eyes open (5), eyes closed (4), and other states. Preprocessing steps included dropping unnecessary unnamed columns, separating the features and labels, converting the multi-class labels into binary format, and standardizing the data using StandardScaler. This preparation is crucial for training machine learning models for effective epilepsy detection.

METHODOLOGY

This methodology outlines the systematic approach taken to develop a Recurrent Neural Network (RNN) model using Long Short-Term Memory (LSTM) architecture for detecting epileptic seizures from electroencephalogram (EEG) data. The methodology is organized into key phases, including research design, tools and technologies used, and the detailed procedures followed throughout the project.

Research Design

The research was structured into several crucial phases:

1. **Data Preparation**: The initial phase involved loading and preprocessing the dataset to make it suitable for training the RNN model.
    - **Data Loading**: The dataset, "Epileptic Seizure Recognition.csv," was imported using the Pandas library, which facilitates data manipulation.
    - **Feature Selection**: The dataset was divided into features (X) and labels (y). Features included all columns except the last one, while the last column indicated seizure activity.
    - **Label Encoding**: Seizure labels were converted to binary values (0 and 1), with values greater than 1 being set to 0, representing no seizure. This binary classification was essential for the model's training process.
2. **Model Architecture Design**: The model was constructed using the Sequential API in Keras, implementing the LSTM architecture to effectively capture temporal dependencies within the data.
    - **LSTM Layers**: The architecture included two LSTM layers, each with 64 units, allowing the model to learn sequential patterns in the EEG data.
    - **Dropout Layers**: To mitigate overfitting, dropout layers with a rate of 0.2 were included after each LSTM layer. This technique randomly sets a fraction of input units to zero during training, enhancing the model's generalization capability.
    - **Dense Layers**: Following the LSTM layers, two dense layers were added, with the first dense layer containing 64 units and a ReLU activation function, followed by a second dense layer with 32 units. The output layer employed a sigmoid activation function to predict binary outcomes.
3. **Model Compilation and Training**: The model was compiled using the binary cross-entropy loss function and the Adam optimizer, which is efficient for training deep learning models.
    - **Early Stopping and Model Checkpointing**: Early stopping monitored validation loss, allowing training to halt when no improvements were

observed over ten epochs. Additionally, model checkpointing saved the best model based on validation loss during training.

- **Training the Model**: The model was trained for a maximum of 150 epochs with a batch size of 128 and a validation split of 20%, which facilitated performance evaluation during training.

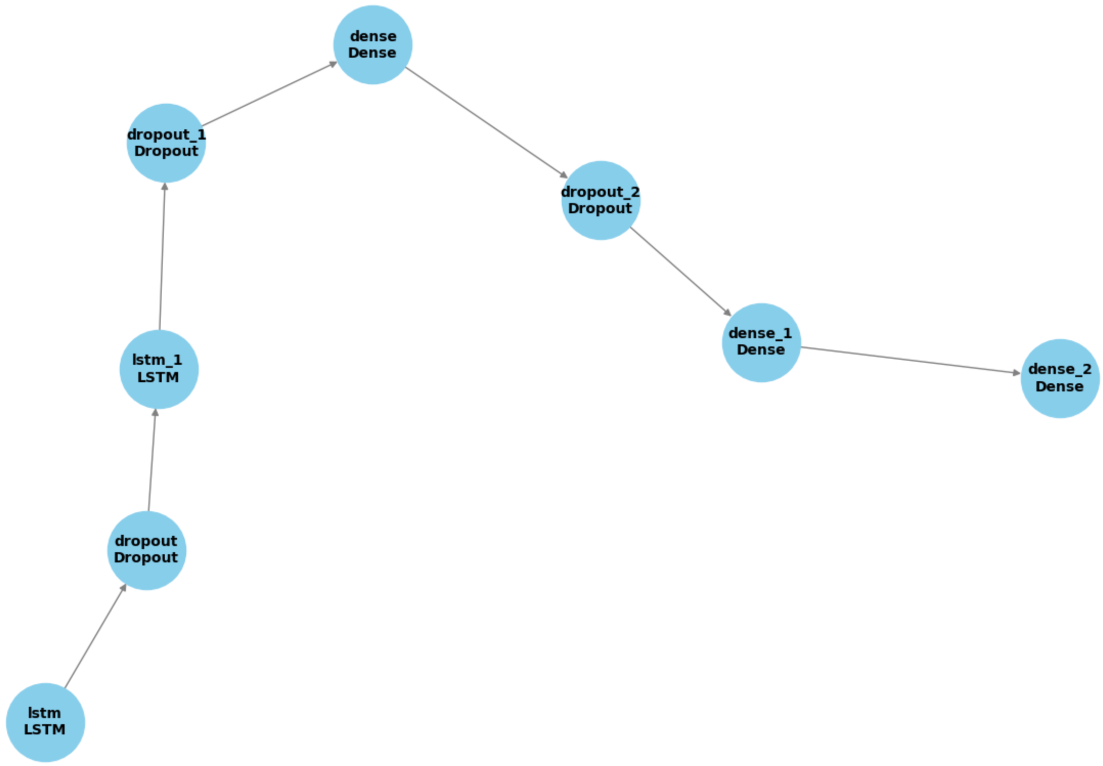
4. **Model Evaluation**: After training, the model's performance was assessed on a separate test dataset. A different test dataset was used to evaluate the model's performance following training.
    - **Accuracy and Loss:** The test set was used to calcuscikit-learnel's accuracy and loss, which gave an overall performance evaluation.
    - **Classification Metrics:** Using functions from the scikit-learn package, predictions were made based on the test data, and metrics including precision, recall, F1-score, and confusion matrix were presented.
5. **Model Visualization**: Using NetworkX and Matplotlib, a directed graph was made to show the RNN model's architecture.
    - **Visualization Function:** To provide a visual depiction of the RNN structure,a directed graph displaying the layers and connections of the model was created using a function and saved as a PNG file.

Tools and Technologies

The following tools and technologies were employed throughout the project:

- **Python**: The primary programming language used for data processing and model implementation.
- **TensorFlow and Keras**: Libraries utilized for building and training the RNN model.
- **Pandas**: Used for data manipulation and analysis.
- **scikit-learn**: Employed for evaluating model performance through various classification metrics.
- **NetworkX and Matplotlib**: Utilized for visualizing the model architecture.

RNN Model Visualization



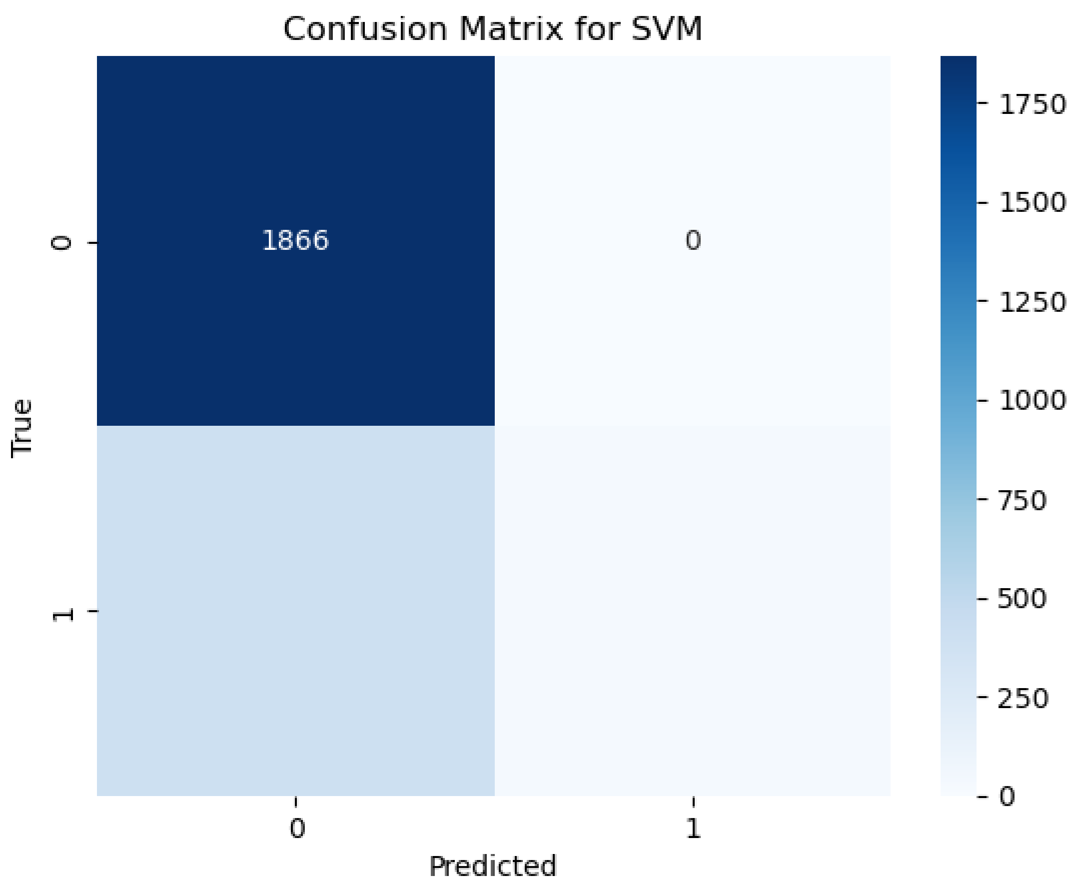
RESULTS AND DISCUSSION

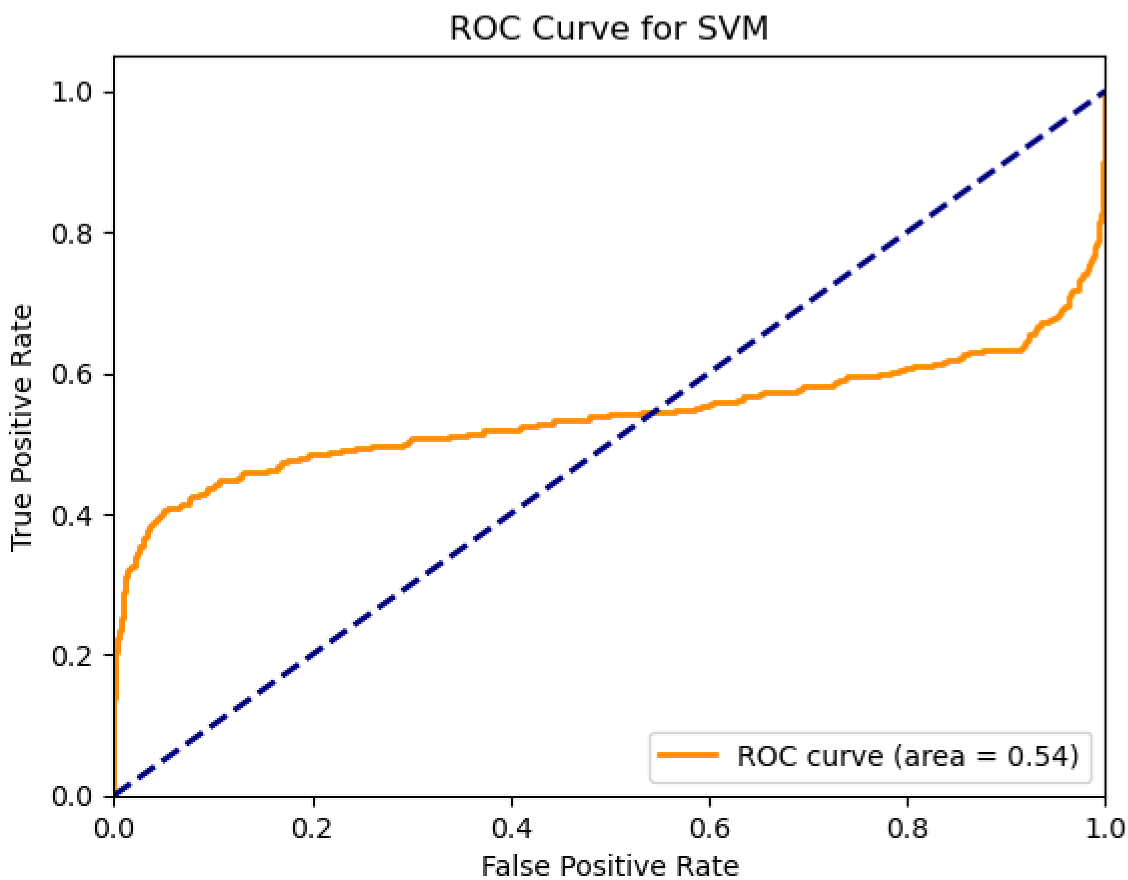
The performance of various models was evaluated based on precision, recall, F1-score, and accuracy.

Analysis

SVM Model

- **Precision**: 0.82 indicates moderate accuracy in predicting seizures.
- **Recall**: 1.00 shows excellent detection of true seizure cases.
- **F1-Score**: 0.90 indicates a decent balance between precision and recall.
- **Conclusion**: While the SVM had a high recall, its overall accuracy was limited, suggesting potential issues with false positives.



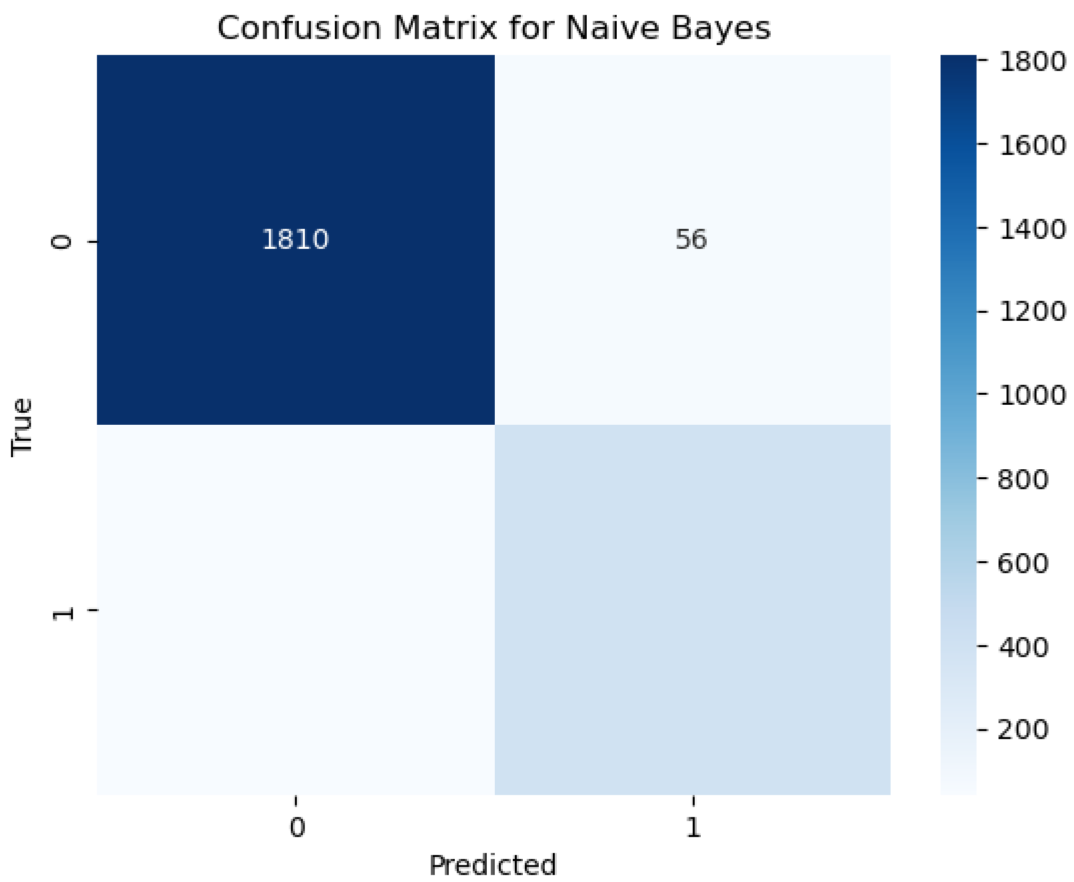


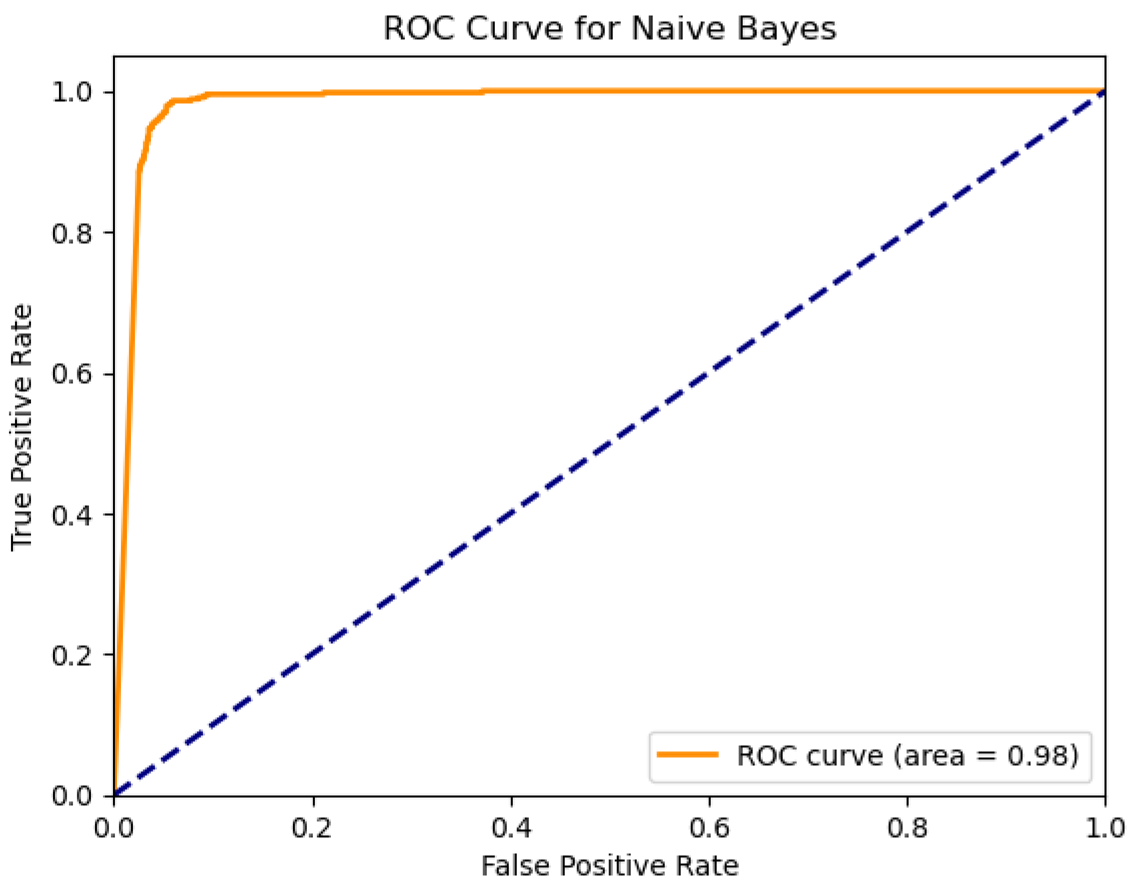
SVM ROC Curve

- **Curve Characteristics**: The ROC curve for SVM, on the other hand, is much less favorable. The curve is closer to the diagonal line (which represents random guessing), indicating that the SVM model struggles to differentiate between the positive and negative classes.
- **Area Under the Curve (AUC)**: The AUC for SVM is 0.54, which is only slightly better than random guessing (AUC = 0.5). This suggests that the SVM model is not performing well in this scenario.

Naive Bayes Model

- **Precision**: 0.98 reflects high accuracy in seizure predictions.
- **Recall**: 0.97 demonstrates effective detection of seizures.
- **F1-Score**: 0.97 shows a strong balance between precision and recall.
- **Conclusion**: Naive Bayes performed well overall, making it a solid choice for this classification task.



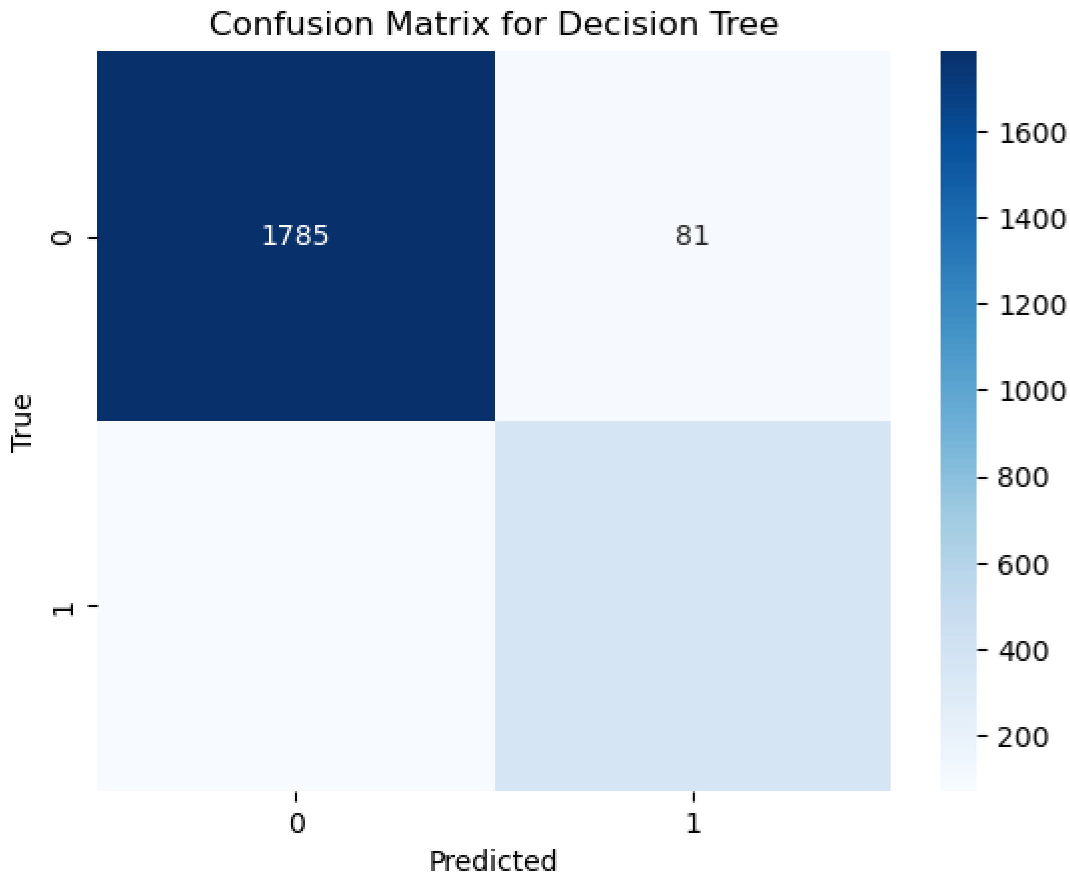


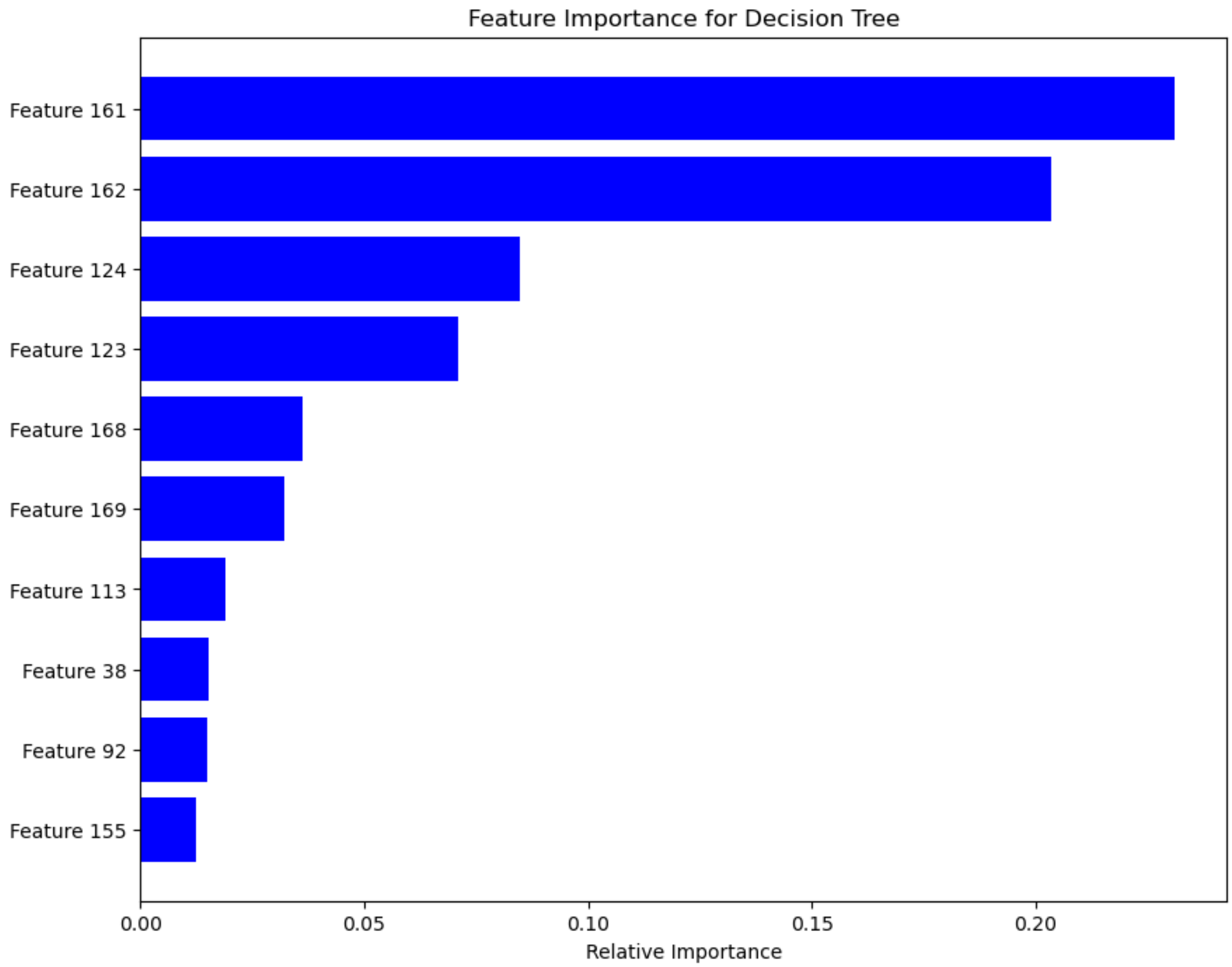
Naive Bayes ROC Curve

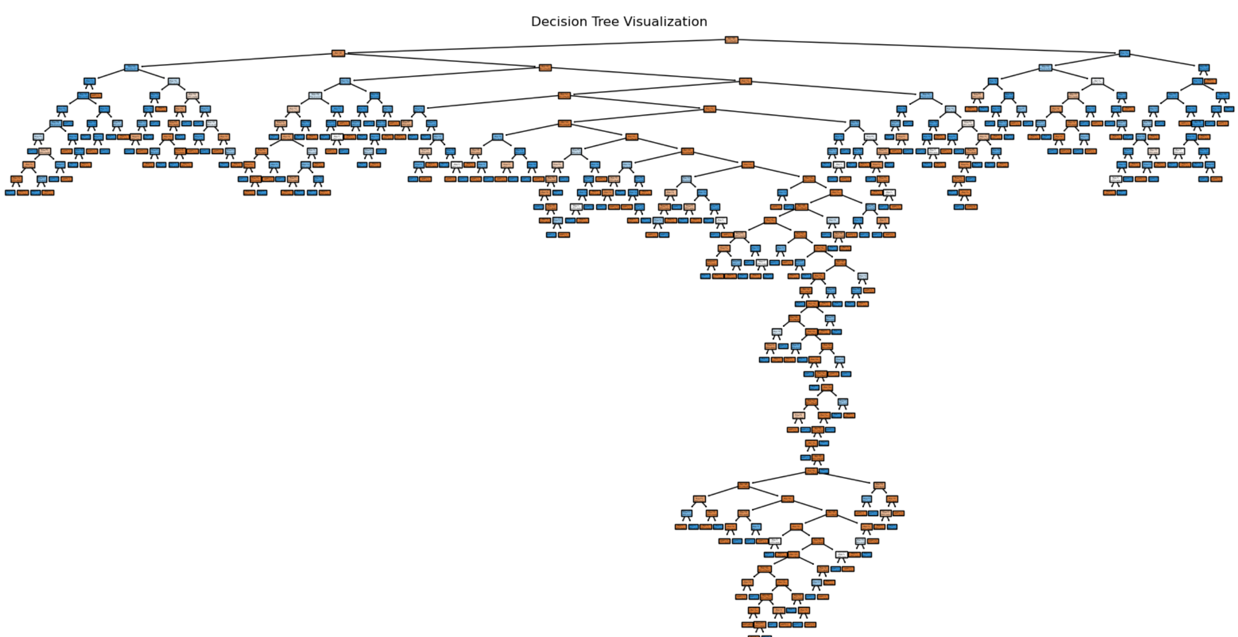
- **Curve Characteristics**: The ROC curve for Naive Bayes is almost perfect, showing a sharp rise toward the top left corner, indicating that the model performs very well in distinguishing between the two classes.
- **Area Under the Curve (AUC)**: The AUC is 0.98, which is very close to 1. This suggests that the Naive Bayes classifier has excellent predictive power, with a high true positive rate (sensitivity) and a low false positive rate.

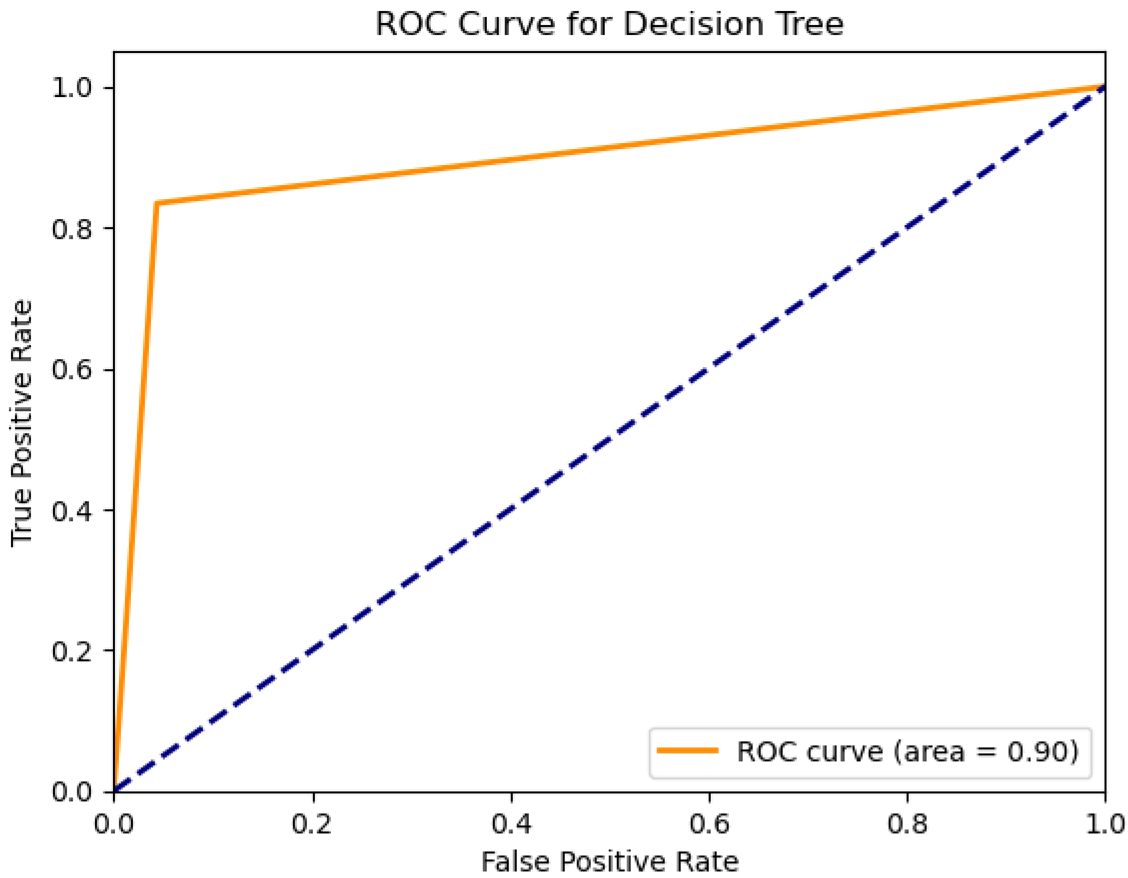
Decision Tree Model

- **Precision**: 0.96 indicates strong predictive performance.
- **Recall**: 0.96 shows effective seizure detection.
- **F1-Score**: 0.96 reflects a good balance between precision and recall.
- **Conclusion**: The Decision Tree model performed well but may be prone to overfitting, given its decision-making nature.


Confusion Matrix for Decision Tree
1785
81
True
0
1
Predicted
1600
1400
1200
1000
800
600
400
200


Feature Importance for Decision Tree
Feature 161
Feature 162
Feature 124
Feature 123
Feature 168
Feature 169
Feature 113
Feature 38
Feature 92
Feature 155
0.00
0.05
0.10
0.15
0.20
Relative Importance


Decision Tree Visualization



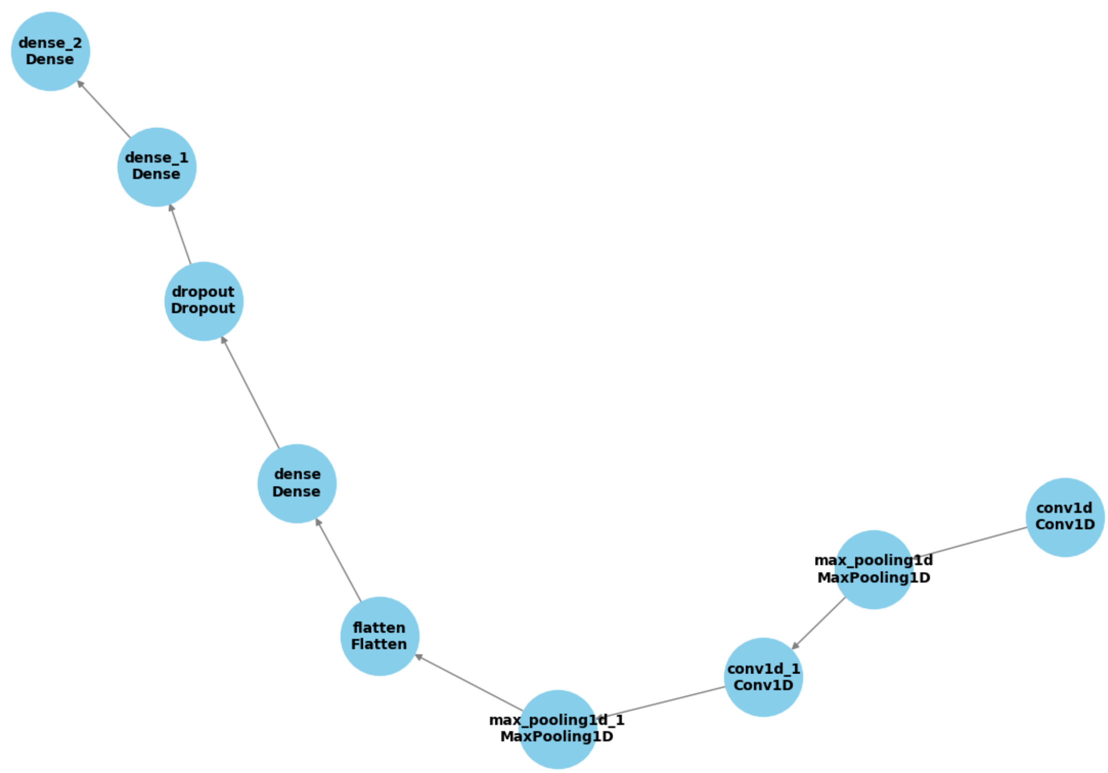
Decision tree ROC Curve

- **Curve Characteristics**: The ROC curve for the Decision Tree model shows a strong performance, with a significant rise toward the top left corner, although not as steep as a perfect model. This indicates that the Decision Tree is effective at distinguishing between the two classes, but there is a slight trade-off between the true positive rate (sensitivity) and the false positive rate. The curve's shape suggests that the model has a good ability to correctly classify positive instances while keeping false positives reasonably low.
- **Area Under the Curve (AUC)**: The AUC for this ROC curve is 0.90. While not as close to 1 as in an ideal scenario, an AUC of 0.90 still suggests that the Decision Tree classifier has strong predictive power. It indicates a high true positive rate and a controlled false positive rate, demonstrating that the model performs well in distinguishing between the positive and negative classes. Although not perfect, this AUC value shows that the model is reliable and effective for most classification tasks.

CNN Model

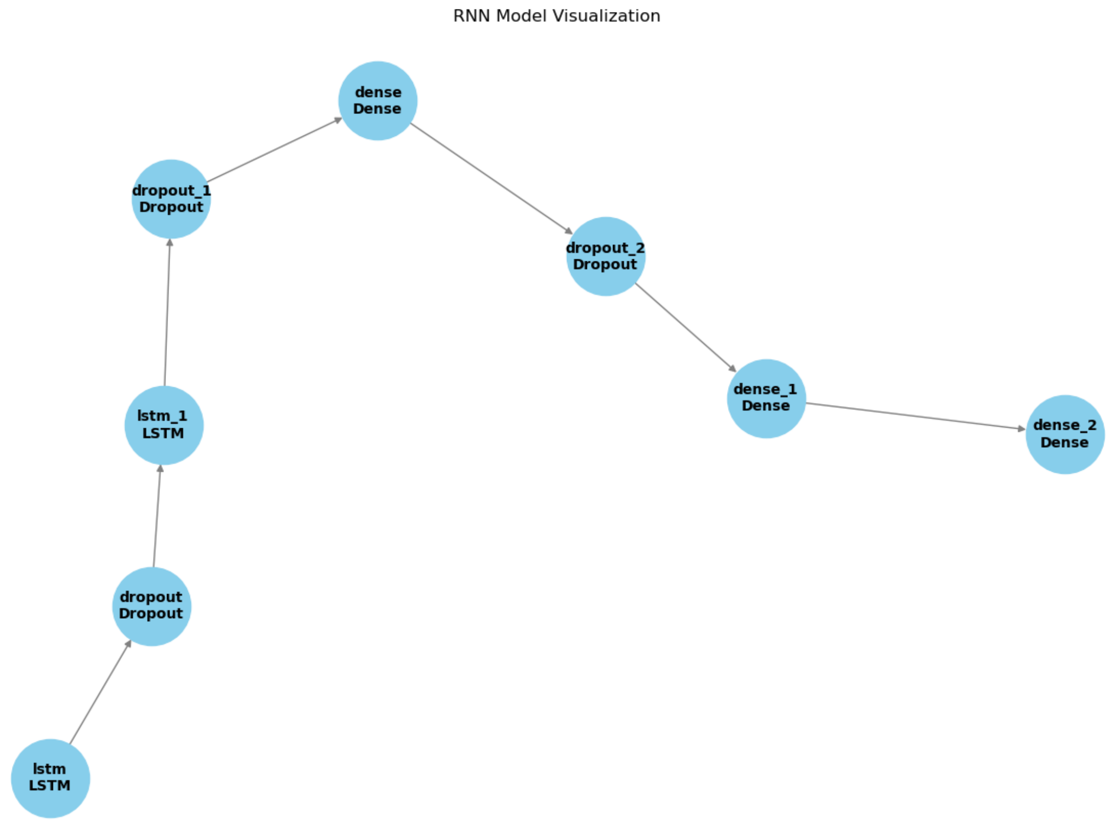
- **Precision**: 0.97 shows high accuracy in predicting seizures.
- **Recall**: 0.97 indicates effective detection of actual seizures.
- **F1-Score**: 0.97 demonstrates a strong balance between precision and recall.
- **Conclusion**: The CNN model performed excellently, proving to be suitable for the seizure detection task.

CNN Model Visualization



RNN Model

- **Precision**: 0.97 suggests high accuracy in predicting seizures.
- **Recall**: 0.98 indicates excellent identification of actual seizures.
- **F1-Score**: 0.97 reflects a good balance between precision and recall.
- **Conclusion**: The RNN achieved the best accuracy and demonstrated strong performance, making it particularly suitable for sequential data like EEG signals.



CONCLUSION

Summary of Findings

This project demonstrated that the RNN model outperformed other machine learning techniques (SVM, Naive Bayes, Decision Tree, and CNN) in early epilepsy detection using EEG data, achieving a precision of 0.97 and a recall of 0.98. All models showed promise, but deep learning approaches proved particularly effective for sequential data analysis.

Future Scope

Future research could explore hybrid models, such as combining CNN and RNN architectures, to further enhance performance. Additionally, leveraging transfer learning and data augmentation techniques may improve generalization and robustness, paving the way for more accurate and reliable epilepsy detection systems.

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