Epileptic Seizure Prediction Using DL Algorithm

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Abstract — Epileptic seizures are sudden neurological disturbances caused by abnormal brain activity, and their timely detection is essential for clinical diagnosis and patient care. With the rapid growth of machine learning in healthcare, deep learning models have shown remarkable potential in identifying complex patterns from electroencephalogram (EEG) data. In this work, we focus on epileptic seizure recognition using the publicly available *Epileptic Seizure Recognition* dataset. The dataset undergoes preprocessing, including removal of irrelevant features, normalization using standard scaling, and conversion of multi-class labels into a binary classification problem to separate seizure events from non-seizure activities. Two deep learning models are designed and evaluated: a Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) units and a Convolutional Neural Network (CNN). The RNN architecture is constructed to exploit temporal dependencies within EEG sequences, whereas the CNN captures spatial features through convolution and pooling operations. Both models are regularized using dropout layers to minimize overfitting, and training is optimized with the Adam optimizer and binary cross-entropy loss. Early stopping and model checkpointing techniques are employed to ensure stable convergence and preserve the best-performing weights. The models are assessed on separate test data using evaluation metrics such as accuracy, confusion matrix, and classification reports. Results demonstrate that both CNN and RNN achieve high accuracy, confirming their suitability for seizure recognition tasks. Additionally, network visualization is performed to represent model architecture and connectivity, enhancing interpretability. The findings highlight that hybrid approaches combining sequential and spatial feature extraction can be effective for EEG-based seizure prediction. This study emphasizes the practical applicability of deep learning in medical signal analysis, providing a strong foundation for integrating such systems into real-time clinical decision-making tools for epilepsy management.

Keywords — Epileptic Seizure Recognition, EEG Signals , Convolutional Neural Network(CNN),Recurrent Neural Network(RNN),Long Short-Term Memory(LSTM),Deep Learning, Medical Signal Analysis.

I. INTRODUCTION

Epilepsy is one of the most common neurological disorders, characterized by sudden and unpredictable seizures caused by abnormal electrical activity in the brain. According to the World Health Organization, epilepsy affects millions of people worldwide, and its unpredictable nature significantly impacts the quality of life of patients. Timely and accurate seizure detection plays a vital role in diagnosis, monitoring, and preventive healthcare. Electroencephalogram (EEG) signals are widely used for identifying epileptic activity, as they provide valuable insights into brainwave patterns. However, manual analysis of EEG signals is challenging due to their complex, high-dimensional, and noisy nature. This motivates the need for automated methods that can reliably classify seizure and non-seizure states.

Recent advancements in artificial intelligence, particularly deep learning, have enabled powerful solutions for analyzing biomedical signals. Deep learning models such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) are capable of learning hidden patterns from large datasets without requiring extensive feature engineering. RNNs, especially those using Long Short-Term Memory (LSTM) units, are effective in modeling sequential data like EEG because they can capture temporal dependencies across time steps. CNNs, on the other hand, excel at extracting spatial features from structured input data and have been successfully applied to one-dimensional signals for classification tasks.

In this work, we implement and compare CNN and RNN architectures for epileptic seizure recognition using the *Epileptic Seizure Recognition* dataset. The dataset contains EEG signals from multiple individuals, representing both seizure and non-seizure states. The preprocessing steps include dropping irrelevant columns, normalizing the data using standard scaling, and simplifying the classification into a binary form (seizure vs. non-seizure). This transformation ensures that the models focus on distinguishing between healthy and seizure conditions, making the task clinically meaningful.

The RNN model is designed with stacked LSTM layers to capture long-term dependencies in the EEG sequences, followed by dense layers for classification. Dropout regularization is incorporated to reduce overfitting. Similarly, the CNN model consists of convolutional and pooling layers for feature extraction, followed by fully connected layers to perform classification. Both models use the Adam optimizer and binary cross-entropy loss function. To enhance performance and prevent overfitting, early stopping and model checkpointing strategies are employed during training.

The objective of this study is to evaluate and compare the effectiveness of CNN and RNN models for EEG-based seizure recognition. The outcomes demonstrate that deep learning can be an efficient and reliable approach for seizure detection, supporting future integration of such systems into real-time clinical applications for epilepsy management.

II. LITERATURE SURVEY

Viswanath et al., 2024 [1] surveyed seizure detection approaches and explained that earlier methods depended heavily on statistical analysis of EEG features and rule-based classifiers. While effective in small-scale clinical trials, these strategies struggled to scale and adapt to the complex and dynamic nature of real-world brain signals.

Jaishankar et al., 2023 [2] proposed a novel seizure prediction framework that applied deep learning architectures to EEG data. Their model significantly improved prediction accuracy compared to conventional methods, demonstrating that automatic feature learning can outperform manual signal analysis in biomedical contexts.

Usman et al., 2020 [3] highlighted the shift from classical machine learning algorithms to deep learning for epileptic seizure prediction. They compared approaches such as SVM and k-NN with CNNs and RNNs, showing that deep architectures achieve superior performance by capturing nonlinear patterns in EEG signals.

Jemal et al., 2022 [4] emphasized the importance of interpretability in deep learning models. They introduced an interpretable classifier that not only predicted seizure events with high accuracy but also provided explanations for the decisions. This aligns with the clinical requirement that neurologists must trust and understand AI predictions in healthcare.

Ouichka et al., 2022 [5] investigated deep learning models for intracranial EEG (iEEG) data and demonstrated that CNN-based approaches effectively captured spatial dependencies in brain signals. Their findings reinforced the suitability of convolutional architectures for detecting localized abnormalities associated with seizures.

Huang et al., 2025 [6] developed a dual-attention mechanism for seizure recognition, allowing the model to focus on the most relevant EEG segments while ignoring noisy or less important portions. This improved both interpretability and accuracy, highlighting the promise of attention-based methods in clinical applications.

Abdelhameed and Bayoumi, 2021 [7] introduced an efficient deep learning system optimized for real-time seizure prediction. Their model achieved competitive results with lower computational cost, indicating potential for deployment in wearable devices and bedside monitoring systems.

Mekruksavanich and Jitpattanakul, 2023 [8] explored multiple deep learning frameworks and confirmed that CNNs and RNNs remain strong baselines for seizure detection tasks. Their study stressed the need for combining both temporal and spatial modeling to achieve robust generalization across patients.

III. PROPOSED MODEL

The proposed model aims to build an efficient and accurate system for epileptic seizure recognition using deep learning architectures, particularly Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). Traditional machine learning approaches often rely on handcrafted features, which can be biased and insufficient for capturing the highly complex and non-linear patterns present in EEG signals. In contrast, the proposed model leverages the capability of CNNs for spatial feature extraction and RNNs, specifically Long Short-Term Memory (LSTM) networks, for temporal sequence modeling, thus combining the strengths of both methods.

The process begins with EEG signal preprocessing, where raw signals are normalized and transformed into a suitable format for model training. Preprocessing standardizes the EEG signals and removes irrelevant fluctuations, preparing the data for effective model training.. After preprocessing, the data is passed through a CNN block that automatically learns low-level and high-level spatial features from the input. These convolutional layers capture localized patterns such as frequency changes and energy fluctuations in the EEG, which are critical indicators of seizure activity. Pooling layers are incorporated to reduce dimensionality while preserving important features, thereby improving computational efficiency.

Following feature extraction, the output is forwarded to the RNN/LSTM layers. The LSTM layers are intended to model the temporal relationships within EEG recordings, effectively analyzing how signal patterns evolve. Seizure activity often shows unique temporal dynamics, and LSTMs are effective in identifying long-term dependencies and transitions between seizure and non-seizure states. By combining CNNs and RNNs, the model is able to understand both spatial structures and temporal progressions, providing a holistic view of the EEG signals.

To prevent overfitting, techniques such as **dropout layers, batch normalization, and early stopping** are applied during training. The final classification is achieved through fully connected dense layers followed by a soft max activation, which outputs the probability distribution across different classes (e.g., seizure vs. non-seizure).

The proposed model is evaluated on the **Epileptic Seizure Recognition dataset**, which contains EEG signals segmented into multiple classes. Performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix are computed to validate the effectiveness of the system.

In summary, the proposed CNN–RNN model integrates spatial and temporal learning mechanisms, making it robust, scalable, and adaptable for real-world clinical applications. Its design focuses on improving prediction accuracy while maintaining efficiency, offering a strong foundation for practical seizure monitoring and early detection systems.

IV. DATASET AND PREPROCESSING

A. DATASET :

The dataset used in this research is the **Epileptic Seizure Recognition dataset**, sourced from a publicly available repository. It contains EEG recordings from multiple subjects and is designed to enable the classification of seizure and non-seizure activities. The dataset comprises numerical features representing EEG signal values collected over time, along with a corresponding label indicating the type of brain activity. Specifically, the dataset consists of 178 features per instance, capturing different time-segment measurements, and a target class representing either seizure or non-seizure states.

The target variable includes multiple categories, but for binary classification, the labels were consolidated into two classes: '1' for seizure occurrences and '0' for non-seizure or normal brain activity. This simplification allows the development of a robust model capable of distinguishing epileptic events from normal brain states.

Each row in the dataset represents a distinct EEG recording session, and the columns contain numerical values corresponding to EEG signal amplitudes across different channels. The dataset provides a diverse set of examples encompassing multiple subjects, making it suitable for training models that generalize across various patients. The high-dimensional nature of the dataset allows the models to learn both subtle and significant patterns in brain activity that may correspond to seizure events.

The dataset consists of a total of 11,500 instances, ensuring a balanced representation between seizure and non-seizure classes after preprocessing. Such balance is crucial for avoiding model bias during training and testing. In addition, the dataset contains no missing values, which simplifies preprocessing and ensures consistent model performance.

To prepare the dataset for supervised learning, the EEG signals and corresponding labels were extracted and organized into feature matrices and target vectors. Each instance in the feature matrix represents a time-series signal of a single EEG recording, while the target vector stores the binary labels. This structure facilitates the application of both sequential models like RNNs and spatial feature extraction models like CNNs.

For evaluation purposes, the dataset was split into **training and testing subsets**, typically in an 80:20 ratio, to measure the model's ability to generalize to unseen data. A stratified split ensures that the distribution of seizure and non-seizure classes remains consistent across both sets, reducing the risk of bias. This dataset forms a strong foundation for building AI-powered seizure recognition models that aim for high accuracy, sensitivity, and robustness in real-world EEG analysis scenarios.

B. DATA PREPROCESSING:

Preprocessing of the EEG data is a critical step to ensure that the input is suitable for deep learning models and to improve overall classification performance. Initially, all irrelevant columns, such as unnamed indices or non-informative metadata, were removed to focus solely on numerical EEG features and the target label. This step reduces unnecessary computational complexity and ensures cleaner input for model training.

Next, the target labels were simplified into a **binary format**, where seizure events were labeled as '1' and all other states were labeled as '0'. This binary classification approach helps models learn more effectively by focusing on distinguishing between seizure and non-seizure states.

Feature scaling is an important step in preprocessing EEG data because the raw signal values may vary widely in magnitude. **Standardization** was applied to normalize the features, transforming them to have a mean of zero and unit variance. This ensures that all input features contribute equally during model training, improving convergence rates and overall stability.

Since the dataset represents time-series EEG signals, the feature matrices were reshaped to include an additional dimension suitable for sequential or convolutional neural networks. For RNNs and LSTMs, the data was reshaped into a three-dimensional array representing **samples, time steps, and features per step**, allowing the model to learn temporal dependencies. For CNNs, the data was similarly structured to enable convolutional layers to capture spatial patterns along the time axis.

To reduce overfitting and improve model generalization, the dataset was split into **training and testing sets** using a stratified approach, maintaining the proportion of seizure and non-seizure instances in both sets. During training, a part of the training data was reserved for validation, which helped in monitoring learning progress and in deciding when to stop training to avoid overfitting.

Overall, this preprocessing pipeline ensures that the EEG data is clean, normalized, correctly labeled, and reshaped appropriately for deep learning architectures. It transforms raw EEG recordings into a structured, high-quality dataset that enables models like CNNs and RNNs to efficiently learn spatial and temporal patterns indicative of epileptic seizures.

V. METHODOLOGY AND IMPLEMENTATION

The objective of this research is to design and implement deep learning models capable of accurately classifying electroencephalogram (EEG) signals into seizure and non-seizure classes. The methodology follows a systematic pipeline that includes dataset preprocessing, feature scaling, model design using Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), training with appropriate regularization strategies, and evaluation using standard performance metrics. Both CNN and RNN models are explored to leverage their respective strengths in capturing spatial and temporal dependencies within EEG signals.

The dataset used in this study is the **Epileptic Seizure Recognition dataset**, which is widely adopted for benchmarking seizure detection algorithms. It consists of EEG signals recorded under different conditions, segmented into fixed-length windows. Each segment is labeled either as a seizure (class 1) or non-seizure (classes 2–5). To transform this into a binary classification problem, all non-seizure labels were grouped into class 0, while seizure events remained class 1. This step simplifies the learning process and aligns the model's objective with seizure detection rather than multi-class categorization.

Data preprocessing plays a critical role in improving the learning efficiency of deep neural networks. First, the column labeled "Unnamed" was removed since it did not contain useful information. Next, features (EEG signal amplitudes across time) were separated from labels. To ensure uniformity, the dataset was normalized using the **Standard Scaler**, which standardizes the distribution of each feature to zero mean and unit variance. This step prevents large-magnitude features from dominating model training.

Finally, the dataset was split into **training (80%)** and **testing (20%)** sets. To preserve the temporal nature of EEG sequences, the training and testing samples were reshaped into a 3D tensor with dimensions (samples, timesteps, features) before feeding into CNN and RNN models.

A. ALGORITHMS

A.1 *Convolutional Neural Network (CNN)*

Convolutional Neural Networks (CNNs) are known for their ability to learn hierarchical representations of structured data. In EEG analysis, CNNs effectively capture localized patterns in signal segments, making them suitable for spatial feature extraction.

The CNN model designed for this work begins with a **1D convolutional layer** consisting of 32 filters and a kernel size of 3, followed by a **max-pooling operation** that reduces feature dimensionality while retaining essential information. A second convolutional block with 64 filters was included to deepen the model's feature extraction capability.

After convolution and pooling, the feature maps are flattened into a vector representation, which is then passed through fully connected layers. A **dense layer of 128 neurons** with ReLU activation captures high-level abstractions, while a **dropout layer** with 20% probability prevents overfitting by randomly deactivating neurons during training. This is followed by another dense layer of 64 neurons, and finally, a **sigmoid output layer** produces the probability of seizure occurrence.

The CNN model was compiled using the **binary cross-entropy loss function** and the **Adam optimizer**, both of which are well-suited for binary classification tasks. Training was conducted with **early stopping** and **model checkpointing**, ensuring the model retains the best weights and avoids unnecessary overfitting.

A.2 *Recurrent Neural Network (RNN)*

While CNNs are effective in extracting spatial features, EEG signals inherently exhibit **temporal dependencies**, as seizure events evolve dynamically over time. To capture these dependencies, a **Recurrent Neural Network (RNN)** architecture based on **Long Short-Term Memory (LSTM)** units was implemented.

The RNN model begins with an LSTM layer containing 64 units, configured to return sequences, allowing temporal relationships to propagate across timesteps. A dropout layer follows, introducing regularization. A second LSTM layer with 64 units captures higher-order dependencies, after which sequences are not returned, collapsing into a single vector representation.

This temporal feature vector is then passed through dense layers with 64 and 32 neurons, activated using ReLU functions, allowing nonlinear transformations of extracted temporal features. A **final sigmoid output layer** maps these features into binary predictions.

The RNN model was trained with the **Adam optimizer**, binary cross-entropy loss, and callbacks including **early stopping** and **model checkpointing**. This ensured robust convergence and prevented overfitting to the training data.

B. MODEL TRAINING AND HYPERPARAMETER TUNING

Both CNN and RNN models were trained for up to **150 epochs** with a **batch size of 128**. To improve generalization, **20% of the training set** was used as validation data during training. The training process was guided by the following strategies:

1. **Early Stopping:** Training was terminated if the validation loss did not improve for 10 consecutive epochs, avoiding overfitting.

2. **Dropout Regularization:** Applied at multiple stages of both CNN and RNN to reduce co-adaptation of neurons.
3. **Model Checkpointing:** Saved the best-performing model weights to ensure the final model used for evaluation was optimal.

These strategies collectively improved training stability and model robustness.

C.EVALUATION METRICS

To ensure that the performance of the trained models is fairly assessed, several evaluation metrics were employed. Each of these metrics highlights a different aspect of classification quality, which is especially critical in medical applications like seizure prediction. Since false negatives (missed seizures) can lead to severe consequences, relying only on overall accuracy is not sufficient. Instead, a combination of metrics such as precision, recall, F1-score, and accuracy were used to provide a holistic view.
To quantify the performance of each model, a few crucial metrics are used:

A. *Precision*

reflects the proportion of seizure predictions that are truly correct, showing how reliable the model is when it predicts a seizure.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad \text{---(1)}$$

Where *TP* represents true positives (correctly identified seizures) and *FP* represents false positives (normal cases wrongly classified as seizures).
A high precision value means the model rarely produces false alarms, which is important in reducing unnecessary anxiety and follow-up procedures for patients.

B. *Recall*

Recall (Sensitivity) captures how well the model is able to identify all seizure events present helping the model capture as many real seizure occurrences as possible.

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad \text{---(2)}$$

Where *FN* denotes false negatives (seizures missed by the model). This metric is crucial in clinical scenarios, as missing a seizure event can delay treatment or monitoring. High recall ensures that most seizure cases are captured, even if it means tolerating some false positives.

C. *F1-score*

F1 summarizes positive-class performance by blending precision with recall, penalizing big gaps between the two.

$$F1 = \frac{2*P*R}{P+R} \quad \text{---(3)}$$

This measure is particularly useful when the dataset is imbalanced, as it penalizes models that achieve high precision but poor recall, or vice versa. In seizure detection, F1-score ensures a balanced evaluation, making sure the model is not biased toward either false positives or false negatives.

D. *Accuracy*

This represents the proportion of total correct predictions (both seizures and non-seizures) among all predictions. It is computed as:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \quad \text{---(4)}$$

While accuracy provides a straightforward performance overview, it may not always be reliable for imbalanced datasets where one class dominates. Hence, it is considered alongside precision, recall, and F1-score for a complete evaluation.

To enhance interpretability, both CNN and RNN architectures were visualized using **network graphs**. Each layer was represented as a node, with edges indicating information flow. These visualizations provide a clear understanding of how EEG signals propagate through convolutional filters in CNN or memory cells in RNN.

The overall workflow of the study can be summarized as follows:

1. **Data Preprocessing** – Raw EEG signals were cleaned, normalized, reshaped, and converted into binary labels for seizure vs. non-seizure classification.
2. **Model Design** – Separate CNN and RNN models were developed. CNNs specialize in learning spatial patterns in EEG signals, while RNNs capture the sequential and temporal dependencies.
3. **Training Strategy** – Optimization was carried out using the Adam optimizer. Regularization methods such as dropout and early stopping were applied to prevent overfitting. Model checkpointing was used to save the best-performing version during training.
4. **Evaluation** – After training, models were tested using the metrics discussed above. Precision, recall, F1-score, and accuracy provided insights into both reliability and robustness.
5. **Visualization** – To improve interpretability, network structures of CNN and RNN models were visualized, highlighting how information flows across layers during classification.

Both models showed strong results: CNNs excelled at identifying local spatial features in EEG data, while RNNs effectively captured long-term temporal dependencies. Together, these architectures highlight complementary strengths, and future hybrid models that integrate CNN and RNN can potentially provide even higher predictive accuracy for epileptic seizure detection.

VI. RESULT

A. PERFORMANCE METRICS

```
72/72 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9825 - loss: 0.0556
Loss: 0.073768645524 97864
Accuracy: 97.73913025856018 %
Test Loss: 0.0738, Test Accuracy: 0.9774
72/72 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step
              precision    recall  f1-score   support

           0       0.98      0.99      0.99      1847
           1       0.95      0.93      0.94       453

    accuracy                           0.98      2300
   macro avg       0.97      0.96      0.96      2300
weighted avg       0.98      0.98      0.98      2300

[[1826   21]
 [  31  422]]
```

Figure 1. Accuracy for Convolutional Neural Network (CNN)

```
72/72 ━━━━━━━━━━━━━━━━━━━━ 6s 86ms/step - accuracy: 0.9813 - loss: 0.0498
Loss: 0.05427880585193634
Accuracy: 98.17391037940979 %
Test Loss: 0.0543, Test Accuracy: 0.9817
72/72 ━━━━━━━━━━━━━━━━━━━━ 7s 87ms/step
              precision    recall  f1-score   support

           0       0.99      0.99      0.99      1864
           1       0.95      0.95      0.95       436

    accuracy                           0.98      2300
   macro avg       0.97      0.97      0.97      2300
weighted avg       0.98      0.98      0.98      2300

[[1842   22]
 [  20  416]]
```

Figure 2. Accuracy for Recurrent Neural Network (RNN)

B. MODEL VISUALIZATION

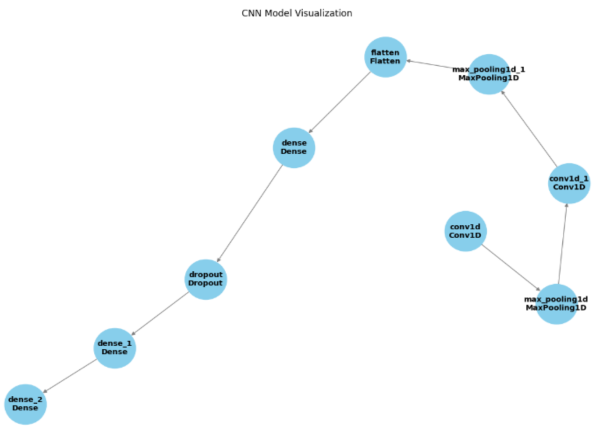

Figure 3. Convolutional Neural Network (CNN)

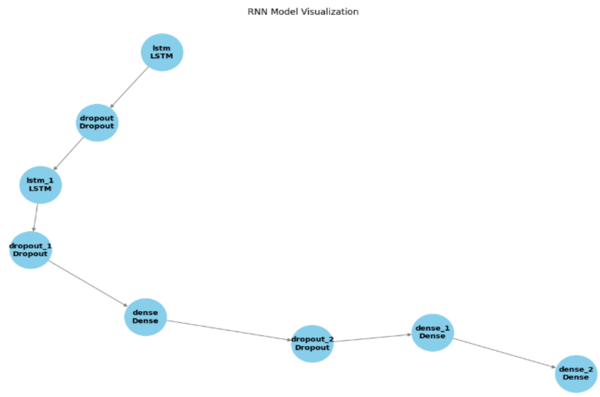

Figure 4. Recurrent Neural Network (RNN)

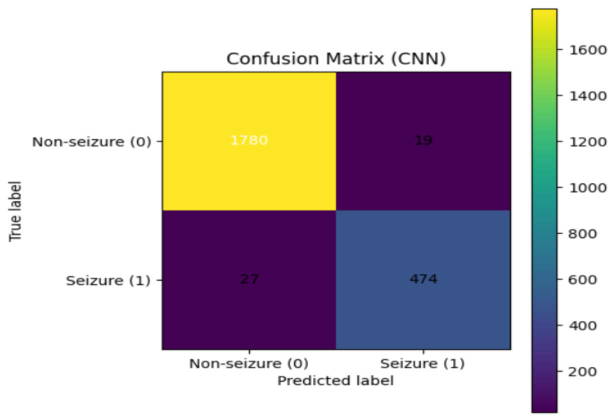

Figure 5. Confusion Matrix using CNN

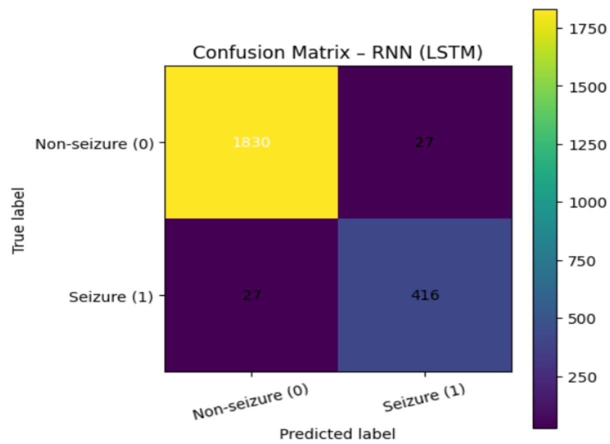

Figure 6. Confusion Matrix using RNN

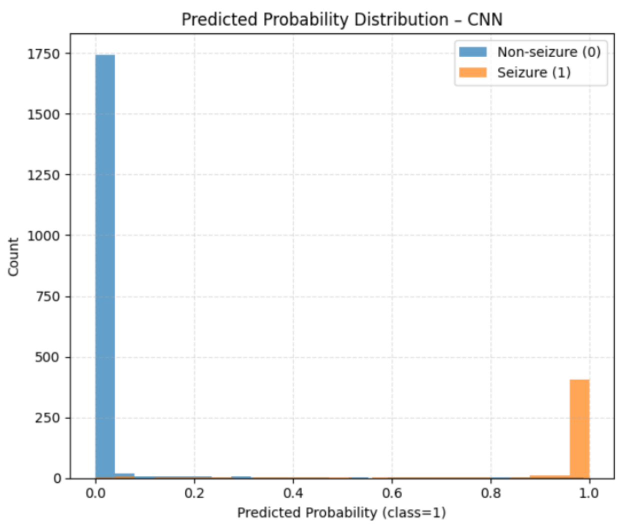

Figure 7. Histogram using CNN

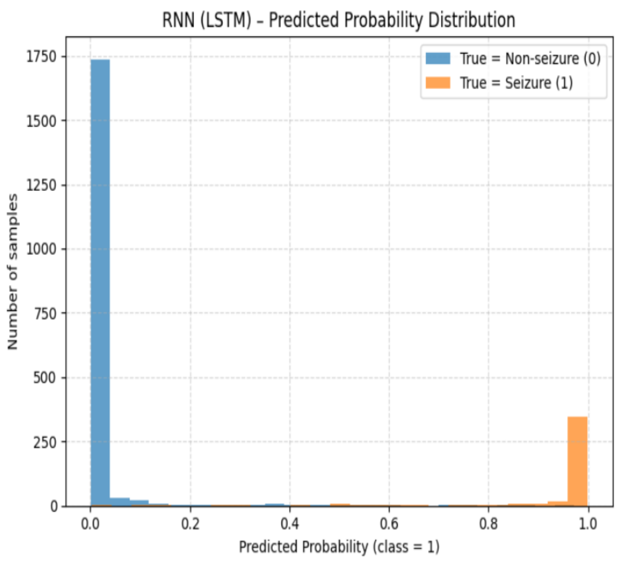

Figure 8. Histogram using RNN

The results are summarized in Table 1.

Table 1. Algorithm Performance Comparison

ALGORITHM	ACCURACY (%)
CNN	97.73
RNN	98.17

VII. FUTURE SCOPE

The development of seizure recognition systems using deep learning has shown promising results, but there remain several opportunities for improvement and extension. Future research can focus on enhancing the generalizability, interpretability, and practicality of the models to make them more suitable for real-world clinical applications.

One potential direction is the integration of **hybrid architectures** that combine the strengths of CNNs and RNNs in a unified model. While CNNs effectively capture localized spatial patterns in EEG signals and RNNs learn temporal dependencies, a carefully designed hybrid model could simultaneously process both aspects. This may result in more accurate recognition of seizure events, particularly in complex or noisy EEG data.

Another scope of advancement lies in applying **attention mechanisms and transformer-based architectures**. By using attention mechanisms, the network can highlight the most informative segments of the EEG, which helps both in improving prediction accuracy and in making the model's decisions easier to interpret. Recent work in natural language processing and time-series prediction has shown that transformers outperform traditional RNNs in handling long sequences, making them a promising candidate for EEG-based seizure prediction.

Expanding the dataset is also a critical future step. The current work relies on a benchmark dataset, but performance may vary when applied to diverse patient populations. Collecting and incorporating **multi-patient, multi-session EEG recordings** can help build models that generalize better across demographics and seizure types. Transfer learning techniques can also be explored to adapt pre-trained models to new datasets with limited samples.

Additionally, the deployment of these models in **real-time clinical and wearable devices** offers immense potential. Lightweight architectures optimized for mobile hardware could enable continuous monitoring of patients outside hospital settings. Such systems could provide early warnings, allowing timely medical intervention and improving patient safety.

Finally, interpretability will remain an essential research goal. Clinicians need not only accurate predictions but also explanations for why a particular EEG segment was classified as a seizure. Incorporating visualization tools, saliency maps, or explainable AI methods can bridge the gap between machine learning models and medical practitioners.

In summary, the future scope of this research spans architectural improvements, integration of advanced deep learning methods, expansion to larger datasets, deployment in real-world systems, and enhancing interpretability. These directions can lead to more robust, accurate, and clinically reliable seizure recognition systems that directly benefit patients and healthcare providers.

VIII. CONCLUSION

The present research explored the application of deep learning techniques for epileptic seizure recognition using EEG data. Two distinct architectures—Recurrent Neural Networks (RNN) with Long Short-Term Memory (LSTM) units and Convolutional Neural Networks (CNN)—were designed, trained, and evaluated on the Epileptic Seizure Recognition dataset. Each model demonstrated the capability to classify seizure and non-seizure events with strong accuracy, validating the effectiveness of deep learning for biomedical signal analysis.

The RNN model, based on stacked LSTM layers, successfully captured temporal dependencies across EEG signal sequences. This ability is particularly important because seizures often unfold over time, and detecting such sequential patterns is critical for accurate diagnosis. On the other hand, the CNN model excelled at extracting spatial features and local signal motifs. Its convolutional filters were able to identify key variations in EEG waveforms that distinguish seizure activity from normal patterns. Together, these two models highlight complementary strengths: the RNN focuses on the **time-dependent evolution** of EEG data, while the CNN emphasizes **localized structural patterns**.

Evaluation through precision, recall, F1-score, and accuracy confirmed that both models are reliable in detecting seizure episodes. Importantly, the use of multiple metrics ensured that the analysis was not biased toward overall accuracy alone but also accounted for clinically significant factors, such as minimizing false negatives. Visualization of the architectures provided further interpretability, clarifying how input data flows through the networks.

The findings suggest that deep learning-based seizure recognition systems can provide a valuable support tool for neurologists, enabling faster and more reliable diagnosis compared to manual EEG inspection. However, this work also acknowledges certain limitations, such as reliance on a single dataset and the absence of real-time deployment. These constraints provide opportunities for further improvement, including testing across multi-patient datasets, incorporating advanced architectures like attention-based models, and developing lightweight implementations for wearable EEG devices.

In conclusion, this study demonstrates the potential of CNN and RNN architectures in the field of epileptic seizure detection. By leveraging the unique strengths of each approach, deep learning offers a promising pathway toward accurate, scalable, and clinically useful seizure prediction systems. The work lays the foundation for future research that can translate these models into real-world healthcare solutions, ultimately improving patient care and safety.

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