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Deep Learning Approaches For Epileptic Seizure Detection and Classification

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ABSTRACT

Epileptic seizure detection is a critical task in the domain of healthcare, as early and accurate diagnosis can significantly enhance the quality of life for individuals affected by epilepsy. This project, titled Deep Learning Approaches for Epileptic Seizure Detection and Classification, presents a comparative study between traditional machine learning methods and advanced deep learning architectures for accurate and efficient seizure identification using EEG (Electroencephalogram) signals. The study initially employs a Random Forest Classifier (RFC) as the existing system, leveraging its ensemble-based decision-making capability for baseline classification of EEG data into seizure and non-seizure classes. Although RFC provides reasonable accuracy and interpretability, it falls short in capturing the spatial and temporal features inherent in EEG signals. To address the limitation, a Convolutional Neural Network (CNN) is proposed as the advanced deep learning model, capable of automatically extracting deep spatial features from EEG signal representations. CNNs are particularly effective for time-series data and can learn hierarchical feature representations, thereby offering superior performance in both detection accuracy and generalization. Prior to modeling, Exploratory Data Analysis (EDA) was conducted to understand the distribution, patterns, and anomalies in the EEG dataset. Visualization techniques such as signal plotting, correlation heatmaps, and class distribution analysis were employed to gain meaningful insights and guide the preprocessing phase. The dataset was also cleaned, normalized, and appropriately reshaped for CNN compatibility. Experimental results show that the CNN model significantly outperforms the RFC in terms of classification accuracy, sensitivity, specificity, and F1-score. This confirms the effectiveness of deep learning in biomedical signal processing and its potential to be integrated into real-time clinical decision support systems for epilepsy diagnosis. The study demonstrates that CNN-based deep learning models can provide a more reliable and automated solution for epileptic seizure detection, thereby contributing to early intervention and improved patient outcomes.

Keywords: Neural Networks, Time-Series Analysis, Seizure Classification Algorithms, AI in Neurology, Machine Learning for Epilepsy

1. INTRODUCTION

In recent years, there has been a growing interest in leveraging deep learning techniques for the detection and classification of epileptic seizures. This innovative approach marks a significant departure from traditional methods, as deep learning models demonstrate remarkable capabilities in handling complex patterns and extracting meaningful features from raw data. The history of employing deep learning in the context of epileptic seizure detection can be traced back to the increasing availability of large-scale datasets and the advent of powerful computing resources. Earlier attempts at seizure detection primarily relied on handcrafted features and conventional machine learning algorithms.

However, these approaches often struggled to capture the intricate and subtle patterns present in electroencephalogram (EEG) signals, which are crucial for accurate seizure identification. The turning point came with the emergence of deep neural networks, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs). CNNs excel at spatial feature extraction, making them well-suited for analyzing the spatial characteristics of EEG signals. Meanwhile, RNNs are adept at capturing temporal dependencies in sequential data, aligning with the time-varying nature of EEG signals during seizures. Researchers began to explore the integration of these deep learning architectures into epilepsy detection frameworks. Early successes were achieved with models that could automatically learn relevant features from EEG data, eliminating the need for manual feature engineering.

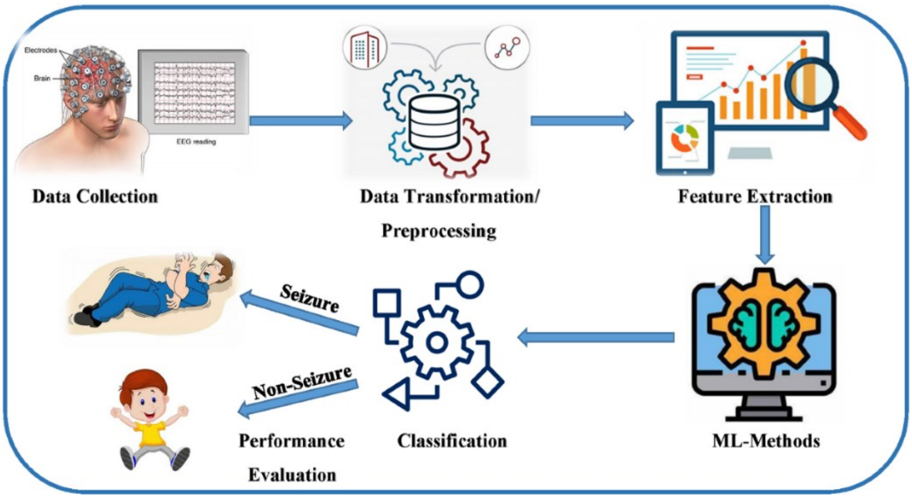

Fig 1: Overview of Seizure detection

The adaptability of deep learning models to diverse EEG patterns and the ability to generalize across different patient profiles marked a significant advancement in the field. As technology progressed, more sophisticated deep learning architectures, such as long short-term memory networks (LSTMs) and attention mechanisms, were incorporated. These enhancements aimed to address the challenges associated with the variability in seizure patterns among individuals and the potential occurrence of subtle seizures that might be overlooked by traditional methods. The evolution of deep learning for epileptic seizure detection also witnessed the exploration of multimodal approaches, where additional patient information, such as medical history or imaging data, was integrated into the models. This holistic perspective aimed to improve the overall accuracy and reliability of seizure detection systems. Furthermore, the widespread adoption of open-source deep learning frameworks and the collaborative efforts within the scientific community contributed to the rapid progress in this field. Benchmark datasets and standardized evaluation metrics became essential tools for comparing the performance of different models and fostering healthy competition among researchers.

2. LITERATURE SURVEY

Usman et al. [1] proposed a DL-related ensemble learning technique for predicting ESs. In the presented approach, EEG signals were pre-processed through empirical mode decomposition, and bandpass filtering was applied to remove noise. With synthetic preictal segments generated by utilizing GAN, the class imbalance problem was mitigated. Hilal et al. [2] introduced an intelligent deep canonical sparse AE-related ES detection and classification (DCSAE-ESDC) method using an EEG signal. In the end, the parameter tuning of a DSCAE process is carried out through the krill herd algorithm (KHA). Anter et al. [3] modelled a novel technique for distinctly recognizing seizure conditions (for instance, interictal, ictal, and preictal) from EEG from the IoT structure to monitor patients. Divya et al. [4] devised a fully automatic system similar to Hybrid GWO-Improved Sine Cosine Algorithm (HGWOISCA) with improved SVM called HGWOISCA-SVM for classifying EEG signals. Bhandari et al. [5] devised the new ES recognition utilizing the Improved Ensemble Learning Model (I-ELM). A novel meta-heuristic technique named Modified Tunicate Swarm Algorithm (M-TSA) was implemented to reduce the feature length, manage the training difficulty, and improve detection performance for precise FS.

In [6], a technique for classifying EEG data utilizing DNN structure was presented. Bi-LSTM, a type of RNN, has been used in this technique. In [7], a projected hybrid cuckoo finch optimizer tuned DCNN classifier for predicting and recognizing the incidence of ES using EEG signal data gained by IoT. The author [8] explained each component's detailed explanation and an overview of the many diagnostic approaches used for epilepsy. In conclusion, the study proposed several novel ideas for seizure detection using DL methods, which are gaining popularity. In [9], medical professionals in the field of neurology have a time-consuming challenge when they must visually examine long-term electroencephalography (EEG). The suggested seizure detection approach was tested using the CHB-MIT scalp EEG database, which achieved a sensitivity of 93.89 per cent and a specificity of 98.49 per cent. In the article [10], to alleviate the burden of data labelling, the author presented a hybrid system that combines unsupervised learning (UL) with traditional supervised learning (SL). Through testing on the CHB-MIT scalp EEG dataset, the proposed seizure detection system is shown to have an overall accuracy of 92.62%, a sensitivity of 95.55%, and a specificity of 92.57%. An improved evolutionary approach is suggested to extract the same features from many networks with different numbers of layers (IGA) [11]. Results for ACC, SPE, SEN, and F1 on the Siena scalp database are 99.13%, 98.36%, and 98.75%, respectively.

In [12], the author presented a unique approach to the few-shot issue by reducing the need for vast data: an automated system based on Deep Metric Learning (DML) for identifying epileptic episodes. Based on the Bonn dataset, the most challenging classification of interictal vs. ictal, an impressive accuracy of 98.60% and specificity of 100% was attained. Because of an unacceptable amount of false alarms [13] produced by cutting-edge technology, automated long-term detection of focal seizures remains one of the most pressing concerns in epilepsy. To speed up the diagnosis of epilepsy, automatic seizure identification from an electroencephalogram (EEG) is crucial [14]. In the study [15], the author implemented an automated learning framework for EEG seizure detection based on the Fourier-Bessel expansion-based empirical wavelet transform (FBSE-EWT) technique.

3. PROPOSED METHOD

The project aims to perform a series of tasks related to building, training, and evaluating machine learning models for classifying epileptic seizure data. The description of the main sections and functionalities of the code:

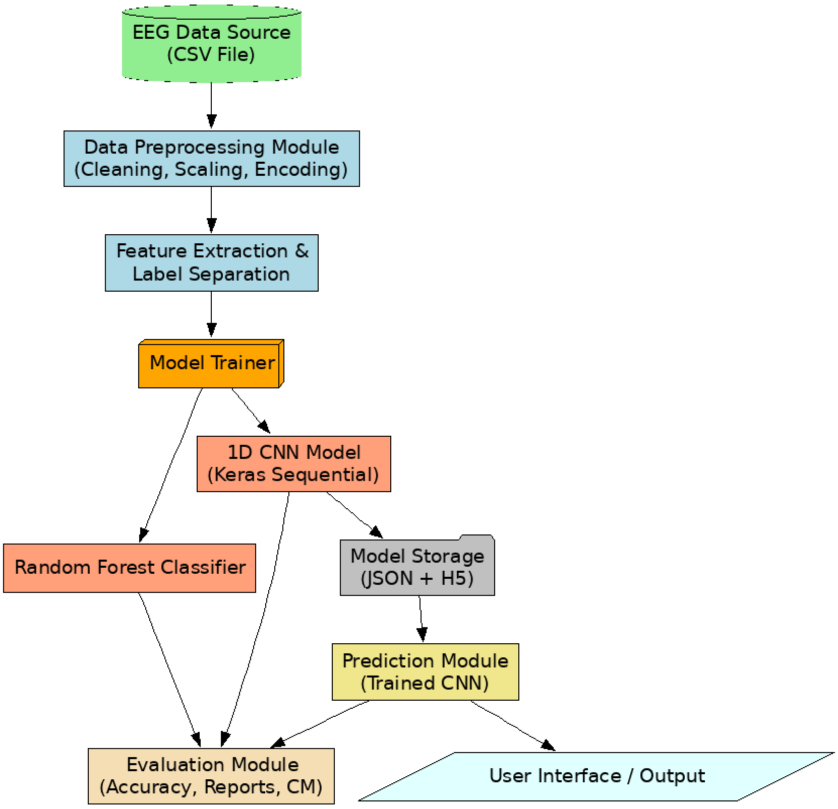

Figure: 2 Block diagram of proposed Model

Loading and Exploring the Dataset:

The project reads a dataset named 'Epileptic Seizure Recognition.csv' using pandas and displays basic information about the dataset, including columns, data types, and the number of missing values. It also visualizes the distribution of classes in the target column using a count plot.

Data Visualization:

There's a section dedicated to plotting subplots of specific features ('X1', 'X2', 'X3', 'X4', 'X5') against samples to visualize the data.

Data Preprocessing:

The code performs some basic data cleaning by dropping a column named 'Unnamed'. It then splits the dataset into features (X) and the target variable (y) and encodes the target variable using Label Encoder. Subsequently, it splits the data into training and testing sets and applies feature scaling using Standard Scaler.

Convolutional Neural Network (CNN):

The code defines a simple Convolutional Neural Network (CNN) using Keras and TensorFlow, compiles it, and trains it on the training data. It then evaluates the CNN's performance on the training set, generates a classification report, and visualizes the confusion matrix as a heatmap.

Model Saving and Loading:

It checks whether pre-trained model files ('model_architecture.json' and 'model_weights.h5') exist. If they do, it loads the model, prints the model summary, and calculates the training accuracy. If the files do not exist, it creates, compiles, and trains a new CNN, saves its architecture and weights, and optionally saves the entire model.

Making Predictions on Test Data:

The code attempts to make predictions on a test dataset ('test.csv') after reading and preprocessing it. However, there's an issue with the ordering of the code, as the test data should be defined before attempting predictions. There are some typos or potential issues in the code, such as the missing import statement for json and the incorrect usage of print (loaded_model_json. summary ()). Additionally, the full_model.h5 file is saved but not used later in the code. To improve the code, make sure to define the test dataset before attempting predictions and fix any typos or issues with the usage of variables.

3.2 Data preprocessing

Step 1: Dataset Collection

Start by collecting the relevant data needed for training and testing your model. The dataset is likely stored in a CSV file, such as 'Epileptic Seizure Recognition.csv', which could be sourced from open repositories like the UCI Machine Learning Repository or Kaggle. This dataset will typically include features representing various signals (e.g., X1, X2, X3, ... X178) measured from EEG or other biosignal data, and the target column (y) will indicate whether a seizure occurred (0 for no seizure, 1 for seizure). The dataset file could be in formats like .csv, .tsv, or .xlsx.

Step 2: Data Inspection and Initial Exploration

Once the dataset is collected, load it using libraries like pandas into a DataFrame. Begin by inspecting the first few rows of the dataset to get a sense of its structure and contents. Check the basic statistics and summary of the data using methods like describe(). This will provide an overview of the data types, summary statistics, and any potential outliers. Also, verify the data types of each column using info () to ensure they are as expected (e.g., integers, floats, or strings). Identify and handle any missing data by checking for null values with methods like isnull().sum().

Step 3: Data Cleaning

Data cleaning ensures that your dataset is free from errors that could affect the model's performance. Drop any unnecessary columns, such as "Unnamed" columns or identifiers that don't contribute to the model. Check for missing data and decide whether to impute missing values (e.g., using the mean, median, or mode for numerical columns) or drop rows/columns with too many missing values. Additionally, identify and remove any duplicate entries using the duplicated() method. For numerical features, inspect the data for outliers and consider removing them using methods like the IQR method or z-scores to avoid having extreme values negatively affect model performance.

Step 4: Data Transformation

Now that the data is cleaned, transform it into a suitable format for machine learning models. If the target labels (y) are not in numerical format, encode them using techniques such as Label Encoding or One-Hot Encoding to convert categorical data into numerical data. Scale the features using methods like Standardization (e.g., StandardScaler()) to ensure that all numerical features are on a similar scale, which can speed up convergence and improve performance in algorithms like neural networks and distance-based models. If you are working with sequential data (e.g., time series), consider reshaping the data into a 3D format suitable for neural networks, such as (samples, time_steps, features).

Step 5: Exploratory Data Analysis (EDA)

Explore the dataset further to uncover any patterns or insights. Visualize the distribution of the target variable (y) using a count plot to check if there is a class imbalance. Create visualizations for individual features (e.g., X1, X2) by plotting them against the target variable using techniques such as line plots, box plots, and histograms to identify potential relationships between the features and the target. Additionally, create a correlation matrix heatmap to see how numerical features correlate with each other. If some features are highly correlated, consider dropping one to avoid redundancy. Review the statistical summary of each feature to identify skewed distributions or large deviations.

Step 6: Splitting the Data

Once the data is preprocessed, split it into training and testing sets. This is crucial for ensuring that your model can generalize well to unseen data. Use techniques like **train-test split** to partition the dataset, typically using a ratio of 70-80% for training and 20-30% for testing. This ensures that the model is evaluated on data it has not seen before. Optionally, you can implement **cross-validation** (such as K-fold cross-validation) to improve the reliability of the model's performance by training and testing on different subsets of the data.

Step 7: Feature Engineering (Optional)

In some cases, creating new features or modifying existing ones can improve the model's performance. For example, you can combine multiple features to create interaction features, which may provide more useful information for the model. If the dataset contains too many features, consider using Principal Component Analysis (PCA) to reduce dimensionality while preserving as much variance as possible. This can make the model more efficient and potentially improve performance by focusing on the most important features.

Step 8: Model Selection and Training

At this stage, you can select the machine learning model you want to use for training. For the seizure recognition task, you could choose models such as Random Forest for traditional machine learning or Convolutional Neural Networks (CNN) if you are dealing with sequential or signal-based data. Train the model on the preprocessed training data using appropriate hyperparameters, and track performance metrics such as accuracy, precision, recall, and F1 score. For neural networks, ensure sufficient epochs are used and avoid overfitting by using validation data during training.

Step 9: Model Evaluation

Evaluate the trained model's performance on the test data, which was not seen during the training process. Use performance metrics like accuracy, precision, recall, and F1 score to assess how well the model is performing. Additionally, plot a confusion matrix to visually inspect how well the model is distinguishing between seizure and non-seizure cases. If the model performs much better on the training set compared to the test set, this could indicate overfitting, in which case you may need to apply techniques like regularization, dropout (for CNNs), or gather more data.

3.3 Train and Build Model

3.3.1 Convolutional Neural Network (CNN) Model

The Convolutional Neural Network (CNN), as proposed in the framework, is a deep learning architecture well-suited for handling structured spatial and temporal data such as EEG signals. CNNs are highly effective for extracting local features and learning hierarchical patterns through convolutional operations, pooling, and non-linear activations. In epileptic seizure detection, CNNs autonomously learn patterns in EEG signal matrices, eliminating the need for manual feature engineering, and improving both detection accuracy and adaptability across patients.

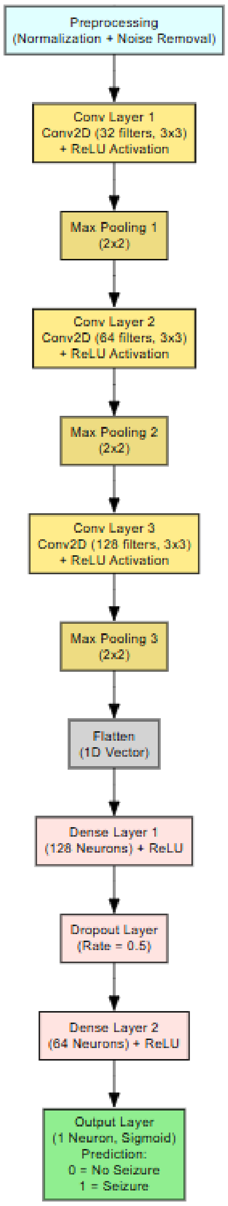

Figure 3: Convolutional Neural Network Block Diagram

Step 1: Input EEG Signal Transformation (Matrix Formation for CNN Input)

To prepare EEG signal data for CNN processing, raw EEG time-series are first preprocessed (e.g., filtering, normalization) and then reshaped into 2D or 3D matrices. This transformation allows the CNN to treat EEG sequences as image-like inputs to exploit spatial dependencies in frequency or electrode domains.

- **EEG Input Matrix (X_train):** Each EEG segment is reshaped into a fixed-size grid (e.g., [channels × time]) representing time-frequency features or electrode mappings.
- **Label Vector (y_train):** Binary target labels indicating seizure (1) or non-seizure (0) states for supervised training.

CNN models do not require hand-crafted features; they automatically extract relevant spatial-temporal features through layered transformations.

Step 2: Training the CNN Model

The CNN architecture is composed of stacked layers with distinct roles:

- **Convolutional Layers:** Perform feature extraction via filters (kernels) that slide over the EEG matrix, capturing signal variations, edges, and rhythmic patterns.
- **Activation Layers (ReLU):** Introduce non-linearity to capture complex seizure-related EEG characteristics.
- **Pooling Layers (Max/Average):** Downsample the feature maps to reduce dimensionality and emphasize dominant signal patterns.
- **Flattening Layer:** Converts 2D features into a 1D vector to feed into dense layers.
- **Fully Connected Layers:** Integrate learned features and perform classification based on seizure likelihood.
- **Output Layer (Sigmoid/Softmax):** Produces a binary output—Seizure or Non-Seizure.

Training involves minimizing a binary cross-entropy loss using backpropagation and optimizers like Adam or SGD, iterating over several epochs for convergence.

Step 3: Testing the CNN Model with New EEG Segments (X_test)

Once trained, the CNN model is evaluated on unseen EEG data (X_test), formatted in the same matrix structure as the training data.

- The model processes each EEG segment through its learned layers.
- Features are automatically extracted and classified into seizure or non-seizure.
- Output predictions are generated based on activation of the final layer neurons.

CNN models are capable of real-time classification due to optimized matrix operations and GPU acceleration, making them suitable for live EEG monitoring systems.

Step 4: Prediction and Evaluation (y_test)

The predicted outputs (y_test) are compared against the true labels to measure model performance:

- If CNN successfully identifies seizure segments, it confirms effective deep pattern learning.
- Misclassifications highlight data noise or edge cases in EEG variability.

Evaluation metrics include:

- **Accuracy:** Overall correct predictions.
- **Precision/Recall:** Sensitivity to seizure detection and avoidance of false alarms.
- **F1-Score:** Balanced metric for performance.
- **AUC-ROC:** Measures separability between seizure and non-seizure classes.

Advanced techniques like dropout, batch normalization, or attention mechanisms can be integrated to further enhance generalization and robustness.

4. RESULTS AND DISCUSSION

4.1 Dataset description

The Epileptic Seizure Recognition dataset is a well-structured and widely-used resource aimed at evaluating machine learning models for detecting epileptic seizures from EEG (Electroencephalogram) signals. Its primary objective is to support automated seizure classification tasks by providing preprocessed EEG signal segments labeled with their respective seizure activity. Publicly available, the dataset has been extensively used in biomedical signal processing research. It comprises 11,500 rows and 179 columns, with each row representing a 1-second EEG recording. The first 178 columns (f1 to f178) are numeric features recording the amplitude values of EEG signals sampled at approximately 178 Hz over a 1-second duration. The 179th column, labeled as "y", represents the class label for that particular EEG signal segment. This consistent signal length and feature structure make the dataset particularly suitable for deep learning-based models like 1D Convolutional Neural Networks (CNNs). The class label "y" contains five distinct integer values from 1 to 5, corresponding to different brain states: Class 1 represents seizure activity (the target class), while Classes 2 through 5 represent non-seizure states, including recordings from non-seizure patients, healthy individuals with eyes open or closed, and tumor-affected brain regions without seizures. For binary classification, the dataset is simplified by recoding Class 1 as ‘1’ (Seizure) and grouping Classes 2 to 5 under ‘0’ (Non-Seizure). Each EEG signal is uniformly sampled at about 178 data points per second, producing fixed-length sequences that capture subtle fluctuations in brain activity—key for identifying seizure patterns. As the data is pre-segmented into 1-second windows, it is already synchronized and ready for model input without additional segmentation. Several preprocessing steps are required to make the dataset compatible with machine learning or deep learning pipelines. These include label encoding to transform the problem into binary classification, normalization techniques like Min-Max scaling or Z-score standardization to ensure uniform feature contribution, and reshaping the data into (178, 1) format to make it suitable for CNNs, treating each sequence as a single-channel input. However, the dataset presents a class imbalance issue, with only 2,300 samples labeled as seizures and 9,200 as non-seizures. This imbalance may bias the model toward the majority class, so techniques like SMOTE (Synthetic Minority Oversampling Technique), random undersampling, or class weighting during training are employed to improve model sensitivity to seizures. The dataset's structure and temporal consistency make it especially suitable for 1D CNN architectures, which can effectively learn local signal variations and temporal dependencies essential for recognizing sudden bursts or rhythmic patterns typical of seizures. This relevance to CNNs enhances the model’s ability to extract meaningful temporal features for classification. In real-world scenarios, the dataset’s labeled and structured nature supports the development of real-time EEG-based seizure detection systems. Such applications range from mobile health monitoring and intelligent hospital alert systems to embedded AI solutions in EEG headsets.

Additionally, the diversity in non-seizure states enhances the model's generalization capability across different patient profiles.

4.2 Result analysis

Figure 4 shows Count Plot of Epileptic Seizures presents a count plot depicting the distribution of epileptic seizures within the dataset. It visualizes the balance or imbalance of different classes related to seizures.

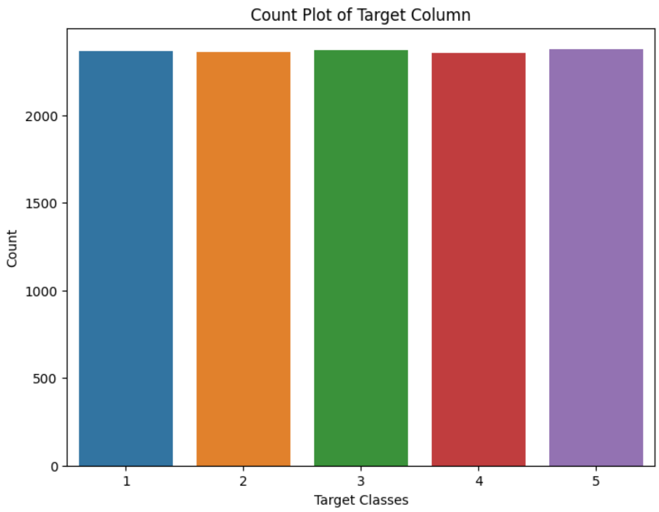

Figure 4: Count plot of Epileptic seizures

Figure 5 Plot Shows the Signal of ECG for Single Row in Dataset displays a plot showing the signal of an Electrocardiogram (ECG) for a single row in the dataset. It provides a visual representation of the ECG signal, which is likely a crucial aspect for epileptic seizures detection.

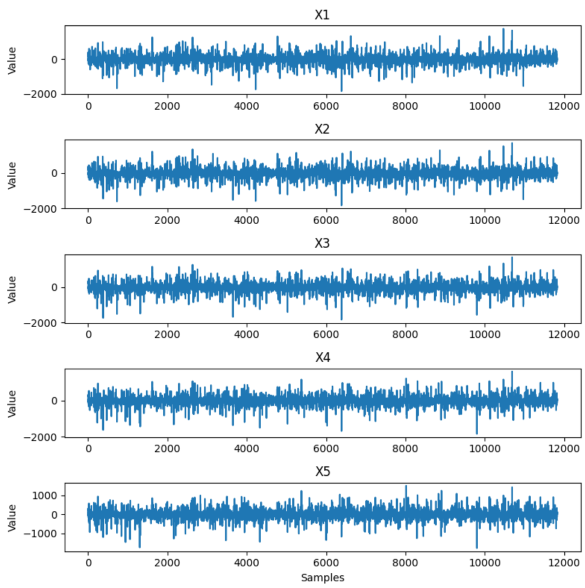

Figure 5: plot shows the signal of ECG for single Row in dataset

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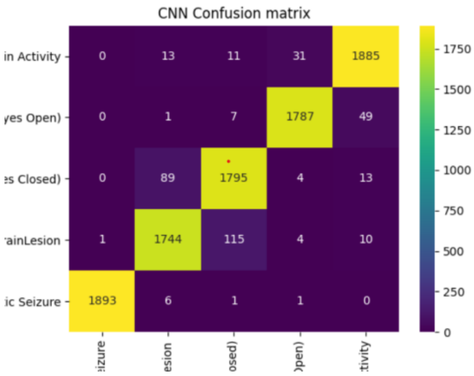
(a)



(b)

Fig 6 (a),(b) Confusion matrix of existing RFC and proposed CNN

The confusion matrices of the existing Random Forest Classifier (RFC) and the proposed Convolutional Neural Network (CNN) model provide a clear visual representation of the classification performance across different classes. In the RFC confusion matrix, there is significant misclassification among several classes. For instance, many instances of the Epileptic Seizure class are misclassified into other categories such as Eyes Closed and Brain Activity, with 436 samples being wrongly predicted as Seizure from various classes. Similarly, the RFC model struggles with distinguishing between Eyes Open and Eyes Closed, showing considerable overlap. In contrast, the CNN confusion matrix shows remarkable improvement in correctly identifying the classes. For example, 1893 instances of Epileptic Seizure are accurately classified, and classes like Eyes Closed and Brain Lesion also show high precision, with minimal confusion among adjacent categories. The CNN model’s ability to sharply differentiate between complex neurological states is evident in the sharply defined diagonal and significantly reduced misclassifications. The stark contrast confirms that the CNN model delivers a much more reliable and robust classification, minimizing cross-category errors and offering superior predictive capability over the RFC model.

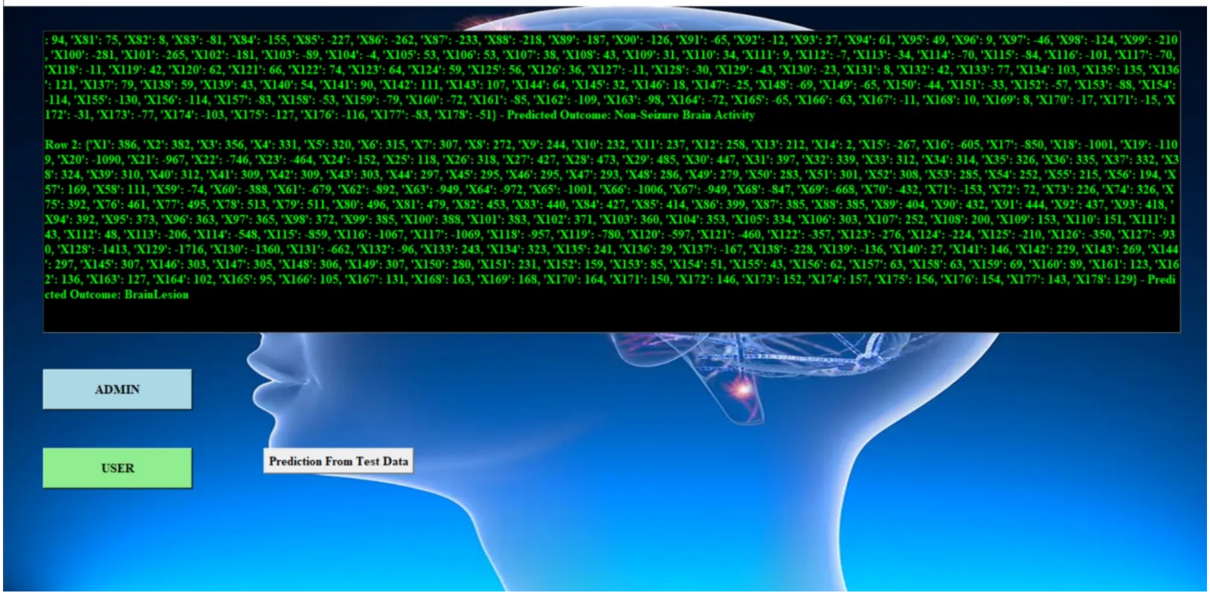


Fig 7: After user login Prediction of test Data using CNN

Figure 7 describes Upon logging in as a user and clicking the "Prediction From Test Data" button in the system interface for Deep Learning Approaches for Epileptic Seizure Detection and Classification, the application processes EEG data through a trained Convolutional Neural Network (CNN) model to predict neurological conditions. The interface displays the input feature values (such as X1, X2, ..., X178) for each test data row and provides a corresponding predicted outcome based on the analysis. For example, in the output shown, Row 1 is classified as Non-Seizure Brain Activity, while Row 2 is identified as BrainLesio*n*. These predictions are generated by analyzing the complex patterns within the EEG signal data, allowing for precise detection of epileptic seizures and related brain conditions. The detailed results, along with the clear presentation of input features and predictions, enhance the usability of the model for medical professionals in making informed decisions.

Table.1 Performance Comparison of Various Algorithms

Performance Comparison Table: Existing RFC vs. Proposed CNN

Metric	Existing RFC	Proposed CNN
Accuracy	89.89%	96.32%
Precision	89.97%	96.32%
Recall	89.92%	96.31%
F1-Score	89.90%	96.31%

The Table 1 performance evaluation between the existing Random Forest Classifier (RFC) and the proposed Convolutional Neural Network (CNN) model demonstrates a clear improvement across all key classification metrics. The proposed CNN achieved an impressive accuracy of 96.32%, significantly surpassing the RFC's accuracy of 89.89%, indicating a stronger overall prediction capability. In terms of precision, which measures the model's ability to correctly identify positive results, the CNN scored 96.32%, again outperforming the RFC's 89.97%. Similarly, the recall value, reflecting the model's ability to detect all relevant instances, improved from 89.92% with RFC to 96.31% with CNN. Lastly, the F1-Score, which is the harmonic mean of precision and recall, rose from 89.90% in the RFC model to 96.31% in the CNN model. This consistent improvement across all metrics signifies that the CNN model provides a more robust and accurate solution, making it a superior alternative for the problem domain compared to the traditional machine learning approach using RFC.

5. CONCLUSION

The application of these advanced architectures has demonstrated a tangible impact on diagnostic accuracy, enabling the identification of intricate patterns within electroencephalogram (EEG) signals. This breakthrough holds the potential to revolutionize epilepsy diagnosis, providing healthcare professionals with timely and precise information for effective intervention and treatment planning. Moreover, the integration of patient-specific data into deep learning models offers a path towards personalized treatment strategies, contributing to improved outcomes and quality of life for individuals with epilepsy.The long-term monitoring capabilities afforded by deep learning models further support comprehensive disease management. Continuous tracking of EEG signals allows for a nuanced understanding of seizure frequency, duration, and patterns, facilitating the refinement of treatment plans over time. The insights gained from deploying advanced deep learning architectures also contribute to a deeper understanding of the underlying mechanisms of epileptic events, opening avenues for further research and the development of novel therapeutic approaches. The integration of multimodal data, such as genetic information and lifestyle factors, could further enrich the depth of analysis, paving the way for even more personalized and targeted interventions. Additionally, the scalability and accessibility of deep learning solutions present opportunities for widespread implementation across diverse healthcare settings. The development of user-friendly interfaces and integration into existing medical infrastructure can democratize advanced diagnostic tools, ensuring that the benefits of these innovations reach a broader spectrum of patients, including those in remote or underserved areas. Collaborative efforts within the scientific community, along with ongoing advancements in computing technology, will likely contribute to the creation of standardized benchmarks and evaluation metrics. This collaborative approach fosters healthy competition, accelerates progress, and establishes a foundation for the continued refinement of deep learning models in epilepsy research.

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