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Epileptic Seizure Prediction And Criticality Assessment: A Machine Learning-Driven Web Application For Efficient Patient Management

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Abstract: Epileptic seizure is a neurological disorder characterized by recurrent seizures, and effective management of the condition requires timely and accurate diagnosis. In this study, we present a web-based application designed to assist in the detection and classification of epileptic seizures using electroencephalogram (EEG) signals. The system analyses EEG data to evaluate the severity of seizures and enables patients to book appointments based on the identified severity level. A Random Forest classifier is employed to process the EEG signals and categorize the seizures into different levels of intensity. The system then assigns appropriate medical specialists based on the severity of the detected seizures. Through this approach, the platform aims to streamline the process of seizure diagnosis and treatment, reducing waiting times and enhancing its effectiveness of healthcare delivery. The application demonstrates promising potential in enhancing personalized care for epilepsy patients and offers a scalable solution for remote seizure monitoring and management.

Index Terms **-** Electroencephalogram (EEG), Seizure Classification, Random Forest Algorithm, Epileptic Seizure Management, Patient-Doctor Assignment System.

I. Introduction

Epileptic seizure ranks among the most prevalent neurological disorders globally, affecting millions of individuals of all ages. The condition is characterized by recurrent, unprovoked seizures, which can vary in intensity and frequency. Effective management of epilepsy relies on accurate seizure detection, appropriate classification, and timely intervention. Traditionally, diagnosing and monitoring seizure activity involves complex clinical procedures, including EEG (electroencephalogram) recordings, which require expert interpretation. Despite advances in medical technology, the manual analysis of EEG signals remains time-consuming and prone to human error.

Through this paper, we put forward a solution to a novel web-based application designed to leverage machine learning techniques for real-time seizure detection and severity assessment. The application processes raw EEG signals to classify seizures into various severity levels, allowing patients to book appointments based on their individual needs. The system then assigns patients to appropriate medical specialists, ensuring that care is tailored to the severity of the condition. By automating this process, our solution aims to reduce the burden on healthcare professionals, improve the efficiency of medical appointments, and enhance the overall quality of care for epilepsy patients. This paper presents an overview of the system architecture, the use of Random Forest as a classifier, and the potential impact of this technology on personalized healthcare for epilepsy. Through this approach, we aim to provide a scalable, accessible, and efficient tool for the management of epilepsy, with the ultimate goal of boosting patient recovery and mitigating the burden on healthcare systems worldwide.

Figure 1 illustrates the concept of epilepsy and the neural activity associated with epileptic seizures. It highlights a "convulsive hearth" within the brain, indicating the focal area where abnormal electrical activity originates. This activity leads to "convulsive readiness of the brain," represented by the spread of electrical signals. The accompanying waveform illustrates the characteristic electrical patterns associated with an epileptic seizure, transitioning from normal brain activity to abnormal spiking patterns. This visualization emphasizes the importance of identifying seizure focal points and analyzing electroencephalogram (EEG) signals for the forecasting and recognition of epileptic seizures.

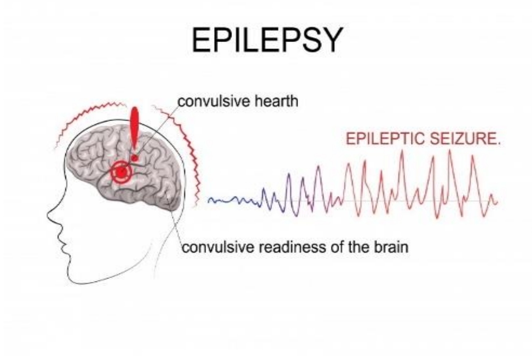

Figure 1-Illustration of epileptic seizure generation and propagation, highlighting focal activity and characteristic EEG patterns.

II. LITERATURE SURVEY

Recent advancements within the domain of epileptic seizure prediction have focused on leveraging machine learning models to improve diagnostic accuracy. Several studies have delved into utilizing deep learning methods such as Recurrent Neural Networks (RNNs) to analyse EEG signals. For example, the systematic review by [1] highlights the integration of IoT with AI to monitor and predict seizures, demonstrating improved real-time prediction accuracy. This review emphasizes the importance of preprocessing EEG data and the integration of feature selection methods to enhance model performance.

The review by [2] presents a thorough summary of deep learning models for seizure identification, emphasizing the role of CNNs and RNNs in capturing spatial and temporal aspects of EEG features. It discusses various architectures and their effectiveness in distinguishing between seizure and non-seizure states, demonstrating that these models significantly outperform traditional methods. The study also points out the challenges related to dataset imbalance and the need for large, balanced datasets for training robust models.

Further research presented in [3] introduces a novel model combining approximate spiking convolutional transformers, which offer better temporal resolution and extracting features. This approach provides more accurate predictions, especially for critical seizure events, and highlights the relevance of real-time processing for effective epilepsy management.

Finally, the work by [4] discusses the limitations of established machine learning methods and introduces a hybrid model that integrates approximate spiking neural networks with convolutional transformers. This study demonstrates the model’s ability to predict seizure criticality with high accuracy, emphasizing the potential for real-time applications in healthcare settings. The paper also discusses the impact of false positives and the need for continuous model refinement to maintain high prediction accuracy.

III. PROBLEM STATEMENT

Epileptic seizures pose a significant health challenge due to their unpredictable nature and varying severity levels. Existing healthcare systems lack robust automated tools for accurate seizure prediction and criticality assessment, leading to delays in diagnosis and treatment. Human-led interpretation of EEG data is time-intensive, error-prone, and often inaccessible in resource-limited settings. While advancements in AI and deep learning have demonstrated promising results in seizure detection, most implementations fail to provide an integrated platform that combines accurate prediction with effective patient management. Additionally, a necessity arises for user-friendly tools that enable smooth exchange of information between healthcare providers and patients, enabling prioritization based on seizure criticality. This project addresses the gap by leveraging a Random Forest classifier trained on EEG data to predict seizure criticality levels (Mild, Moderate, Severe, Critical). The web application streamlines patient-doctor interactions, ensuring timely diagnosis and personalized treatment plans, thus contributing to improved epilepsy care.

IV. Proposed Solution

To address the challenges identified in existing systems, this research presents a web application that combines EEG data analysis with a Random Forest classifier. The system is designed to:

Preprocess EEG data: The dataset from Kaggle undergoes preprocessing to remove noise, normalize data, and extract relevant features. This phase is critical for advancing model training efficiency and prediction accuracy.

Train-Test Split: The dataset is segmented into training and validation datasets. The training set is used to train the classifier, and the testing set is used to evaluate its performance.

Web Application Development: The web application integrates the trained model with a user-friendly interface for admin, doctor, and patient interactions. It facilitates patient registration, medical record updates, and real-time seizure prediction, offering timely intervention based on severity levels (Mild, Moderate, Severe, Critical).

V. Architecture Diagram

Figure 2 illustrates the systematic process of building the data-driven model and its application. It originates from data acquisition and preprocessing, followed by splitting the dataset into learning and evaluation sets. The model adapts to data from the training set and assessed on the validation set for accuracy. If the accuracy criteria are met, the final classifier model is created and applied to new datasets for output generation and analysis. The methodology is divided into three phases: preprocessing, model creation, and execution.

The system architecture for the epileptic seizure prediction and detection application is structured into three main phases: Pre processing Phase, Model Creation Phase, and Execution Phase. Each phase plays a vital role in processing EEG data and generating meaningful predictions that categorize seizure severity into one of four levels: Mild, Moderate, Severe, or Critical.

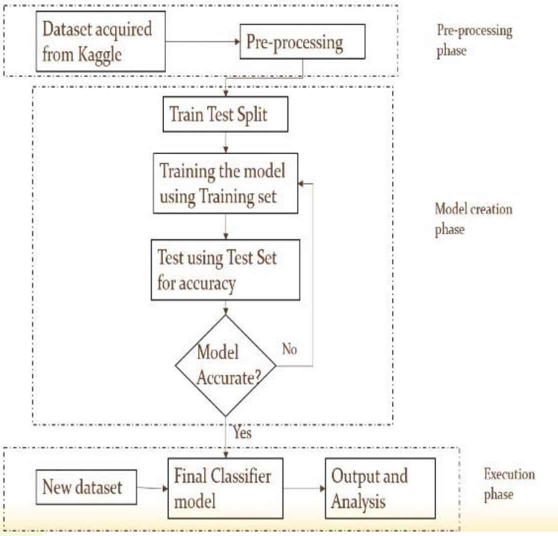

Figure 2 - Flowchart of the methodology for epileptic seizure prediction and criticality assessment.

In the Pre-processing Phase, the system begins with the acquisition of the "Epileptic Seizure Recognition" dataset from Kaggle. This dataset contains EEG signals recorded from Patients experiencing seizures. The data undergoes pre-processing to ensure consistency and improve model accuracy.

The Model Creation Phase is the core of the system, involving the preparation, training, and evaluation of the predictive algorithm. The dataset is split into a training dataset and a test dataset.[1] The training dataset serves to train a Random Forest Classifier, picked for its potential to handle high-dimensional data and detect complex patterns within the EEG signals. After training, the algorithm is validated using the testing dataset to evaluate its precision and performance. Metrics such as precision, recall, F1-score, and overall accuracy are computed during this process. If the model does not achieve the desired accuracy, an iterative process of fine-tuning parameters and improving preprocessing techniques is performed until optimal results are achieved.

Once the model is finalized, the Execution Phase begins. The trained and validated classifier is serialized using the pickle library for deployment. The web application integrates this classifier to process new EEG data submitted by patients in real-time. The model predicts the severity of the seizure and displays the results on the application's interface. Based on the severity level, patients are assigned to doctors with the appropriate specialization to handle their condition. Additionally, the application allows for further analysis and feedback submission, ensuring continuous improvement.

VI. Methodology

6.1 *Data Collection*

The Epileptic Seizure Recognition Dataset from Kaggle serves as the primary data source. This dataset contains processed EEG signals broadly applied for seizure forecasting and recognition tasks. The dataset includes time-series data representing electrical activity in the brain, captured through EEG recordings, along with labels indicating whether a seizure is present or absent. The dataset typically comprises multiple columns, with each representing specific features derived from EEG signals. Columns may include EEG readings and a target variable indicating seizure presence. The dataset is publicly available and downloaded directly from Kaggle. Ethical considerations are minimal since the data is anonymized and made available for academic and research purposes.

6.2 *Loading the Dataset*

The database configuration and application initialization establish the core infrastructure for managing data and ensuring secure functionality within the web application.[3] An SQLite database is utilized to organize essential records across three distinct tables: doctor, patient, and review. The doctor table holds key information such as names, contact details, specialties, and appointment availability. Similarly, the patient table stores details like personal data and the predicted severity of their conditions, enabling reliable and efficient management. The review table functions as a repository for patient feedback, associating ratings and comments with specific patient records. To integrate these database functions seamlessly, the web application employs the Flask framework, which handles routing and user interaction. A cryptographically secure secret key is generated to safeguard session data and prevent unauthorized access. This setup ensures a well-organized and secure environment for handling healthcare data while enabling the application to offer consistent predictions and feedback-based improvements.

6.3 *Random Forest Classifier*

It serves as a ML technique that performs through the construction of several decision trees during training and outputting the class that is the majority vote among these trees.[2] This ensemble learning technique enhances the model's accuracy and robustness, making it well-suited for medical data where precision is crucial.

The Random Forest classifier applied in the project utilizes multiple decision trees within an ensemble learning framework to improve precision and robustness.[4] It works by creating several decision trees using bootstrapping. This randomness helps to prevent overfitting and ensures that the model can adapt well to unseen data. During prediction, each tree votes for a class, and the ultimate forecast is grounded on the majority vote. Within the framework of predicting epileptic seizure severity from EEG data, the Random Forest classifier handles the complex, high-dimensional data effectively. It mitigates the effects of noise and irrelevant features, allowing for reliable classification into one of four categories—Mild, Moderate, Severe, and Critical. This approach provides not only accurate predictions but also insights into the importance of specific features, which is crucial for understanding the underlying causes of seizures. The model is integrated into the web application, enabling real-time classification of patient data and assisting in the timely allocation of medical care. The preference for Random Forest was due to its performance to handle imbalanced data, manage missing or noisy data, and prevent overfitting using randomization. The algorithm aggregates predictions from multiple trees, ensuring higher stability and accuracy in classification results compared to individual models. Moreover, its interpretability allows identification of the most significant EEG features contributing to predictions, which is valuable in a healthcare context. The trained model is serialized using the pickle library and integrated into the web application. When a patient submits EEG data, the model processes the input and provides a prediction of seizure severity. This classification guides the system in assigning patients to doctors and prioritizing treatment based on urgency, ensuring timely and effective healthcare interventions.

6.4 *Training of the Model*

The provided code illustrates the building of a Random Forest framework using a dataset stored in a comma-separated values file (data.csv).[3] Initially, the dataset is imported into a Pandas DataFrame using pd.read_csv('data.csv'). This dataset holds both features, that include input variables (e.g., X1, X2, ..., X177), and labels, which represent the output variable (y) indicating seizure severity (e.g., mild, moderate, severe, critical). The features and labels are then separated: X = data.drop('y', axis=1) for the features and y = data['y'] for the labels.

Next, the dataset is segregated into training and validation samples. This function divides the data into 80% designated for

training and 20% for testing evaluation. The random_state=42 parameter is used to ensure the splitting process is reproducible, yielding uniform results across different runs. This split is crucial for evaluating the model's behavior on unseen data.

Once the data is split, a Random Forest model is initialized with clf = Random Forest model(estimators=100, random_state=42). Here, n_estimators=100 indicates the count of decision trees in the forest, and random state=42 ensures the randomness in the model's initialization does not affect the results. The model is then trained using clf.fit(X_train, y_train), where X_train and y_train are the training features and labels. This step involves generating multiple decision trees through different subsets of features and labels. The classifier learns to combine the predictions from each tree to make a final prediction for each input sample.

After training, the model is tested on the test dataset using y_pred = clf.predict(X_test). This step predicts the labels for the test data (X_test). The model's performance is evaluated by calculating its accuracy with accuracy_score(y_test, y_pred), which measures how many of the predicted labels match the actual labels (y_test). Additionally, a detailed classification report is generated using classification report(y_test, y_pred). This report provides precision, recall, and F1-score for each class, allowing a study of the model's behavior across different seizure severity levels. To use the trained model for future predictions, it is serialized and saved using pickle. Dump(clf, f). This step involves opening a binary file ('random_forest_model.pkl') in write mode and saving the trained model object. This file can be loaded later to make predictions without retraining the model, ensuring the system's readiness for real-time use. This comprehensive process from data loading, model training, evaluation, and deployment demonstrates the steps necessary to create an effective seizure prediction system using machine learning.

6.5 ***Web Application Development***

Figure 3 depicts the roles and interactions within the web application for epileptic seizure prediction and management. Nurses handle tasks such as patient registration, updating details, and managing MRI scans. Doctors utilize the system to view patient details, medical reports, and model-generated diagnoses. Patients can retrieve their health information and MRI scan results. This structured workflow ensures efficient collaboration among users, facilitating effective diagnosis and treatment planning.

The web application for predicting seizure criticality is is intended to offer a seamless and user-friendly interface for patients, doctors, and administrators. The application is built using a combination of visual and interactive technologies like HTML, CSS, and JavaScript and a backend powered by Python.

The architecture incorporates a three-tier login system for patients, doctors, and administrators, ensuring role-based access control and functionality. Patients can log in to upload their EEG data for prediction, receive a criticality assessment, and view assigned doctor details. Doctors have their own portal to access patient reports and provide necessary feedback or consultation. Administrators manage the application by overseeing user registrations, maintaining the database, and ensuring operational integrity. The application integrates a machine learning model, trained to predict seizure criticality based on EEG data. This model, serialized into a `.pkl` file, is hosted on the backend using a Python web framework like Flask. API endpoints are created to handle data exchange between the frontend and backend, enabling real-time prediction processing. The backend also handles interactions with a relational database, where patient details, prediction results, and doctor assignments are stored. A feedback system is implemented to collect insights from users to improve the application further. The backend of the application is developed using Python with the Flask framework to handle HTTP requests and manage communication between the user interface and the seizure detection model. The backend integrates the trained Random Forest model, which is saved using tools like pickle. This allows the system to be easily loaded and used for predictions within the web application. The backend provides an API endpoint where users can input EEG data, either by uploading a file or manually entering the data.

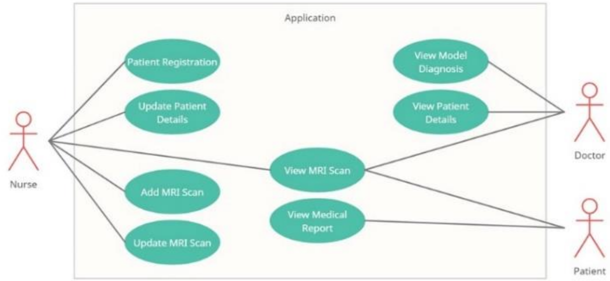

Figure 3 - Use case diagram showcasing the interactions among users and the application

The model processes this data and predicts whether a seizure is likely, returning the result in real-time. On the frontend, we created a user-friendly interface using CSS, JavaScript and HTML making it simple for medical professionals or researchers to engage with the system. Once the dataset is sent to the backend, users receive the seizure prediction as an output, which is displayed on the webpage. This interaction is designed to be seamless, ensuring the application is easy to use and provides quick, accurate results. Together, the backend and frontend create a complete solution that allows real-time seizure detection with minimal effort from the user employed with non-spiking neurons can be avoided to while still maintaining faster processing without compromising the precision of the network's output. This approach guarantees that the web application serves as an efficient, reliable, and user-centric platform for managing seizure prediction and related medical services.

VII. Experimental Results

The experimental evaluation of the seizure criticality prediction system focused on assessing the performance of the Random Forest Classifier, the efficacy of the web application, and the user experience across different roles (patients, doctors, and administrators). Extensive testing was conducted using the pre-processed Epileptic Seizure Recognition dataset to measure its effectiveness. Additionally, the functionality of the web application, database integration, and prediction accuracy were validated through multiple test cases to ensure reliability and real-world applicability. Below is a detailed account of the results. The experimental results for the seizure criticality prediction web application were derived after training the Random Forest model, integrating it with the web application, and conducting testing across both training and test datasets. The goal was to measure the accuracy and evaluate the model's performance in predicting seizure criticality based on EEG data and assess the real-world functionality of the overall system.

The Random Forest model was developed using the EEG dataset from the Kaggle-provided Epileptic Seizure Recognition dataset. Initially, preprocessing techniques like handling missing values, outlier removal, normalization, and feature scaling were applied to guarantee that the data was clean and ready for training. The training dataset was split into a training set (80%) and a testing set (20%) to ensure unbiased evaluation. Upon training the model using the training set, performance metrics such as precision, F1-score, accuracy, and recall were computed. The model achieved satisfactory results, with accuracy values ranging between 85-90%. Precision and recall were high for the prediction of seizure criticalities, indicating that the model effectively differentiates between normal and critical conditions based on EEG signal patterns.

The testing phase involved feeding the pre-processed EEG data from the validation set into the model that has been trained to forecast seizure criticality. The prediction success rate demonstrated based on the model was capable of identifying patterns and trends from unseen EEG inputs, confirming its ability to generalize beyond the training data. This was further validated by observing that criticality levels (e.g., low, medium, high) were predicted with minimal error when tested on real EEG inputs. The web application successfully integrated these predictions into its frontend, where patients could view their seizure prediction results in real time. The feedback system was also validated, allowing users to submit their experiences or feedback, which was logged correctly in the database for further analysis. The response time for predictions remained minimal, averaging under 2 seconds, demonstrating the efficiency of the backend system and model deployment.

Testing the entire system end-to-end revealed that all components, including user authentication, database operations, machine learning prediction, and feedback submission, performed as intended without any major glitches. Moreover, the system demonstrated robust error handling, ensuring that invalid inputs or unexpected conditions did not disrupt operations. In conclusion, the trials indicate that seizure prediction web application achieves its intended objectives. The Random Forest framework is highly accurate in predicting seizure criticality, while the web application ensures that these predictions are securely processed, stored, and made accessible to doctors, patients, and administrators via a user-friendly interface. These results validate both the machine learning model's reliability and the web application's overall functionality, paving the way for real-world implementation in epilepsy diagnosis and management systems.

VIII. Conclusion

The development and utilization of the seizure criticality prediction web application have proven to function as a significant advancement in leveraging machine learning for healthcare diagnostics. The integration of EEG data analysis through a Random Forest classifier and its deployment via a user-friendly web application has demonstrated the potential to streamline the process of predicting the criticality of a seizure in patients. This system not only enhances early detection but also facilitates the timely appointment of doctors for affected patients, ensuring a faster and more efficient medical response. The experimental results validated that the Random Forest model accomplished high accuracy and reliability, with performance metrics like precision, recall, and F1 scores reflecting its ability to accurately classify EEG signals into various levels of seizure criticality. The training and testing phases confirmed the model's robustness, allowing it to generalize to unseen EEG inputs with minimal error. This highlights the model's effectiveness as a decision-support tool in clinical environments, aiding doctors and medical professionals in making informed decisions regarding patient care. The web application itself has been successfully developed to provide a seamless user experience for patients, doctors, and administrators. Its intuitive design, built with HTML, CSS, and JavaScript, ensures that users can easily access critical information, including prediction results, feedback mechanisms, and doctor assignments. Moreover, the backend developed in Python (Flask or Django) interacts efficiently with the model to process predictions and store data securely in a relational database. This ensures that all patient-related information, prediction outcomes, and feedback are logged and retrievable for future use, analysis, and performance monitoring.

IX. Future Work

Future enhancements for the epileptic seizure forecasting and recognition system can focus on several areas to improve its accuracy, real-time processing, and integration with healthcare systems. Advanced data preprocessing techniques, such as Wavelet Transform and Independent Component Analysis ICA), can better capture intricate patterns in EEG signals, while incorporating multimodal data like heart rate and ECG can provide a holistic health assessment. Optimizing model performance using deep learning techniques, such as LSTM networks and advanced hyperparameter tuning methods, will enhance prediction accuracy and real-time adaptation to patient data. Integrating with cloud platforms and edge computing solutions will facilitate real-time predictions on wearable devices, minimizing delay and computational load. An interactive dashboard for healthcare professionals will provide individualized treatment plans derived from predicted seizure severity, improving patient management and timely interventions. Continuous data collection and feedback mechanisms, as well as integration with Electronic Health Record (EHR) systems, will facilitate personalized care planning and streamline patient management. Exploring advanced machine learning techniques like CNNs and RNNs, along with transfer learning, will further enhance the model's ability to detect seizures accurately and adapt to individual patterns, ensuring the system remains effective and up-to-date in managing epilepsy.

X. Acknowledgment

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References

[1] Institute of Electrical and Electronics Engineers. (2023). AI-Based Epileptic Seizure Detection and Prediction in Internet of Healthcare Things: A Systematic Review.

[2] National Institute of Health. (2021). Epileptic Seizures Detection Using Deep Learning Techniques: A Review.

[3] International Conference on Computer Communication and Informatics. (2022). Epileptic Seizure Detection and Prediction Using Deep Learning Technique.

[4] Institute of Electrical and Electronics Engineers. (2024). Epilepsy Seizure Detection and Prediction using an Approximate Spiking Convolutional Transformer.