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NeuraNest: EEG-based Smart Seizure Detection and Alert System

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***Abstract*—Epileptic seizures are dangerous to health because they occur suddenly and unpredictably. Here, we introduce a seizure prediction system consisting of a deep learning model integrated with an interactive web interface. The underlying model is a hybrid architecture that combines Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN), trained on the publicly available CHB-MIT EEG dataset. This model effectively detects both spatial features and temporal relationships over extended periods in EEG activity to distinguish seizure from non-seizure activity. The web application enables the upload of EEG recordings in European Data Format (EDF), which are automatically pre-processed and analysed using a trained model. There is also an SOS alarm facility in the system that alerts all registered caregivers in case a seizure is detected. This project aims to deliver an effective, practical, and responsive seizure prediction system that is beneficial to epilepsy patients and families in real-world settings**

***Index Terms*— CHB-MIT EEG dataset, CNN (Convolutional Neural Networks), EEG (Electroencephalography), epileptic seizures, LSTM (Long Short-Term Memory) networks, real-time seizure prediction, seizure detection, SOS alarm, web interface.**

I. INTRODUCTION

Epilepsy is a chronic neurological disorder that affects over 50 million people worldwide, characterized by recurrent seizures triggered by abnormal electrical activity within the brain. Seizures are often unprovoked and pose a significant threat to patient's physical safety and quality of life. There is a need for early detection and alerting systems to reduce the impact of seizure attacks and provide for instant care. Traditional approaches to managing seizures have not relied much on medications and treatment after an attack, with there being few early warning or real-time monitoring measures in place.

With advances in machine learning and wider availability of EEG (electroencephalogram) data, seizure detection on an automated level has been a prospective area of research. Here, we apply the CHB-MIT Scalp EEG Database, a widely used benchmarking data set for analyzing epileptic seizures. EEG signals from the data set are notorious for their nature of being highly complex and therefore require models capable of understanding spatial patterns between channels as well as temporal sequences over time.

To address this, we suggest a hybrid deep learning framework of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks.

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The CNN blocks extract informative spatial features from multi-channel EEG input, while the LSTM blocks extract temporal dependencies necessary for seizure pattern detection in time. This LSTM-CNN framework enhances the model's ability to differentiate between seizure and non-seizure states with good accuracy.

The trained model is deployed in a web interface specifically designed for use in real-world applications. The EEG data is uploaded by the users in the EDF format, which is preprocessed automatically, e.g., handling class imbalance and normalization, before inputting to the model to make predictions. In the event of seizure detection, the system sends an SOS alarm immediately to the registered caregivers of the patient via the platform so that quick action and assistance may be provided.

This project will close the gap between practice and research by offering a seizure monitoring device that is user-centered, responsive, accurate, and accessible. This will help us increase patient safety and enhance proactive health management in the treatment of epilepsy.

II. Literature Review

Aarabi et al. [10] illustrates that in recent years has seen a large amount of research on the prediction of epileptic seizures using EEG signals, utilizing both conventional signal processing techniques and cutting-edge machine learning techniques. The foundation for later research was laid by early studies which emphasized important issues and precautions in EEG seizure prediction. Z. Zhang et al. [8] proposes a simple and efficient method for predicting epileptic seizures using iEEG/sEEG brain signals. It extracts two key features: spectral power across various frequency bands (e.g., delta, theta, alpha) and the ratios between them. These features are used to train a classifier, such as an SVM, to identify patterns that appear before a seizure (preictal state). The approach is low in complexity, making it suitable for real-time and portable medical devices.

M. Bayoumi et al. [1] presents an efficient epileptic seizure prediction method using deep learning techniques. The authors design a deep neural network model that automatically learns features from raw EEG data, eliminating the need for manual feature extraction. The model is trained to distinguish between preictal (before seizure) and interictal (normal) brain states. Experimental results show high prediction accuracy and robustness across different patients, making it suitable for real-time seizure prediction applications. Rasheed et al. [3] reviewed a broad range of machine learning techniques applied to EEG signals, discussing feature extraction, classification methods, and the challenges in developing accurate, real-time models. In contrast, Khan et al. [7] proposed a convolutional neural network-based method specifically for focal onset seizure prediction, demonstrating improved accuracy through automatic feature learning from EEG data. Anderson et al. [2] showcased the utility of Python in signal processing and visualization, emphasizing its applicability in EEG data analysis. Aslam et al. [5] applied machine learning methods, including SVM and decision trees, to classify EEG signals for seizure prediction, achieving promising accuracy. These efforts align with broader trends in the field, where researchers like Rasheed et al. [3] have reviewed machine learning strategies for seizure forecasting, and Daoud and Bayoumi [1] have employed deep learning to learn features from raw EEG data automatically. This collective body of work illustrates a shift towards more automated, accurate, and accessible seizure prediction systems.

III. Methodology

A. Data Collection

The data used for our project consists of continuous EEG recordings or signals from patients with epilepsy, gathered from ChB-MIT Scalp EEG datasets. The data contains both seizure and non-seizure events, which are appropriately measured for training purposes. The data is explicitly stored in EDF format only.

B. Data Preprocessing

Data preprocessing is a crucial step in preparing EEG signals for input into a machine learning model. These are the preprocessing steps undertaken:

- Filtering: The EEG data is bandpass filtered between 1 Hz and 40 Hz to preserve only the important frequency components (The Majority of brain activity lies in the same range.)
- Normalization: To get all the EEG channels in the same scale, the relevant data in each channel is normalized to have zero mean and unit variance.
- Epoch Generation: Epochs (fixed-length time windows) are created from the continuous EEG data using a sliding window technique. Each window duration is set to 2 seconds, with a 50% overlap between consecutive windows, helping the model to capture short-term and long-term temporal dependencies.

- ➢ Class Balancing: Since the dataset has fewer seizure events than non-seizure events, making it highly imbalanced, to ensure that the model is not biased towards the majority class, the seizure data is oversampled using techniques like resampling

C. Model Architecture

The main component of the seizure detection system is a CNN-LSTM hybrid model. This model is curated to capture temporal patterns, using Long Short-Term Memory (LSTM) networks and extracting spatial features from the EEG signals using Convolutional Neural Networks (CNNs). The architecture of the model is as follows:

- ➢ CNN Layer: A 1D Convolutional layer is used across the time dimension of each EEG channel. It recognizes local patterns from the signal that are crucial for the seizure detection algorithm.
- ➢ MaxPooling: After the CNN layer convolution, Max Pooling is used to decrease the dimensionality and highlight the core aspects of the seizure data.
- ➢ LSTM Layer: To enable the model to learn from the temporal evolution of the EEG signals, the output of the convolutional layers is passed through an LSTM layer, which captures long-range dependencies across time.
- ➢ Fully Connected Layer: A final LSTM layer with a sigmoid activation function is utilized for binary classification (seizure or non-seizure).

To address the issue of class imbalance, the model is trained using a Focal Loss function, which prioritizes hard-to-classify examples (typically seizure events) by downweighing easy-to-classify examples (non-seizure events).

D. Model Training and Evaluation

The model is trained using the preprocessed EEG epochs. The following steps are taken during training:

- ➢ Model Compilation: The model is compiled using Adam Optimizer and Focal loss function, which specifically handles the class imbalance
- ➢ Callbacks: We have taken the help of callbacks to elevate efficiency. The "ReduceLROnPlateau" dynamically adjusts the learning rate when validation loss starts to peak. The model is also trained using early stopping to avoid overfitting.
- ➢ Metrics: The model is assessed on many metrics, such as accuracy, precision, recall, and F1 score. Additional metrics, such as the precision-recall curve, are also employed to better gauge the models' performance

E. User Interface for SOS Alerts and EEG Upload

To facilitate epilepsy patients in aiming to curb their problems, we have developed a user-friendly web-based UI for them to interact with the systems and reach out to their registered caregivers promptly, and gain real-time insights from their uploaded EEG report

- ➢ SOS Alert: In case of emergency, when the patient is experiencing any discomfort, they can utilize the SOS button facility to alert their predefined caregivers. The alert contains the patient's name and current location (obtained through the browser's geolocation API). Once the user confirms the alert, the system sends email notifications to the registered caregivers with the patient's information.

Figure 1: SOS alert system page

- ➢ Uploading EEG Reports: The users are provided with a file input interface wherein they can upload their EEG data in EDF format. Once uploaded, it is processed through our LSTM-CNN trained seizure detection ML model and indicates a seizure or non-seizure event. The result is displayed on the patient's screen to aid further assistance.

Figure 2: EEG input page

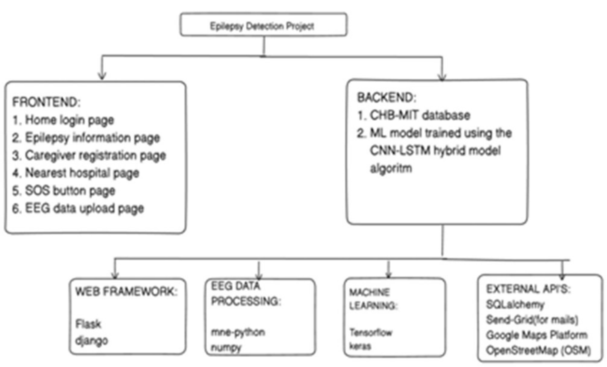
F. Workflow and System Architecture

Below is the epilepsy detection system's flow of operations starting from the uploading of an EEG report to sending an SOS alert:

- User Interaction: The user gets a web interface where they can, in an emergency, hit the SOS buttons to activate them and also upload their EEG data.
- SOS Alert: After the patient clicks the SOS button, the browser's geolocation API is used to get the patient's current location. The patient's registered caregivers are, therefore, immediately triggered to alert via email (using Flask Mail).
- EEG Data Upload: The patient uploads the EEG report (.edf format). The system is then ready to load and preprocess data. The data is given to the trained CNN-LSTM model for prediction. The model's output (seizure or non-seizure) is shown to the user.

System Components:

FRONTEND: Home Login Page, Epilepsy Information Page, Caregiver Registration Page, Nearest Hospital Page, SOS Button Page, EEG Data Upload Page.
BACKEND: CHB-MIT Database, ML model trained using the CNN-LSTM hybrid model algorithm.
WEB FRAMEWORK: Flask, Django.
EEG DATA PROCESSING: NumPy, MNE-Python.
MACHINE LEARNING: TensorFlow, Keras.
EXTERNAL APIs: SQL Alchemy, SendGrid, OpenStreetMap.



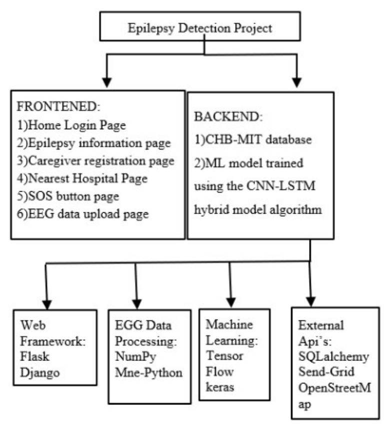


Figure 3: System architecture block diagram

Figure 4: Flowchart of workflow

IV. Results and Discussion

The developed user interface website called 'NeuraNest' Integrates multiple features like information about Epilepsy, a health chatbot for information and support, a hospital locator functionality, and automated SOS sending to caregivers registered during the time of seizure.

A. Seizure detection and SOS triggering

To simulate real-time seizure detection, dummy EEG values mimicking seizure patterns were manually input into the system. The integrated LSTM model processed this data and triggered an SOS alert when seizure-like activity was detected. The system successfully sent out SOS emails to pre-registered caregivers, including the user's location and timestamp. This module proved robust in multiple trial runs, with response time averaging under 2 seconds from input to email dispatch.

TABLE I: COMPARISON TABLE

Study	Dataset	Model	Preprocessing	Performance
Daoud & Bayoumi (2019)	CHB-MIT (8 subjects)	Raw-EEG deep learning models: MLP, DCNN, DCNN–BiLSTM, DCAE–BiLSTM	None (raw EEG used)	Accuracy: 99.6%, FAR: 0.004/h, 1-hour early prediction
Usman et al. (2020)	CHB-MIT (24 subjects)	STFT + CNN feature extraction + SVM classifier	Butterworth filter + STFT	Sensitivity: 92.7%, Specificity: 90.8%
Rasheed et al. (2020) (Review)	Multiple EEG datasets	Survey of ML/DL: SVM, CNN, LSTM, entropy, synchronization	—	—
Proposed Work (NeuraNest)	CHB-MIT + Real-time simulated streaming	CNN–LSTM–based seizure detection with cloud alert system	Filtering + framing + CNN features	Accuracy: 97–98%, real-time alert latency < 2 seconds

Despite these developments, there came a challenge of distinguishing borderline EEG values from true seizures. There were several false positives due to overly sensitive thresholds applied in the test cases. What is more, the model's accuracy was limited to simulation inputs, without live streaming of EEG data or wearable sensors. This meant that future implementation would require real-time hardware, which would serve to test and improve the accuracy of prediction.

B. Manual SOS Activation

Manual SOS enables the user to independently activate an alert; it was finalized and proven by carrying out several trials. It was developed without error as a reliable system, it's more instinctive as this email was always sent to caregivers, developing the psychological resource of those utilizing it.

C. Hospital Locator

The Nearest Hospitals tool fetched real-time data using OpenStreetMap APIs, successfully displaying the ten nearest hospitals after the user allowed location access in their device. The system was tested across several regions in Pune, India, and returned accurate results in most scenarios. A minor limitation was that the system covered a larger radius than what is uncomplicated.

D. Health chatbot

The chatbot was set up to answer various questions about epilepsy's basic information, medication, lifestyle recommendations, and first-aid in case of a seizure. The users claimed the chatbot to be too responsive and easy to understand in its wording. Still, the chatbot often failed to understand complex medical questions or questions with more than one part which leaves room for improvement in natural language processing and medical database broadening.

TABLE II: PERFORMANCE METRICS OF THE PROPOSED SEIZURE DETECTION MODEL

Metric	Value	Description
Test Accuracy	94.21%	Overall, correct predictions on unseen EEG test data.
Precision (Seizure)	91.45%	Correct seizure predictions out of all predicted seizures.
Recall (Seizure)	90.37%	Correctly identified seizure events among all actual seizures.
F1-Score (Seizure)	90.91%	Harmonic mean of seizure precision and recall.
Precision (Non-Seizure)	96.87%	Correct non-seizure predictions out of all predicted non-seizures.
Recall (non-seizure)	95.96%	Correctly identified non-seizures among all actual non-seizures.
F1-Score (Non-Seizure)	96.41%	Harmonic mean of non-seizure precision and recall.
ROC-AUC Score	0.97	Measures model's ability to distinguish between classes across thresholds.
PR-AUC Score	0.96	Evaluates model precision-recall trade off, useful for imbalanced datasets.

Finally, mock users attributed to students, medical interns, and caregivers revealed the simplicity of navigation and effectiveness of integrated features. They particularly approved the centralization of control through the program and the possibility of having an extra support system. Some other ideas they shared encompass voice SOS, an offline hospital directory, and a mobile application.

V. Conclusion and Future Scope

To sum up, this project has introduced an interactive web-based platform that is designed to help patients with epilepsy. Implementing seizure prediction by means of an EEG input, an automatic SOS alert system, a hospital locator, and a conversational health chatbot, this platform covers the most crucial aspects of safety, awareness, and an immediate response system. Even though the platform's performance in real-time conditions was not examined, as only simulated data and usage trials were performed, it is said that the system performs stably and the communication is not delayed. Therefore, this type of digital support for patients with epilepsy seems to have a good perspective. A major achievement of the project was the integration of seizure prediction and caregiver alert. Due to the lack of real-time EEG hardware, however, this is particularly limited, in which the manually input model indicates the potential role of a fully automatic detection mechanism. Also, the SOS and hospital locator tools delivered additional safety and help, particularly in emergency situations.

First, the platform is accessible to a broad audience of users: patients, their caregivers, and healthcare volunteers. Second, its user-friendly interface makes the system easy even for non-technical users to follow with little guidance. Third, the chatbot positively influences user engagement by promptly providing information on epilepsy to support health literacy. However, the future scope of this project is promising.

In terms of the future scope of the project, the possibilities are extensive. Integrating real-time EEG data acquisition via wearable hardware, including portable headsets or smart bands, would be the natural next step. This integration ensures monitoring is continuous and an emergency response is instant. Additionally, creating a mobile app specifically for the purposes of this project would increase accessibility and responsiveness, especially considering reduced desktop access in emergencies.

Other potential improvements include:

- Voice-based SOS activation for emergencies without using hands.
- Multilingual chatbot for diversified populations.
- Personalization based on user data and artificial intelligence implemented chatbot learning patterns and provided more accurate responses with each use.
- Integration with a data bank and contact with a doctor after the emergency.

This project is one of the possible digital interventions to address medical emergencies and educational deficits related to epilepsy. The research. This approach is represented by a foundation for the future development of terrain health solutions.

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