© May 2026 | IJIRT | Volume 12 Issue 12 | ISSN: 2349-6002

EEG-Based Epileptic Seizure Prediction Using Ensemble Learning

Arun Kumar[1], Mohammed Irfan[2], Muguntha Sureshkumar[3], Moheshwaran[4]
[1,2,3,4]*Department of Electronics and Communication Engineering, SSM Institute of Engineering and Technology, Dindigul, Tamilnadu, India*

***Abstract*—Epilepsy is a neurological disorder that is described by recurrent seizures due to unusual electrical discharges in the brain. This unpredictable nature of seizures puts the patient in a position of great risk or injury. This project aims at designing a smart system for predicting seizures based on Electroencephalogram (EEG) signals using machine learning and Internet of Things (IoT) technology. In this project, the proposed system will be able to process the EEG signals by applying different techniques for feature extraction. The features extracted from the signals will be used for predicting seizures by applying different machine learning algorithms like Support Vector Machine (SVM), Random Forest (RF), and Extreme Gradient Boosting on the extracted features. The prediction will be done by using ensemble learning for improving the accuracy of the proposed system. The proposed system will be implemented using IoT technology by integrating ESP32 and a Flask server. The proposed system will be able to send alerts to the patient before the seizure occurs.**

***Index Terms*—Epilepsy, Electroencephalogram (EEG), Seizure Prediction, Machine Learning, Ensemble Learning, Internet of Things (IoT), Real-Time Monitoring.**

I. INTRODUCTION

Epilepsy is one of the most common neurological disorders that affect the normal functioning of the brain. Epilepsy is caused by abnormal electrical activity in the brain that leads to repeated seizures or convulsions. The seizures can lead to a loss of consciousness, uncontrolled movement
making it a serious issue for global health. The most challenging part of managing epilepsy is that seizures can occur at any time without any prior symptoms, which can lead to accidents or even threaten the lives of the patients.

Electroencephalography (EEG) is one of the most common techniques for monitoring brain activity. The EEG records the electrical signals generated by the neurons in the brain by placing electrodes on the scalp. The EEG signals play an important role in understanding brain activity. The EEG is commonly used for diagnosing various neurological disorders like epilepsy. The EEG signals are complex, non-linear, and highly variable. Analyzing the EEG signals is complex and time-consuming. Hence, automated analysis is required for efficiently analyzing the EEG signals.

However, EEG signals are complex, non-linear, and highly non-stationary. Manual analysis of EEG signals by neurologists is time-consuming and prone to human error. Recent advancements in machine learning and artificial intelligence have enabled automated analysis of EEG signals for seizure detection and prediction.
Traditional seizure detection systems focus on identifying seizures after they occur (ictal stage). In contrast, seizure prediction systems aim to detect the pre-ictal stage, which occurs before the seizure onset. Detecting the pre-ictal stage allows early intervention and preventive measures.

In this project, an intelligent seizure prediction system is developed using ensemble machine learning algorithms and IoT technology. The proposed system processes EEG signals, extracts important features, trains multiple machine learning models, and combines their predictions using ensemble techniques. The final model is integrated with an IoT device (ESP32) and a Flask web server for real-time monitoring and prediction.

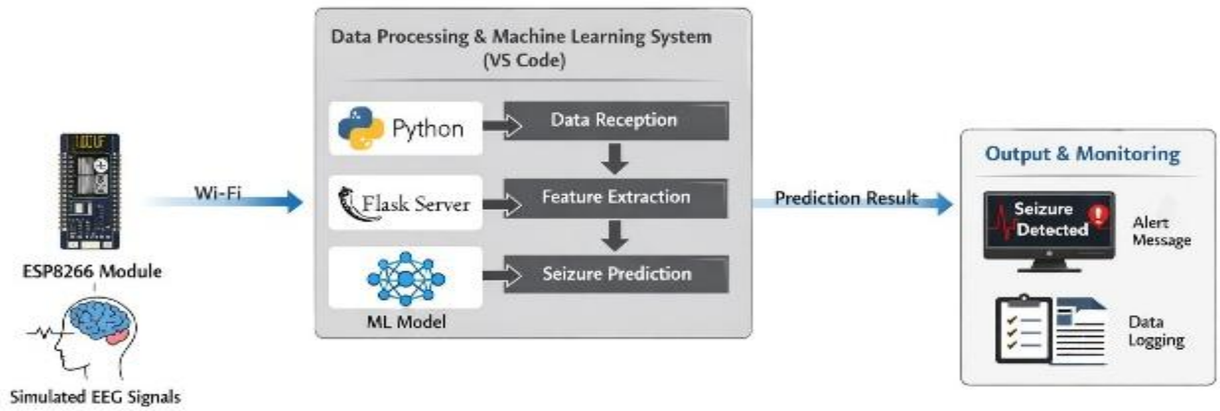

FIG 1 Block diagram for proposed model

II. METHODOLOGY

Epileptic seizures occur due to abnormal electrical discharges in the human brain. These discharges tend to occur in an unpredictable manner and pose significant risks to the health and safety of the patient. Prediction of such seizures even a few seconds in advance has the potential to improve patient health conditions considerably. However, the existing EEG-based systems tend to be expensive and limited to the hospital domain.

Keeping in mind the need for an affordable and cost-effective system for seizure prediction, this work proposes a small-form-factor seizure prediction system. The system has been designed with the goal of reducing the cost of the system and improving the ease of deployment. Unlike existing systems, which use EEG signals for prediction, this system relies on the use of pre-computed spectral feature values. The system uses eight feature values, namely delta power, theta power, alpha power, and beta power from the hemispheric channels. These feature values are transmitted over the local Wi-Fi network using a light-weight communication protocol.

The system is designed with four layers to ensure modularity and scalability.

Signal Acquisition & Feature Extraction Layer

The layer is implemented with an ESP8266 (NodeMCU) microcontroller. This layer is responsible for generating or extracting eight normalized spectral features within the range of 0 to 1. These features include brain wave activities over specific frequency ranges. The features are then sent out as a comma-separated value at one-second intervals.

Wireless Communication Layer

For the purpose of data transmission, the User Datagram Protocol (UDP) has been used. This is because UDP is a lightweight protocol with minimal delay in data transmission. It does not require setting up a connection like TCP/IP, which makes it suitable for real-time applications. In this application, the feature data will be transmitted to a local server at a defined IP address and port number (5007).

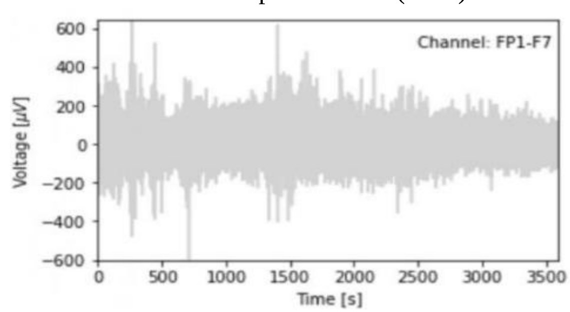

FIG 2 EEG SAMPLE SIGNAL

Server & Inference Layer

The backend application has been implemented in Python using the Flask framework. The application has a UDP listener thread that accepts incoming data packets without blocking the main application. The application uses a pre-trained random forest classifier in the form of a serialized file (.pkl file), which has been loaded in the application. The classifier accepts feature vectors and returns the corresponding prediction in the form of 'inter-ictal' or 'pre-ictal.' The classifier also returns the probability of the prediction.

The recent prediction and feature values are shared in the application.

Presentation Layer
A responsive web-based dashboard is developed using HTML, CSS, and JavaScript technologies. The interface is designed to poll the endpoint at intervals of 500-700 milliseconds to retrieve updated predictions. Various components are included in the interface, such as the dynamic status display (Normal/Seizure Risk), probability display, table display of feature values, and radar chart display. A radar chart is included for better interpretability of the features.

Key Design Decisions
Some key design decisions have been made for better performance and usability of the system. These decisions are as follows using UDP instead of TCP: This reduces latency and other costs of communication offline Capability: This reduces the need for any cloud dependency, hence ensuring better privacy lightweight Features: This is ensured by restricting the input features to just eight radar Chart Visualization: This is a compact way of representing multi-channel EEG activity.

III. IMPLEMENTATION DETAILS

Microcontroller Firmware
The firmware code is written in Arduino's C++. In the code, the main loop calculates or reads eight values for spectral features and sends the information in CSV format. This is achieved by utilizing the WiFiUDP library.

Machine Learning Model
The model used for machine learning is a Random Forest ensemble model comprising 100-200 decision trees. This model performs classification for the application. It is trained offline and uses scikit-learn for labeled dataset training. It provides a binary output and probability.

Backend Server
The backend server code uses Flask and listens on port 5007. It has a UDP listener for continuous receiving of information from the microcontroller. This ensures the system does not crash even in cases of incorrect packets. It has a REST endpoint for retrieving the latest prediction and features in JSON format.

Frontend Dashboard
The application's frontend is responsive and works on both mobile and desktop devices. It has a darkmode for better user interface. It has animations for high-risk conditions. The radar chart works effectively in highlighting brainwave activity changes for different frequencies.

The system also shows its capability to perform well in a real-time manner in a local network environment.
Latency: The end-to-end time taken to generate the data and visualize it lies in the range of 400 to 900 milliseconds. Reliability: Despite the fact that the UDP protocol might lead to a loss of data, the system remains reliable by holding the last state of the data.
Power Consumption: The ESP8266 chip consumes a power range of 70-170 mA while in use with the Wi-Fi connection.
User Experience: The system has a user-friendly interface and is accessible on different devices. Additionally, the radar chart gives a quick overview of the variation in the features.

There are several advantages to this system
Total hardware cost is low. This system performs all processing locally without any cloud dependency. This system has fast data transmission and inference, making it near-instantaneous. This system is scalable, and other sensors can be easily added.

Live Channel Values

Channel	Current Value
F1	0.120
F2	0.070
F3	0.000
F4	0.440
F5	0.990
F6	0.890
F7	0.010
F8	0.470

FIG 3 DASHBOARD VALUE

IV. RESULTS AND DISCUSSION

The system was tested and validated using a real-time operating environment with simulated EEG spectral features transmitted to the server using the ESP8266. The results show the system's capability to carry out continuous seizure risk monitoring. The output on the dashboard displays the probability of a seizure occurring, which is 36.0%. This value represents a moderate range. This output suggests that the model does not classify the state as pre-ictal but has detected a minor abnormality in the state, which is not totally normal or interictal. The output generated by the Random Forest model makes the output more interpretable because the user understands the probability associated with the output.

The high values of the live channels (F1 to F8) show variations with respect to the spectral features:
High values observed:
F5 = 0.990
F6 = 0.890
High values suggest that activity is high in certain frequency bands, which might be abnormal patterns of brain activity depending on the features.

Moderate values observed:
F4 = 0.440
F8 = 0.470
Moderate values suggest balanced activity.

Low values observed:
F1 = 0.120
F2 = 0.070
F3 = 0.000
F7 = 0.010
These values reflect a lesser contribution.
The uneven distribution in the features is clearly depicted in the radar chart, where the spikes in the different axes (F5 and F6) clearly indicate the activity. Such activity is significant because the onset of a seizure is usually characterized by disproportionate activity in certain bands of the EEG.

The figure displayed above indicates the Seizure Risk Probability, which is 36.0%, as well as a radar chart illustrating the present state of the EEG features for eight different channels (F1 – F8). This output, therefore, offers quantitative as well as visual information regarding the decision-making process.

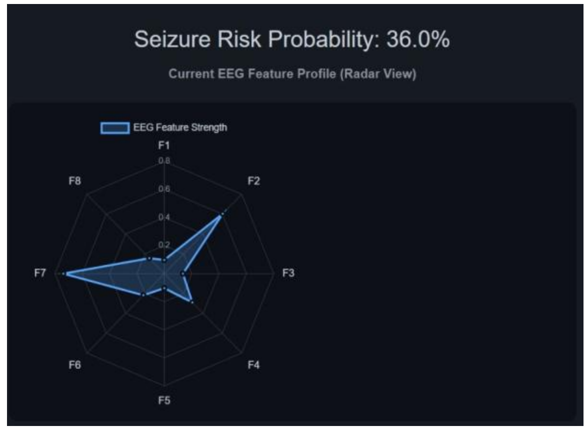

FIG 4: FINAL OUTPUT GRAPH

Interpretation of Seizure Probability
The system has recorded a 36% probability reading, which indicates the presence of a mild to moderate deviation from a normal brain state. In general terms, in a two-class classification scenario:
0 – 30% Likely in a normal state (interictal)
30 – 60% Uncertain state
> 60% High risk of a seizure (pre-ictal state)
The reading, therefore, implies that although the subject is not in a state of seizure, there are some signs of deviation from the normal state, which might require careful monitoring. This intermediate reading is very useful in preventive medicine.
The radar chart helps in visualizing the contribution of each of the features in the prediction. From the radar chart:

Prominent Peak at F7:
This implies a high level of activation in a single frequency band or brain hemisphere. Localized peaks in the radar chart are more important than uniform increases because abnormal brain function, like a seizure, is usually accompanied by abnormal brain synchronization.
Moderate Activity at F2 and F4:
These features have a moderate level of activity, indicating some involvement of other frequency bands.
Low Activity in Remaining Channels (F1, F3, F5, F6, F8):

These features have low levels of activity.
The unbalanced pattern in the radar chart indicates unbalanced brain activity, which is an important

indicator. In a normal state, brain features usually have balanced patterns, but abnormal patterns indicate neurological instability.
Each feature (F1 to F8) represents the power of the EEG spectrum. From the result. There is an increase in specific bands (possibly beta or theta) There is no global synchronization. It is an early-stage deviation and not a pre-seizure feature

This is consistent with the EEG characteristics where seizure onset is preceded by gradual changes.

System Behaviour and Responsiveness
The output is consistent with the expectation that the system is working correctly. This is because the radar chart is responsive to changes based on the received data. The probability value is an immediate inference from the model
The smooth update is an indication that communication is efficient between ESP8266, server, and dashboard
The update time and consistent display confirm that the system is working correctly based on the UDP streaming and flask

From a user/caregiver perspective:
A 36% risk does not warrant intervention, but instead warrants continued monitoring
If these trends persist and/or escalate, it could imply increasing likelihood of a seizure occurrence
The radar chart enables easy recognition of which brain activity features are changing without requiring in-depth technical understanding

Key Insight
The key realization from this output is that it demonstrates the system's capability to recognize not extreme cases of variation in patterns of EEG features, but early stages of variation. This is in line with its potential as an early warning support tool, rather than a purely reactive system.

V. CONCLUSION

In this research work, a low-cost and real-time epileptic seizure risk prediction system has been successfully designed and implemented. By utilizing a minimal set of eight pre-computed EEG features, the system has effectively reduced computational complexity while retaining considerable prediction capabilities. The inclusion of the ESP8266 microcontroller and lightweight UDP-based communication, coupled with the Flask-based inference server, demonstrates a viable solution to real-time and wireless health monitoring without the need to rely on cloud computing. The utilization of the Random Forest ensemble classifier has ensured reliable classification and prediction with probabilistic outputs. This is advantageous and enhances interpretability. From the experimental results obtained, including the risk probability value of 36% seizure risk, the system has effectively identified subtle changes in EEG feature patterns and provided this information to the end user through an intuitive interface. The utilization of the radar chart-based visualization interface has ensured that users can easily interpret their neurological states and detect irregularities. From the results obtained, the system has an end-to-end latency of less than one second and is thus suitable for near real-time health monitoring. Overall, this proposed solution has effectively ensured a balance between cost, performance, and usability and is thus promising

REFERENCES

[1] L. De Clerck, A. Nica, and A. Biraben, "Clinical aspects of seizures in the elderly," *Geriatric Psychology and Neuropsychiatry of Aging*, vol. 17, no. 1, pp. 7–12, Mar. 2019.

[2] S. Nalla and S. Khetavath, "A review on epileptic seizure detection and prediction," in Intelligent Manufacturing and Energy Sustainability. Cham, Switzerland: Springer, 2023, pp. 225–232.

[3] A. S. Daoud, A. Batieha, M. Bashtawi, and H. El-Shanti, "Risk factors for childhood epilepsy: A case-control study from Irbid, Jordan," Seizure, vol. 12, no. 3, pp. 171–174, Apr. 2003.

[4] K. Harris, "The dangers of seizures: Why you need immediate treatment," 2018.

[5] J. W. Britton, L. C. Frey, and J. L. Hopp, An Introductory Text and Atlas of Normal and Abnormal EEG Findings in Adults, Children, and Infants. Chicago, IL, USA: American Epilepsy Society, 2016.

[6] L. L. Chen, J. Zhang, J. Z. Zou, C. J. Zhao, and G. S. Wang, "A framework on wavelet-based nonlinear features and extreme learning machine for epileptic seizure detection," Biomedical Signal Processing and Control, vol. 10, pp. 1–10, Mar. 2014.

[7] A. Dogra, S. A. Dhondiyal, and D. S. Rana, "Epilepsy seizure detection using optimized KNN

algorithm based on EEG," in Proc. Int. Conf. Advancement Technology (ICONAT), 2023, pp. 1–6.

[8] Y. Kaya, M. Uyar, R. Tekin, and S. Yıldırım, "1D-Local Binary Pattern based feature extraction for classification of epileptic EEG signals," Applied Mathematics and Computation, vol. 243, pp. 209–219, Sep. 2014.

[9] S. Ryu et al., "Pilot study of a single-channel EEG seizure detection algorithm using machine learning," Child's Nervous System, vol. 37, pp. 2239–2244, 2021.

[10] M. Mursalin, Y. Zhang, Y. Chen, and N. V. Chawla, "Automated epileptic seizure detection using improved correlation-based feature selection with random forest classifier," Neurocomputing, vol. 241, pp. 204–214, Jun. 2017.

[11] A. A. Asadi-Pooya et al., "Machine learning applications to differentiate comorbid functional seizures and epilepsy," Journal of Psychosomatic Research, vol. 153, Feb. 2022.

[12] T. Wadhera, "Brain network topology unraveling epilepsy and ASD association: Automated EEG-based diagnostic model," Expert Systems with Applications, vol. 186, Dec. 2021.

[13] N. K. C. Pratiwi, I. Wijayanto, and Y. N. Fu'adah, "Performance analysis of automated epilepsy seizure detection using EEG signals based on 1D-CNN approach," in Proc. Int. Conf. Electronics, 2022.

[14] Md. N. A. Tawhid, S. Siuly, and T. Li, "A convolutional long short-term memory neural network for epilepsy detection from EEG," IEEE Transactions on Instrumentation and Measurement, vol. 71, 2022.

[15] M. Woodbright, B. Verma, and A. Haidar, "Autonomous deep feature extraction-based method for epileptic EEG seizure classification," Neurocomputing, vol. 444, pp. 30–37, Jul. 2021.

[16] U. R. Acharya et al., "Deep convolutional neural network for automated detection and diagnosis of seizure using EEG signals," Computers in Biology and Medicine, vol. 100, pp. 270–278, Sep. 2018.

[17] A. Abdelhameed and M. Bayoumi, "A deep learning approach for automatic seizure detection in children with epilepsy," Frontiers in Computational Neuroscience, vol. 15, 2021.

[18] Q. Wu and E. Fokoue, "Epileptic seizure recognition dataset," 2017.

[19] R. G. Andrzejak et al., "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity," Physical Review E, vol. 64, 2001.

[20] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in Proc. ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining, 2016, pp. 785–794.

[21] S. Ö. Arik and T. Pfister, "TabNet: Attentive interpretable tabular learning," AAAI Conference on Artificial Intelligence, vol. 35, no. 8, pp. 6679–6687, 2021.

[22] M. Varlı and H. Yılmaz, "Multiple classification of EEG signals and epileptic seizure diagnosis with combined deep learning," Journal of Computer Science, vol. 67, 2023.

[23] S. M. Beeraka et al., "Accuracy enhancement of epileptic seizure detection: A deep learning approach with hardware realization of STFT," Circuits, Systems, and Signal Processing, vol. 41, no. 1, pp. 461–484, 2022.

[24] G. Xu et al., "A one-dimensional CNN-LSTM model for epileptic seizure recognition using EEG signal analysis," Frontiers in Neuroscience, vol. 14, 2020.

[25] H. RaviPrakash et al., "Deep learning provides exceptional accuracy to ECOG-based functional language mapping for epilepsy surgery," Frontiers in Neuroscience, vol. 14, 2020.

[26] Y. Kumar, M. L. Dewal, and R. S. Anand, "Epileptic seizure detection using DWT based fuzzy approximate entropy and SVM," Neurocomputing, vol. 133, pp. 271–279, 2014.

[27] K. M. Almustafa, "Classification of epileptic seizure dataset using different machine learning algorithms," Informatics in Medicine Unlocked, vol. 21, 2020.

[28] I. Ahmad et al., "A hybrid deep learning approach for epileptic seizure detection in EEG signals," IEEE Journal of Biomedical and Health Informatics, 2023.