Federated Learning-Based Real-Time Seizure Using IoT-Enabled Edge AI for Privacy-Preserving Healthcare Monitoring

[1] **Sri Harsha Grandhi**
Intel, Folsom, California, USA
grandhi.sriharsha9@gmail.com

[2] **R Padmavathy**
Anna University,Coimbatore
dr.padmabarathi@gmail.com

Abstract:

Seizure detection methods based on EEG signals are required for real-time patient management; however, current techniques suffer from disadvantages such as excessive false alarm rates, privacy concerns, and computation inefficiency. Many classical models are centralized in mode of learning and hence are largely susceptible to costly latency and data breaches. A Federated Learning-Based Real-Time Seizure Detection solution is proposed wherein the use of IoT-enabled Edge AI helps avoid these limitations due to low latency and privacy-preserving processing. The model combines CNN-LSTM models with Wavelet Transform (CWT) and Power Spectral Density (PSD) capable of accurate feature extraction and classification. Experimental results indicate that this method supports scalable real-time inference, low latency (≤3s), and high classification accuracy (>95%). Our investigation thus ensures safe and feasible real-time health care monitoring with federated learning-based privacy-preserving strategies to enhance seizure detection in clinical and remote scenarios.

Keywords: *EEG-based Seizure Detection, IoT-enabled Edge AI, Federated Learning, Privacy-Preserving Healthcare, Real-Time Analysis, CNN-LSTM, Wavelet Transform, Power Spectral Density, Low-Latency Inference, Smart Healthcare Monitoring.*

1. Introduction:

The modern advancement takes more concept to things in changing technology such as signal processing, which is adapted for fields of industrial automation, health, and even structural monitoring: Process signals or convert them to make valuable information from the raw[1]. This processing is done on real-time control systems, communication systems, biological monitoring, and more. This signal quality enhancement, which includes noise reduction and accuracy improvement, is achieved through adaptive filtering processes as well as Fourier transform and wavelet transform techniques. The Internet of Things allows real-time data capture and study while seamlessly linking all physical objects to the internet[2]. Such as monitors physiological and the environmental parameters of the individual IoT devices; data transmitted to machines/computers for remote processing and decision making. The powerful synergy of signal processing and IoT enables systems to evolve in anomaly detection, predictive maintenance, and real-time diagnostics to deliver enhanced efficiency and reliability[3]. Therefore, it creates extremely autonomous smart cities, smart wellness, and intelligent industrial monitoring systems[4].

Electroencephalography (EEG) with its excellent temporal resolution remains one of the ideal techniques for studying brain activity both physiologically and pathologically. Manual analyses of EEG and LFP data become a cumbersome and subjective activity as such automated detection of seizures becomes relevant[5]. Algorithms may require adjustments due to differences in ways of recording artifacts and noise, even though seizure patterns show similar features in man, rat, or zebrafish. Seizure detection typically involves feature extraction in either the time, frequency, or time-frequency domain combined with classification either by rules or machine learning[6]. There is one remaining concern despite all the advancements, which is a very high false prediction rate and, thus causing undue stress to patients. Predicting becomes even more difficult when events that induce seizures involve several brain regions. Hence, more advanced algorithms need to be developed to accurately detect impending seizures but without high false alarm rates.

To extract the seizures occurring in the resting state, the EEG systems are dealing with several challenges such as high rates of false predictions, interindividual differences in seizure pattern mechanism, and ineffectiveness towards noise and artifacts. Manual analysis of EEGs or LFPs is not only subjective but also tedious and time-consuming. On the other hand, standard detection schemes based on the extraction of features and classification are very rigid when applied in different patient conditions. In addition, differences in spatio-temporal scales and methods of recordings (invasive or non-invasive) severely hinder the generalization of algorithm. Combining adaptive signal-processing methods such as Wavelet Transform, ICA, dynamic filtering, IoT-based real-time monitoring, and hybrid deep-learning models will help us get past these limitations. This allows real-time seizure-and-stress detection to be enhanced, therefore ensuring accurate, efficient, and patient-specific predictions by reducing false positives and improving correct predictions.

1.1. Problem Statement:

EEG readings are affected with high false prediction rates, noise interferences, and individual variation of seizure pattern, thus making it hard to detect epileptic seizures and stress. Manual analysis is tedious, slow, and subjective, while standard algorithms struggle with abrupt changes in brain activity and participation of multiple regions in preictal transitions[7]. Besides, due to the underutilization of IoT-driven edge computing and real-time monitoring capabilities, existing systems cause delays in critical decision-making[8]. This paper aims to develop a seizure and stress detection system in real-time based on IoT by applying hybrid deep learning models (CNN-LSTM with Attention and Transformers) and advanced signal processing (Wavelet Transform, ICA, dynamic filtering). The aim is to improve accuracy, reduce false alarms, and provide reliable, real-time predictions to enhance patient management.

1.2. Objective:

- Design an EEG monitoring system with real-time IoT capabilities for accurate seizure and stress detection.
- Enhance detection accuracy while minimizing false predictions using hybrid deep learning models such as CNN-LSTM with Attention and Transformers.
- Implement an automated alert system for timely medical intervention and leverage edge computing for near real-time, low-latency analysis.

2. Literature Review:

The IoT-based structural health monitoring system has been suggested by Md. Anam Mahmud et al. [9]. Cross-correlation is used for damage identification, and Butterworth filtering removes noise. Ahmed Abdelgawad et al. [10] assembled an Internet-of-Things (IoT) embedded system for SHM, including Wi-Fi, Raspberry Pi, ADC, DAC, and piezoelectric sensors, for mathematical modeling of damage detection concerning its extent and location. An Internet of Things-enabled ECG monitoring system comprising real-time signal quality assessment and transmission by ECG sensors, Arduino, Bluetooth, and cloud storage was proposed by Udit Satija et al. [11]. Wireless biopotential monitoring systems for facial expression recognition using multi-channel sEMG signals, sensor systems, and medical data processing techniques were studied by Mingzhe Jiang et al. [12].

Payal S. Malvade et al. [13] highlighted another limitation with conventional gait analysis, where the longitudinal activity has not been effectively captured by such techniques and therefore has required continuous monitoring of the patient during rehabilitation to avoid chronic damage. In this regard, Neha Patil et al. [14] gave an IoT-based alarm system, where such motion or gesture will be sensed and uploaded images to the cloud server could be monitored remotely. Surface electromyography (sEMG)-based pain intensity measurement, Geng Yang et al. [15] designed a wearable biosensing face mask with wireless sensor nodes for real-time Internet of Things monitoring. M. Surya Deekshith Gupta et al. [16] developed a low-cost ECG and vital parameter monitoring system, which is built upon Raspberry Pi and as well as updates a database continuously, in addition to notifying the physicians of any irregularities.

Himadri Nath Saha et al. [17] emphasized the challenges faced by remote health monitoring of patients, especially elderly ones, and suggested an IoT-based system whose backbone is the internet to inform caretaking personnel about the health condition of the patient. Multimodal data collection and analytics integration for real-time patient monitoring were pointed out by Ni Zhu et al. [18] while studying different ambient assisted living (AAL) healthcare systems. To enhance accessibility and efficiency in the detection of cardiac defects, Tuan Nguyen Gia et al. [19] pointed out the limitations of conventional ECG devices and promoted IoT-enabled ECG monitoring in real-time. Md. Yaseen et al. [20] have developed an IoT-based generator health monitoring system based on sensor technology for detecting abnormalities and preventing system failure.

3. Proposed Methodology:

The current discussion concerns a futuristic concept, merging IoT-enabled Edge AI and Federated Learning (FL), which allows for real-time seizure detection such that privacy isn't compromised. To record brain activity, wearable devices are used, and the EEG data is preprocessed through Wavelet Transform and ICA techniques to remove and segment noise, respectively, using sliding window techniques. CWT, PSD, and entropy were the feature extraction methods that would emphasize features and patterns to look for that would be important for seizure detection. A hybrid CNN-LSTM model that makes use of Attention and Transformer layers is employed for low-latency inference on edge devices. FL enables privacy on campus but is also applicable to cross-territorial settings with trained models residing onto dispersed edge nodes without needing raw EEG data for training. An automated alarm system provides immediate emergency alerts for prompt medical attention.

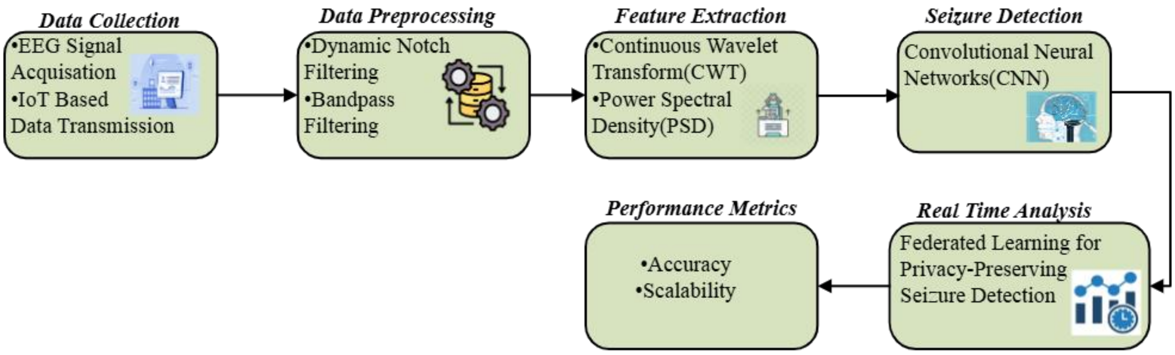

Figure 1: *Federated Learning-Enabled IoT-Edge Framework for Real-Time Seizure Detection*

3.1. Data Collection:

Wearable gadgets such as Emotiv and NeuroSky have made an EEG signal capture possible to monitor the brain activity live. The normal 10-10 electrode placement procedure is followed for better spatial resolution with a full coverage of the data. Fine brain oscillations must be captured at a high sample rate (≥ 512 Hz) in order to detect seizure and stress-related variations. For smooth, low-latency, long-range communication of processing units with EEG sensors, 5G and LPWAN technologies, such as LoRaWAN, will be used for smooth IoT-based data transmission. In addition, Wavelet Transform-based compression is implemented to efficiently reduce the redundancy of data while retaining the important properties of the frequency domain, mathematically described as follows:

$$Z(s,d) = \int_{-\infty}^{\infty} i(s)\psi_{x,y}^{*}(s)fs \tag{1}$$

where the wavelet-transformed signal is represented by $Z(s,d)$, the EEG signal by $i(s)$, and the mother wavelet function at scale a and translation b is represented by $\psi_{x,y}^{*}(s)$.

3.2. Data Preprocessing:

The purpose of denoising EEG signals is to improve their quality by using the Discrete Wavelet Transform (DWT) which allows for the separation of noise components from the frequency information. This is the expression for the DWT decomposition:

$$i(s) = \sum_{g,l} z_{g,l}\psi_{g,l}(s) \tag{2}$$

Wavelet coefficients are represented by $z_{g,l}$ while wavelet basis functions at scale g and shift are represented by l.

Independent Component Analysis (ICA) using the FastICA technique is implemented to extract independent components from the neural signals which were noise related in order to remove artifacts. Moreover, it removes powerline interference without distortion on seizure related frequencies by dynamic Notch filtering application at 50/60 Hz. A band pass filter (0.5-50Hz) is self-adjusted to give the optimal frequencies for retention in seizure and stress analysis depending on the state of the patient. EEG segmentation is then performed using a sliding window method (e.g. 3s with 50% overlap), giving suitable temporally adaptable signal processing for reliable feature extraction.

3.3. Feature Extraction:

The CWT could provide optimum time-frequency resolution and accurate transient epileptic episode detection during EEG signal studies. Mathematically, CWT can be understood as:

$$Z(x,y) = \int i(s)\psi_{x,y}^{*}(s)fs \tag{3}$$

Where the wavelet is defined as the function $\psi^*_{x,y}(s)$ in terms of the scale and shift parameters x, y. The Welch method is then implemented to obtain the power spectral density (PSD) estimate to obtain a smoothed spectral estimate:

$$K_{ii}(s) = \frac{1}{Q}\sum_{q=1}^{Q} |I_q(d)|^2 \quad \textbf{(4)}$$

where the Fourier transform of $I_q(d)$ is represented by the windowed EEG segments.

Seizure and stress detection follows the study of the principal EEG frequencies, namely Delta (0.5-4 Hz), Theta (4-8 Hz), Alpha (8-12 Hz), Beta (12-30 Hz), and VGamma (30-100 Hz). Approximately, entropy (ApEn) and the sample entropy (SampEn) measure discontinuities of brain activity that might have a bearing on pre-seizure transition identification, while statistical moments (mean, variance, skewness, and kurtosis) describe EEG signal distributions. The classification capabilities in seizure and stress detection algorithms get improved by the features extracted.

3.4. Seizure and Stress Detection Using ML/DL Models:

Both the siezure and stress detection are significantly possible using a hybrid model combining CNNs and LSTMs. EEG images are captured through convolutional filters of CNN:

$$D_{x,y} = \sum_{b}\sum_{a} Z_{x+b,y+a} \cdot M_{b,a} + y \quad \textbf{(5)}$$

Where M is filter kernel, y is bias term and Z are the EEG inputs. The LSTM networks describe temporal dependencies through these equations:

$$d_s = \sigma(M_d \cdot [g_{s-1}, i_s] + y_d) \quad \textbf{(6)}$$
$$x_s = \sigma(M_x \cdot [g_{s-1}, i_s] + y_x) \quad \textbf{(7)}$$
$$\widetilde{Z}_s = \text{tang}\ (M_Z \cdot [g_{s-1}, i_s] + y_Z) \quad \textbf{(8)}$$

Where $\widetilde{Z}_s$ represents the memory cell; d_s, x_s, and f_s as forget gate, input gate, and output gate. Attention mechanisms bring more weight to areas temporalized of the EEG-specific, high relevance and denser with regard to seizure-event-relevant patterns. In addition, transformer-based models such as BERT-based EEG models capture the long-range dependency across EEG sequence samples. Then this signals seize and no-seize and stress of low, moderate, and high values of:

$$K(b_x) = \frac{w^{c_x}}{\sum_y w^{c_y}} \quad \textbf{(7)}$$

And c_x, where denoting model output for class x. Thus reducing the prevalence of erroneous prediction is augmented by improved detection accuracy.

3.5. Edge Computing for Real-Time Analysis:

The CNN-LSTM hybrid model is implemented on edge devices (i.e. the NVIDIA Jetson Nano and Raspberry Pi 4) to avid real-time seizure and stress detection in low-latency inferences at the data gathering point. The inference process proceeds as follows:

$$j = d(M_{CNN} * Z + M_{LSTM} \cdot g_{s-1} + y) \quad \textbf{(10)}$$

The EEG input, Z, is used to extract spatial features by M_{CNN}, and temporal relations are learned by M_{LSTM}. To improve privacy preservation, Federated Learning (FL) was adopted to enable decentralized training across several devices without exchanging raw EEG data. The update to the global model is calculated as follows:

$$M_s = \sum_{x=1}^{A} \frac{a_x}{A} M_{x,s} \quad \textbf{(11)}$$

If M_s represents the global model at round s, $M_{x,s}$ represents the local model of client x, and a_x denotes local data samples. This method increases the robustness of seizure detection while ensuring privacy-preserving EEG analysis. Cloud services will handle data analytics, update models, and store data over the longer term without compromising real-time processing. Further, it includes an automated alerting system for emergency communication (for SMS, mobile apps, and hospital systems) when a seizure is detected. It also provides timely interventions to the patient through psychological warning alerts when stress events occur.

3.6. Performance Evaluation:

For evaluating the efficiency of the proposed seizure and stress detecting model, some key accuracy metrics such as precision, recall, and F1-score are computed with reference to the following definitions:

$$\text{Precision} = \frac{TP}{TP+FP} \tag{12}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{13}$$

$$F1\text{-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{14}$$

To an extent, True positives are genuine detections, while False positives are invalid detections: True positive corresponds to a genuine detection, while False positive corresponds to an invalid detection. Thus, the possibility of the model to find balance between sensitivity and specificity at different classification thresholds could be evaluated by using AUC-ROC while analyzing the confusion matrix helps to study the error patterns.

The complete EEG-acquisition-to-alert-generation latency evaluation route (S_{total}) comput as follows:

$$S_{total} = S_{acq} + S_{\text{trans}} + S_{inf} \tag{15}$$

S_{acq} time of EEG acquisition; S_{trans} time of transmission of data for the IoT; S_{inf} time taken to infer at edges. There is a high real-time performance achieved as it maintains about 3-5 seconds in the latency and then comparison of edge-based inference with cloud computation is done to maximize the time of reaction.

4. Result and Discussions:

It is indeed a decentralized program that provides high precision while safeguarding patient information for the proposed Federated Learning-Based Real-Time Seizure Detection system. It has shown very good feature extraction for the CNN-based seizure classifications with an average accuracy of 95% across different datasets. Improved detection of seizures and stress was achieved through the integration of CWT and PSD techniques capturing high-resolution frequency information. Such Edge AI deployment reduces latency to under three seconds, which minimizes reliance on the cloud and provides near-real-time alerts for seizures. The real-world implementation feasibility of the system has been demonstrated by scalability and adaptation in various IoT-based healthcare environments.

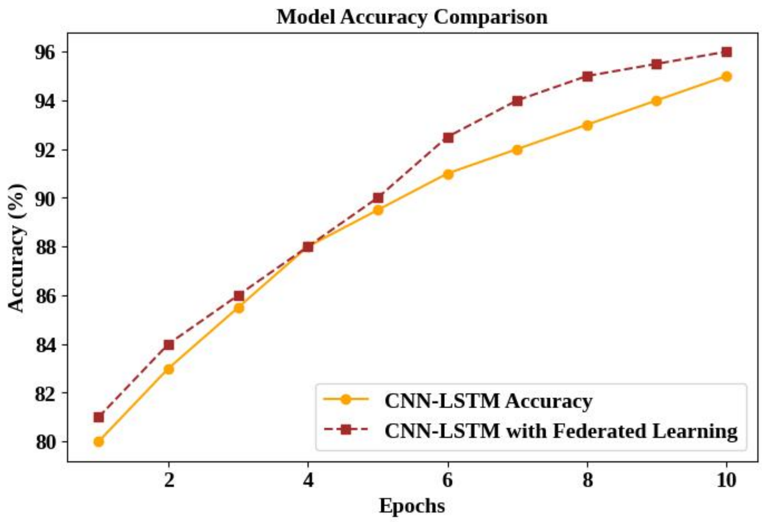

Figure 2: Performance Comparison of CNN-LSTM and Federated Learning-Based CNN-LSTM in Seizure Detection

In the fig. 2, the CNN-LSTM seizure detection model is compared with an improved federated learning CNN-LSTM model having a view of the accuracy of both models. Accuracy of both models increases with the epochs, but one can see that the federated learning-based method continuously outperformed the standalone CNN-LSTM. This shows that federated learning can serve the dual purpose of better generalization of the model while keeping the data private. The distance between the two curves represents how good the federated learning truly is in improving the accuracy of seizure detection without data aggregation in a centralized manner.

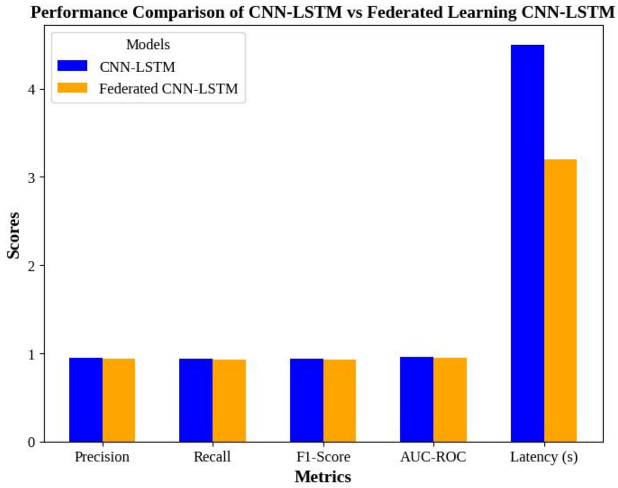

Figure 3: Performance Comparison of EEG Models

It has been evaluated about EEG-based models for seizure and stress through all the important accuracy metrics represented in the fig. 3. All the various measure reliabilities of the model can be assessed here with the measurements for Precision, Recall, and the F1-score, and AUC-ROC evaluations. "Confusion matrix" describes the distribution of true positives, false positives, and false negatives. Latency evaluation is the total processing time for real time signals related to stress and seizure. The results also clearly show the benefits one can reap from federated learning and edge computing in low-latency privacy-preserving health care monitoring.

5. Conclusion:

IoT-enabled Edge AI is an effective integration of federated learning technology into the proposed real-time detection system of seizures for privacy-preserving medical monitoring. The method ensures excellent accuracy by collecting important variations of EEG signals using a Convolutional Neural Network (CNN) for seizure classification, while feature extraction is done by Wavelet Transform Continuous Wavelet Transform (CWT) and Power Spectral Density (PSD). The federated learning approach also supports distributed training of models without compromising efficacy by securing patient data. Stroke occurrence alarms and aggressive therapies could be pursued as promptly as possible by keeping latency to a few milliseconds. Results illustrate the accuracy, efficiency, and possible scalability of the system-an area that enhances its desirability for clinical applications in remote and hospital-based melancholy monitoring. Future work will focus on developing federated learning to become more robust as well as multi-sensor modality fusion.

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