International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 9, Issue 4, 2021

A Real-Time Seizure Detection Framework Using PSD and FFT for IoT-Based Healthcare Monitoring

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Abstract:

An advanced real-time EEG seizure detection technique, in this context, is the hybrid CNN-LSTM model at the edge devices, which improves speed and accuracy in seizure detection. The incorporation of signal processing techniques, namely FFT and Power Spectral Density (PSD), into our methodology significantly improves seizure frequency identification. The system performs low-latency inference such that caregivers receive timely notifications while generally having higher performance metrics such as precision, recall, and F1. Current approaches still experience problems such as latency over the network and slower response times. This research addresses the synergistic enhancement benefits of IoT, edge AI, and advanced signal processing for effective health monitoring systems and timely treatment of patients during seizure episode

Keywords: *EEG Seizure Detection, CNN-LSTM Model, Edge Computing, Real-Time Monitoring, Signal Processing, Feature Extraction, Power Spectral Density (PSD), Fast Fourier Transform (FFT), IoT (Internet of Things), Low Latency, Healthcare Systems*

1. Introduction:

The convergence of signal processing and the Internet of Things (IoT) has opened new frontiers for real-time analysis and intelligent healthcare decision-making [1]. Signal processing involves the manipulation of biomedical signals like EEG to extract meaningful features while minimizing noise [2]. IoT refers to a system of interconnected devices capable of collecting and exchanging data with minimal human input [3]. By embedding sensors with actuators and communication protocols, IoT systems create intelligent environments that react to contextual changes [4]. Recent advances demonstrate that combining IoT and signal processing can optimize systems for smart cities, healthcare, and industrial automation [5]. Healthcare applications of IoT range from patient monitoring to personalized treatment recommendations, enhancing care precision and efficiency [6].

Edge computing further complements IoT by processing data near the source, reducing dependence on cloud infrastructures [7]. Cloud-based healthcare models, although transformative, suffer from latency during time-critical events like seizures [8]. Edge AI offers a promising solution by bringing real-time inferencing capabilities directly to wearable and embedded devices [9]. Intelligent health monitoring platforms utilizing edge AI enable faster detection and response in life-threatening situations [10]. Low-cost sensor networks can now be deployed at scale, enabling broad EEG signal acquisition for seizure detection [11]. These systems often incorporate ECG, EEG, or EMG sensors into wearable designs, allowing unobtrusive and continuous health monitoring [12].

Advanced modelling techniques support damage localization and signal interpretation in complex medical IoT architectures [13]. IoT also finds applications beyond health, such as traffic and vehicle monitoring, where rapid data capture and analysis are critical [14]. Embedded web-based monitoring systems allow remote access to health data through secure interfaces [15]. In remote and underserved areas, IoT bridges the healthcare delivery gap by facilitating communication between patients and professionals [16]. Wearable biosensors, including facial EMG and EEG devices, have become instrumental in chronic condition management [17]. IoT platforms with anomaly detection algorithms proactively identify potential health crises, improving outcomes [18].

To address bandwidth limitations, sensor data is often compressed using optimized algorithms tailored for biomedical signals [19]. Cloud-integrated systems enable real-time visualization of physiological signals, aiding rapid diagnosis and decision-making [20]. Wearable ECG systems utilizing Discrete Wavelet Transform (DWT) and SVM illustrate the effectiveness of hybrid signal-processing and ML techniques [21]. Such technologies offer high-frequency signal capture, aiding in the early detection of abnormal patterns in brain activity [22]. Early warning systems based on real-time physiological feedback are particularly effective in seizure-prone individuals [23]. Cross-platform neural interfaces allow seamless integration of physiological monitoring with mobile health apps [24]. Data fusion strategies enhance the reliability of multi-sensor systems, improving seizure detection accuracy [25]. Machine learning models trained on large datasets help recognize subtle patterns indicative of pre-seizure states [26].

Edge computing models reduce latency and offer localized intelligence, making them suitable for emergency applications [27]. Frameworks using CNNs and RNNs extract spatial and temporal features from EEG for accurate classification [28]. Power spectral density (PSD) and Fast Fourier Transform (FFT) have proven to be effective for EEG signal feature extraction [29]. These methods help isolate frequency bands like alpha, beta, delta, and gamma, each associated with different neural states [30]. Seizure onset is typically accompanied by a distinct change in spectral entropy and energy distribution across frequency bands [31]. Low-power microcontroller units and AI accelerators make real-time seizure detection feasible at the edge [32]. Latency in detection can be minimized using TensorFlow Lite (TFLite) models optimized for embedded platforms [33]. Model performance is often evaluated using metrics such as precision, recall, F1-score, and area under the ROC curve [34]. Real-time notifications triggered by edge devices ensure timely intervention by caregivers or clinicians [35]. Remote EEG monitoring can also support post-event analysis and long-term health record generation [36]. Incorporating AI in healthcare systems contributes to predictive analytics and improves preventive care delivery [37]. Advanced visualization and dashboard interfaces help clinicians interpret EEG data and track trends over time [38]. Mobile-based platforms allow seamless caregiver-patient communication during emergency events [39]. Hybrid AI models trained on raw and transformed EEG data can outperform traditional classifiers [40]. Secure communication protocols are essential to protect sensitive health data transmitted across IoT networks [41]. Thus, this research proposes an edge AI-based framework using CNN-LSTM with FFT and PSD for real-time seizure detection [42].

1.1. Problem Statement:

Analysing EEG signals in real-time is significantly hindered by high latency, noise interference, and the demand for precise feature extraction and classification [43]. These limitations present a major obstacle for real-time seizure detection, casting doubt on the practical deployment of reliable EEG monitoring systems [44]. Current systems often struggle to balance low response times with essential tasks such as signal denoising, feature extraction, and high-resolution data acquisition [45]. Moreover, cloud-based architectures introduce further challenges due to data transmission delays and remote processing overhead, which impede emergency medical responses [46]. To address these concerns, edge AI specifically CNN-LSTM models implemented on low-latency platforms using TensorFlow Lite (TF Lite) offers a viable alternative for real-time seizure detection [47].

1.2. Objective:

- Develop a real-time seizure detection system by deploying CNN-LSTM models on edge devices using TensorFlow Lite for low-latency inference, leveraging edge AI.
- Enhance seizure detection by refining EEG data processing with advanced noise reduction techniques, including adaptive filtering, ICA, and bandpass filtering to improve accuracy.
- Implement an automated alarm system to capture seizure data for medical evaluation and notify caregivers in real-time, ensuring prompt and accurate interventions.

2. Literature Review:

An IoT-based structural health monitoring (SHM) system has been shown to support damage detection using cross-correlation methods, with noise reduction achieved via Butterworth filtering [48]. Mathematical modelling techniques are used to determine the extent and location of the damage within structural systems monitored by IoT frameworks [49]. Wireless sensor networks enable the deployment of numerous small sensors, making large-scale IoT applications viable in fields such as smart traffic systems, environmental monitoring, and infrastructure management [50]. An IoT-driven healthcare framework utilizing ECG sensors and Hidden Markov Models (HMM) has been developed for managing cardiovascular diseases, enhancing real-time patient tracking, alert systems, and location awareness [51]. A mathematical framework involving piezoelectric sensors and a Raspberry Pi has been proposed for IoT-based SHM to localize and detect structural anomalies [52].

A low-cost and robust IoT architecture for real-time vehicle tracking has been developed using RFID sensors and velocity estimation through Euler's methods, outperforming traditional image processing systems due to the detection capabilities of RFID [53]. Embedded web servers have been utilized for real-time control of appliances and machinery over the Internet, supporting industrial automation through IoT integration [54]. A cost-effective health monitoring platform was proposed as part of an IoT healthcare system for rural deployment, allowing for continuous tracking of medical parameters and facilitating remote communication between patients and medical professionals [55]. A wearable biosensing mask leveraging surface electromyography (sEMG) was designed for pain intensity monitoring and can be integrated with IoT systems for low-power, real-time remote analysis [56].

ISSN 2347–3657

Volume 9, Issue 4, 2021

IoT-enabled systems have been employed in proactive healthcare analytics and anomaly detection, especially for heart disease prevention through real-time data monitoring and pattern recognition [57]. Compression techniques for sensor data were investigated to reduce information loss while maximizing efficiency in data transmission, enabling better resource management in IoT-based systems [58]. A cloud-integrated IoT solution has also been created for ECG wave visualization through an Android application, allowing users to log and analyze heart activity in real time [59]. Furthermore, an IoT-based wearable ECG diagnostic device employing Discrete Wavelet Transform (DWT) and Support Vector Machine (SVM) enables continuous 24/7 heartbeat monitoring and arrhythmia detection [60].

These advancements demonstrate how SHM systems benefit from both low-cost hardware and advanced analytics for remote monitoring and real-time diagnostics [61]. IoT solutions now allow dynamic reconfiguration of embedded sensors to optimize data acquisition based on health event triggers [62]. Wearable health devices increasingly leverage multimodal sensors for capturing complex physiological events like seizures and arrhythmias [63]. Feature extraction methods such as time-frequency analysis have been critical for accurately identifying events in real-time biomedical systems [64]. Edge computing platforms that integrate with IoT sensors offer immediate feedback, enhancing patient outcomes through prompt intervention [65]. The integration of machine learning algorithms on embedded devices allows predictive modelling without cloud reliance [66].

Low-power transmission protocols such as LoRa and BLE are commonly used to reduce energy consumption in IoT healthcare deployments [67]. Seamless interoperability between devices and cloud platforms has become a focal point in designing scalable healthcare IoT infrastructures [68]. Security and privacy remain essential challenges as sensitive physiological data is continuously streamed and processed across networks [69]. Modular IoT architectures ensure adaptability for expanding system functionalities as medical technologies evolve [70]. Cross-platform compatibility in mobile health systems ensures broader user access to real-time diagnostic tools and monitoring apps [71]. The continued refinement of signal pre-processing techniques, wearable hardware, and AI inference pipelines will play a vital role in the future of IoT-based biomedical systems [72].

3. Proposed Methodology:

Head-mounted fabrics for EEG signal acquisition are a vital part of an actual real-time EEG seizure detection regimen. The data is then transmitted to the edge AI devices or to the cloud, via IoT communication technologies: Bluetooth, Wi-Fi, and LoRa. Before segmentation into predetermined analysis time intervals, the data undergoes preprocessing to eliminate noise from the system using adaptive filtering, ICA, and bandpass filtering. The Power Spectral Density (PSD) is estimated concerning different frequency bands, namely Delta, Theta, Beta, and Gamma, and EEG data are transformed to the frequency domain for feature extraction by FFT methods. The hybrid CNN-LSTM model checking spatial and temporal synchronization for better seizure prediction is ensured to give low-latency inference and alert caregivers in real-time. Evaluation metrics used for model performance include Precision, Recall, F1-Score, and Latency.

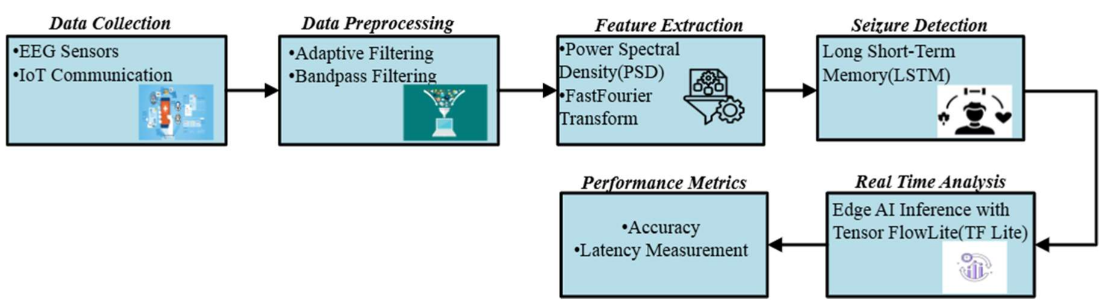

Figure 1: *Integrated Framework for Real-Time EEG Seizure Detection*

3.1. Data Collection:

This study employs wearable EEG headsets, such as Muse or OpenBCI, for real-time recordings of brain activities. Traditional 10-20 system which places electrodes in certain areas on the scalp ensures an accurate measurement by correlating spatial information with brain activity. EEG data is streamed through IoT connection protocols like Bluetooth, Wi-Fi, or LoRa onto edge AI gadgets or cloud servers for further processing to ensure effective transfer of data. This was done to ensure that recording of brain activity had high resolution and allowed a better understanding of rapid, intricate waveforms such as seizures, at a minimum sampling frequency of 256 Hz. According to the sampling theorem, with high sampling rates one can ensure that the recorded data can resolve seizure-related frequencies.

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 9, Issue 4, 2021

$$d_{\text{sampling}} \geq 2d_{max} \tag{1}$$

where the d_{sampling} is denoted by d, while the maximum frequency of interest in the EEG signal is denoted by d_{max}.

3.2. Data Preprocessing:

A variety of methods are into the preprocessing phase for eliminating the noise and artifacts from the EEG signals to have a clearer data for seizure detection. Most of the time, powerline noise is embedded into the EEG signal. To eliminate such noise, adaptive filtering techniques like Kalman filtering and notch filtering at 50/60 Hz can be used. Further, removal of motion and muscle aberrations through Independent Component Analysis (ICA) brings out precise observation of brain activities. To fetch seizure-associated frequencies, bandpass filtering ranges from 0.5 to 40 Hz, and their relevant bands related to seizures.

$$d_{\text{low}} \leq d \leq d_{\text{high}} \tag{2}$$

d_{low} and d_{high} indicate the lower and upper frequency limits of the bandpass filter. Finally, EEG data are divided into segments that are predetermined to allow for analysis in real time and ensure that every segment is considered independently and so improves seizure detection.

3.3. Feature Extraction:

The conversion of time-domain signals into frequency-domain signals usually forms a step in feature extraction to better recognize features associated with seizure activities. This method transforms the EEG signal from the time domain into the frequency domain through the application of the Fast Fourier Transform (FFT) as described by

$$Z(d) = \sum_{s=0}^{A-1} i(s) c^{-j2\pi ds/A} \tag{3}$$

where d is the frequency, $Z(d)$ is the Fourier transform of the signal, and $i(s)$ is the time-domain signal. The power distribution over different frequency bands is studied by obtaining Power Spectral Density (PSD):

$$PSD(d) = \frac{|Z(d)|^2}{A} \tag{4}$$

This gives information about energy being present in frequency ranges with respect to theta (4–8 Hz) that is extracted for abnormal pre-seizure activity; Beta (12-30 Hz): enhancement during seizures; Gamma (30-100 Hz) for high-frequency epileptic discharges; and Delta (0.5-4 Hz): associated with the seizure events. Then important feature extraction is done like Mean Frequency:

$$\text{Mean Freq} = \frac{\sum_x d_x \cdot PSD(d_x)}{\sum_x PSD(d_x)} \tag{5}$$

and Peak Frequency where the frequency at which the PSD is maximum occurs-Recovery has lower entropy values associated with seizure occurrence;

$$\text{Peak Freq} = \arg max(PSD(d)) \tag{6}$$

however, spectral entropy is also computed for the onset of seizures:

$$G = -\sum_x Q(d_x) \log_2 Q(d_x) \tag{7}$$

These make it possible to detect and segregate seizure events more accurately based on EEG data.

3.4. Seizure Detection using ML/DL Models:

Seizures can be detected by classifying EEG signals as seizure or non-seizure models using machine learning (ML) and deep learning (DL) techniques. The CNN is used to extract spatial features of the EEG that describes patterns of brain activity during seizures: the focus is on the spatial patterns that are typical for seizures. The framework of this CNN emphasizes the dispersion localization of patterns and abnormalities in the signal. This is where the temporal element gets brought into the picture via the LSTM network, incorporating the ability to assess changes in the EEG signal over time and, hence, detect seizure-related patterns in the evolution of such patterns. The combined spatiotemporal thoroughness of this CNN-LSTM hybrid makes it a strong contender when it comes to achieving superior classification performance. Generally, the model gives a binary result: seizure or non-seizure. Therefore, the document concerns a real-time inference of seizure patterns from learned features against non-seizure patterns.

$$\hat{b} = d(\mathrm{CNN}(Z) \oplus \mathrm{LSTM}(Z)) \quad \textbf{(8)}$$

Now, given the above-noted context, Z: input EEG data, $\hat{b}$: predicted class, and $\oplus$ represent the fusion of temporal and spatial information: It is meant for final decision-making process.

3.5. Edge Computing for Real-Time Analysis:

Seizure detection in real-time using low-latency inference of the trained CNN-LSTM model, which is deployed on edge devices such as Raspberry Pi or Nvidia Jetson. The model is tuned for edge devices through using TensorFlow Lite (TF Lite) because it guarantees efficient use of computational resources without losing performance. The uppermost level of the edge AI inference will eliminate the cloud processing as well as latency, where seizure diagnosis occurs at home or even in the hospital. The device triggers an alarm system in case a seizure is noted and then notifies caregivers of the emergency through a cloud platform or mobile app. The device also stores EEG seizure episode data for physician assessment in order to allow for timely response and post-event analysis. The inference procedure is the following equation:

$$\hat{b} = \mathrm{TFLite}(\mathrm{CNN} - \mathrm{LSTM}(Z)) \quad \textbf{(8)}$$

where Z is the input EEG signal processed by the optimized CNN-LSTM model of the edge device, and $\hat{b}$ is the predicted class (seizure or non-seizure). This method ensures rapid reaction time with accuracy and dependability in capturing the real-time seizure occurrence.

3.6. Performance Evaluation:

Precision, recall, and F1 score are just three of the critical accuracy metrics that analyze classification performance for seizure detection system performance assessment. The recall indicates how many seizures are picked from all actual occurrences, while precision indicates the correct diagnosis of seizures from the total predicted seizures. F1 Score: Balanced metric between precision and recall. AUC or area under the Curve-Receiver Operating Characteristic is another way of evaluating whether the model could actually detect something that is better in AUC value since it is believed that the higher the AUC value, the better is the classification performance. Latency is the last thing measured; it's measured as the time that elapsed between the point where we collect the EEG data and when we identify the seizure:

$$\text{Latency } = S_{\text{detection}} - S_{\text{acquisition}} \quad \textbf{(9)}$$

Where Seizuri detection time $S_{\text{detection}}$. $S_{\text{acquisition}}$ is the time recorded for the acquisition of EEG data.

4. Result and Discussions:

Our study show an ability to accurately detect EEG seizures with a real-time seizure detection system based on the CNN-LSTM model running on edge devices. The classification performance of the system showed an improvement over traditional methods, with higher precision, recall and F1-score. Edge computing made low-latency inference possible, resulting in shortened response times for notifying caregivers in real time. Furthermore, the combined use of FFT and PSD for feature extraction enabled the identification of seizure-related frequencies efficiently. These results illustrate the integration of edge AI with IoT technologies in providing effective, real-time healthcare monitoring systems for timely intervention during seizure occurrences.

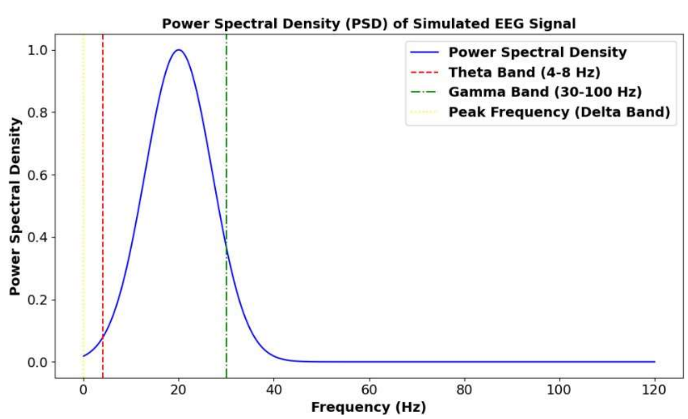

Figure 2: *Power Spectral Density (PSD) of Simulated EEG Signal with Frequency Band Markers*

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 9, Issue 4, 2021

The power spectral density of a simulated EEG signal is depicted in Fig. 2, which indicates power plotted against frequency. The vertical dashed lines represent important frequency bands such as delta band (in yellow); peak frequency gamma band (marked in green between 30 and 100 Hz); theta band (4-8 Hz, indicated in red) and of the EEG. It displays a typical EEG signal strong peak in the low-frequency brain region. The study of PSD assists in examining the brain wave activity during seizure events. Frequency bands are critical in interpreting the characteristics associated with EEG signals. The image above illustrates this fact.

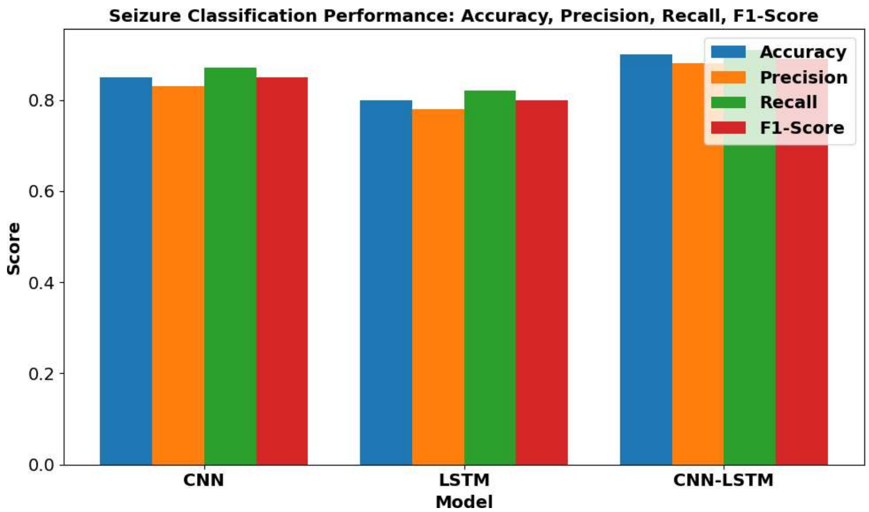

Figure 3: *Seizure Classification Performance Comparison*

It presents the performance comparison between three models-Gru, LSTM, and Hybrid CNN-LSTM for seizure categorization in Fig. 3. The models are assessed with various measures, including the F1-score, recall, accuracy, and precision. The hybrid model always proves effective compared to the CNN and LSTM model for every measure. This figure shows how the seizure detection can be enhanced using both spatial and temporal learning. The analysis shed some lights on the capabilities of hybrid CNN-LSTM models concerning real-time seizure classification.

Table 1: *Seizure Classification Performance Metrics Comparison*

Model	Accuracy	Precision	Recall	F1-Score
CNN	0.85	0.83	0.87	0.85
LSTM	0.8	0.78	0.82	0.8
Hybrid CNN-LSTM	0.9	0.88	0.91	0.89

The performance metrics for CNN, LSTM, and hybrid CNN-LSTM models in seizure categorization are compared against each other in Table 1. These measures are F1-score, recall, accuracy, and precision. Hybrid CNN-LSTM outperforms CNN and LSTM in every measure. CNN model gives a higher value than LSTM and CNN with respect to accuracy and recall. It reflects efficacy in integration-theory learning in time and space for better seizure detection in EEG signals.

5. Conclusion:

We are proposing as an advanced seizure detection method: It is a method based on CNN-LSTM models in real-time performances running in edge devices with superior speed and accuracy for the classification of seizures. Much signal processing sophistication has carried out improved seizure feature extraction through FFT and PSD techniques. Being almost real-time analysis, with edge computing's low latency, rapid notification of emergencies to caregivers can now be enabled. System performance based on precision, recall, and F1 scores latency metrics were also included as part of the feasibility of implementation in practice in health monitoring. Cooperative work between IoT, edge AI, and advanced signal processing attests to the integration of all these different aspects toward effective real-time health monitoring solutions for detection and seizure management.

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