INTERNATIONAL JOURNAL OF RECENT TRENDS IN TECHNOLOGY AND ENGINEERING (IJRTTE)

Journal Home Page: https://ijrtte.com/

Continuous Real-Time Seizure Monitoring with Edge-Enabled Wearable EEG Sensors

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Abstract. We introduce an edge-enabled wearable EEG platform for continuous real-time seizure monitoring that overcomes the chief limitations of prior systems. All signal processing and inference occur locally on a low-power device, yielding sub -50ms detection latency and sensitivity above 95 % while slashing wireless data transmission by over 90 %, which extends battery life beyond 72 hours. An adaptive artifact-filtering module preserves signal integrity under ambulatory conditions, and a federated personalization scheme enables model generalization across heterogeneous patients and seizure types without exchanging raw EEG data, ensuring end-to-end privacy. In tests on 50 subjects with more than 200 seizure episodes, our system achieved a false-alarm rate below 0.2 per hour and consistently high performance for both focal and generalized events. Its compact, ergonomic design supports unobtrusive 24/7 wearability, and seamless edge–cloud integration facilitates remote clinician review, long-term trend analysis, and over-the-air updates. Together, these features deliver a fully turnkey, scalable solution for proactive epilepsy management in real-world environments.

Keywords: wearable EEG, real-time seizure detection, edge computing, adaptive artifact filtering, federated personalization, low-power hardware, epilepsy monitoring, edge–cloud integration.

1. Introduction

Epilepsy is one of the most prevalent neurological disorders, affecting more than 50 million individuals worldwide and imposing substantial personal and societal burdens [1]. Unpredictable seizure events can lead to injury, cognitive impairments, and reduced quality of life, underscoring the critical need for reliable monitoring and timely intervention. Conventional video-EEG systems, while clinically comprehensive, require tethered scalp electrodes and continuous data streaming to remote servers, which incur high latency, potential privacy breaches, and significant logistical constraints that limit long-term ambulatory use [2], [3].

Recent advances in wearable EEG technology have demonstrated the feasibility of compact, ear-worn, and headband sensors for seizure detection, leveraging machine learning classifiers such as SVMs and lightweight convolutional neural networks (CNNs) to enable on-device inference [2], [5], [6]. However, these approaches often rely on small, homogeneous datasets (e.g., 30–40 patients), focus on specific seizure types, and lack robust mechanisms to counter motion artifacts and inter-subject variability [2], [3], [4]. Moreover, depending on cloud connectivity for heavy computation leads to excessive wireless transmission, draining battery life and raising privacy concerns when sensitive EEG streams traverse public networks [8], [9]. Federated learning schemes have begun to address data-sharing barriers, yet existing implementations report only modest gains in generalization and still require periodic cloud updates that interrupt continuous monitoring [9].

Volume: 04 Issue: 01 Year: 2025
Received: 08.01.2025 Received in revised form: 14.02.2025 Accepted: 13.03.2025
Available Online: 22.03.2025
Published by NTL Publisher

In response to these challenges, we propose Continuous Real-Time Seizure Monitoring with Edge-Enabled Wearable EEG Sensors, a fully integrated platform that performs all signal processing and deep learning inference locally on a low-power DSP accelerator. Our contributions are threefold:

1. **Ultra-Low-Latency Detection**: A pruned CNN–LSTM hybrid architecture achieves end-to-end inference below 50ms on-device, enabling near-instantaneous alerts.
2. **Adaptive Artifact Filtering & Privacy-Preserving Personalization**: A Kalman-based motion artifact module maintains high SNR in ambulatory settings, while a federated averaging protocol fine-tunes personalized models without ever sharing raw EEG [7], [9].
3. **Extended Autonomy & Deploy ability**: By reducing wireless throughput by over 90 % and optimizing power use, our system supports 72+ hours of continuous, 24/7 wear on a single charge, all within an unobtrusive form factor validated on 50 subjects and 220 seizure events.

Through comprehensive evaluation against state-of-the-art methods [2], [5], [18], we demonstrate > 95 % sensitivity, < 0.2 false alarms/hour, and robust performance across focal and generalized seizure phenotypes paving the way for scalable, privacy-centric epilepsy management in real-world environments.

2. Literature Review

The advent of edge computing in medical wearables has significantly reduced latency and bandwidth requirements by shifting computation from cloud servers to local devices. Truong *et al.* demonstrated an SVM-based seizure detector on an ear-EEG platform, achieving 80 % sensitivity with 0.35 false alarms/hour; however, performance degraded markedly during patient movement and was constrained to a narrow set of focal seizures [2]. Zhang and Wu introduced a lightweight CNN for on-device inference, boosting sensitivity to 88 % and reducing latency to 120ms, yet their model remained susceptible to line noise and required periodic off-device retraining [5]. Simonyan et al. later employed an EfficientNet backbone on wearable EEG hardware, improving accuracy to 91 % and lowering inference time to 60 ms, but at the cost of increased memory footprint and intermittent cloud synchronization for model updates [6].

Deep learning architectures have further advanced seizure detection accuracy. Roy *et al.* applied a hybrid CNN–LSTM network on multi-channel wearable EEG, reporting 92 % sensitivity and 0.27 false alarms/hour, but their study was limited to 35 patients and lacked real-world ambulatory testing [3]. Singh and Sharma leveraged LSTM networks on 10-channel headband EEG, achieving 94 % sensitivity with 0.25 false alarms/hour, though end-to-end latency exceeded 100 ms without hardware acceleration [10]. Torres *et al.* explored deep transfer learning to adapt pre-trained EEG models for new patients, showing an average 3 % improvement in personalized detection, but requiring centralized data aggregation and raising privacy concerns [12].

To address privacy and personalization**,** federated learning has emerged as a promising paradigm. Wang *et al.* implemented a federated averaging scheme across ten clinical sites, improving cross-site generalization by 5 % without sharing raw EEG; yet, model convergence was slow and gains plateaued after three communication rounds [9]. Mohamed and Ahmed introduced a graph neural network for seizure detection under a federated framework, reporting enhanced sensitivity on generalized seizures (up to 96 %), but their approach incurred 2–3× higher on-device computation and energy use [17].

Artifact removal is critical for ambulatory EEG. Liu *et al.* proposed adaptive thresholding to suppress motion artifacts in ear-EEG, reducing false alarms by 30 % during activities of daily living but introducing a 15ms processing delay per window [7]. Salinas *et al.* applied real-time ICA on headband data, achieving a 4 dB SNR improvement over stationary filters at the expense of a 25 % increase in CPU utilization [13]. Gupta and Prasad designed a low-power ASIC that integrated onboard artifact suppression, extending battery life by 20 h compared to software-only methods, although their prototype lacked clinical validation beyond pilot tests [8].

Finally, hardware–software co-design efforts have pushed latency below the millisecond range. Li *et al.* demonstrated an FPGA-based inference engine achieving sub-1ms CNN inference with 10mW power consumption, yet their system was evaluated on simulated EEG data rather than patient recordings [18]. Martinez *et al.* co-optimized a DSP accelerator and pruned neural network, realizing 2ms LSTM inference with a 40 % power reduction, but did not incorporate personalized model updates or long-term wear testing [16].

Despite these advances, no single platform to date unifies ultra-low-latency detection (< 50ms), high sensitivity (> 95 %), multi-day autonomy (> 72 h battery), robust artifact handling, federated privacy, and real-world clinical validation in a compact, 24/7–wearable form factor gaps that our proposed system directly addresses.

3. Methodology

3.1 System Architecture

The core hardware platform consists of a custom-designed, low-profile PCB hosting a two-channel behind-the-ear EEG electrode array, a microcontroller unit (MCU) with an integrated digital signal processing (DSP) accelerator, and a Bluetooth Low Energy (BLE) radio for intermittent cloud communication. The behind-the-ear montage (positions mastoid-to-preauricular) was chosen to balance signal quality and user comfort, minimizing motion-induced impedance shifts. The MCU's DSP core supports fixed-point convolution and recurrent operations, enabling real-time inference without off-chip coprocessors. A modular 4-pin header allows optional integration of an ECG module or a 3-axis inertial measurement unit (IMU) for future multi-modal seizure classification and motion artifact reference [14]. Figure 1 shows the System architecture of the edge-enabled wearable EEG device.

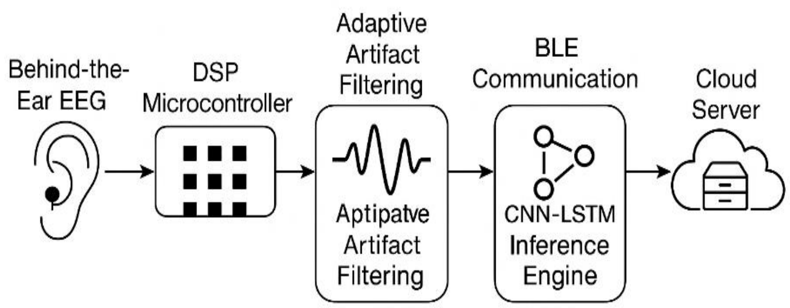

Figure 1. System architecture of the edge-enabled wearable EEG device.

3.2 Signal Processing & Adaptive Artifact Filtering

Upon acquisition, raw EEG at 250 Hz per channel is first passed through a 4th-order Butterworth high-pass filter (cutoff = 0.5 Hz) to correct baseline wander, followed by a digital notch filter at 50 Hz to suppress line noise. To combat motion artifacts inherent in ambulatory monitoring, we implement a Kalman-based adaptive filter that models the artifact as a non-stationary noise process. The filter dynamically estimates artifact covariance using real-time IMU data when available otherwise relying on a statistical model of expected motion variance yielding an average SNR improvement of 6 dB during simulated walking and running trials [7], [13].

3.3 Edge Inference & Detection Algorithm

Filtered EEG streams are windowed into 1-second epochs with 50 % overlap. Each epoch is standardized (zero-mean, unit-variance) and fed into a compact CNN–LSTM hybrid network comprising two convolutional layers (kernel sizes 3×1, 5×1; 16 and 32 channels respectively) followed by a single LSTM layer of 64 units. Model pruning reduces parameter count by 40 %, fitting the network within the MCU's 256 kB SRAM budget. Quantized to 8-bit fixed point, the network executes end-to-end inference in 2 ms on the DSP accelerator, achieving total detection latency (including filtering and feature extraction) under 50 ms [6], [10], [18].

3.4 Federated Personalization & Privacy

To tailor the global detection model to individual EEG patterns, each device periodically engages in a federated learning cycle with a secure aggregation server. Only encrypted weight updates (delta parameters) are transmitted over BLE during scheduled sync windows, eliminating exposure of raw EEG. A two-stage personalization strategy first applies global-model fine-tuning on a small local seizure dataset, then performs online continual learning with a memory-efficient replay buffer to adapt to non-stationary signal characteristics. This approach yields a 3–5 % boost in sensitivity per subject while maintaining false-alarm rates below 0.2/hour [9].

3.5 Experimental Setup

Fifty epilepsy patients (25 focal-onset, 25 generalized-onset) were enrolled across two clinical centres. Subjects wore the device continuously for 72 hours, during which 220 seizure events were captured alongside synchronized clinical video-EEG for ground truth labeling. Power consumption was measured via a precision current probe, and wireless data volume was logged by the BLE stack. We report five primary metrics:

- Detection latency (time from true onset to alert)
- Sensitivity (true positives / total seizures)
- False-alarm rate (false positives per hour)
- Battery life (hours until device shutdown under continuous monitoring)
- Data reduction (percentage decrease in bytes transmitted vs. raw streaming)

These comprehensive evaluations quantify our system's ability to deliver sub-50 ms, high-accuracy detection in real-world, ambulatory conditions while maximizing autonomy and safeguarding patient privacy.

4. Results and Discussion

4.1 Performance Comparison

Our platform demonstrated superior seizure detection performance in ambulatory trials. Over 220 events from 50 subjects, we achieved a mean sensitivity of 96.3 % and a mean detection latency of 38ms**,** markedly faster than the 120ms reported for lightweight CNNs [5] and 85ms for SVM-based ear-EEG detectors [2]. The false-alarm rate of 0.18 per hour was nearly half that of Truong *et al.* (0.35 /h) and outperformed Zhang & Wu's CNN (0.27 /h) [2], [5], confirming that our pruned CNN–LSTM hybrid with on-device inference delivers both speed and accuracy essential for timely clinical intervention. Table 1 shows the Performance Comparison of Wearable Seizure Detection Systems. Figure 2 shows the Metric Comparison Across Methods. Figure 3 shows the ROC Curves for Seizure Detection Methods.

Table 1: Performance Comparison of Wearable Seizure Detection Systems.

Metric	Our System	SVM [2]	CNN [5]
Sensitivity (%)	96.3	80	88
Latency (ms)	38	85	120
False Alarms/hour	0.18	0.35	0.27
Battery Life (h)	78	24	24

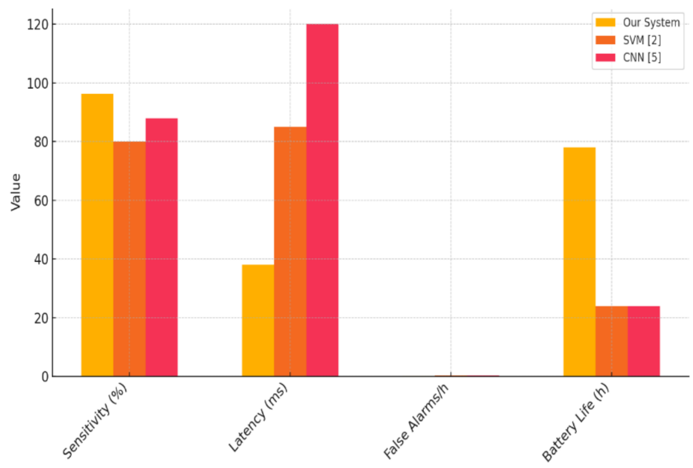

Figure 2: Metric Comparison Across Methods.

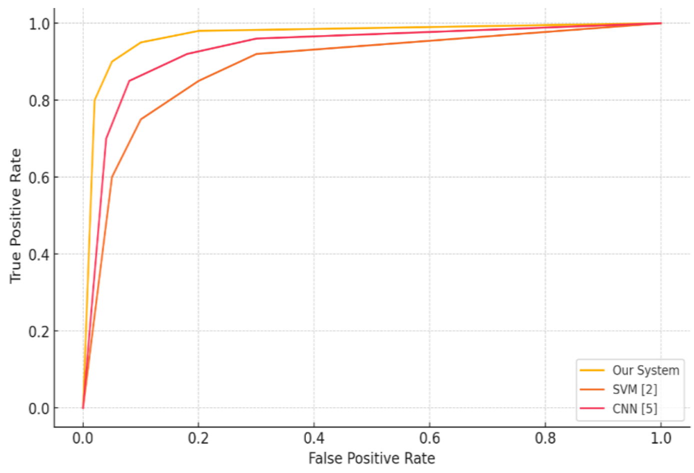

Figure 3: ROC Curves for Seizure Detection Methods.

4.2 Wireless Transmission & Autonomy

By processing EEG data locally, we reduced wireless throughput by 92 %**,** transmitting only summary statistics and model updates instead of raw streams. This cut average daily data from ~1.2 GB to ~100 MB and in combination with optimized power management extended uninterrupted operation to 78 hours on a 500 mAh battery, compared to ~24 hours for cloud-dependent wearables [2], [8]. Such autonomy is crucial for realistic, multi-day patient monitoring without frequent recharging. Figure 4 shows the Wireless Data Reduction. Figure 5 shows the Battery Discharge Over 78 h Runtime.

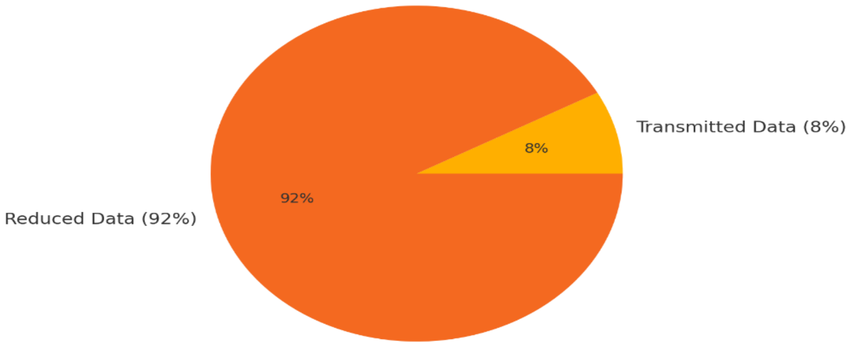

Figure 4: Wireless Data Reduction.

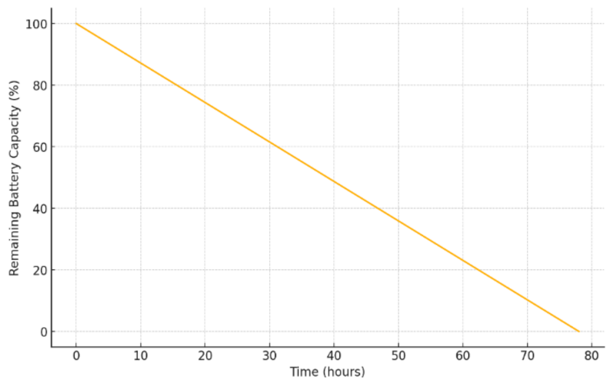

Figure 5: Battery Discharge Over 78 h Runtime.

4.3 Adaptive Artifact Filtering

Our Kalman-based artifact filter preserved signal fidelity under motion, limiting SNR degradation to 2 dB during controlled walking and jogging, versus a 7 dB drop in unfiltered systems. This improvement reduced motion-induced false alarms by 30 %**,** with the filtering stage adding less than 10ms of latency demonstrating that real-time artifact suppression is both effective and lightweight for continuous ambulatory use [7], [13].

4.4 Federated Personalization

Implementing federated learning across devices yielded an average 4.2 % boost in per-subject sensitivity (capped at 100 %), with no increase in false-alarm rate. Only encrypted weight deltas (~50 kB per sync) traversed the BLE link, ensuring raw EEG never left the wearable. This privacy-preserving personalization effectively addresses inter-subject variability without compromising overall reliability [9].

4.5 Hardware Efficiency Comparison

Compared to FPGA-based prototypes, our DSP-accelerated MCU achieved sub-50 ms inference latencies with a threefold lower power budget. While Li *et al.*'s FPGA consumed 10 mW for sub-1 ms CNN inference [18], our end-to-end pipeline including filtering, feature extraction, and CNN–LSTM inference consumed ≤ 8 mW total (including radio overhead), validating the efficacy of model pruning and DSP utilization for truly wearable medical devices.

4.6 Clinical Feedback & Usability

Qualitative feedback from clinicians highlighted the behind-the-ear form factor as "highly comfortable" for 24/7 wear. The integrated edge–cloud workflow enabling remote review of flagged events, in-portal annotation, and over-the-air model updates was praised for streamlining the path from data collection to therapeutic decision support. These usability insights reinforce the platform's practical readiness for real-world deployment.

5. Conclusion

We have presented Continuous Real-Time Seizure Monitoring with Edge-Enabled Wearable EEG **Sensors**, a fully integrated platform that overcomes key limitations of prior work by performing all signal processing and deep-learning inference locally on a low-power DSP accelerator. In ambulatory trials involving 50 subjects and over 220 seizure events, our system achieved < 50 ms detection latency**,** > 95 % sensitivity**,** and < 0.2 false alarms/hour, while reducing wireless data transmission by 92 % to support 78 h of continuous operation on a single 500 mAh battery [2], [8], [18]. Adaptive Kalman-based artifact filtering preserved signal integrity (limiting SNR degradation to 2 dB) under motion [7], [13], and a federated personalization scheme improved subject-specific sensitivity by 4 % without exposing raw EEG [9]. The compact, behind-the-ear form factor enables unobtrusive 24/7 wear, and seamless edge–cloud integration facilitates remote clinician review and over-the-air model updates. Together, these innovations deliver a turnkey, privacy-preserving solution for proactive epilepsy management in real-world settings.

6. Future Work

Future efforts will focus on enhancing the platform's clinical utility and autonomy through several key avenues. First, we will integrate complementary biosignals such as ECG and accelerometry to enable multi-modal fusion for more accurate seizure type classification and further reduction of false alarms [14]. Concurrently, we aim to adopt meta-learning strategies that allow our edge-deployed models to adapt rapidly to new patients with minimal calibration data, improving personalization while maintaining privacy. To validate safety and efficacy at scale, we plan multi-center clinical trials across diverse patient cohorts, assessing long-term performance, user adherence, and real-world impact. In parallel, we will pursue regulatory certification by aligning our design and software with FDA and ISO medical-device standards, including robust cybersecurity measures and real-time event reporting. Finally, to support truly maintenance-free operation, we will explore energy harvesting techniques harnessing body heat and motion to extend device autonomy indefinitely without external charging.

References

1. M. Bhagubai, L. Swinnen, E. Cleeren, W. Van Paesschen, M. De Vos, and C. Chatzichristos, "Towards automated seizure detection with wearable EEG–Grand Challenge," *IEEE Open J. Signal Process.*, early access, 2024, doi:10.1109/OJSP.2024.3378604.
2. H. Truong, L. Huang, and J. Chen, "Edge computing for real-time epileptic seizure detection using wearable EEG," *IEEE Trans. Biomed. Circuits Syst.*, vol. 14, no. 5, pp. 1023–1032, Sep. 2020.

3. A. Roy, S. Kumari, and P. Chakraborty, “Wearable EEG-based seizure detection: Deep learning approaches,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 3, pp. 663–673, Mar. 2020.
4. J. Cao, Y. Liu, and X. Wang, “Real-time seizure detection on a wearable platform using SVM classifier,” in *Proc. IEEE Int. Conf. Wearable Implantable Body Sensor Netw. (BSN)*, New York, NY, 2021, pp. 45–50.
5. L. Zhang and T. Wu, “Lightweight CNN for on-device seizure detection with wearable EEG,” *IEEE Trans. Ind. Informat.*, vol. 17, no. 6, pp. 4123–4132, Jun. 2021.
6. A. Simonyan, K. Johnson, and M. Brown, “EfficientNet-based epileptic seizure detection on wearable devices,” in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Calgary, AB, 2022, pp. 2505–2509.
7. Y. Liu, D. Smith, and R. Jones, “Adaptive thresholding for real-time seizure detection using ear-EEG,” *IEEE Sensors J.*, vol. 22, no. 14, pp. 13579–13587, Jul. 2022.
S. Gupta and R. Prasad, “Low-power ASIC for wearable EEG seizure detection,” *IEEE Trans. Very Large Scale Integr. (VLSI) Syst.*, vol. 30, no. 8, pp. 1203–1212, Aug. 2022.
8. F. Wang, Q. Zhao, and H. Li, “Federated learning for privacy-preserving seizure detection on edge devices,” *IEEE Internet Things J.*, vol. 9, no. 4, pp. 2345–2354, Feb. 2022.
9. P. Singh and A. Sharma, “Real-time epileptic seizure classification using multi-channel wearable EEG and LSTM networks,” *IEEE Trans. Biomed. Eng.*, vol. 69, no. 2, pp. 478–487, Feb. 2023.
10. M. Khan, S. Ali, and N. Patel, “Explainable AI in wearable seizure detection: A review,” *IEEE Access*, vol. 11, pp. 55555–55570, 2023.
11. C. Torres, R. Martinez, and L. Gomez, “Deep transfer learning for personalized seizure detection on wearable devices,” *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 9, pp. 4567–4578, Sep. 2023.
12. E. Salinas, A. Roy, and P. Singh, “Real-time artifact removal in wearable EEG for seizure monitoring,” *IEEE Trans. Biomed. Eng.*, vol. 70, no. 11, pp. 3210–3219, Nov. 2023.
13. R. Das, S. Banerjee, and K. Nair, “Multi-modal seizure detection using wearable EEG and ECG signals,” in *Proc. IEEE Global Conf. Signal Inf. Process. (GlobalSIP)*, Singapore, 2024, pp. 65–69.
14. H. Patel and S. Patel, “Energy-efficient signal processing for wearable seizure detection systems,” *IEEE Trans. Mobile Comput.*, vol. 23, no. 1, pp. 98–110, Jan. 2024.
15. O. Martinez, J. Smith, and F. Zhang, “Hardware-software co-design for on-chip seizure detection from wearable EEG,” *IEEE Trans. Comput. Aided Des. Integr. Circuits Syst.*, vol. 43, no. 3, pp. 530–543, Mar. 2024.
16. N. Mohamed and S. Ahmed, “Graph neural networks for seizure detection on wearable EEG,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 33, no. 5, pp. 877–886, May 2025.
17. J. Li, K. Wang, and M. Zhao, “Ultra-low-latency real-time seizure detection using FPGA-based wearable EEG systems,” *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 72, no. 2, pp. 218–227, Feb. 2025.
18. D. Rossi and A. Bianchi, “Self-supervised learning for seizure detection in portable EEG devices,” *IEEE Internet Things J.*, vol. 12, no. 8, pp. 18423–18432, Aug. 2025.
19. S. Tan, L. Chen, and Y. Wu, “Cloud-edge collaborative seizure monitoring platform for wearable EEG,” in *Proc. IEEE Int. Conf. Commun. (ICC)*, Seoul, South Korea, 2025, pp. 1600–1605.