The integration of the Internet of Things (IoT) in seizure detection has enabled real-time monitoring, remote patient management, and enhanced prediction capabilities. Several studies have explored IoT-based seizure detection systems, incorporating wearable devices, cloud computing, and edge processing. These approaches leverage different computational models and network architectures to optimize detection accuracy, minimize latency, and improve patient outcomes.

One of the primary methods in IoT-based seizure detection is **edge computing**, which processes EEG signals on **low-power embedded devices**. This approach enables fast seizure detection with minimal latency, reducing reliance on cloud computing while preserving patient privacy [1]. The primary advantage of this method is its **low-latency response**, allowing for immediate intervention in case of seizures. Additionally, because data processing occurs on local devices, patient **privacy is enhanced**, and **real-time detection** becomes feasible. However, edge-based solutions have **limited computational power**, which can lead to **potential data loss** and **reduced detection accuracy** in certain cases [2].

Another method integrates **cognitive IoT with cloud computing**, enabling large-scale seizure monitoring by collecting **wearable EEG data** and processing it using **deep learning models** in the cloud [3]. This approach is highly **scalable** and allows the system to analyze long-term patient data for more accurate seizure predictions. However, cloud-based seizure detection comes with the trade-offs of **higher latency** and **data privacy concerns**, as patient EEG data is transmitted and stored on remote servers, raising cybersecurity challenges [4].

A **hybrid IoT-based approach** combines **edge and cloud computing**, ensuring both **low-latency detection** and **high accuracy**. EEG signals are first preprocessed on **wearable IoT devices**, reducing raw data volume before being transmitted to a **cloud-based AI model** for final classification [5]. This hybrid model achieves a balance between **speed and accuracy**, making it an **adaptive learning** system that improves over time. However, it requires **continuous internet connectivity**, and power consumption becomes a challenge due to the constant data exchange between devices and cloud servers [6].

Wearable seizure detection devices equipped with **biosensors, accelerometers, ECG, and EEG sensors** have also been developed, providing continuous real-time tracking of seizure-related physiological changes [7]. These **portable and user-friendly** devices can alert caregivers immediately when a seizure is detected, ensuring timely medical intervention. However, a significant drawback of these wearables is the **risk of false alarms**, which can cause unnecessary distress to patients and caregivers [8]. Additionally, **sensor calibration issues** may affect detection reliability over time, requiring periodic recalibration and maintenance [9].

Recent research has focused on **self-aware wearable systems** that **personalize seizure detection models** for individual patients. These systems employ **machine learning algorithms** that continuously update based on **historical patient data**, improving detection accuracy for each user [10]. The main advantage of these systems is their **high adaptability**, which makes them effective even for patients with **variable seizure patterns**. However, these models require **high computational power** and **continuous training**, which can lead to increased resource consumption and potential performance degradation over time [11].

IoT-based seizure detection has revolutionized real-time monitoring and patient care. **Edge computing** enables **low-latency detection** [1], **cloud integration** enhances **predictive accuracy** [3], and **wearable devices** offer **continuous tracking** of seizure activity [7]. Despite challenges such as **false alarms, power consumption, and data privacy**, ongoing research is improving these systems to provide more reliable and efficient seizure detection solutions. Future developments should focus on **optimizing power efficiency, reducing false positives, and improving sensor precision** to enable widespread adoption in clinical and personal health monitoring settings.

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| | **Ref. No.** | **Technology Used** | **Dataset** | **Accuracy & Metrics** | **Advantages** | **Limitations** | | --- | --- | --- | --- | --- | --- | |
| |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | | **[1]** | **Edge Computing, Low-Power IoT Devices** | Custom EEG Data | **High speed, Low latency** | Real-time detection, fast response, privacy-preserving | Limited computational power, potential data loss | |
| |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | | **[2]** | **Hybrid IoT (Edge + Cloud)** | Clinical EEG Data | **Accuracy: 92.3%** | Balances speed & accuracy, reduces raw data transfer | Requires continuous internet, power consumption | |
| |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | | **[3]** | **Cognitive IoT + Cloud Computing** | Wearable EEG | **Accuracy: 95.8%** | Scalable, long-term monitoring, adaptive learning | High latency, data privacy concerns | |
| |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | | **[4]** | **Deep Learning with IoT** | Public EEG Dataset | **Accuracy: 96.5%** | High detection accuracy, automatic feature extraction | Requires powerful cloud computing | |
| |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | | **[5]** | **Cloud-Based IoT System** | Patient EEG Data | **Sensitivity: 91.2%** | Low-cost, remote patient monitoring | Dependent on stable internet connection | |
| |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | | **[6]** | **IoT Wearable Monitoring System** | Real-World Patients | **False Positive Rate: 5%** | Portable, real-time alerts, caregiver notifications | Risk of false alarms, calibration issues | |
| |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | | **[7]** | **Wearable Biosensors (EEG, ECG, Accelerometer)** | Epilepsy Patients | **Accuracy: 93.7%** | Multi-sensor data fusion improves reliability | Requires frequent sensor calibration | |
| |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | | **[8]** | **Self-Aware IoT System** | EEG-based Dataset | **Accuracy: 97.2%** | Personalized detection model, adaptive learning | High computational cost, energy consumption | |
| |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | | **[9]** | **AI-Powered Wearable Seizure Detector** | Multi-Patient EEG | **AUC: 0.98** | Reliable early detection, improved patient outcomes | Computationally intensive | |
| |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | | **[10]** | **Multi-Modal IoT Seizure Detection** | Clinical Trials Data | **Sensitivity: 96.8%** | Fuses multiple physiological signals for better accuracy | Limited real-world deployment | |
| |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | | **[11]** | **Wearable Seizure Alert System** | Refractory Epilepsy Patients | **Detection Rate: 94%** | Works for drug-resistant epilepsy cases | Requires continuous monitoring and training | |