

# A Multi-Sensor Wearable System for Real-Time Epileptic Seizure Detection Using Machine Learning

N.M.K Ramalingam Sakthivelan<sup>1</sup>, M.E (Ph.D), Ebin Andrews K<sup>2</sup>, Dinesh M<sup>3</sup>, Jagan N<sup>4</sup>

<sup>1,2,3,4</sup>Department of Computer Science and Engineering, Paavai Engineering College, Namakkal, Tamil Nadu, India – 637108

**Emails:** [velannmk@gmail.com](mailto:velannmk@gmail.com)<sup>1</sup>, [ebinandrewski@gmail.com](mailto:ebinandrewski@gmail.com)<sup>2</sup>, [mdineshm525@gmail.com](mailto:mdineshm525@gmail.com)<sup>3</sup>, [jagannarasimman@gmail.com](mailto:jagannarasimman@gmail.com)<sup>4</sup>

## Abstract

Epileptic seizures occur suddenly and can lead to severe health risks if not detected early. Continuous and real-time monitoring is essential for timely intervention; however, most existing systems rely on hospital-based EEG setups that are costly and impractical for daily use. This paper presents an AI-based wearable device for early seizure detection using multiple physiological sensors, including EEG, heart rate, galvanic skin response (GSR), and body movement. Sensor data is processed in real time to identify seizure-related patterns. Upon detecting abnormal activity, it triggers immediate alerts via wireless communication to notify caregivers. The wearable solution is portable, energy-efficient, and suitable for continuous monitoring, achieving an accuracy of approximately 88–92%, improving detection reliability while reducing false alarms and enhancing patient safety.

**Keywords:** Epileptic Seizure Detection, Wearable Devices, Machine Learning, Random Forest Algorithm, Real-Time Health Monitoring.

## 1. Introduction

Epilepsy is a chronic neurological disorder characterized by recurrent and unpredictable seizures [1] that can significantly affect the quality of life and safety of affected individuals. Seizures often occur without warning, increasing the risk of injury and delaying medical intervention. Early detection of epileptic seizures plays a critical role [2], [3] in minimizing these risks by enabling timely assistance and appropriate response. Consequently, reliable and continuous seizure monitoring systems are essential for effective epilepsy management. Traditional seizure detection methods primarily rely on electroencephalography (EEG) recordings obtained in clinical or hospital environments. Although EEG-based analysis provides valuable insights into brain activity, continuous monitoring using such systems is expensive, uncomfortable, and impractical for daily use. In addition, these systems often require expert supervision and complex preprocessing techniques, limiting their suitability for real-world, long-term monitoring applications. Recent advancements in wearable technology, embedded systems, and

machine learning have opened new opportunities for developing portable healthcare solutions. Wearable devices equipped with physiological sensors can continuously monitor vital signals such as heart rate, skin conductance, and body movement in a non-invasive manner. When combined with machine learning algorithms, these systems can analyze complex physiological patterns and identify abnormal conditions associated with epileptic seizures. In this paper, we propose an AI-based wearable device for early detection of epileptic seizures using a multi-sensor approach. The system integrates EEG, heart rate, galvanic skin response (GSR), and motion sensors to capture real-time physiological data. A Random Forest machine learning model is employed to detect seizure-related patterns with improved reliability. Upon identifying abnormal activity, the device generates immediate alerts through audio, vibration, and wireless communication to notify caregivers. The proposed solution is designed to be portable, low-cost, and energy-efficient, making it suitable for continuous

monitoring during daily activities and offering a practical approach to enhancing patient safety.

## 2. Related Work

Traditional epileptic seizure detection systems primarily rely on electroencephalography (EEG) signals analyzed using machine learning techniques such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Artificial Neural Networks (ANN) [1], [7]. While these approaches provide good accuracy in clinical environments, they require complex preprocessing and are not suitable for continuous real-world monitoring. Recent studies have explored deep learning and generative models, such as Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GAN), to improve detection performance and address data limitations [5], [6]. However, these methods are computationally intensive and less feasible for deployment in resource-constrained wearable devices. Wearable-based seizure detection systems using motion sensors and accelerometers have also been proposed [2]. Although these systems are simple and portable, they mainly detect convulsive seizures and often produce high false alarms during normal physical activities. Additionally, research has investigated physiological signals such as heart rate and galvanic skin response (GSR) for seizure detection [4], but single-sensor approaches lack reliability due to variability among patients. IoT-enabled wearable systems have introduced real-time monitoring and caregiver notification features [3]. However, many of these systems depend on cloud-based processing, leading to latency and connectivity issues. To overcome these limitations, recent approaches focus on multi-sensor fusion combined with machine learning to improve detection accuracy and reliability. The proposed system follows this direction by integrating EEG, heart rate, GSR, and motion data with an embedded Random Forest model for real-time, on-device seizure detection. Recent advancements in wearable healthcare systems have emphasized the use of edge computing and lightweight machine learning models for real-time seizure detection. Studies have shown that on-device processing reduces latency and improves response time compared to cloud-dependent systems [11]. Hybrid approaches combining multiple physiological signals with

efficient classifiers such as Random Forest and decision tree ensembles have demonstrated improved accuracy and robustness in noisy environments [13]. Furthermore, research on IoT-based health monitoring highlights the importance of integrating real-time alert mechanisms and remote communication to ensure timely medical assistance [19]. These developments indicate a shift toward intelligent, portable, and energy-efficient wearable solutions for continuous epileptic seizure monitoring.

## 3. Existing System

Current epileptic seizure detection systems mainly rely on clinical EEG-based monitoring, which provides accurate analysis of brain activity but is expensive, bulky, and unsuitable for continuous daily use outside hospitals [1], [10]. Wearable systems using motion sensors such as accelerometers can detect seizure-related movements, but they are limited to specific seizure types and often produce high false alarms [2]. Other approaches utilize physiological signals like heart rate and galvanic skin response (GSR), which are more suitable for wearable devices; however, single-sensor systems lack consistency and reliability across different patients [4]. IoT-based solutions enable remote monitoring and caregiver alerts, but they depend on cloud processing, leading to latency, connectivity issues, and potential privacy concerns [3]. Many existing seizure detection systems rely on single-modality sensing or partial integration of physiological signals, limiting their effectiveness in real-world scenarios. EEG-based systems, although accurate, are constrained by high setup complexity and lack of mobility, making them unsuitable for continuous monitoring [10]. Wearable solutions focusing only on motion or cardiac signals often fail to detect non-convulsive seizures and are prone to false positives during daily activities [2], [4]. Additionally, several systems depend on cloud-based processing, which introduces delays and reduces reliability in emergency situations due to network dependency [3]. These limitations highlight the need for a more robust, multi-sensor, and real-time wearable approach [20]. Overall, existing systems are constrained by single-sensor dependency, lack of portability, and delayed response, highlighting the need for a real-time, multi-sensor wearable solution.

## 4. Proposed System

**Table 1 Proposed System**

Sensor	Physiological Parameter	Purpose
EEG Sensor	Brain electrical activity	Detect abnormal neural patterns
Heart Rate Sensor	Heart rate / HRV	Capture cardiovascular changes
GSR Sensor	Skin conductance	Monitor autonomic nervous response
Accelerometer	Body movement	Detect seizure-related motion

The proposed system presents an AI-based wearable device designed for the early detection of epileptic seizures through continuous monitoring of multiple physiological signals [8]. Unlike conventional hospital-dependent solutions, the system operates as a portable and low-cost wearable platform suitable for daily use. By integrating multiple biosensors with an embedded processing unit and a machine learning algorithm, the system enables real-time seizure detection and immediate caregiver notification, thereby improving patient safety and response time.

### 4.1. Wearable Multi-Sensor Unit

The wearable device integrates multiple physiological sensors, including an electroencephalography (EEG) sensor, heart rate sensor, galvanic skin response (GSR) sensor, and an accelerometer. The EEG sensor captures brain electrical activity associated with abnormal neural patterns during seizures. Table 1. Sensors used in the proposed system. The heart rate sensor monitors cardiovascular variations, while the GSR sensor measures changes in skin conductance linked to autonomic nervous system responses. The accelerometer detects body movement and posture changes that commonly occur during convulsive seizures. By combining these complementary signals,

the system achieves comprehensive physiological monitoring and improves detection reliability compared to single-sensor approaches. Accelerometer Body movement Detect seizure-related motion [12].

### 4.2. Data Acquisition and Preprocessing

Physiological signals from all sensors are continuously collected in real time through the embedded platform. Since raw sensor data may contain noise due to motion artifacts, environmental interference, or sensor limitations, preprocessing techniques are applied to improve signal quality. These techniques include noise filtering, normalization, and smoothing. Basic statistical features such as mean, variance, standard deviation, and signal energy are extracted from each sensor stream. Feature extraction reduces data dimensionality while preserving important characteristics related to pre-seizure and seizure conditions.

### 4.3. Machine Learning-Based Seizure

#### 4.3.1. Detection

A Random Forest machine learning algorithm [13] is employed to classify physiological patterns into seizure and non-seizure states. Random Forest is selected due to its high classification accuracy, robustness to noisy and heterogeneous data, and low risk of overfitting. The algorithm combines multiple decision trees to enhance generalization performance. The extracted features from all sensors are used as input to the model, enabling effective multi-sensor data fusion [14]. This approach improves seizure detection accuracy while maintaining low computational complexity, making it suitable for real-time embedded implementation.

### 4.4. Embedded Processing Unit

An embedded microcontroller platform, such as ESP32 or an Arduino-based system, serves as the core processing unit of the wearable device. The microcontroller handles sensor data acquisition, preprocessing, feature extraction, and execution of the trained machine learning model. On-device processing ensures minimal latency, allowing rapid detection of seizure events without reliance on cloud-based computation. Additionally, local processing reduces network dependency, enhances data privacy, and optimizes power consumption for long-term

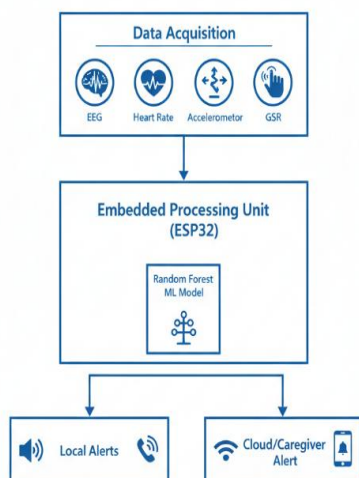
wearable operation. The overall system architecture is illustrated.

#### 4.5. Real-Time Alert Mechanism

When the machine learning model detects abnormal physiological patterns indicative of a seizure, the system immediately triggers real-time alert mechanisms. These include vibration motors, buzzer alarms, and LED indicators integrated into the wearable device. Local alerts ensure that the patient and nearby individuals are promptly informed, even in situations where wireless connectivity is unavailable. Immediate alert generation plays a critical role in reducing response time and preventing injury during seizure episodes [15].

#### 4.6. Wireless Communication and Caregiver Notification

In addition to local alerts, the wearable device supports wireless communication through Wi-Fi, Bluetooth, or GSM modules [3], [19]. Upon seizure detection, alert messages containing relevant information are transmitted to caregivers or medical personnel in real time. This remote notification capability enables quick assistance and improves emergency response, particularly when the patient is alone. The combination of local and remote alerts wearable epileptic seizure detection system. ensures reliable communication and enhances the overall effectiveness of the seizure monitoring system shown in Figure 1 and Table 2.



**Figure 1** System architecture of the proposed wearable epileptic seizure detection system.

**Table 2** Comparison of existing systems and proposed systems

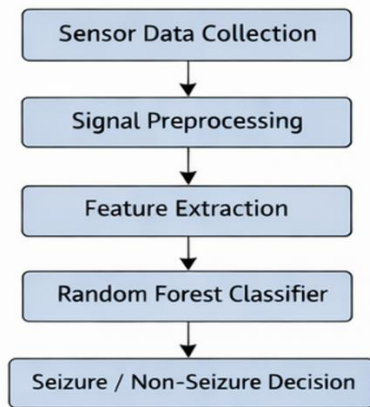
Feature	Existing Systems	Proposed System
Monitoring Type	Single sensor / EEG only	Multi-sensor
Portability	Low	High
Real-time Detection	Limited	Yes
False Alarms	High	Reduced
Caregiver Alert	Optional	Immediate
Daily Use	Not suitable	Suitable

## 5. Methodology

The methodology of the proposed system outlines the systematic process followed to design, implement, and evaluate the wearable epileptic seizure detection device. The approach integrates continuous physiological signal acquisition, machine learning–based analysis, and real-time alert generation to achieve reliable, low-latency seizure detection. Each stage of the methodology is designed to ensure accuracy, robustness, and suitability for deployment on a resource-constrained wearable platform.

### 5.1. Data Acquisition

Physiological data is continuously acquired using multiple integrated wearable sensors, including an electroencephalography (EEG) sensor, heart rate sensor, galvanic skin response (GSR) sensor, and an accelerometer. The EEG sensor captures electrical activity of the brain, which reflects abnormal neural discharges during seizure events. The heart rate sensor monitors cardiovascular variations, while the GSR sensor measures changes in skin conductance related to autonomic nervous system activity. The accelerometer records body movement and posture changes commonly observed during convulsive seizures. This multi-sensor data acquisition strategy [9], [11] enables comprehensive monitoring of seizure-related physiological patterns and minimizes dependency on any single signal source. The step-by-step methodology of the proposed approach is shown in Figure 2.



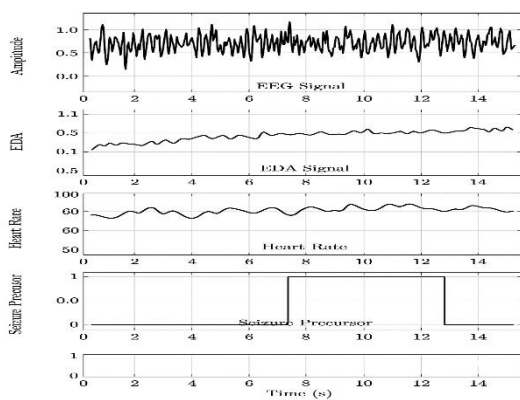
**Figure 2 Methodology Flow of The Proposed Seizure Detection System**

### 5.2. Signal Preprocessing

The raw sensor data collected from wearable devices is often affected by noise and artifacts arising from motion, sensor displacement, environmental interference, and hardware limitations. To enhance signal quality, preprocessing techniques such as noise filtering, normalization, and smoothing are applied to each sensor stream.

$$y[n] = \frac{1}{N} \sum_{i=0}^{N-1} x[n-i] \quad (1)$$

Where  $y[n]$  represents the smoothed signal at time index  $n$ ,  $x[n-i]$  denotes the input signal samples,  $N$  is the window size, and  $i$  is the index variable. Filtering removes unwanted high-frequency and low-frequency noise, while normalization ensures consistent scaling across different sensor signals.



**Figure 3 Sample Visualization of Simulated Signals**

$$x' = (x - \mu) / \sigma \quad (2)$$

Where  $x$  represents the original signal value,  $x'$  denotes the normalized signal,  $\mu$  is the mean of the signal, and  $\sigma$  is the standard deviation. This formula standardizes the signal by subtracting the mean ( $\mu$ ) and dividing by standard deviation ( $\sigma$ ), ensuring all sensor signals are on the same scale. These preprocessing steps improve data reliability and ensure uniformity across sensor inputs before further analysis shown in Figure 3.

### 5.3. Feature Extraction

After preprocessing, relevant features are extracted from each physiological signal to represent meaningful characteristics associated with seizure activity. Statistical features such as mean, variance [17], standard deviation, and signal energy are computed over fixed time windows for each sensor. Standard deviation provides information about signal variability and helps differentiate seizure and non-seizure states. These features capture temporal variations, signal intensity, and amplitude fluctuations that differentiate seizure and pre-seizure states from normal physiological conditions. Feature extraction reduces data dimensionality while preserving essential information required for accurate classification.

- Mean

$$\mu = \frac{1}{N} \sum_{i=1}^N x_i \quad (3)$$

Where  $\mu$  represents the mean of the signal,  $x$  denotes individual signal samples, and  $N$  is the total number of samples.

- Variance

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2 \quad (4)$$

Where  $\sigma^2$  represents the variance,  $x$  denotes individual signal samples,  $\mu$  is the mean, and  $N$  is the total number of samples.

- Standard deviation

$$SD = \sqrt{\sigma^2} \quad (5)$$

Quantifies signal fluctuations, useful for distinguishing seizure activity.

- Signal Energy

$$E = \sum_{i=1}^N (x_i^2) \quad (6)$$

Represents the intensity of the signal; higher during seizure events.

#### 5.4. Machine Learning Model Training

A Random Forest machine learning algorithm is employed to classify physiological patterns into seizure and non-seizure categories.

$$y = \text{mode}\{T1(x), T2(x), \dots, Tn(x)\} \quad (7)$$

Where  $y$  represents the final predicted class label,  $T_i(x)$  denotes the prediction of the  $i$ th decision tree,  $n$  is the total number of trees, and  $x$  is the input feature vector. The final prediction is obtained by majority voting among all decision trees. Random Forest is selected due to its robustness to noisy data, resistance to overfitting, and high classification accuracy. By combining multiple decision trees, Random Forest improves generalization performance. The extracted feature vectors are labeled and used to train the model using supervised learning. Signal energy represents the intensity of physiological signals such as EEG activity, which often increases during epileptic seizures. By combining multiple decision trees, Random Forest improves generalization [13] performance and handles heterogeneous multi-sensor data effectively, making it well suited for wearable seizure detection applications.

#### 5.5. Real-Time Classification

The trained Random Forest model is deployed on the embedded processing unit of the wearable device. Incoming sensor data is processed in real time through the preprocessing and feature extraction pipeline, and the resulting features are fed into the classifier [6]. The system continuously evaluates physiological data streams and identifies abnormal patterns indicative of epileptic seizures. On-device classification ensures low latency, allowing rapid detection without dependence on cloud-based computation.

#### 5.6. Alert Generation and Communication

Upon detection of seizure activity, the system immediately activates alert mechanisms integrated into the wearable device, including vibration motors, buzzer alarms, and LED indicators. These local alerts notify the patient and nearby individuals of the emergency situation. Simultaneously, wireless communication modules such as Wi-Fi, Bluetooth, or GSM transmit alert notifications to caregivers or medical personnel in real time. This dual alert strategy ensures reliable communication and enables

timely medical intervention even when the patient is alone.

#### 5.7. System Evaluation

The performance of the proposed system is evaluated based on key parameters such as detection accuracy, response time, and overall reliability. Experimental observations obtained during real-time monitoring are analyzed and compared with expected seizure patterns to assess the effectiveness of the multi-sensor fusion approach and the machine learning model. The evaluation highlights the system's ability to operate continuously with low latency while maintaining reliable seizure detection performance, demonstrating its suitability for real-world wearable healthcare applications shown in Table 2.

### 6. Proposed Algorithm

#### 6.1. Algorithm 1: System Initialization and Main Loop Variables

**Table 2 Main Loop Variables**

Variable	Description
$s$	Time interval (5–15 sec)
$SS_{\{Alert\}}$	Alert state (0/1)

##### 6.1.1. Initialize\_System

- Initialize sensors and serial communication.
- Connect to ThingSpeak and Telegram.
- Set  $SS_{\{Alert\}} \leftarrow 0$ .

##### 6.1.2. Loop Main Process

- Read sensor data (EEG, HR, SpO<sub>2</sub>, GSR, Motion).
- Execute Algorithm 2 (Detection).
- Send data to cloud every  $\Delta t$ .
- If  $SS_{\{Alert\}}=1$ , execute Algorithm 3 (Alert).
- Wait  $\Delta t$ .

##### 6.2. Algorithm 2: Detection

- If  $EEG_f > 25$  OR  $EEG_a > 120 \rightarrow SS_{\{Alert\}}=1$ .
- If  $HR < 50$  OR  $HR > 110$  OR  $SpO_2 < 94 \rightarrow SS_{\{Alert\}}=1$ .
- If  $GSR > 10 \rightarrow SS_{\{Alert\}}=1$ .
- If  $A_{\{total\}} > 2.5$  OR  $G_{\{gyro\}} > 150 \rightarrow SS_{\{Alert\}}=1$ .
- Else  $\rightarrow SS_{\{Alert\}}=0$ .

### 6.3. Algorithm 3: Alert Mechanism

- If  $\$S_{\{Alert\}}=1\$$  and cooldown satisfied:
- Send alert via Telegram
- Update ThingSpeak
- Else continue monitoring.

## 7. Result and Discussion

The proposed wearable epileptic seizure detection system demonstrated reliable real-time monitoring by integrating EEG, heart rate, GSR, and accelerometer sensors. The Random Forest model effectively classified seizure and non-seizure patterns, while the multi-sensor approach improved detection accuracy and reduced false alarms compared to single-sensor systems. Real-time processing on the embedded platform ensured low latency, and immediate alert mechanisms (vibration, sound, and wireless communication) enabled quick response. Overall, the system showed improved portability, efficiency, and suitability for continuous daily monitoring.

## 8. Future Scope

The system can be improved technically by integrating advanced deep learning models for early seizure prediction, optimizing multi-sensor fusion, and enhancing battery efficiency for continuous monitoring. Key challenges include reducing false alarms, handling patient variability, and achieving reliable real-time performance on low-power devices. From a commercial perspective, the system can be developed into a market-ready wearable with mobile and cloud integration for remote healthcare services. However, challenges such as regulatory approvals, data privacy, cost reduction, and user adoption must be addressed to ensure successful large-scale deployment.

## 9. Social Impact

The proposed wearable epileptic seizure detection system has significant social impact by improving the safety, independence, and quality of life of individuals affected by epilepsy. By enabling real-time monitoring and immediate alert generation, the system helps reduce the risk of injury and ensures timely medical assistance, especially in unattended situations. It also provides reassurance to caregivers and family members through continuous tracking and notifications. The low-cost and portable design makes the solution accessible to a wider population,

including those in remote or resource-limited areas. Overall, the system promotes inclusive healthcare, supports early intervention, and contributes to better management of neurological disorders in society.

## Conclusion

This work presents an AI-based wearable system for early epileptic seizure detection using multi-sensor data and an embedded Random Forest model. The system enables real-time monitoring, low-latency detection, and immediate alert generation, improving patient safety and caregiver response. Its portable, low-cost, and energy-efficient design makes it suitable for everyday use. Although further clinical validation is required, the proposed solution offers a practical and scalable approach for real-world seizure monitoring and future intelligent healthcare applications.

## References

- [1]. K. Rasheed, J. Qadir, T. J. O'Brien, L. Kuhlmann, and A. Razi, "A Generative Model to Synthesize EEG Data for Epileptic Seizure Prediction," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 201–212, 2021.
- [2]. S. Kusmakar, C. K. Karmakar, B. Yan, T. J. O'Brien, R. Muthuganapathy, and M. Palaniswami, "Automated Detection of Convulsive Seizures Using a Single Wrist-Worn Accelerometer Device," *IEEE Transactions on Biomedical Engineering*, vol. 66, no. 2, pp. 421–432, 2019.
- [3]. R. Khan, S. Ullah, and M. Raza, "IoT-Enabled Wearable System for Epileptic Seizure Monitoring," *IEEE Access*, vol. 8, pp. 154179–154189, 2020.
- [4]. E. A. Seth, J. Watterson, J. Xie, et al., "Feasibility of Cardiac-Based Seizure Detection and Prediction: A Systematic Review of Non-Invasive Wearable Sensor-Based Studies," *Epilepsia Open*, vol. 8, no. 1, pp. 1–15, 2023.
- [5]. W. T. Kerr, T. A. O'Brien, S. Beniczky, et al., "The Present and Future of Seizure Detection, Prediction, and Forecasting with Machine Learning," *Frontiers in Neurology*, vol. 15, pp. 1–14, 2024.
- [6]. U. R. Acharya, S. L. Oh, Y. Hagiwara, et al.,

- “Deep Convolutional Neural Network for the Automated Detection and Diagnosis of Seizure Using EEG Signals,” *Computers in Biology and Medicine*, vol. 100, pp. 270–278, 2018.
- [7]. A. Shoeb and J. Guttag, “Application of Machine Learning to Epileptic Seizure Detection,” *Proceedings of the 27th International Conference on Machine Learning (ICML)*, pp. 975–982, 2010.
- [8]. H. Daoud and M. A. Bayoumi, “Efficient Epileptic Seizure Prediction Based on Deep Learning,” *IEEE Transactions on Biomedical Circuits and Systems*, vol. 13, no. 5, pp. 804–813, 2019.
- [9]. S. Rajaguru and S. Prabhakar, “Wearable Sensor-Based Epileptic Seizure Detection Using Machine Learning Techniques,” *Journal of Medical Systems*, vol. 44, no. 3, pp. 1–12, 2020.
- [10]. P. Fergus, D. Hignett, A. Hussain, D. Al-Jumeily, and K. Abdel-Aziz, “Automatic Epileptic Seizure Detection Using Scalp EEG and Advanced Artificial Intelligence Techniques,” *BioMed Research International*, pp. 1–17, 2015.
- [11]. R. Hussein, A. Abdel-Rahman, and M. Salem, “Real-Time Seizure Detection Using Wearable Sensors and Machine Learning,” *Procedia Computer Science*, vol. 170, pp. 782–789, 2020.
- [12]. J. R. Smith, “Wearable Technologies for Health Monitoring,” *IEEE Engineering in Medicine and Biology Magazine*, vol. 36, no. 1, pp. 16–24, 2017.
- [13]. L. Breiman, “Random Forests,” *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.
- [14]. M. Shoaib, S. Bosch, O. Incel, H. Scholten, and P. J. M. Havinga, “Complex Human Activity Recognition Using Smartphone and Wearable Sensors,” *Sensors*, vol. 16, no. 4, pp. 1–24, 2016.
- [15]. A. T. Tzallas, M. G. Tsipouras, and D. I. Fotiadis, “Epileptic Seizure Detection in EEGs Using Time–Frequency Analysis,” *IEEE Transactions on Information Technology in Biomedicine*, vol. 13, no. 5, pp. 703–710, 2009.
- [16]. S. Seneviratne, Y. Hu, T. Nguyen, et al., “A Survey of Wearable Devices and Challenges,” *IEEE Communications Surveys & Tutorials*, vol. 19, no. 4, pp. 2573–2620, 2017.
- [17]. A. Subasi, “EEG Signal Classification Using Wavelet Feature Extraction and a Mixture of Expert Model,” *Expert Systems with Applications*, vol. 32, no. 4, pp. 1084–1093, 2007.
- [18]. F. Mormann, R. G. Andrzejak, C. E. Elger, and K. Lehnertz, “Seizure Prediction: The Long and Winding Road,” *Brain*, vol. 130, no. 2, pp. 314–333, 2007.
- [19]. Y. Yang, Q. Xie, J. Wang, and G. Zhang, “Wearable Health Monitoring Systems Using IoT and Machine Learning,” *Sensors*, vol. 21, no. 9, pp. 1–20, 2021.
- [20]. World Health Organization, “Epilepsy: A Public Health Imperative,” WHO Press, Geneva, Switzerland, 2019.