

# Design And Implementation of An IOT System for Detecting Epileptic Seizures Based on Fuzzy Logic

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## ABSTRACT

Epileptic seizures pose a significant health challenge, impacting millions of individuals worldwide and necessitating effective systems for timely detection and intervention. This study presents an innovative IoT-based system for detecting epileptic seizures using fuzzy logic techniques. The system leverages an STM32F103C8T6 microcontroller connected to various sensors, including a 3-axis accelerometer, a heart rate sensor, and a temperature sensor, to gather real-time physiological data. These data are processed using MATLAB, where fuzzy logic algorithms analyse the input to identify potential seizure events. When a seizure is detected, the system promptly sends notifications via GSM, accompanied by the patient's precise GPS location, ensuring rapid medical response. The system achieved an accuracy of 94% in detecting seizures, demonstrating its potential to provide continuous and automated patient monitoring. This research highlights the transformative power of integrating IoT with wearable devices to enhance patient safety and deliver innovative, personalized healthcare solutions.

**Keywords:** Internet of Things (IoT), Epilepsy, Epileptic seizure detection, Fuzzy logic inference, Wearable device.

## 1. Introduction

Today the combination of the Internet of Things (IoT) and machine learning is becoming a trend in healthcare communication [1]. IoT improves healthcare by enabling applications; for instance, tiny computers gather sensor data. Send it through networks so that healthcare providers can monitor health indicators in real time [2]. Wearable technologies do more than sense things [3]. They help with communication, record data, and display information. Play a key role in healthcare. This blending of technologies shows potential for enhancing how we deliver healthcare and improving patient outcomes [4]. Epilepsy is particularly risky due to its nature and possible life-threatening consequences. In several Middle Eastern nations, societal stigma linked to epilepsy induces a fear of community exposure among patients [5]. Consequently, it is essential to utilize modern technology, particularly wearable devices, to proactively identify cases of epilepsy before they manifest [6]. This thesis aims to design and implement an IoT system based on artificial intelligence techniques to detect epileptic seizures [7]. The project is based on an IoT monitoring system that integrates three monitoring units: 3-Axis Accelerometer sensor, heartbeat sensor, Temperature sensor and a microcontroller (STM32F103C8T6) as control modules with GSM and GPS [8].

## 2. Literature Review

Several studies were conducted to detect an epileptic seizure Lamrani et al. [9] In Canada, research was similarly conducted in a small patient cohort of sixteen on efficacy and reliability measures associated with seizure detection devices. Here we tested three devices, the Embrace2 from Empatica, the Inspyre smartphone software by Smart Monitor and a prototype of The Movement Monitor (EmfitMM) by us. They can include

puzzles along with tasks around the house that monitor more than one type of seizure using accelerometry, electrodermal activity and pressure sensors. Subjects used these devices continuously during their stay at an Epilepsy Monitoring Unit [EMU]. Embrace2 evaluated skin conductance and wrist movement, while the Inspyre software paired with a smartwatch to specifically assess tremor activity. The EmfitMM on hand used a sensor that was under the mattress, to pick up movements of the sleeping body. Prior surveys were done to test how comfortable these devices are as well as their user friendliness and their efficiency. The Inspyre app demonstrated a sensitivity of 92% for tonic clonic seizures (GTCS) with an alarm rate of 1.8, per day. On the hand EmfitMM displayed an 89% sensitivity in identifying tonic clonic seizures (GTCS) with a false alarm rate of 0.13, per day. While some users reported discomfort, most found these devices user friendly.

Leon et al. 2023 [10] performed a research study to determine whether the skin sensor worn on top of clothing would detect seizures. Researchers tracked seizure activity in thirty subjects using sensors that measure heart rate and skin capacitance. As a wearable device, it monitored the heart rate and skin capacitance, which said something about seizures. Wearers used the device often, connecting it with a smartphone app via Bluetooth. The app was specifically designed to send a rapid alert to family members or emergency contact when it detects signs of an oncoming seizure. Subjects completed surveys preceding the intervention. They levelled with the device they were using to provide feedback on how well it detected seizures any discomfort or pain; Skin Sensor Results They appreciated the app for its helpful alerts when detecting a seizure.

Habtmu et al. 2022 [11] In a research study: How well does the Seizure Detecting device work? Sixteen people volunteered for the study. Performing using a set of accelerometers, pulse oximeters and vibration sensors to watch for seizures. This is intended to be worn throughout the day and track body movements and even variations in heart rate and oxygen levels for seizure detection. Sensors were attached to the participants during the trial to monitor their heart rates and oxygen levels as they wore the arousal tracker. The criteria used for detection such as an increase in heart rate by 10 beat per minute oxygen saturation falling below a threshold to 90% acceleration exceeding value range of (23.4 meters/square.) and vibrations above the range provided 317 Hertz. Before and after the monitoring period, participants also completed surveys to assess the findings that the wearable device achieved a level of accuracy. The heart rate sensor had a 98% accuracy rate while the accelerometer/vibration sensors reached a 90.2% accuracy rate. Despite some discomfort, users generally found it easy to use the gadget. The trial results indicated that the device provided seizure notifications thereby enhancing safety and care.

Balster et al. 2022 [12]The study was conducted to determine the sensitivity of an engineered detector fitted onto a patient for detecting seizures. Sixteen people with forms of epilepsy took part in the research. Sensors built into the device (which included an accelerometer vibration sensor, a pulse oximeter and a thermistor) were used to detect signs of seizure activity. Those devices were then worn by participants while collecting/monitoring data. During the tonic phase of seizures, falls were detected by the accelerometer; during the convulsion phases vibrations on hip identified these events. The pulse oximeter measured heart rate and oxygen saturation, and the thermistor recorded body temperature. Following device usage participants were asked to complete surveys regarding their seizure episodes, satisfaction level, with the device and any discomfort experienced while wearing it. Results showed that the wearable gadget accurately detected seizures with sensitivity and accuracy. While some participants mentioned discomfort, they generally found it tolerable despite being somewhat unpleasant. Moreover, they found it relatively easy to incorporate the device into their routine.

Yamakawa et al. 2020 [13], In this study, we evaluated the performance of a system that predicts epileptic seizures based on three types of signals including an electrocardiogram (ECG), photoplethysmograph signal (PPT) and Electroencephalography (EEG). This study evaluated 10 patients with epileptic seizures. The device collected ear data at 250 Hz for 40 minutes. Subjects undertook a variety of activities to provoke seizures opening and closing their eyes, exposure to high-intensity light, deliberate hyperventilation or rest periods including sleep. The data was clear over the course of the next several hours there were rising HRV values. The patients found the device to be easy and comfortable for use. The efficiency of the system was 91.5% for predicting seizures, with a sensitivity value of 85.4%.

Regalia et al. 2019 [14] aimed to assess the performance of wrist-worn devices (bracelets, watches), such as the Embrace and E4 watch from Empatica, for GTCS detection. Six subjects who wore an accelerometer (ACC) and submitted to electrodermal activity (EDA), served as the test group for a prediction of fit plus detection study. This was done in an epilepsy monitoring unit (EMU) where the patients were being monitored. Most reported that the devices were comfortable for them, but some experienced pain. In the results,

approximately 92.2% of hemorrhages were detected with a false alarm rate per day over an interval between 0.2 and device component proof from 1% and sorted by physiological constants.

### **3. Materials and method**

#### **3.1. Materials**

##### **3.1.1. Accelerometer**

The ADXL345, a 3-axis accelerometer created by Analog Devices, is well known for its precision and energy efficiency [15]. This sensor can detect acceleration on the X, Y and Z axes, making it suitable for uses like motion sensing, tilt detection and shock or vibration measurement. With a measurement range from  $\pm 2g$  to  $\pm 16g$  and a resolution of up to 13 bits the ADXL345 offers versatility [16]. It supports both I2C and SPI interfaces for integration with different microcontrollers and digital systems. Moreover, this accelerometer includes features like tap detection, free fall detection and activity/inactivity monitoring to enhance its functionality, for applications. Because of its adaptability and reliability, the ADXL345 is used in consumer electronics, industrial machinery, medical devices and automotive systems [17].

##### **3.1.2. ECG**

The ECG Heartbeat Sensor HW 827 is a device designed to measure the hearts activity by providing important information, on heart rate and rhythm [18]. It is utilized to track functions by detecting the signals produced by the heart's actions. Equipped with electrodes that capture these signals, HW 827 processes them to create an ECG waveform. This waveform can be examined to identify heart conditions and irregularities [19]. The sensor is commonly used in settings, health monitors and fitness devices. Its capability to provide real time data makes it an asset, for both clinical monitoring and personal health tracking purposes [20].

##### **3.1.3. Temperature sensor**

The LM35 stands out as a notch temperature sensor crafted by Texas Instruments, known for its temperature readings [21]. This sensor generates a voltage output that correlates directly with the temperature, in Celsius following a linear scale factor of 10 mV/°C. With the ability to measure temperatures ranging from 55°C to 150°C, the LM35 proves versatile for applications such as monitoring, industrial temperature regulation and consumer electronics [22]. Its low output impedance, consistent linear output and accurate calibration make it user friendly and dependable, positioning the LM35 as a favored option, for tasks requiring temperature measurements [23].

##### **3.1.4. STM32F103C8T6 Microcontroller**

The STM32F103C8T6 microcontroller, created by STMicroelectronics, belongs to the STM32 family. It is built on the ARM Cortex M3 architecture [24]. This 32-bit RISC processor is well known for its performance, power consumption and versatile features making it a favored option for embedded applications [25]. It runs at speeds of up to 72 MHz. It has 64 KB of flash memory and 20 KB of SRAM for storing programs and data. An important aspect of this microcontroller is its power management features, which include low power modes, like Sleep Stop and Standby to optimize energy usage in scenarios [26]. For programming and debugging tasks the STM32F103C8T6 works seamlessly with integrated development environments (IDEs) including STM32CubeIDE [27].

##### **3.1.5. GSM and GPS**

This component is often used in a variety of IoT (Internet of Things) endeavors because of its ability to connect to GSM networks and pinpoint locations through GPS [28]. The A9G is a module that combines GSM for communication and GPS (for location tracking) features. It is commonly utilized in projects requiring real time location monitoring, such as vehicle tracking systems, personal safety gadgets or smart wearable devices [29]. The integration of both GSM and GPS within a module makes it a versatile option, for applications necessitating both communication capabilities and accurate location tracking [30]. The GSM module can send and receive SMS messages, make voice calls, and connect to the internet via a mobile network and GPS can track and provide precise location information, which can be sent via GSM to a server or another device for monitoring purposes [31].

### 3.2. Method

The process of detecting physiological signals is achieved through sensors strategically placed on the patient's wrist. Each sensor collects specific data: temperature, heart rate, and movement. The collected signals are amplified and sent to the STM32F103C8T6 microcontroller. The microcontroller processes the signals and applies the fuzzy logic algorithm to interpret the patient's physiological state. After processing, the system can activate two main actions. It can display the patient's data on the IoT platform for real-time monitoring by healthcare providers or caregivers. The system also utilizes GSM and GPS technologies to send phone notifications and provide the patient's location, alerting the patient or caregivers about critical changes or potential seizure events, as shown in Figure 1.

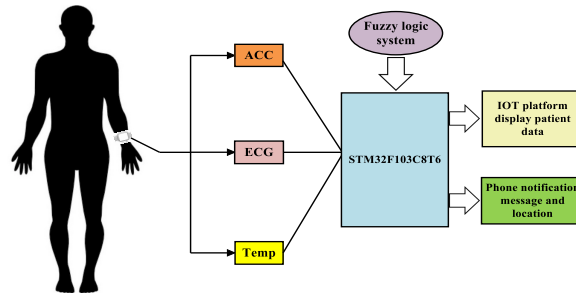


Figure 1. The Schematic illustration of the proposed system.

#### 3.2.1. IoT system architecture

The system algorithm for monitoring epileptic seizures will be as shown in the figure below:

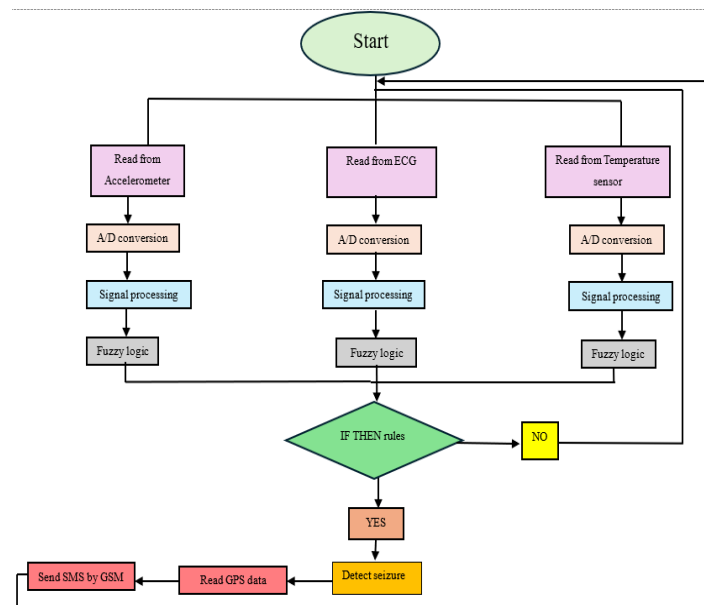


Figure 2. Flowchart of the algorithm system to monitor epileptic patients.

As shown in the Figure 2 when the wearable device is turned on and is in contact with the patient's wrist, it will receive data continuously from the sensors in the device. The steps for detecting seizures in a patient with epileptic seizures can be explained as follows:

- Sensor Data Acquisition

The sensors data is initially captured in analogue format. This data represents the physical quantities measured by the sensor:

1. Accelerometer (3-axis ADXL345): Monitor movement and vibration.

2. ECG (HW-827): Measure the electrical activity of the heart.
3. Temperature Sensor (LM35): Measure body temperature.

- Data Conversion

The Analog-to-Digital Conversion (ADC) process in the STM32F103C8T6 microcontroller necessitates configuring the ADC for the required resolution, sampling rate, and input channel. The analogue signal from the sensor is converted into a digital format using successive approximation, with the resultant digital data being stored in a buffer for subsequent processing.

- Data Transmission

The transmission of digital data is facilitated through the utilization of the Protocol (UART). UART is a connectionless protocol that enables efficient and low-latency communication by sending data packets without establishing a prior connection, thereby making it suitable for applications requiring rapid data transfer.

- Fuzzy Logic

The data collected from various sensors, reflecting patients' behaviours, are utilized as inputs for the fuzzy logic system. The system is executed using MATLAB2023 script commands to establish the membership functions for each input and to conduct the fuzzy input-output inference mapping. The vibration rate, temperature rate, and heart rate are influenced by various factors. For instance, if the vibration signal satisfies the condition where its amplitude surpasses the threshold value and persists continuously and repeatedly for a duration of 5 seconds or longer, as illustrated in the Figure 3 .

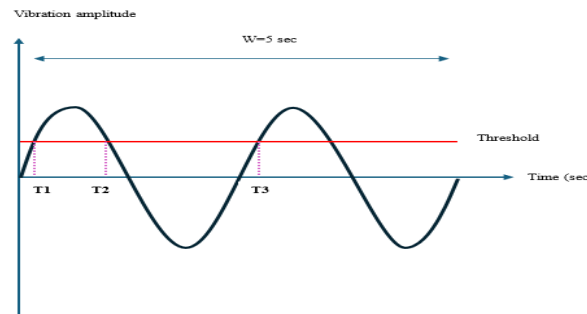


Figure 3. The relationship between vibration amplitude and time

- Send notification

By integrating GSM and GPS modules, the system ensures that notifications about seizure events, along with precise location data, are promptly sent to the patient's relatives, doctors, and caregivers. This comprehensive approach enhances the response time and ensures timely medical intervention, leveraging both direct SMS notifications and IoT platforms for real-time monitoring and data visualization.

### 3.3. Fuzzy Logic Algorithm

The data output from sensors that capture behaviors is used as input for a fuzzy logic system. This system is created using MATLAB2023 script commands to define the membership functions for each input and carry out input output inference mapping. The fuzzy inference system follows the Mamdani type inference method, a used approach in logic for decision making. This method is known for its nature, making it well suited for tasks that require human reasoning. Operating on a series of IF rules that govern the inference process, each rule, in the system can be represented as:

$$R_j: \text{IF } x_1 \text{ is } M_{j1}(x_1) \text{ AND } \dots \text{ AND } x_n \text{ is } M_{jn}(x_n) \text{ THEN } (y \text{ is } N)$$

Where

- $x_1, x_2, \dots, x_n$  are the input variables.
- $M_{j1}(x_1), M_{j2}(x_2), \dots, M_{jn}(x_n)$  are the membership functions corresponding to the input variables.
- $y$  is the output variable.
- $N$  is the membership function of the output variable.

This system works by matching the input data with membership functions through a set of IF rules making it easier to establish the fuzzy input output inference mapping.

### 3.4. Results

#### 3.4.1. MATLAB simulation results

We used IF- THEN fuzzy rules to implement the fuzzy logic rules inference. linguistic variables are used to build rules. Fuzzy rules are a collection of linguistic statements that will describe how fuzzy inference systems should make decisions to classify anything, and these rules are shown in Table 1.

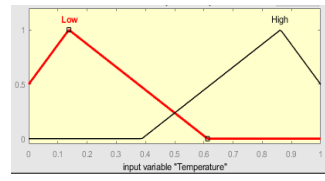
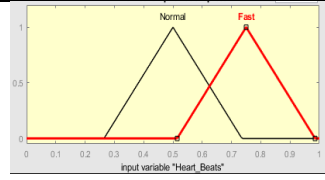
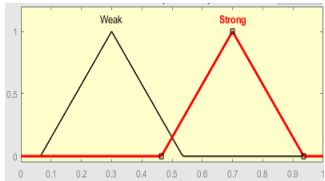
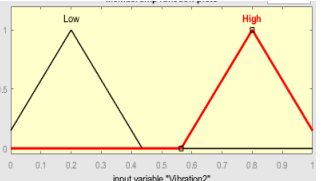
Table 1 Rules of fuzzy inference system

| Rule | IF Conditions                                                                        | THEN Output |
|------|--------------------------------------------------------------------------------------|-------------|
| 1    | Vibration is Normal <b>AND</b> Heart Rate is Low <b>AND</b> Temperature is Low       | No Seizure  |
| 2    | Vibration is Normal <b>AND</b> Heart Rate is Low <b>AND</b> Temperature is Normal    | No Seizure  |
| 3    | Vibration is Normal <b>AND</b> Heart Rate is Low <b>AND</b> Temperature is High      | No Seizure  |
| 4    | Vibration is Normal <b>AND</b> Heart Rate is Normal <b>AND</b> Temperature is Low    | No Seizure  |
| 5    | Vibration is Normal <b>AND</b> Heart Rate is Normal <b>AND</b> Temperature is Normal | No Seizure  |
| 6    | Vibration is Normal <b>AND</b> Heart Rate is Normal <b>AND</b> Temperature is High   | No Seizure  |
| 7    | Vibration is Normal <b>AND</b> Heart Rate is High <b>AND</b> Temperature is Low      | No Seizure  |
| 8    | Vibration is Normal <b>AND</b> Heart Rate is High <b>AND</b> Temperature is Normal   | No Seizure  |
| 9    | Vibration is Normal <b>AND</b> Heart Rate is High <b>AND</b> Temperature is High     | No Seizure  |
| 10   | Vibration is High <b>AND</b> Heart Rate is Low <b>AND</b> Temperature is Low         | Seizure     |
| 11   | Vibration is High <b>AND</b> Heart Rate is Low <b>AND</b> Temperature is Normal      | Seizure     |
| 12   | Vibration is High <b>AND</b> Heart Rate is Low <b>AND</b> Temperature is High        | Seizure     |
| 13   | Vibration is High <b>AND</b> Heart Rate is Normal <b>AND</b> Temperature is Low      | Seizure     |
| 14   | Vibration is High <b>AND</b> Heart Rate is Normal <b>AND</b> Temperature is Normal   | Seizure     |
| 15   | Vibration is High <b>AND</b> Heart Rate is Normal <b>AND</b> Temperature is High     | Seizure     |
| 16   | Vibration is High <b>AND</b> Heart Rate is High <b>AND</b> Temperature is Low        | Seizure     |
| 17   | Vibration is High <b>AND</b> Heart Rate is High <b>AND</b> Temperature is Normal     | Seizure     |
| 18   | Vibration is High <b>AND</b> Heart Rate is High <b>AND</b> Temperature is High       | Seizure     |

These steps have been programmed practically in MATLAB2023 and the rule viewer editor displays fuzzy rules graphically to calculate the output as shown in Table 2 and Figure 4.

Table 2 Membership function input/output variables with fuzzy system

| Inputs/Outputs | Membership functions | Graphical representation of Membership functions |
|----------------|----------------------|--------------------------------------------------|
|----------------|----------------------|--------------------------------------------------|

|                                                                                                                                                  |                                                                                                                                                                                                                          |                                                                                      |
|--------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------|
| Body temperature: The membership functions of body temperature have two linguistic variables: low, high defined body temperature ( $\mu_{BT}$ ). | $\mu_{BT} \text{ Low}(b) = \max\left(1, \frac{36-b}{5}, 0\right) \quad (1)$ $\mu_{BT} \text{ High}(b) = \max\left(\frac{b-39.1}{5}, 1, 0\right) \quad (2)$                                                               |   |
| Heart rate: The membership functions of heart rate have two linguistic variables: normal, fast defined as heart rate ( $\mu_{HR}$ ).             | $\mu_{HR} \text{ Normal}(h) = \left\{ \max\left(\left(1, \frac{100-h}{20}\right), 0\right) \right\} \quad (3)$ $\mu_{HR} \text{ Fast}(h) = \max\left(\frac{h-120}{20}, 1, 0\right) \quad (4)$                            |   |
| Vibration 1: The membership functions of Vibration 1 have two linguistic variables: weak, high defined as Vibration ( $\mu_{Vib}$ ).             | $\mu_{Vib} \text{ weak}(f) = \left\{ \max\left(\left(1, \frac{3-f}{3}\right), 0\right) \right\} \quad (5)$ $\mu_{Vib} \text{ High}(f) = \left\{ \max\left(\left(\frac{f-15}{3.1}; 1\right), 0\right) \right\} \quad (6)$ |   |
| Vibration 2: The membership functions of Vibration 2 have two linguistic variables: weak, high defined as Vibration ( $\mu_{Vib}$ ).             | $\mu_{Vib} \text{ weak}(f) = \left\{ \max\left(\left(1, \frac{3-f}{3}\right), 0\right) \right\} \quad (7)$ $\mu_{Vib} \text{ High}(f) = \left\{ \max\left(\left(\frac{f-15}{3.1}; 1\right), 0\right) \right\} \quad (8)$ |  |

It should be clarified that two vibration inputs were designed, and the reason for this is that the vibration sensor available in the market is either unidirectional or 3D-vibration, and therefore we had to choose a three-dimensional vibration sensor. However, after many experiments, we concluded that it is possible to delete the Z axis and suffice with the X and Y axes, since the vibrations of an epilepsy patient are limited to these two axes. Therefore, when the final design of the inputs in the (fuzzy logic algorithm) was done, we specified vibration 1 and vibration 2, which means vibration on the X axis and vibration on the Y axis.

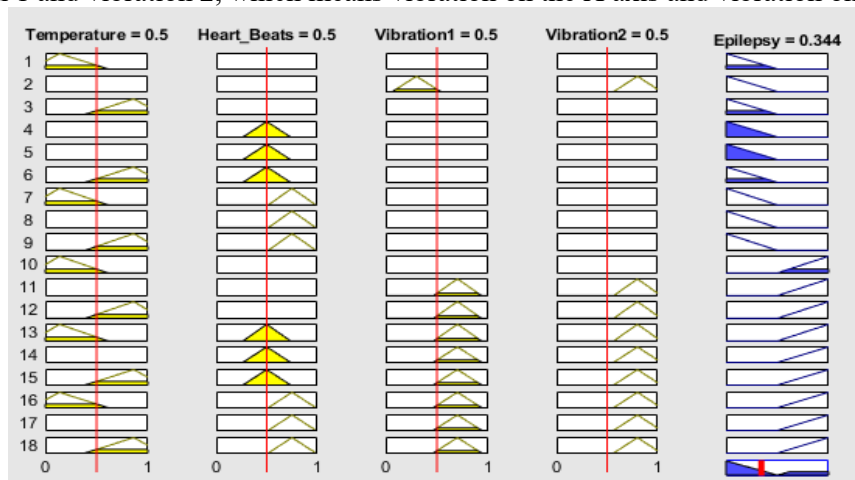
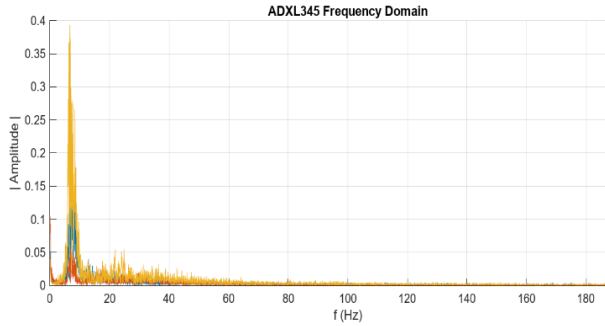


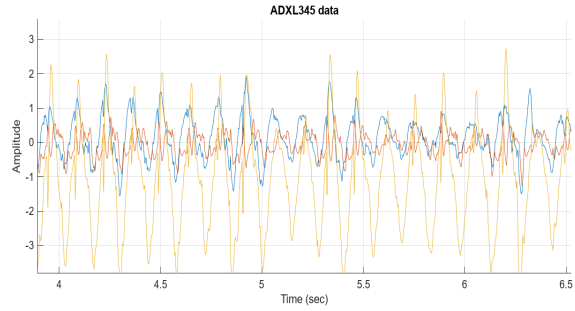
Figure 4. The rules of fuzzy logic system according to Mamdani type

### 3.4.2. Result from hardware device

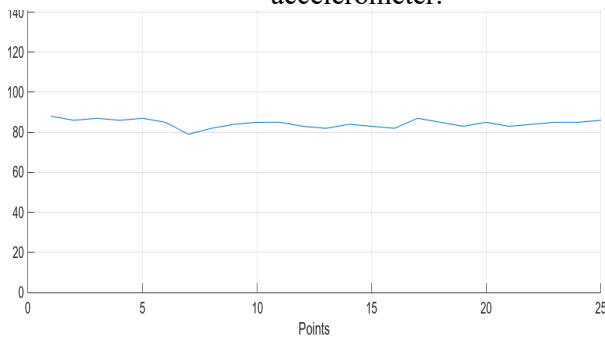
In this section, we described the process of conducting initial tests on healthy individuals. After the designed device demonstrated its efficiency, it was subsequently tested on individuals experiencing epileptic seizures. In this chapter, we will discuss the results obtained from the tests conducted on healthy individuals who met the conditions necessary to trigger an epileptic seizure alert, as illustrated in Fig. 5.



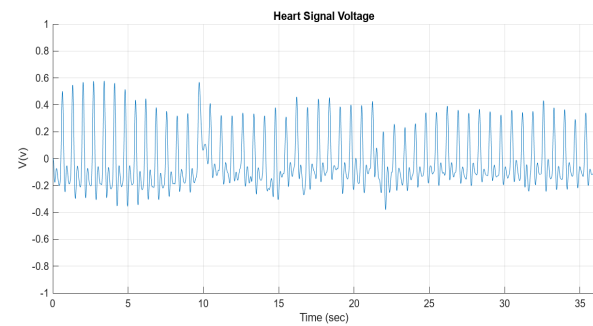
(A) The relationship between normalized amplitude and frequency represents frequency domain analysis of data collected from the ADXL345 accelerometer.



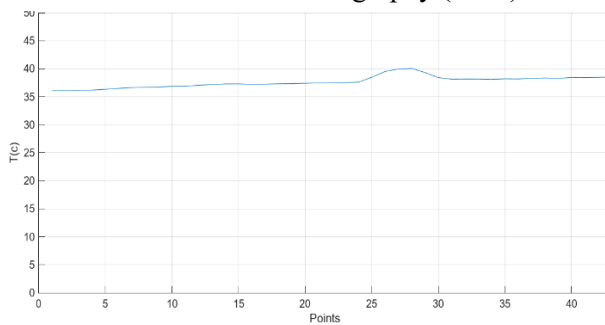
(B) Time-domain analysis of the random data collected from the ADXL345 accelerometer.



(C) The heart rate data captured by the Electrocardiography (ECG)



(D) The heart signal voltage over a period.



(E) The body temperature

Figure 5 Results from hardware device.

Regarding the evaluation of the device's accuracy specifically on individuals with the condition, it was applied to those experiencing epileptic seizures as shown in Fig. 6.

The device successfully generated a notification of a seizure occurrence in the form of a message, along with identifying the location of the affected individual, as depicted in the images in Fig. 7.

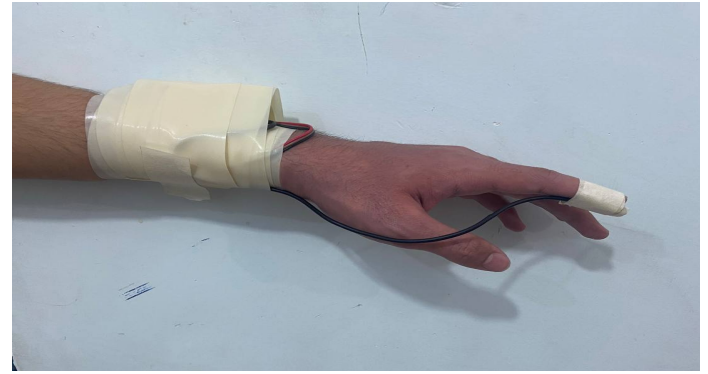
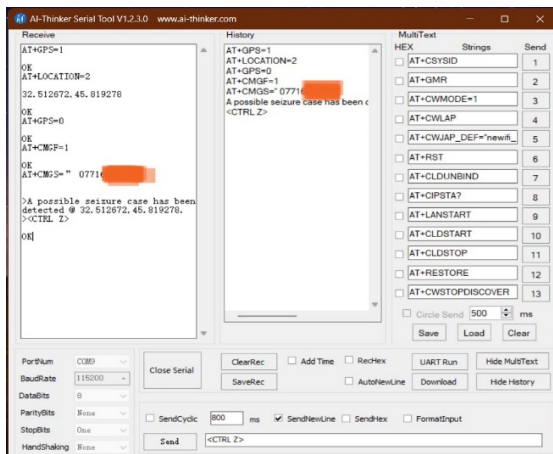
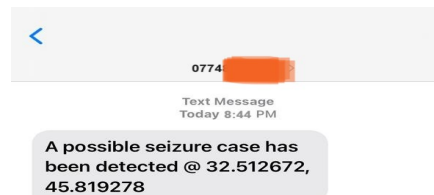


Figure 6 An epilepsy patient wearing the device that was designed.

The device successfully generated a notification of a seizure occurrence in the form of a message, along with identifying the location of the affected individual, as depicted in the images in Fig. 7.



(A) AI-Thinker Serial Tool V1.2.3.0.



(B) A text message (SMS) received on a mobile phone.



(C) A screenshot from Google Maps displaying a specific location based on the GPS

Figure 7 The device successfully generated a notification of a seizure.

The Table 3 provides a comparative analysis of various seizure detection methods, highlighting the adjustments between sensitivity and accuracy. This information is crucial for developing and selecting

appropriate technologies for epilepsy management. It should also be noted that the accuracy of our proposed device was based mainly on the results of the simulation method.

Table 3 Comparison of the proposed model with other model

| Article                             | Method Of Detection                                             | Connection                                  | Results                                                                       |
|-------------------------------------|-----------------------------------------------------------------|---------------------------------------------|-------------------------------------------------------------------------------|
| Becq et al. [32]                    | accelerometer, magnetometer                                     | Connect to wrist                            | Sensitivity 90%, FDR (False Detection rate)0.7/night                          |
| Cogan et al. [33]                   | photoplethysmography, blood oxygenation, electrodermal activity | Watch, finger cuff                          | Sensitivity 58%, FDR0.01/hour                                                 |
| Jallon [34]                         | accelerometer                                                   | Connect to wrist                            | Sensitivity 88-89%, PPV (Positive Predictive Value) 55-75%, FDR 0.5-0.7/night |
| Massé et al., van Elmpt et al. [35] | electrocardiography                                             | Necklace or arm device and chest electrodes | HR changes in 48% of 8 patients, Sensitivity                                  |
| Milosevic et al.[36]                | accelerometer, electromyography                                 | Connect to limbs                            | Best ACM result: Sensitivity 86.36%, FDR 1.94/12h                             |
| Beniczky et al.[37]                 | accelerometer                                                   | Bracelet                                    | Sensitivity 89.7%, FDR 0.2/day                                                |
| Carlson et al.[38]                  | Audio                                                           | Between bed and Sleeping pillow             | Sensitivity 63%, PPV 3.3%                                                     |
| Conradsen et al.[39]                | electromyography                                                | Electrodes on leg                           | Sensitivity 57%, Latency 25s, FDR 0.003/h                                     |
| Lockman et al. [40]                 | accelerometer                                                   | Watch                                       | Sensitivity 87.5%, PPV >50%                                                   |
| Narechania et al.[41]               | accelerometer                                                   | Sleeping pillow                             | Sensitivity 89%                                                               |
| Patterson et al.[42]                | accelerometer                                                   | Watch                                       | Sensitivity 16-34% for all seizures, High FDR                                 |
| proposed                            | Accelerometer, heartbeat, temperature                           | Watch                                       | Sensitivity 94%                                                               |

### 3.5. Conclusions

The proposed IoT-based system for epileptic seizure detection represents a significant advancement in healthcare through the integration of modern technologies. This system effectively combines multiple sensors, such as accelerometers, heart rate, and temperature sensors, with fuzzy logic algorithms to accurately identify potential seizure events. Beyond mere detection, the system is designed to send instant notifications via GSM, including the patient's precise GPS location, enabling swift and efficient responses during emergencies.

The achieved accuracy of 94% underscores the reliability and effectiveness of the system in healthcare applications. Moreover, the system facilitates continuous and automated monitoring of patients, reducing the need for manual oversight and significantly enhancing patient safety. By leveraging the capabilities of IoT and wearable devices, this research highlights the transformative potential of advanced technologies in delivering innovative and integrated healthcare solutions. This work sets the foundation for further exploration and development of intelligent health monitoring systems that can be extended to address other medical conditions in the future.

## References

- [1] S. Hassan, E. Mwangi, and P. K. Kihato, "IoT based monitoring system for epileptic patients," *Heliyon*, vol. 8, no. 6, Jun. 2022, doi: <https://doi.org/10.2139/ssrn.3977513>.
- [2] P. Wal, A. Wal, N. Verma, R. Karunakakaran, and A. Kapoor, "Internet of Medical Things – The Future of Healthcare," *Open Public Health J*, vol. 15, no. 1, Dec. 2022, doi: <https://doi.org/10.21275/sr23726161859>.
- [3] T. Tamura, Y. Maeda, M. Sekine, and M. Yoshida, "Wearable Photoplethysmographic Sensors—Past and Present," *Electronics 2014, Vol. 3, Pages 282-302*, vol. 3, no. 2, pp. 282–302, Apr. 2014, doi: <https://doi.org/10.3390/electronics3020282>.
- [4] V. Teohari, C. Ungureanu, ... V. B.-C., and undefined 2014, "Epilepsy seizure detection app for wearable technologies," *researchgate.netVM Teohari, C Ungureanu, V Bui, J Arends, RM AartsConference Proceedings Aml, 2014•researchgate.net*, doi: <https://doi.org/10.15760/honors.1523>.
- [5] A. Mishra, A. Kumari, P. Sajit, P. P.- Development, and undefined 2018, "Remote web based ECG Monitoring using MQTT Protocol for IoT in Healthcare," *researchgate.netA Mishra, A Kumari, P Sajit, P PandeyDevelopment, 2018•researchgate.net*, vol. 5, 2018, doi: <https://doi.org/10.1109/actea.2019.8851094>.
- [6] H. Yamamoto, A. Okumura, and M. Fukuda, "Epilepsies and epileptic syndromes starting in the neonatal period," *Brain Dev*, vol. 33, no. 3, pp. 213–220, Mar. 2011, doi: <https://doi.org/10.1016/j.braindev.2010.10.009>.
- [7] C. Baumgartner, J. Koren, M. Britto-Arias, S. Schmidt, and S. Pirker, "Epidemiology and pathophysiology of autonomic seizures: a systematic review," *Clinical Autonomic Research*, vol. 29, no. 2, pp. 137–150, Apr. 2019, doi: <https://doi.org/10.1007/s10286-019-00596-x>.
- [8] J. Munch Nielsen, I. C. Zibrandtsen, P. Masulli, T. Lykke Sørensen, T. S. Andersen, and T. Wesenberg Kjær, "Towards a wearable multi-modal seizure detection system in epilepsy: A pilot study," *Clinical Neurophysiology*, vol. 136, pp. 40–48, Apr. 2022, doi: <https://doi.org/10.1016/j.clinph.2022.01.005>.
- [9] Y. Lamrani, A. Jahani, L. Gagliano, D. K. Nguyen, and E. Bou Assi, "Evaluation of Commercially Available Seizure Detection Wearables in Canada: Current Evidence," *Canadian Journal of Neurological Sciences*, 2024, doi: <https://doi.org/10.1017/cjn.2024.58>.
- [10] L. Leon, N. Contreras, F. Polanco, E. Fentry, S. Sajal, and I. Parvez, "A Skin Sensor for Epileptic Seizure Detection and Notification Applications," in *SoutheastCon 2023*, IEEE, Apr. 2023, pp. 118–125. doi: <https://doi.org/10.1109/southeastcon51012.2023.10114958>.
- [11] M. Habtamu *et al.*, "A novel wearable device for automated real-time detection of epileptic seizures," *BMC Biomed Eng*, vol. 5, no. 1, Jul. 2023, doi: <https://doi.org/10.1186/s42490-023-00073-7>.
- [12] W. Li, G. Wang, X. Lei, D. Sheng, T. Yu, and G. Wang, "Seizure detection based on wearable devices: A review of device, mechanism, and algorithm," *Acta Neurol Scand*, vol. 146, no. 6, pp. 723–731, Dec. 2022, doi: <https://doi.org/10.1111/ane.13716/v1/decision1>.
- [13] T. Yamakawa *et al.*, "Wearable epileptic seizure prediction system with machine-learning-based anomaly detection of heart rate variability," *Sensors (Switzerland)*, vol. 20, no. 14, pp. 1–16, Jul. 2020, doi: <https://doi.org/10.3390/s20143987>.
- [14] G. Regalia, F. Onorati, M. Lai, C. Caborni, and R. W. Picard, "Multimodal wrist-worn devices for seizure detection and advancing research: Focus on the Empatica wristbands," Jul. 01, 2019, *Elsevier B.V.* doi: <https://doi.org/10.1016/j.eplepsyres.2019.02.007>.
- [15] N. Zamani-Siahkali *et al.*, "SPECT/CT, PET/CT, and PET/MRI for Response Assessment of Bone Metastases," May 01, 2024, *W.B. Saunders*. doi: <https://doi.org/10.1053/j.semnuclmed.2023.11.005>.
- [16] T. J. von Oertzen, G. Gröppel, S. Katletz, M. Weiß, M. Sonnberger, and R. Pichler, "SPECT and PET in nonlesional epilepsy," May 01, 2023, *Springer Medizin*. doi: <https://doi.org/10.5698/1535-7597-14.3.121>.
- [17] G. Muhammad, F. Alshehri, F. Karray, A. El Saddik, M. Alsulaiman, and T. H. Falk, "A comprehensive survey on multimodal medical signals fusion for smart healthcare systems," *Information Fusion*, vol. 76, pp. 355–375, Dec. 2021, doi: <https://doi.org/10.1016/j.inffus.2021.06.007>.
- [18] K. Xu, Y. Lu, and K. Takei, "Multifunctional Skin-Inspired Flexible Sensor Systems for Wearable Electronics," *Adv Mater Technol*, vol. 4, no. 3, p. 1800628, Mar. 2019, doi: <https://doi.org/10.1002/admt.201800628>.

- [19] S. Beniczky *et al.*, “Automated seizure detection using wearable devices: A clinical practice guideline of the International League Against Epilepsy and the International Federation of Clinical Neurophysiology,” *Epilepsia*, vol. 62, no. 3, pp. 632–646, Mar. 2021, doi: <https://doi.org/10.1016/j.clinph.2020.12.009>.
- [20] O. Gharbi *et al.*, “Detection of focal to bilateral tonic–clonic seizures using a connected shirt,” *Epilepsia*, 2024, doi: <https://doi.org/10.1111/epi.18021>.
- [21] D. Zambrana-Vinaroz, J. M. Vicente-Samper, J. Manrique-Cordoba, and J. M. Sabater-Navarro, “Wearable Epileptic Seizure Prediction System Based on Machine Learning Techniques Using ECG, PPG and EEG Signals,” *Sensors*, vol. 22, no. 23, Dec. 2022, doi: <https://doi.org/10.3390/s22239372>.
- [22] J. Verdru and W. Van Paesschen, “Wearable seizure detection devices in refractory epilepsy,” Dec. 01, 2020, *Springer Science and Business Media Deutschland GmbH*. doi: <https://doi.org/10.1007/s13760-020-01417-z>.
- [23] T. Fair and A. A. Pollen, “Genetic architecture of human brain evolution,” Jun. 01, 2023, *Elsevier Ltd*. doi: <https://doi.org/10.1016/j.conb.2023.102710>.
- [24] T. Traub-Weidinger *et al.*, “EANM practice guidelines for an appropriate use of PET and SPECT for patients with epilepsy,” *Eur J Nucl Med Mol Imaging*, 2024, doi: [https://doi.org/10.1007/978-3-031-51633-7\\_10](https://doi.org/10.1007/978-3-031-51633-7_10).
- [25] R. Sankowski *et al.*, “Multiomic spatial landscape of innate immune cells at human central nervous system borders,” *Nat Med*, vol. 30, no. 1, pp. 186–198, Jan. 2024, doi: <https://doi.org/10.1038/s41591-023-02673-1>.
- [26] C. Harden *et al.*, “Practice guideline summary: Sudden unexpected death in epilepsy incidence rates and risk factors: Report of the Guideline Development, Dissemination, and Implementation Subcommittee of the American Academy of Neurology and the American Epilepsy Society,” *Neurology*, vol. 88, no. 17, pp. 1674–1680, Apr. 2017, doi: <https://doi.org/10.1212/wnl.00000000000004663>.
- [27] J. Sheng, S. Liu, H. Qin, B. Li, and X. Zhang, “Drug-Resistant Epilepsy and Surgery,” *Curr Neuroparmacol*, vol. 16, no. 1, Jun. 2018, doi: <https://doi.org/10.1016/j.eplepsyres.2003.10.001>.
- [28] R. Kumar, M. R.-2016 I. C. on, and undefined 2016, “An IoT based patient monitoring system using raspberry Pi,” *ieeexplore.ieee.orgR Kumar, MP Rajasekaran2016 International Conference on Computing Technologies and, 2016•ieeexplore.ieee.org*, doi: <https://doi.org/10.1109/icctide.2016.7725378>.
- [29] M. M. Islam, S. Nooruddin, F. Karray, and G. Muhammad, “Multi-level feature fusion for multimodal human activity recognition in Internet of Healthcare Things,” *Information Fusion*, vol. 94, pp. 17–31, Jun. 2023, doi: <https://doi.org/10.1016/j.inffus.2023.01.015>.
- [30] F. Firouzi *et al.*, “Fusion of IoT, AI, Edge-Fog-Cloud, and Blockchain: Challenges, Solutions, and a Case Study in Healthcare and Medicine,” *IEEE Internet Things J*, vol. 10, no. 5, pp. 3686–3705, Mar. 2023, doi: <https://doi.org/10.1109/jiot.2022.3191881>.
- [31] Pritika, B. Shanmugam, and S. Azam, “Risk Assessment of Heterogeneous IoMT Devices: A Review,” *Technologies 2023, Vol. 11, Page 31*, vol. 11, no. 1, p. 31, Feb. 2023, doi: [10.3390/TECHNOLOGIES11010031](https://doi.org/10.3390/TECHNOLOGIES11010031).
- [32] G. Becq, S. Bonnet, L. Minotti, M. Antonakios, R. Guillemaud, and P. Kahane, “Classification of epileptic motor manifestations using inertial and magnetic sensors,” *Comput Biol Med*, vol. 41, no. 1, pp. 46–55, Jan. 2011, doi: <https://doi.org/10.1016/j.compbimed.2010.11.005>.
- [33] D. Cogan, M. Nourani, J. Harvey, and V. Nagaraddi, “Epileptic seizure detection using wristworn biosensors,” *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, vol. 2015–November, pp. 5086–5089, Nov. 2015, doi: <https://doi.org/10.1109/embs.2015.7319535>.
- [34] P. Jallon, “A Bayesian approach for epileptic seizures detection with 3D accelerometers sensors,” *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC’10*, pp. 6325–6328, 2010, doi: <https://doi.org/10.1109/iembs.2010.5627636>.
- [35] F. Masse, M. Van Bussel, A. Serteyn, J. Arends, and J. Penders, “Miniaturized wireless ECG monitor for real-time detection of epileptic seizures,” *Transactions on Embedded Computing Systems*, vol. 12, no. 4, Jun. 2013, doi: <https://doi.org/10.1145/1921081.1921095>.
- [36] M. Milošević, A. Van de Vel, ... B. B.-I. journal of, and undefined 2015, “Automated detection of tonic–clonic seizures using 3-d accelerometry and surface electromyography in pediatric patients,” *ieeexplore.ieee.orgM Milošević, A Van de Vel, B Bonroy, B Ceulemans, L Lagae, B Vanrumste, S Van*

- HuffelIEEE journal of biomedical and health informatics*, 2015•[ieeexplore.ieee.org](https://ieeexplore.ieee.org), doi: <https://doi.org/10.1109/jbhi.2015.2462079>.
- [37] P. Meritam, P. Ryvlin, and S. Beniczky, “User-based evaluation of applicability and usability of a wearable accelerometer device for detecting bilateral tonic-clonic seizures: A field study,” *Epilepsia*, vol. 59 Suppl 1, pp. 48–52, Jun. 2018, doi: <https://doi.org/10.1111/epi.14051>.
  - [38] C. Carlson, V. Arnedo, M. Cahill, and O. Devinsky, “Detecting nocturnal convulsions: Efficacy of the MP5 monitor,” *Seizure*, vol. 18, no. 3, pp. 225–227, Apr. 2009, doi: <https://doi.org/10.1016/j.seizure.2008.08.007>.
  - [39] S. N. Larsen, I. Conradsen, S. Beniczky, and H. B. D. Sorensen, “Detection of tonic epileptic seizures based on surface electromyography,” *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC 2014*, pp. 942–945, Nov. 2014, doi: <https://doi.org/10.1109/embc.2014.6943747>.
  - [40] J. Lockman, R. S. Fisher, and D. M. Olson, “Detection of seizure-like movements using a wrist accelerometer,” *Epilepsy & Behavior*, vol. 20, no. 4, pp. 638–641, Apr. 2011, doi: <https://doi.org/10.1016/j.yebeh.2011.01.019>.
  - [41] A. P. Narechania, I. I. Garić, I. Sen-Gupta, M. P. Macken, E. E. Gerard, and S. U. Schuele, “Assessment of a quasi-piezoelectric mattress monitor as a detection system for generalized convulsions,” *Epilepsy & Behavior*, vol. 28, no. 2, pp. 172–176, Aug. 2013, doi: <https://doi.org/10.1016/j.yebeh.2013.04.017>.
  - [42] A. L. Patterson *et al.*, “SmartWatch by SmartMonitor: Assessment of Seizure Detection Efficacy for Various Seizure Types in Children, a Large Prospective Single-Center Study,” *Pediatr Neurol*, vol. 53, no. 4, pp. 309–311, Oct. 2015, doi: <https://doi.org/10.1016/j.pediatrneurol.2015.07.002>.