



Research article

IoT based monitoring system for epileptic patients

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ABSTRACT

The unpredictable nature of epileptic seizures makes it challenging to detect and effectively treat this disorder. The seizures are random, and most epileptic patients experience dangerous physical symptoms during an attack that renders the patient uneasy when conducting their daily tasks. This paper focuses on the generalised type of epilepsy, namely "Grand mal epilepsy Tonic-Clonic (GTC) seizure. The research aims to monitor symptoms of epileptic disease behaviour signals in humans and prevent it at its early stage of illness. To achieve this objective, we used the Electrocardiogram (ECG), Electromyography (EMG), accelerometer 3-axes for fall detection, and Dallas sensor for body temperature signals monitoring for updating the IoT system. The fuzzy logic algorithm that has been used to assess specified data set of diseased patients' parameters allows the classification into diverse types of seizures such as heart rate, body temperature, muscles spasm and falls. These are used as inputs to obtain the seizure type as an output which is then illustrated graphically on the dashboard of an IoT platform (Think-Speak), where abnormal conditions have been used to notify the medical personnel by sending an SMS message through "If This Then That" (IFTTT) technology. A prototype of an epileptic monitoring system has been successfully built and tested. It has an average accuracy of 98.90%, 95.49%, 83.0%, and 87.21% for body temperature, heart rate monitoring, muscle spasm, and fall detection.

1. Introduction

The fast improvement of Internet of things (IoT) innovation makes it workable to associate different objects together through the Internet and to give more information on Interoperability techniques for application purposes [1]. More potential uses of IoT in data-intensive modern domains, such as medical care services, are being investigated. With the help of the Internet of Things and developments in sensor technology, monitoring epilepsy patients has never been easier with IoT assistance [2]. This paper aims to discuss monitoring epilepsy seizures and develop a wearable sensor network for patient monitoring. The project is based on an IoT monitoring system that integrates three monitoring units: an ECG signal transmitter, a MyoWare muscles sensor (EMG), an accelerometer sensor, a Dallas temperature sensor, and a microcontroller (EsP32) as control modules.

2. Related work

Giulia Regalia et al. [3] Developed Wearable automated seizure detection devices offer tremendous potential to enhance seizure

management through continuous ambulatory monitoring, accurate seizure detection, and notifications for fast action. Machine learning is utilised in a bracelet with the accelerometer (ACC) and electrodermal activity (EDA) sensors to automatically utilise recognised an event based on symptoms of ongoing GTCS and send an alarm to a mobile app, which prompts designated caregivers with a call and text via a cloud-based system. The patient's GPS location can be sent to the caregivers. The wearer can quickly silence the alert in the event of a false alarm., Before the signal is delivered to caregivers, the user can promptly silence it. Pranjat T. et al. [4] Proposed an approach for epilepsy patients who utilise a sensor to assess temperature, patient fall, handshaking, and sound. The patient's condition may be viewed on a P.C. via IoT. The system was created to identify Atonic Seizure: This type of Seizure results in a lack of muscular control, as seen by the patient's temperature dropping. Myoclonic seizure, this type of seizure involves jerking movements throughout the body. These changes are most noticed in children and occur in the arms and legs. They have shown jerking hands in this way. Tonic-clonic seizure, this type of seizure results in a lack of bodily control and shaking. Only a few people will be able to maintain control where the patient's fall has been

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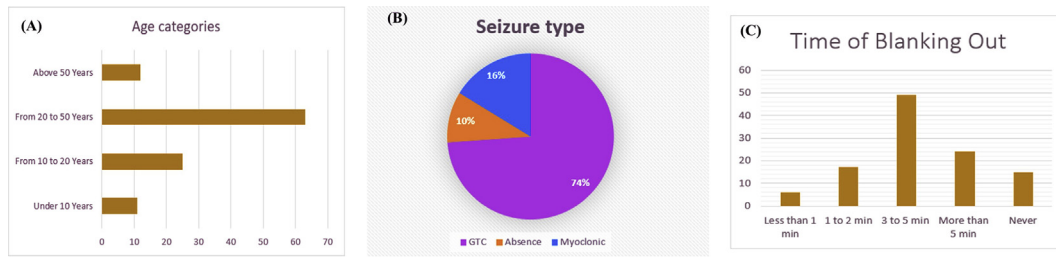


Figure 1. Data conducted from Epileptic patients, (A) Age category, (B) Seizure type, (C) Time of blanking out.

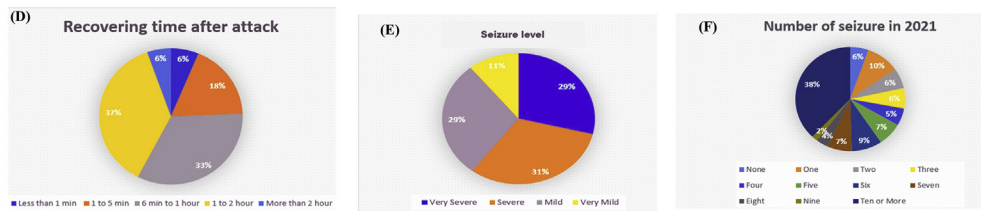


Figure 2. The graphical statistic of epilepsy parameters (D) Recovering time after the attack, (E) Seizure level, and (F) Number of seizures in 2021.

demonstrated. Simple Focal seizure: This type of seizure involves jerks in any body area, and the patient shouts during the seizure. These changes may be seen in the arms and legs regularly. They have shown how to shake their hands and make sounds. Using sympathetically mediated electrodermal activity (EDA) and accelerometry with a new wrist-worn biosensor, an algorithm for automated identification of generalised tonic-clonic (GTC) seizures was developed by Ming-Zher Poh et al. [5].

3. Materials and method

3.1. Materials

3.1.1. ECG

Electrocardiography has added value to automatically detect seizures in temporal lobe epilepsy (TLE) patients. The wired hospital system is unsuitable for a long-term seizure detection system at home [6].

3.1.2. EMG

It is a technique for evaluating & recording the electrical activity produced by skeletal muscles [7]. It is performed using an electromyograph instrumentally to make a record called an electromyogram where a resting muscle does not show recordable electrical potential. with an increased force of contraction, the amplitude of potential increases, and an EMG detects the electrical potential generated by muscle cells when these cells are electrically or neurologically activated [8].

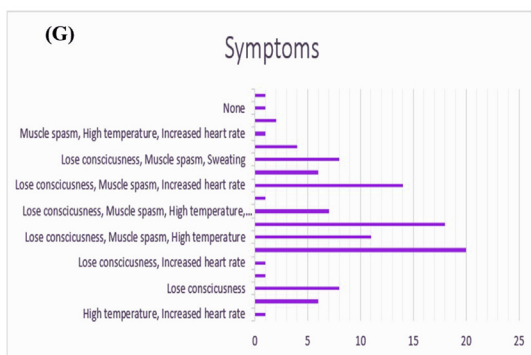


Figure 3. Categories of epilepsy symptoms in terms of the number of patients (G).

3.1.3. Dallas temperature sensor

The DS18B20 is a small temperature sensor with a built-in 12bit ADC. It can be easily connected to an Arduino digital input. The sensor over a one-wire bus requires little in the way of additional components. The sensor has a quoted accuracy of $\pm 0.5^\circ\text{C}$ in the range of -10°C to $+85^\circ\text{C}$ [9].

3.1.4. ESP32

This is a low-cost, low-power System on Chip (SoC). It consists of integrated Wi-Fi and dual-mode Bluetooth. It has Tensilica Xtensa LX6 microprocessor. It was created and developed by Espressif Systems and Manufactured by TSMC. It is the successor of ESP8266, created by the same company. ESP32 can be used in the form of a module or NodeMCU [10].

3.1.5. Accelerometer

The accelerometer sensor utilised as a part of the exhibited framework is ADXL335. In this system, two accelerometers are utilised accelerometer one is utilised to identify the fall of the patients, and accelerometer two is utilised for shaking the patients' hands. The accelerometers are orthogonal. It implies that ADXL335 reaction to both tilt and increasing speed is physical information [10, 11].

3.2. Method

This work comes with ethical approval from the Kenya Association for the Welfare of people with epilepsy (KAWE), and informed consent was obtained from all patients for the experiments.

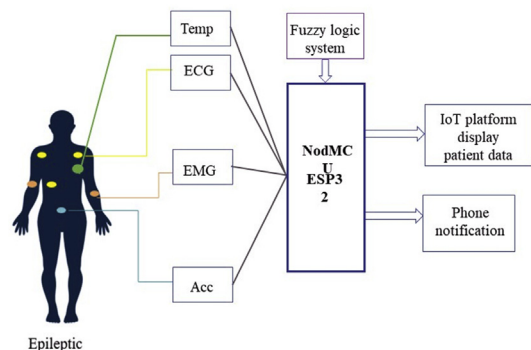


Figure 4. Blok diagram of epileptic monitoring system using fuzzy logic.

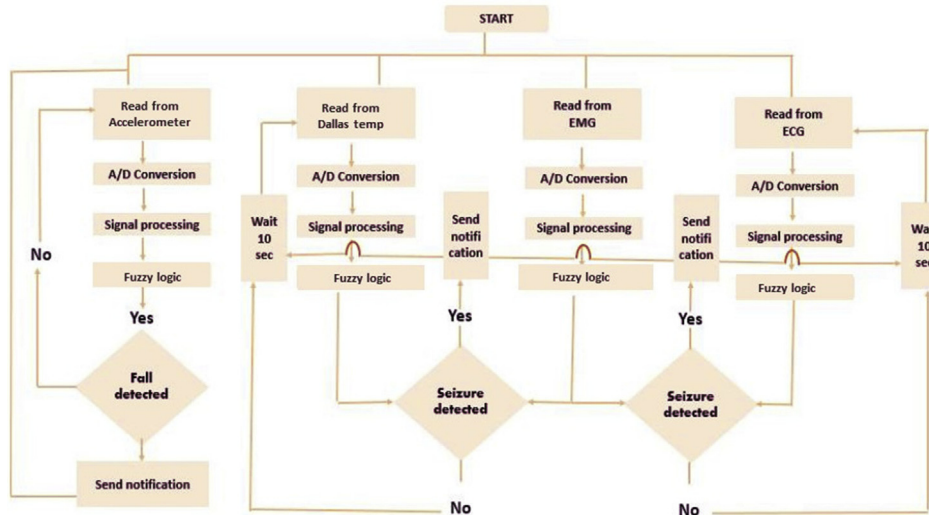


Figure 5. Flowchart of the algorithm system to monitor epileptic patient's.

3.2.1. Field epilepsy study

A field survey was conducted with the Kenya Association for the Welfare of people with epilepsy (KAWWE) in three health clinics based in Nairobi, Kenya, to determine the actual behaviour that can be monitored through the system. One hundred eleven patients participated in the questionnaire study, with 51% male and 49% female.

3.2.2. IoT system architecture

The NodMCU ESP32 reads data from the s ECG (heart rate), EMG (Muscles spasm), as well as Acc (3-axes) for fall detection and Dallas (body temperature). Then the data is converted from analogue to digital format. A user Datagram Protocol (UDP) receives the data, and a Fuzzy Logic Controller (FLC) makes a classification. The IoT architecture system is illustrated in Figure 4.

The FL algorithm does a pre-analysis of data that will help the process of decision making to detect seizure types in a specific range. In case of seizure is detected, notification will be sent to the relatives and doctor from the system to the mobile application; in case of emergency, the caregivers are notified through IFTT notification to act accordingly. The outputs data then being sent through HTTP protocol to the server Thing-Speak IoT platform used for real-time data streaming and visualization for Hospital monitoring. Figure 5 shows the flowchart of the algorithm system to monitor epileptic patients:

We have in this paper the Dallas temperature sensor is a digital temperature sensor with only one wire. This means only one data line (and GND) is required to connect with the ESP32. It can be powered by an external power supply or by drawing power directly from the data line (known as "parasitic mode"), preventing an external power supply requirement. This sensor allows us to monitor the patient's body temperature with a power supply range of 3.0V–5.5V and an operating

temperature range of -55 °C to +125 °C, with an accuracy of ±0.5 °C (between -10 °C and 85 °C).

Three lead ECG transmitter (AD8232) is an integrated signal conditioning block for ECG and other biopotential measurement applications that measures heart rate. It's made to extract, amplify, and filter tiny biopotential signals in noisy environments like those caused by mobility or remote electrode placement [12].

The AD8232 module breaks out nine connections from the I.C. where pins can be soldered, wires, or other connectors. SDN, LO+, L.O., OUTPUT, 3.3V, GND provide essential pins for operating this monitor with the development board ESP32. Also offered on this board are R.A. (Right Arm), L.A. (Left Arm), and R.L. (Right Leg) pins to attach and use our custom sensors. Additionally, an LED indicator light will pulsate to the rhythm of a heartbeat. Figure 6 illustrates the ECG electrodeposition on the body patient [6].

EMG is a MyoWare board that measures a muscle's filtered and rectified electrical activity. Depending on the level of activity in the particular muscle, the output ranges from 0 to Vin Volts. The sensor is simple to operate. When muscles are flexed, you must attach a few electrodes and read the voltage [8].

We can attach biomedical sensor pads directly to the board because the sensor has a wearable design. This board has a single-supply voltage range of +3.1V to +5V, a RAW EMG output, polarity-protected power pins, indication LEDs, and an on/Off switch. It also features a few shields attached to the MyoWare Muscle Sensor to expand its adaptability, such as cable, cover, and proto shield and functionality [7]. The position of the EMG MyoWare electrode on the muscle is shown in Figure 7.

The ADXL335 is a small, thin, low-power, complete 3-axis accelerometer with conditioned voltage outputs. The product measures acceleration with a minimum full-scale range of ±3 g. It can measure the static acceleration of gravity in tilt sensing applications and dynamic acceleration resulting from motion, shock, or vibration. This research selects the accelerometer bandwidth using the CX, C.Y., and C.Z. capacitors at the XOUT, YOUT, and ZOUT pins. Bandwidths were chosen to suit our system, with a range of 0.5 Hz–1600 Hz for the X and Y axes and 0.5 Hz–550 Hz for the Z-axis [13]. We aim to detect the fall. Fall detecting can be achieved by analysing accelerometer extradited data. The most common method of detecting a fall is calculating the absolute sum of ACC signal differences, as shown in Eq. (1).

$$Acc = \sqrt{(Ax)^2 + (Ay)^2 + (Az)^2} \tag{1}$$

[13] The thresholding fall value is utilized to inform the user when a fall is detected.

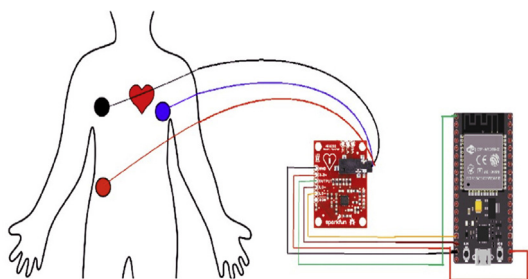


Figure 6. ECG electrodeposition on the body patient [15].

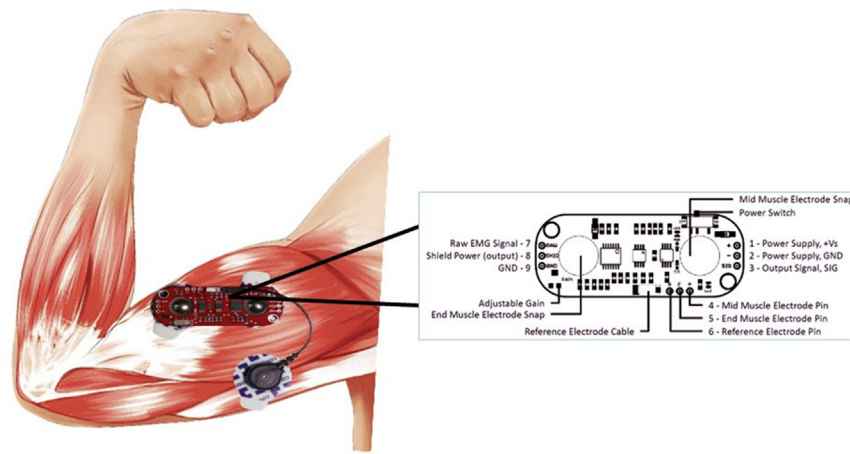


Figure 7. EMG Myoware electrodeposition on the muscle.

Table 1. The number of patients participated in the study.

Clinic Name	No of Male	No of Female	Total
Karen Health Centre	9	15	24
Riruta Health Centre	18	14	32
Lions Health Clinic	30	25	55

- A. The age categories of patients were 57% (From 21 to 50 years), 22% (from 10 to 20 years), and 11% (Above 50 years), then 10% (Under ten years). As it is illustrated in Figure 1
- B. GTC seizures affect 74% of individuals, with 16% developing Myoclonic attacks and 10% experiencing Absence seizures. As it is shown in Figure 1
- C. 5% of patients blanked out for less than 1 min during the attack, 14% never blanked out during the seizure, 15% of patients blanked out for 1–2 min during the attack, then 22 % blanked out for more than 5 min, and 44 % blanked out between 3 to 5 min. As it is illustrated in Figure 1
- D. The recovery time after the attack is significant for the patients who have GTC seizures, so we figure out that 37% of the patient take from 1 to 2 h and 33% of them take from 6 min to 1 h, and as a minimum and 2 h as maximum to be expected. As it is illustrated in Figure 2
- E. The seizure level was varied as 29% of the patients experienced a very severe seizure, and 31% of them have usually experienced a severe episode, then 29% had mild attacks, and 11% of the patients experienced very mild seizures. As it is illustrated in Figure 2
- F. The number of seizures is significant to know the repetitive rate of attack for each particular patient; where we figure out that 38% of patients experience ten or more during 2021, and most of them have GTC seizure type Figure 2 shows the graphical statistic of epilepsy behaviours
- G. Based on the study, 74% of the patients with GTC seizures have common symptoms and behaviours came as follows, loss of consciousness that can cause falling of the body, which the accelerometer sensor can detect, and muscles spasm that can be detected by the EMG sensor and increasing heart rate that will be detected by ECG sensor.
 - 28% of the patients with GTC seizures have additional symptoms, such as the increasing temperature that the Dallas temperature sensor will detect. As it is illustrated in Figure 3.

3.2.3. Fuzzy logic simulations

In this work, we consider the outputs data sensor, which represents the patients' behaviours as an input for the fuzzy logic system using MATLAB script command to identify the membership function of each input. Fuzzy Input-Output Inference Mapping.

The Mamdani type inference is used in this paper fuzzy modelling, prompting to replicate and express knowledge concerning the experience of healthcare professionals.

Described as a series of IF-THEN rules:

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

$$\text{THEN } \langle y \text{ is } N \rangle, \tag{2}$$

[14] The antecedent part, IF proposition, specifies the premise, while the subsequent part, THEN proposition, relates to the conclusion; propositional language phrases define both, $P = x \text{ is } M$. The number of rules is represented by the j -the rule, $j = 1, 2, \dots, m$. The elements x_i and y correspond to the i -the input and output about items inserted in discrete classes (sets) known as the universe of discourse, $x_i \in X_i$ and $y \in Y$, also given linguistic variables. The input vector, $x = [x_1, \dots, x_n]^T$, is related to the premises, whereas the output vector, y , is related to the conclusion. The language term "AND" is equivalent to the T-norm, $t(x, y)$. The T-model is conducted via minimal operation when employing the Mamdani fuzzy system. The defuzzification procedure is carried out here by utilising the area's centre. The components $M_i \in X_i$ and $N \in Y$ are both fuzzy sets with linguistic words attached to them, splitting the respective discourse universes.

In language terms, illustrating crisp values is "fuzzification." In this way, the fuzzifier correlates the crisp input values with particular levels, and the fuzzifier can generate linguistic values for each input variable for the inference engine. The setpoint of the fuzzifier is based on data that includes two input variables: "ECG," "TEMP," and EMG and ACC.

The linguistic values map the importance of the fuzzy input variables with the M.F. occupied in the regions. As we use four variables, four linguistic values are demonstrated in the following Table2 (see Table 1).

4. Results and discussion

4.1. Part.1 MATLAB simulation results

We used a collection of IF-THEN rules to build the fuzzy logic rules inference. The IF section of the rule is the antecedent, and the THEN part is the consequent. Linguistic variables are used to create rules. These variables take on fuzzy values expressed in words and modelled as fuzzy subsets of a domain. The fuzzy logic system's final step is to convert the fuzzy variables created by the fuzzy rules back into actual values, which can then be utilized to perform the intended action. The fuzzy output is finally mapped to crisp output using the membership function. Fuzzy rules are a set of linguistic statements that describe how the FIS should decide whether to classify anything, an input or controlling an output fuzzy system rule generated by MATLAB, as shown in Table 3.

The MATLAB toolbox R2021b is used to create MATLAB simulations. The following are MATLAB simulations for a seizure control system. All other control systems' simulations are based on the same patterns. The rule viewer editor displays fuzzy rules graphically to calculate the output. Essentially, this is the complete approach to the fuzzy output method. The rule viewer confirms the algorithm by perceiving the fuzzy rules for the crisp value, assigning the values of inputs to the two input variables (Heart rate = 110, Temperature = 26.2, and Muscles spasm = 5.06 and

Table 2. Membership function input/output variables with fuzzy system: The X-axis shows the input variables such as heart rate, muscular spasm, body temperature, and fall detection, and the output variable named seizure type, while the Y-axis represents the degrees of membership in the [0, 1] interval.

Inputs/Outputs	Membership functions	Graphical representation of M.F.
<p>Heart Rate (ECG): The membership functions of heart rate input come with five linguistic variables which are very low (VL), low (L) and normal (N), then high (H), very high (VH). denfeded as <i>Heart Rate</i> = $\mu_{HR}(h)$</p>	$\mu_{HR\ VL}(h) = \{\max((1, \frac{20-h}{20}), 0)\}$ $\mu_{HR\ L}(f) = \{\max((\frac{h-20}{20}, 1, \frac{70-h}{10}), 0)\}$ $\mu_{HR\ N}(f) = \{\max((\frac{h-70}{10}, 1, \frac{115-h}{15}), 0)\}$ $\mu_{HR\ H}(f) = \{\max((\frac{h-115}{15}, 1, \frac{150-h}{10}), 0)\}$ $\mu_{HR\ VH}(f) = \{\max((\frac{h-150}{10}, 1), 0)\}$	
<p>Muscles spasms (EMG): The membership functions of the muscles spasms (EMG) have four linguistic variables: rest (R), start (S), end (E), and relax (r), denfeded as <i>Muscles spasms</i> = $\mu_{MS}(m)$</p>	$\mu_{MS\ Rest}(m) = \{\max((1, \frac{2-m}{0.5}), 0)\}$ $\mu_{MS\ Start}(m) = \{\max((\frac{m-2}{0.5}, 1, \frac{4-m}{0.5}), 0)\}$ $\mu_{MS\ End}(m) = \{\max((\frac{m-4}{0.5}, 1, \frac{6-m}{0.5}), 0)\}$ $\mu_{MS\ Relax}(m) = \{\max((\frac{m-6}{0.5}, 1, \frac{10-m}{0.5}), 0)\}$	
<p>Fall detection (ACC): The membership functions of the fall detection (Acc) contain three linguistic variables: low, medium, high denfeded as <i>Fall detection</i> = $\mu_{Fd}(f)$</p>	$\mu_{Fd\ Low}(f) = \{\max((1, \frac{20-f}{20}), 0)\}$ $\mu_{Fd\ Medium}(f) = \{\max((\frac{f-20}{20}, 1, 0), 0)\}$ $\mu_{Fd\ High}(f) = \{\max((\frac{f-100}{50}, 1), 0)\}$	
<p>Body Temperature: The membership functions of the body temperature (Dallas) have three linguistic variables: low, normal, high denfeded as <i>Body Temperature</i> = $\mu_{BT}(b)$</p>	$\mu_{BT\ Low}(b) = \{\max((1, \frac{35-b}{5}), 0)\}$ $\mu_{BT\ Normal}(b) = \{\max((\frac{b-35}{5}, 1, \frac{60-b}{5}), 0)\}$ $\mu_{BT\ High}(b) = \{\max((\frac{b-60}{5}, 1), 0)\}$	
<p>Muscles spasms (EMG): The membership functions of the muscles spasms (EMG) have four linguistic variables: rest (R), start (S), end (E), and relax (r) denfeded as <i>Muscles spasms</i> = $\mu_{MS}(m)$</p>	$\mu_{ST\ Clonic}(s) = \{\max((1, \frac{20-s}{5}), 0)\}$ $\mu_{ST\ Myoclonic}(s) = \{\max((\frac{s-20}{5}, 1, \frac{40-s}{5}), 0)\}$ $\mu_{ST\ Tonic}(s) = \{\max((\frac{s-40}{5}, 1, \frac{60-s}{5}), 0)\}$ $\mu_{ST\ Atonic}(s) = \{\max((\frac{s-60}{5}, 1, \frac{80-s}{5}), 0)\}$ $\mu_{ST\ Absence}(s) = \{\max((\frac{s-80}{5}, 1), 0)\}$	

Table 3. Fuzzy inference system rules.

RULES	IF THEN OUTPUTS
Rule 1	If (ECG is H) or (EMG is Start), then (Seizure Type is Clonic)
Rule 2	If (Temperature is High) and (EMG is Start), then (Seizure Type is Clonic)
Rule 3	If (ECG is N) and (EMG is Start), then (Seizure Type is Tonic)
Rule 4	If (ECG is H) and (EMG is Start) and (Accelerometer is Medium), then (Seizure Type is Tonic)
Rule 5	If (ECG is H) and (Temperature is Low) and (EMG is Start), then (Seizure Type is Tonic)
Rule 6	If (ECG is N) and (Temperature is Low) and (EMG is End) and (Accelerometer is High), then (Seizure Type is Atonic)
Rule 7	If (ECG is N) and (Temperature is Low) and (EMG is Relax) and (Accelerometer is High), then (Seizure Type is Atonic)
Rule 8	If (ECG is N) and (Accelerometer is High), then (Seizure Type is Atonic)
Rule 9	If (Temperature is High) and (EMG is Start), then (Seizure Type is Myoclonic)
Rule 10	If (ECG is N) and (Temperature is High) and (EMG is Start), then (Seizure Type is Myoclonic)
Rule 11	If (ECG is N) and (Temperature is High) and (EMG is Rest) and (Accelerometer is Medium), then (Seizure Type is Absence)
Rule 12	If (Temperature is High) then (Seizure Type is Absence)

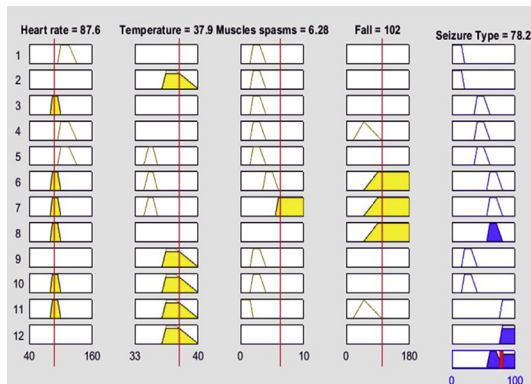


Figure 8. Rule Viewer of Seizure type classification System.

fall = 90), and using $S_i * R_i/R_i$ to determine and produce crisp values for the output variable (Seizure type = 30.7) as it is shown in Figure 8.

Reaching a computed result in bloated logic and acceptable fuzzy groups and comparing the degree of membership requires a defuzzification method. The approach generates a new set from a fuzzy set, which is also needed by fuzzy control systems. De-Fuzzifiers are classified into numerous categories. In the proposed model, a centroid type of De-Fuzzifier is applied. The illustrations represent the graphical explanation of the De-Fuzzifier. The De-Fuzzifier visual explanation of FIS is shown in Figure 9.

Figure 9 (a): Shows a 3D depiction of the suggested system's ruled surface related to heart rate and temperature, with a yellow hue

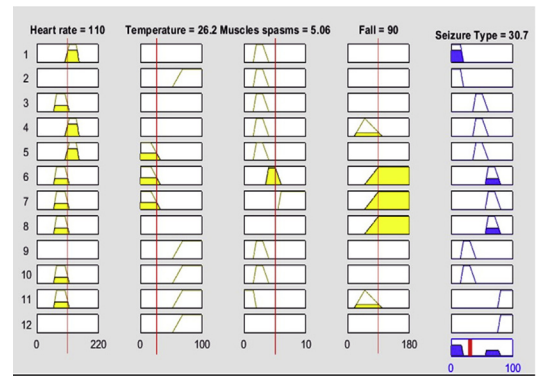


Figure 10. Rule Viewer of Seizure type classification System.

indicating that the results of the presented approach are positive. If the temperature is between 34.2 °C and 36.8 °C and the heart rate is over 75. When the temperature is between 33 °C and 35 °C, the heart rate is between 0 and 75, and 150 to 200, it provides average results. It has a bluish tinge and generates horrible effects. If the temperature is less than 35.2 °C and the heart rate is between 125 and 150 beats per minute. At the same time, the remainder of the surface area is close to normal.

Figure 9 (b): displays a 3D rendering of the proposed system's ruled surface about heart rate and muscular spasm. The outcomes of the proposed method are acceptable, with a yellow colour. Suppose the heart rate range between 70 to105 and the muscles spasm lies between 4.7 to10 and 0 to 2.5. It produces average results when the heart rate range between 0 to 55, 125 to 150 and 150 to 200, and the muscles spasm range between 2.2 to 4.2, 0 to 10 and 2.2 to 4.2, respectively. It produces awful effects with a blue tint if the temperature is under 35.2 °C and the heart rate lies between 125 to 150. At the same time, the rest of the surface area is near the average results.

Figure 9 (c): Shows a 3D illustration of the presented system's ruled surface as a heart rate and fall function. It should be mentioned that the suggested systems. The findings are promising if the heart rate is between 66 and 114.5 and falls lie between 50 to 180. Consider that the outcomes will be average if the Heart rate lies between 114.5 and 129 and the Fall range between 60 to 180. It will provide poor results if the heart rate is between 114.5 and 166 and the fall lies between 0 to 180.

The seizure type remains constant when the muscles spasm and fall value increases in most of the ranges of membership functions. However, the seizure type does not remain stable when the heart rate and temperature and fall values increase in all the fields of membership functions, as shown in Figure 10.

The type of seizure changes directly with the difference in the heart rate value and temperature with neglecting muscles spasm values which mean some types of seizure can happen without muscles spasm symptoms, as shown in Figure 11.

Following the prediction layer, the output is sent to the performance layer, where it is checked for accuracy and miss rate, so if the results are not satisfactory to the learning condition, it is rejected, then the prediction layer is updated; if Yes, the value is communicated to the IoT

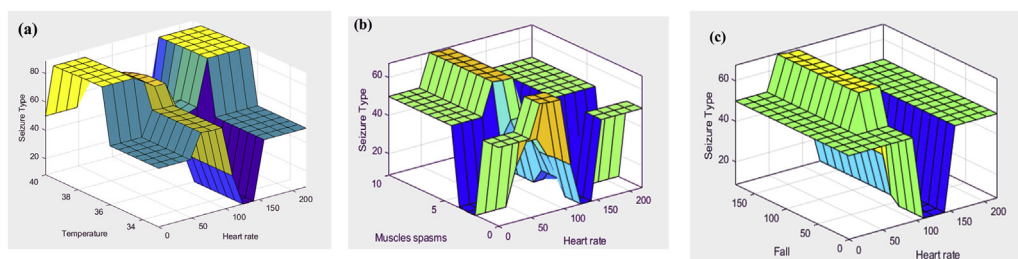


Figure 9. Rule surface of the proposed system based on (a) heart rate and temperature, (b) heart rate and muscles spasm, (c) heart rate and fall.

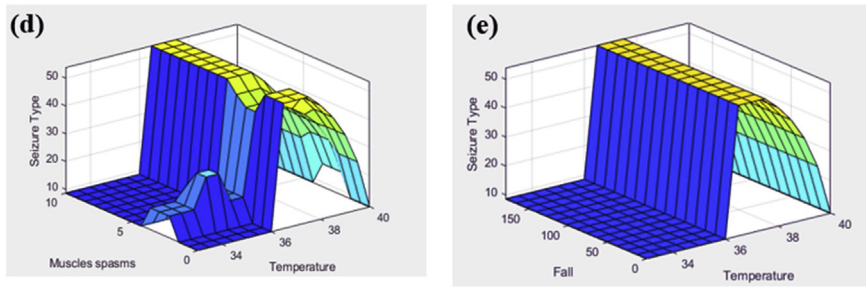


Figure 11. Rule surface of the proposed system based on (d) Temperature and Muscles spasm, (e) Temperature and Fall.

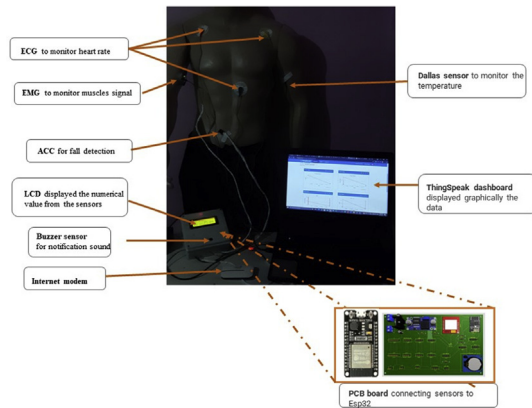


Figure 12. Final prototype of IoT based monitoring system for epileptic patients.

platform database. The system then proceeds to the validation step, where a Fuzzy-based smart epilepsy classifier is loaded, and the type of seizure is determined. The device will display a message notifying the user of the kind of seizure that has been diagnosed.

4.2. Comparison with other methods

Alternative researchers have proposed numerous other approaches for identifying epileptic episodes, the majority of which used EEG-based techniques to detect seizures by implementing classifications of EEG signal analysis in the second step of the process [15], the most widely used classifiers being SVN [16, 17, 18], KNN [19], Neural networks [20, 21], Decision trees [22], and Naive Bayes [14].

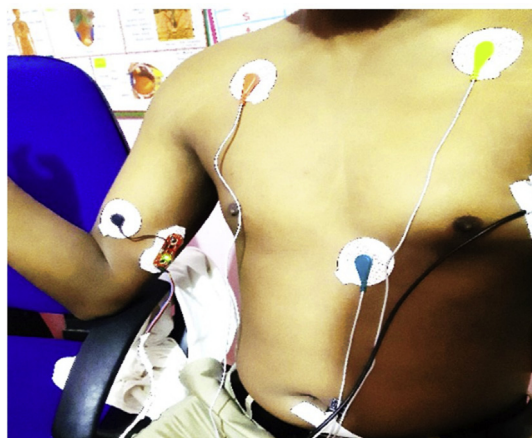


Figure 13. Final Test of IoT based monitoring system for epileptic patients.

The loss of some information throughout the classification process added to the uncertainty of data generated after the pre-processing phase and used as input for the classification stage. This uncertainty should be recognised and included in signal classification algorithms and procedures. The EEG-based strategies concentrate on brain activity where many variables contribute to uncertainty. In contrast, this research work focuses on the patients' symptoms that can be observed and remotely monitored through a group of sensors. Then the signals will be classified by fuzzy logic technique to deal with the uncertainty and help the doctor diagnose. The classification performance was evaluated using statistical metrics such as accuracy (Acu), sensitivity (Sen), and specificity (Spe), which were derived as follows:

$$S_{en} = \frac{T_p}{T_p + F_N} \tag{3}$$

$$S_{pe} = \frac{T_p}{F_p + F_N} \tag{4}$$

$$A_{cu} = \frac{T_p + T_N}{P + N} \tag{5}$$

[23] where TP = True Positive, FN = False Negative, TN = True Negative, FP = False Positive.

4.3. Part.2 electronic system results

After integrating the fuzzy logic algorithm and connecting the device to a human body Figure 12, we visualize graphically sensor data of body temperature, heart rate, muscles signal, and body balance on the Thing-Speak dashboard IoT platform shown in Figure 12.

The final prototype includes information on the epileptic patient's heart rate, temperature, muscle spasms, and the patient fall and alarm notification (Figure 13). The end product displays prototype architecture and reports, which can be recorded on the Thing-Speak platform as shown in Figure 14 and Figure 15.

Notification: In case of seizure accrue, a message will be sent through IFTTT to the phone number of the caregivers. Figure 16 shows the notification process.

5. Conclusion

A fuzzy inference system was applied as the fuzzy classifier for epileptic seizure detection. Its application enables the accurate classification of epileptic seizures. Compared to previous research, FIS is particularly successful in detecting epileptic seizures. Furthermore, the prototype of an epileptic monitoring system has been successfully built. Unlike a traditional healthcare device, the created IoT-based system can visualize data graphically and send out notification requests when a patient has a seizure. The system's operation was confirmed in the test, with an average accuracy of 98.90%, 95.49%, and 83.0%, 87.21% for body temperature and heart rate monitoring and muscle signal, fall

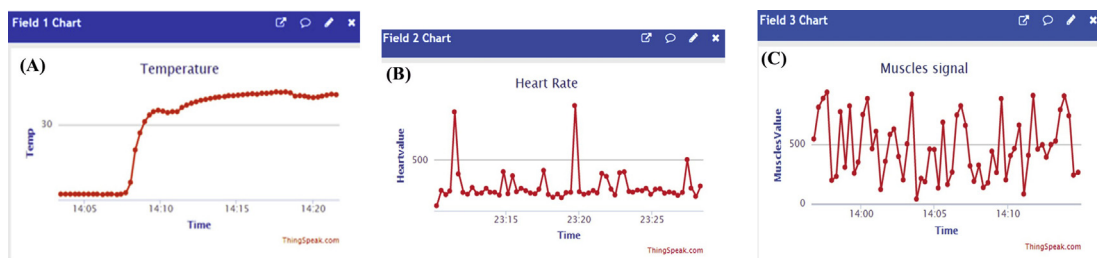


Figure 14. Graphical waveform of the sensors ECG, EMG, and Dallas temp on IoT platform, (A)Temperature, (B)Heart rate, (C) Muscles signal.

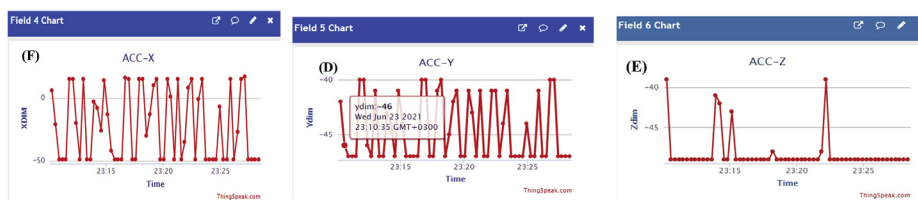


Figure 15. Graphical waveform of the sensor ACC on IoT platform, (D)ACC-Y, (E)ACC-Z, (F)ACC-X.

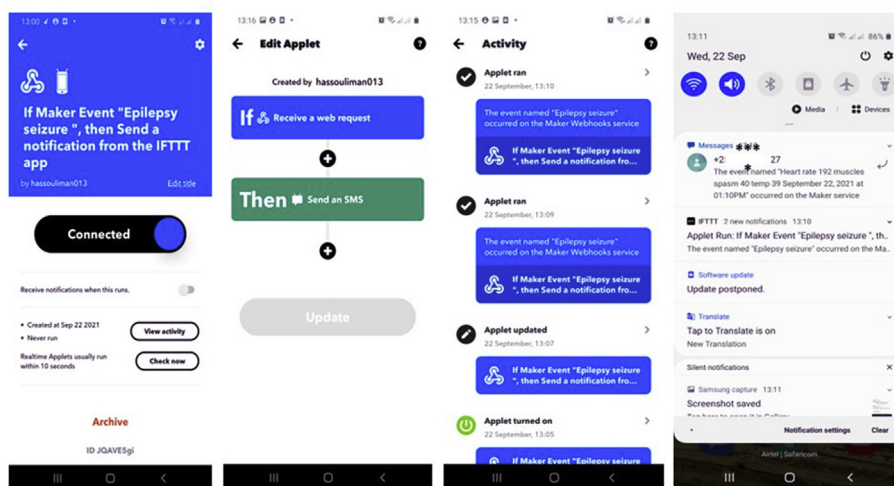


Figure 16. Seizure notification through IFTTT.

detection, respectively. With this system, doctors may give quick assistance. Still, they can also monitor the patient's condition through an IoT platform that updates the data case every 15 s. Patients can be monitored and tracked through any computer or smartphone Android/iOS in complete freedom with easy tools such as IFTTT services or the Blynk application. We can also know the variation of seizure time for each person. The approaches described in this research for further development and clustering analysis can be used in any condition where recognized symptoms per patient can be customized and classified. However, to fully utilize this approach, the proposal of the Fuzzy inference system merging with the IoT systems framework (FISIoT) can be especially applied to patients who have symptoms that can be monitored with multiple IoT sensor-based gadgets and personalized further by wearing the device on different physical positions. The suggested FISIoT framework can manage different categories of patients in the future.

6. Recommendations

This model prototype of an IoT-based monitoring system fabricated using various sensors to be used for epilepsy seizure detection; however, it requires additional testing in real-world scenarios as well as a tiny

wireless sensor to be worn on a shirt to be comfortable and accurate in monitoring epilepsy seizures and detecting false alarms. These sensors can be fully realized considering, for example, BMD101 Micro Wireless ECG, EDA to detect electrodermal activities, and wearable nano EMG sensor. These sensors can control and monitor all the random occurrences with the help of a fuzzy logic system. The GPS can track the subject's position (Global Positioning System). This system has an ARM 7 LPC2138 processor, an R.F. modem, an accelerometer sensor, a sound detection sensor, and a temperature sensor. The parameters are displayed on a P.C. and sent to Thing-speak using Visual Basics.

Declarations

Author contribution statement

Souleyman Hassan: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Elijah Mwangi, Peter Kamita Kihato: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

Data included in article/supplementary material/referenced in article.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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