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A Model for real time monitoring of epileptic patients

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A Model for Real Time Monitoring of Epileptic Patients

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Declaration

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the research thesis itself.

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Abstract

Effective treatment and therapy in epileptic patients require thorough monitoring of seizures. Medical care givers require information on number of seizure occurrences, duration of seizure and magnitude. People suffering from epilepsy face tremendous problems in regards to epileptic seizure monitoring. The typical way to diagnose and monitor epileptic patients is by use of electroencephalography (EEG) which requires monitoring within the confines of the hospital. EEG equipment is available in very few hospitals in Kenya and that is an impediment to proper therapy and treatment for epileptic patients. The challenges faced in using the existing methods include; lack of flexibility for the patient as there is need for long term monitoring in a hospital setup, financial burden on the patients when they are hospitalized and obtrusive nature of the EEG monitoring making it not suitable for monitoring outdoors. This study applies agile methodology to design, develop and test a model for real time monitoring of patients with tonic-clonic epileptic seizures. This model is hardware based, with the capability to send alerts to a family member in the event of a seizure. The patient can also view their seizure history from a mobile application installed on their smartphones. The device was created using Arduino Uno, a tri-axis accelerometer for motion detection and a Global system for Mobile Communication (GSM) module for communication. This model promotes long term, flexible and inexpensive mode of epileptic seizure monitoring therefore contributing to effective treatment of epileptic patients.

Acknowledgements

I acknowledge my thesis supervisor Dr. Joseph Orero for his guidance and feedback and for being willing to lead me through this research. I would also like to appreciate my family and friends for their encouragement and support.

Dedication

This thesis is dedicated this to my little girl, Ivy, to whom the future belongs.

Abbreviations/Acronyms

ANN	**-**	Artificial Neural Networks
EEG	**-**	Electroencephalogram
FFT	-	Fast Fourier Transform
GSM	**-**	Global System for Mobile Communication
KAWE	**-**	Kenya Association for the Welfare of People with Epilepsy
MEMS	**-**	Microelectromechanical systems
SMS	**-**	Short Messaging Service
SVM	**-**	Support Vector Machine
WHO	**-**	World Health Organization

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Chapter 1 : Introduction

1.1 Background

Epilepsy is a disease in the central nervous system. It stands out amongst the most widely recognized brain disorders in the world as it affects not less than 50 Million individuals in the world (WHO, 2004). In Kenya, the occurrence of epilepsy is around 18.2 per 1000 population (Feksi and Kaamugisha 1991), which translates to around 800,000 to 1,000,000 people living with epilepsy. The condition has serious physical, mental, social and financial burdens for the in sick individuals and their families. Epilepsy is usually characterized by seizures which are manifested differently depending on the epileptogenic zone in the brain (Fisher eta al., 2005).

A vast majority of the causes of symptomatic epilepsy are preventable and treatable. Recent research has shown that up to 70% of newly diagnosed children and adults with epilepsy can be successfully treated with anti-epileptic drugs and after 2-5 years of fruitful treatment, drugs can be withdrawn in about 70% of children and 60% of adults without relapses (Ministry of Health, 2016). For treatments and therapy, a doctor needs an account of if and when seizures occur. By the use of video-electroencephalography (vEEG) the aforementioned information can be acquired enabling diagnosis and detailed information on the seizure features to determine therapeutic options and treatment (Benbadis et al., 2004).

Despite the disease being treatable, there is a wide treatment gap between high and low income countries and between rural and urban settings (Ministry of Health, 2016). WHO (2005), state that the factors that contribute to the large treatment gap include; lack of available, accessible, affordable health care and awareness. According to Ministry of Health (2016), the factors that contribute to the huge gap include; Inadequate health delivery systems, lack of trained personnel, lack of essential drugs, traditional beliefs and practices that often do not consider epilepsy as a treatable condition (De Boer et al., 2008), high cost of drugs and poor infrastructure.

With advancements in technology over the years, attempts have been made to automate the process of monitoring epileptic patients. The most common methods of achieving this, is the EEG monitoring. EEG monitoring takes a number of days. As a result, patients have to stay in hospitals for monitoring, with electrodes placed on the scalp the entire period. There has been an increase in the adoption of wearable devices in the medical sector for monitoring patient’s health. The design and creation of wearable biosensor models for health monitoring has generated a lot of interest for the people in the scientific community (Pantelopoulos & Bourbakis, 2010). Together with classification algorithms, wearable devices are highly applicable in the monitoring of epileptic patients with physical motor manifestations. As opposed to the EEG monitoring, wearable devices are less obtrusive and promote self-monitoring at home for patients. With the increasing cost of healthcare, patients prefer self, proactive monitoring.

1.2 Problem statement

In spite of global advances in diagnosis and treatment in recent years, about eight million people with epilepsy in Africa are not treated with modern antiepileptic drugs. Epilepsy is a treatable condition and relatively cheap medication is available, however the treatment gap in developing countries remains very high (WHO, 2004).

The standard way of analyzing seizures in epileptic patients is through vEEG monitoring (Fisher et al., 2005). A typical EEG recording session lasts between 20 minutes to 9 hours (Duque-Muñoz et al., 2014). This might require a patient to be hospitalized therefore putting a financial burden on the patient. The second problem with method is that electrodes have to be placed on the patients scalp during the entire time they are being examined which is quite intrusive. Furthermore, some of the epileptic seizures do not originate from the scalp- an example is seizures of frontal lobe origin.

For treatment of epilepsy, a doctor needs to know if and when a patient had a seizure. This might be difficult to keep track of especially in children.

An easier, long-term monitoring tool would be suitable to facilitate event monitoring at home without necessarily having to carry out EEG examination. This method relieves the patients of financial burdens.

1.3 Research Objectives

I. To review the current methods used in monitoring of epileptic patients
II. To identify the challenges being faced in epileptic seizure monitoring,
III. To appraise the algorithms, models, and architectures that can been in real-time monitoring of epileptic patients.
IV. To develop a model for epileptic seizure monitoring using the appraised architectures.
V. To validate the model

1.4 Research Questions

I. Which methods are currently being used in the monitoring of epileptic patients?
II. What challenges are faced in epileptic seizure monitoring?
III. What are the existing models and architectures applied to monitor epileptic seizures?
IV. How can the appraised algorithms and architectures be used to develop the model for real time monitoring of epileptic patients?
V. How can the model be validated?

1.5 Justification

To begin with, this model enables users to have an account of if and when they experience seizures. This information is important to doctors as the treatment and therapy decisions are based on the aforementioned information.

Secondly, epileptic patients like any other individual go on with their day to day activities and do not necessarily have their kin nearby. By sending alerts, this model will enable families and doctors to be aware of any seizures experienced by a patient.

Thirdly, unlike the EEG examination, this wearable device gives patients freedom to monitor their seizures as they carry on with their day to day activities as opposed to spending long hours in the hospital. This is cost effective. Also, the wearable device is less obtrusive and practical for long term use compared to the EEG monitors.

Lastly, this research will be useful to the MOH, Kenya Association of people with Epilepsy as well as academicians for the purposes for future research. It will contribute greatly in narrowing the gap in existing literature by adding to the technology applied in the medical field, specifically in epileptic seizures monitoring. Also, it will contribute greatly to narrowing the treatment gap by providing constructive data that will be used in treatment and therapy of epileptic patients.

1.6 Scope and Limitation

The journey of an individual with epilepsy begins with diagnosis. After which medication is administered accompanied by constant monitoring which guides the regulation of medication. The proposed system is limited to monitoring of already diagnosed patients. The system should be able to sense seizures with visible motor signs and send alerts to doctors and next of kin. The seizure events will also be available for the patient on their smartphone.

Chapter 2: Literature review

2.1 Introduction

In order to understand the concept and investigate the research problem, a review of the challenges faced by epileptic patients in monitoring of seizures, current methods that exist to minimize these challenges as well as the technology that were employed to solve these problems. Different types of seizures were reviewed as well in this section in order to understand the characteristics they possess to make them detectable by the proposed system.

Relevant publications by accredited scholars and researchers were further reviewed to elaborate the theoretical framework. This is made up of the concept of wearable sensors for biomedical monitoring and classification algorithms application in identification of epileptic seizures. A conceptual framework that represents the context is included to conclude the literature review.

2.2 Epilepsy in Kenya

Epilepsy is a notable health issue in Kenya with an impact on not only the patients but their families, community and the whole population. It is one of the oldest known diseases but despite that fact, it is surrounded by beliefs and misconceptions that perpetuate discrimination and social stigma making treatment and follow up difficult (Ministry of Health, 2016). To be able to resolve this issue, Kenya Association for the Welfare of People with Epilepsy (KAWE), is a nonprofit organization that offers trainings for the purposes of making people aware that epilepsy is treatable.

Research shows that up to 70% of freshly diagnosed children and adults can be successfully treated with drugs. Despite epilepsy care in Kenya improving over the years, there is still a large number of people that do not seek treatment.

Epileptic patients face a number of challenges. Quite often, people living with any mental illness become victims of stigma (Janz & Becker, 1984) which includes self-stigma, public stigma and label avoidance. This is a great contributor to the treatment gap as such people abscond treatment.

Secondly, patients with epilepsy have to seek help from local hospitals that only have clinical officers and nurses. Training in neurology is limited and nurses and clinical officers posted to rural districts report significantly more discomfort with diagnosis, care, and treatment of neurological disorders as compared to medical disorders (Cettomai et al., 2011). Kenya only has eight adult neurologists and four child neurologists in public service at Kenyatta National Hospital.

There are no specific fund allocated for epilepsy (Ana-Claire & David, 2015). There are several groups actively advocating for and improving services and financing for the people with epilepsy in Kenya. The list includes; Kenya Association for the Welfare of people with Epilepsy (KAWE), National Epilepsy Coordination Committee (NEEC) and Kenya society for Epilepsy.

2.3 Types of Epileptic Seizures

Seizures are characterized based on which part of the brain is involved in a seizure. Seizures have divided into generalized, which affect the whole brain, and partial seizures, which affect only a given part of the brain. Partial seizures are the most common types of seizures. For partial seizures, the activity might start in one part of the brain and then move to other parts. Partial seizures affect functionality of whichever part of the brain is affected. During partial seizures, an individual will still be conscious. They usually carry on with conversations and will often remember what went on during the seizure. During simple partial seizures, a person stays awake and aware throughout seizure. A person might move uncontrollable depending on which part of the brain is affected. Complex partial seizures affect a bigger fraction of the brain than simple partial seizures and they also affect consciousness. During these seizures the person stops networking with the environment and with other people. They often chew, pick at their clothes, mumble inaudible things and make uncoordinated movements.

Generalized seizures occur on both sides of the brain. They are classified as;

Absence Seizures – these seizures usually last for between two to fifteen seconds and may occur up to 100 times in a single day. They are characterized by plain gazing, twitching of facial and body muscles. It is not easy for quite a number of people to recognize this type of seizures.

Generalized tonic clonic seizures- this type of seizure is characterized by arms and legs first stiffening during the tonic stage. Next, the person’s limbs and head begin jolting in the clonic phase. A patient might bite his tongue and cease to breathe. After the seizure, the person is likely to be confused and not remember what went on. They might even have headaches or have the urge to sleep for a while. It might take from minutes to hours to fully recover.

Myoclonic Seizures- these type of seizures might cause a part of the body to jerk. This kind of a seizure does not need first aid.

Atonic Seizures- This type of seizures usually makes a part of the body to go totally limp. The person’s head could drop or the person could fall down completely. This type of seizure does not require any first aid unless the person is hurt.

2.4 Epileptic Seizure Detection

2.4.1 Electroencephalogram (EEG) based

EEG is a multi-electrode recording of the current flows, which are generated by the many neurons in the brain. The electrodes are placed on the scalp to measure brain activity, both spatial and temporal. The spatial data consists of the brain's electrical activity emerging from a particular brain region, while the temporal data describes how the brain's electrical activity changes over time (Binne & Prior, 1994).

In a computer assisted EEG analysis system, the EEG signals are divided into multiple groups. The signals are then classified using signal processing and machine learning techniques as epileptic or non-epileptic. Epileptic seizures cause changes in certain frequency bands so the EEG signal’s spectral content is commonly used while diagnosing an epileptic disorder (Ahmad et al., 2014). These are identified as δ (0.4 – 4 Hz), θ (4 – 8 Hz), α (8 - 12 Hz) and β (12 – 30 Hz).

The process of seizure detection is divided into feature extraction, feature processing and classification. For feature extraction, different signal transforms for analyzing non-stationery signals are used to mine the frequency related features. Feature reduction techniques are then used to clean the data to remove redundant and noisy data in order to allow easy classification. Finally, the features are classified using Artifact Neural Networks (ANN) and Support Vector Machines (SVM) among other classifiers.

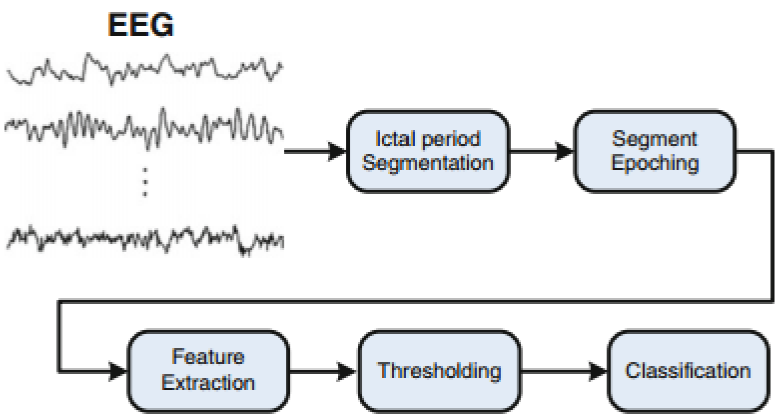


Figure 2.1 Illustration of a seizure detection system based on EEG

(Lyshevski, 2002)

2.4.2 Smart phone camera based detection

One other way of detecting seizures is the use of mobile applications. This method is based on a statistical criterion known as Maximum Likelihood (ML). Since clonic seizures are manifested by periodic movements of some body parts, it is possible to detect the presence of seizures by evaluating the periodicity from the video stream of the smartphone's camera (Cattani et al., 2011). Seizure detection is carried out two steps namely; Motion signal extraction and detection of periodicity.

2.4.3 Wearable devices

The most common way to monitor is the use of EEG monitoring equipment. The use of this equipment is only feasible for short time monitoring. EEG involves wearing EEG equipment with electrodes placed on the cap. Epilepsy assessment is much more efficient if the frequency and occurrence of seizures is monitored over an extended period of time (Deckers, 2003). Because of this, there is need for a device that can measure frequency over a long period of time.

Wearable devices are built with diagnostic and monitoring capabilities. Their current functionality include physiological and biochemical sensing, as well as motion sensing (Bonato, 2010). Sensors are used to collect motion data therefore enabling monitoring of patients status. Wireless communication is used for transmitting the captured information to a mobile phone via internet. Both family members and clinical caregivers can monitor a patient's progress.

2.4.4 Human Visual Identification

People are able to identify epileptic seizures by their observable characteristics. Each type of seizure has a different manifestation. Some of the seizures can pass off as normal day to day activities and may not be recognized especially if they last for short durations. An example of such a seizures is, absence seizures. Some seizures have very visible and abnormal characteristics making them pretty easy to identify. An example is the generalized tonic clonic seizure which is characterized by sudden stiffening of the body followed by jerking of the limbs. The demerit of this method is that at every instance when a seizure occurs, there needs to be a second party to be able to see the seizure.

2.5 Existing Technologies

There are a number of technologies that are being applied to resolve the challenges faced by the epilepsy patients. One of these technologies is M-Kifafa, a mobile technology for epilepsy. This is a project by the Kenya Association for the Welfare of people with Epilepsy (KAWE). M-Kifafa is designed to use mobile phones to relay information between key stakeholders in epilepsy care. This results in better access as well as improved quality of patient care. The project is aimed at reducing treatment gap, lift off the burden of high administrative costs of workshops that are organized for the purposes of training and to facilitate timely support to the trained health workers and consequently to the patients that they attend to.

Lu et al. (2013) proposed a color-based video analysis system for quantifying limb movements in epileptic seizures. This system requires a patient to wear pyjamas that are colored on the limb portions. A camera is then placed on the ceiling to capture video of patient's activities in a clinical epilepsy monitoring unit. Lights in the room are not completely turned off but are dimmed instead. The colors on the pyjamas are yellow and magenta to support visibility and finally, the room temperature is kept at 20-24 degrees such that a patient does not need to cover themselves. This method is limited to monitoring within the hospital. This implies that it is not a long term monitoring tool since it is only limited to the duration for which the patient is hospitalized. Also, patients cannot monitor themselves in the course of their day to day activities unless in a hospital setting.

Cattani et al. (2012) developed SmartCED, a smart phone based contactless Epilepsy detector. It is an android based monitoring application to recognize neonatal clonic seizures in real-time. Seizure recognition is based on a statistical criterion called Maximum Likelihood (ML). Since clonic seizures are characterized by quasi periodic movements of some body parts, images are captured using the smartphone's camera. Motion signal is extracted and properly processed in order to detect potential abnormal motor patterns. This system is used to monitor all newborns into a neonatal intensive care unit. This system would not be suitable for monitoring of patients that are carrying on with their activities.

2.6 MEMS accelerometer

An accelerometer is an electromechanical sensor that measures acceleration forces. Forces could be static, or dynamic- because of moving or vibrating the accelerometer. A MEMs accelerator works by sensing change in capacitance (Beeby et al., 2004). Capacitive interfaces have many attractive features. In most micro machining technologies, very minimal extra processing is required. Capacitors can operate as both sensors and actuators. Capacitive sensing does not rely on the base material but on the variation of capacitance when the geometry of capacitor is changing (Beeby et al., 2004). Parallel plate capacitance is (Lyshevski, 2002):

$$\boldsymbol{C0 = \epsilon 0 \epsilon \frac{A}{d} = \epsilon A \frac{1}{d}}$$ Equation 2.1 Parallel capacitance

Where $\epsilon A = \epsilon 0 \epsilon A$ and A is the area of the electrodes, d is the distance between them and ϵ the permittivity of the material separating them. A variation in any one of these parameters is measured as a change in capacitance, and a variation of each of the three variables is used in MEMs sensing (Andrejasic, 2008).

A typical MEMs accelerometer is made up of movable proof mass with plates attached through a mechanical suspension system to a reference frame, as in Figure 2.2. The movable plates and fixed outer plates act as capacitors. The deflection of proof mass is measured as the capacitance difference (Lyshevski, 2002).

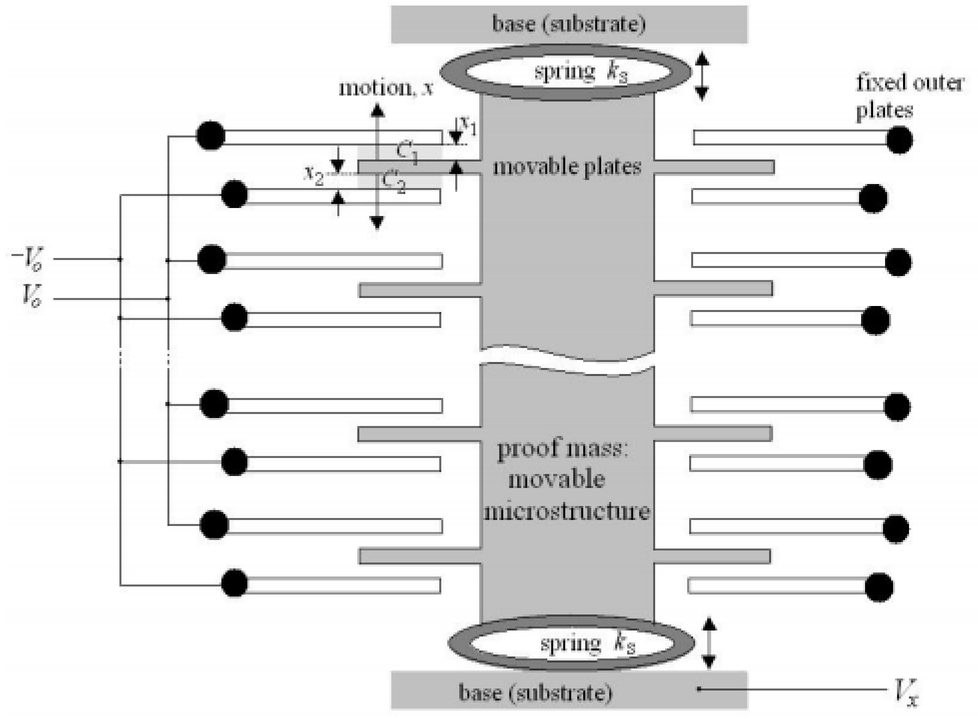


Figure 2.2: MEMS Accelerometer

(Lyshevski, 2002)

2.6.1 Accelerometer applications

Accelerometers have been widely accepted as useful and practical sensors for wearable devices to measure and assess physical activity. Physical activity is regarded as any bodily motion produced by the skeletal muscles which results in an energy expenditure (Yang & Hsu, 2010). Accelerometers can be used in ambulatory monitoring to continuously measure long term activities of subjects in a free living environment. The recorded motion data can be used to identify postures and to classify daily movements which are related to an individual's functional status. Accelerometers can be applied in;

Posture and movement classification – Movement classification using accelerometer can be achieved in two ways; threshold based or statistical classification schemes (Yang & Hsu, 2010). Threshold based methods exploits the knowledge and information about the movements to be classified. It utilizes a progressive algorithm (like decision tree) to segregate between different activities states. Tilt recognition is one of the basic functions offered by the accelerometers which respond to gravity or constant acceleration. Therefore, human postures, such as upright and lying, can be distinguished according to the magnitude of acceleration signals along sensitive axes from only one accelerometer worn at the waist and torso (Karantonis et al, 2006). Machine learning methods can be used to classify movements that are based on statistical schemes. This method maps an observation of movement to probable movement states in terms of the likelihood of the observation. These classification methods include k-nearest neighbor (KNN) classification (Vetlink et al, 1996), support vector machines (SVM) (Lau et al, 2009), Naïve Bayes Classifier (Huynh & Schiele, 2006), Gaussian mixture model (GMM)(Allen et al, 2006) and hidden Markov model (HMM)(Manini & Sabatini, 2010).

Fall detection and Balance Control Evaluation – Injuries that result from falling, cause trauma and fractures which to a very large extent affects the health of elderly people. The first approach to using accelerometry in fall detection. Falls could be described as a fast change from and upright position to a lying position on the ground, or a lower level usually not as a result loss of consciousness, sudden paralysis (Yang & Hsu, 2010). The first attempt to applying accelerometry to fall detection was published by Williams et al.(1987). This approach adopted two piezoelectric shock sensors to detect the sway and a mercury tilt to determine whether one was lying or upright. A threshold was set above which a potential fall is registered in the first stage. If the reclining posture remains unchanged for a given period of time, then a fall is registered. This led to the commercialization of a fall detector by Tunstall group.

Another fall detector is one that is fixed behind the ear. Two high g accelerometers were then placed in the detector in a way that accelerations along all sensitive axes would be measured. The fall detection algorithm used three trigger thresholds of sum-vector of acceleration in a plane (>2 g), the velocity before the initial impact (>0.7 m/s), and the sum-vector of acceleration in all spatial axes (>6 g) to recognize a fall (Yang & Hsu, 2010).

2.7 Arduino Uno

Arduino is a small microcontroller board with a USB plug to connect to the computer and a number of connection sockets that can be wired up to external electronics, such as motors, sensors, relays and speakers. They obtain their power either via a USB cable from the computer or from a 9V battery. They can be controlled from the computer or programmed from the computer and then left to work independently.

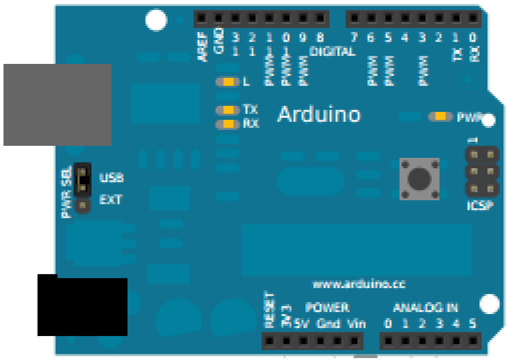


Figure 2.3: Components of an Arduino Board

(Smith, 2011)

An Arduino board is made up of the following components;

Power Supply- Power is supplied via the USB port. Right below the USB connector, there is a 5V voltage regulator that regulates the power input to a constant 5V.

***Power Connections*-**The first power connector is reset, which resets the microcontroller by momentarily setting the pin high i.e connecting it to +5v. The remaining pins provide 3.3,5, GND and 9 voltages where ground is equivalent to zero volts.

***Analog inputs*-**Analog connections are labelled zero to five. They comprise of six pins that can be used to measure the voltage connected to them so that the value can be used in a sketch. These inputs double up as digital inputs or outputs.

***Digital Connections*-**Digital connectors are labelled 0 to 13. They can be used as either inputs or outputs and can supply 40 mA at 5V.

***Microcontroller*-**This is a black rectangular chip with 28 pins. The microcontroller controls everything that goes on within the Arduino. It fetches programs and executes them.

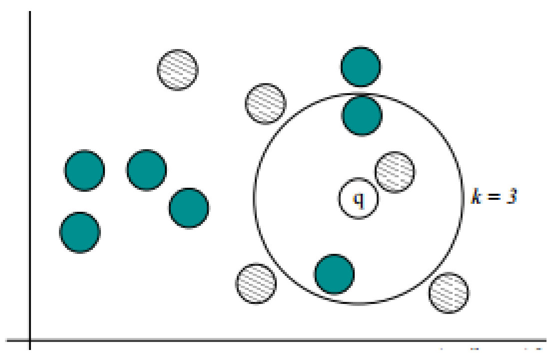
2.8 *k*-Nearest Neighbor Classification

The K nearest neighbor is one of the simplest techniques for predicting the class of an instance (Elkan, 2008). The training phase is very important. It involves the storing every training example with a label. In order to predict the class of a given example, one must compute the Euclidean distance between the instance and every training example, which is usually labeled. The Euclidean distance is calculated using the formula:

$$\boldsymbol{d(x,y) = \left|\left|x-y\right|\right| = \sqrt{(x-y).(x-y)} = (\textstyle\sum_i (x_i - y_i)2)1/2}$$ Equation 2.2 Euclidean distance

The next step is to select the *k* nearest training data, where $k \geq 1$ is an integer. Among the chosen *k* closest examples, select the label or class that is the most repeated. The illustration below there are only two classes, class C1 and class C2 which are represented by the differently shaded circles. The new instance q is then classified based on its three nearest neighbors.

Class C1



Class C2

Figure 2.4: K -nearest neighbor

One of the methods of selecting the class that q belongs to, is majority voting, as described above. The second method is inverse distance-weighted voting. In this approach, closest training example gets higher votes. The neighbors vote is taken to be inverse to its distance from *q*.

$$\boldsymbol{vote(x_i) = def \begin{Bmatrix} \frac{1}{dist(x_i - q)} & \infty \quad \textbf{if dist}(x_i, q) = 0 \\ & otherwise \end{Bmatrix}}$$ Equation 2.3 *k*NN voting algorithm

The votes are summed up and the class with the highest vote is selected.

One disadvantage of the kNN approach is the time involved in predicting. Suppose there are n training examples in d dimensions. Then applying the method to one test example requires O(nd) time, compared to just O(d) time to apply a linear classifier such as a perceptron. If the training data are stored in a sophisticated data structure, for example a kd-tree, then finding nearest neighbors can be done much faster if the dimensionality d is small. However, for dimensionality $d \geq 20$ about, no data structure is known that is useful in practice (Ashraf & Eibe, 2007).

2.9 Conceptual Model

The conceptual framework below connects the reviewed literature with the research problem and the research objectives. This is subject to scrutiny and testing and can be reformed as a result of investigation.

The model is made up of a wearable sensor, an application as well as the coordination components. The wearable sensor plays the role of capturing motion data from the users' limb during day to day activity. This data is then sent to the server where algorithms is applied to classify the data as either normal movement or movements as a result of an epileptic seizure. If a movement is classified as a seizure, the system sends two text messages to contacts of choice by the patient. A seizure event log is also maintained on the patient's mobile application detailing all the seizures that a patient has undergone. This information is important to a patient for their medical appointments.

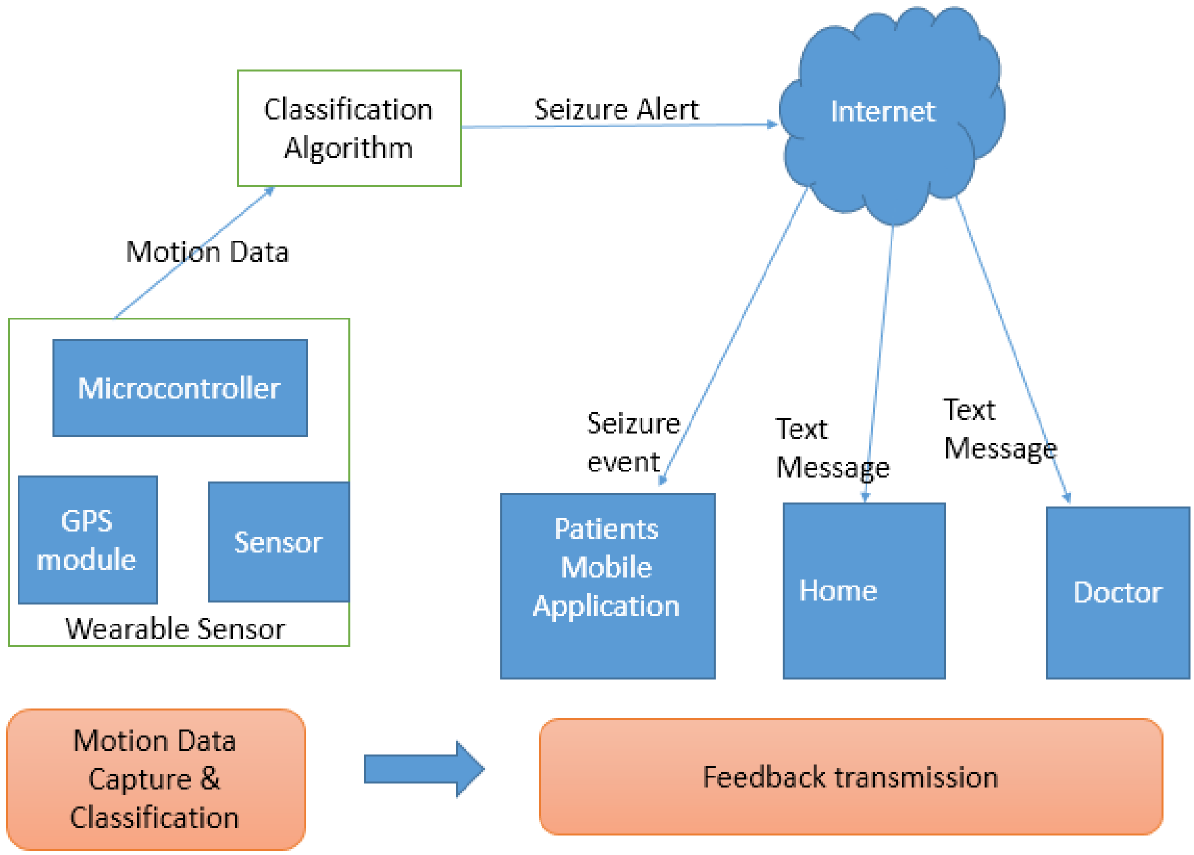


Figure 2.5: Conceptual Model

Chapter 3: Research Methodology

3.1 Introduction

This research was aimed at finding out the challenges faced by epileptic patients in monitoring their seizures and to create a solution that is effective and efficient. This chapter entailed the methods that were used while conducting the research. The target population, sample size that was used in the research, data gathering procedures and analysis of the results were discussed. In addition, this section highlighted the approaches applied in system analysis, system architecture, system design, system development as well and implementation and testing.

The software development approach that was used in this research was Agile Software Development. This approach allowed the building of a system incrementally by creating a series of prototypes and constantly modifying them to suit the user's needs (Shelly & Rosenblatt, 2011). Figure 3.1 shows the steps that were followed to create the end product.

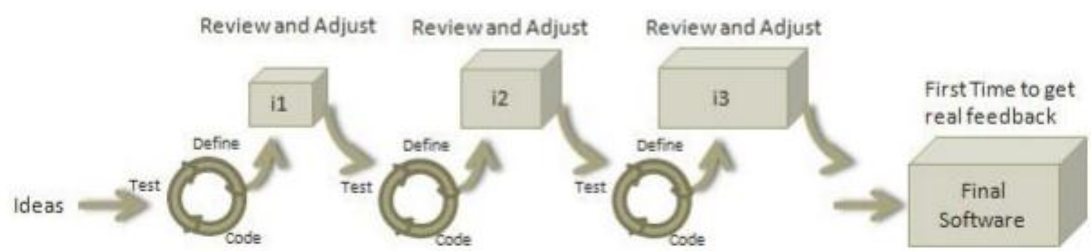


Figure 3.1: Agile Software Development (Agile Software Development Methods, 2014)

The first step was to define the requirements. After the requirements were gathered, the design was created which were then developed. Once the prototype was developed, it was tested for conformity to requirements. The prototype was then reviewed and adjusted. This was done iteratively until the final desired product was achieved.

3.2 Research Design

3.2.1 System Architecture

The system is comprised of physical layer, a coordination layer and an application layer. The physical layer/node was created using, Arduino-uno micro-controller, a GSM module for communication, a GPS module to send location information and a motion sensor (MEMs accelerometer). The coordination layer will be made of a server that will manage the communication between the hardware and the application. IBM Bluemix will be used to act as the coordination layer. The application layer of the system will be made up of a mobile application on the user's phone from which the user can view their seizure history. These three components will work together to accomplish the requirements.

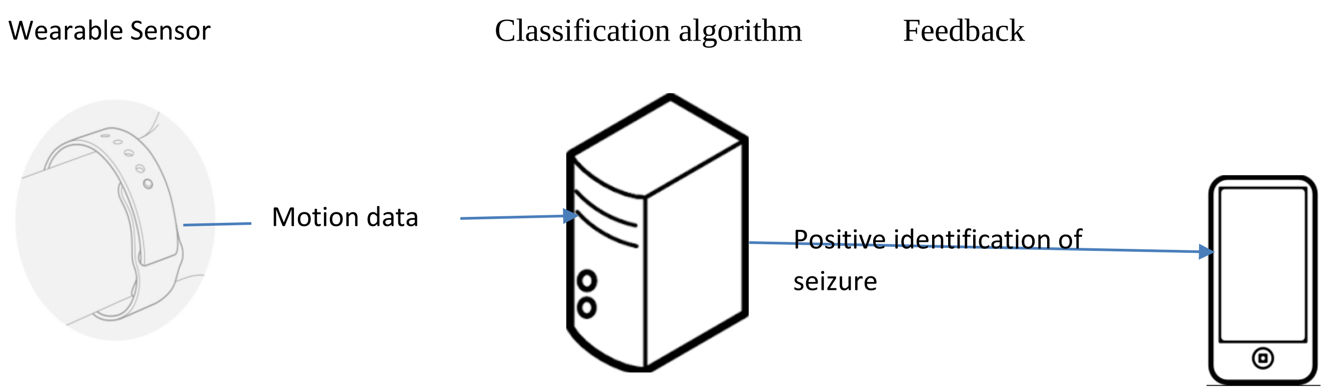


Figure 3.2: System Architecture

3.2.2 System Analysis

Object oriented analysis approach will be employed in this research. Whereas in structured analysis, data and processes are separate components, in object oriented analysis data and processes are combined and they act on objects (Shelly & Rosenblatt, 2012). Object oriented analysis is used to model real world business processes and operations. As a result, this method enables an easy transition from the analysis phase to the design phase.

Use cases will be developed in this stage to in order to gain a clear understanding of the functional requirements of the system. A use-case is a representation of a discrete set of work performed by a use (or another system) using the operational system. A use-case model consists of actors and use cases. An actor is an external entity that interacts with the system and a use case represents a sequence of related actions initiated by an actor to accomplish a specific goal (Hoffer, 2001).

3.2.3 System Design

Object Oriented Design (OOD) techniques will be used to define software objects and how they collaborate to full fill user requirements. Design class diagrams will be used to form the overview of the system. This will comprise of main methods and their relationships. Entity relationship Diagrams (ERD) will also be adopted, which is a graphic representation of the relationship between objects, places, people and events within the system

3.2.4 System Implementation

The system will be developed using Arduino IDE for node programming. Server side communication will be handled by IBM Bluemix.

3.2.5 System Testing

Usability testing was used to test the functionality of the system. Usability testing entails testing; validation of communicating components on each screen e.g. text inputs and buttons, validation of navigation flow, Ease of navigation, responsiveness and user friendliness (Belatrix, 2015).

3.3 Target population

This research was carried out in Kenya and the target population was epileptic patients within Nairobi County for all age groups.

An estimated 1 million people suffer from epilepsy in Kenya, according to Dr.Osman Miyanji, founding director at the Kenya Association for the Welfare of People with Epilepsy (KAWE) retrieved from *www.kawe-kenya.org.*

3.4 Sample Techniques and sample size

In Kenya, the occurrence of epilepsy is around 18.2 per 1000 population (Feksi and Kaamugisha 1991). From this, the population of the people with epilepsy in Nairobi is approximately 78,450. Due to the large population number, a probability sampling technique was used, where a sample is chosen at random from the whole population.

$$\boldsymbol{n} = \frac{\boldsymbol{NZ}\ \mathbf{2}\times\mathbf{0.`25}}{[\boldsymbol{d}\mathbf{2}\times(\boldsymbol{N}-\mathbf{1})]+(\boldsymbol{Z}\mathbf{2}\times\mathbf{0.25})}$$ Equation 3.1 Random Sampling

n=sample size

N=Total population (estimated)

d=Precision level (usually 0.1. or 0.05)

Z=Z statistic for a level of confidence

Equation 3.1 is the formula that was used to come up with the sample population.

The sample size is 96 and therefore questionnaires will be administered to the same number.

3.5 Data collection Procedure

The data collection procedure that was employed included questionnaire as well as observation. The questionnaires were used to elicit requirements from the users as well as to determine the need for the proposed system. Questionnaires were the chosen method because they can be used to contact a large number of people at a relatively low cost; it was also easy to reach people who are spread across a wide geographical error (Oppenheim, 1992).

3.6 Data Analysis procedure

Data analysis was done using content analysis technique. This is whereby the data gathered is categorized in themes and sub-themes to make them comparable (Moore & McCabe, 2005). The main benefit of content analysis is that the data collected is reduced and made simple while producing results may be measured using quantitative techniques. Content analysis also makes it possible to structure the qualitative data collected in a way that it fulfills the research objectives (Langkos, 2014).

3.7 Research Quality Aspects

Research quality aspects define the extent to which the research is carried out correctly. Validity and reliability are the factors that will be used to test quality aspects.

3.7.1 Validity

Validity is the extent to which a study measures what it is intended to measure (Thatcher, 2010). Content-description validation was applied and it involved the systematic examination of the test content to determine whether it covers a representative sample of the behavior domain to be measured (Anastasi & Urbina, 1997).

The initial idea, research objectives and questions were analyzed to determine data to be collected and how it was clustered. Also, how close the concept would be to an actual system that the intended users would adopt as a solution to their problem. Questionnaires were sent to respondents and the responses analyzed in a bid to determine user experience.

3.7.2 **Reliability**

Test retest reliability was employed. In this case, the method involved administering the questionnaire to a group of respondents and then administering the same questionnaire to the same respondents at a later date (Zikmund, 2003). The correlation between the identical tests given at different times defined the reliability.

3.7.3 Ethical Considerations

During the research, consent was obtained from the participants before the survey. The participant was made aware of the extent to which their information was used in the research. Data from the participants was solely for the purposes of this research.

The model proposed ensured confidentiality of the patients' information by only making it available to him\her as well as a doctor and family member of choice.

Chapter 4: System Design and Architecture

4.1 Introduction

This chapter covers the design of the proposed model by factoring in the requirements collected in chapter three through questionnaires with the probable users and other stakeholders. To make this possible design diagrams were drawn using Unified Modelling Language. Requirements analysis was also carried out at this stage.

4.2 Results from Questionnaire

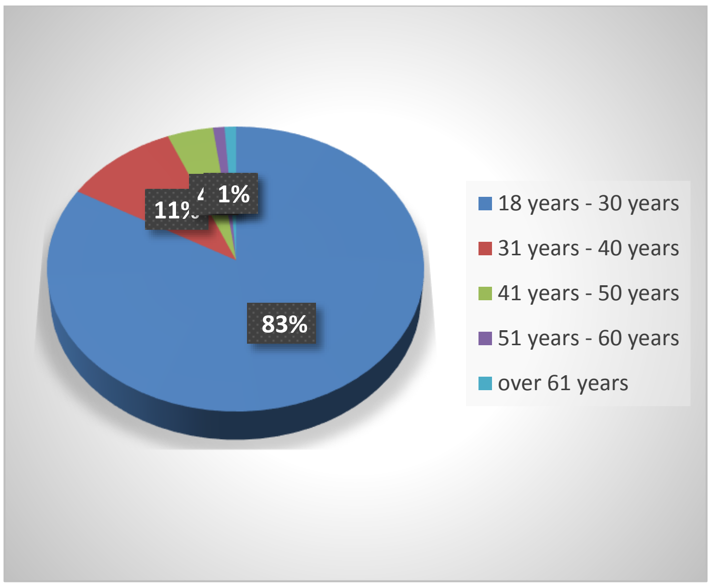


Figure 4.1: Age group

83% of the respondents interviewed belonged to the 18 to 30 years age group, 11% range between 31 years to 40 years and 4% range between 41 to 50 years of age.

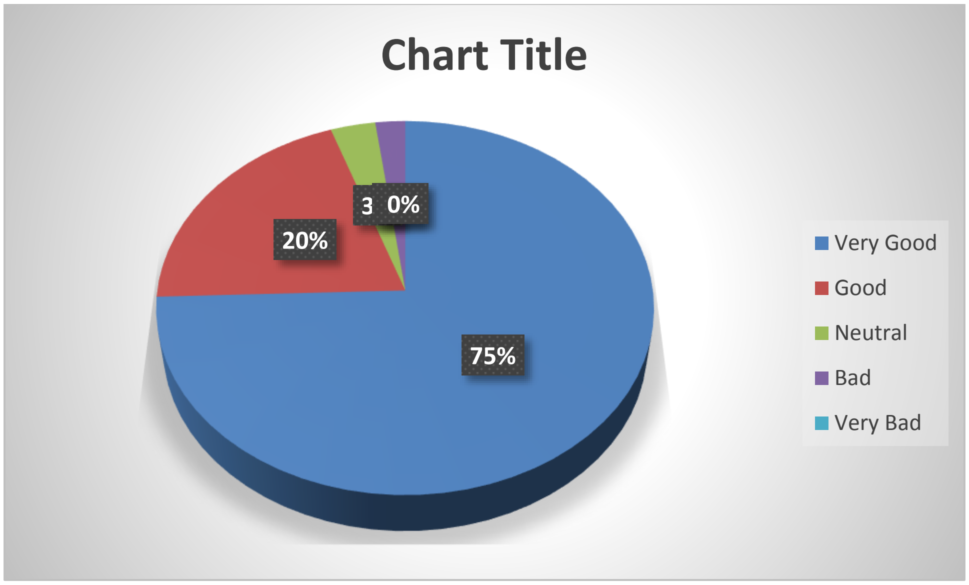


Figure 4.2: Ability to use mobile phones

75% of the respondents are very good at mobile phone usage while 20% are fairly good and only two 3 people were rated as neutral.

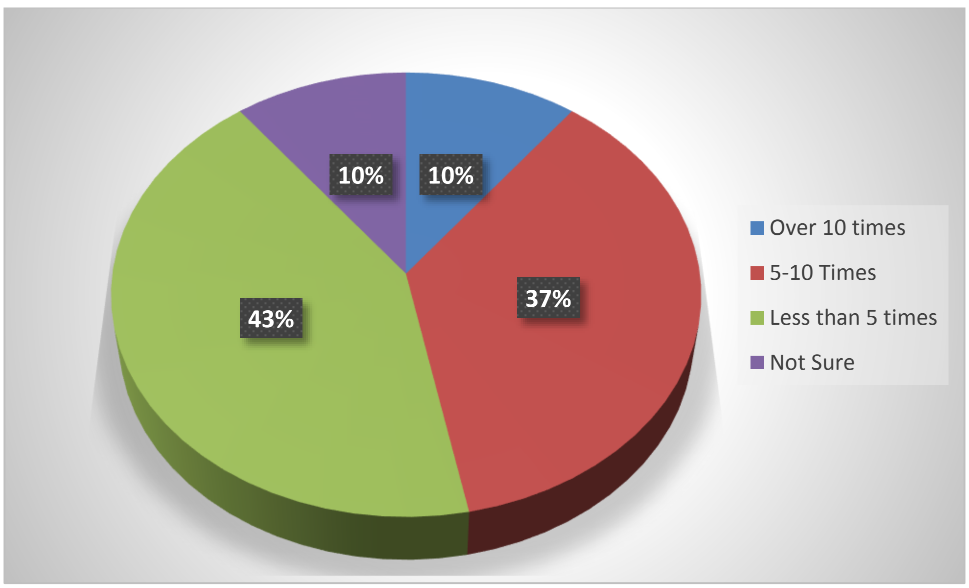


Figure 4.3: Frequency of occurrence of epileptic seizures

According to figure 4.3, 43% of the patients experience seizures less than 5 times a month while 37% get between 5 to 10 seizures in a month. 10% are not sure and 10% get over 10 seizures in a month. Respondents stated that the values were an estimation because the seizures are quite unpredictable.

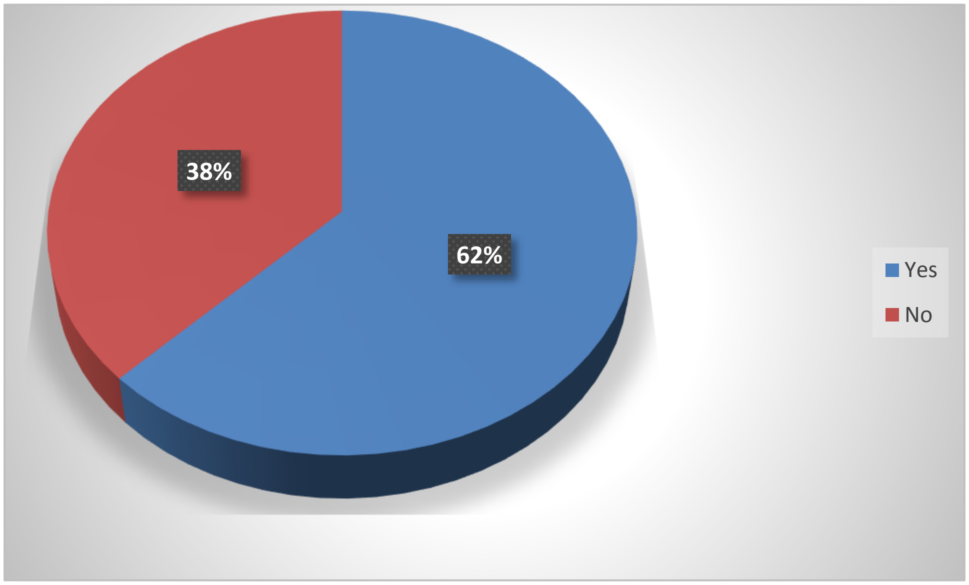


Figure 4.4: having been hospitalized because of epileptic seizures

According to figure 4.4, 62% of patients have been hospitalized because of seizures while 38% have never been hospitalized.

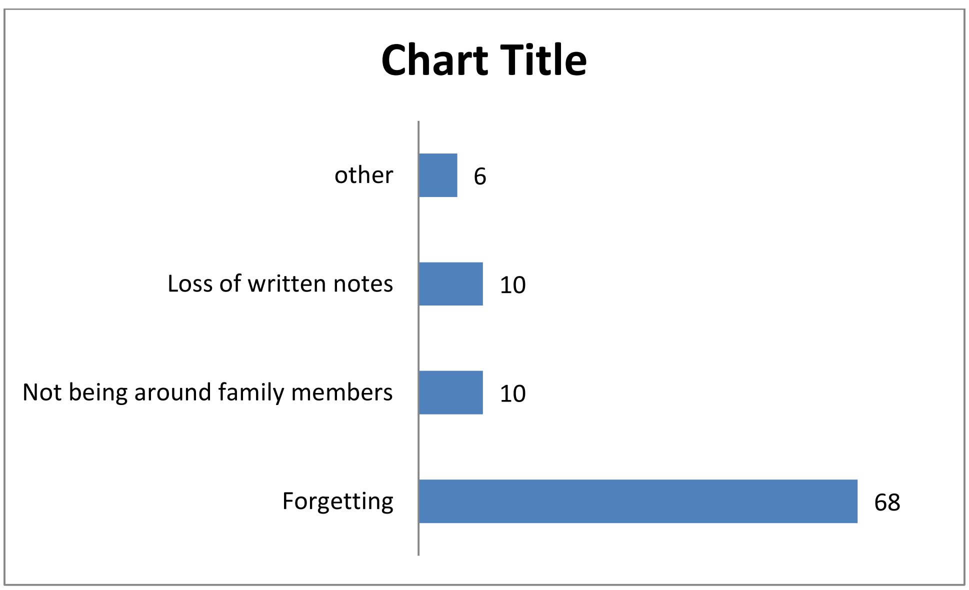


Figure 4.5 Methods for monitoring epileptic seizures

Figure 4.5 above describes the methods used to monitor seizures. This was relevant in determining the gap that needs to be filled by the proposed system. This was achieved by asking the patients on the challenges faced in the use of the methods highlighted above.

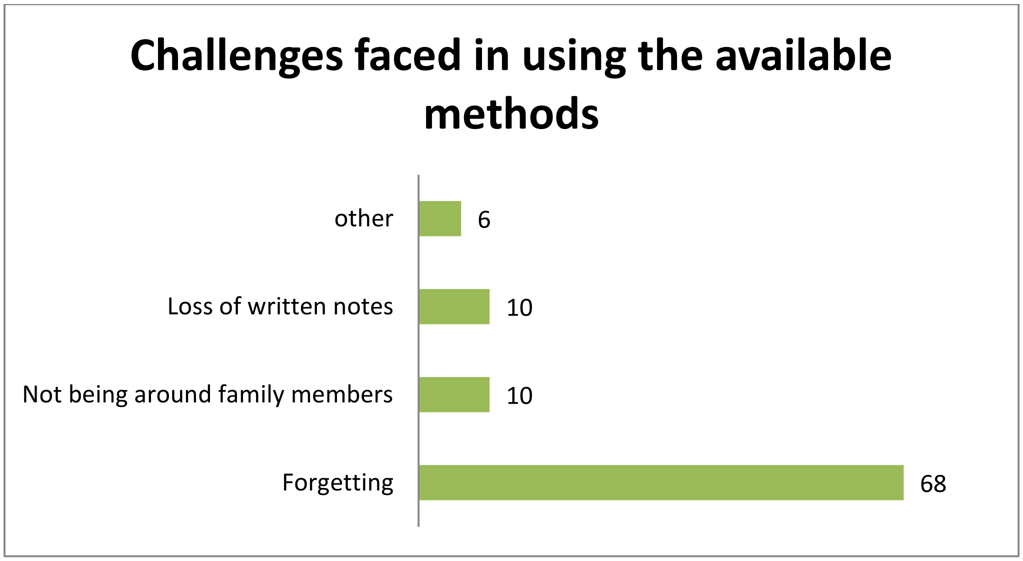


Figure 4.6 Challenges faced in using the available methods

Figure 4.6 details the challenges faced by the patients in utilizing the existing methods. This was relevant in determining the features that should be incorporated in the model to solve the problems. It was evident that memorizing seizure events is the biggest problem.

4.3 Requirements Analysis

Based on the objectives as well as the user requirements as derived from the questionnaires and interviews administered, this section outlines the various requirements to be met in the research.

4.3.1 Functional requirements

i. The model should have a mobile application that lists seizure events
ii. The mobile app should have the following information; seizure duration and time
iii. The model should generate two text messages to be sent to a family member and personal doctor.
iv. The text messages should contain location information as well as the time the seizure began.

4.3.2 Usability Requirements

The system will be used by a range of patients and should therefore be easy to use. The information on the mobile app should be simple and clear. The mobile app interfaces should not be congested to make it more pleasant to use.

4.3.3 Reliability requirements

i. In the event of a seizure, the system should generate text messages at any time
ii. A record of the seizure must be captured on the smart phone in every occurrence without a fail.

4.3.4Supportability Requirements

The system should run on a smartphone with the phones default settings without the need to change any settings in order to accommodate it.

4.4 System Architecture

Figure gives an illustration of the system architecture. The process begins when an accelerometer sensor captures motion data from a patient’s limbs. This motion data is then sent to a coordinator which classifies the data. The data is classified as either normal motion or motion as a result of epileptic seizures. If the motion is as a result of an epileptic seizure, an SMS is sent to the patient’s contacts of choice.an event log is also maintained in a mobile application on the patients phone for future references.

4.5 Diagrammatic representation of the model

4.5.1 Use Case Diagram

The use case diagram in figure 4.7 describes interaction between various actors. The actors are made up of; the system, patient, their next of keen and doctor. The scope, which is defined by the system boundary is the identification of seizure motions for the purposes of patient monitoring.

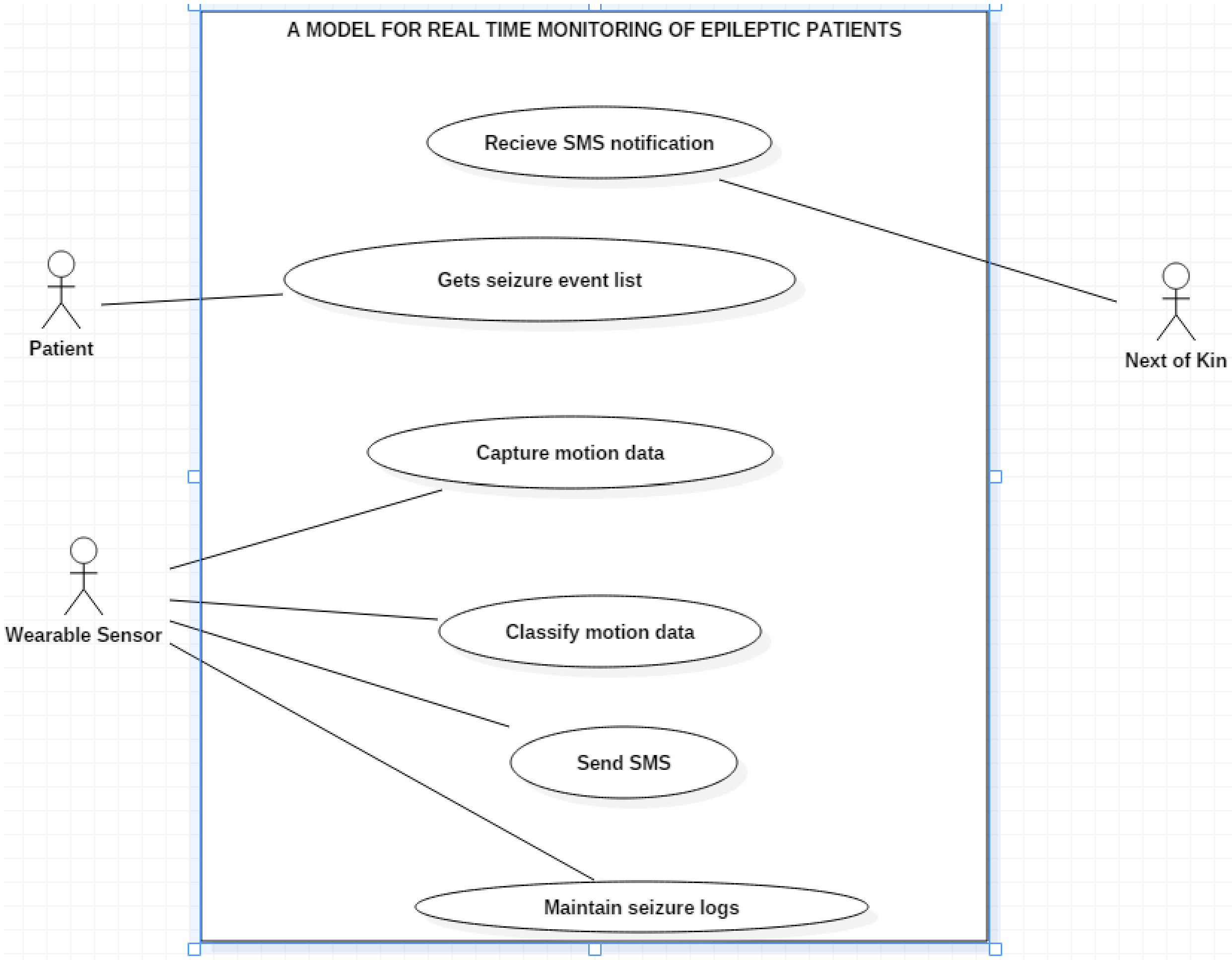


Figure 4.7: Use case Diagram

4.5.2 Use Case Description

The description below details the use case, capture motion data. It includes the actors, preconditions, post conditions, the main success scenario and the extensions. Additional use case descriptions for classify motion data and receive feedback are in Appendix B.

Use Case: Capture Motion Data

Primary Actor

Patient

Precondition

Wearable Sensor is on

Post condition

Motion data captured is from the patient wearing the sensor

Main Success Scenario

Actor Intention	**System Responsibility**
1. Patient wears the sensor	
	2. Capture motion from the patient's limbs
	3. Relay the data to the classifier
4. View the feedback	

Extensions

At any time the system fails to capture the motion

Confirm that the sensor is powered on

4.6 Domain Model

The domain model in figure 4.8 is a visual illustration of conceptual classes in the domain of this research. This domain model describes the association between the conceptual classes. The associations begin from the when the sensors capture the motion data resulting from movement of the patients limb. The motion data is then classified as an epileptic seizure or normal movement. In the event of an epileptic seizure, the system sends an SMS to the doctor/next of kin phone. At the same time, a seizure event log is maintained on the patient's mobile application for future reference.

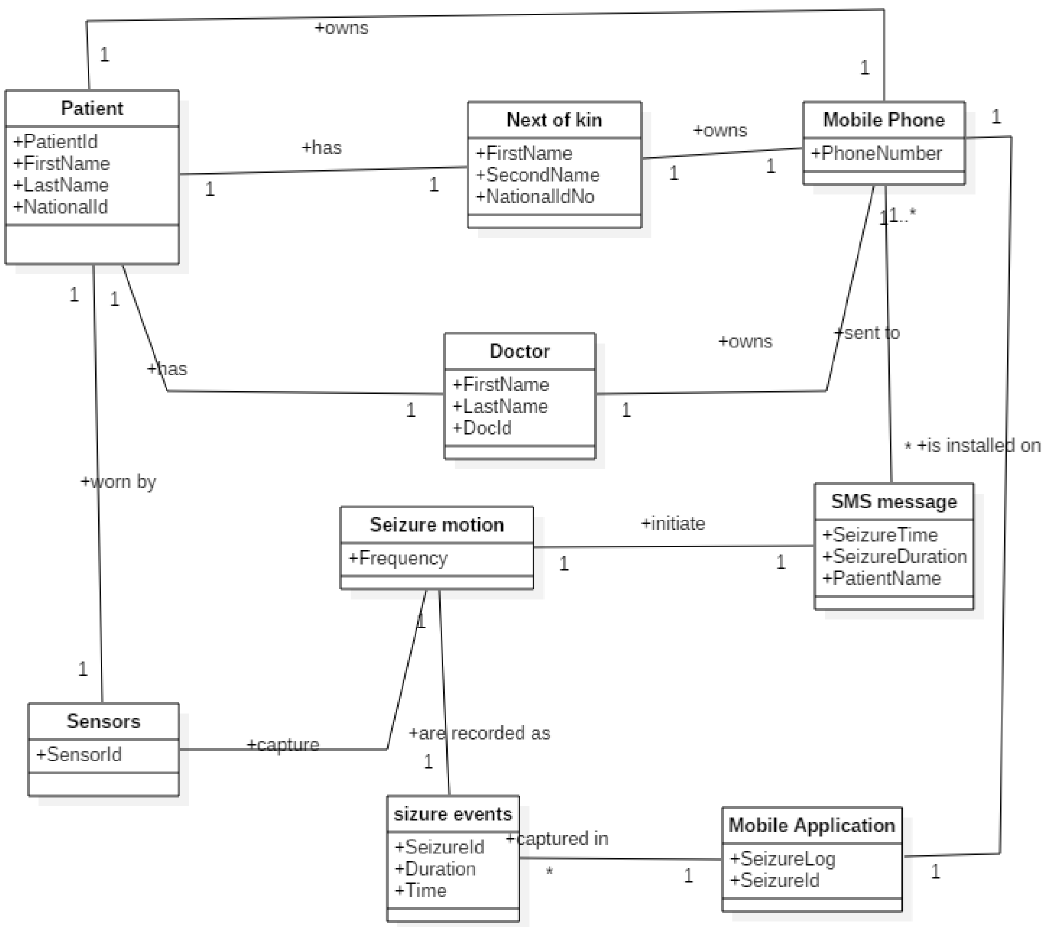


Figure 4.8: Partial Domain Diagram

4.6 Activity Diagram

The activity diagram in figure 4.9 represents the sequential flow of activities in the system that ultimately satisfies the user needs.

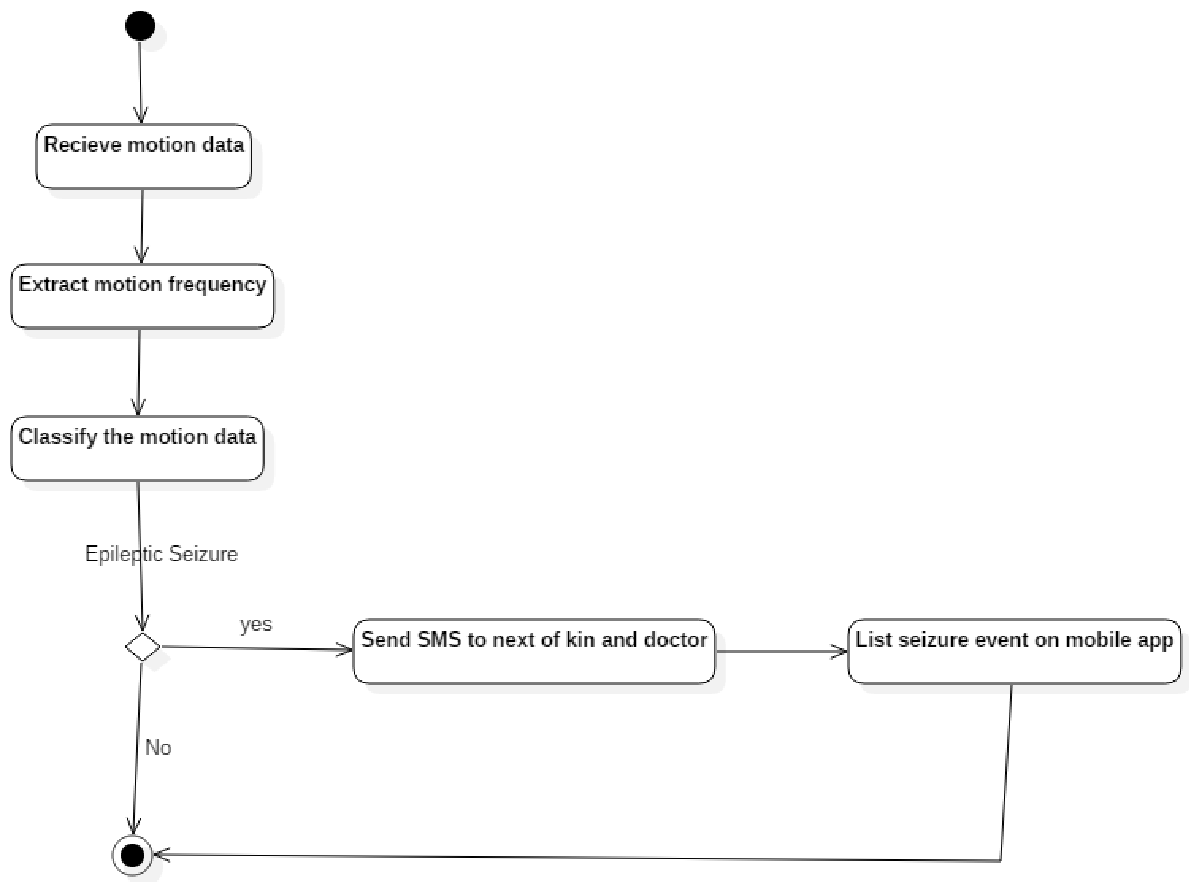


Figure 4.9: Activity Diagram

In the epileptic seizure monitoring system, there were activities that were involved in satisfying the objective of classifying patients' motion data as either epileptic seizures or normal movement and consequently communicating the feedback. They include;

a) Capture the motion data – the sensors that are worn by the patient capture motion data from the patient's movements.
b) Extract motion frequency- Each of the motions captured by the sensors occur within different frequency ranges. The frequency of each motion is extracted to be used for classification.
c) Classify the motion data- based on the frequency of the motion, it can be classified as either normal movement or movement resulting from epileptic seizures.
d) If a movement is classified as a seizure, the system should send text messages to the patient's next of kin and doctor.
e) Consequently, the system should maintain a seizure event log in the mobile application hosted in the patient's phone for future reference.

4.7 Sequence Diagram

Figure 4.10 illustrates the sequence of activities in the system. The sensor worn by the patient captures the motion data. Features are then extracted from the raw motion data that is sent. Once the features are extracted, the data is then classified as either normal motion or motion as a result of an epileptic seizure. Once the classification is done, the doctor and relative receive text messages.

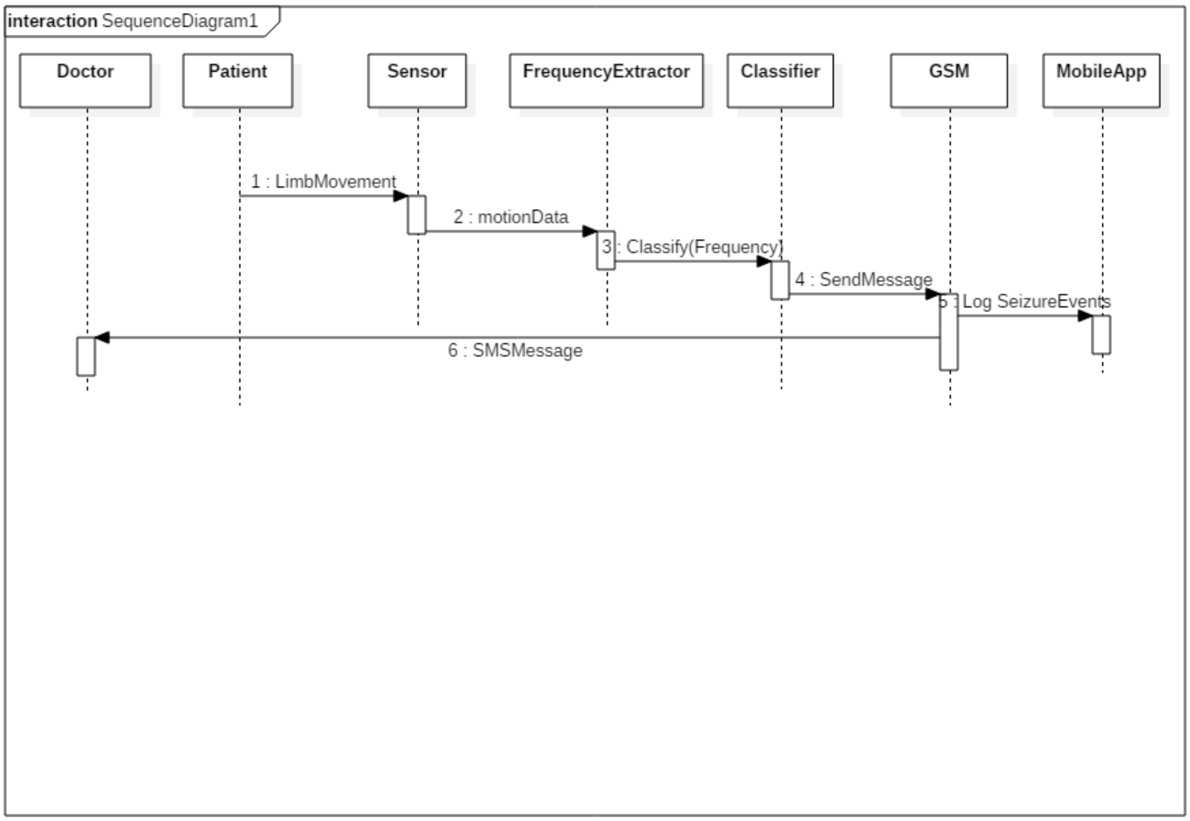


Figure 4.10: Sequence Diagram

4.8 Model Design

4.8.1 Context Diagram

The context diagram below illustrates the high-level functionalities of the system. It describes the interaction of the entities with the system. The main users of the system are the patient, their relative and doctor. The sensor worn by the patient sends motion data into the system that is then classified and feedback sent to the doctor and relative of the patient.

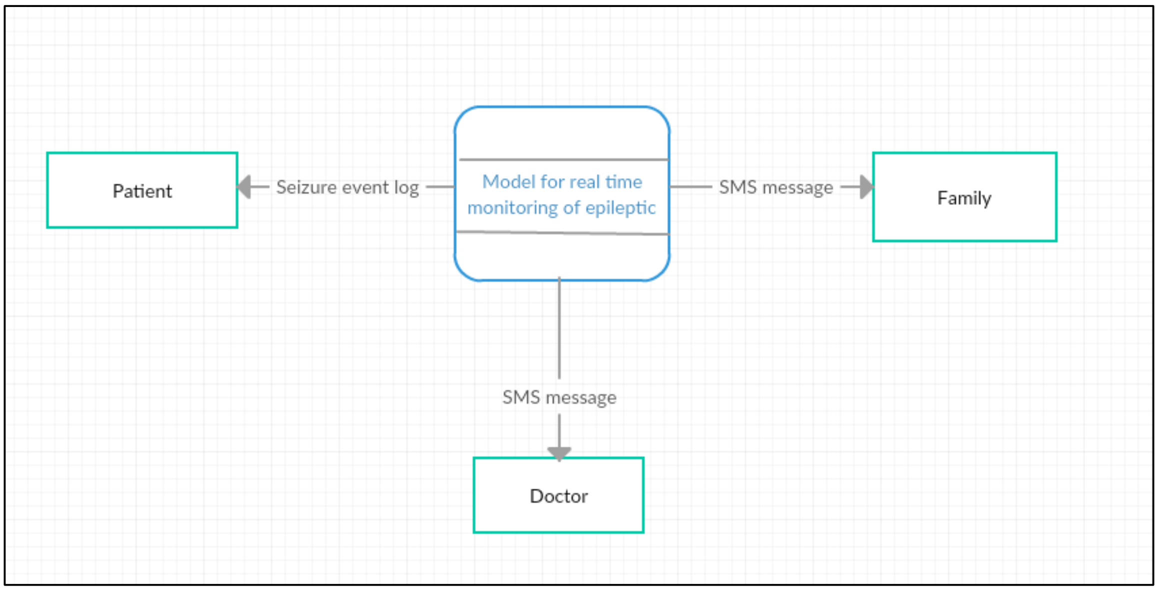


Figure 4.11: Context Diagram

4.9.2 Level 1 Data Flow Diagram

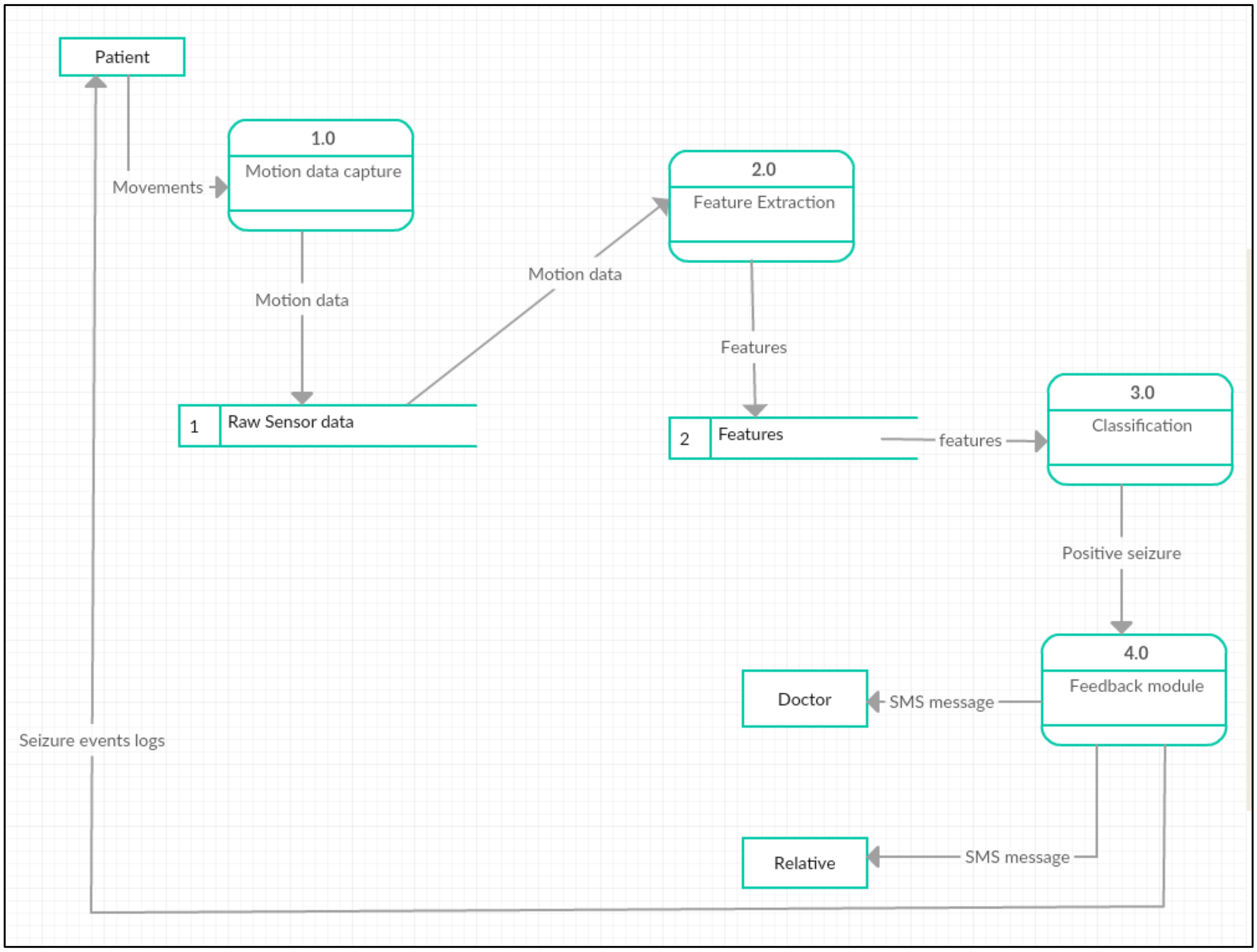


Figure 4.12: Level 1 Data Flow Diagram

The level 1 DFD diagram, illustrates in a lower level, the processes within the system, the data that they fetch and output as well as the entities that they interact with. This model describes four processes. The first process is motion data capture. This data is obtained saved. The data will then be fetched by the feature extraction process that then extracts features that will be used in the classification. The classification process fetches the features which is fed into the algorithm as parameters. Finally, based on the classification, SMS messages are sent to the patient's doctor and relative's phone.

Chapter 5: Model Implementation and Testing

5.1 Introduction

This section details the implementation and testing of the model. The implementation focuses on the different modules of the system, how they are implemented and their functionality. Testing of the system involves verifying that the system satisfies usability requirements as well as the functional requirements.

5.2 Model Components

The application comprises of a wearable device, coordination layer and application layer. The hardware device is implemented using Arduino Uno, an accelerometer sensor and a GSM shield. The coordination layer will be implemented using IBM bluemix. The hardware will be programmed using Arduino IDE. The mobile application will be simulated on the IBM bluemix platform.

5.2.1 Hardware Components

Accelerometer Sensor - The hardware component of the model has an accelerometer that is used to capture motion data in the x,y,z dimension.

GSM shield – the GSM module was responsible for connection to the coordinator for the purposes of sending sensor data. It is the GSM module that is also responsible for the text message sending to the recipients.

Arduino uno – this is the micro-controller that will coordinate the interfacing of the GSM and sensor.

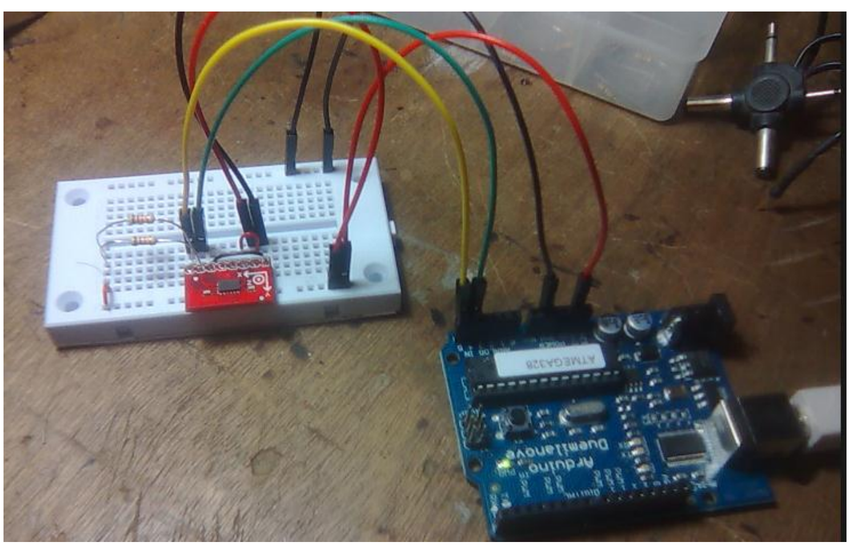


Figure 5.1: Hardware Connection Diagram

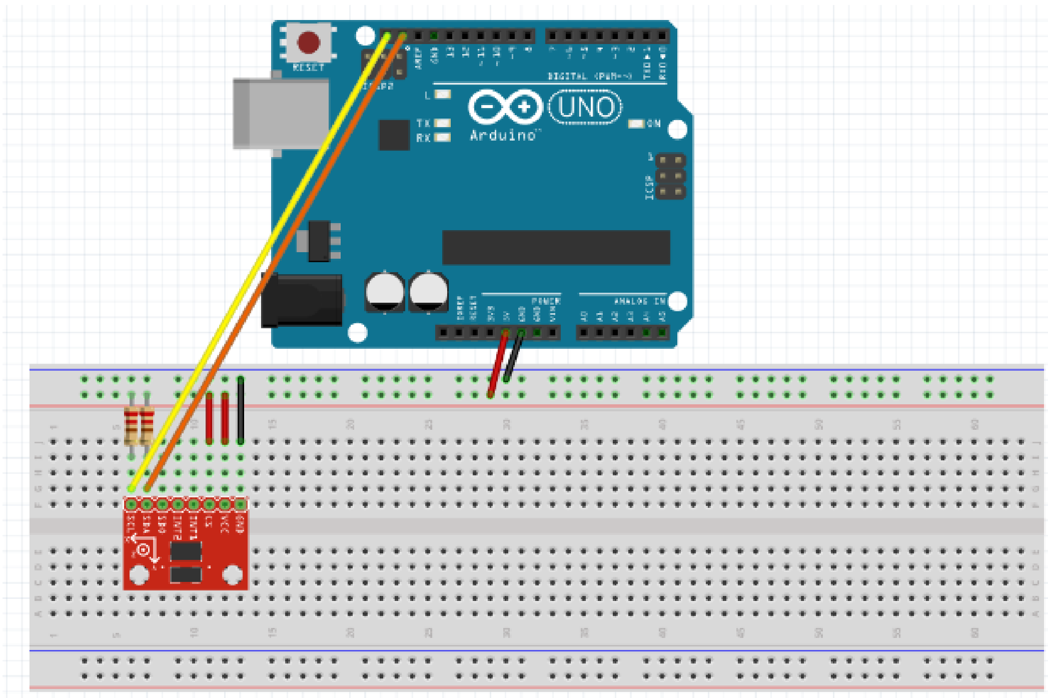


Figure 5.2 ADXL sensor connection to Arduino Uno

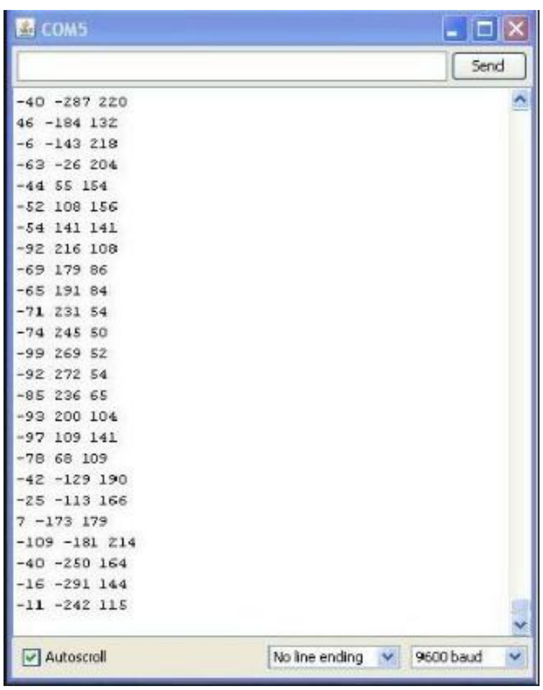


Figure 5.3 Sample output read on IDE serial monitor

Figure 5.3 is an illustration of the accelerometer output displayed when the code is uploaded on the Arduino board. The output displayed represents the x, y and z outputs from the sensor

5.2.2 Coordination Layer Components

Software for classifying sensor data – The purpose of this software is to classify data motion data from the sensor into either a normal movement or seizure movement. This was developed using Bluemix. Sensor data was classified using K-Nearest Neighbor.

Storage of the sensor data- This involves short-term storage which enables fast access that allows the classifier to obtain data to classify. It may involve online storage that is essential for relatively fast access.

5.2.3 Application Layer

This component of the model is responsible for graphical presentation of the sensor data. This mobile application was used to keep a log of movements positively identified as seizure movements. This was available to the patient's mobile phone.

5.3 Model Implementation

5.3.1 Motion Data Capture

Motion data was obtained using the accelerometer sensor. The sensor data was then sent to Bluemix via the GSM module. Data from the accelerometer has 3 attributes: time, acceleration along the x-axis, acceleration along the y-axis and acceleration along the z-axis. The motion data is then the divided into 5 second segments and then the generated features were based on the readings contained in each 5 second segment. 5 seconds were chosen because it is sufficient time to capture several repetitive movements. Data was collected from people while carrying out the following activities; standing, sitting, running, walking, sweeping, washing face, going up the stairs and going down the stairs. One person held a timer and told the other individual simulating when to start and when to stop. The individual responsible for simulating the activities the simulated an epileptic seizure movement which was done on a window of 5 seconds severally.

5.3.1 Data Classification

Data set generation – half of the data set was labeled for both the normal and the epilepsy movements were classified as training set. The other half was labeled as the test set.

Feature Extraction- feature extraction was done on raw accelerometer data using a window size of 256 each containing 128 samples overlapping between consecutive windows. (Bao & Intillle, 2004) have previously demonstrated that windows with 50% overlap was successful. This data represents 5.12 seconds of data for each window at a frequency of 50Hz. A window of 256 samples allows for fast computation of Fast Fourier Transform (FFT) which was used as one of the features. During this research, feature extraction was done for each of the three axes of the accelerometers. The features were;Mean, Standard Deviation, Energy and Correlation.

Standard deviation was selected for the fact that the range of probable acceleration values are different for different movements. The periodicity of the data is captured in the frequency domain. The DC feature is the mean acceleration value of the signal over the window. The energy feature was obtained in order to capture the data periodicity. Energy which is the sum of the squared discrete FFT component. For normalization, this is then divided by the window length. Correlation is calculated between each pair of axes as the ratio of the covariance and the product of the standard deviations. Correlation is important for distinguishing activities that occur in only one dimension.

Sensor data classification- Once the data was preprocessed by feature extraction, *k*-Nearest neighbor was used to classify the new instance based on the training set. The purpose of this algorithm was to classify a new instance based on the training data. The training data is derived from the data that is captured using the sensor. 5 nearest neighbors was used and the new instance was classified based on the majority voting method, where the most occurring class among the five instances was selected. The Euclidean distance was calculated to determine the nearest neighbor.

5.4 Data for training the model

The training of the model was done using the data collected in during the study. The body movements were recorded during several activities; standing, sitting, running, walking, sweeping, washing face, going up the stairs and going down the stairs. Epileptic seizure motions were simulated and data stored for that as well. The activities were put into two groups namely; normal activity and epileptic seizure. This data was used to train the model.

The tables 5.1, 5.2 and 5.3 below represent a sample of raw data in x, y and z for the first ten recordings of the tri-axis accelerometer for different activities.

Table 5:1 First ten accelerometer outputs for sweeping and washing face activities

Sweeping				**Washing Face**		
x	y	z		X	y	z
1.385	8.715	5.205		4.927	7.828	4.742
2.009	8.752	5.181		4.782	7.76	4.85
2.085	8.757	5.006		4.727	7.714	4.921
2.145	8.491	4.897		4.659	7.685	4.845
2.713	8.026	6.175		4.505	7.494	4.908
2.558	7.474	5.946		4.318	7.359	4.957
2.443	7.196	5.746		4.027	7.343	4.851
3.63	8.334	6.928		3.961	7.216	4.843
1.886	7.891	6.231		4.228	7.485	4.741
1.258	6.733	5.447		3.785	7.436	4.64

Table 5.1 contains the x, y and z components captured from the accelerometer during sweeping and face washing activities. These two actions characterize normal movement and were used to train the model.

Table 5:2 First ten accelerometer outputs for walking and standing activities

Walking				**Standing**		
x	y	Z		x	y	z
2.896	2.089	9.654		-1.052	9.534	2.277
2.602	2.169	9.482		-1.033	9.52	2.221
2.541	2.436	9.39		-1.018	9.515	2.21
2.25	2.397	9.511		-1.018	9.541	2.216
1.929	2.075	9.547		-0.993	9.509	2.222
1.472	1.626	9.211		-1.008	9.536	2.163
1.362	1.477	9.166		-1.052	9.539	2.21
1.586	1.746	8.951		-1.064	9.566	2.266
1.902	2.191	8.851		-1.055	9.51	2.233

2.204	2.627	8.851		-1.017	9.519	2.208

Table 5.2 above contains the x, y and z components captured from the accelerometer during walking and standing activities. These two actions characterize normal movement and were used to train the model.

Table 5:3 First ten accelerometer outputs for going up the stairs and brushing teeth activities

Going up the stairs				**Brushing teeth**		
X	Y	Z		x	y	z
-3.299	2.709	2.657		4.701	5.246	9.759
-5.357	3.503	3.287		4.711	5.07	9.299
-1.978	7.723	7.471		4.915	5.009	8.499
0.517	10.095	9.771		5.029	4.969	7.624
0.265	9.118	8.472		5.137	4.888	6.095
0.63	7.809	7.87		4.726	5.036	4.643
0.123	7.175	7.49		4.514	5.359	4.587
-0.558	6.962	6.77		3.979	5.615	4.56
-0.863	6.64	6.182		4.701	5.246	9.759
-1.245	6.1	6.205		4.711	5.07	9.299

Table 5.3 above contains the x, y and z components captured from the accelerometer during two activities namely: going up the stairs and brushing teeth. These two actions characterize normal movement and were used to train the model.

5.5 Software Flow

The model comprises of a hardware part that has inbuilt sensor for capturing movement data as well as a GSM module for sending the sensor data to a server. Features extraction is done to the data, which is then classified as either seizure motion or normal movement. In the event of a seizure, text message is sent to two contacts; doctor and relative. The seizure events are also logged in the patient’s mobile app. The environment for developing the application is; IBM Bluemix, Arduino node programming and Java.

5.6 Model Testing

This process involved the testing of system for conformance to functional requirements as well as the ease of the model by the users. The parameters that were used are captured below in table 5.4

Table 5:4: Model testing test cases

Test class	Test case description	Priority
Functional	Confirm that the system sends text messages when a seizure like movement is simulated	High
Functional	Confirm that the system logs positive seizure events on the patients mobile app	High
Functionality	Does the system correctly classify movements	High

5.6.1 Model testing results

The model correctly classified the motion data captured by the sensor. On sensing a positive seizure movement, the model sent two text messages.

Table 5:5: Model testing results

Test class	Test case description	Actual Outcome
Functional	Confirm that the system sends text messages when a seizure like movement is simulated	The system sends text messages when a seizure like movement is simulated
Functional	Confirm that the system logs positive seizure events on the patients mobile app	The system logs positive seizure events on the patients mobile app
Functionality	Does the system correctly classify movements	The system correctly classifies movements

5.7 Acceptance Testing

The main aim of this test was to confirm that the features desired by the users were satisfied by the system. The table below outlines the test cases/objectives of testing.

Test Class	Test case description	Priority
Usability	Does the system capture the user specifications?	High
Usability	Does the user provide accurate feedback	Critical

Chapter 6: Discussions

6.1 Introduction

The epileptic patient monitoring model development was based on the findings obtained during the research. The model was tested to confirm that all its functionalities conform to the research. In this chapter, an analysis was done to determine the correlation between the findings and the research objectives as well as the literature review.

6.2 Challenges faced in epileptic patients monitoring

The first objective of this research as stated in chapter 1, was to identify the challenges faced by epileptic patients in seizure event monitoring. From the research, firstly, it was determined that some of the epileptic patients shy away from seeking help because of stigma. As a result, it is quite impossible to monitor such patients because they avoid being associated with the label “epilepsy”. Secondly, most of the local hospitals are not equipped with personnel with knowledge of neurology. Only main Kenyatta National hospital has neurologists. Thirdly, the only available methods of monitoring epileptic seizures, is monitoring a hospitalized patients. This puts a financial burden on the patients.

6.3 Existing approaches for epileptic patients monitoring

The second objective was to investigate the existing approaches used to monitor epileptic patients. From the research, it was established that most epileptic patients are monitored by memorizing the number of epileptic seizures and noting the approximate time interval as well as magnitude. Some respondents indicated that they are not able to monitor seizures at all.

The study further exposes that respondents face challenges in the use of the existing method. This is because during seizures, an epileptic patient might not be aware of the exact events that occurred during the seizure. If not accompanied by another individual, it is completely impossible to provide accurate information to the doctor for the purposes of treatment.

6.4 Epileptic Patients Monitoring Technologies

The third objective was to analyze technologies that are available for epileptic patients monitoring. Research findings show that hospitals use EEG monitors for seizure monitoring. This is mostly used in hospital units. The literature review elaborates the EEG technology which is in line with the study findings.

6.5 Model for real-time monitoring of epileptic patients

The fourth objective was to develop a model for Epileptic patients monitoring. Research shows that users find it necessary to develop a model that enables monitoring of patients, not only in hospitals but also during their day to day activities. The model is made up of a wearable sensor based hardware which captures motion data on the limb. The motion data is then classified as either as a result of an epileptic seizure or normal movement. In the event of a seizure, a doctor and the patients family member receives a text message. A mobile application hosted on the patient's mobile phone that logs the seizure events.

6.6 Advantages of the model as compared to the current methods of monitoring

The model in this research allows for monitoring of patients during their day to day activities without there being need to be hospitalized. This is in comparison to the EEG monitor that requires that a user be monitored within the confines of a hospital. Secondly, this model allows the users to wear the device which is less conspicuous as compared to the EEG monitor that has to be worn on the scalp. This makes the patients more comfortable in using it and this increases the chances of its adoption.

6.7 Disadvantages of the model for monitoring of epileptic patients

The model needs that the users have mobile phones for the purposes of communication in the form of text messages. This is a limitation in the low income earners households and this affects adoption of the model.

Chapter 7: Conclusions and Recommendations

7.1 Conclusions

As highlighted in the background, epilepsy is a treatable condition if diagnosed early and treatment administered. Up to 70% of newly diagnosed children and adults with epilepsy can be successfully treated with anti-epileptic drugs and after 2-5 years of fruitful treatment, drugs can be withdrawn in about 70% of children and 60% of adults without relapses (Ministry of Health, 2016). For effective management of patients, constant monitoring of the seizures is important. This helps in the selection of treatment and therapy options that are suitable based on the intensity and frequency of the seizures.

Based on this background, the research exposes the fact that due to the nature of epileptic seizures, constant monitoring of epileptic patients is important. From the research findings, it is evident that most respondents face challenges using the current methods of patient monitoring. The challenge with the most negative impact is insufficient technology solutions for monitoring of epileptic patients. Using sensor based technology as described in the literature review, a model for epileptic patients monitoring was developed. Agile methodology was used during the model development. The methodology was chosen basically for its flexibility to incremental building. Usability testing was also carried out to validate that the system is easy to use and acceptable to the users. It is anticipated that if fully adopted and supported, the system will help in effective monitoring of epileptic patients.

7.2 Recommendations

The epileptic patients monitoring model is undeniably an advancement that will facilitate easier management of epileptic patients and is therefore a good thing to the health sector in the country. Given this premise, the recommendations are as listed below;

i) Given that one of the challenges that epileptic patients face is stigmatization, the Ministry of health in Kenya should fight this setback. By fighting the challenge of stigmatization, more epileptic patients would seek help and treatment.

ii) In collaboration with the ministry of health, this model could be adopted in both public and private hospitals for monitoring within and without the hospital.

iii) This model is a source of a lot of motion data that can be explored for further enhancements in this field. The data can be used in research in the academia. For this the researcher recommends a collaboration with universities for further research and development.

7.3 Suggestions for future research

Further to this research, the researcher envisions an improvement of this model in a way that can not only detect but also predict epileptic seizures. This will be made possible by incorporating skin monitors and heart rate monitoring. The essence of this is that, as a preventive measure, the model will be able to provide early warning signs enabling the patient in decision making as to the best actions. As a fall back, the model will go a next step in notifying the patient's caregivers. Finally, the approach will be used to monitor patients with other medical conditions.

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Appendices

Appendix A: Questionnaire

Dear Respondent.

I am a Masters student in the Faculty of Information Technology, Strathmore University conducting a research entitled IoT MOBILE APPLICATION BASED MODEL FOR REAL-TIME MONITORING OF EPILEPTIC PATIENTS.
You have been selected to form part of this study. I kindly request you to complete the questionnaire below. The information requested is needed for academic purposes only and will be treated in strict confidence.

Kind Regards,
Christine Onyango

*Required

1. What is your age group? *
   Mark only one oval.

   - 18 years-30 years
   - 31 years-40 years
   - 41 years-50 years
   - 51 years-60 years
   - Over 61 years

SECTION A: ICT CAPACITY

2. Kindly rate how good you are in using a mobile phone *
   Tick all that apply.

   - Very Good
   - Good
   - Average
   - Bad
   - Very bad

3. Do you own a mobile phone? *
   Mark only one oval.

   - Yes
   - No

SECTION B: SEIZURE HISTORY

4. How often do you encounter seizures on a monthly basis? *
   Mark only one oval.

   - More than 5 times
   - Less than 5 times
   - Not Sure

5. Have you ever been hospitalized because of a seizure? *
   Mark only one oval.

   - ◯ Yes
   - ◯ No

SECTION C: APPROACHES TO MONITORING SEIZURES

6. Which method have you been using to track your seizure history?
   Mark only one oval.

   - ◯ Noting it down
   - ◯ Memorizing
   - ◯ Seeking help from family users
   - ◯ Other: ______________________

7. What challenges have you been encountering in using the above method?
   Tick all that apply.

   - ☐ Forgetting
   - ☐ Not being around family members
   - ☐ Loss of written notes
   - ☐ Other: ______________________

SECTION D: MODEL FOR REAL TIME MONITORING OF EPILEPTIC PATIENTS

8. Do you thing that a model for real time monitoring of epileptic patients is necessary?
   Mark only one oval.

   - ◯ Yes
   - ◯ No

Appendix B: Use-Case Descriptions

Use Case Description: Classify motion data

Primary Actor

System

Preconditions

Motion data was successfully captured

Post Condition

Motion data was accurately classified

Main Success Scenario

The motion data that was captured is relayed to the coordinator by the wearable sensor. The frequency of the motion is then extracted and compared against the set threshold. If the frequency is below the threshold then it is classified as normal movement. If the motion frequency is above the threshold then it is classified as an epileptic seizure.

Use Case: Get seizure event list

Primary Actor

Patients

Precondition

Motion data was accurately classified

Main Success Scenario

Actor Intention	**System Responsibility**
1. Launch application to view seizure log	
	2. List the seizure event logs

3. View feedback for action and decision making

4. Exit the application

Extensions

At any time mobile application is launched but feedback is not available

Check the wearable sensor for connectivity

Use Case: Send SMS

Primary Actor

Next of Kin

Precondition

Motion data was accurately classified

Phone is switched on

Main Success Scenario

Actor Intention	System Responsibility
1. View phone to get feedback	
	2. Send SMS message to the user's phone
3. View feedback for action and decision making	
4. Exit the application	

Extensions

At any time mobile application is launched but feedback is not available

Check the wearable sensor for connectivity

Appendix C: Originality Report

EPILEPTIC

ORIGINALITY REPORT

25%	19%	12%	15%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Strathmore University Student Paper	4%
2	mdpi.com Internet Source	2%

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089596

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