ASHESI UNIVERSITY

THE DESIGN & FABRICATION OF AN EPILEPTIC SEIZURE DETECTION WATCH

CAPSTONE

B.Sc. Electrical & Electronic Engineering

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2019

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CAPSTONE

Capstone submitted to the Department of Engineering, Ashesi University in partial fulfilment of the requirements for the award of Bachelor of Science degree in Electrical & Electronic Engineering.

Samantha Kyei

2019

Declaration

I hereby declare that this capstone is the result of my own original work and that no part of it has been presented for another degree in this university or elsewhere.

Candidate's Signature: ……

Candidate's Name: ……..

Date: …….

I hereby declare that preparation and presentation of this capstone were supervised in accordance with the guidelines on supervision of capstone laid down by Ashesi University College.

Supervisor's Signature: …….....

Supervisor's Name: …….

Date: ……

Acknowledgements

First of all, I want to thank God for guiding me throughout this journey. For seeing me through all the challenges, confusion, frustration and anxiety, I say, “Thank You Very Much”.

Secondly, I want to express my deepest gratitude to my supervisor, Dr. Elena Rosca. She has been a great help to me in more ways than I could describe and I am forever grateful to her for all the encouraging words and well-intended blastings. Finally, I want to thank Dr. Robert Sowah for taking his time to explain in-depth, the processes involved in designing filters to me.

Special thanks to my biggest supporters in life, Mr. & Mrs. Kyei, Angela, Michelle, Elma, William, Brendon, Caeli, Jerry, Anto, Christabel, Selorm & Jay. I love you all.

Abstract

This paper describes the design and fabrication of an epileptic seizure detection watch for the timely detection of Generalized Tonic-Clonic (GTC) seizures; using skin conductance (SC) signals. The watch's circuit was designed in EasyEDA and implemented on a Breadboard to showcase the dispatch of a seizure event alert to a phone via a Bluetooth module; in the event of an ongoing seizure and vice versa. Due to the unavailability of SC signal databases, Electroencephalography (EEG) signals, acquired from a physiological database known as PhysioNet were used in showcasing the signal processing of incoming SC signals, temporal and spectral feature extraction of these signals, and the classification of these signals using a trained machine learning algorithm. Twenty-five machine learning algorithms provided by the MATLAB Classification Learner App were trained using 80 EEG signals (both seizure and non-seizure) and only two algorithms, namely the Medium Tree and Linear Support Vector Machine (SVM) had the highest training prediction accuracy. However, in determining their prediction accuracy with two different data sets, the Medium Tree model had the highest cumulative prediction accuracy of 76.7%; as compared to the Linear SVM model which had a cumulative prediction accuracy of 73.3%. Based on these results, the Medium Tree model was recommended as a good seizure detection algorithm to prevent fatal and non-fatal injuries; and even Sudden Unexpected Death in Epilepsy (SUDEP).

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Chapter 1: Introduction

1.1 Project Objective

This project will describe the design and fabrication of a smart watch for the timely detection of generalized tonic-clonic (GTC) seizures which typically occur in people diagnosed with epilepsy; by monitoring Electrodermal Activity (EDA) in order to alert the parent(s)/caregiver(s) of that person.

1.1.1 Project Motivation

In Ghana, one per cent of the population has epilepsy, thus approximately 250,000 people have been diagnosed with epilepsy [6]. When these people are having an epileptic seizure, specifically the GTC seizure, they become physically unable to call for help. A watch-like sensor capable of detecting these GTC seizures could significantly improve the quality of life for these Ghanaians who are constantly placed in life-threatening situations; in danger of acquiring serious and even fatal injuries while going about their daily activities. Even during sleep, in the event of a GTC seizure, a person can injure themselves and/or can experience airway obstruction which could be fatal; so if the parent(s)/caregiver(s) of that person are alerted that a grand mal seizure is ongoing, the person could receive timely treatment if injured and/or they could be placed in a recovery position to avoid airway obstruction [1]. Additionally, because most epileptic deaths are unwitnessed, timely detection of a GTC seizure is vital in SUDEP (Sudden Unexpected Death in Epilepsy) prevention [1].

1.1.2 Background

About 65 million people around the world have epilepsy [2], one of the most common neurological disorders characterized by recurring seizures of different degrees of severity which have potentially deadly consequences. Epilepsy is not one condition, but a variety of disorders

reflecting underlying brain dysfunction that may result from many different causes; nonetheless more than half of the time the underlying cause is unknown [1].

An epileptic seizure is defined as a transient occurrence of signs and/or symptoms due to abnormal excessive or synchronous neuronal activity in the brain and when asked as observed, people with epilepsy often describe seizures as occurring "like a bolt from the blue" which reflects the unforeseen way in which seizures tend to strike [1]. International classification of epileptic seizures give rise to two main categories: focal seizures and generalized seizures which were established by the ILAE (International League Against Epilepsy) [1]. Focal seizures, also known as auras are seizures which occur at one cerebral hemisphere of the brain (the left/right) [3]. They normally occur without a change in awareness and consciousness [2]. These seizures make a person with epilepsy twitch, experience abrupt changes in sensation (taste and/or smell), become confused or dazed [3]. Generalized seizures occur in both cerebral hemispheres of the brain (left and right) and they normally start with a loss of consciousness or awareness [3,4]. These seizures are easily detectable by outsiders – as they can be convulsive (sporadic or jerky movements of the limbs and face) or non-convulsive, such as rapid blinking and staring [2,4]. They can also involve a tonic phase where the muscles in the person become stiff and an atonic phase where the person abruptly loses their muscle tone [3]. The emotional state alterations occurring during frontal and generalized seizures produce a variety of autonomic footprints which result in increased sympathetic activity in the sympathetic subdivision of the Autonomic Nervous System (ANS) [1]. These autonomic footprints in the sympathetic nervous system (SNS) include elevated heart rate, blood pressure, respiratory rate and sweating [1].

Sweat (the subtle change in perspiration that is only detectable by precise instrumentation and is quite different than the amount of sweat produced by physical activity) is a weak electrolyte

and good conductor [1,5]. The filling of sweat ducts by sweat results in many low-resistance parallel pathways, thereby increasing the conductance of an applied current [1]. Since sweating causes variations in skin conductance at the skin surface, formally known as EDA (Electrodermal Activity), activity within the sympathetic axis of the ANS (caused by these variations) is reflected and this provides a sensitive and convenient measure of assessing alterations in sympathetic arousal associated with emotion, cognition and attention [1]. So far, physiological alterations during epileptic seizures have mostly been studied using indirect parameters such as heart rate, respiratory rate and blood pressure changes that are dually modulated by both divisions (Parasympathetic & Sympathetic) of the ANS but the additional use of EDA (singly modulated by the Sympathetic division of the ANS) potentially provides more insight given that EDA can be considered to act as an indicator of both psychological and physiological arousal [1,9].

1.2 Overview of Device

At the heart of this seizure detection watch is a circuitry which measures the variation of the user's skin conductance by applying a constant, low voltage to the user's skin via two electrodes positioned on the dorsal side of the user's wrist. After the measurement of the variation in skin conductance, amplification of these skin conductance (SC) signals occur via an operational amplifier. Analog signal processing and event detection sequentially occur via an algorithm. The microcontroller activates the Beetle BLE (Bluetooth 4.0 Low Energy) module to dispatch a seizure event alert to the user's parent(s)/caregiver(s) phones if a GTC seizure is detected, using an event detection algorithm. If a seizure is not detected after the skin SC signals go through the processing and event detection algorithm, the Bluetooth module does not dispatch an alert.

Below is the operational logical structure of the seizure detection watch:

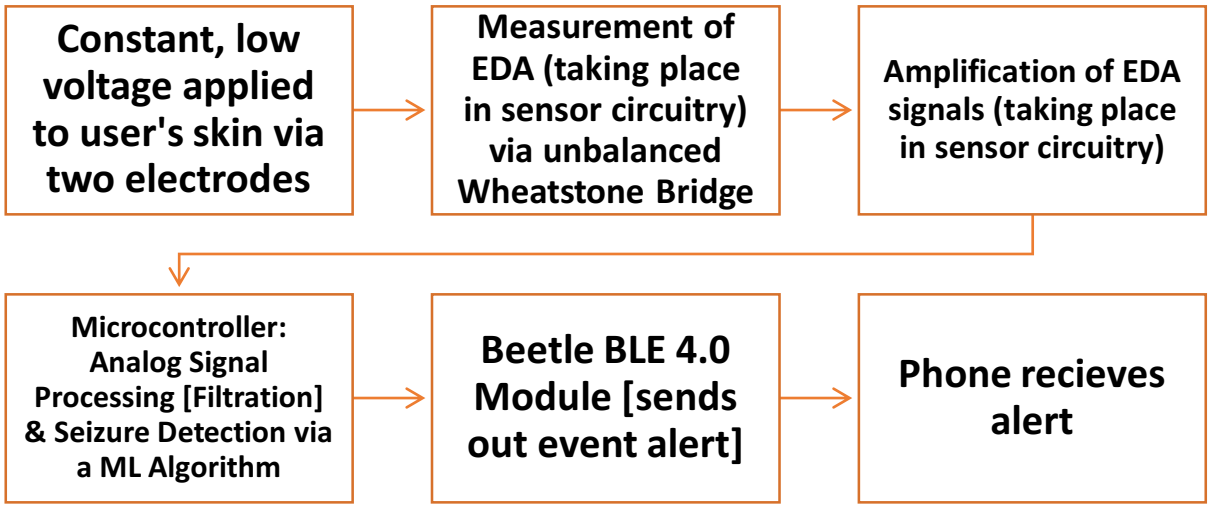

Figure 1-1. *Operational Logical Structure of Seizure Detection Watch*

*ML: Machine Learning

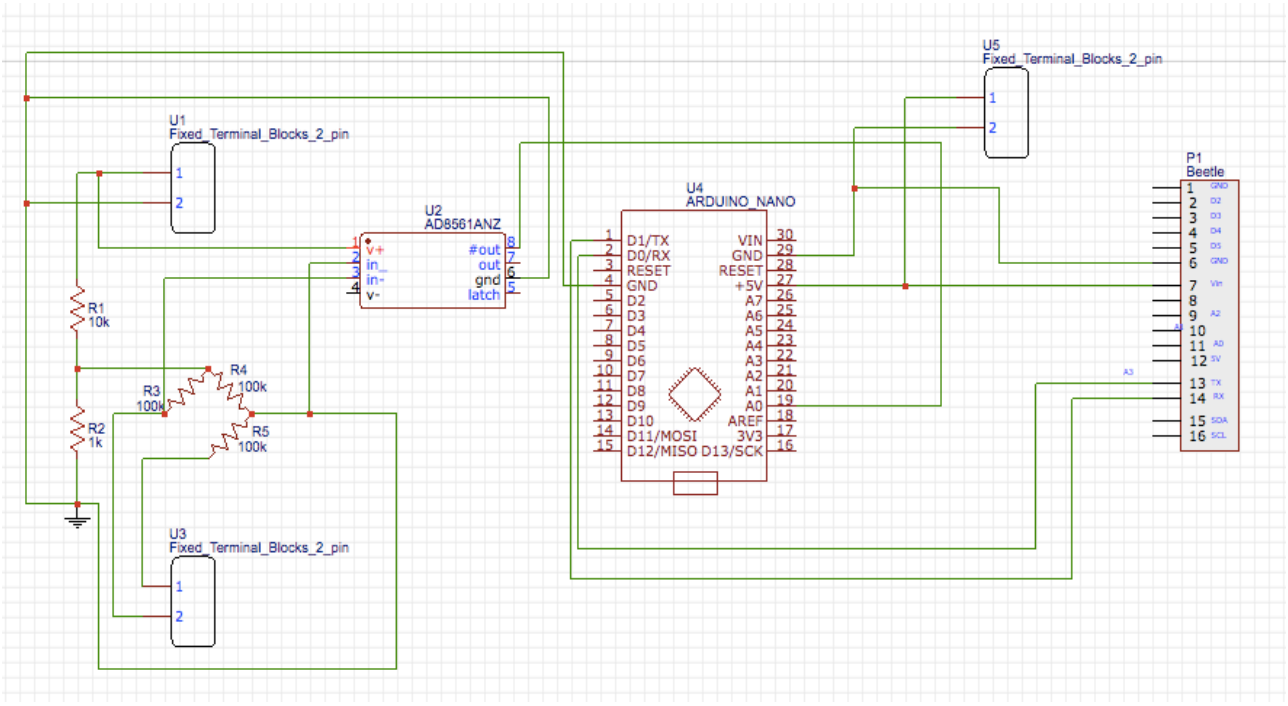

Figure 1-2. *Circuit Schematic of Seizure Detection Watch*

In Figure 1-2, the sensor circuitry is depicted and it is powered by a 3.7V lithium polymer-rechargeable battery whose positive and negative terminals are represented by the fixed terminal block labelled U1. The Vin and GND pins of the Arduino Nano are connected to the terminals of U5 in order to get powered and the terminal block labelled U5 represents a 5V lithium polymer battery. The Beetle BLE module has its Vin and GND pins connected to the Vin and GND pins of the Arduino Nano.

The 3.7V supplied to the circuitry is divided by the two resistors, R1 and R2. This divided voltage is then routed towards the unbalanced Wheatstone bridge (made up of known resistances R3, R4, R5 and the unknown varying resistance of the user's skin), specifically to the two electrodes placed on the dorsal side of the user's wrist in order to apply a low, constant voltage to the person's skin. Terminal 1 of the fixed terminal block labelled U3 in Figure 1-2, represents the negative/ground terminal of one the electrodes; while terminal 2 represents the positive terminal of the other electrode. The unbalanced Wheatstone bridge is utilized because the resistances of R3,

R4 and R5 are fixed and as a result, it is used for measuring an unknown resistance [10]. The voltages at the two nodes of this Wheatstone bridge (created by R3 and the user's skin, and R5 and R4) have their voltages sent to the inverting and non-inverting inputs of the amplifier (AD8651ANZ), respectively. The amplifier is also powered by the 3.7V battery.

After amplification, the SC signals are sent to the analog input (A0) of the Arduino Nano in order to get filtered, de-convoluted, have their temporal and spectral features extracted and get sent through a trained machine learning algorithm for GTC seizure detection. The Pins TX and RX of the Arduino Nano are connected to pins RX and TX of the Beetle BLE respectively. Therefore, at the onset of a GTC seizure, through this connection, the Bluetooth module dispatches an alert to the parent(s)/caregiver(s) phone.

Chapter 2: Literature Review

Depending on the patient, epileptic seizure treatments include antiepileptic drugs (AEDs), surgery to remove a small part of the brain causing the seizures, the implantation of a small electrical device in the body and a ketogenic diet to help control seizures [11]. The aim of these forms of treatments is to severely reduce the occurrence of seizures and/or to completely stop them from occurring [11].

Despite antiepileptic drugs (AEDs), one-third of people with epilepsy continue to have seizures [13]. However, even when seizures are well controlled with other treatment methods, self-reported quality of life is significantly lowered by the anxiety associated with the unpredictability and apparent randomness of epileptic seizures which can cause severe non-fatal and fatal injuries [11, 13]. That is why methods or devices capable of accurately detecting seizures could promote therapies aimed at rapidly treating seizures, help prevent injury or even death and significantly improve quality of life for epileptic patients [11,13]. Electroencephalography (EEG) is an electrophysiological, non-invasive, multi-channel monitoring technique meant to record electrical activity in the brain; measured by an Electroencephalogram [12, 13]. The electroencephalogram is a device made up of electrodes, conductive gel, amplifiers and an Analog to Digital Converter [12]. The electrodes are placed along specific places on a person's scalp according to 10-20 standards for EEG placement and they are labelled by letters which indicate the lobes of the brain (i.e. F-Frontal, T-Temporal, C-Central, P-Parietal, O-Occipital) [12].

EEG waveforms are generally classified according to their frequency, amplitude, shape as well as the position of the electrodes on the person's scalp [12]. In regards to classification of these waveforms according to their frequency, there are five broad spectral sub-bands of the EEG signal which are generally of particular interest: delta (0-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-

30 Hz) and gamma (30-100 Hz) [12]. Brain issues like Alzheimer's, Attention Deficit Disorder (ADD), epilepsy, anxiety disorders, autism, insomnia, chronic pain and dyslexia all produce electrical signals with specific frequencies from one or more of these five broad spectral sub-bands [12]. High frequencies are often more common in abnormal brain states from an epileptic patient as there is a shift of EEG signal energy from lower to higher frequency bands before and during a seizure [12]. Thus, monitoring the electrical activity of the brain from scalp electroencephalograms (EEG) is the conventional and easy way to observe an epileptic patient before, during and after a seizure. As a result, feature analysis of EEG signals from an epileptic patient is a powerful and enabling way for the prediction and timely detection of the onset of seizures (both partial and generalized tonic-clonic seizures) usually using a seizure detection algorithm.

Although this method of seizure detection is considered to be more accurate because the electric signals being analyzed are directly from the brain, it becomes a stigmatizing and obtrusive method not suitable for long-term continuous monitoring outside of the hospital. In a survey of 141 patients with uncontrolled epilepsy from two different epilepsy centers, almost 80% of patients were opposed to wearing scalp EEG electrodes to obtain seizure warnings [1]. This strong aversion could have been due to the discomfort associated with wearing scalp electrodes, the fear of stigmatization, or both [1]. Alternatively, monitoring EDA via a compact sensor circuitry and two electrodes on the ventral/dorsal side of a patient's distal forearm [8] is an unobtrusive and non-stigmatizing method of seizure detection.

Electrodermal activity (EDA) is the umbrella term used for defining autonomic changes in skin conductance [14]. Skin conductance can be quantified by applying an electrical potential between two points of skin contact and measuring the resulting current flow between them [14]. Typical units of EDA are microSiemens (μS) or micromho (μmho) [14]. The EDA signal has a

frequency bandwidth of 0–2 Hz and they are made up of background tonic (skin conductance level: SCL) and rapid phasic components (Skin Conductance Responses: SCRs) that result from sympathetic neuronal activity [14,17]. The measure of the tonic component (general tonic-level EDA) is the SCL and this component relates to the slower acting components and background characteristics of the signal (the overall level, slow climbing and slow declinations over time) [14]. Skin conductance level (SCL), represents the baseline of the skin conductance as it varies among people, depending on their physiological states and autonomic regulation [15]. On the other hand, the measure of the phasic component is the SCR which refers to the faster changing characteristics of the skin conductance signal [14].

These tonic and phasic (SCL & SCR) components can be obtained from a EDA signal through a de-convolution process [16]. De-convolution reverses the process of convolution which is a mathematical way of combining two signals (an input signal and an impulse response) to form a third signal, the output signal [18,19]. Research shows that SudoMotor Nerve Activity (SMNA) causes sweat secretion and thus triggers a specific change in skin conductivity and as such, in mathematical terms, it can be considered as a driver; consisting of a sequence of mostly distinct impulses (i.e. SudoMotor Nerve Bursts), which in turn, trigger a specific impulse response (i.e., SCRs) [18]. The bi-exponential impulse response function (IRF) which is also known as the Bateman function describes the course of the impulse response (i.e., SCRs) over time [18]. Therefore, the result of this process can be represented by the convolution of SMNA with the IRF [16, 18]. That is, $\mathrm{EDA} = \mathrm{SMNA} \otimes \mathrm{IRF}$. $\mathrm{IRF} = \left(e^{-\frac{t}{\tau_1}} - e^{-\frac{t}{\tau_2}}\right) \times u(t)$ where τ_1 and τ_2 are, respectively, the slow and the fast time constants of the phasic curve shape, and u(t) is the unit step function; and $\mathrm{SMNA} = (\mathrm{DRIVER}_{\mathrm{tonic}} + \mathrm{DRIVER}_{\mathrm{phasic}})$ [16,17].

SMNA is unknown and is evaluated by de-convolving the EDA signal with the IRF [16]. To decompose the obtained SMNA signal into the $\mathrm{DRIVER}_{\mathrm{tonic}}$ and $\mathrm{DRIVER}_{\mathrm{phasic}}$ components, some algorithmic steps are taken [16]. In the first algorithmic step, a smoothing Gauss window of 200ms is applied to the SMNA signal, then in the second step, a peak detection algorithm is used in order to find the peaks over a threshold of 0.2μS [16]. In the third step, all the points below the threshold get interpolated with a cubic spline fitting method; resulting in the $\mathrm{DRIVER}_{\mathrm{phasic}}$ component [16]. In the final step, the $\mathrm{DRIVER}_{\mathrm{phasic}}$ component, is computed by subtracting the previously estimated $\mathrm{DRIVER}_{\mathrm{tonic}}$ from the SMNA, under the hypothesis that tonic activity is observed in the absence of any phasic activity [16]. It is after this process of de-convolution and decomposition that the SCR signals that represent the responsive characteristics of EDA can have their features extracted, analysed and classified for the detection of seizures. Figure 2-1 shows an SCR signal obtained from the de-convolution process of a raw and filtered EDA signal.

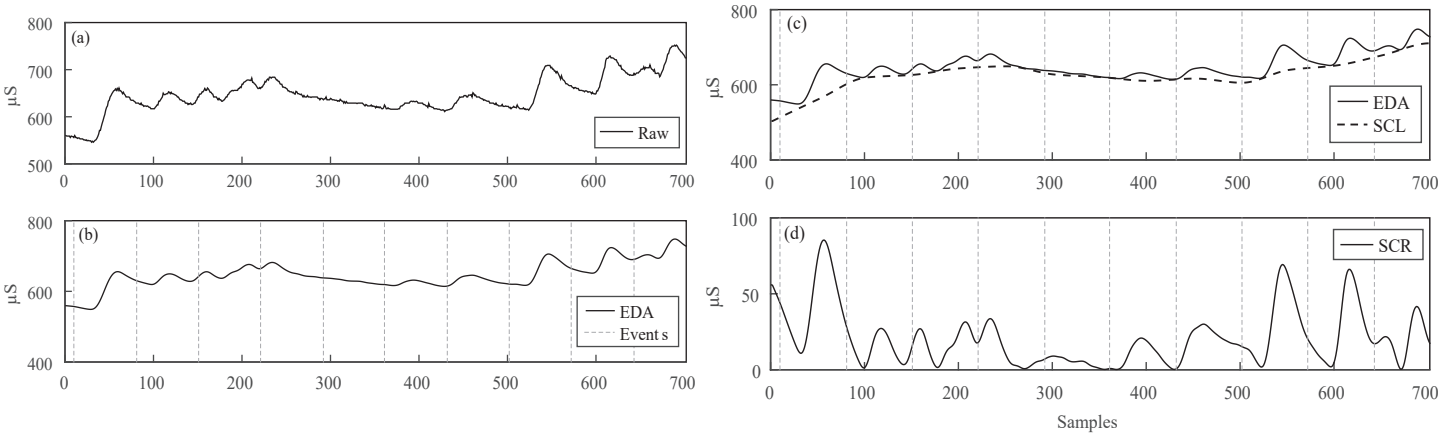

Figure 2-1. *Different stages in EDA signal processing.* ***(a)*** *Raw EDA signal before filtering.* ***(b)*** *Raw EDA signal after low-pass filtering.* ***(c)*** *Filtered EDA Signal & Skin conductance level (SCL) component.* ***(d)*** *Skin conductivity response (SCR) obtained after the de-convolution process.* ***[15]***

In regards to using alternative methods like monitoring EDA (as compared to EEG signals) via a compact sensor circuitry for the timely detection of GTC seizures, a PhD thesis published in

2011 by Ming-Zher Poh introduced a non-obtrusive and non-stigmatizing wearable Electrodermal activity (EDA) and accelerometry (ACM) wristband biosensor; purposed to detect the onset of GTC seizures. This wristband biosensor was designed and evaluated on 80 patients. The machine learning algorithm used in the evaluation of this biosensor, to detect the onset of GTC seizures was the Support Vector Machine. The algorithm was tested on 80 patients containing a wide range of ordinary daily activities and achieved high seizure detection accuracy of 94% with a low rate of false alarms (≤ 1 per 24 h) [1]. A comparison of the key features of other wearable GTC seizure detectors to the MIT Wrist-worn Biosensor can be seen in Figure 2-2.

As seen from Figure 2-2, unlike utilizing electroencephalogram (EEG) and video-monitoring collectively for seizure detection, in Epilepsy Monitoring Units (EMUs), in the confines of a hospital, using wearable, non-obtrusive and non-stigmatizing sensors serve as great methods for detecting GTC seizures.

Features	Schulc et al. [158]	SmartWatch Lockman et al. [107]	EpiLert Kramer et al. [90]	**MIT Wearable Biosensor**
Signals	ACM	ACM	ACM	**ACM + EDA**
Setup	Wii Remote on forearm	Wrist-worn motion sensor	Wrist-worn motion sensor	Wrist-worn biosensor
Number of patients tested	3	40 (6 with seizures)	31 (**15** with seizures)	**80** (7 with seizures)
Number of seizures tested	4	8	**22**	16
Duration of recordings tested	27 – 43 h	Unspecified	1692 h	**4213 h**
Algorithm described?	**Yes**, heuristic selection of thresholds for ACM intensity and time span	No	No	**Yes**, Support Vector Machine
Sensitivity	100%†(4/4)	88% (7/8)	91% (20/22)	**94%** (15/16)
False alarms	Not reported	204	**0.11 per 24 h***(8 in 1692 h)	0.74 per 24 h (130 in 4213 h)
Latency	Not reported	5–43 s	17 s (median)	31 s (median)

ACM accelerometry; EDA electrodermal activity
† Training results only (no independent testing performed).
* Patients with dystonic posturing, subtle behavioral automatism, and suspected pseudoseizures were excluded.

Figure 2-2. *Comparison of the key features other wearable GTC seizure detectors to the MIT wearable sensor.* ***[1]***

Chapter 3: Design

3.1 Review of Existing Designs

In Chapter 1, it was stated that a novel way of detecting GTC seizures was by continuously monitoring the changes in EDA since epileptic patients emotionally sweat during seizures. The traditional form of measurement of skin conductance on all human beings has been via two disc electrodes (mainly Silver Chloride) housed in straps which are then normally placed on the palmar surface of a person's hands; the most popular sites being the medial and distal phalanges of their fingers (middle and index) and the thenar and hypothenar eminences [7,8].

A direct current is simultaneously and constantly applied through the two disc electrodes to these sites from the sensor's circuity whose size makes the entire device unmovable [7]. Furthermore, the electrodes placed on the hand are often very sensitive to motion and thus require the person's hand to stay absolutely still [9]. Despite being the common form of EDA measurement, it is not an ideal and practical choice for the continuous measurement of EDA. Another means of monitoring EDA has been explored via a ring prototype called the Moodmetric EDA Ring. The creation and testing of this prototype EDA ring was inspired by the fact that novel wearable skin conductivity sensors offer portable low-cost solutions for accurate and precise long-term monitoring [9]. A psychophysiological experiment was conducted for the comparison of the similarity of the SCR signals obtained by both the prototype of the EDA ring and a laboratory-grade skin conductance sensor known as SA9309M [9]. Results from this experiment revealed that even though the ring sensor can be used to measure skin conductance, its accuracy might not, however, be enough for clinical use [9].

Another means of unobtrusively measuring EDA is by wearing a small, portable enclosure (housing a compact EDA sensor module) on a person's wrist and placing two disc electrodes at

the bottom of the enclosure so that they rest on the dorsal side of the person's distal forearm [8]. This chosen form of monitoring the changes in EDA is more accurate and precise than the prototype of the Moodmetric EDA ring, as it is unobtrusive and portable when compared to the traditional method (electrodes housed in straps and a bulky sensor module) of monitoring EDA. This form of monitoring EDA does not require the person to remain absolutely still as compared to the traditional method. There exists an FDA-approved seizure detection watch on the market known as Embrace2. Embrace2 monitors EDA via two small electrodes that get placed on the dorsal side of its user's distal forearm; when it is worn. This watch also houses a compact EDA sensor circuit, an accelerometer and gyroscope for unobtrusive and long-term monitoring of EDA; for the detection of epileptic seizures to prevent non-fatal and fatal injuries, and even SUDEP.

3.2 Thesis Design Objective

The design objective of this project is to develop an affordable, portable and unobtrusive watch to provide EDA monitoring for epileptic patients in Ghana, anytime and anywhere; for the timely detection of generalized tonic-clonic seizures. In order to prevent fatal and non-fatal injuries, and even SUDEP. Ideally, the prototype of this seizure detection watch would have its sensor circuitry implemented on a printed circuit board (PCB). This PCB, including all the electronic components soldered unto it will be enclosed in a rectangular 3D printed case and two electrodes will be placed in circular slots at the bottom of this case. By being placed at the bottom of the case, these electrodes will be placed on the dorsal side of the user's wrist and this site will be where the changes in EDA will be obtained and monitored continuously.

3.3 Design Decisions

The various factors involved in the design decision of the suitable form of long-term, unobtrusive EDA monitoring are as follows: cost, accuracy of measurement (by sensor circuitry), weight which dictates how portable the watch would be and size.

3.3.1 Pugh Matrix

Criteria	**Baseline [Embrace2]**	**Weight**	**Moodmetric EDA Ring [Prototype]**	**Seizure Detection Watch [Prototype]**
Cost	0	7	0	+7
Size	0	4	+4	0
Weight [Portability]	0	5	+5	+5
Accuracy of measurement (by sensor circuitry)	0	6	-6	0

Table 3-1

According to the Pugh Matrix above, the watch design of a GTC seizure sensor is the best choice in comparison with Embrace2 (the only FDA-approved Epilepsy Management Watch on the market) which was used as the baseline in the Pugh Matrix. Further analysis on the following factors is done below to support the previous statement.

3.3.1.1 Cost

Table 3-2 shows the bill of required materials employed to fabricate the prototype of the seizure detection watch.

Components	**Quantity**	**Price ($)**
3.7V Lithium Polymer Battery [500mAh]	1	1.49
5V Lithium Polymer Battery [2500mAh]	1	2.20
1 kΩ resistor	1	0.0184

10 kΩ resistor	1	0.0197
100kΩ resistors	3	0.0178×**3**
Electrodes	2	0.14×**2**
Operational Amplifier (AD8651ANZ)	1	4.4927
Arduino Nano	1	8.99
Bluetooth Module [Beetle BLE]	1	14.90
Printed Circuit Board (PCB	1	1.00
3D-Printed Case	1	2.00
TOTAL		**35.4442**

Table 3-2

As seen from Table 3-2, the materials cost of this seizure detection watch will be $35.4442 which is approximately $35. This amount in Ghana Cedis is GHc178.66 and it is highly affordable for middle-income families in Ghana. Low-income families in Ghana will also be able to afford this watch if they follow a good payment plan.

3.3.1.2 Size

Ideally, the size of the 3D printed case, for unobtrusive and continuous monitoring will mimic the dimensions of the Apple Watch Series 4 with a Stainless Steel Case; as a reference. The dimensions of the Apple Watch Series 4 are as follows: Height = 44mm, Width = 38mm and Depth = 10.7mm. Consequently, the dimensions of the PCB should be 2-4mm less than the height and width of the case. Figure 3-1 and Figure 3-2 (a) and (b) are the Apple Watch Series 4 (with a Stainless Steel Case) and the top and bottom view of the 3D model of the casing of the prototype of the seizure detection watch; respectively.

Figure 3-1. *[20]*

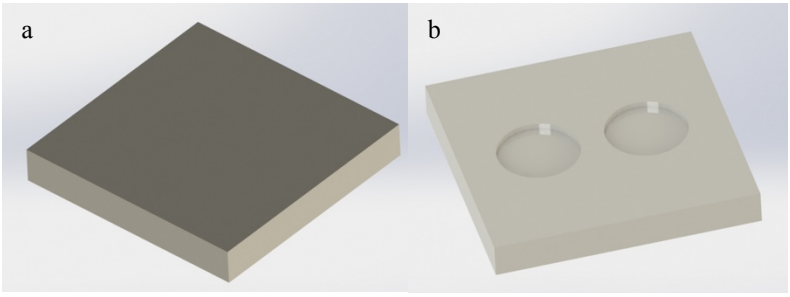

Figure 3-2. *(a) Top of Case (b) Bottom of Case.*

3.3.1.3 Weight [Portability]

Ideally, using the Apple Watch Series 4 (with a Stainless Steel Case) as a reference, the weight of the seizure detection watch should be ± 5g of 47.90g; where 47.90g is the weight of the Apple Watch. The weight of a PCB (without all electronic components soldered unto it) as provided by EasyEDA, ranges from 1oz to 2oz. In grams, the range is as follows: 28.30g – 56.70g. Thus, the weight of the case should be such that the collective weight of the seizure detection watch should be in the range of ± 5.00g of 47.90g.

Chapter 4: Implementation

4.1 Design Factors

4.1.1 Size [Dimensions]

In regards to the size of the seizure detection watch, the dimensions of the PCB produced in EasyEDA were greater than the ideal dimensions stated in Chapter 3. Consequently, the 3D printed case had larger dimensions than the dimensions proposed in using the Apple Watch Series 4 as a reference. The measured dimensions of the PCB generated from EasyEDA are as follows: Length = 74.3mm and Width = 72.14mm. As seen from these values, the length of the PCB is 30.3mm lengthier than the length of the Apple Watch and 31.14mm wider than the width of the Apple Watch. Below in Figure 4-1(a) is the PCB schematic designed from the circuit schematic in Figure 1-2 by EasyEDA. In order to accommodate the PCB, the dimensions of the 3D printed case of the seizure detection watch were as follows: Length = 78.00 mm and Width = 76.00 mm.

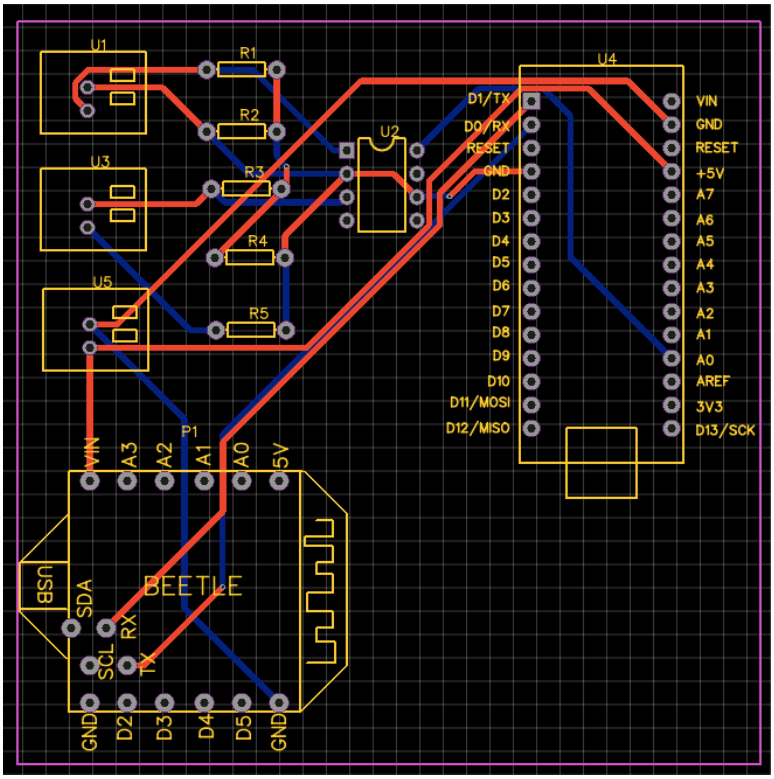

Figure 4-1(a). *Designed PCB schematic*

4.1.2 Weight [Portability]

The weight of the PCB was measured to be 28.60g which is 0.30g heavier than 28.30g. According to the Tech Specifications of the Arduino Nano from the Arduino Store, the weight of this microcontroller is 7g. Due to a constraint in resources, the delivery of the Beetle BLE (of range 50m) never occurred. In its place, the HC-05 Bluetooth module; of range 10m was utilized. The weight of the HC-05 is 10g, according to its tech specifications. Considering the weights of the five resistors used and the operational amplifier to be negligible, the collective weight of the PCB (with all electronic components soldered) is 45.60g. The measured weight of the 3D Printed Case is 6.25g. Collectively, the weight of the seizure detection watch, made up of the PCB, all electronic components and the 3D printed case is 51.85g. Therefore, the weight of this seizure detection watch is well within the range of $\pm 5.00\text{g}$ of 47.90g.

4.2 Proof of Concept

Ideally, to showcase the entire operational logical structure of the seizure detection watch, it should be placed on the dorsal side of the user's wrist to continuously measure and monitor the variation of the user's skin conductance; and alert the user's parent(s)/caregiver(s) when the onset of a GTC seizure is detected. Due to the fact that at this stage, the watch is a prototype, it was not placed on any human being for proof of concept and data collection. In order to prove that the functionality of the watch's circuit, as proposed in Chapter 1, the circuit in Figure 4-2 (a) will be utilized.

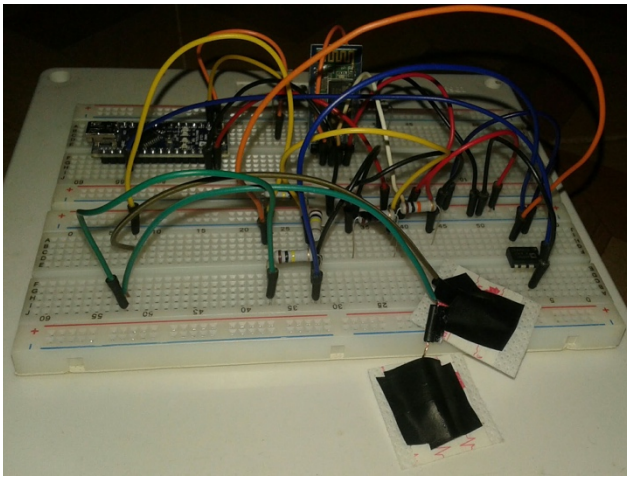

Figure 4-2(a). *Seizure Detection Watch Circuit*

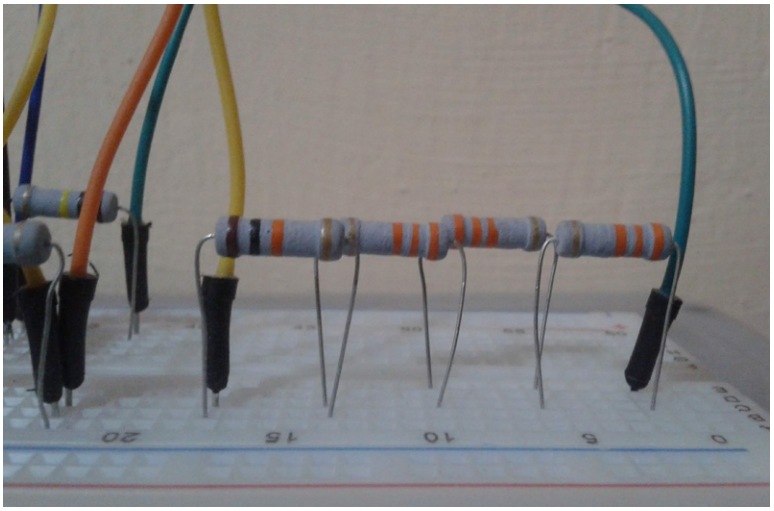

***Figure 4-2(b)**. Resistors in series representing varying skin resistance*

4.2.1 Measurement of EDA & Seizure Dispatch Alert via HC-05

The two electrodes in Figure 4-2 (a) will be replaced by resistors of different values. That is to say that the variation in skin resistance due to the neuronal activity in the SNS (Sympathetic Nervous System), will be represented as the variation of resistors of different values as seen in Figure 4-2 (b). The values of conductance will be calculated as resistance varies to prove that a decrease in skin resistance increases skin conductance; and vice versa.

Conductance is defined as the inverse of resistance where, $G = \frac{1}{R}$; G is skin conductance in μS and R is resistance in Ω (ohms) [1]. Resistance is defined by Ohm's law as the following equation, $\mathrm{R} = \frac{\mathrm{V}}{\mathrm{I}}$. Substituting R in the conductance formula, the resulting formula is as follows: $\mathrm{G} = \frac{\mathrm{I}}{\mathrm{V}}$. For proof of concept, the channel 1 scope of the Analog Discovery was used to read the output voltage from the output pin of the operational amplifier and the current entering and exiting the op-amp, was calculated using the formula below; as resistance varied.

$\cdot\ \mathrm{I} = \frac{\mathrm{V_{source}}/10}{\mathrm{R_{eq}}}$; where $\mathrm{V_{source}} = 3.7\ \mathrm{V}$ and $\mathrm{R_{eq}} = \left(\frac{100\mathrm{k\Omega}\times 100\mathrm{k\Omega}}{100\mathrm{k\Omega}+100\mathrm{k\Omega}}\right) + \left(\frac{100\mathrm{k\Omega}\times \mathrm{R}}{100\mathrm{k\Omega}+\mathrm{R}}\right)$.

The formula R_{eq} represents the equivalent resistance of an unbalanced Wheatstone Bridge Circuit [24].

R (kΩ)	R_{eq} (kΩ)	V_{out} (V)	I (μA)	G (μS)
10	59.09	3.03	6.26	2.07
43	80.07	2.95	4.62	1.57
76	93.18	2.86	3.97	1.39
109	102.15	2.78	3.62	1.30

Table 4-1

From Table 4-1, it is observed that an increase in skin resistance produces a decrease in skin conductance and vice versa. A GTC seizure alert is to be sent to the phone of the user's parent(s)/caregiver(s) via a Bluetooth module (HC-05). The seizure alert is received through an application named Event Detection Alert. This application was created on the MIT-App Inventor website and this application runs on lines of code (represented as blocks) that pair the Bluetooth module to the parent(s)/caregiver(s) phone and enables the user to receive information from the Arduino Nano via the Bluetooth module. The code blocks used to create the application can be seen in the Appendix. Initially, a pseudo-MATLAB algorithm was going to be utilized to dispatch an ongoing seizure alert but due to the limitations in interfacing the HC-05 with a phone in MATLAB, the algorithm was written in Arduino IDE (Integrated Development Environment). To elaborate, before using any type of Bluetooth module in MATLAB, the module must be paired with the laptop MATLAB is running on. Consequently, it becomes impossible to pair the

Bluetooth module with a phone in order to receive data from the Arduino via the Bluetooth module to the phone. The pseudo-algorithm written in Arduino IDE can be seen in the Appendix.

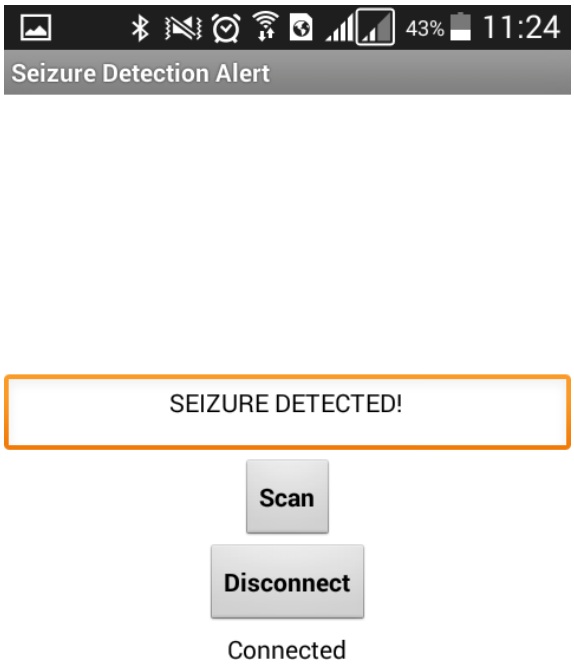

Figure 4-3(a). *Ongoing Seizure Event Alert dispatched to parent(s)/caregiver(s) phone*

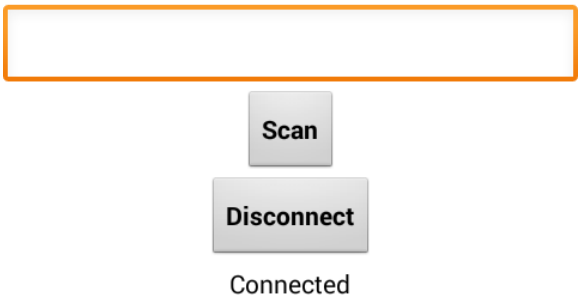

Figure 4-3(b). *No Seizure Event Alert dispatched to parent(s)/caregiver(s) phone*

4.2.2 Filtration, De-convolution, Feature Extraction & Training of Machine Learning Algorithms

Before a seizure alert is dispatched to the parent(s)/caregiver(s) phone, the incoming SC signals attained from the Wheatstone Bridge Circuit first get filtered by a filter designed in MATLAB. Their temporal and spectral features then get extracted by four MATLAB functions and their extracted features are sent through a trained machine learning algorithm for seizure detection. This section will showcase the software implementation of the filter and the results obtained from training twenty-five machine-learning algorithms provided by MATLAB for seizure detection.

In Chapter 2, according to literature, the frequency bandwidth of EDA signals is in the following range: 0 to 2 Hz. To ensure that all the signals get adequately processed, a Finite Impulse Response (FIR) band-pass filter was designed. The band-pass filter is a filter that allows signals between two specific frequencies to pass, but significantly attenuates signals at other frequencies from passing [21]. In designing this type of filter (in MATLAB) for the incoming SC signals, certain vital parameter choices needed to be made. They were the filter structure, the pass-band frequency range and stop-band frequency threshold. The filter structure was chosen as FIR instead of Infinite Impulse Response (IIR) because FIR filters are always stable as compared to IIR filters which are not always stable. The pass-band frequency range was chosen as 0.1-2 Hz; so that all signals with frequency components lower than 0.1 Hz and higher than 2 Hz get heavily attenuated.

Ideally, this frequency range is enough in designing this filter but the stop-band frequency threshold is required because realistically, all filters are unable to perfectly attenuate all signals beyond or below the chosen cut-off frequency. The stop-band frequency threshold used in the design was 0.03 Hz. That is, an additional 0.03 Hz allowance was assigned to the filter's pass-band frequency range. Therefore, realistically, the band-pass filter designed only allows signals with frequency bandwidths within this range: 0.07 to 2.03 Hz to pass through without getting

attenuated. Figure 4-3 shows the Magnitude Response of the software implementation of the FIR band-pass filter. See the Appendix for the signal processing code.

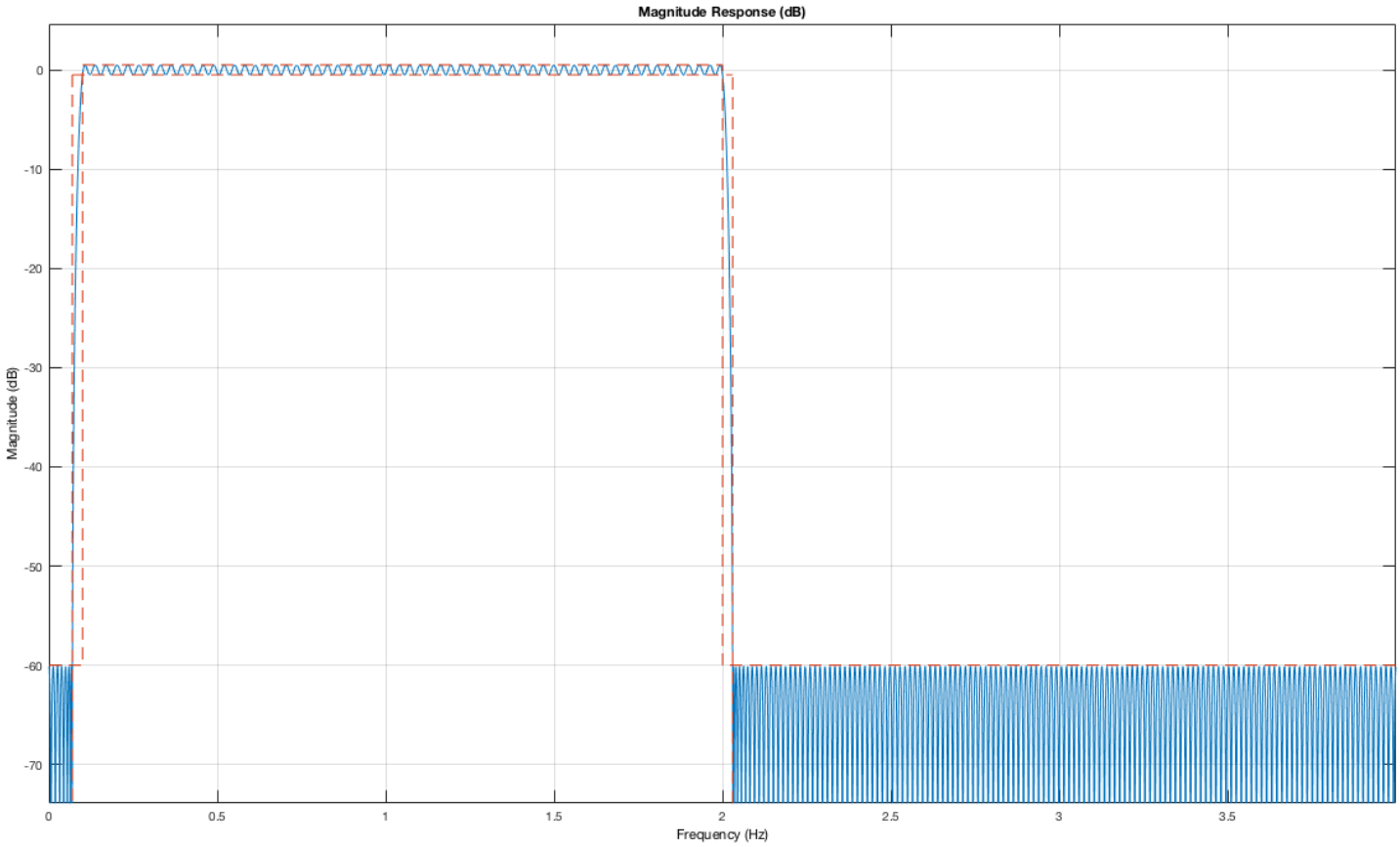

Figure 4-3. *Magnitude Response (dB) of FIR band-pass filter*

Table 4-2 showcases vital information on the characteristics of the FIR band-pass filter.

Stable	Linear Phase	Design Algorithm
Yes	Yes	Equiripple

Table 4-2. *Characteristics of the designed FIR band-pass filter*

The phase response of a filter is conventionally preferred to be linear because it will not distort the wave-shape of the filtered signal [22]. Equiripple, the design algorithm of the FIR band-pass filter causes the attenuated signals with frequency bandwidths higher than 2.03Hz (including the

threshold frequency of 0.03Hz) to continuously alternate at a magnitude of -60dB. The standard de-convolution MATLAB code purposed to separate the phasic and tonic components of a skin conductance signal, written by Alberto Greco and Luca Citi can be seen in the Appendix. In the training of the twenty-five machine learning algorithms provided by the Classification Learner Application in MATLAB, 80 resting and seizure EEG signals in total, each a minute long were utilized due to the fact that the seizure watch was not used in data collection and due to the unavailability of EDA signal databases. These signals were obtained from a physiological database known as PhysioNet. Two temporal and two spectral features of the 80 EEG signals were extracted and their values were recorded in an excel spreadsheet file.

The two temporal features extracted were maximum peak and peak-to-peak distance. The maximum peak function in MATLAB finds the maximum amplitude of a signal. The peak-to-peak distance function in MATLAB obtains it value from a signal by subtracting the amplitude of signal's maximum peak from the amplitude of the signal's minimum peak; along the y-axis. The two spectral features extracted were mean frequency and bandwidth power. The mean frequency function used in this section of the algorithm estimates the mean normalized frequency. The bandwidth power function returns the average power of a signal. See code for feature extraction on an EEG signal in the Appendix. Table 4-3 shows the results of the feature extraction process on one of the 80 EEG signals.

Maximum Peak	**Peak-to-Peak Distance**	**Mean Frequency**	**Bandwidth Power**
59.357	96.856	0.1058	88.3075

Table 4-3

After extraction, the respective signals from all 80 people were classified as representing a seizure or not. An excerpt from the excel file can be seen in Table 4-4.

Maximum Peak	**Peak-to-Peak Distance**	**Mean Frequency**	**Bandwidth Power**	***Class***
59.357	96.856	0.1058	88.3075	*No Seizure*
509.89	842.979	0.0456	5148.90	*Seizure*

Table 4-4

The arrangement of data in this file was done to train the twenty-five machine learning algorithms to determine which algorithm had the highest prediction accuracy. After training the models with the data set, two models had the highest training prediction accuracy of 85.0%. They were the Medium Tree Model and the Linear SVM (Support Vector Machine) Model.

Type of Model	**Training Time (sec)**	**Prediction Speed (obs/sec)**
Medium Tree	19.53	300
Linear SVM	23.462	710

Table 4-5

From Table 4-5, it is seen that the trained Medium Tree Model has the lowest training time and prediction speed as compared to the trained Linear SVM model. Despite this, training time and prediction speed were not good deterministic factors to indicate which trained model, in

comparison to each other, would have the highest prediction accuracy when fed with new data sets. Therefore, Chapter 5 shows the results obtained when two different data sets where fed to both trained models to determine which one was more accurate in detecting the onset of seizures. The model with the highest prediction accuracy will be the recommended choice model for detecting the onset of GTC seizures in epileptic patients.

Chapter 5: Results

5.1 Introduction

The purpose of the seizure detection algorithm is to perform band-pass filtering, de-convolution of the EDA signal to obtain its phasic component (SCR signal), feature extraction (temporal and spectral feature) and classification of the features extracted from the SCR signal; all in order to detect the onset of GTC seizures. However, in this Chapter, all signals utilized (to showcase filtering and classification of these features for seizure detection) were EEG signals obtained from a physiological signal database known as PhysioNet.

5.2 Signal Processing – Filtering

Figure 5-1 below shows the plot of a non-seizure EEG signal before and after passing through the FIR band-pass filter implemented in MATLAB.

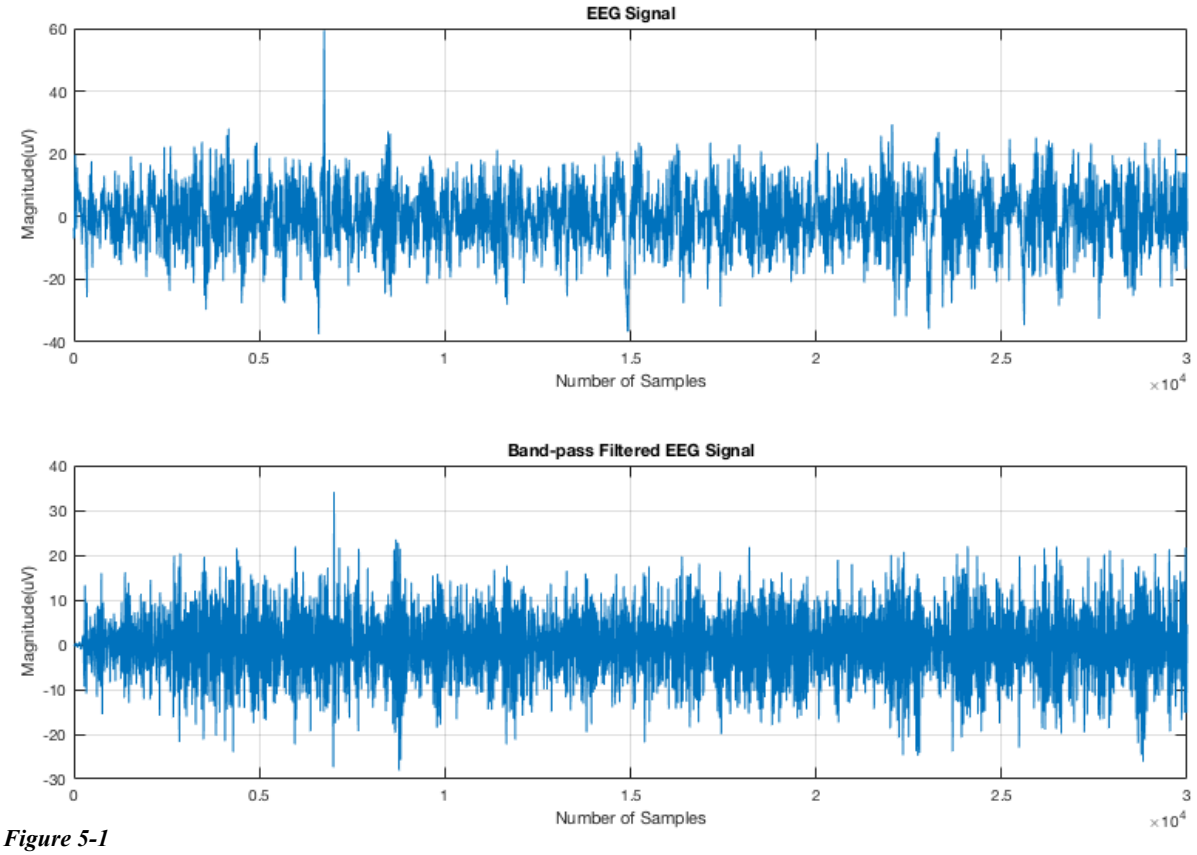

Figure 5-1

5.3 Determining the prediction accuracy of the trained Medium Tree & Linear SVM Models

In determining which trained model was more accurate in detecting the onset of a seizure, two different data sets containing the extracted features of EEG signals, were fed into the two trained models. The first set contained data on the extracted features of twenty non-seizure EEG signals. The second data set was made up of ten seizure EEG signals. Figure 5-2 shows the first data set made up of twenty non-seizure signals represented with bar charts.

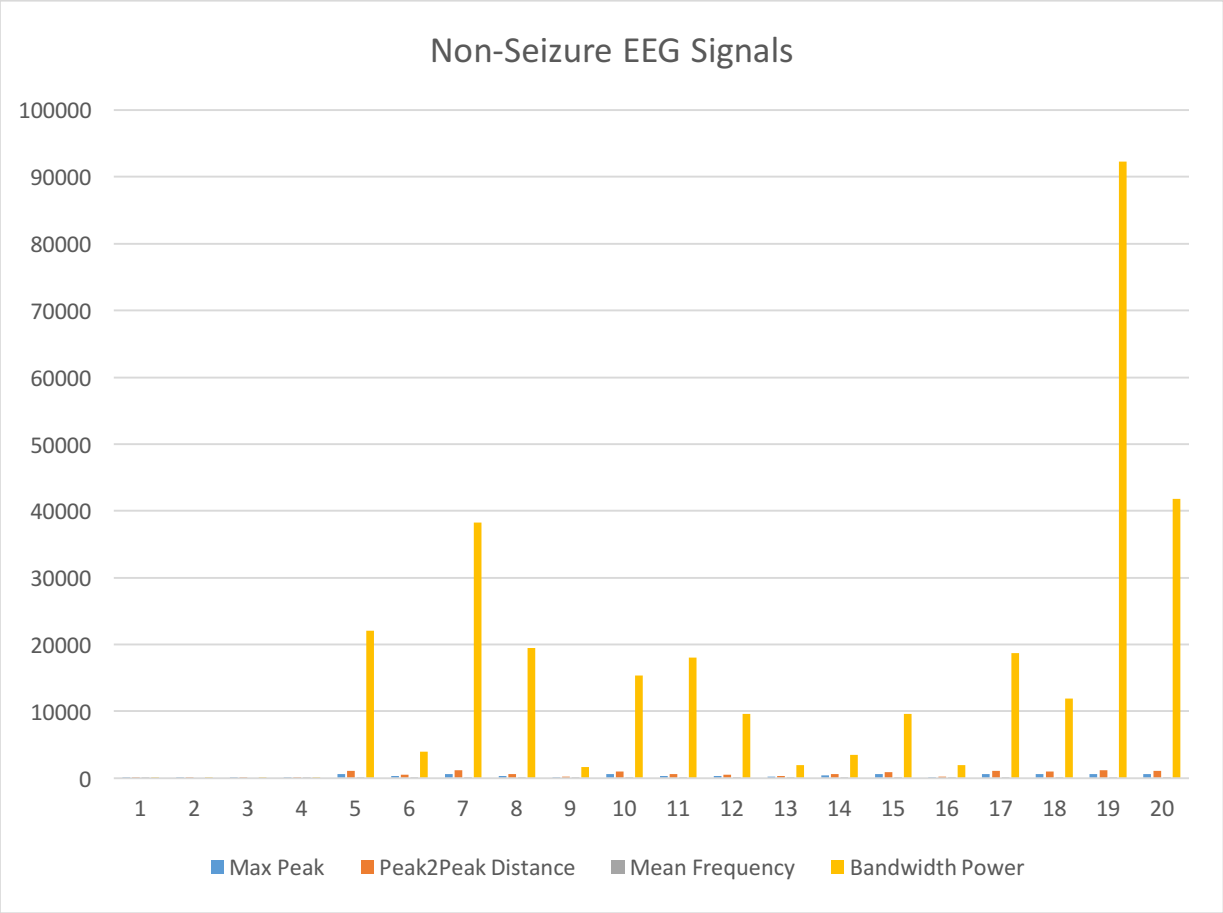

Figure 5-2

Figure 5-3 shows the second data set made up of ten seizure EEG signals represented with bar charts.

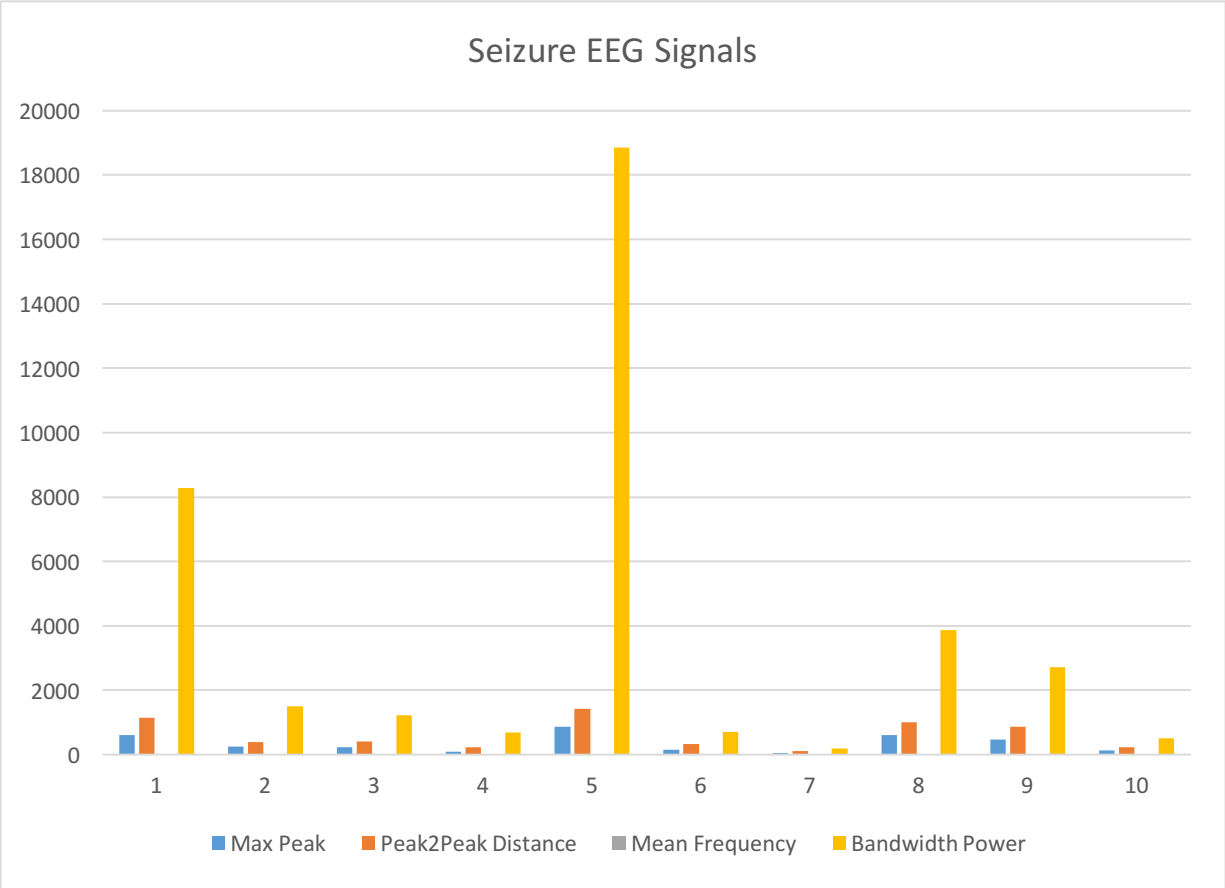

Figure 5-3

Upon feeding the data in the first and second data set into the two trained models (Medium Tree & SVM), the results in Table 5-3 were obtained. The seizure detection code and results using the two trained models can be seen in the Appendix.

Trained Models	**Medium Tree**	**Linear SVM**
1st Data Set [20 Non-seizure EEG signals]	16/20	18/20
2nd Data Set [10 Seizure EEG signals]	7/10	4/10
Prediction Accuracy	16+7/30 = 23/30	18+4/30 = 22/30

Prediction Accuracy (in percentage)	76.7%	73.3%

Table 5-1

From Table 5-1, the prediction accuracy of the trained Medium Tree model was found to be higher than the prediction accuracy of the trained Linear SVM model. For the first data set, containing twenty non-seizure EEG signals, the Medium Tree model falsely detected four seizures while the Linear SVM model falsely detected only two seizures. For the second data set, containing ten seizure EEG signals, the Medium Tree model was unable to detect only three seizures; whereas the Linear SVM model was unable to detect six seizures. In using these two data sets, the trained Medium Tree model was found to have the highest cumulative prediction accuracy. An accuracy of 76.7%. As a result of this, the Medium Tree model was the recommended choice for a good seizure detection algorithm. Hence, this model could be trained with SC signal data for the detection of the onset of GTC seizures; when EDA databases are made available.

Chapter 6: Conclusion

6.1 Discussions

Due to the lack of numerous seizure EEG signals on PhysioNet, the training data set utilized, contained 56 non-seizure EEG signals and 24 seizure EEG signals. Consequently, this data set caused the Medium Tree model to be biased towards non-seizure signals. Since this project is centered on using skin conductance (SC) signals to detect the onset of GTC seizures, to avoid working with a biased model, it should be trained with an equal amount of non-seizure and GTC seizure signals. Additionally, the training data set should contain more than 80 signals to improve seizure prediction accuracy. Since SC signals are psycho-physiological signals, unlike EEG signals which are purely physiological signals, the Medium Tree model might no longer be the recommended choice for a good seizure detection algorithm.

6.2 Limitations

A limitation of this project was the unavailability of SC signal databases. As a result of this, a data set containing the feature extraction of SC signals was unavailable and hence not used in training the machine learning algorithms provided by MATLAB. Another limitation faced had to do with using MATLAB as the chosen programming platform for signal acquisition, signal processing, the de-convolution of the SC signals, the training of a chosen machine learning algorithm, the use of that algorithm to classify de-convoluted SC signals as seizures or non-seizures and finally, the dispatch of a seizure detection alert via a Bluetooth module; to a phone. Due to certain connection protocols using MATLAB, the dispatch of a seizure event alert to a phone via a Bluetooth module could not happen. The Classification Learner App in MATLAB allows the user to only use a batch data set to both train and use a model for predictive applications.

Additionally, MATLAB does not have libraries that support the continuous training of the user's choice of model to constantly increase prediction accuracy.

6.3 Future works

In future works, an accelerometer could be implemented in the watch's circuitry to improve seizure detection since the watch is supposed to detect the onset of GTC seizures. Regarding the electronic components used in the circuit of this prototype, for future works, alternative components which are smaller in size can be utilized in order to fabricate the case and PCB of the watch using the Apple Watch Series 4 dimensions as a reference. For future works, a programming platform capable of running the following operations in real-time will be used. They are the acquisition of EDA data in packets (using an on-board MicroSD card), the filtering of this data, extraction of both temporal and spectral features from these packets of data, the seizure/non-seizure classification of these packets of data using a machine-learning algorithm and finally, the dispatch of a seizure event alert in the case of an ongoing seizure and vice versa via a Bluetooth module of large range.

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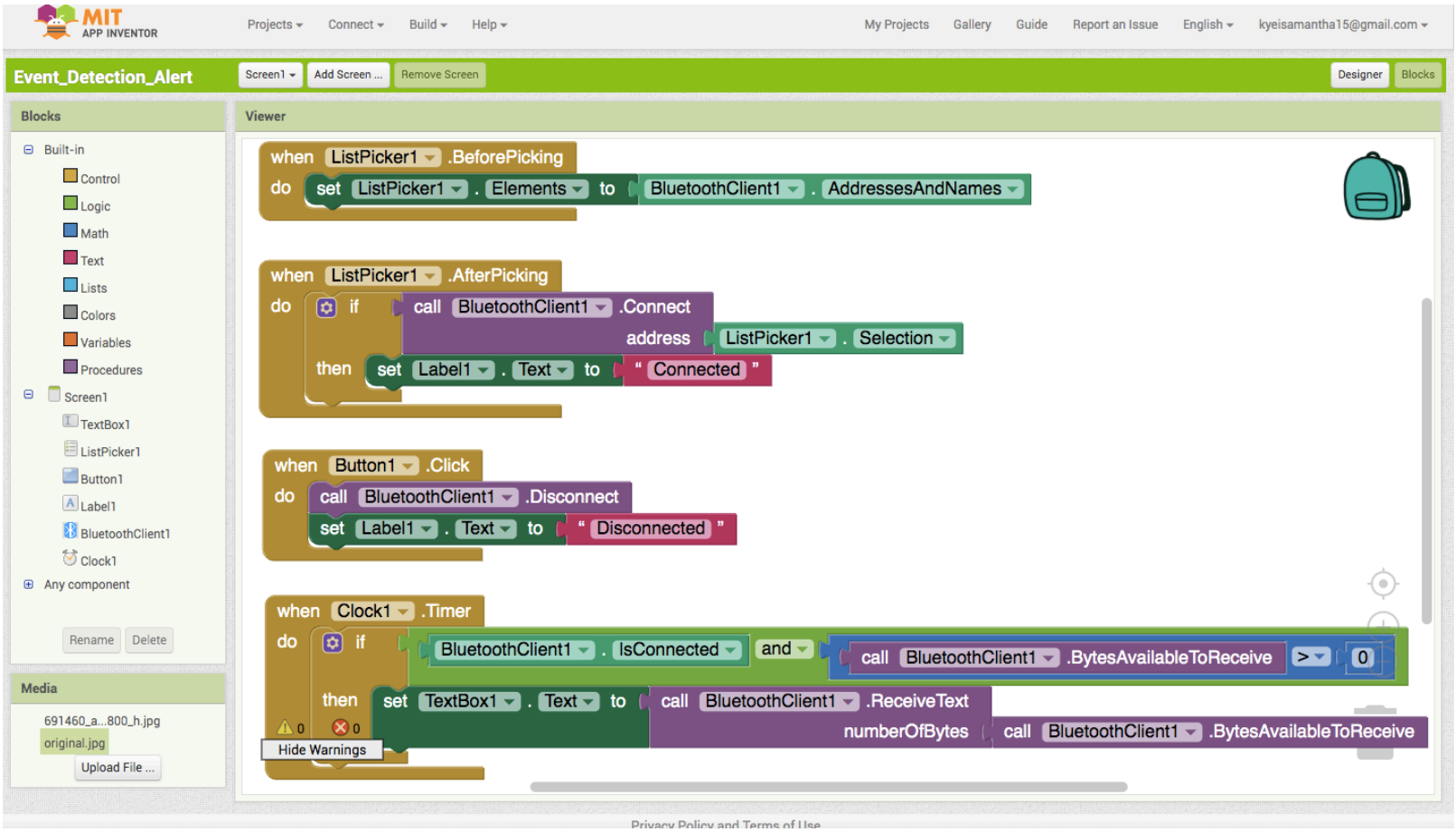
Appendix

1. This pseudo-algorithm is written in Arduino IDE and uploaded unto the Arduino Nano to demonstrate the event alert dispatch via the HC-05 when the onset of a GTC seizure is detected.

```
#include <SoftwareSerial.h>
SoftwareSerial BTserial(0, 1); // RX | TX
//Inputs
int sensorPin = A0;
int sensorValue = 0;
void setup() {
BTserial.begin(9600);
}
void loop() {
//Read the analog value
float sensorValue = analogRead(sensorPin);
//Divide by 205 to obtain a range from 0 to 5V
float sV = sensorValue/205;
BTserial.println(sensorValue);
BTserial.println(sV);
//A voltage greater or equal to 2.88V indicates a low 'skin' resistance;
representing that there has
//been a significant increase in skin conductance
if (sV >= 2.88) {
  BTserial.println("JENNY IS HAVING A SEIZURE!");
}
//A voltage less than 2.88V indicates a high 'skin' resistance;
representing that there has been a
```

```
//significant decrease in skin conductance
else if (sV <= 2.88) {
  BTserial.println("    ");
}
delay(5000);
}
```

2. The code blocks used to create the app on the website, MIT App Inventor. Assistance from The Roboindia team was employed in creating this app [25].



3. Band-pass Filter Design & Implementation

```
%%BAND-PASS FILTER DESIGN
Fstop1 = 0.07;  % First Stopband Frequency
Fpass1 = 0.1;   % First Passband Frequency
Fpass2 = 2;     % Second Passband Frequency
Fstop2 = 2.03;  % Second Stopband Frequency
Astop1 = 60;    % First Stopband Attenuation (dB)
Apass  = 1;     % Passband Ripple (dB)
Astop2 = 60;    % Second Stopband Attenuation (dB)
Fs     = 8;     % Sampling Frequency

h = fdesign.bandpass('fst1,fp1,fp2,fst2,ast1,ap,ast2', Fstop1, Fpass1,
...
        Fpass2, Fstop2, Astop1, Apass, Astop2, Fs);

Hd = design(h, 'equiripple', ...
     'MinOrder', 'any');

set(Hd,'PersistentMemory',true);

%%PASSING EEG SIGNAL THROUGH BAND-PASS FILTER
%Extracting data from non-seizure EEG signal
fid = fopen('samplesfilter.csv','r');
readData = textscan(fid,'%f %f','HeaderLines',2,'Delimiter',',');
x_Data = readData{1,1}(:,1);
y_Data = readData{1,2}(:,1);

y = doFilter(y_Data);
figure(1)
subplot(2,1,1)
plot(y_Data)
grid on
title('EEG Signal')
xlabel('Number of Samples')
ylabel('Magnitude(uV)')
```

```
subplot(2,1,2)
plot(y)
grid on
title('Band-pass Filtered EEG Signal')
xlabel('Number of Samples')
ylabel('Magnitude(uV)')
```

4. Data and Feature Extraction Code

```
%Open data file
fid = fopen('samples-1.csv','r');
%Read data in csv file
readData = textscan(fid,'%f %f','HeaderLines',2,'Delimiter',',');
%Extract data from readData
xData = readData{1,1}(:,1);
yData = readData{1,2}(:,1);
%Plot data
figure(1)
plot(xData,yData,'b')
grid on
axis tight
xlabel('Elapsed Time (s)')
ylabel('EEG Fp1 (uV)')
title('EEG Signal - Patient 01')

%%EXTRACT BOTH TEMPORAL AND SPECTRAL FEATURES FROM EEG SIGNAL
%Temporal Features
MAX_pk = max(yData)
pp_D = peak2peak(yData)
%Spectral Features
freq = meanfreq(yData)
p = bandpower(yData)
```

5. De-convolution MALTAB code written by Luca Citi & Alberto Greco [23]

```
function [r, p, t, l, d, e, obj] = cvxEDA(y, delta, varargin)
```

```
%CVXEDA Convex optimization approach to electrodermal activity
processing
%   This function implements the cvxEDA algorithm described in
"cvxEDA: a
%   Convex Optimization Approach to Electrodermal Activity Processing"
%(http://dx.doi.org/10.1109/TBME.2015.2474131 also available from the
%   authors' homepages).
%
%   Syntax:
%   [r, p, t, l, d, e, obj] = cvxEDA(y, delta, tau0, tau1, delta_knot,
%                                    alpha, gamma, solver)
%
%   where:
%      y: observed EDA signal (we recommend normalizing it: y =
zscore(y))
%      delta: sampling interval (in seconds) of y
%      tau0: slow time constant of the Bateman function (default 2.0)
%      tau1: fast time constant of the Bateman function (default 0.7)
%      delta_knot: time between knots of the tonic spline function
(default 10)
%      alpha: penalization for the sparse SMNA driver (default 0.0008)
%      gamma: penalization for the tonic spline coefficients (default
0.01)
%      solver: sparse QP solver to be used, 'quadprog' (default) or
'sedumi'
%
%   returns (see paper for details):
%      r: phasic component
%      p: sparse SMNA driver of phasic component
%      t: tonic component
%      l: coefficients of tonic spline
%      d: offset and slope of the linear drift term
%      e: model residuals
%      obj: value of objective function being minimized (eq 15 of
paper)

%
_____________________________________________________________________
________
%
% File:                             cvxEDA.m
% Last revised:                     22 Oct 2015 r68
%
_____________________________________________________________________
________
%
% Copyright (C) 2014-2015 Luca Citi, Alberto Greco
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%
```

```
%
% This method was first proposed in:
% A Greco, G Valenza, A Lanata, EP Scilingo, and L Citi
% "cvxEDA: a Convex Optimization Approach to Electrodermal Activity
Processing"
% IEEE Transactions on Biomedical Engineering, 2015
% DOI: 10.1109/TBME.2015.2474131
%
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%
```

```
% parse arguments
params = {2, 0.7, 10, 8e-4, 1e-2, 'quadprog'};
i = ~cellfun(@isempty, varargin);
params(i) = varargin(i);
[tau0, tau1, delta_knot, alpha, gamma, solver] = deal(params{:});

n = length(y);
y = y(:);

% bateman ARMA model
a1 = 1/min(tau1, tau0); % a1 > a0
a0 = 1/max(tau1, tau0);
ar = [(a1*delta + 2) * (a0*delta + 2), 2*a1*a0*delta^2 - 8, ...
       (a1*delta - 2) * (a0*delta - 2)] / ((a1 - a0) * delta^2);
ma = [1 2 1];

% matrices for ARMA model
i = 3:n;
A = sparse([i i i], [i i-1 i-2], repmat(ar, n-2, 1), n, n);
```

```
M = sparse([i i i], [i i-1 i-2], repmat(ma, n-2, 1), n, n);

% spline
delta_knot_s = round(delta_knot / delta);
spl = [1:delta_knot_s delta_knot_s-1:-1:1]'; % order 1
spl = conv(spl, spl, 'full');
spl = spl / max(spl);
% matrix of spline regressors
i = bsxfun(@plus, (0:length(spl)-1)'-floor(length(spl)/2),
1:delta_knot_s:n);
nB = size(i, 2);
j = repmat(1:nB, length(spl), 1);
p = repmat(spl(:), 1, nB);
valid = i >= 1 & i <= n;
B = sparse(i(valid), j(valid), p(valid));

% trend
C = [ones(n,1) (1:n)'/n];
nC = size(C, 2);

% Solve the problem:
% .5*(M*q + B*l + C*d - y)^2 + alpha*sum(A,1)*p + .5*gamma*l'*l
% s.t. A*q >= 0

if strcmpi(solver, 'quadprog')
    % Use Matlab's quadprog
    H = [M'*M, M'*C, M'*B; C'*M, C'*C, C'*B; B'*M, B'*C,
B'*B+gamma*speye(nB)];
    f = [alpha*sum(A,1)'-M'*y; -(C'*y); -(B'*y)];

    [z, obj] = quadprog(H, f, [-A zeros(n,length(f)-n)], zeros(n, 1),
...
        [], [], [], [], [], optimset('Algorithm', 'interior-point-
convex', ...
        'TolFun', 1e-13));
    %z = qp([], H, f, [], [], [], [], zeros(n,1), [A
zeros(n,length(f)-n)], []);
    obj = obj + .5 * (y' * y);
elseif strcmpi(solver, 'sedumi')
    % Use SeDuMi
    U = [A, sparse(n,nC), -speye(n), sparse(n,n+nB+4); ...
         M, C, sparse(n,n+2), -speye(n), sparse(n,2), B; ...
         sparse(1,2*n+nC), 1, sparse(1,n+nB+3); ...
         sparse(1,3*n+nC+2), 1, sparse(1,nB+1)];
    b = [sparse(n,1); y; 1; 1];
    c = sparse([n+nC+(1:n), 2*n+nC+2, 3*n+nC+4], ...
               1, [alpha*ones(1,n), 1, gamma], 3*n+nC+nB+4, 1);
    K = struct('f', n+nC, 'l', n, 'r', [2+n 2+nB]);
    pars.eps = 1e-6;
    pars.chol.maxuden = 1e2;
    z = sedumi(U, b, c, K, pars);
    obj = c' * z;
    %objd = b' * s;
```

```
end

l = z(end-nB+1:end);
d = z(n+1:n+nC);
t = B*l + C*d;
q = z(1:n);
p = A * q;
r = M * q;
e = y - r - t;

end
```

6. Seizure Detection Function – Using Trained Models [Medium Tree & Linear SVM]

```
%Structure 'trainedModel_MediumTree' exported from Classification Learner. To make predictions on a new table, T1.
T1 = findaccuracy1;
yfit = trainedModel_MediumTree.predictFcn(T1)

RESULTS OBTAINED AFTER FEEDING FIRST DATA SET [20 NON-SEIZURE EEG SIGNALS] INTO TRAINED MEDIUM TREE MODEL:
>> testmodel

yfit =

  20×1 categorical array

     No Seizure
     No Seizure
     No Seizure
     No Seizure
     No Seizure
     No Seizure
     No Seizure
     No Seizure
     Seizure
     No Seizure
     No Seizure
     No Seizure
     Seizure
     Seizure
     No Seizure
     Seizure
     No Seizure
     No Seizure
     No Seizure
```

```
     No Seizure

%Make predictions on a new table, T2.
T2 = findaccuracy2;
yfit = trainedModel_MediumTree.predictFcn(T2)

RESULTS OBTAINED AFTER FEEDING SECOND DATA SET [10 SEIZURE EEG SIGNALS]
INTO TRAINED MEDIUM TREE MODEL:

>> testmodel

yfit =

  10×1 categorical array

     No Seizure
     Seizure
     Seizure
     Seizure
     Seizure
     Seizure
     No Seizure
     No Seizure
     Seizure
     Seizure

%Structure 'trainedModel_SVM' exported from Classification Learner. To
make predictions on a new table, T1.
T1 = findaccuracy1;
yfit = trainedModel_SVM.predictFcn(T1)

RESULTS OBTAINED AFTER FEEDING FIRST DATA SET [20 NON-SEIZURE EEG
SIGNALS] INTO TRAINED LINEAR SVM MODEL:

>> testmodel

yfit =

  20×1 categorical array

     No Seizure
     No Seizure
     No Seizure
     No Seizure
```

```
    No Seizure
    No Seizure
    No Seizure
    No Seizure
    No Seizure
    No Seizure
    No Seizure
    No Seizure
    No Seizure
    Seizure
    Seizure
    No Seizure
    No Seizure
    No Seizure
    No Seizure
    No Seizure
```

```
%Make predictions on a new table, T2.
T2 = findaccuracy2;
yfit = trainedModel_SVM.predictFcn(T2)
```

RESULTS OBTAINED AFTER FEEDING SECOND DATA SET [10 SEIZURE EEG SIGNALS] INTO TRAINED LINEAR SVM MODEL:

```
>> testmodel

yfit =

  10×1 categorical array

     Seizure
     No Seizure
     No Seizure
     No Seizure
     Seizure
     No Seizure
     No Seizure
     Seizure
     Seizure
     No Seizure
```

7. MATLAB Generated Code of the Trained Medium Tree Model

```
function [trainedClassifier, validationAccuracy] =
trainClassifier(trainingData)
```

```
% [trainedClassifier, validationAccuracy] =
trainClassifier(trainingData)
% The function above returns a trained classifier and its accuracy.
This code recreates the classification model trained in Classification
Learner app.
%
%  Input:
%      trainingData: a table containing the same predictor and      %
response columns as imported into the app.
%
%  Output:
%      trainedClassifier: a struct containing the trained
%       classifier.
%      The struct contains various fields with information about the
%      trained classifier.
%
%      trainedClassifier.predictFcn: a function to make predictions
%       on new data.
%      validationAccuracy: a double containing the accuracy in
%       percent.
% To make predictions with the returned 'trainedClassifier' on new
data % T2, use
% yfit = trainedClassifier.predictFcn(T2)
%
% T2 must be a table containing at least the same predictor columns as
%used during training.

% Auto-generated by MATLAB on 01-Apr-2019 00:40:09

% Extract predictors and response
% This code processes the data into the right shape for training the
% model.
inputTable = trainingData;
predictorNames = {'MaxPeak', 'Peak2PeakDistance', 'MeanFrequency',
'BandwidthPower'};
predictors = inputTable(:, predictorNames);
response = inputTable.Class;
isCategoricalPredictor = [false, false, false, false];

% Train a classifier
% This code specifies all the classifier options and trains the
classifier.
classificationTree = fitctree(...
    predictors, ...
    response, ...
    'SplitCriterion', 'gdi', ...
    'MaxNumSplits', 100, ...
    'Surrogate', 'off', ...
    'ClassNames', categorical({'No Seizure'; 'Seizure'}));

% Create the result struct with predict function
predictorExtractionFcn = @(t) t(:, predictorNames);
```

```
treePredictFcn = @(x) predict(classificationTree, x);
trainedClassifier.predictFcn = @(x)
treePredictFcn(predictorExtractionFcn(x));

% Add additional fields to the result struct
trainedClassifier.RequiredVariables = {'BandwidthPower', 'MaxPeak',
'MeanFrequency', 'Peak2PeakDistance'};
trainedClassifier.ClassificationTree = classificationTree;
trainedClassifier.About = 'This struct is a trained model exported
from Classification Learner R2019a.';
trainedClassifier.HowToPredict = sprintf('To make predictions on a new
table, T, use: \n  yfit = c.predictFcn(T) \nreplacing ''c'' with the
name of the variable that is this struct, e.g. ''trainedModel''. \n
\nThe table, T, must contain the variables returned by: \n
c.RequiredVariables \nVariable formats (e.g. matrix/vector, datatype)
must match the original training data. \nAdditional variables are
ignored. \n \nFor more information, see <a
href="matlab:helpview(fullfile(docroot, ''stats'', ''stats.map''),
''appclassification_exportmodeltoworkspace'')">How to predict using an
exported model</a>.');

% Extract predictors and response
% This code processes the data into the right shape for training the
% model.
inputTable = trainingData;
predictorNames = {'MaxPeak', 'Peak2PeakDistance', 'MeanFrequency',
'BandwidthPower'};
predictors = inputTable(:, predictorNames);
response = inputTable.Class;
isCategoricalPredictor = [false, false, false, false];

% Perform cross-validation
partitionedModel = crossval(trainedClassifier.ClassificationTree,
'KFold', 5);

% Compute validation predictions
[validationPredictions, validationScores] =
kfoldPredict(partitionedModel);

% Compute validation accuracy
validationAccuracy = 1 - kfoldLoss(partitionedModel, 'LossFun',
'ClassifError');
```