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**Electronics, Communications and Computer Engineering Department**

**Computer and Software Engineering Section**

## Project Name

# AI-based assistance System for the Epilepsy Patient

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# Executive Summary

**Epilepsy can affect any age group from young children to seniors about 25% of persons with epilepsy have generalized tonic-clonic seizures, So available solutions capable of detecting, tacking, and reporting seizures require either subscription services, prescriptions, or both, so Our proposed solution, implements an advanced and wearable seizure detection capability using unconventional smartwatch technology capable of automatically detecting epileptic seizures using measures of heart rate, movement and other parameters, and tracking and recording all information about seizure events, such as in addition to a detection algorithm to match the characteristics of the bracelet. Wrist with headband for precise action**

**In this report, we explore the feasibility of using this approach and report on our findings and early experiments in recording and classifying signal values and graphs in each sensor and their use in how this seizure is detected on the wristband and also how EEG signals are used as an important parameter in detecting the seizure that the patient is exposed and this is about the Headband.**

# AI-based assistance System for Epilepsy Patient

## Abstract

**Living normally is the least right for all people. so, everyone is looking for a private independent life without anyone's help.**

The main problem **we are solving is epilepsy as it is the 4th most common neurological disease in the world. More than 50 million people are living with epilepsy globally and 75% do not receive retreatment. Undetected seizures can result in injury or even death it also has 3-6 times risk of premature death.**

### The importance of this problem

**Epilepsy patients do not feel relevant with living their lives in the society, as they always need a companion or someone to help them if the seizure ever raided them, which make them feel that they are up normal people. So, our idea is to create device that enables relatives, family, or doctors to know whenever the seizure occurred. The problem of recording the number of seizures that occur to the patient daily, weekly, and annually is one of the most important details. These details which doctors use in charge of the case of a patient with epilepsy. Because its importance lies in identifying the doctor and distinguishing him for the patient's condition, either a serious or not dangerous condition, and accordingly the doctor determines the appropriate medicine for the patient.**

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# Chapter 1
# Introduction

## 1.1. Project Description

### 1.1.1. Problem statement

- **EPI helps the epilepsy patients to make their life more comfortable.**
- **EPI monitors a patient's heart rate, temperature, neurological activity, vibration motion and other physiological data. It will recognize the patient is having a seizure within 10-15 seconds of a fit starting, automatically contacting the patient's caregivers, which are registered on the patient's account on the EPI.**
- **EPI will provide info to caregivers like the severity of the seizure which is measured by the seizure length, and the patient's location exactly. The alarms can be sent via phone call or SMS.**
- **we cannot notice the changes in the parameters mentioned previously except in tonic-clonic, clonic, and atonic seizures as their symptoms is muscles stiffen, jerking movements and absence.**
- **The most important parameters that help in defining the seizure are pressure level and heart rate.**
- **in case if the patient is practicing any activity that has an approximate symptom to the seizure's we made a question in the device that could be vocal or written that asks the patient if he is facing a seizure or not it lasts for around 3-5 seconds, in case of not replying by no from the patient, the device starts to send alarms to doctor and relatives...etc.**

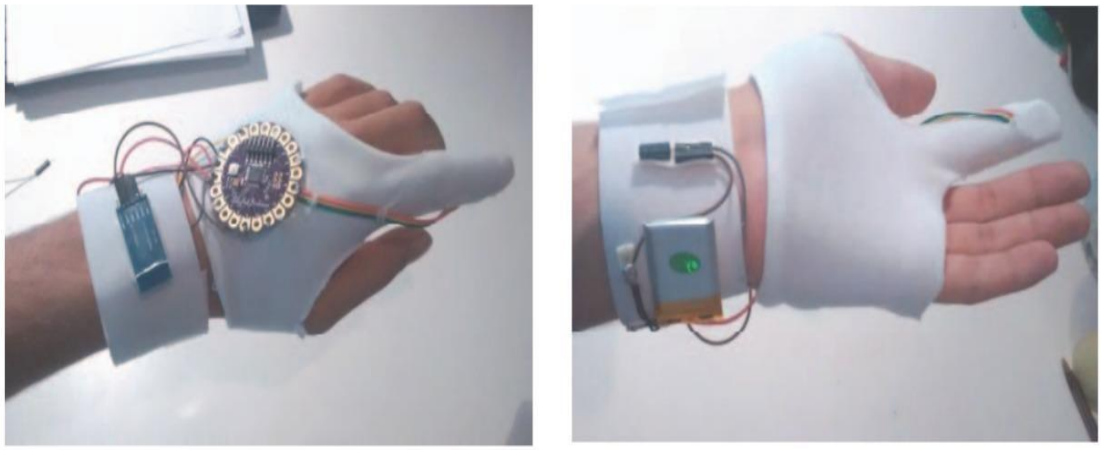


**Figure1. wristband**

## 1.1.2. Project scope and expected outcome

a. **a. This project includes making a prototype of a wristband that can be worn on the wrist that measures some of the signals that result from the physical change in the patient's body during an epileptic seizure and detects the epileptic seizure without the need for brain signals.**

b. **This project also includes a prototype for a hi-band that can be worn on the head, as it continuously measures brain signals and sends them to the server via the mobile phone to detect the presence of an epileptic seizure or not.**

c. **It also includes the development of an Android-OS application that the user can use to show some biological measurements such as heart rate, oxygen content in the blood, and electrical conductivity of the skin, as well as identifying epileptic seizures or not.**

d. **It also includes a machine learning device that takes brain signals and determines if there is epilepsy or not.**

If an epileptic fit comes out of the wristband and from the model as well, then we can confirm that the patient is suffering from an epileptic seizure. Then the mobile will send a warning message to the relatives that the patient has an epileptic seizure.

## 1.2. Project Plan

Due to the risky nature of our project we have followed waterfall model with a feedback loop from the testing phase back to the system design, changing the Design and different system unit's implementation depending on the results in the testing phase and its analysis.

we have followed V-shape development cycle so as to assure that every module in the project is working and testable and able to be modified easily

Milestone 1

At first, we contacted physiological doctors to help us understanding the nature of the epilepsy. Then to understand the nature of the signals that we use like EEG and EDA to help us for using it in our system.

We started to understand previous works which we mentioned earlier. Then we collected datasets for the parameters to help the ML model to get more accurate results.

Milestone 2

After defining the system requirements, we have designed an abstracted architecture for the system and the different phases of the project.

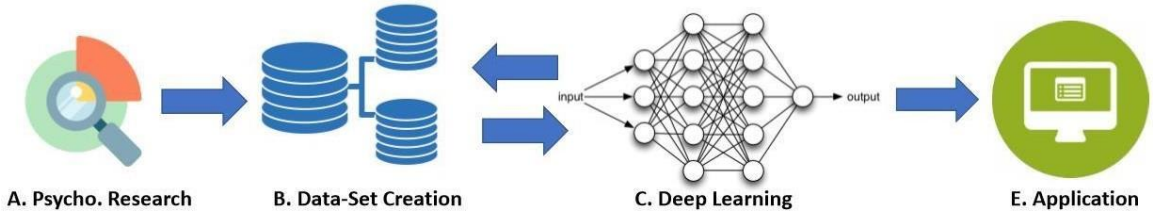



*Figure 1. Project Processes Overview*

**Then we designed each process in details answering those three main questions**

- **What is the input of this process?**
- **What is the output of this process?**
- **What should this process include?**

**After defining the main processes with its input and output each member in the team was assigned to a process designing it in details and then document what is designed in clear organized way for other team members to understand and review.**

Milestone 3

**This stage is an iteration loop between different units' implementation, testing and then analysis of the results to understand what should be changed in the system design and implementation to meet the main requirements of the system. Finally, we integrate the hardware with the software and show the result.**

Milestone 4

**After integrating the system, we are going to test it in the reality. Patients will use it and doctors will follow with. We will compare our results with doctors to make sure that we do not need any changes again. If we noticed that we need to change anything then change it and return to doctors. And with this we have finished the development process.**

# 1.3. Gantt chart

EPI - 30 Dec 2020

| | Task Name | Planned Duration | Planned Start Date | Planned Finish Date |
|---|---|---|---|---|
| 1 | phase 1 | 23 days | 01/12/2020 | 31/12/2020 |
| 2 | Researching and paper resources | 9 days | 01/12/2020 | 11/12/2020 |
| 3 | EEG and EDA Signal study | 6 days | 08/12/2020 | 15/12/2020 |
| 4 | Human Speech Doctors | 6 days | 09/12/2020 | 16/12/2020 |
| 5 | Machine Learning Consultation | 13 days | 14/12/2020 | 30/12/2020 |
| 6 | Signal Analysis Consultation | 9 days | 21/12/2020 | 31/12/2020 |
| 7 | phase 2 | 24 days | 30/12/2020 | 01/02/2021 |
| 8 | Problem defination and features | 7 days | 01/01/2021 | 11/01/2021 |
| 9 | Overview Main Phases | 9 days | 04/01/2021 | 14/01/2021 |
| 10 | Resource Planning | 9 days | 30/12/2020 | 11/01/2021 |
| 11 | Hardware Requirments | 14 days | 04/01/2021 | 22/01/2021 |
| 12 | Software Requirments | 16 days | 11/01/2021 | 01/02/2021 |
| 13 | phase 3 | 44 days | 01/02/2021 | 01/04/2021 |
| 14 | Signal Acquiring System Design | 14 days | 27/01/2021 | 15/02/2021 |
| 15 | Feature Extraction Design | 37 days | 18/01/2021 | 09/03/2021 |
| 16 | Classification Model Design | 30 days | 18/02/2021 | 01/04/2021 |
| 17 | Feature Extraction Design | 26 days | 29/01/2021 | 05/03/2021 |
| 18 | Dataset Creation | 33 days | 10/03/2021 | 23/04/2021 |
| 19 | Phase 4 | 73 days | 01/04/2021 | 12/07/2021 |
| 20 | Feedback Loop to System Design | 36 days | 03/05/2021 | 21/06/2021 |
| 21 | Backend Server for Application | 15 days | 26/04/2021 | 14/05/2021 |
| 22 | Android Developing | 6 days | 17/05/2021 | 24/05/2021 |
| 23 | Headband Interfacing | 11 days | 24/05/2021 | 07/06/2021 |
| 24 | System Testing | 30 days | 01/06/2021 | 12/07/2021 |

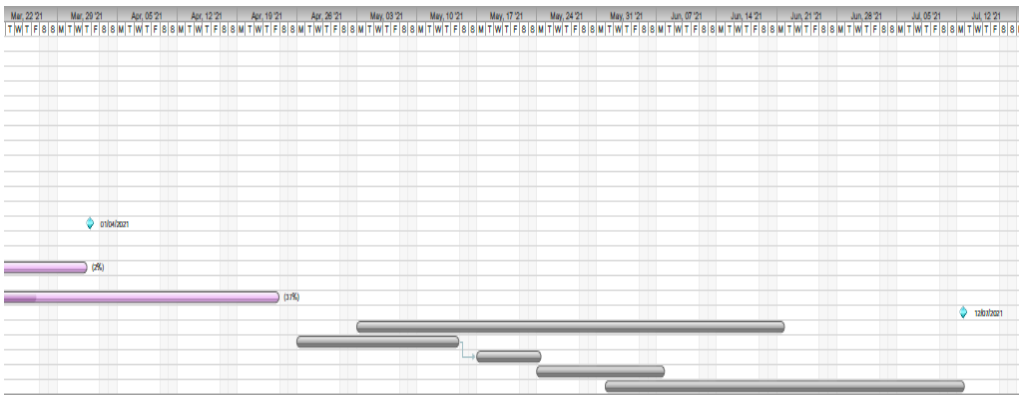
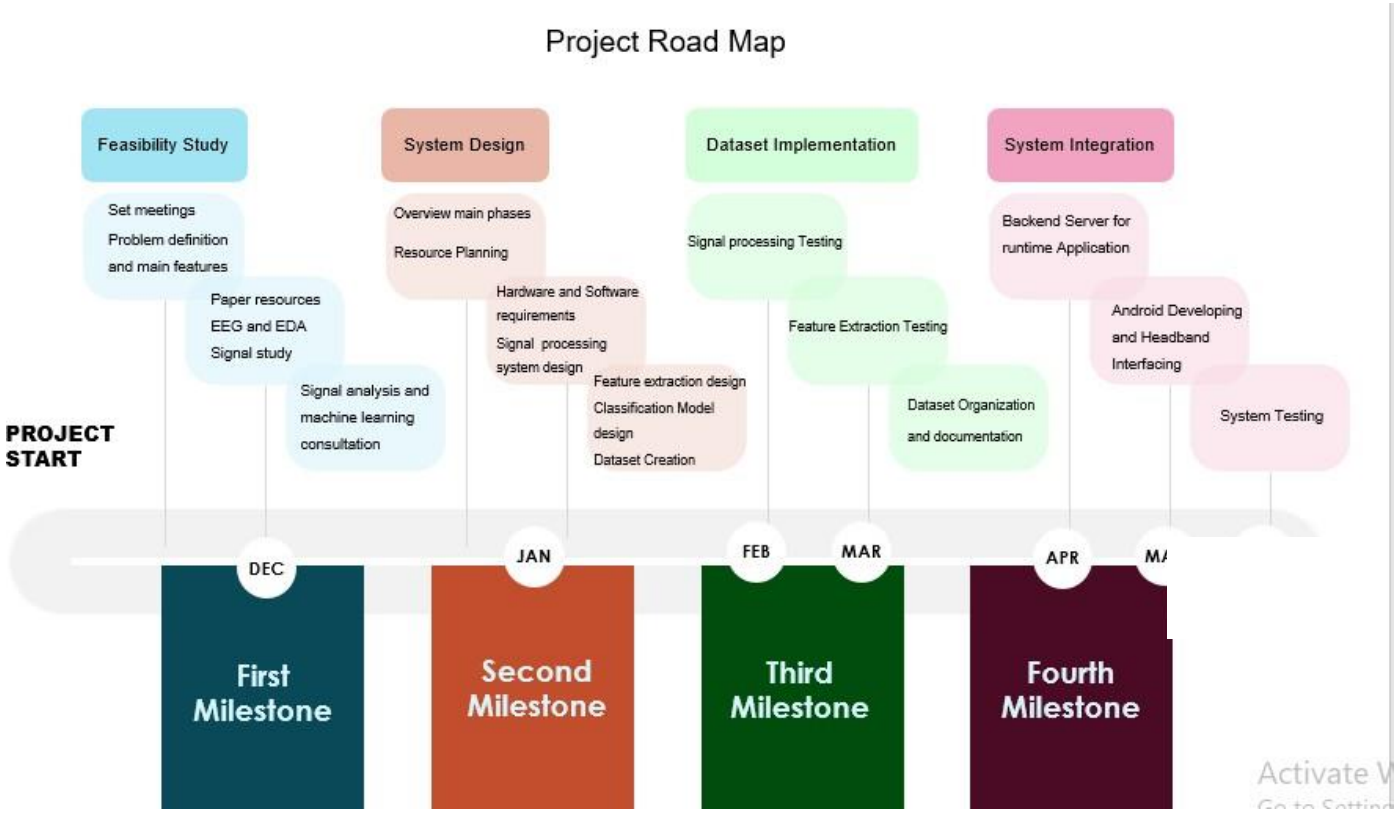


**Table.1 Gantt chart**

## Time schedule of our project




# 1.3.1. Risk mitigation and plan resource

## Risk mitigation

1- At the phase of dataset collection, we might get some challenges like lake of data
2- So, we go to dataset collection if we need but may have some problems like losing it for bad connections
3- The hardware delivery phase has more challenges right now because of COVID-19 so it may be late or declined
4- Components integration with each other is the hardest part of any project so we may have some challenges also
5- Finally, at result validation phase we might have results which is different from what we should have so it's a risky phase also.

## Resource Plan

1- We got our researches from journals and institutions like:
   1- IEEE
   2- NCBI
   3- MIT
   4- MDPI electronics
   5- ELSEVIER
   6- Nature
   7- Springer
   8- Epilepsia
2- We asked physiological doctors from different hospitals and clinics like:
   1- El-Demerdash (University hospital).
   2- El-Qasr El-Einy (University hospital).
   3- Other private clinics.
3- We will get our hardware component from local and global if we needed like amazon

# 1.4. Book organization

A. During this report, we will discuss different aspects of the proposed solution including

B. Literature review: During this part, we will make a survey on the theoretical backgrounds including the Physiological Background, Feature Extraction Background, Machine learning, etc. The recent related researches to the proposed point.

C. EEG and the physical quantities available to measure to detect seizures: This part includes a description of the system.

D. System architecture and system flow diagram.

E. System Integration: This chapter concerns system Implementation, system testing and Data set creations.

F. Results and discussion. G. Conclusion and future work.

# Chapter 2
# Literature Review

## 2.1. Introduction and Background Review

**In this section, we're about to discuss the Epileptic seizure background, EEG signal background, Heart rate and Spo2 background, EDA background and current solutions of our problem.**

## 2.1.1. Epilepsy Background

**In this section the background of Seizures, causes and types of seizures.**

### 2.1.1.1. Definition of Epilepsy

**Epilepsy is a disorder of the brain characterized by repeated seizures. A seizure is usually defined as a sudden alteration of behavior due to a temporary change in the electrical functioning of the brain. Normally, the brain continuously generates tiny electrical impulses in an orderly pattern. These impulses travel along neurons — the network of nerve cells in the brain — and throughout the whole body via chemi messengers called neurotransmitters.**

**Fig.2 seizure in a brain**

**In epilepsy, the brain's electrical rhythms have a tendency to become imbalanced, resulting in recurrent seizures. In patients with seizures, the normal electrical pattern is**

disrupted by sudden and synchronized bursts of electrical energy that may briefly affect their consciousness, movements or sensations.

Epilepsy is usually diagnosed after a person has had at least two seizures that were not caused by some known medical condition, such as alcohol withdrawal or extremely low blood sugar.

If seizures arise from a specific area of the brain, then the initial symptoms of the seizure often reflect the functions of that area. The right half of the brain controls the left side of the body, and the left half of the brain controls the right side of the body. For example, if a seizure starts from the right side of the brain in the area that controls movement in the thumb, then the seizure may begin with jerking of the left thumb or hand.

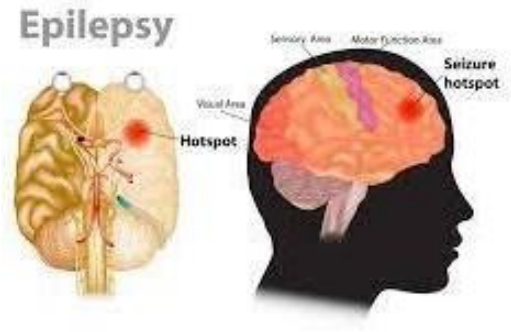



Fig.3 seizure hotspot

### 2.1.1.2. Seizure Types:

- Focal (partial) seizures
- Generalized seizures
- Status-Epilepticus
- Diagnosis often confused for epilepsy: Non-epileptic seizures

### Focal (partial) seizures:

Focal seizures occur when nerve cells in a part of the brain are involved. The way the child acts during a focal seizure depends on the area of the brain that is affected. The

right side of the brain controls the left side of the body. Therefore, a seizure involving the right side of the brain will affect the left side of the body. A seizure involving the left side of the brain will affect the right side of the body.

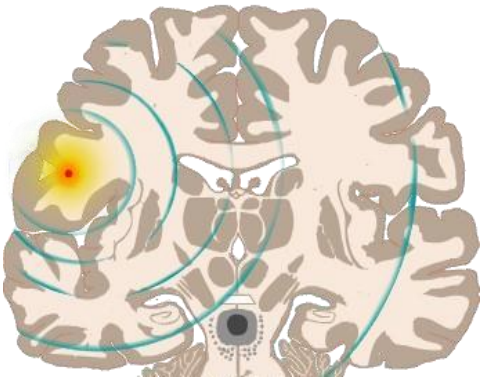


Fig.4 seizure partial

During a focal seizure, sometimes a child knows what is happening and is somewhat aware of his or her surroundings. He may be able to describe what happened. This type of focal seizure may be referred to as a simple partial seizure.

Sometimes during a focal seizure, a child does not know what is happening and is not aware of his surroundings. This type of focal seizure may be referred to as a complex partial seizure.

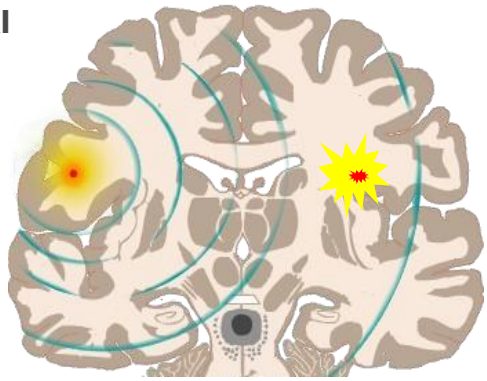


Fig.5 seizure 2 hotspots

## Generalized seizures:

**Epileptic activity affects both hemispheres of the brain from onset of seizure**

**Types of generalized Seizures:**

- Tonic-Clonic seizure
- Tonic
- Clonic
- Myoclonic seizure
- Absence seizure
- Atonic

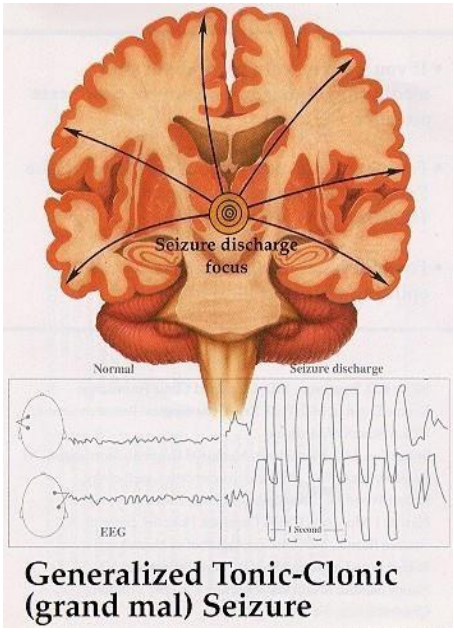



Fig.6 Generalized Tonic-Clonic

## Tonic-Clonic Seizures

**Consciousness is lost, no recollection Body stiffens, may fall, scream Arm and leg jerking**

**Frothing at the mouth Incontinence Bitten tongue**

**May occur in sleep or upon awakening**

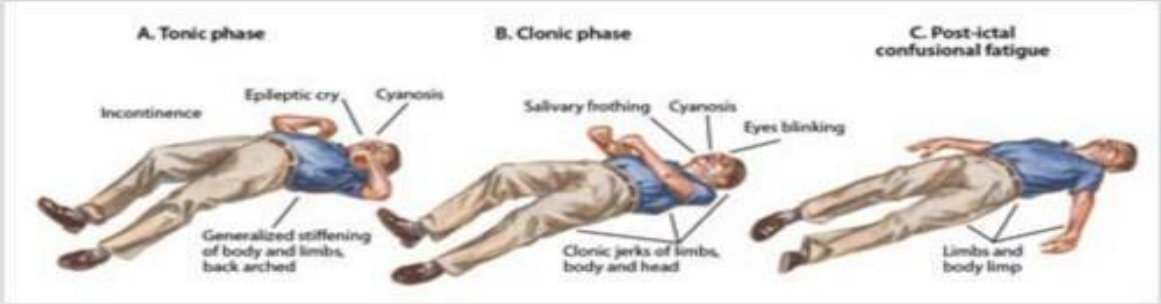



**Fig.7 status of the patient during**

### Tonic

- **muscles stiffen.**
- **Consciousness lost.**
- **affects whole or part of body.**
- **can last 10-20 seconds.**

### Clonic

- **consist of rhythmic jerking.**
- **various ages.**

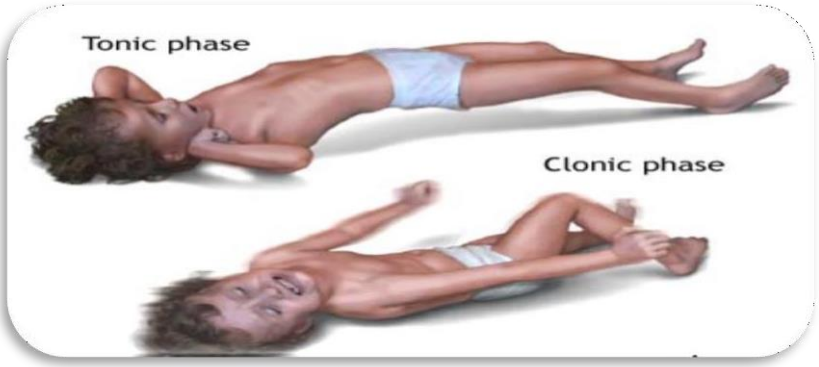



**Fig.8 comparison between the two seizures**

## Myoclonic seizure

- **Abnormal movements of arms/shoulder both sides, sometimes entire body.**
- **May fall and injure themselves Sometimes triggered by flashing lights.**
- *For example: Juvenile Myoclonic Epilepsy.*

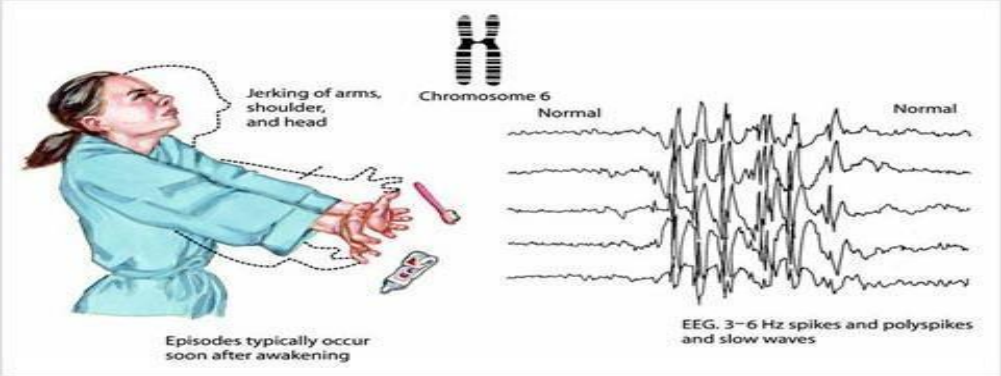



**Fig.9** *Myoclonic Epilepsy*

## Absence Seizures

- **Short interruption of consciousness with staring.**
- **Brief 5-12 seconds.**
- **So brief, may escape detection.**
- **More common in children than adults.**
- **No warning or after-effect.**

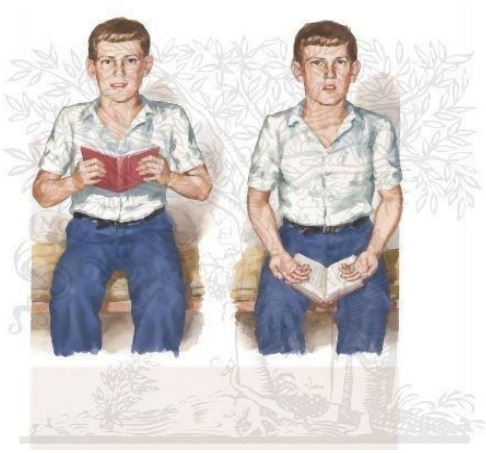


**Fig.10** *Absence seizure*

## Atonic Seizures

- **Atonic means "without tone".**
- **Head nods, neck muscles suddenly lose tension, fall.**
- **Can injure themselves when they fall, helmet for protection.**

- **Often begin in childhood and last into adulthood.**

## Status-Epilepticus

- **One seizure quickly follows another**
- **Any seizure can develop into status epilepticus (tonic-clonic status, absence status, complex partial status)**
- **Tonic-clonic convulsive status is a medical emergency**
- **Tonic-clonic seizures longer than 5 minutes or happens again after a short break, call an ambulance.**

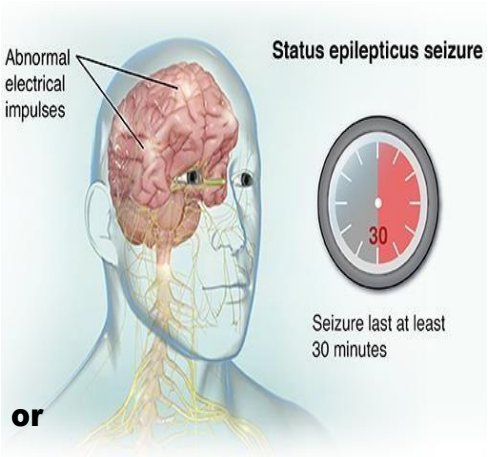



**Fig.11 Status-Epilepticus**

## Non-Epileptic Seizures (NES)

- **People with nonepileptic seizures (NES) have periods of seizure-like activity. NES are characterized by a loss of or change in physical function without a central nervous system problem. The loss or change causes periods of physical activity or inactivity that resemble epileptic seizures. A person can have both nonepileptic and epileptic seizures.**
- **NES are usually related to a mental health problem, like an emotional conflict or stress. But, sometimes NES are related to a problem like low blood sugar or the way the heart is working. One example of NES is psychogenic seizures, sometimes called pseudo seizures.**
- **NES symptoms usually appear suddenly and at times of extreme emotional stress. Some doctors believe that the symptoms of NES may be an attempt to reduce anxiety by not recognizing or responding to an emotional conflict.**

- **People with NES have periods of loss of or change in physical activity that resemble epileptic seizures or the aura of a seizure, such as:**
- **Impaired or jerky movements, Disturbances in coordination, Temporary blindness, Tunnel vision, Loss of the sense of smell or touch and Tingling sensation to the skin.**

## What To Do If Someone Has A *Non -Convulsive Seizure ?*

1. **Stay with the person. Let the seizure take its course. Speak calmly and explain to others what is happening.**
2. **If the patient is standing or sitting when seizure begins, ease him or her to the floor to prevent fall.**
3. **Move dangerous objects out of the way.**
4. **Don't restrain the patient.**
5. **Gently guide the person away from danger or block access to hazards.**
6. **After the seizure, talk reassuringly to the person.**

## Some statistics for the number of epilepsy patients

**According to the World Health Organization, the proportion of patients with epilepsy in the world:**

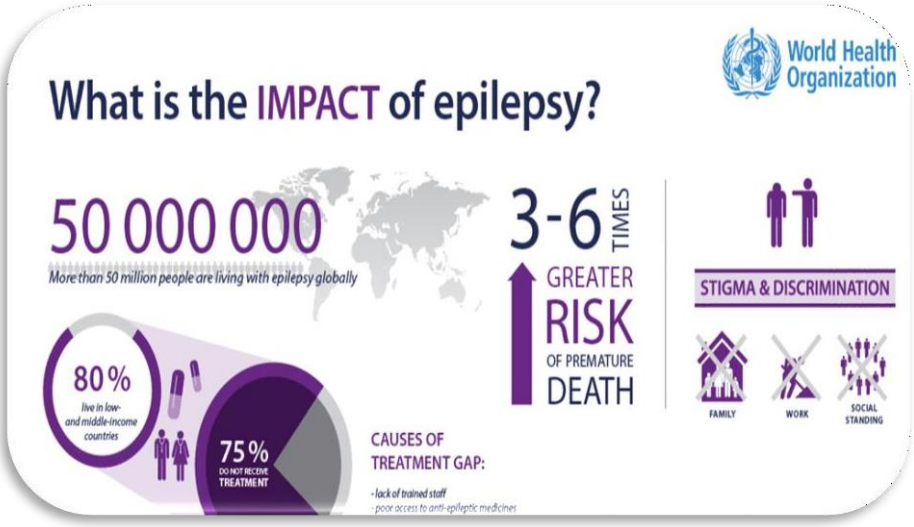
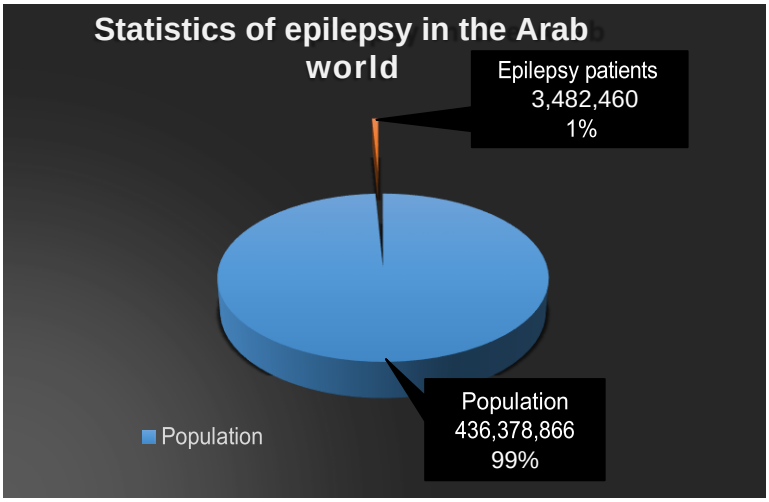



Table.2 **The number of epilepsy patients**

**The number of epilepsy patients in the Arab world is 3,482,460 patients.**



## 2.1.2. EEG Background

**An EEG is a test that detects abnormalities in your brain waves, or in the electrical activity of your brain. During the procedure, electrodes consisting of small metal discs with thin wires are pasted onto your scalp. The electrodes detect tiny electrical charges that result from the activity of your brain cells. The charges are amplified and appear as a graph on a computer screen, or as a recording that may be printed out on paper. Your healthcare provider then interprets the reading. During an EEG, your healthcare provider typically evaluates about 100 pages, or computer screens, of activity. He or she pays special attention to the basic waveform, but also examines brief bursts of energy and responses to stimuli, such as flashing lights.**

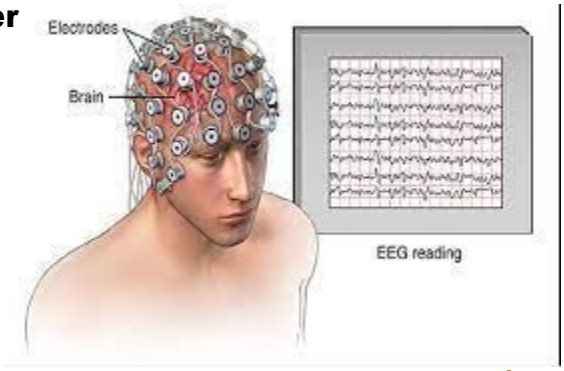



**Fig.12 EEG signals**

**Evoked potential studies are related procedures that also may be done. These studies measure electrical activity in your brain in response to stimulation of sight, sound, or t**ouch.

**EEG is a test that helps us detect anomalies in your brain waves, or in the electrical activity of your brain. Electrodes made from small metal discs with thin wires are attached to your scalp during the procedure. El**

**ectrodes show us the small electrical charges caused by brain cell activity. The graphics are improved, and they appear on the computer screen as a graph as shown in figure [3.9] EEG is one of the most important major diagnostic tests that**

**reveal brain disorders. Below we review the properties of the resulting waves EEG.**

**As shown in figure [3.10] the brain waves graph**

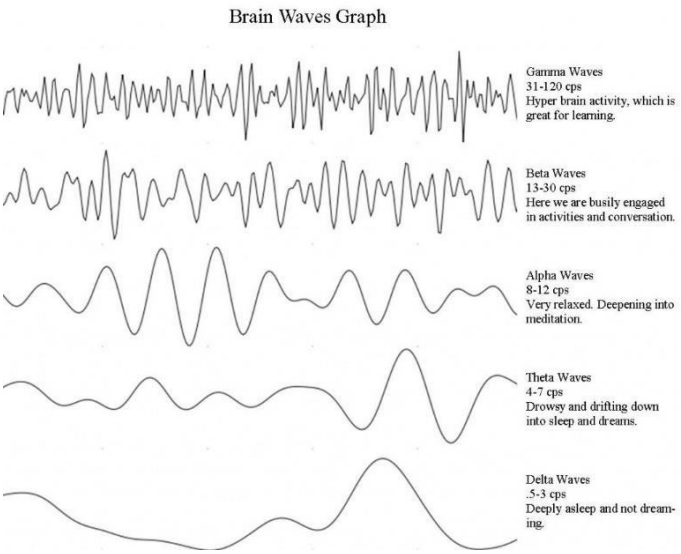



Figure 12 the properties of the resulting waves EEG

**Increased activity results in EEG to a higher frequency and lower capacity as shown in figure [22] called gamma waves. When person falls asleep the dominant EEG frequency will decrease in this case called alpha waves, Because the person asleep dreams and during the dream his eye moves. In deep sleep, A signal called delta waves. With this measurement, it is possible to know the efficiency of brain signals.**

## EEG TEST

**There are three different tests to do EMG test**

### 1. The EEG Regular Test

**As shown in figures [3.11,12] The nurse or technician in charge uses a washable conductive paste of about 16-**

**Fig.13 testing EEG**

20 electrodes on the patient's scalp. Those electrodes are not painful. these electrodes are painless made to measure electrical activity in different parts of the brain. The patient should relax for the duration of the test. Which takes less than an hour. Optical stimuli can be used to stimulate the brain for a specific activity. During the procedure, the EEG machine records the patient's brain activity in the form of a graphical record,

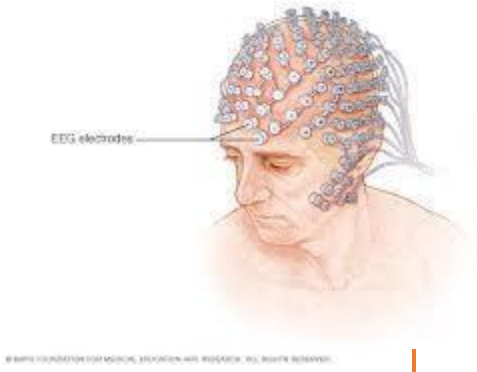



Fig.13 testing EEG

on a strip of recording paper or shown on a computer screen. This graph is called the EEG.

### 2. The EEG sleeping Test.

In this test the equipment and procedures used are also used in normal EEG.

This test takes lasts up to three hours. It may give patients a sedative to induce sleep

### 3. The EEG Monitoring Test.

In this test, patients are connected to a portable recorder. They are required to perform their normal daily activities and to take a period of normal sleep for up to 24-72 hours. The patient's family is required during this period to record any strange behavior that occurs to the patient.

EMG test It is used in the diagnosis and treatment of epilepsy, encephalitis, tumors, stroke, Parkinson's and also Alzheimer's.

## 2.1.3. Heart rate and Spo2 Background

**Pulse oximetry is a noninvasive and painless test that measures your heart rate oxygen saturation level, or the oxygen levels in your blood. It can rapidly detect even small changes in how efficiently oxygen is being carried to the extremities furthest from the heart, including the legs and the arms'.**

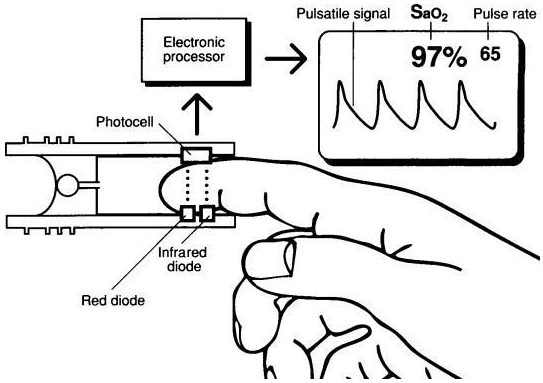


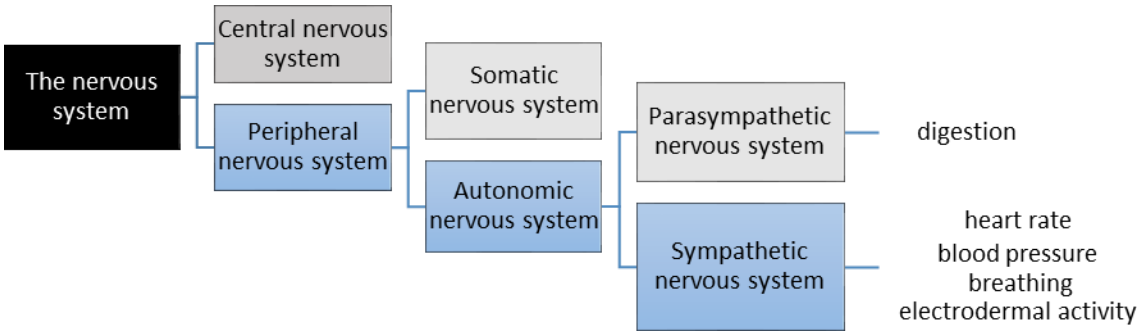

**Fig.14 EDA measuring**

**The pulse oximeter is a small, clip-like device that attaches to a body part, like toes or an earlobe. It's most commonly put on a finger, and it's often used in a critical care setting like emergency rooms or hospitals. Some doctors, such as pulmonologists, may use it in office.**

## 2.1.4. EDA Background

**Electrodermal activity (EDA) is an electrical property of the human skin dependent on changes in the sympathetic part of a human autonomic nervous system. EDA varies as a result of changes in human psychological state. Nowadays it is used at an increasing rate, because the industry and research institutions are interested in acquiring an objective information about the human emotional state or perception of products, services and tasks. The main reason for the growing EDA popularity is the relatively low cost of the measuring instruments, simplicity of their manufacturing and use combined with relatively fast response time. The paper is a collection of the most important issues regarding EDA monitoring (i.e. electrodes, their placement, acquisition devices and signal analysis) a**

**researcher has to take into account to perform a reliable, accurate and robust electrodermal activity measurement. EDA can be monitored in a controlled laboratory environment or in an environment outside the lab setting. In stable laboratory conditions, humans perform their tasks in a static, usually sedentary position (e.g. sitting at a computer) under controlled environmental conditions (e.g. air humidity and temperature, vibration, acoustic noise, room lightning) resulting in smaller extraneous disturbances, errors due to the used measuring instruments, less unwanted moving artefacts and more focused and involved humans. EDA monitoring in real-life conditions outside a laboratory provides a more natural and more ecologically valid setting for humans. On the other hand, the measuring errors due to the EDA device malfunctioning, fluctuations in environmental conditions, moving artefacts, dynamic instrumentation errors increase significantly**




**EDA is part of the sympathetic nervous system.**

## MEASURING INSTRUMENTS FOR EDA MONITORING

**In principle, there are two types of the EDA measurements - the endosomatic and the exosmotic. The exosmotic type applies an external electric current to the skin and the endosomatic type applies no external current. There are three main measuring methods used:**

i) endosomatic method, ii) AC exosmotic method (applying an AC current) and iii) DC exosmotic method (applying a DC current via electrodes). The exosmotic measurement applying a DC current is the most widely used EDA method nowadays.

### DC exosomatic measuring instruments

The core of any DC exosomatic measuring instrument is a differential amplifier used to amplify the difference between two input signals from the two EDA electrodes. The use of a differential amplifier is preferred over the use of operation amplifier because of the removed endosomatic contamination of the exosomatic measurement.

The sampling frequency should be of the order of 10 Hz and above, but this strongly depends on the application and signal processing a researcher wants to perform. If the phasic skin conductance (SCR) and other fast changing events in EDA are needed, the sampling rate should be at least 200 Hz, 1 kHz being the most common value with laboratory measuring systems.

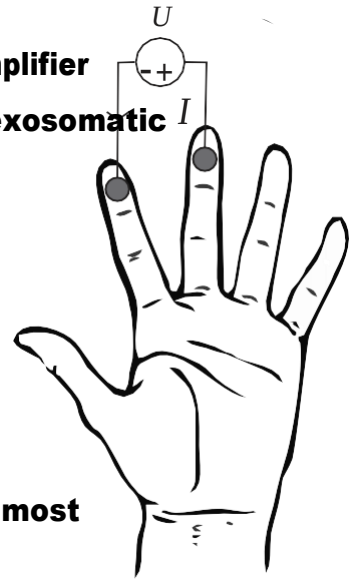



Fig.15 EDA measuring

Wearable and especially wireless streaming systems usually have a lower acquisition rate (up to a couple of tens of Hz).

## 2.2. Current solutions of our problem

### The current solutions of this problem

Through the many researches that we have found and read closely and sorted to get the latest research that has recently emerged in which some engineering assistive technology has emerged for epilepsy patients, including:

## 1- Embrace

**A general image of the definition of embrace first is Empatica's main goal is to make recognizing, responding to, and addressing epileptic seizures easier. As it monitors your nervous system, the device has an alert platform set up to address abnormal readings.**

**Fig.16 Embrace**

**-A lot of wearables monitor sleep and physical activity, but the Embrace Watch uses physiological data to track convulsive seizures. The device features a plethora of sensors — an accelerometer, a gyroscope, an electrodermal activity sensor — that all work together to give the user more insight into their epilepsy. Users receive feedback on their habits and behavior through the app, which helps them find patterns and better understand their day.**

## 2-Earpiece

**An overview of the definition of Earpiece first is a device is placed in the ear canal, we can collect very good measurement data. Basically, we use standard processes, which have been miniaturized and optimized for the applications, so that the power consumption is significantly lower as well. The standard parameters include heart rate, body core temperature, oxygen saturation in the blood (SPO2) and respiratory rate. These are the basic parameters, from which further parameters such as stress level or fatigue level can be derived. All these parameters are based on heart rate variability (HRV). Other variables are then included in the medical set-up to use it as an early warning score system.**

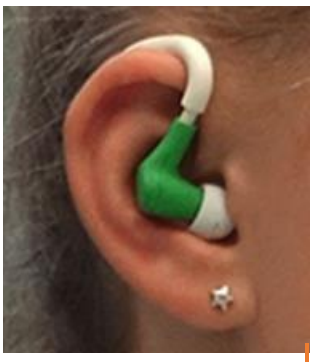


**Fig.17 Earpiece**

### 3- bracelet

**A general image of the identification of bracelet first is that Consortium researchers have therefore developed a bracelet that recognizes two essential characteristics of severe attacks: an abnormally fast heartbeat, and rhythmic jolting movements. In such cases, the bracelet will send a wireless alert to carvers ornurses.**

**Fig.18 Bracelet**

# Chapter 3
# Proposed Solution

## 3.1 Our solution for this problem

- **Based on the previous biographies we have presented; we have reached the best results which is the work of the entire system component. The system consists of smartwatch similar to embrace and basic simulate for EEG signal and through dataset that we collected from the physical parameters and EEG signals. We estimated the threshold of parameters and change in EEG signal which gives us the best changes at the time of the seizure and on which we distinguish whether it is a seizure or not.**

- **Our system will dispense with EEG signal later and rely entirely on physical parameters after we make sure that the best and least error result is achieved. We will do that in order to enable the patient to exercise his life freely and without restrictions. Only by wearing the smartwatch will we receive a detailed report on the patient's condition and his seizure.**

- **Our system monitors a physical parameter like heart rate, spo2, accelerometer, a gyroscope, electrodermal activity.**

- It cannot notice the changes in the parameters mentioned previously except in tonic-clonic, clonic, and atonic seizures as their symptoms is muscles stiffen, jerking movements and absence.

- It will recognize the patient is having a seizure within 15-30 seconds of a fit starting, automatically contacting the patient's caregivers, which are registered on the patient's account on the EPI.

- If the patient is practicing any activity that has an approximate symptom to the seizure's, we made a question in the device that could be vocal or written. The device asks the patient if he is facing a seizure or not it lasts for around 5-10 seconds, in case of not replying by no from the patient, the device starts to send alarms to doctor and relatives.
- Using voice-over to help patient's neighbors helping him following dedicated instructions,

- It will provide information to caregivers like the severity of the seizure which is measured by the seizure length, and the patient's location exactly. The alarms can be sent via phone call or SMS.

- All important information has been recorded to help patient's doctor and family.
- With all previous steps, we guarantee that the patient will still safe.
- We will use Artificial Intelligence and machine learning to teach our system to understand the dataset that we have introduced. Then we will give it the possibility to do the profession of the doctor in determining the changes that occur on the EEG signal. Also, it makes threshold for physical parameters so that if the parameters measured exceed the value of threshold this indicates the occurrence of a seizure.

## The expected impact of our solution from various perspectives

### Socially:

- We will make epilepsy patients feel more relevant and save in their lives as they will move freely without constrains of having a companion all the time.

- It makes easier for people with epilepsy to detect seizures and let others know when they need help, especially for kids whenever they are away from their parents (in school- sleeping ...etc).

- This project guarantee safety to epilepsy patients from risks of being alone or not getting immediate help if no one is around which could lead to deteriorating level of patient or even death.

**Medically**:

- Provides end-users with the ability to track activities, detect, and record seizures using a seizure profile specially made for them.

- It will help them more in following up the patient and make changes on the medications if there is a need for that, so it helps in decreasing number of seizures that can happen to patients.

**Environmentally:**

- save to wear all the day in all environments.

- practical to use as it only needs a mobile phone to work.

**Commercially:**

As we went to many hospitals and talked with epilepsy patients. They said it was a good idea and most of doctors and patients here in Egypt have never heard of devices like those. So, we think it will help many of patients as it would be an essential part of their lives.

**Patient can use our product by**

- EEG headband –wrest band will be attached on the patient's head and wrest prospectively as they will work simultaneously.

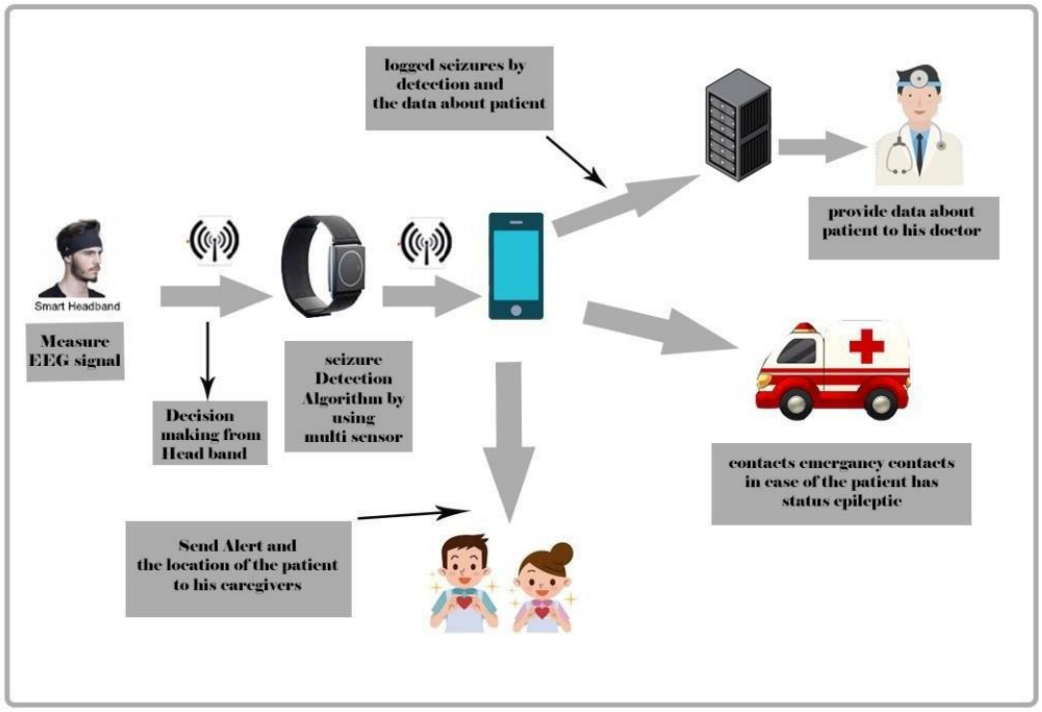
- **Both will be connected via Bluetooth to mobile application.**

- **A few seconds before the seizure occurs, EEG signal form (pre-ictal) is changed (up normal).**

- **During seizure (inter-ictal), frequency and amplitude of EEG signal change.**

- **Physically: heart rate is highly increased and sometimes a Muscle- - Spasms occur (specially in tonic clonic seizure), spo2 increases in a remarkable way and temperature increase.**

- **Headband will measure EEG signal, and by practicing signal processing on this signal using a machine learning model, the output of this model will decide if this is seizure or not.**
- **The same with the physical parameters (heart rate-temperature-electrodermal activity -accelerometer and gyroscope -spo2).**
- **Also with the help of the dataset for epilepsy patients used in machine learning model which contains all these parameters, the model will decide if it is a seizure or not.**
- **Both of the EEG headband and wrest-band will send the output of models via Bluetooth to the mobile application which in turn will alert the relatives, doctors ...etc if there is a seizure and send the exact location of the patient.x**




Major Functional Component Diagram

**Fig.19 Whole System**

## 3.2 Hardware of each part of the system

### 3.2.1 Smart wristband

#### Technical description of Smart Wristband

**wearable seizure detection is able to:**

- **Wireless wearable multi sensor that depend on heart rate, Electrodermal Activity(EDA) and motion metrics,**
- **Detect seizures using an algorithm which matches individual patient seizure characteristics,**

- **Record and transmit all information surrounding seizure events to the application mobile that send it to caregivers and the emergency and send to server that can the doctor show this information.**

### Hardware of Smart wristband

**Due to the significant change in our parameters during the occurrence of the seizure**
**such as a change in heart rate, SPO2, EDA, acclimator and gyroscope.**
**For example, the heart rate increases by 30% and SPO2 decreases significantly,**
**so, we used sensors to help us measure these parameters.**

- **We used MPU6050 sensor to measure acclimator and gyroscope**
- **We used the MAX301 sensor to measure heart rate and SPO2**
- **We used the GSR sensor to measure the EDA**
- **We connected all the sensors to the esp32 microcontroller that would take sensor readings and output a message indicating whether a seizure occurred or not.**

**The components that are used in the circuit of wristband:**

**-MPU6050 sensor** **-battery**

**-MAX301 sensor** **-two regulators**

**-GSR sensor** **-esp32 microcontroller**

- MPU6050 sensor


Fig.20 MPU6050

**Blue line: acclimator**
**Red line: gyroscope**

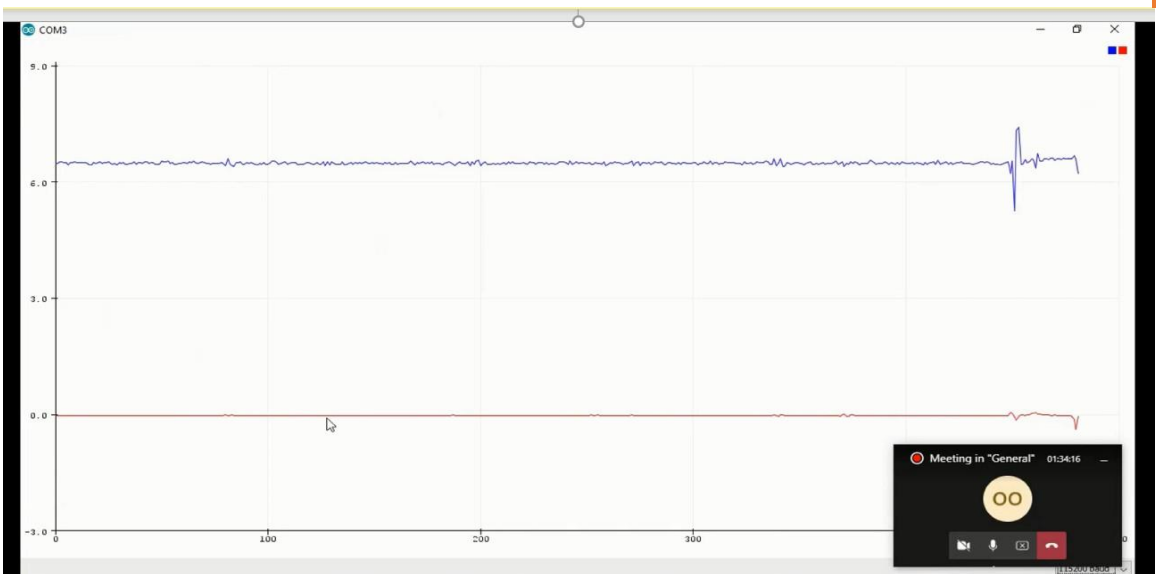



Fig.21 Normal state

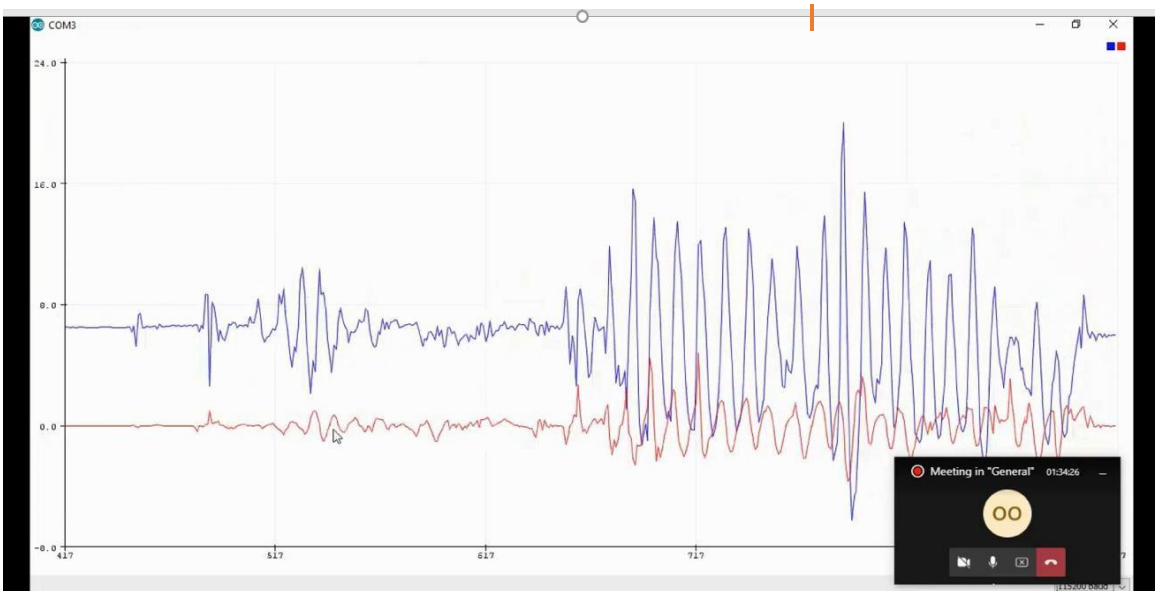



Fig.22 seizure occurrence

**MPU6050 sensor module is complete 6-axis Motion Tracking Device. It combines 3-axis Gyroscope, 3-axis Accelerometer and Digital Motion Processor all in small package. Also, it has additional feature of on-chip Temperature sensor. It has I2C bus interface to communicate with the microcontrollers.**

**It has Auxiliary I2C bus to communicate with other sensor devices like 3-axis Magnetometer, Pressure sensor etc.**

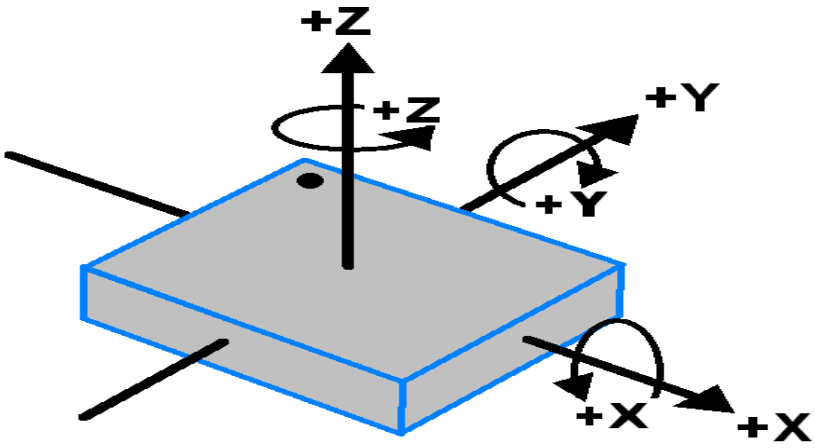
**If 3-axis Magnetometer is connected to auxiliary I2C bus, then MPU6050 can provide complete 9-axis Motion Fusion output.**

**Let us see MPU6050 inside sensors.**

# 3-Axis Gyroscope

**The MPU6050 consist of 3-axis Gyroscope with Micro Electromechanical System (MEMS) technology. It is used to detect rotational velocity along the X, Y, Z axes**

**- When the gyros are rotated about any of the sense axes, the Coriolis Effect causes a vibration that is detected by a MEM inside MPU6050.**




MPU-6050
Orientation & Polarity of Rotation

**Fig.23 Orientation of MPU**

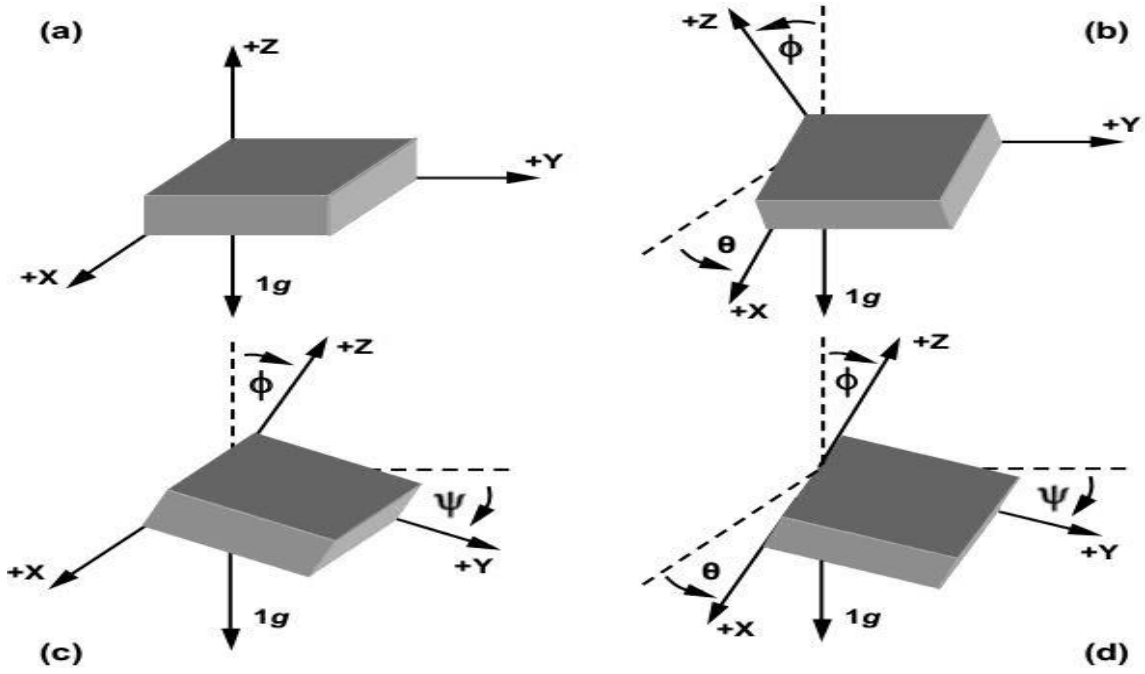
**- The resulting signal is amplified, demodulated, and filtered to produce a voltage that is proportional to the angular rate.**

**- This voltage is digitized using 16-bit ADC to sample each axis.**

- The full-scale range of output are +/- 250, +/- 500, +/- 1000, +/- 2000.
- It measures the angular velocity along each axis in degree per second unit.

# 3-Axis Accelerometer

The MPU6050 consist of 3-axis Accelerometer with Micro Electromechanical (MEMs) technology. It used to detect angle of tilt or inclination along the X, Y and Z axes as shown in below figure.




- Acceleration along the axes deflects the movable mass.
- This displacement of moving plate (mass) unbalances the differential capacitor which results in sensor output. Output amplitude is proportional to acceleration.
- 16-bit ADC is used to get digitized output.
- The full-scale range of acceleration are +/- 2g, +/- 4g, +/- 8g, +/- 16g.
- It measured in g (gravity force) unit.
- When device placed on flat surface it will measure 0g on X and Y axis and +1g on Z axis.

# DMP (Digital Motion Processor)

**The embedded Digital Motion Processor (DMP) is used to compute motion processing algorithms. It takes data from gyroscope, accelerometer, and additional 3rd party sensor such as magnetometer and processes the data. It provides motion data like roll, pitch, yaw angles, landscape, and portrait sense etc. It minimizes the processes of host in computing motion data. The resulting data can be read from DMP registers.**

# On-chip Temperature Sensor

**On-chip temperature sensor output is digitized using ADC. The reading from temperature sensor can be read from sensor data register.**

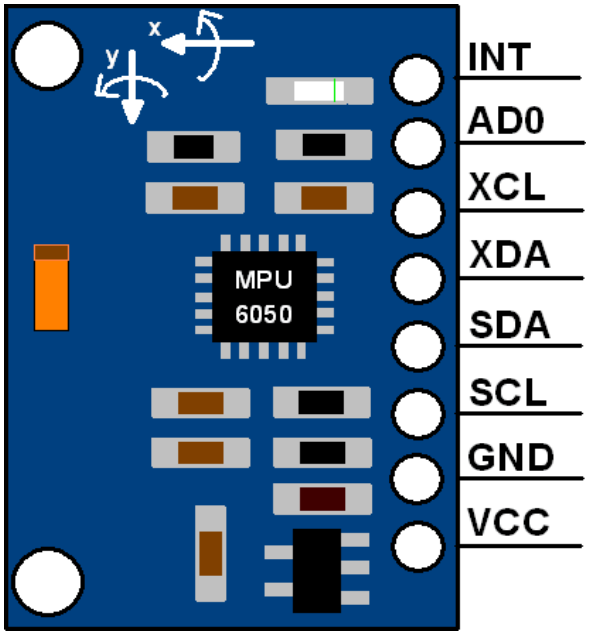



**Fig.24 MPU6050**

**The MPU-6050 module has 8 pins,**

INT: **Interrupt digital output pin.**

AD0: **I2C Slave Address LSB pin. This is 0th bit in 7-bit slave address of device. If connected to VCC then it is read as logic one and slave address changes.**

XCL: **Auxiliary Serial Clock pin. This pin is used to connect other I2C interface enabled sensors SCL pin to MPU-6050.**

XDA: **Auxiliary Serial Data pin. This pin is used to connect other I2C interface enabled sensors SDA pin to MPU-6050.**

SCL: **Serial Clock pin. Connect this pin to microcontrollers SCL pin.**

SDA: **Serial Data pin. Connect this pin to microcontrollers SDA pin.**

GND: **Ground pin. Connect this pin to ground connection.**

VCC: **Power supply pin. Connect this pin to +5V DC supply.**

**MPU-6050 module has Slave address (When AD0 = 0, i.e. it is not connected to Vcc) as,**

Slave Write address (SLA+W)**: 0xD0**

Slave Read address (SLA+R)**: 0xD1**

**MPU-6050 has various registers to control and configure its mode of operation. So, kindly go through** MPU-6050 datasheet **and** MPU-6050 Register Map**.**

## Calculations

Note that **gyroscope and accelerometer sensor data of MPU6050 module consists of 16-bit raw data in 2's complement form.**

**Temperature sensor data of MPU6050 module consists of 16-bit data (not in 2's complement form).**

**Now suppose we have selected,**

**- Accelerometer full scale range of +/- 2g with Sensitivity Scale Factor of 16,384 LSB(Count)/g.**

**- Gyroscope full scale range of +/- 250 °/s with Sensitivity Scale Factor of 131 LSB (Count)/°/s.**

**then, to get sensor raw data, we need to first perform 2's complement on sensor data of Accelerometer and gyroscope.**

**After getting sensor raw data we can calculate acceleration and angular velocity by dividing sensor raw data with their sensitivity scale factor as follows,**

Accelerometer values in g (g force)

**Acceleration along the X axis = (Accelerometer X axis raw data/16384) g.**

**Acceleration along the Y axis = (Accelerometer Y axis raw data/16384) g.**

**Acceleration along the Z axis = (Accelerometer Z axis raw data/16384) g.**

Gyroscope values in °/s (degree per second)

**Angular velocity along the X axis = (Gyroscope X axis raw data/131) °/s.**

**Angular velocity along the Y axis = (Gyroscope Y axis raw data/131) °/s.**

**Angular velocity along the Z axis = (Gyroscope Z axis raw data/131) °/s.**

Temperature value in °/c (degree per Celsius)

**Temperature in degrees C = ((temperature sensor data)/340 + 36.53) °/c.**

For example,

**Suppose after 2's complement we get accelerometer X axes raw value = +15454**

**Then Ax = +15454/16384 = 0.94 g.**

- ## MAX30100 sensor

**The MAX30100 is an integrated pulse oximetry and heart-rate monitor sensor solution. It combines two LEDs, a photodetector, optimized optics, and low-noise analog signal processing to detect pulse oximetry and heart-rate signals.**


**Fig.25 MAX30100**

**The MAX30100 operates from 1.8V and 3.3V power**

supplies and can be powered down through software with negligible standby current, permitting the power supply to remain connected at all times.

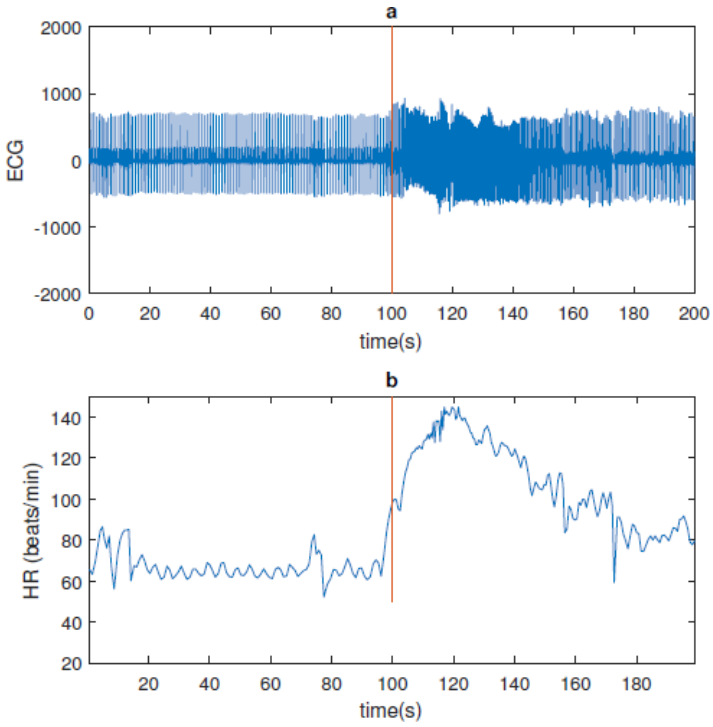



**Fig.28 Heart rate and ECG graph**

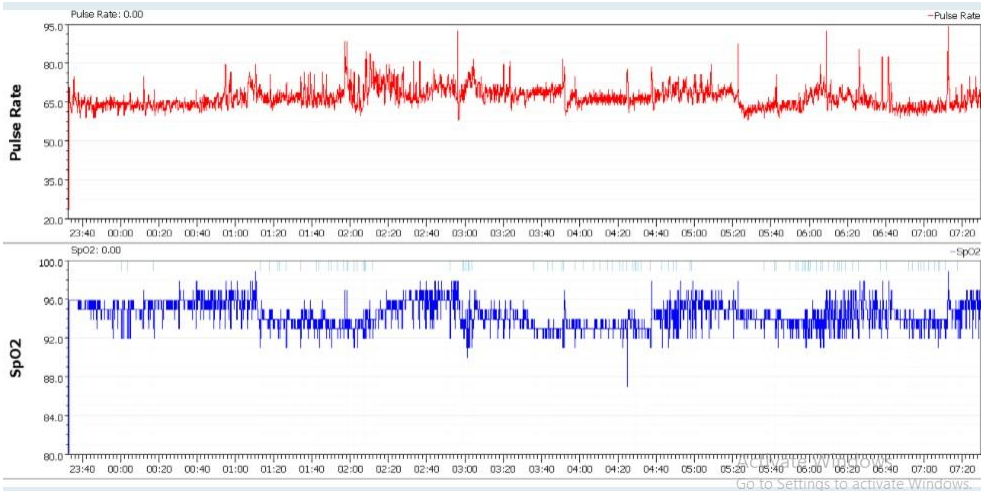



**Fig.27 Heart rate and SpO2 graph**

## MAX30100 Breakout Overview

**MAX30100 is an integrated pulse oximeter and heart-rate monitor sensor solution. It's an optical sensor that derives its readings from emitting two wavelengths of light from two LEDs – a red and an infrared one – then measuring the absorbance of pulsing blood through a photodetector. This particular LED colour combination is optimized for reading the data through the tip of one's finger. It is fully configurable through software registers and the digital output data is stored in a 16-deep FIFO within the device. It has an I2C digital interface to communicate with a host microcontroller.**

**The pulse oximetry subsystem in MAX30100 consists of ambient light cancellation (ALC), 16-bit sigma delta ADC, and proprietary discrete time filter. It has an ultra-low-power operation which makes it ideal for battery operated systems. MAX30100 operates on a supply in the range of 1.8 to 3.3V. It can be used in wearable devices, fitness assistant devices, medical monitoring devices, etc. The MAX30100 operates from 1.8V and 3.3V power supplies and can be powered down through software with negligible standby current, permitting the power supply to remain connected at all times.**

Pin Configuration of MAX30100 Pulse Oximeter Heart Rate Sensor Module: -

| SN | PINS | DEFINITION OF PINS |
|---|---|---|
| 1 | VIN | Input voltage (1.8V to 5.5V) |
| 2 | SCL | IIC-SCL |
| 3 | SDA | IIC-SDA |
| 4 | INT | MAX30100INT |
| 5 | IRD | MAX30100 IR_DRV |
| 6 | RD | MAX30100 R_DRV |

**7 GND Ground**

Specifications and Features of MAX30100 Pulse Oximeter Heart Rate Sensor Module: -

- **It is an integrated pulse oximetry and heart rate monitor sensor solution.**
- **Integrated LEDs, Photo Sensor, and High-Performance Analog Front-End**
- **Complete Pulse Oximeter and Heart-Rate Sensor Solution Simplifies Design**
- **Measures absorbance of pulsing blood**
- **I2C interface plus INT pin**
- **Tiny 5.6mm x 2.8mm x 1.2mm 14-Pin Optically Enhanced System-in-Package**
- **Ultra-Low-Power Operation Increases Battery Life for Wearable Devices**
- **Programmable Sample Rate and LED Current for Power Savings**
- **Ultra-Low Shutdown Current (0.7µA, typ)**
- **Advanced Functionality Improves Measurement Performance**
- **High SNR Provides Robust Motion Artifact Resilience**
- **Integrated Ambient Light Cancellation**
- **High Sample Rate Capability**
- **Fast Data Output Capability**

Applications of MAX30100 Pulse Oximeter Heart Rate Sensor Module: -

- **Fitness Assistant Devices**
- **Medical Monitoring Devices**
- **Wearable Devices**

**The IC itself runs at 1.8V, so we have included the interface logic to allow you to hook the MAX30100 Breakout Board to any board that has 5V, 3.3V, even 1.8V level I/O.**

| Pin Label | Input/Output | Description |
|---|---|---|
| **INT** | **Output** | **Interrupt, active low** |
| **GND** | **Supply Input** | **Ground (0V) supply** |
| **5V** | **Supply Input** | **Power supply** |
| **SDA** | **Bi-directional** | **$I^2C$ bus clock line** |
| **SCL** | **Input** | **$I^2C$ bus clock line** |

**Table 2. MAX30100 Pulse Oximeter datasheet**

**The GND/5V/SDA/SCL pin-out is the standard $I^2C$ connection on most of our products. This allows you to easily connect $I^2C$ boards to many of our platforms.**

- ## GSR sensor

**What you need to know about GSR sensors?**

**Skin conductance is typically captured from the hand and foot regions, using easy-to-apply skin electrodes. Most modern GSR electrodes have an Ag/AgCl**

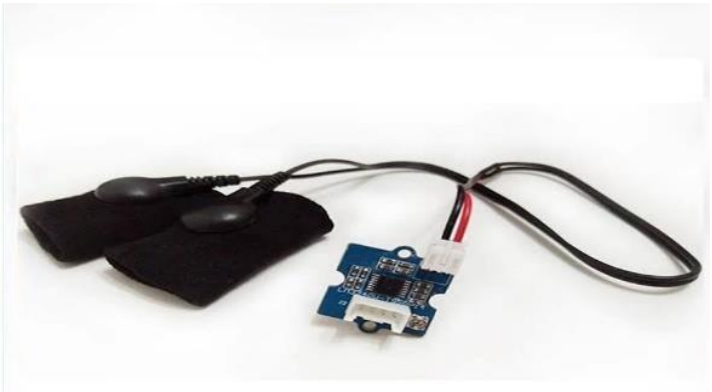


**Fig.28 GSR sensor**

(silver-chloride) contact point with the skin. These electrodes are cheap, robust, safe for human contact, and accurately transmit the signal from the ionic activity.

Some electrodes come pre-packaged with ionic gel to increase the signal fidelity. Alternatively, ionic gel can be applied to achieve the same effect. The signal is sent through the electrode, to the wire (usually lead) that passes the information to the GSR device.

Data is acquired with sampling rates between 1 – 10 Hz and is measured in units of micro-Siemens (µS). Once the data is passed to the GSR device, it is either:

- stored within the device to be later uploaded.
- transmitted wirelessly to a computer system.
- or the signal is sent through a further wired connection to a computer. Of course, different GSR sensors allow different means of transmission, and the choice of each depends on the kind of research you are carrying out.

### GSR signals explained

The time course of the signal is the result of two additive processes: a tonic base level driver, which fluctuates very slowly (seconds to minutes), and a faster-varying phasic component (fluctuating within seconds). Changes in phasic activity can be identified in the continuous data stream, as these bursts have a steep incline to a distinctive peak, and a slow decline relative to the baseline level.

Researchers focus on the latency and amplitudes of the phasic bursts with respect to stimulus onset when investigating GSR signal changes in response to sensory stimuli (images, videos, sounds). When there are significant changes in GSR activity in response to a stimulus, it is referred to as an Event-Related Skin Conductance

**Response (ER-SCR). These responses, otherwise known as GSR peaks, can provide information about emotional arousal to stimuli.**

**Other peaks in GSR activity that are not related to the presentation of a stimulus are referred to as non-Stimulus-locked Skin Conductance Responses (NS-SCR). By using the skin conductance values, or the number of GSR peaks, it is possible to add quantitative data to studies of emotional arousal. With more data at hand, it is easier to uncover new findings and make new discoveries about human behavior.**

## 3.2.1 Headband hardware:

### Technical description of Smart Headband

1. **Headband main :**

**First of all we will discuss the main idea and function of this stage in our project. As shown in previous section which was wrist band we have chosen parameters to**

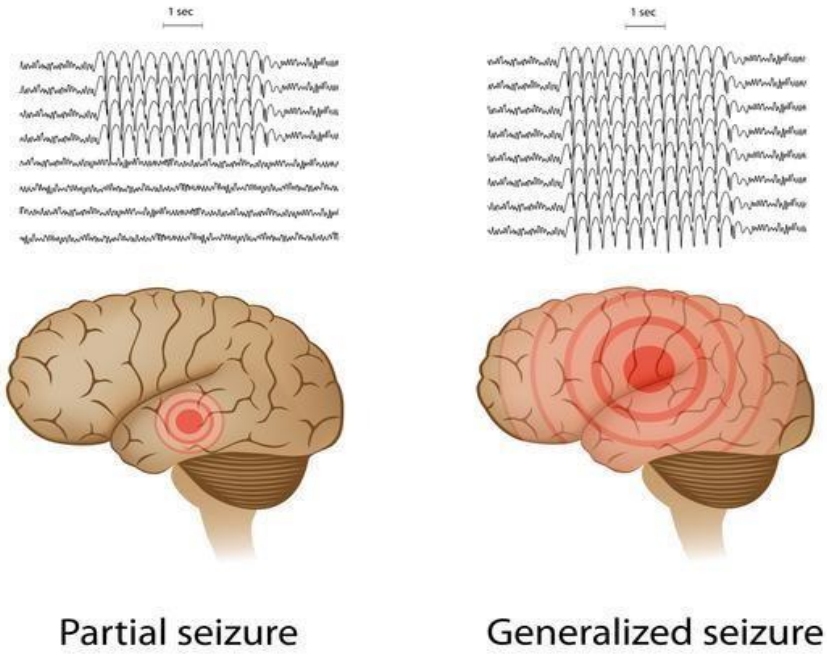



**Fig.29 shows the difference between partial and generalized seizure**

**measure. These parameters are a must to detect the seizure. In this section we have chosen EEG signal as the**

**parameter which our system depends on for detecting any generalized seizure. And as we showed previously any seizure has its reflection on the nervous system. But differs between parts in the brain. The generalized seizure reflects on all parts of the brain. So as a start we need one channel to detect this type of seizures. The generalized seizure is like the figure.1 below.**

**.**

2. **Headband as a block of the whole system:**

**As any part of the system this headband has its inputs and outputs. First we will discuss inputs. We have one input which is**

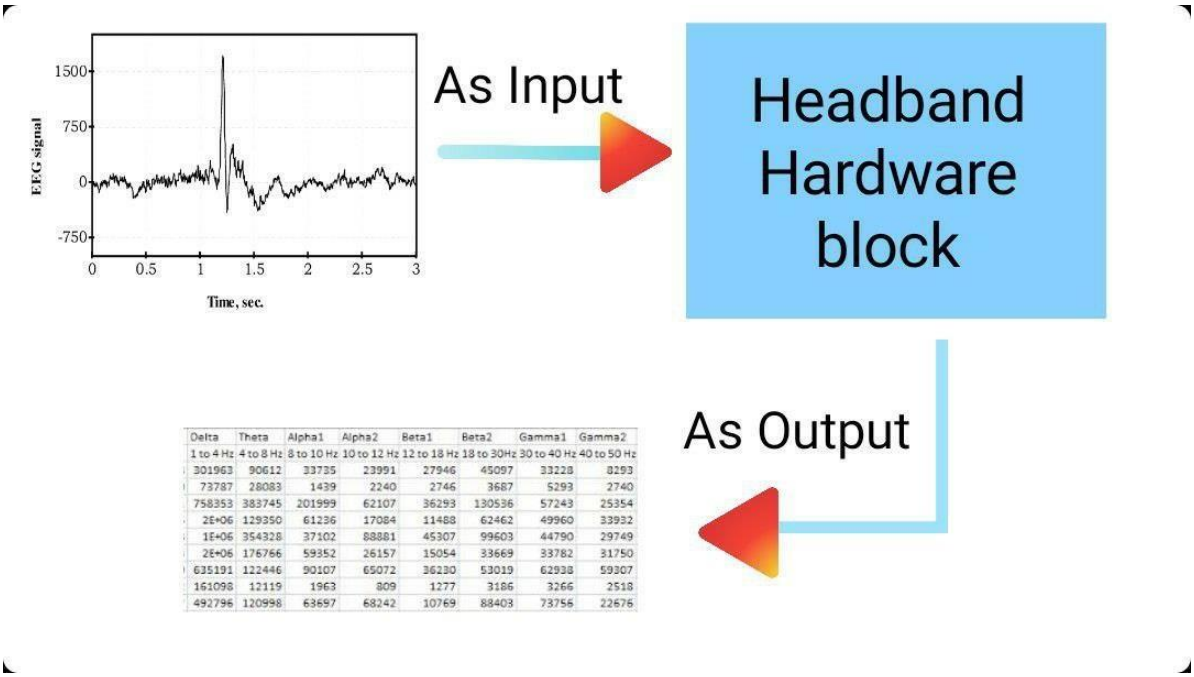
**Inputs:**

**1- The EEG signal at the real time of the patient measured using electrodes. This input will travel in a journey to the end of this part.**

**Outputs:**

**1- The EEG signal as amplified filtered digitized signal to move to the next stage which is the ML model will take a decision if its normal or not.**

**And the inputs and outputs of the system as the figure.2 below.**




| Delta | Theta | Alpha1 | Alpha2 | Beta1 | Beta2 | Gamma1 | Gamma2 |
|---|---|---|---|---|---|---|---|
| 1 to 4 Hz | 4 to 8 Hz | 8 to 10 Hz | 10 to 12 Hz | 12 to 18 Hz | 18 to 30Hz | 30 to 40 Hz | 40 to 50 Hz |
| 301963 | 90612 | 33735 | 23991 | 27946 | 45097 | 33228 | 8293 |
| 73787 | 28083 | 1439 | 2240 | 2746 | 3687 | 5293 | 2740 |
| 758353 | 383745 | 201999 | 62107 | 36293 | 130536 | 57243 | 25354 |
| 2E+06 | 129350 | 61236 | 17084 | 11488 | 62462 | 49960 | 33932 |
| 1E+06 | 354328 | 37102 | 88881 | 45307 | 99603 | 44790 | 29749 |
| 2E+06 | 176766 | 59352 | 26157 | 15054 | 33669 | 33782 | 31750 |
| 635191 | 122446 | 90107 | 65072 | 36230 | 53019 | 62938 | 59307 |
| 161098 | 12119 | 1963 | 809 | 1277 | 3186 | 3266 | 2518 |
| 492796 | 120998 | 63697 | 68242 | 10769 | 88403 | 73756 | 22676 |

**. fig.30 inputs and outputs of the Headband**

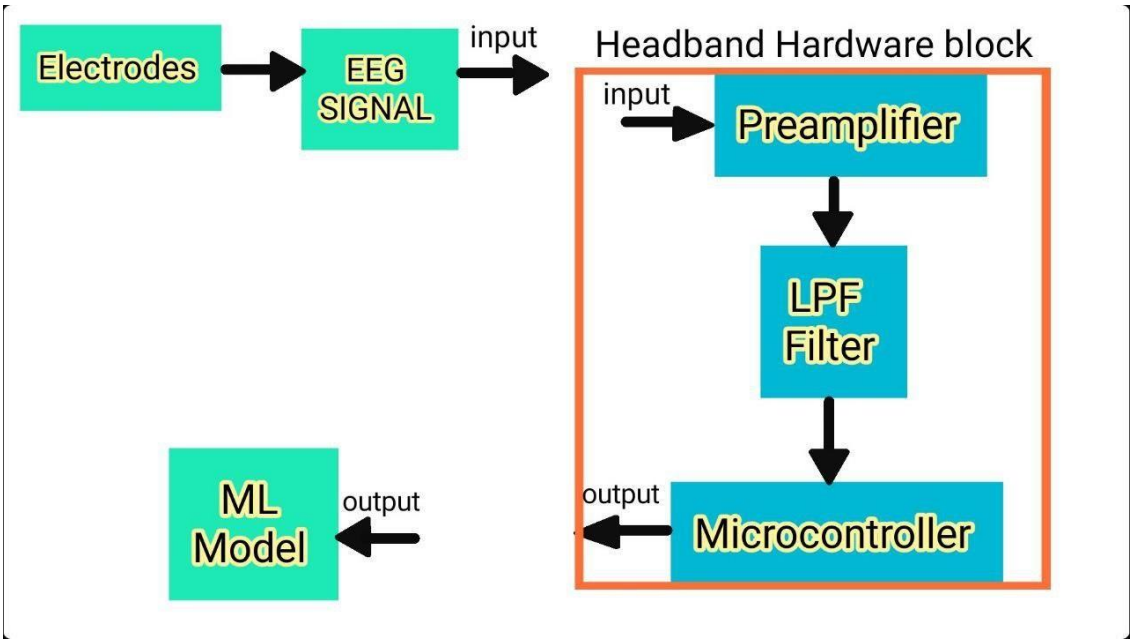



**fig.31 Headband Hardware components.**

**And the full stage pieces as the figure.3 below.**

3. **Component specification:**

**we will discuss each component and why we have selected it.**

**1- GOLD cup Electrodes to measure EEG signal as fig.4**

**2- AD620 Instrumentation amplifier as fig.5**

**3- LM324 QUAD OP-AMP as fig.6**

**4- Arduino UNO as a Microcontroller as fig.7**

**Reasons and Obstacles:**

1- **We have used Gold cup Electrodes because it's the most common and used for EEG measures. Another reason is quality of the signal it affords. We wanted at first to use dry electrodes to make it easier for the patient, but we could not afford this type of electrode due to the market restrictions.**

**Fig.32 gold cup electrodes**

## Recording Electrodes

**We Choose the OpenBCI Gold Cup Electrodes because of its high sensitivity:**

**The OpenBCI Gold Cup Electrodes comes as a ribbon cable with 10 passive gold electrodes that can be used with ANY OpenBCI board to sample brain activity (EEG), muscle activity (EMG), and heart activity (EKG).**

**OpenBCI Electrode**

- **26 gauge stranded wire**

a. **1-meter, color-coded cable**
b. **Single female header termination per cable**
c. **Insulation = PVC rated to 80*C**
d. **Overall cable OD = 1.45mm/0.057"**
e. **Cup diameter is 10 mm**


**Figure 33. Ten20 Conductive Paste It has the following features**

**For better conductivity with the face we used the Ten20 conductive paste,**

**Ten20 conductive paste is used to stick EEG electrodes directly to the skin for a secure connection. Simply place a small mound on the prepared site and gently press the flat disk or cup sensor into the mound of paste. The more you spread the mound, the more area the sensor will "see". Try to spread within the diameter of the sensor itself.**

- **Fast Clean Up: The Ten20's washable, non-drying formula makes it very easy to clean up. Simply wash with warm water to remove; no harsh chemicals are required.**

- **Simple to Use: Ten20 Conductive Paste is supplied in a 3-pack of convenient jars or tubes for every need. All products contain an expiration date and a complete list of ingredients to promote patient safety.**

- **Easy to Store: All products are packaged in easy to store boxes that should be stored at room temperature. Every product has a 3-year shelf-life marked on the box and the individual containers.**

2- **The AD620 is a low cost, high accuracy instrumentation amplifier that requires only one external resistor to set gains of 1 to 10,000. Furthermore, the AD620 features 8-lead SOIC and DIP packaging that is smaller than discrete designs and offers lower power (only 1.3 mA max supply current), making it a good fit for battery-powered, portable (or remote) applications like EEG and ECG applications. Gain set with one external resistor (Gain range 1 to 10,000). Wide power supply range (±2.3 V to ±18 V). And its specification as the following:**

## 1- FEATURES

1. **Easy to use**
2. **Gain set with one external resistor**
3. **(Gain range 1 to 10,000)**
4. **Wide power supply range (±2.3 V to ±18 V)**
5. **Higher performance than 3 op amp IA designs**
6. **Available in 8-lead DIP and SOIC packaging**
7. **Low power, 1.3 mA max supply current**
8. **Excellent dc performance (B grade)**
    a. **50 µV max, input offset voltage**
    b. **0.6 µV/°C max, input offset drift**
    c. **1.0 nA max, input bias current**

d. 100 dB min common-mode rejection ratio (G = 10)

9. Low noise
    a. 9 nV/√Hz @ 1 kHz, input voltage noise
    b. 0.28 µV p-p noise (0.1 Hz to 10 Hz)
10. Excellent ac specifications
    a.120 kHz bandwidth (G = 100)
    b. 15 µs settling time to 0.01%

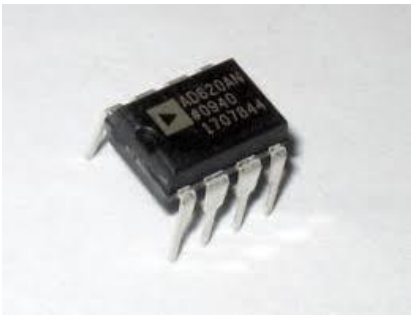


Fig.34 AD620 INA

3- The LM324-N series consists of four independent, high-gain, internally frequency compensated operational amplifiers designed to operate from a single power supply over a wide range of voltages. And its specification as following:

1- Features

1. Internally Frequency Compensated for Unity Gain
2. Large DC Voltage Gain 100 dB
3. Wide Bandwidth (Unity Gain) 1 MHz (Temperature Compensated)
4. • Wide Power Supply Range:
    a. Single Supply 3 V to 32 V
    b. or Dual Supplies ±1.5 V to ±16 V
5. • Very Low Supply Current Drain (700 µA)
    a. —Essentially Independent of Supply Voltage
6. • Low Input Biasing Current 45 nA (Temperature Compensated)
7. • Low Input Offset Voltage 2 mV and Offset Current: 5 nA
8. • Input Common-Mode Voltage Range Includes Ground

9. • Differential Input Voltage Range Equal to the Power Supply Voltage
10. • Large Output Voltage Swing 0 V to V+ − 1.5 V

## 2- Advantages:

1- – Eliminates Need for Dual Supplies

2- – Four Internally Compensated Op Amps in a Single Package

3- – Allows Direct Sensing Near GND and VOUT also Goes to GND

4- – Compatible with All Forms of Logic

5- – Power Drain Suitable for Battery Operation

6- – In the Linear Mode the Input Common-Mode, Voltage Range Includes Ground and the Output Voltage

7- – Can Swing to Ground, Even Though Operated from Only a Single Power Supply Voltage

8- – Unity Gain Cross Frequency is Temperature Compensated

9- – Input Bias Current is Also Temperature Compensated

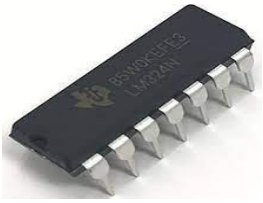


Fig.35 LM324

4- As we all know Arduino MC and its advantages so we will not exceed this level. And its specification as the following:

1. Microcontroller: ATmega328
2. Operating Voltage: 5V
3. Input Voltage (recommended): 7-12V

4. **Input Voltage (limits): 6-20V**
5. **Digital I/O Pins: 14 (of which 6 provide PWM output)**
6. **Analog Input Pins: 6**
7. **DC Current per I/O Pin: 40 mA**
8. **DC Current for 3.3V Pin:50 mA**
9. **Flash Memory: 32 KB (ATmega328) of which 0.5 KB used by bootloader**
10. **SRAM: 2 KB (ATmega328)**
11. **EEPROM: 1 KB (ATmega328)**
12. **Clock Speed: 16 MHz**

**Fig.36 Arduino UNO**

## The steps our part will go through it are as next:

1- **We use one channel using three electrodes. To measure any signal like EEG, EMG and ECG we need 2 electrodes and measure the difference between them. And we need another third electrode to be the GND of the circuit. As shown in fig.37**

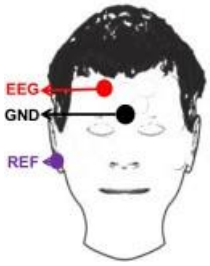



**Fig.37 Positions of electrodes**

2- The difference between these two electrodes amplified using AD620AN. And went to the next step. And we included simulation for this part also in fig.38.

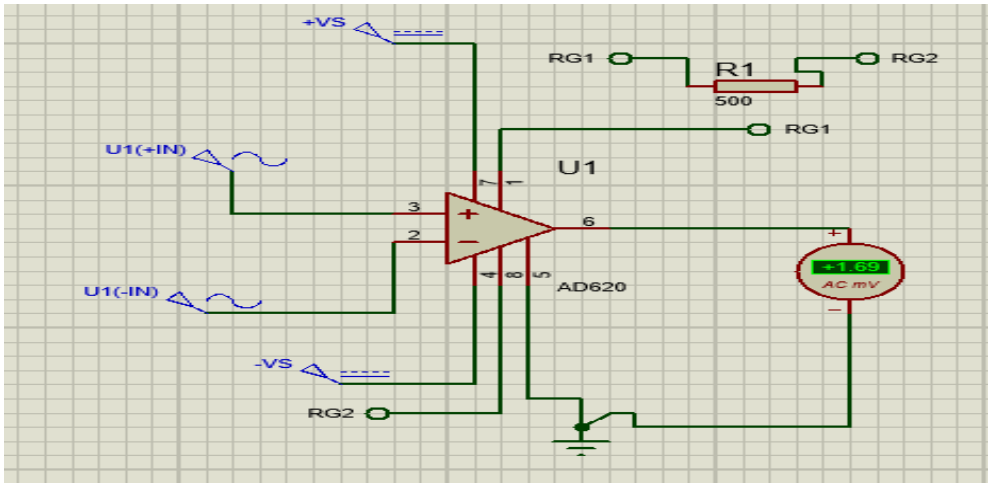



Fig.38 shows that output volt reaches 1.69 mv for input equal 20 uv

3- This wave we need to eliminate noise and unwanted data by using LPF with cutoff freq. = 30Hz like researchers said in scientific papers. And then amplified

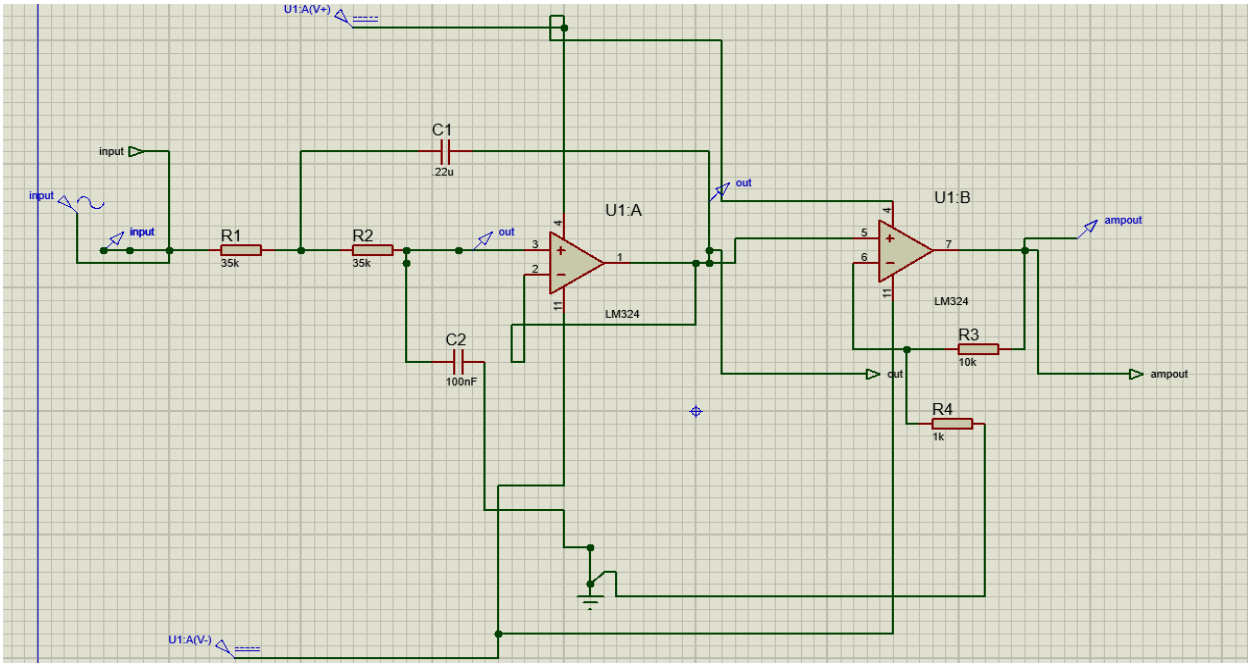



fig.39 shows the circuit diagram of the LPF with gain equal 11dB cutoff freq=30Hz

**again using op-amps. And we included simulation for this part also in fig.39 and fig.40.**

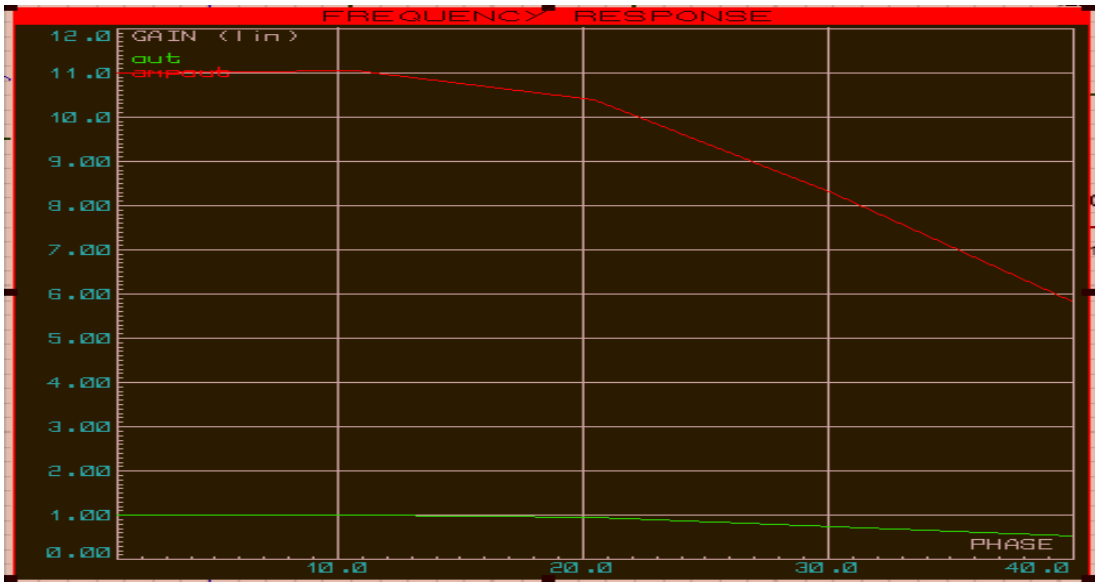



**fig.40 Freq response of the circuit diagram in fig.12**

**4- And finally, these signals can be plotted on a graph and send as a csv file to the ML model also using Arduino UNO.**

The output of the headband circuit which is the EEG signal will be the input of the EEG machine learning model which will follow the following sequence

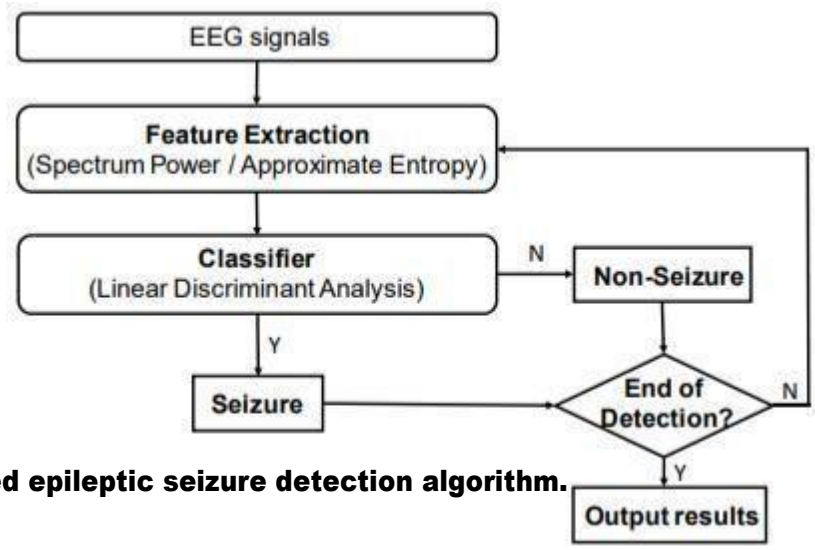



**Figure 41 Flow chart of proposed epileptic seizure detection algorithm.**

Data preprocessing in Machine Learning is a crucial step that helps enhance the quality of data to promote the extraction of meaningful insights from the data. Data preprocessing in Machine Learning refers to the technique of preparing (cleaning and organizing) the raw data to make it suitable for a building and training Machine Learning models

## 3.3 Why Data Preprocessing in Machine Learning?

When it comes to creating a Machine Learning model, data preprocessing is the first step marking the initiation of the process. Typically, real-world data is incomplete, inconsistent, inaccurate (contains errors or outliers), and often lacks specific attribute values/trends. This is where data preprocessing enters the scenario – it helps to clean, format, and organize the raw data, thereby making it ready-to-go for Machine Learning models. Let us explore various steps of data preprocessing in machine learning.

## Steps in Data Preprocessing in Machine Learning

There are seven significant steps in data preprocessing in Machine Learning:

### 3.3.1. Acquire the dataset

Acquiring the dataset is the first step in data preprocessing in machine learning. To build and develop Machine Learning models, you must first acquire the relevant dataset. This dataset will be comprised of data gathered from multiple and disparate sources which are then combined in a proper format to form a dataset. Dataset formats differ according to use cases. For instance, a business dataset will be entirely different from a medical dataset. While a business dataset will contain relevant industry and business data, a medical dataset will include healthcare-related data.

### 3.3.2. Import all the crucial libraries

**Since Python is the most extensively used and the most preferred library by Data Scientists around the world, we will show you how to import Python libraries for data preprocessing in Machine Learning. Read more about, the predefined Python libraries can perform specific data preprocessing jobs. Importing all the crucial libraries is the second step in data preprocessing in machine learning. The three core Python libraries used for this data preprocessing in Machine Learning are:**

- NumPy – **NumPy is the fundamental package for scientific calculation in Python. Hence, it is used for inserting any type of mathematical operation in the code. Using NumPy, you can also add large multidimensional arrays and matrices in your code.**
- Pandas – **Pandas is an excellent open-source Python library for data manipulation and analysis. It is extensively used for importing and managing the datasets. It packs in high-performance, easy-to-use data structures and data analysis tools for Python.**
- Matplotlib – **Matplotlib is a Python 2D plotting library that is used to plot any type of charts in Python. It can deliver publication-quality figures in numerous hard copy formats and interactive environments across platforms (IPython shells, Jupyter notebook, web application servers, etc.).**

### 3.3.3. Import the dataset

**In this step, you need to import the dataset/s that you have gathered for the ML project at hand. Importing the dataset is one of the important steps in data preprocessing in machine learning. However, before you can import the dataset/s, you must set the current directory as the working directory.**

- **The original dataset from the reference consists of 5 different folders, each with 100 files, with each file representing a single subject/person. Each file is a recording of brain activity for 23.6 seconds.**
- **The corresponding time-series is sampled into 4097 data points. Each data point is the value of the EEG recording at a different point in time. So, we have total 500 individuals with each has 4097 data points for 23.5 seconds.**
- **We divided and shuffled every 4097 data points into 23 chunks, each chunk contains 178 data points for 1 second, and each data point is the value of the EEG recording at a different point in time.**
- **So now we have 23 x 500 = 11500 pieces of information(row), each information contains 178 data points for 1 second(column), the last column represents the label y {1,2,3,4,5}.**
- **The response variable is y in column 179, the Explanatory variables X1, X2, ..., X178**

The column y contains the category of the 178- dimensional input vector.

Specifically, y in {1, 2, 3, 4, 5}:

1. **Recording of seizure activity**
2. **They recorded the EEG from the area where the tumor was located**
3. **Yes they identify where the region of the tumor was in the brain and recording the EEG activity from the healthy brain area**
4. **eyes closed, means when they were recording the EEG signal the patient had their eyes closed**
5. **eyes open, means when they were recording the EEG signal of the brain the patient had their eyes open**

- **All subjects falling in classes 2, 3, 4, and 5 are subjects who did not have epileptic seizure. Only subjects in class 1 have epileptic seizure.**
- **Our motivation for creating this version of the data was to simplify access to the data via the creation of a .csv version of it.**
- **Although there are 5 classes most authors have done binary classification, namely class 1 (Epileptic seizure) against the rest.**

| nnamed: | X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 | ... | X170 | X171 | X172 | X173 | X174 | X175 | X176 | X177 | X178 | y |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 21.V1.791 | 135 | 190 | 229 | 223 | 192 | 125 | 55 | -9 | -33 | ... | -17 | -15 | -31 | -77 | -103 | -127 | -116 | -83 | -51 | 4 |
| 15.V1.924 | 386 | 382 | 356 | 331 | 320 | 315 | 307 | 272 | 244 | ... | 164 | 150 | 146 | 152 | 157 | 156 | 154 | 143 | 129 | 1 |
| 8.V1.1 | -32 | -39 | -47 | -37 | -32 | -36 | -57 | -73 | -85 | ... | 57 | 64 | 48 | 19 | -12 | -30 | -35 | -35 | -36 | 5 |
| 16.V1.60 | -105 | -101 | -96 | -92 | -89 | -95 | -102 | -100 | -87 | ... | -82 | -81 | -80 | -77 | -85 | -77 | -72 | -69 | -65 | 5 |
| 20.V1.54 | -9 | -65 | -98 | -102 | -78 | -48 | -16 | 0 | -21 | ... | 4 | 2 | -12 | -32 | -41 | -65 | -83 | -89 | -73 | 5 |

/s × 180 columns

**Figure 43. The imported data set**

**Here is the imported data set**

```
Features:
[[ 135  190  229 ... -116  -83  -51]
 [ 386  382  356 ...  154  143  129]
 [ -32  -39  -47 ...  -35  -35  -36]
 ...
 [  14    6  -13 ...   -2   -1   -8]
 [ -40  -25   -9 ...   68   59   55]
 [  29   41   57 ...   -2    2   20]]
(11500, 178)

Target:
[[0]
 [1]
 [0]
 ...
 [0]
 [0]
 [0]]
(11500, 1)
```

**Figure 44. The imported data set**

## 3.3.4. -Splitting the dataset

**Splitting the dataset is the next step in data preprocessing in machine learning. Every dataset for Machine Learning model must be split into two separate sets – training set and test set.**

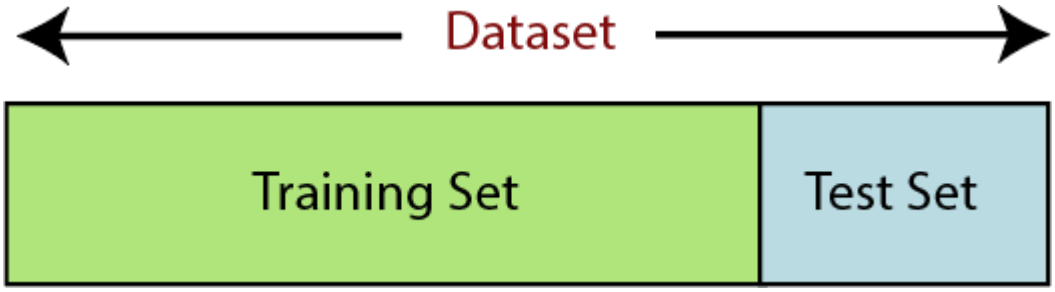



**Figure 45. Splitting the dataset**

**Training set denotes the subset of a dataset that is used for training the machine learning model. Here, you are already aware of the output. A test set, on the other hand, is the subset of the dataset that is used for testing the machine learning model. The ML model uses the test set to predict outcomes. Usually, the dataset is split into 70:30 ratio or 80:20 ratio. This means that you either take 70% or 80% of the data for training the model while leaving out the rest 30% or 20%. The splitting process varies according to the shape and size of the dataset in question.**

## Data after splitting

```
X_train:
[[  -1  -19  -22 ...   -6  -24  -28]
 [  23   28   28 ...  -37  -44  -49]
 [  16   19   27 ...    6    7   16]
 ...
 [  18   20   26 ...  -44  -42  -36]
 [ 285  282  311 ...  -22 -173 -308]
 [-118   55  272 ... -554 -502 -375]]
(9775, 178)

X_test:
[[ -16   -3  -16 ...  -16  -12  -12]
 [ 154  144  132 ... -401 -437 -357]
 [   3    1    3 ...   19   14   12]
 ...
 [ 562  475  376 ... -117 -129 -165]
 [ -58  -61  -49 ...    9    6   -1]
 [ 112   97   77 ...  112  139  156]]
(1725, 178)
```

```
y_train:
[[0]
 [0]
 [0]
 ...
 [0]
 [1]
 [1]]
(9775, 1)

y_test:
[[0]
 [1]
 [0]
 ...
 [1]
 [0]
 [1]]
(1725, 1)
```



**Figure 47. The output of Splitting the dataset**

## 3.3.5. -Feature scaling

**Feature scaling marks the end of the** data preprocessing in Machine Learning. **It is a method to standardize the independent variables of a dataset within a specific range. In other words, feature scaling limits the range of variables so that you can compare them on common grounds.**

**You can perform feature scaling in Machine Learning in two ways:**

## Standardization

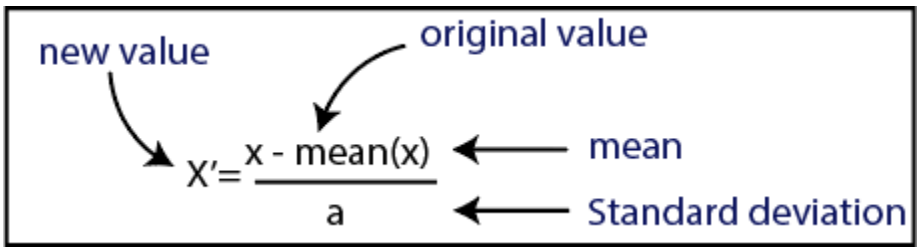



**Figure 48. Standardization**

## Normalization

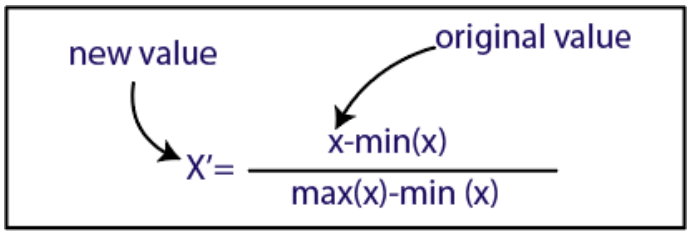
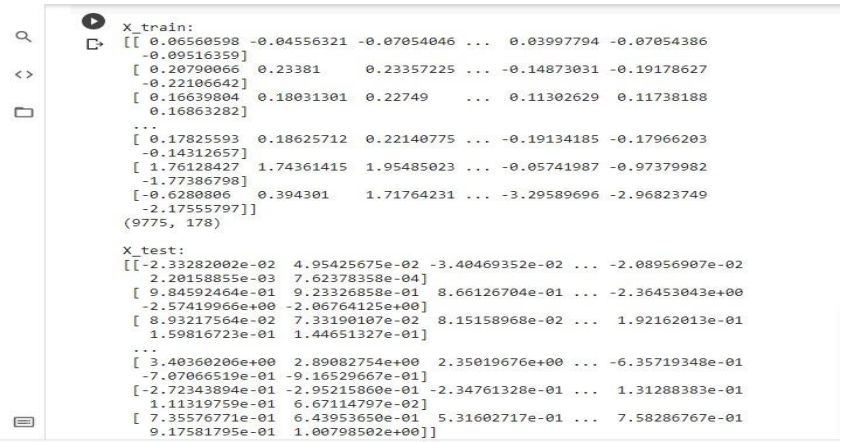



**Figure 49. Normalization**

**-For our dataset, we will use the standardization method. To do so, we will import StandardAero class**

**-For the test dataset, you can directly apply transform () function (you need not use the fit transform () function because it is already done in training set)**

## 3.3.6. The scaled dataset



```
X_train:
[[ 0.06560598 -0.04556321 -0.07054046 ...  0.03997794 -0.07054386
  -0.09516359]
 [ 0.20790066  0.23381     0.23357225 ... -0.14873031 -0.19178627
  -0.22106642]
 [ 0.16639804  0.18031301  0.22749    ...  0.11302629  0.11738188
   0.16863282]
 ...
 [ 0.17825593  0.18625712  0.22140775 ... -0.19134185 -0.17966203
  -0.14312657]
 [ 1.76128427  1.74361415  1.95485023 ... -0.05741987 -0.97379982
  -1.77386798]
 [-0.6280806   0.394301    1.71764231 ... -3.29589696 -2.96823749
  -2.17555797]]
(9775, 178)

X_test:
[[-2.33282002e-02  4.95425675e-02 -3.40469352e-02 ... -2.08956907e-02
   2.20158855e-03  7.62378358e-04]
 [ 9.84592464e-01  9.23326858e-01  8.66126704e-01 ... -2.36453043e+00
  -2.57419966e+00 -2.06764125e+00]
 [ 8.93217564e-02  7.33190107e-02  8.15158968e-02 ...  1.92162013e-01
   1.59816723e-01  1.44651327e-01]
 ...
 [ 3.40360206e+00  2.89082754e+00  2.35019676e+00 ... -6.35719348e-01
  -7.07066519e-01 -9.16529667e-01]
 [-2.72343894e-01 -2.95215860e-01 -2.34761328e-01 ...  1.31288383e-01
   1.11319759e-01  6.67114797e-02]
 [ 7.35576771e-01  6.43953650e-01  5.31602717e-01 ...  7.58286767e-01
   9.17581795e-01  1.00798502e+00]]
```

**Figure 51. scaled dataset**

## Feature selection consists of two processes:

**search and evaluation. Feature search selects feature candidates and feeds them to the feature evaluation to determine their utility. This process is repeated so different subsets are evaluated, until the optimum subset of features is achieved. The best search strategy generates all possible combinations of feature subsets. However, this approach is exhaustive when the numbers of investigated features are large. Therefore, heuristic search methods are adopted. The common heuristic search approaches are forward search, when the search starts with no features and successively adds features; backward search, when the search starts**

with all features and successively removes features; bidirectional search, when the search starts somewhere in the middle and moves outward from the starting point. Feature evaluation can be conducted using different methods: filters have been adopted in this work. Filter methods evaluate a subset of features using correlation methods. They are fast, efficient, and most frequently used in real world applications (Liu et al., 2010). Two feature-evaluation filter methods have been applied in this work: Correlation-based Feature-Selection (CFS) and Minimum Redundancy Maximum Relevance (MRMR). A.1. CFS CFS is a supervised feature-evaluation method that selects a subset of features that are highly correlated with the class and uncorrelated with each other. Each feature is selected according to its ability to predict the class in areas that are not already predicted by other features. This algorithm can be applied to discrete or continuous data. CFS evaluates features using Equation (1), MS = krcf $\sqrt{k + k(k - 1)rff}$ (1) where MS is the heuristic "merit" of a feature subset containing k features, rcf is the mean feature-class correlation, and rff is the average feature–feature inter-correlation. The correlation type is determined according to the class type when symmetrical uncertainty correlation 174 . Ahmed et al. is applied for discrete classes, while Pearson's correlation is applied to continuous classes. CFS feature-evaluation has been applied with two common heuristic search methods: greedy hill climbing (or greedy stepwise) and best-first. Greedy hill climbing adopts a forward or backward search approach to select feature candidates by searching the entire set of features if the feature-evaluation does not degrade. Best-first adopts a forward, backward, or bidirectional search approach to select feature candidates. Best-first allows backtracking during the search so, when a certain path looks less promising, best-first can backtrack to a more promising previous subset, and continue from there. However, a stopping

criterion is applied if a limited number of fully expanded subsets (normally five) result in no further improvement. More details about CFS can be obtained from Hall. MRMR MRMR is a supervised feature-evaluation method that selects features that are mutually dissimilar to each other, but highly related to the class. The selected features are ranked according to their importance, and the user determines the size of the selected features. MRMR can be applied to discrete or continuous data. For discrete data, the mutual information is used to calculate the level of similarity between the features to measure the minimum redundancy using Equation, and it is also used to calculate the discriminant power between the features and the class to measure the maximum relevance using Equation. For continuous data, the Pearson correlation coefficient is used to calculate the similarity between the features to measure the minimum redundancy using Equation, while the F-test is used to calculate the maximum relevance between the features and the class

## 3.3.7. -classification

### Deep learning

### Artificial Neural Network

An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron that receives a signal then processes it and can signal neurons connected to it. The "signal" at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs.

**The connections are called** *edges*. **Neurons and edges typically have a** *weight* **that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold. Typically, neurons are aggregated into layers. Different layers may perform different transformations on their inputs. Signals travel from the first layer (the input layer) to the last layer (the output layer), possibly after traversing the layers multiple times**

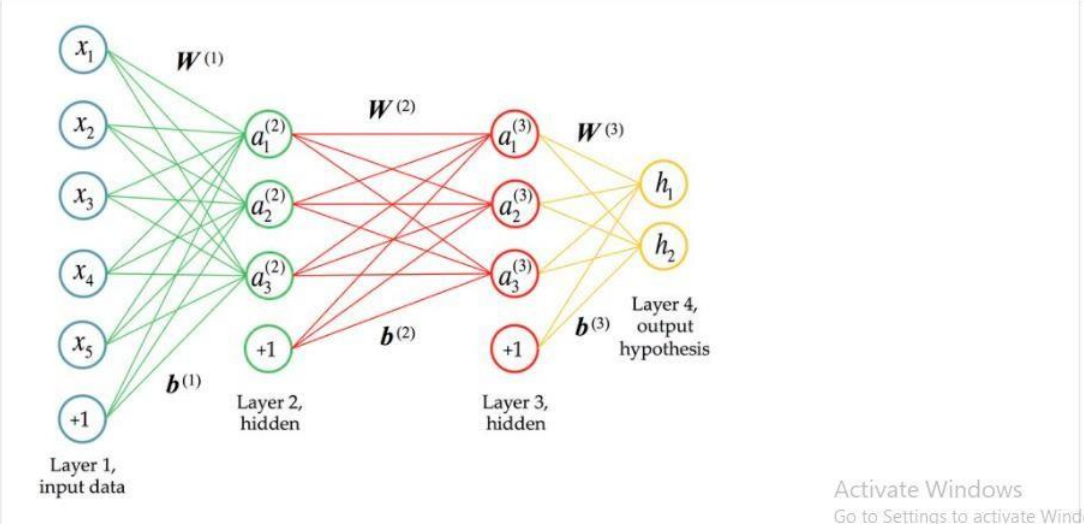



**Figure 52. Artificial Neural Network**

# Components of ANNs

## Neurons

**ANNs are composed of artificial neurons which are conceptually derived from biological neurons. Each artificial neuron has inputs and produces a single output which can be sent to multiple other neurons. The inputs can be the feature values of a sample of external data, such as images or documents, or they can be the outputs of other neurons. The outputs of the final** *output neurons* **of the neural net accomplish the task, such as recognizing an object in an image.**

**To find the output of the neuron, first we take the weighted sum of all the inputs, weighted by the** *weights* **of the** *connections* **from the inputs to the neuron. We add a** *bias* **term to this sum. This weighted sum is sometimes called the** *activation***. This weighted sum is then passed through a (usually nonlinear) activation function to produce the output. The initial inputs are external data, such as images and documents. The ultimate outputs accomplish the task, such as recognizing an object in an image.**

## Connections and weights

**The network consists of connections, each connection providing the output of one neuron as an input to another neuron. Each connection is assigned a weight that represents its relative importance. A given neuron can have multiple input and output connections.**

## Propagation function

**The propagation function computes the input to a neuron from the outputs of its predecessor neurons and their connections as a weighted sum. A bias term can be added to the result of the propagation.**

## Organization

**The neurons are typically organized into multiple layers, especially in deep learning. Neurons of one layer connect only to neurons of the immediately preceding and immediately following layers. The layer that receives external data is the** *input layer***. The layer that produces the ultimate result is the** *output layer***. In between them are zero or more** *hidden layers***. Single layer and unlayered networks are also used. Between two layers, multiple connection patterns are possible. They can be** *fully connected***, with every neuron in one layer connecting to every neuron in the next layer. They can be** *pooling***, where a group of neurons**

in one layer connect to a single neuron in the next layer, thereby reducing the number of neurons in that layer. Neurons with only such connections form a directed acyclic graph and are known as *feedforward networks*. Alternatively, networks that allow connections between neurons in the same or previous layers are known as *recurrent networks.*

## Hyperparameter

**Main article: Hyperparameter (machine learning)**

A hyperparameter is a constant parameter whose value is set before the learning process begins. The values of parameters are derived via learning. Examples of hyperparameters include learning rate, the number of hidden layers and batch size.[46] The values of some hyperparameters can be dependent on those of other hyperparameters. For example, the size of some layers can depend on the overall number of layers.

## Learning rate

The learning rate defines the size of the corrective steps that the model takes to adjust for errors in each observation. A high learning rate shortens the training time, but with lower ultimate accuracy, while a lower learning rate takes longer, but with the potential for greater accuracy. Optimizations such as Quick prop are primarily aimed at speeding up error minimization, while other improvements mainly try to increase reliability. In order to avoid oscillation inside the network such as alternating connection weights, and to improve the rate of convergence, refinements use an adaptive learning rate that increases or decreases as appropriate. The concept of momentum allows the balance between the gradient and the previous change to be weighted such that the weight adjustment

depends to some degree on the previous change. A momentum close to 0 emphasizes the gradient, while a value close to 1 emphasizes the last change.

## Cost function

While it is possible to define a cost function ad hoc, frequently the choice is determined by the function's desirable properties (such as convexity) or because it arises from the model (e.g. in a probabilistic model the model's posterior probability can be used as an inverse cost).

y=0.5(y-y^)^2

## Backpropagation

Backpropagation is a method used to adjust the connection weights to compensate for each error found during learning. The error amount is effectively divided among the connections. Technically, backpropagation calculates the gradient (the derivative) of the cost function associated with a given state with respect to the weights. The weight updates can be done via stochastic gradient descent or stochastic gradient descent, such as Extreme Learning Machines, "No-prop" networks, training without backtracking, "weightless" networks, and non-connectionist neural networks.

## Gradient descent

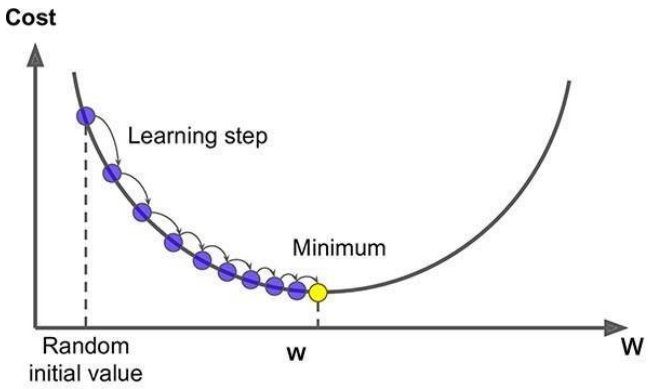



**Figure 53. Gradient descent**

**At each epoch, we determine the new weights as w(new)=w(old)-dy/dx *c where c is the learning rate until we reach the minimum cost function**

### Stochastic gradient descent

**At gradient descent, not in necessary we reach to the global minimum as sometimes we only reach to the local minimum cost function.**
**so here in stochastic gradient descent we reach global minimum cost function through passing the 1 epoch on just a single row of the dataset**

**To understand the architecture of an artificial neural network, we need to understand what a typical neural network contains. To describe a typical neural network, it contains many artificial neurons (of course, yes, that is why it is called an artificial neural network) which are termed units arranged in a series of layers. Let us look at the different kinds of layers available in an artificial neural network**

Input layer:

**The Input layers contain those artificial neurons (termed as units) which are to receive input from the outside world. This is where the actual learning on the network happens, or recognition happens else it will process.**

Output layer:

**The output layers contain units that respond to the information that is fed into the system and whether it learned any task or not.**

Hidden layer:

**The hidden layers are mentioned hidden in between input layers and the output layers. The only job of a hidden layer is to transform the input into something meaningful that the output layer/unit can use in some way.**

**Most of the artificial neural networks are all interconnected, which means that each of the hidden layers is individually connected to the neurons in its input layer and to its output layer leaving nothing to hang in the air. This makes it possible for a complete learning process and learning occurs to the maximum when the weights inside the artificial neural network get updated after each iteration**

## How do Ann work

**Artificial Neural Networks can be best viewed as weighted directed graphs, where the nodes are formed by the artificial neurons and the connection between the neuron outputs and neuron inputs can be represented by the directed edges with**

weights. The Artificial Neural Network receives the input signal from the external world in the form of a pattern and image in the form of a vector. These inputs are then mathematically designated by the notations x(n) for every n number of inputs.

Each of the input is then multiplied by its corresponding weights (these weights are the details used by the artificial neural networks to solve a certain problem). In general terms, these weights typically represent the strength of the interconnection amongst neurons inside the artificial neural network. All the weighted inputs are summed up inside the computing unit (yet another artificial neuron).

If the weighted sum equates to zero, a bias is added to make the output non-zero or else to scale up to the system's response. Bias has the weight and the input to it is always equal to 1. Here the sum of weighted inputs can be in the range of 0 to positive infinity. To keep the response in the limits of the desired value, a certain threshold value is benchmarked. And then the sum of weighted inputs is passed through the activation function.

The activation function, in general, is the set of transfer functions used to get the desired output of it. There are various flavors of the activation function, but mainly either linear or non-linear sets of functions. Some of the most used set of activation functions are the Binary, Sigmoidal (linear) and Tan hyperbolic sigmoidal (non-linear) activation functions. Now let us look at each of them, to certain detail:

## Sigmoidal Hyperbolic:

**The Sigmoidal Hyperbola function in general terms is an 'S' shaped curve. Here tan hyperbolic function is used to approximate output from the actual net input. The function is thus defined as:**

**f (x) = (1/1+ exp(-????x))**

**where ?????is considered the? steepness parameter**

## Rectified linear activation function

**or ReLU for short is a piecewise linear function that will output the input directly if it is positive, otherwise, it will output zero The rectified linear activation function overcomes the vanishing gradient problem, allowing models to learn faster and perform better.**

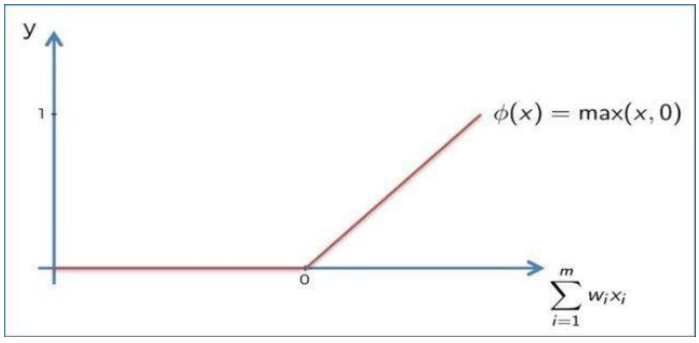



**Figure 54. Rectified linear activation function**

## How do Ann learn

**The learning process of a neural network is configured as an** *iterative process* **of the** *optimization* **of the** *weights* **and is therefore of the** *supervised* **type. The weights are modified because of the network's performance on a set of examples belonging to the training set, that is, the set where you know the classes that the examples belong to.**

**The aim is to** *minimize the loss function*, **which indicates the degree to which the behavior of the network deviates from the desired behavior. The performance of the network is then verified on a testing set consisting of objects (for example, images in an image classification problem) other than those in the training set.**

### ANNs and the backpropagation algorithm

**A commonly used supervised learning algorithm is the** *backpropagation* **algorithm. The basic steps of the training procedure are as follows:**

1. **Initialize the net with random weights**
2. **For all training cases, follow these steps:**

- Forward pass**: Calculates the network's error, that is, the difference between the desired output and the actual output**
- Backward pass**: For all layers, starting with the output layer back to input layer:**

**i: Shows the network layer's output with the correct input (*error function*).**

**ii: *Adapts* the weights in the current layer to minimize the error function. This is backpropagation's *optimization* step.**

**The training process ends when the error on the validation set begins to increase because this could mark the beginning of a phase overfitting, that is, the phase in which the network tends to interpolate the training data at the expense of generalizability.**

**Weight optimization the availability of efficient algorithms to optimize weights, therefore, constitutes an essential tool for the construction of neural networks. The problem can be solved with an iterative numerical technique called** Gradient Descent **(GD). This** technique **works according to the following algorithm:**

Randomly choose initial values for the parameters of the model

1. **Compute the gradient** G **of the error function with respect to each parameter of the model**
2. **Change the model's parameters so that they move in the direction of decreasing the error, that is, in the direction of** -G
3. **Repeat steps 2 and 3 until the value of** G **approaches zero**

**The** *gradient* **(**G**) of the error function** E **provides the direction in which the error function with the current values has the steeper slope; so, to decrease** E**, we have to make some small steps in the opposite direction,** -G**.**

**By repeating this operation several times in an iterative manner, we move *down* towards the minimum of E, to reach a point where G = 0, in such a way that no further progress is possible**

## Stochastic gradient descent

**In GD optimization, we compute the cost gradient based on the complete training set, so we sometimes also call it batch GD. In the case of very large datasets, using GD can be quite costly, since we are only taking a single step for one pass over the training set. The larger the training set, the more slowly our algorithm updates the weights, and the longer it may take until it converges at the global cost minimum.**

**The fastest method of gradient descent is** Stochastic Gradient Descent **(SGD), and for this reason, it is widely used in deep neural networks. In SGD, we use only one training sample from the training set to do the update for a parameter in a particular iteration.**

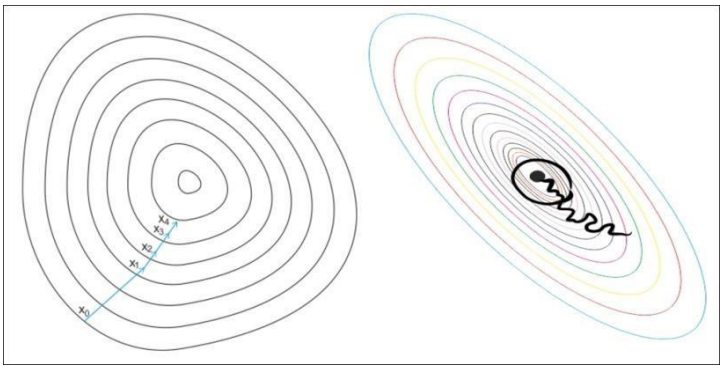


**Figure 55: GD versus SGD: the gradient descent (left figure) ensures that each update in the weights is done in the right direction: the direction that minimizes the cost function**

## Summary of Ann algorithm:

**step1:**

**input the first observation of your dataset in the input layer, each feature in one input node**

**step2:**

**forwarded propagation: from left to right the neurons are activated in a way that the impact of each neurons activation is limited by the weights, propagate the activation until getting the predicted result (y^)**

Step3: **compare the predicted result to the actual result, measure the generated error**

step4**: back-propagation: from right to left the error is back propagated update the weights according to how much they are responsible for the error ,the learning rate decides by how much we update the weights**

**Step5:**

**repeat step 1 to 4 and update the weights after each observation (reinforcement learning, or repeat 1 to 4 and update the weights only after a batch of observations (batch learning)**

**step6:**

**When the whole training set passed through the Ann, that makes an epoch**

**redo more epochs that will increase the accuracy and increase learning rate**

# Chapter 4

## System Implementation

## 4.1. Implementation Details

**In this section, we will discuss in Details the implementation of our proposed system, which can be classified into sub-sections:**

a. **Data Creation**
b. **Wristband Hardware Implementation**
c. **Wristband Software Implementation**
d. **Headband Hardware Implementation**
e. **Model Implementation**
f. **User Interfaces**

### 4.1.1. Data Creation

**Before using our components, some of the team members spent more than three months meeting with the doctors of brain and neurology to benefit from their experiences related to how epilepsy occurs and to obtain information about patients and what are the most important ways and means that the epilepsy patient needs to reduce this burden from on his shoulder, in addition to the most important parameters through which our device will know about the seizures suffered by the epilepsy patient**

**We will get acquainted with the results and drawings deduced from each sensor that was used in the wristband**

## 1. Heart Rate

A period of 5 min was used to analysis the Heart rate pattern, approximately 100 s before and approximately 200 s after the start of the seizure. The fitted heart rate pattern as a function of time t was described as follows. Prior to the seizure the fitted pattern consists of a baseline heart rate. At the time ta the heart rate increases quickly to a maximum, modelled with a constant slope b. After reaching the maximum at tb the heart rate returns slowly to a constant post-seizure baseline heart rate d, modelled by an exponential decaying function with decay constant c, mathematically this pattern can be described as

$$HR_{fit} = \begin{cases} a & \text{for } t < t_a \\ a + b(t - t_a) & \text{for } t_a \le t \le t_b \\ d + e\exp\left(-\dfrac{t - t_b}{c}\right) & \text{for } t > t_b \end{cases}$$

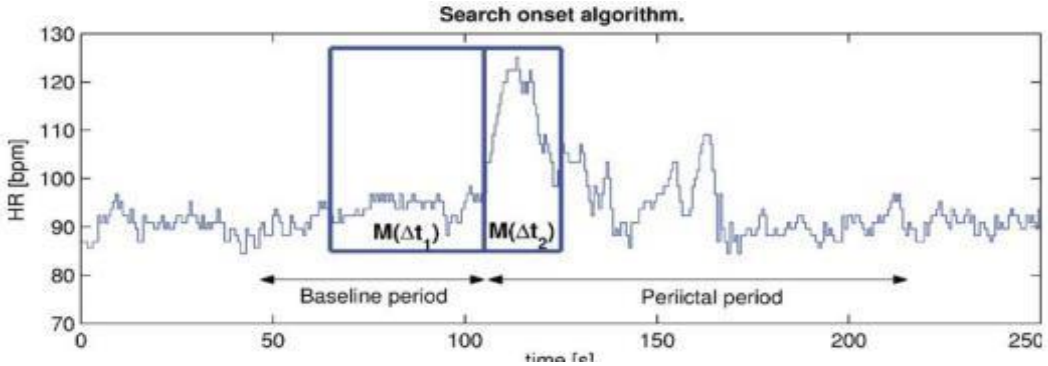



**Figure 56. search onset algorithm of Heart rate signal**

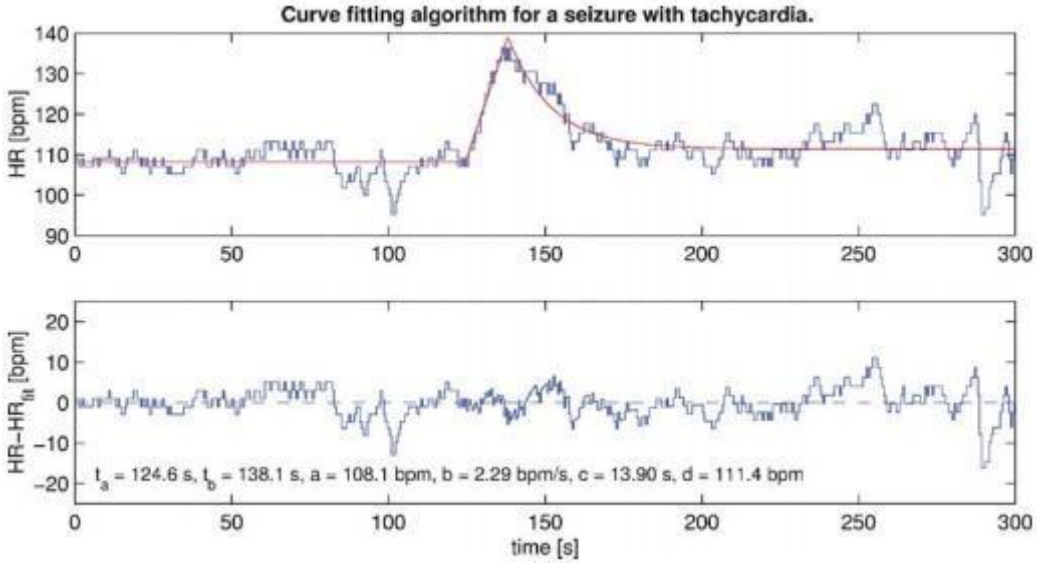



**Figure 57. curve fitting algorithm for a seizure with tachycardia**

The onset detection algorithm was used to detect an increase in heart rate. The algorithm compared the median of the heart rate of a time window Dt1 with the median of as shown at the previous figure Visualization of the onset detection algorithm. The median of a first interval M(Dt1) is compared with the median of an adjacent time interval M(Dt2) and if the medians differ more than a predefined threshold Tup that point in time is documented to be a possible seizure. The two windows are then moved 1 s further in time until the end of the registration is reached. Also the baseline and pre-ictal period are shown

The curve-fitting algorithm is shown in the top figure. The values of fitted parameters and the difference between fitted heart rate and the actual heart rate are shown in the bottom figure.

Table 2 Overview of the heart rate characteristics during a seizure per patient

| Patient number | Seizures with HR change | Seizures without HR change | *B*-Mean ± S.D. | *B*-Max ± S.D. | *B*-Min ± S.D. | I-HR ± S.D. | *P*-Mean ± S.D. | *P*-Max ± S.D. | *P*-Min ± S.D. |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 5 | 73.7 ± 5.3 | 83.2 ± 7.5 | 63.0 ± 7.4 | 67.5 ± 1.1 | 82.0 ± 9.8 | 105.0 ± 11.6 | 62.8 ± 12.2 |
| 2 | 2 | 2 | 77.0 ± 19.0 | 86.3 ± 17.2 | 69.5 ± 19.6 | 71.7 ± 16.5 | 86.1 ± 24.8 | 108.3 ± 6.9 | 63.3 ± 26.7 |
| 3 | 6 | 12 | 82.5 ± 11.9 | 89.3 ± 10.0 | 76.8 ± 11.5 | 81.6 ± 13.4 | 98.3 ± 8.9 | 111.1 ± 11.6[a] | 78.9 ± 12.7 |
| 5 | 3 | 11 | 81.8 ± 2.4 | 84.6 ± 2.4 | 79.0 ± 2.1 | 81.8 ± 1.7 | 92.8 ± 3.3 | 105.3 ± 1.9 | 79.7 ± 2.7 |
| 8 | 11 | 0 | 53.4 ± 4.6 | 57.2 ± 3.9 | 48.1 ± 5.4 | 51.7 ± 4.6 | 55.5 ± 4.1 | 69.2 ± 3.5[b] | 43.5 ± 5.0 |
| 10 | 0 | 4 | | | | | | | |
| 12 | 10 | 0 | 90.1 ± 10.0 | 99.3 ± 10.0 | 82.2 ± 10.6 | 87.4 ± 10.8 | 102.5 ± 9.7 | 136.0 ± 10.3[b] | 84.6 ± 8.7 |
| 15 | 4 | 0 | 75.0 ± 2.1 | 81.1 ± 2.3 | 66.4 ± 1.4 | 72.8 ± 2.9 | 97.2 ± 3.4 | 117.7 ± 3.8 | 69.8 ± 3.9 |
| 16 | 12 | 0 | 87.8 ± 6.3 | 94.3 ± 6.2 | 81.6 ± 6.3 | 87.9 ± 7.1 | 90.8 ± 10.1 | 117.9 ± 5.6[b] | 73.7 ± 10.0 |
| 17 | 0 | 20 | | | | | | | |
| Total | 50 | 54 | 77.9 ± 15.4 | 84.5 ± 16.6 | 71.4 ± 15.3 | 76.4 ± 16.0 | 87.0 ± 18.7 | 109.1 ± 23.3 | 69.5 ± 17.1 |

Significance from B-Mean using Mann–Whitney *U*-test ($n > 5$).
[a] $p = 0.0064$.
[b] $p < 0.001$.

**Table 3. Overview of the heart rate characteristics during a seizure per patient**

The remaining 10 patients had in total 104 seizures, see Table. There were two patients without an alteration of heart rate during a seizure as defined in the methods section. These patients suffered predominantly from very short lasting myoclonic seizures. An increase in HR was seen in 50/104 (48.1%) seizures, 54/104 (51.9%) did not show a HR alteration. Statistics of the baseline and the pre-ictal period are graphically and numerically in Table. Although the patients were fully free to perform their daily routine there were not many movement artefacts.

## 2. SPO2 (Oxygen saturation)

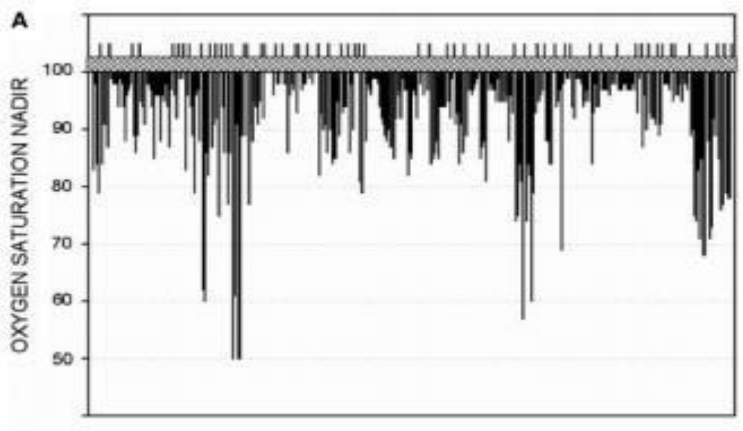



**Figure 58. Oxygen saturation**

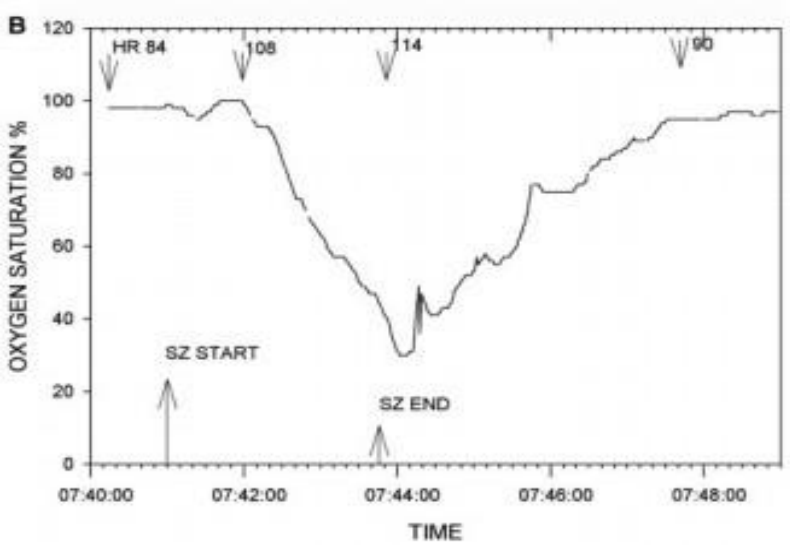



**Figure 59. SpO2 signal with seizure**

**(A) Recorded saturation values below 50% were truncated at 50%. The vertical lines above the hatched bar separate data from the 56 individual patients.**

**(B) Pronounced oxygen desaturation with a complex partial left temporal onset seizure without secondary generalization. Patient was a 19-year-old male with a BMI of 19.9. Seizure onset occurred with the patient awake and sitting in bed. He became unresponsive with lip smacking, a slight head turn to the left**

followed by forceful head turning to the right. He remained sitting for the duration of the seizure. The heart rate (b.p.m.) at various times is shown. Two other complex partial seizures in this patient (one left and one right temporal onset) were accompanied by oxygen desaturations below 50%. Oxygen saturation percent is shown on the ordinate.

## 3. Motor Activity (accelerometer and Gyroscope)

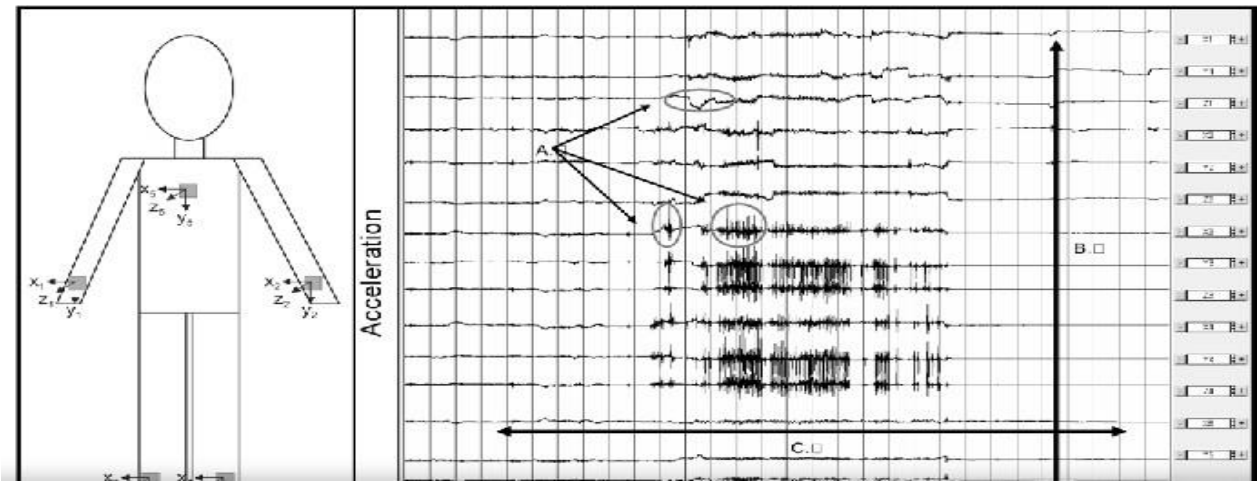



**Figure 60. Acceleration signal**

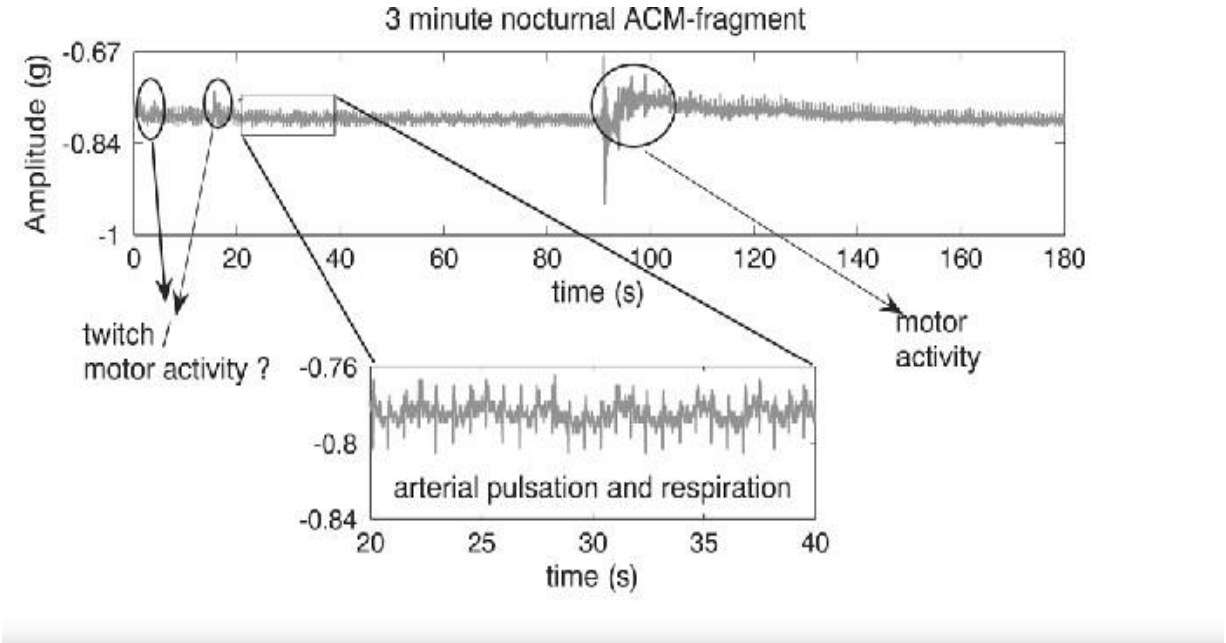



**Figure 61. Acceleration signal**

This paper introduced an automated procedure for the extraction of temporal motor activity signals from video recordings of neonatal seizures. This procedure employs an optical flow computation technique developed to select anatomical sites of interest located on moving body parts and a tracking method based on adaptive block matching. The proposed procedure was used to extract temporal motor activity signals from a database of video recordings of myoclonic seizures, focal clonic seizures, and random infant movements not associated with seizures.

This figure showed that adaptive block matching can be used to extract motor activity signals from video recordings of neonatal seizures. The outcome of this experimental study indicated that the performance of adaptive block matching depends rather strongly on the update strategy employed for the reference block the single-frame update strategies. On the other hand, the multi-frame update strategy performed better than the single-frame update strategy

## 4. Electrodermal activity (EDA)

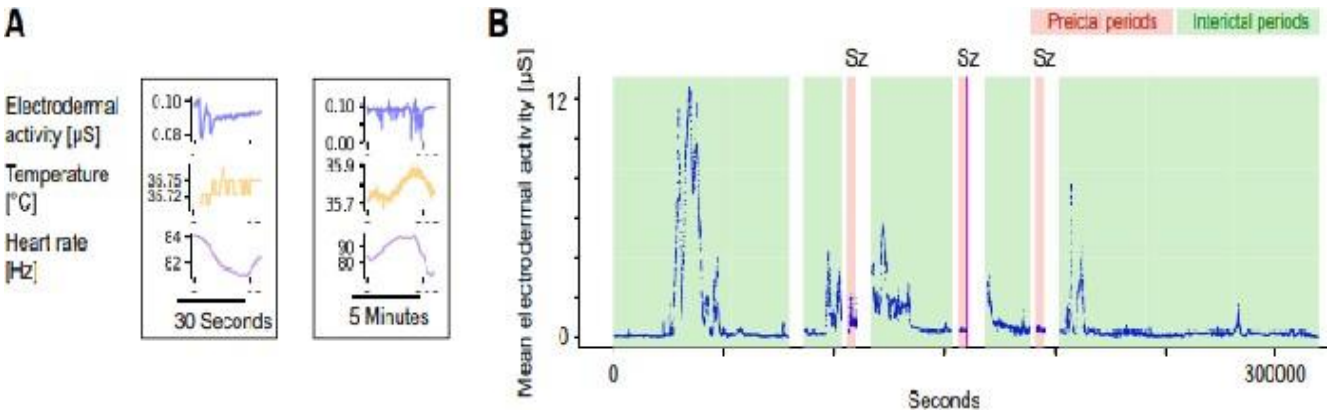



Figure 62. Electrodermal Activity signals

As shown at the previous figure Multimodal wristband sensor data obtained during long-term epilepsy

monitoring. (A) Example of a 30-s (left) and 5-min (right) data segments from one patient containing electrodermal activity (EDA), temperature (TEMP) and heart rate (HR). (B) Time course of mean EDA data from one patient. Magenta vertical lines indicate seizures, green boxes indicate periods classified as inter-ictal, red boxes indicate periods classified as pre-ictal.

## 4.1.2. Wristband Hardware Implementation

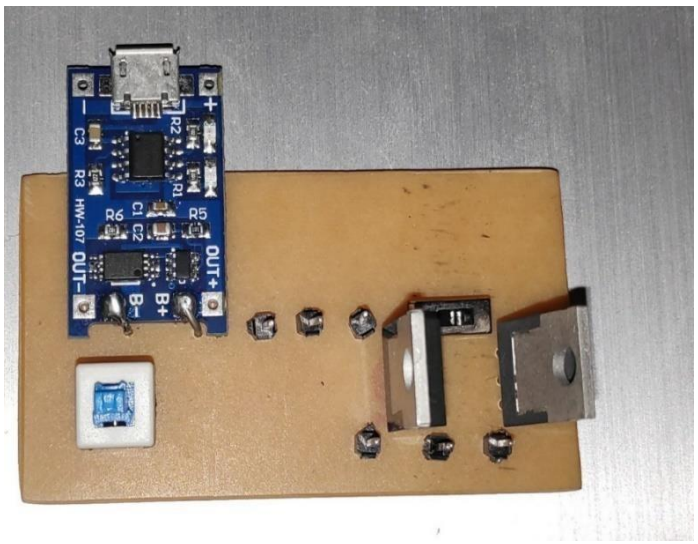
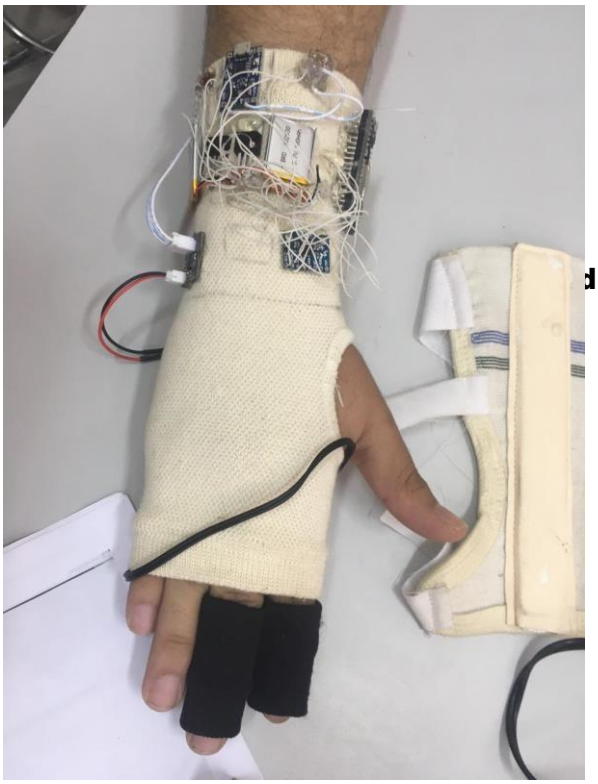



Figure 63. power circuit of the wristband



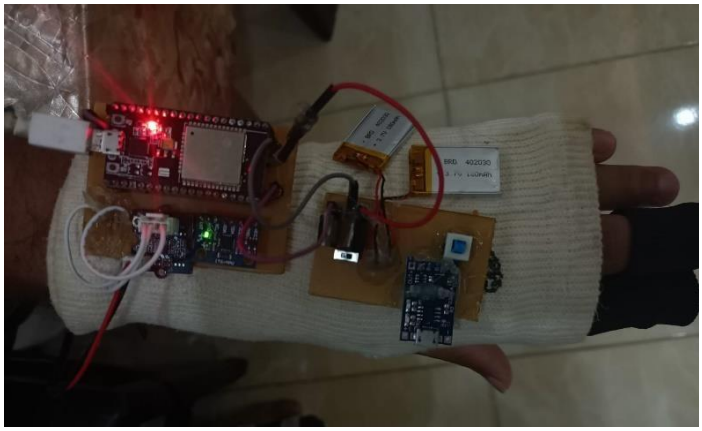


Figure 65. Final prototype of wristband

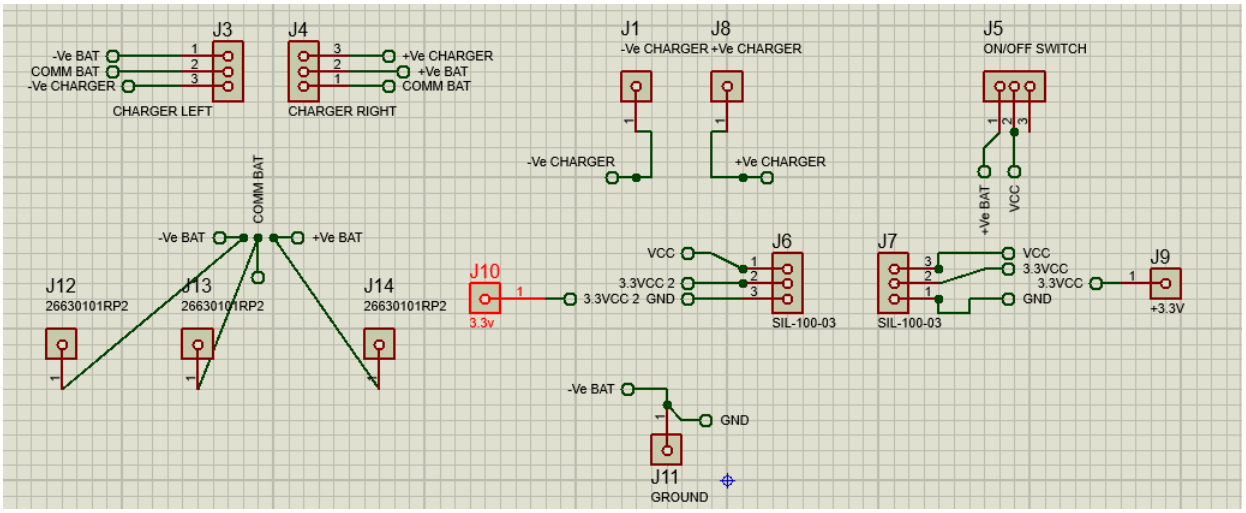



**Fig.66 shows schematic sheet for power circuit**

**Fig.67 shows pcb for power control and Headband**

**1- The output of this pcb equal to 6.6v → -3.3v 0v 3.3v used to supply preamplifier circuit**

**Component of preamplifier circuit is :**

**we will discuss each component and why we have selected it.**

**f. GOLD cup Electrodes to measure EEG signal as fig.4**

**g. AD620 Instrumentation amplifier as fig.5**

h. **LM324 QUAD OP-AMP as fig.6**

i. **resistors and capacitors**

**the job of this circuit is to amplify the input and filter within specific range and we have discussed this function before. So we will go to the implementation part with schematic and pcb designs:**

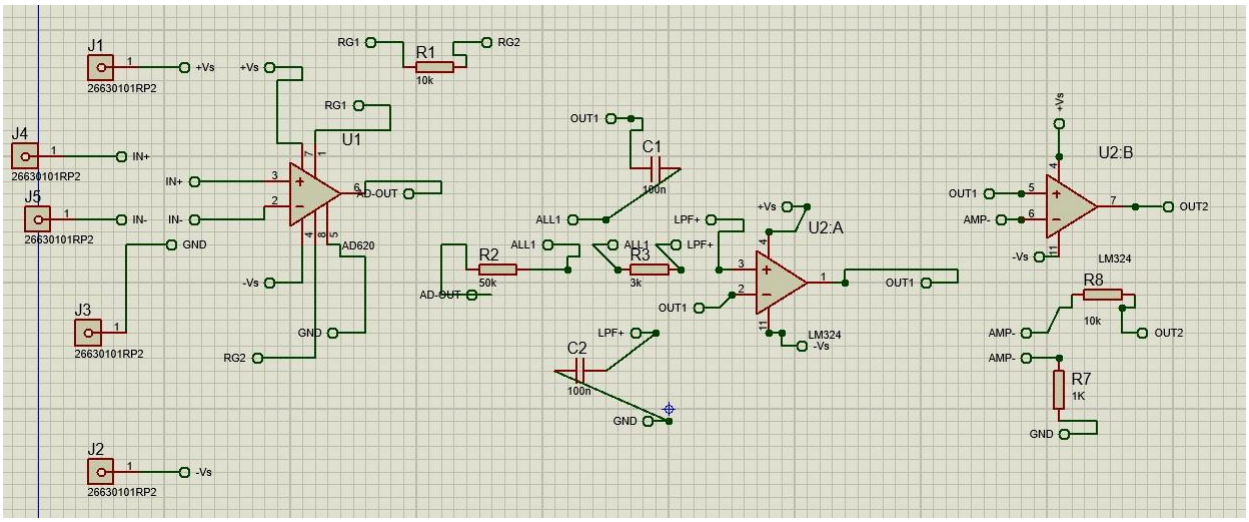



**fig.68 shows schematic sheet of Headband Hardware Part.**

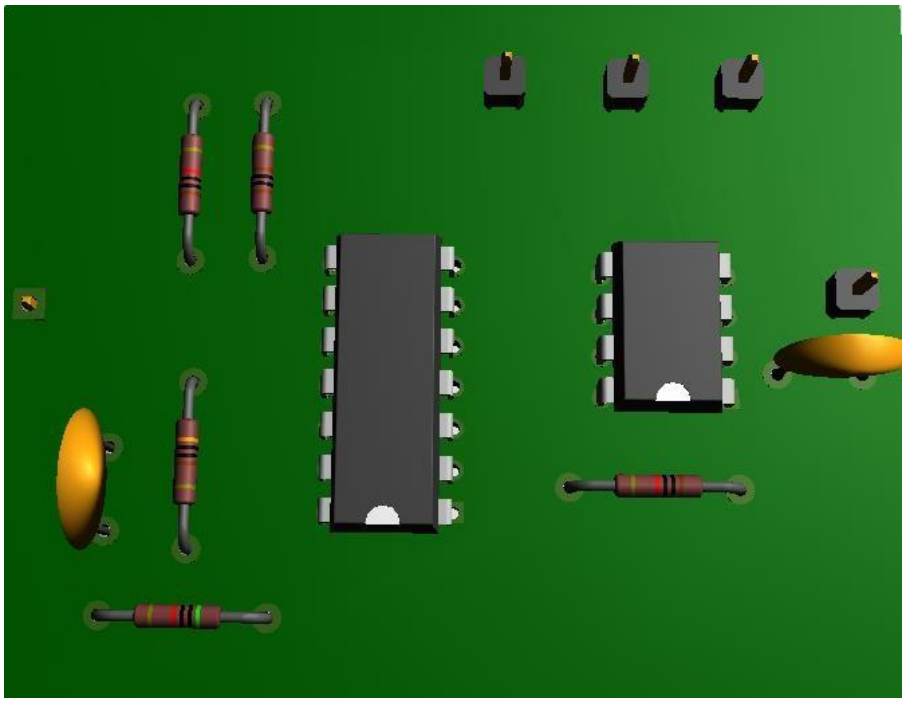


**fig.69 shows pcb 3_design for the Headband part.**

2- **The output of this step is an analoge signal which must have digitalized before go through model step. So here Arduino UNO role comes. To convert this analoge signal to digital signal and store them in csv file will be used by ML model after this stage.**


**fig.70 Arduino UNO**

# Chapter 5

## Results of our project Work

**As we said we have 3 parts:**

1- **Wristband**

2- **Headband**

3- **ML Model**

**As a result of our work, now we can see the Heartrate, SPO2, EDA and the activity of the user using Bluetooth serial monitor. And these parameters indicate if the user in the normal side or abnormal side.**

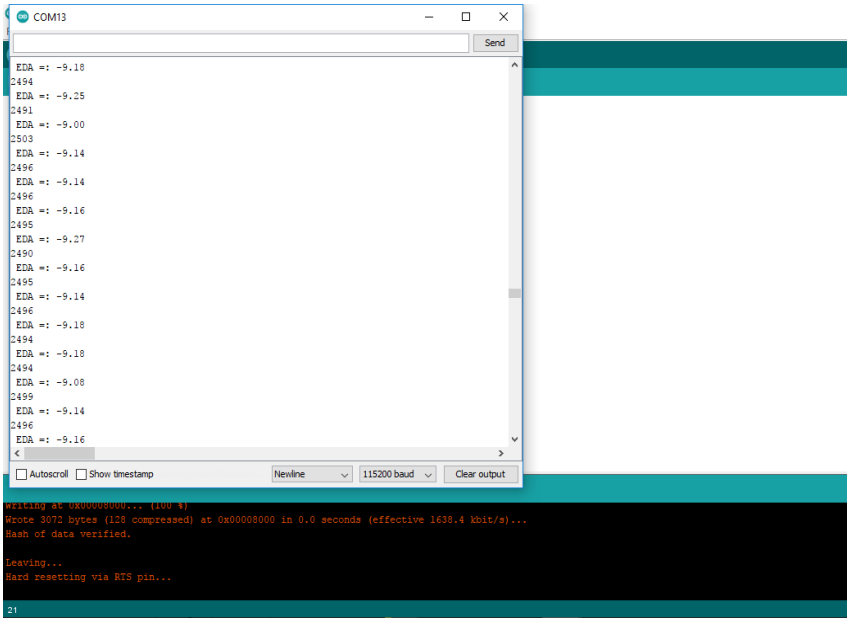



**Fig.76 EDA output**

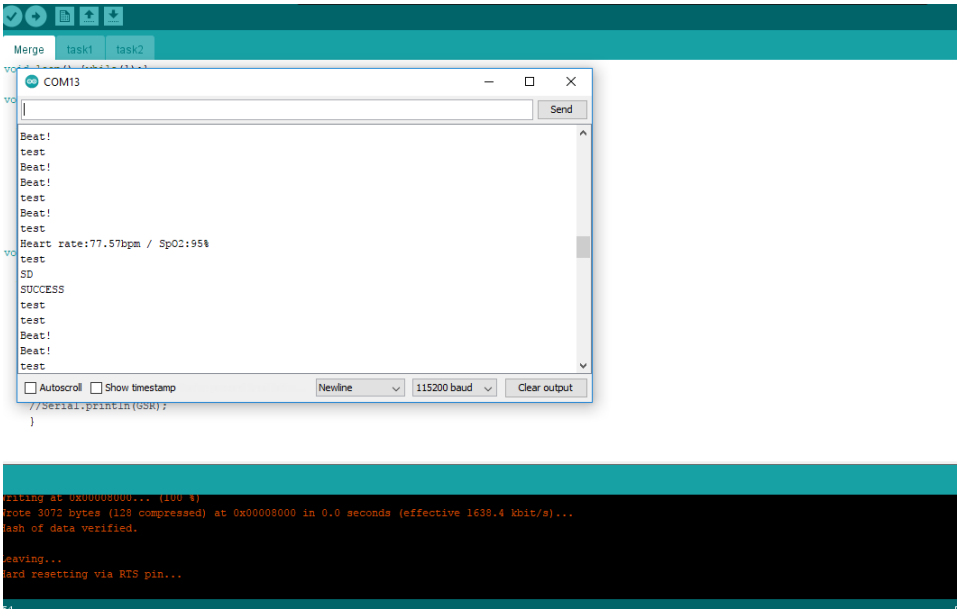



**Fig.77 Heart rate, SpO2 measures and SD flag for ACM**

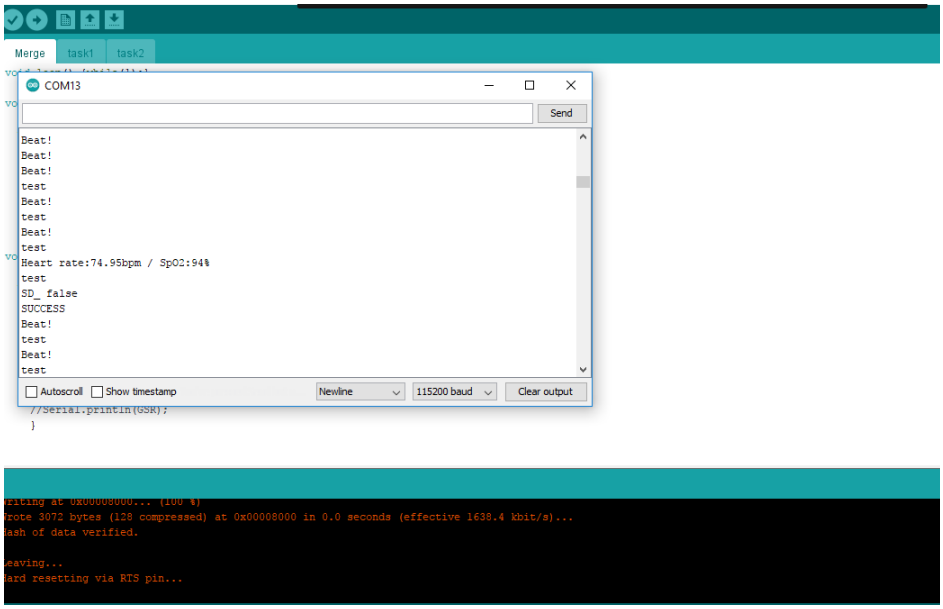



**Fig.78 Heart rate, SpO2 measures and SD flag = false for ACM**

**For Headband, we can now see the status of the user by looking at the plotter in Arduino as the following figures:**

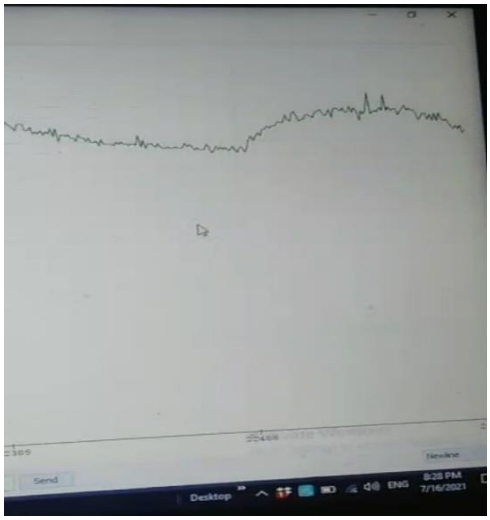


**fig.79 shows when the user close his eye**

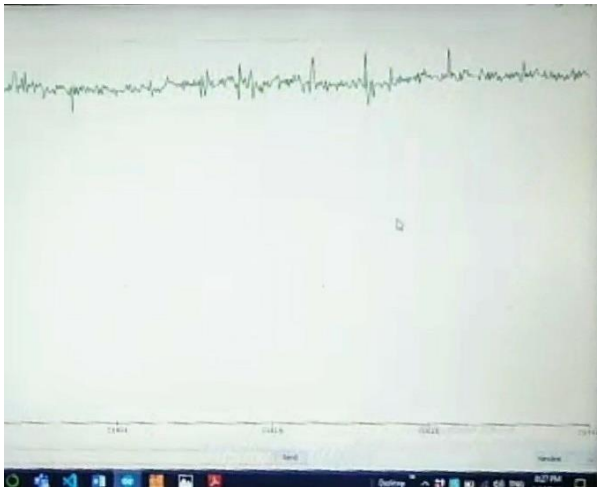


**fig.80 shows normal EEG signal for normal eeg**

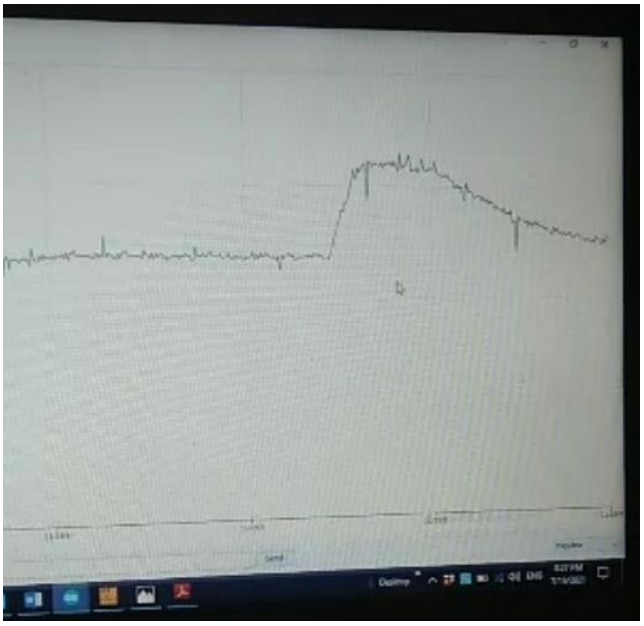


**fig.81 shows when the user making artifacts with**

and with this clear results it's obvious that our headband doing its job in a good way and then going through the ML model will shows the accuracy and results of the model

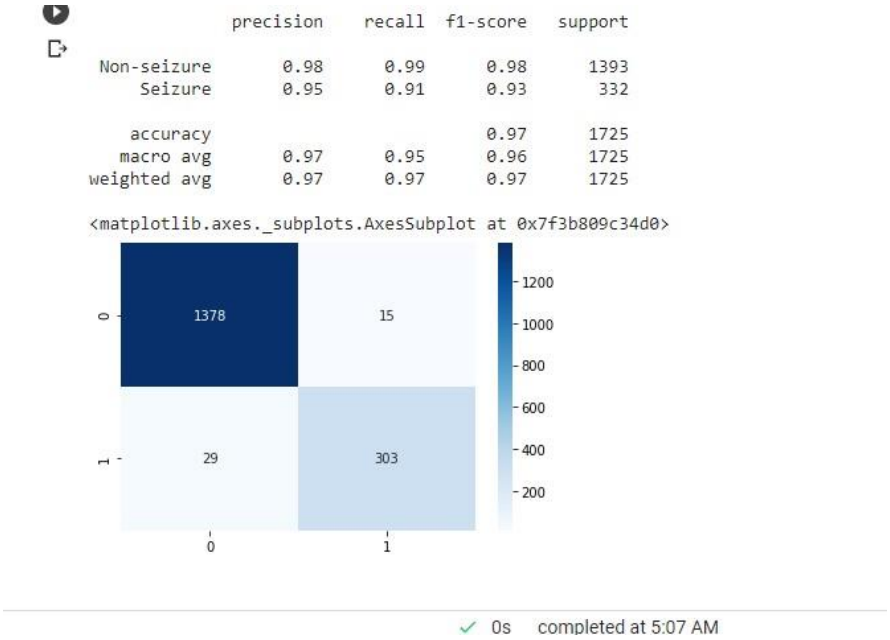



**Figure.82 Final output of our model**

## The overall accuracy as we can see is 97.45%

**where [correct prediction that there is a seizure incorrect prediction that there is a seizure]**

**[incorrect predictions that there is a non-seizure correct predictions that there is no seizure]**

**Here is the accuracy of non-seizure and seizure results, and their plot.**

**In this part, we are going to discuss all results**

**Advantages:**

**1. we could build a ML model with a magnificent accuracy reaches 98% and it's so good result.**

**2. we could build a wristband hardware and software capable of detecting any abnormal activity of the user who wears it.**

**3. we could build an EEG circuit displays EEG signal and send this signal to the ML model.**

**Problems:**

1. **We could not build a mobile app to interface with the user but due to the duration we should build the whole system. And with more time we could build it and make it friendly and easy to the user**
2. **We wanted to use fabric and dry electrodes to make it easy to the user but we could not afford this type of electrodes due to restrictions of the market.**
3. **We wanted to make the system more reliable but due to the time duration was so narrow.**

# Chapter 6

## Conclusions and Recommendations for Future Work

## 6.1. Recommendations for Future Work

**There are still many avenues for future work. In particular, we define the following key future tasks:**

### 6.1.1. Collect more data

**Collect more data to increase the accuracy with which we can increase the efficiency of the devices we are using.**

**Model: We aim to develop a generalized, multi-user system that is independent of the user, but it can also be set and customized for each user when they start using the device.**

### 6.1.2. Extend the system to include a broader vocabulary of words

**Expanding the system to include advanced electronic circuits that can be placed in this headband because we were unable to purchase these circuits from abroad due to the conditions the world is going through from Covid-19 disease**

**In creating an existing instance, we have implemented access to multiple vocabulary sets At one time, albeit on limited data. We plan to increase our recognition models to realize a larger data set, and plan to track it down with an all-in-one multi-user Longitudinal accuracy tests of our system.**

### 6.1.3. Test the system in real-world ambulatory settings

Our current study was conducted in a fixed setting. In the future, we would like

Perform longitudinal usability tests in everyday scenarios.

More efficient communication between the headband and the wristband in order to reduce the delay of the model and its association with the headband in order to be able to take an accurate action about whether the disease has a current seizure or not from brain changes in addition to adjusting and reaching the highest synchronization

# Conclusion

In this project, we describe a system capable of matching two devices (wrist band and headband), in order to detect generalized seizures with relatively high accuracy.

The results are very promising when compared with other techniques and prove that our solution continuously monitor the end-user's heart rate and body movements and also apply machine learning (our model) in order to collect data received from headband to build a unique, personalized, more accurate seizure profile, but the problems that we face current application only check for an increase in heart rate or rapid body movements as well as current applications require a prescription plan in order to detect and track seizures

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Some references that helped us understand how detect works for seizure and how to occur and types of seizures and the best parameters and places in the body that are given the most accurate detect for the occurrence of the seizure and on the basis of which we designed our project to give us the highest accuracy in both aspects to better help patients with epilepsy:

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# AI-based assistance System for Epilepsy Patient