# SEIZURE PREDICTION AND DETECTION ENGINE

# SPADE

**Capstone Project Report End-Semester Evaluation**


**Submitted by:**

**(401503006) AMAN KUMAR**

**(401503013) KESHAV GARG**

**(401503014) KUNAL KISHORE**

**(401503029) SOPHIE KAKKER**

**BE Fourth Year, CSE**

**CPG No: 77**

Under the Mentorship of

Dr. Shalini Batra

Associate Professor

THAPAR INSTITUTE
OF ENGINEERING & TECHNOLOGY
(Deemed to be University)

**Computer Science and Engineering Department**

**TIET, Patiala**


**OCT 2018**

# ABSTRACT


The capstone Project “SPADE” Seizure prediction and detection engine based on brain computing and deep learning is a prior detection of seizure in any person suffering from epilepsy. At first we pre-processed the signal i.e. data coming from the brain and then accessed various machine learning models specific to classification, compared their accuracies and chose the best according to the requirement. We will be training the model on data of about 60GB. The data at the time of working is gathered from the EEG headset and the weights from the best trained models are applied to the collected data and the classification is done. When the class is predicted true for prior Seizure an alert is generated to the user and his emergency contact and sending an SOS.

These products addresses the problem that a lot of people suffering from epilepsy die due to sudden seizures that are not that sudden, the brain signals start changing about 30-40 minutes before and this can be predicted by our project and help the epileptic patients live a better life.

# DECLARATION

We hereby declare that the design principles and working prototype model of the project entitled SPADE is an authentic record of our own work carried out in the Computer Science and Engineering Department, TIET, Patiala, under the guidance of Dr. Shalini Batra during 7th semester (2018).

Date:

| **Roll No.** | **Name** | **Signature** |
|---|---|---|
| 401503029 | AMAN KUMAR | |
| 401503013 | KESHAV GARG | |
| 401503014 | KUNAL KISHORE | |
| 401503029 | SOPHIE KAKKER | |

*Counter Signed By:*

Faculty Mentor:

Dr.Shalini Batra

Designation

Computer Science & Engineering Department,

TIET, Patiala

# ACKNOWLEDGEMENT

We would like to express our thanks to our mentor Dr. Shalini Batra. She has been of great help in our venture, and an indispensable resource of technical knowledge. She is truly an amazing mentor to have.

We are also thankful to Dr. Maninder Singh, Head, Computer Science and Engineering Department, entire faculty and staff of Computer Science and Engineering Department, and also our friends who devoted their valuable time and helped us in all possible ways towards successful completion of this project. We thank all those who have contributed either directly or indirectly towards this project.

Lastly, we would also like to thank our families for their unyielding love and encouragement. They always wanted the best for us and we admire their determination and sacrifice.

Date:

| Roll No. | Name | Signature |
|---|---|---|
| 401503029 | AMAN KUMAR | |
| 401503013 | KESHAV GARG | |
| 401503014 | KUNAL KISHORE | |
| 401503029 | SOPHIE KAKKER | |

# TABLE OF CONTENTS

# LIST OF TABLES

# LIST OF FIGURES

# LIST OF ABBREVIATIONS

| | |
|---|---|
| **ANN** | Artificial Neural Network |
| **API** | Application Program Interface |
| **DWT** | Discrete Wavelet Transform |
| **CSP** | Common Spatial Pattern |
| **EEG** | Electroencephalogram |
| **ICA** | Independent Component Analysis |
| **LDA** | Linear Discriminant Analysis |
| **MEG** | Magnetoencephalography |
| **OSP** | Optimized Spatial Pattern |
| **PCA** | Principal Component Analysis |
| **PSD** | Power Spectral Density |
| **RMS** | Root Mean Square |
| **SNR** | Signal to Noise Ratio |
| **SVM** | Support Vector Machine |
| **TPR** | True Positive Rate |

# INTRODUCTION

## 1.1Project Overview

### 1.1.1 TECHNICAL TERMINOLOGY

- ANN - Artificial Neural Network
- API - Application Program Interface
- DWT - Discrete Wavelet Transform
- CSP - Common Spatial Pattern
- EEG – Electroencephalogram
- ICA - Independent Component Analysis
- LDA - Linear Discriminant Analysis
- MEG – Magnetoencephalography
- OSP - Optimized Spatial Pattern
- PCA - Principal Component Analysis
- PSD - Power Spectral Density
- RMS - Root Mean Square
- SNR - Signal to Noise Ratio
- SVM - Support Vector Machine
- TPR - True Positive Rate

### 1.1.2 PROBLEM STATEMENT

According to the recent surveys out of 1 million people, 688 are suffering from epilepsy and out of these a huge amount of people die suddenly due to these epilepsy seizures. These seizures are not a sudden action, our brain signals starts changing 25-45 minutes before the actual seizure. So in our project we have come with the solution of predicting the occurrence of these seizures prior to its happening. Anyone suffering from surgery can easily connect with our apps and use it to predict seizure all he need will be a wearable headset that will transfer his brain signals to application. This app will also be maintaining a medical record of the patient and his history of previous seizures. Prior prediction of seizures will help in saving a lot of lives by preventing sudden deaths.

### 1.1.3 GOAL

A portable EEG signal reader headset which is able to perform the following tasks:

- Detect signals from the brain
- An Alarm rings at least 10 min before epileptic seizures occurs.

An App is made which acts as an interface to the headset and performs the following tasks:

- Takes location of the persons and places a call to the nearest hospital
- Sends messages to his/her relatives whenever there is a prediction of epileptical seizure.

### 1.1.4 SOLUTION

Predicting the occurrence of these seizures prior to its happening. Anyone suffering from surgery can easily connect with our apps and use it to predict seizure. Only a wearable headset will be needed that will transfer his brain signals to application. This app will also be maintaining a medical record of the patient and his history of previous seizures. Prior prediction of seizures will help in saving a lot of lives by preventing sudden deaths.

## 1.2 Need Analysis

Epilepsy affects nearly 1% of the world's population and is characterized by recurrent and sudden seizures. For many patients, anticonvulsant medications can be given at sufficiently high doses to prevent seizures, but patients frequently suffer side effects. For 20-40% of patients with epilepsy, medications are not effective. Despite the introduction of new anti-epileptic drugs in the last decades, one-third of People with epilepsy continue to have seizures despite treatment.

In case of pregnant women, some anti-epileptic drugs (AEDs) can cause birth defects or developmental problems. Memory may be affected during or after a seizure. This can be because the brain cells in parts of the brain responsible for memory can be sensitive to the effect of seizures. Even after fully recovering from a seizure, some people's memory might be permanently affected. However, even when seizures are well controlled, self-reported quality of life is significantly lowered by the anxiety associated with the unpredictable nature of seizures and the consequences therefrom.

Seizure detection systems are capable of detecting ongoing seizures and provide clinicians with detailed seizure data useful for the management of epilepsy. Closed-loop systems built around seizure detection might also be able to provide rapid therapy in response to seizures early in their clinical onset, thereby limiting the complications or potentially arresting the spread of seizures.

Seizure forecasting systems have the potential to help patients with epilepsy lead more normal lives. For EEG-based seizure forecasting systems to work effectively, computational algorithms must reliably identify periods of increased probability of seizure occurrence. If devices designed to warn patients of impeding seizures would be possible, then patients could avoid potentially dangerous activities like driving or swimming, and medications could be administered only when needed to prevent impending seizures, reducing overall side effects.

## 1.3 RESEARCH GAPS

- Usability challenges

They express the limitations facing the user acceptance of BCI technology utilization. They include the issues related to the training process necessary for classes' discrimination. Information transfer rate (ITR) is one of the system evaluation metrics that combines both performance and acceptance aspects.

- Training process

Training the user is a time-consuming activity either in guiding the user through the process or in the number of recorded sessions. It takes place either in preliminary phase or in the classifier calibration phase. The user is taught to deal with the system as well as to control his\her brain feedback signals in the preliminary phase, while in the calibration phase, trained subject's signal has been used to learn the used classifier.
One of the commonly investigated solutions to this time-consumption problem is to employ single trial instead of multi-trial analysis, which is used for enhancing signal to noise ration, and placing the burden of small training size on subsequent BCI system components to handle.

- Technical challenges

They are issues related to the recorded electrophysiological properties of the brain signals which include non-linearity, non-stationarity and noise, small training sets and the companying dimensionality curse.

- Non-linearity

The brain is a highly complex nonlinear system in which chaotic behavior of neural ensembles can be detected. Thus EEG signals can be better characterized by nonlinear dynamic methods than linear methods.

- Non-stationarity and noise

Nonstationarity attribute of electrophysiological brain signals represents a major issue in developing a BCI system. It originates a continuous change of the used signals over time either between or within the recording sessions. The mental and emotional state background through different sessions can contribute in EEG signals variability. Also fatigue and concentration levels are considered part of internal nonstationarity factors. Noise is also a big contributor in the challenges facing the BCI technology and causing the nonstationarity issue. It includes unwanted signals caused by alterations in electrode placement, and environmental noise. A combination of movement artifacts, such as electrical activity produced by skeletal muscles electromyogram (EMG) and signals created by eye movements and blinking Electrooculogram (EOG), is also reflected in the acquired signals resulting in difficulties in distinguishing the underlying pattern.

- Small training sets

The training sets are relatively small, since the training process is influenced by usability issues. Although heavily training sessions are considered time consuming and demanding for the subjects, they provide the user with necessary experience to deal with the system and learn to control his\her neurophysiological signals. Thus a significant challenge in designing a BCI is to balance the trade-off between the technological complexity of interpreting the user's brain signals and the amount of training needed for successful operation of the interface.

- High dimensionality curse

In BCI systems, the signals are recorded from multiple channels to preserve high spatial accuracy. As the amount of data needed to properly describe different signals increases exponentially with the dimensionality of the vectors, various feature extraction methods have been proposed. They play an important role in identifying distinguishing characteristics. Thus the classifier performance will be affected only by the small number of distinctive traits instead of the whole recorded signals that may contain redundancy.

Generally, it is recommended to use, at least, five to ten times as many training samples per class as the number of dimensions. But this solution cannot be sustained in a highly dimensional environment as the BCI system, causing the expanding of the dimensionality curse

## 1.4 PROBLEM DEFINITION AND SCOPE

According to the recent surveys out of 1 million people, 688 are suffering from epilepsy and out of these a huge amount of people die suddenly due to these epilepsy seizures. These seizures are not a sudden action, our brain signals starts changing 25-45 minutes before the actual seizure. So in our project we have come with the solution of predicting the occurrence of these seizures prior to its happening. Anyone suffering from surgery can easily connect with our apps and use it to predict seizure all he need will be a wearable headset that will transfer his brain signals to application. This app will also be maintaining a medical record of the patient and his history of previous seizures. Prior prediction of seizures will help in saving a lot of lives by preventing sudden deaths.

## 1.5 ASSUMPTIONS AND CONSTRAINTS

- The Epilepsy Detection algorithm should be accurate and moreover the execution of the algorithm should not take more than a second.
- The person should have enough Balance in the phone so that we can place a call and send a message to the emergency contacts.
- The mobile which he/she is using should be bluetooth enabled.
- It is assumed that the system is able to provide necessary requirements for the hardware to operate along with software.

## 1.6 APPROVED OBJECTIVES

- To develop a non-invasive seizure prediction methodology to improve the quality of life of the patients with epilepsy.
- To accurately classify preictal and interictal brain state in humans with naturally occurring epilepsy.
- To predict the onset of a seizure and warn the patient and alarm the nearby medical services for emergency assistance.

## 1.7 METHODOLOGY USED

**Data Acquisition**: About more than 50 GB of data is studied from Kaggle (an online machine learning site), the data is taken for a span of 10 minutes (600 seconds) with a frequency of storing of 380+ records per second. It is the voltage value of EEG recorded by the machine. For real time purposes the data is to be acquired from the EEG device (either the headset and band).

**Data filtering**: A surrogate channel consisting of 3 types of filtering:-
1. Averaging filter
2. Large Laplacian filter
3. Common Spatial pattern filter

**Signal Decomposition**: The Empirical Mode Decomposition - a technique to decompose a given signal into a set of elemental signals called intrinsic Mode Functions (IMFs). Then IMFs are selected and after that non-overlapping window selection.

**Feature Extraction**: It is done to remove redundant features and only selecting a subset of relevant features (variables and predictors). It will be done by keeping two things in mind:

1. Statistical Moments
2. Spectral Moments

**Model Training**: After all the above, data is trained using different machine learning models and different techniques such as ensemble are applied to find the best accuracy. After all these our model will evaluate two things whether it's a case of interictal state or preictal state.

**Interictal state**: Refers to the period between seizures or convulsion that are characteristics of an epilepsy disorder. For most people with epilepsy, the interictal state corresponds with 99% of their life.

**Preictal state**: The state just before ictal is known as preictal.
We will try to increase the time gap between the upcoming seizures and prediction so the patient will have time to report to a hospital and consult a doctor.

**App Development**: For automation, an app will be developed which will automatically send the patients location to nearby hospital and alert the patient too. The app will also consist previous data and patient epilepsy history, this will make easier for the doctor to keep a track of their records.

## 1.8 PROJECT OUTCOMES AND DELIVERABLES

A portable EEG signal reader headset which is able to perform the following tasks:

- Detect signals from the brain
- An Alarm rings at least 10 min before epileptic seizures occurs.

An App is made which acts as an interface to the headset and performs the following tasks:

- Takes location of the persons and places a call to the nearest hospital
- Sends messages to his\her relatives whenever there is a prediction of epileptical seizure.

## 1.9 NOVELTY OF WORK

- Till date this concept has been only circulating in research field but it has never been implemented to fully consumable application. And there is no physical device that does the same.
- Moreover, this device does not require any surgical procedure and is completely non-invasive.

## 2.1 LITERATURE SURVEY

### 2.1.1Theory Associated With Problem Area

Epilepsy is characterized by recurring seizures caused by abnormal discharges in the brain. Electroencephalogram (EEG), a technology directly records electrical activities from the brain, is an important data resource in epilepsy diagnostic tasks, such as, seizure detection, spike detection and localization of epileptic foci. In clinical practice, long-term EEG recording up to a few days, is usually required. Therefore, many computer-aided solutions have been developed to assist neurologists. Combining signal processing and machine learning, most of those approaches model the problem as classification of signals, such as epileptic vs. healthy for epilepsy diagnosis, ictal (on seizure) vs. inter-ictal for seizure onset detection, etc. The most common classification problem is seizure detection, where seizure and non-seizure EEG segments of patients need to be identified.

In this project we will be trying to maximize the time gap between seizure actually happening and predicting. Selecting a model with subsequent set of features after continuous feature extraction and selection will do this. Applying a number of machine learning models with tuned parameters and finding the best accuracy. Later, the model and the list of features with which the best accuracy is observed will be selected and will be applied on the real time data coming from the wearable device by the patient. This all will be done by connecting the device to an app and predicting how much time is left for the seizure to occur.

Our seizure detection algorithms involve two main steps. First, appropriate quantitative values or features, such as EEG features, movements, or other biomarkers, are computed from the data. Second, a threshold or model-based criteria is applied to the features to determine the presence or absence of a seizure. This second step, called classification, might be as simple as thresholding a value or might require models derived from modern machine learning algorithms. Features are computed in a manner that is generally a compromise between the need for speed and the need for detection accuracy and might be preceded by a preprocessing or filtering step. Derivation of a model from machine learning algorithms is done during a training phase and involves three sub steps: preprocessing or filtering, feature computation, and feature reduction or feature extraction.

### 2.1.2 Existing Systems and Solutions

A various number of research papers (shown below) have been published in the past which focus on different techniques.

- Methods of EEG Signal Features Extraction Using Linear Analysis in Frequency and Time-Frequency Domains , Amjed S. Al-Fahoum and Ausilah A. Al-Fraihat
- Feature extraction and recognition of ictal EEG using EMD and SVM , Shufang Li, Weidong Zhou n, Qi Yuan, Shujuan Geng, Dongmei Cai
- Entropies for detection of epilepsy in EEG , N. Kannathala,, Min Lim Choob, U. Rajendra Acharya, P.K. Sadasivana
- Automatic Epileptic Seizure Detection in EEG Signals Using Multi-Domain Feature Extraction and Nonlinear Analysis Lina Wang, Weining Xue, Yang Li, Meilin Luo, Jie Huang, Weigang Cui and Chao Huang.
- Automatic Recognition Of Epileptic Seizures In The EEG , J. GOTMAN
- A Surrogate Channel Based Analysis of EEG Signals for Detection of Epileptic Seizure ,Saqib Ejaz Awan, Sajid Gul Khawaja, Muazzam A. Khan, M. Usman Akram

These are few research papers which are famous but much research has been done.

### 2.1.3 Research Findings for Existing Literature

A numerous techniques have been developed to measure the large amount of variation in EEG signals and to handle the curse of dimensionality. The huge dimensionality of data makes it difficult to detect seizures in real time. In the method proposed by Gotmann for automatic recognition of epileptic seizures in the EEG consist of dividing the signals into halves and finding features like spike-wave bursts , slope and sharpness. Since the EEG signals are continuous wave signals therefore there are multiple ways in which these signals can be interpreted. Two major domains related to analysis of signals are Spectral Domain and Time-Frequency Domain. To reduce and eliminate the problem of spectral importance of difference , Saqib and Sajid proposed a way to extract features from a single channel formed by surrogating all the channels in the original data. Different features like entropy , mean , range , inter-quartile range, standard deviation, skewness and a some more are extracted and then selected on the basis of effciency of the trained model for different subset of features. Zakareya propose an epilepsy seizures detecting method that can be implemented in a hardware device to help epileptic patients. They briefly describe the accuracy of different techniques used for feature extraction from EEG Signals. And processed the EEG signal in both time and frequency domains and applied a Chebyschev filter for preprocessing the signal. Technique used by Abeg involves sub-pattern based PCA (SpPCA) and cross-sub-pattern correlation-based PCA (SubXPCA). For model training Support Vector Machine (SVM) is used for automated seizure detection in EEG signals. In the case of SpPCA, features are extracted by applying PCA on each of subpattern sets. Once the feature extraction from these subpattern sets is over, the extracted features are combined in accordance with the partition sequence of patterns to form the final feature vectors. SubXPCA is a two step process. The first step is constituted by SpPCA. In the second step, PCA is performed on the features extracted in the previous step to further reduce the dimensionality and to extract the global features. Study by Ahmad summarizes the data-analytic methods that have been used for the analysis of EEG signals. The major difference between feature extraction using Time Domain and Spectral Decomposition have been clearly specified. They briefly describe various models and situation in which models are to be used along with their pros and cons. Shufang and Qi proposed a novel method for feature extraction and pattern recognition of ictal EEG, based upon empirical mode decomposition (EMD) and support vector machine (SVM). First the EEG signal is decomposed into Intrinsic Mode Functions (IMFs) using EMD, and then the coefficient of variation and fluctuation index of IMFs are extracted as features. SVM is then used as the classifier for recognition of ictal EEG. SVM is then used as the classifier for recognition of ictal EEG.

### 2.1.4 The Problem That Has Been Identified

According to the recent surveys out of 1 million people, 688 are suffering from epilepsy and out of these a huge amount of people die suddenly due to these epilepsy seizures. These seizures are not a sudden action, our brain signals starts changing 25-45 minutes before the actual seizure. So in our project we have come with the solution of predicting the occurrence of these seizures prior to its happening. Anyone suffering from surgery can easily connect with our apps and use it to predict seizure all he need will be a wearable headset that will transfer his brain signals to application. This app will also be maintaining a medical record of the patient and his history of previous seizures. Prior prediction of seizures will help in saving a lot of lives by preventing sudden deaths.

### 2.1.5 Survey of Tools and Technologies Used

- **Python**: Python is an interpreted high-level programming language for general-purpose programming. It is an open-source language therefore developers around world has contributed by developing libraries. Python has many libraries which provides functions for exploring, visualizing and analysing human neurophysiological data like EEG, MEG, etc.
- **MNE**: It is an open-source Python software for exploring, visualizing and analysing human neurophysiological data like EEG, MEG, etc. It has a python

library which has functions for pre-processing, analysing and applying machine learning to EEG data

- **Signal pre-processing:** In literature, signal pre-processing is defined as a process but mainly involves filtering of raw EEG data in spectral, spatial and temporal domain. In spectral domain, band pass filtering is certainly applied. In spatial domain, Common Spatial Patterns(CSP) algorithm is one of the latest and very effective approach to construct spatial filters. Fourier transform and Wavelet transform are also widely used to take the signal into frequency domain so that certain features can be extracted. In python, there are libraries available that provide functions for signal pre-processing namely scipy and mne.
- **Feature extraction:** In literature survey, different researches have worked with different numerous features in each domain, so we have analysed and picked the most common and effective features. As per our current literature survey, the features under consideration are Power spectral density(PSD), peak frequency, median frequency, root mean square(RMS), entropy, energy, Hurst exponent, Largest Lyapunov exponent, correlation dimension, standard deviation, skewness and kurtosis. MNE library contains functions for many of the feature extraction techniques, but for the rest we will implement the concepts.
- **Feature selection**: In literature, researchers have not shown any preference for univariate or multivariate algorithms of feature selection as both have them has their pros and cons. So, we will experiment with both approaches. We will also employ techniques of dimensionality reduction like PCA, ICA and LDA
- **Machine learning model optimization**: In literature, Support Vector Machine (SVM) is widely celebrated machine learning model for EEG classification. But, this component demands research and innovation therefore we will implement numerous machine learning models to achieve the best classification accuracy. Application of deep learning models in EEG classification is also one of the unexplored areas, so we will experiment with performance of deep learning models in EEG classification task.
- **App development:** App working is divided into two parts firstly at the user ends user need to enter headset details, connect the device and start recording the EEG Signals. The app will then preprocess the recorded data and apply the weights to finally predict whether seizure is going to happen or not. If seizure is predicted then the data at which it is predicted is going to be save and an alert will be raised to the user and his emergency contacts.

## 2.2 STANDARDS

### 2.2.1 Standards used for the proposed design solution

**1. IEEE 1471:** It is the IEEE standard for software/system architecture according to which the entire architecture of our working prototype was designed.

**2. IEEE 1233:** IEEE standard for system requirement specifications. It was followed while preparing the SRS document for this system, which is a structured collection of information that embodies the requirements of a system

**3. IEEE 830:** IEEE standard for software requirement specifications. It was used for the developing the software requirements specification for this system. The software requirements specification is a description of a software system to be developed and lays out functional and non-functional requirements, and includes a set of use cases that describe user interactions that the software must provide.

**4. IEEE 1016**: It is the IEEE standard for software design description. A software design description is a written description of a software product that describes the overall architecture of the software project. An SDD usually accompanies an architecture diagram with pointers to detailed feature specifications of smaller pieces of the design. Practically, the description needs to outline all parts of the software and how they will work. The standard was followed while describing specific details of the system such as data flow diagrams, architecture diagrams etc.

### 2.2.2 Hardware Standards

**1. ETSI EN 300 440-2 V1.4.1 –**

This is part of a set of standards developed by ETSI and is designed to fit in a modular structure to cover all radio and telecommunications terminal equipment within the scope of the R&TTE Directive.

The present document applies to the following Short Range Device major equipment types:

1) Generic Short Range Devices, including alarms, tele-command, telemetry, data transmission in general, etc.;
2) Radio Frequency IDentification (RFID);
3) Radio determination, including detection, movement and alert applications.

These radio equipment types are capable of operating in the permitted frequency bands within the 1 GHz to 40 GHz range as specified in table –

**2. EN 301 489-1 –**

The present document, together with the relevant radio technology part, where required, specifies the applicable EMC tests, the methods of measurement, the limits and the performance criteria for radio equipment and associated ancillary equipment. In case of differences (for instance concerning special conditions, definitions, abbreviations) between part 1of ETSI EN 301 489 series [i.13] and the relevant radio technology part of ETSI EN 301 489 series [i.13], the relevant radio technology part takes precedence.

Technical specifications related to the antenna port of radio equipment and radiated emissions from the enclosure port of radio equipment and combinations of radio and associated ancillary equipment are not included in the present document. Such technical specifications are normally found in the relevant product standards for the effective use of the radio spectrum.

**3. EN 301 489-3 –**

- This standard, together with ETSI EN 301 489-1, covers the assessment of Short Range Devices (SRD) and ancillary equipment in respect of ElectroMagnetic Compatibility (EMC).
- It also specifies specifies the applicable test conditions, performance assessment, and performance criteria for Short Range Devices (SRD) and the associated ancillary equipment.

**4. AS/NZS 4268 :2008 –**

The objective of this Standard is to provide limits and methods of measurement for short range devices placed on the Australian market, and authorized for use by the Radio-communications (Low Interference Potential Devices) Class License 2000 (LIPD) and Radio-communications (Radio-controlled Models) Class License 2002 Class Licenses issued by the Australian Communications and Media Authority, or short range devices placed on the New Zealand market, and authorized for use by the General User Radio License (GURL) issued by the New Zealand Ministry of Economic Development

**5. AS/NZS CISPR22 :2009 –**

The objective of this Standard is to specify uniform requirements for the radio disturbance level of the equipment contained in the scope, to fix limits of disturbance, to describe methods of measurement and to standardize operating conditions and interpretation of results.

This Standard is identical with, and has been reproduced from, CISPR 22, Ed. 6.0 (2006), Information technology equipment—Radio disturbance characteristics—Limits and methods of measurement.

As this Standard is reproduced from an International Standard, the following applies:

(a) Its number does not appear on each page of text and its identity is shown only on the cover and title page.

(b) In the source text ‘this International Standard’ should read ‘this Australian/New Zealand Standard’.

(c) A full point should be substituted for a comma when referring to a decimal marker.

The terms ‘normative’ and ‘informative’ are used to define the application of the Annex to which it applies. A normative annex is an integral part of a Standard, whereas an informative Annex is only for information and guidance.

### 2.2.3 Application Standards

#### 2.2.3.1. Visual design and UI

**2.2.3.1.1 Standard design -**

**2.2.3.1.1.1 UX-B1:** The app does not replace a system icon with a completely different icon if it triggers the standard UI behavior. The app does not redefine or misuse Android UI patterns, such that icons or behaviors could be misleading or confusing to users

**2.2.3.1.2 Navigation**

**2.2.3.1.2.1 UX-N3 :** Pressing the Home button at any point navigates to the Home screen of the device.

**2.2.3.1.3 Notifications**

**2.2.3.1.3.1 UX-S2 :** The app uses notifications only to:

a. Indicate a change in context relating to the user personally (such as an incoming message).

or

b. Expose information/controls relating to an ongoing event (such as music playback or a phone call).

#### 2.2.3.2. Functionality :

**2.2.3.2.1 Permission**

**2.2.3.2.1.1 FN-P1 :** The app requests only the *absolute minimum* permissions that it needs to support core functionality.

**2.2.3.2.2 UI and graphics**

**2.2.3.2.2.1 FN-U1 :** The app supports both landscape and portrait orientations (if possible).

**2.2.3.2.2.2 FN-U2** : The app uses the whole screen in both orientations and does not letterbox to account for orientation changes.

**2.2.3.2.2.3 FN-U3** : The app correctly handles rapid transitions between display orientations without rendering problems.

#### 2.2.3.3. Compatibility performances and stability

**2.2.3.3.1 Stability**

**2.2.3.3.1.1 PS-S1 :** The app does not crash, force close, freeze, or otherwise function abnormally on any targeted device.

**2.2.3.3.2 Performances**

**2.2.3.3.2.1 PS-P1** : The app loads quickly or provides onscreen feedback to the user (a progress indicator or similar cue) if the app takes longer than two seconds to load.

**2.2.3.3.3 SDK**

**2.2.3.3.3.1 PS-T1 :** The app runs on the latest public version of the Android platform without crashing or loss of core function.

**2.2.3.3.3.2 PS-T2 :** The app is built with the latest SDK by setting the compileSdk value.

**2.2.3.4. Security**

**2.2.3.4.1 Data**

**2.2.3.4.1.1 SC-D1** : All private data is stored in the app's internal storage.

**2.2.3.4.1.2 SC-D2** : All data from external storage is verified before being accessed.

**2.2.3.4.1.3 SC-D3 :** No personal or sensitive user data is logged to the system or app-specific log.

**2.2.3.4.2 Networking**

**2.2.3.4.2.1 SC-N1 :** All network traffic is sent over SSL.

**2.2.3.4.2.2 SC-N2 :** Application declares a network security configuration.

**2.2.3.4.3 Execution**

**2.2.3.4.3.1 SC-E1 :** The app does not dynamically load code from outside the app's APK

## 2.3 SOFTWARE REQUIREMENTS SPECIFICATION

### 2.3.1 Functional Requirements:

**Epileptic Seizure Predictor:**

Epileptic Seizure Predictor consists of analyzing and detecting the anomaly in the EEG signals and to predict that whether a person is about to encounter a seizure or not. If a seizure is predicted, the system will raise an alert, an emergency contact specified by the user will be notified and an ambulance will be called. Alongside, system will record and save EEG signals for some time interval before the onset of seizure to collect some user-specific EEG data so that the machine-learning model can be calibrated and improved as per each individual user.

The mobile application will have the following major functionalities:

1. The application will connect to an EEG headset through Bluetooth
2. The application will receive EEG signal data from headset and store the data
3. The application will preprocess the data, extract features and classify the EEG signal using the trained machine learning model in real-time
4. In case onset of a seizure is predicted, the application will raise an alert, notify specified emergency contacts and call an ambulance for quick medical assistance
5. The application will provide every user with their seizure history
6. The application will have the memory access to record and save the EEG data in the vicinity of an onset of a seizure to collect user specific EEG data
7. The developer will be able to update system, add some more features, fix bugs and access user-specific EEG data.

**Mobile Application:**

The control of the mobile application is solely under the user. After installation of application, user needs to sign-up and enter some user details. The application is used to interface the EEG headset with a mobile device having a user-friendly GUI. The user will connect the application with headset via device's Bluetooth. And once the reception of EEG signal will start the application will process and analyze the signal in real-time to predict an upcoming seizure. In case of prediction of onset of a seizure it will raise an alert. Application will maintain a customized user profile along with history of episodes of seizures. Application will also store some EEG data to calibrate and improve the machine-learning model in terms of accuracy and prediction time. The developer will be able to access this user specific EEG data, update system, add some features and fix bugs.

### 2.3.2 Non-Functional Requirements: -

**Reliability:**

System should be reliable enough with high true positive rate and low false positive rate. It must predict the seizure accurately. Also prediction of the seizure should be a good time before seizure begins.

**Response time:**

System should be fast and should have very less response time. It should preprocess and detect the anomaly in minimal time and should call the ambulance and notify the emergency contact well before time. It should take less processing time.

**Accessibility:**

The mobile application should be accessible to user at all times. The interface of mobile application should be easy to use for the user

**Stability:**

The system should be stable enough with minimum number of resets required. It should have exception handling mechanism and should avoid getting in hanged state.

**Maintainability:**

The system should be easy to maintain over long time. Any modifications required after deployment should be easy to make.

## 2.4 COST ANALYSIS

In our app we are going to predict seizures. The efficiency of our app is displayed when a person using the app who is suffering from epilepsy, is wearing that headset and he/she encounters the seizure. But at academic level, where we need to depict the accuracy we cannot depict this procedure in real time, due to many reasons like

1. Legal Obligations
2. Ethical and Moral Dilemma or Disapprovements
3. Potential threats to person's life due to inappropriate medical conditions that may arise during experimentation.

To resolve this conflict, we will depict the accuracy of our model, using pre-saved data , which will be completely unseen by the model.

But for showcasing the complete functions of our app, we are going to need a **EEG Headset**. Its cost is around **12,000 INR**. For, the testing phase, and development stages of the app , we have collaborated with a faculty in TIET, who owns an EEG Headset. The faculty member has selflessly agreed to share the headset with us. So, for now our cost structure for hardware requirements is zero.

In backend and front end, i.e. for our , software functioning , we need :-

1. Python
2. React
3. Android Studio
4. Google Map API

All of the above mentioned software/language are freely available on the internet.

Thus our cost structure for all the **requirements for development** of our app is **ZERO.**

## 3.1 PROPOSED SOLUTION

Predicting the occurrence of these seizures prior to its happening. Anyone suffering from surgery can easily connect with our apps and use it to predict seizure. Only a wearable headset will be needed that will transfer his brain signals to application. This app will also be maintaining a medical record of the patient and his history of previous seizures. Prior prediction of seizures will help in saving a lot of lives by preventing sudden deaths.

## 3.2 TOOLS AND TECHNOLOGIES USED

- **Python**: Python is an interpreted high-level programming language for general-purpose programming. It is an open-source language therefore developers around world has contributed by developing libraries. Python has many libraries which provides functions for exploring, visualizing and analysing human neurophysiological data like EEG, MEG, etc.
- **MNE**: It is an open-source Python software for exploring, visualizing and analysing human neurophysiological data like EEG, MEG, etc. It has a python library which has functions for pre-processing, analysing and applying machine learning to EEG data
- **Signal pre-processing:** In literature, signal pre-processing is defined as a process but mainly involves filtering of raw EEG data in spectral, spatial and temporal domain. In spectral domain, band pass filtering is certainly applied. In spatial domain, Common Spatial Patterns(CSP) algorithm is one of the latest and very effective approach to construct spatial filters. Fourier transform and Wavelet transform are also widely used to take the signal into frequency domain so that certain features can be extracted. In python, there are libraries available that provide functions for signal pre-processing namely scipy and mne.
- **Feature extraction:** In literature survey, different researches have worked with different numerous features in each domain, so we have analysed and picked the most common and effective features. As per our current literature survey, the features under consideration are Power spectral density(PSD), peak frequency, median frequency, root mean square(RMS), entropy, energy, Hurst exponent, Largest Lyapunov exponent, correlation dimension, standard deviation, skewness and kurtosis. MNE library contains functions for many of the feature extraction techniques, but for the rest we will implement the concepts.
- **Feature selection**: In literature, researchers have not shown any preference for univariate or multivariate algorithms of feature selection as both have them has their pros and cons. So, we will experiment with both approaches. We will also employ techniques of dimensionality reduction like PCA, ICA and LDA

- **Machine learning model optimization**: In literature, Support Vector Machine (SVM) is widely celebrated machine learning model for EEG classification. But, this component demands research and innovation therefore we will implement numerous machine learning models to achieve the best classification accuracy. Application of deep learning models in EEG classification is also one of the unexplored areas, so we will experiment with performance of deep learning models in EEG classification task.
- **App development:** App working is divided into two parts firstly at the user ends user need to enter headset details, connect the device and start recording the EEG Signals. The app will then preprocess the recorded data and apply the weights to finally predict whether seizure is going to happen or not. If seizure is predicted then the data at which it is predicted is going to be save and an alert will be raised to the user and his emergency contacts.

## 3.3 WORK BREAKDOWN STRUCTURE

## 4.1 SYSTEM ARCHITECTURE

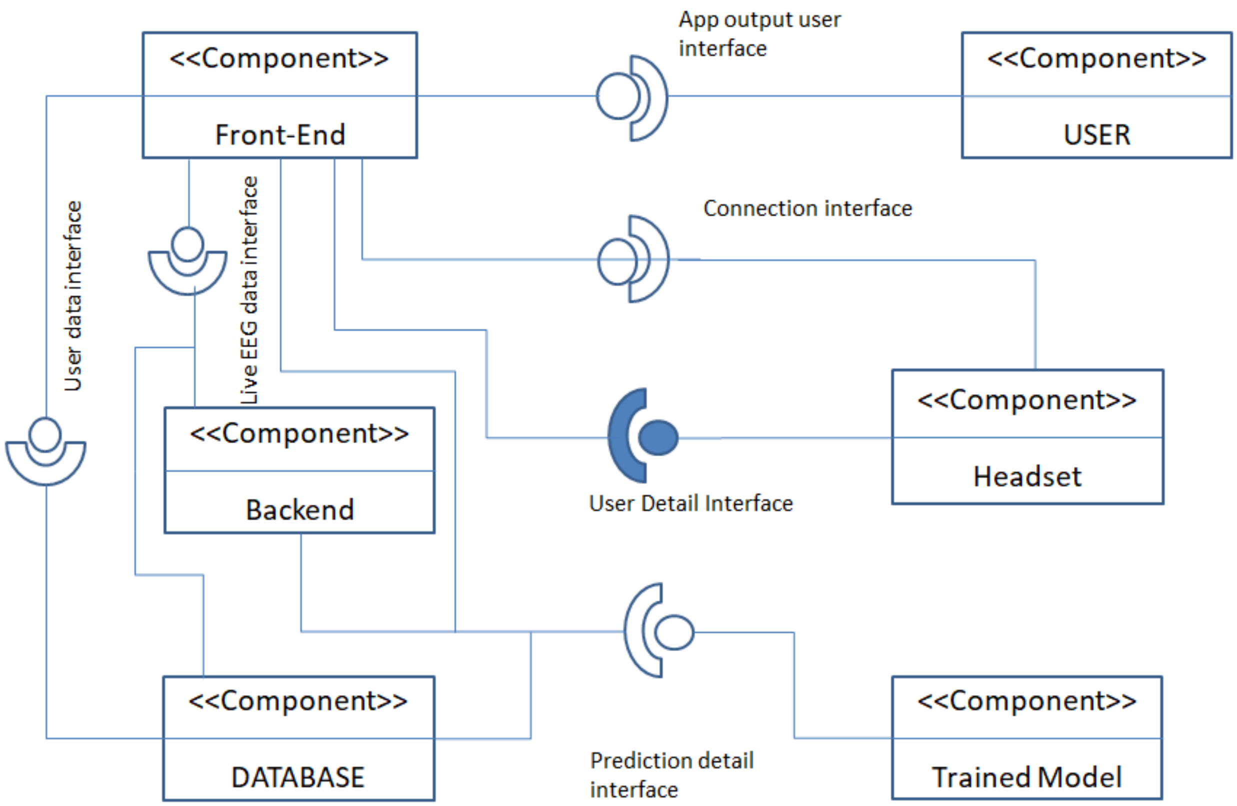


Figure 2: Component Diagram

The System has the following Components.

- Owner/User: The person with the epilepsy and owner of the headset and app to predict prior seizures.
- Headset:- it is the wearable Bluetooth device that the user has to connect and wear at all the time when he require the prior prediction. It will send the signals from 14 channels from the brain to APP in a .csv format.

Application:

- Front-End:- An interface between user to headset and for user to comfortably operate the app.
- Back-end:- Pre-processing the data coming from the headset and send it for predicting the seizure.

- Trained model:- Model's weight are embedded in the app after training and weights are applied for prior prediction.
- Database:- there are in total 4 database

1. The history of seizures
2. User information
3. Medical information
4. The data coming from EEG signal.

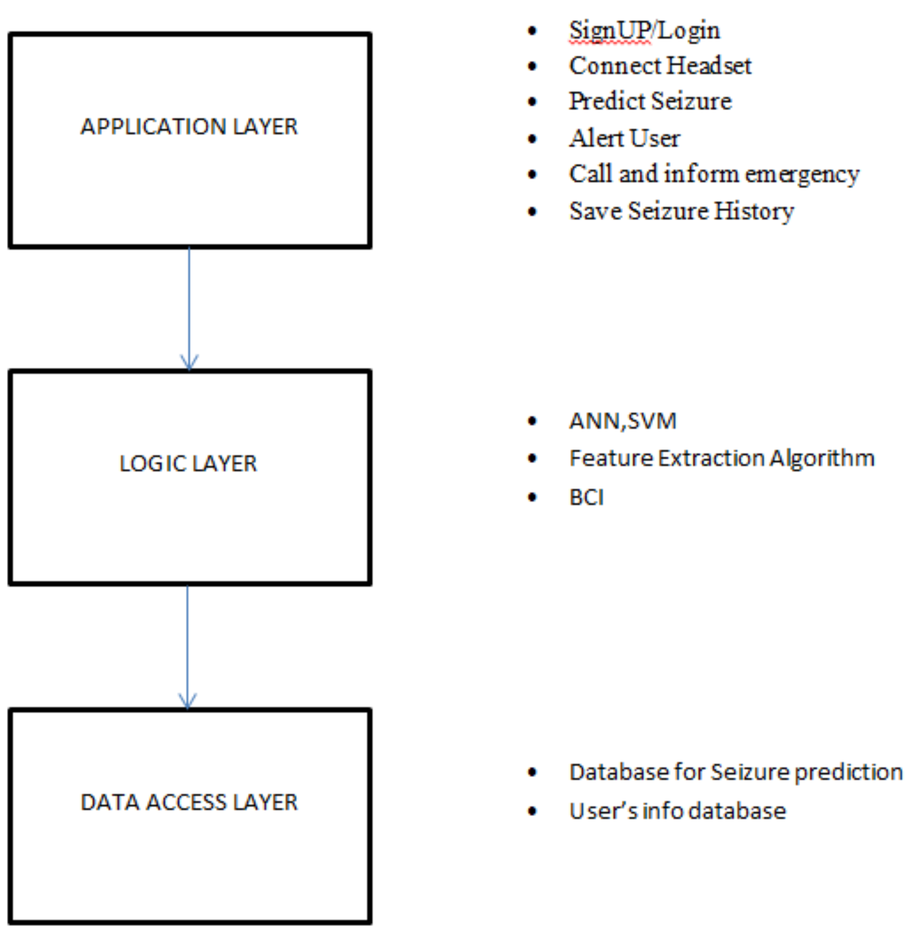


Figure 3: 3 Tier Architecture

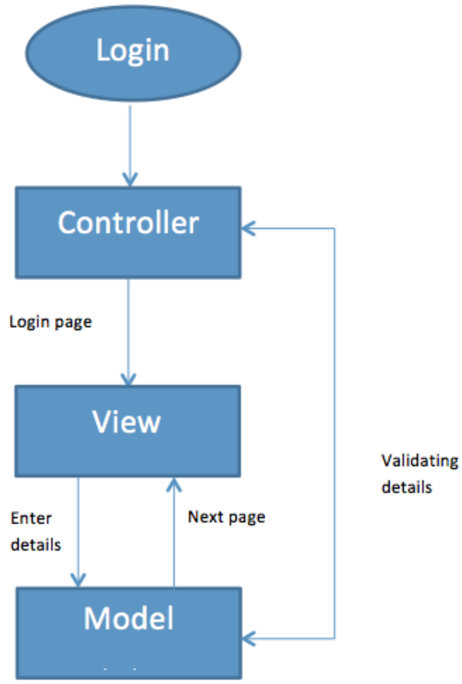


Figure 4: MVC Architecture for LOGIN

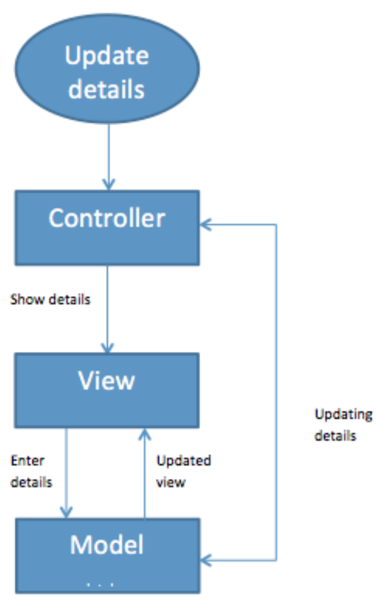


Figure 5: MVC Architecture for UPDATE_DETAILS module

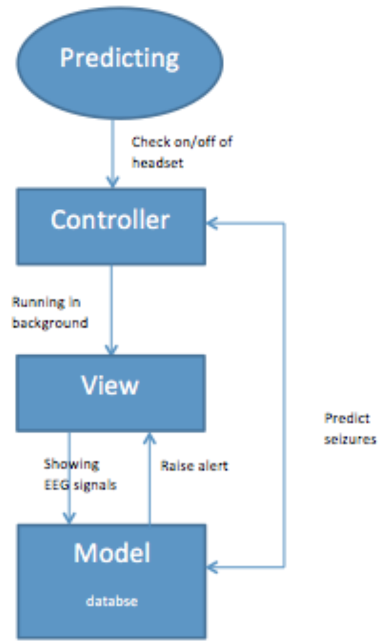


Figure 6: MVC Architecture for PREDICTION  module

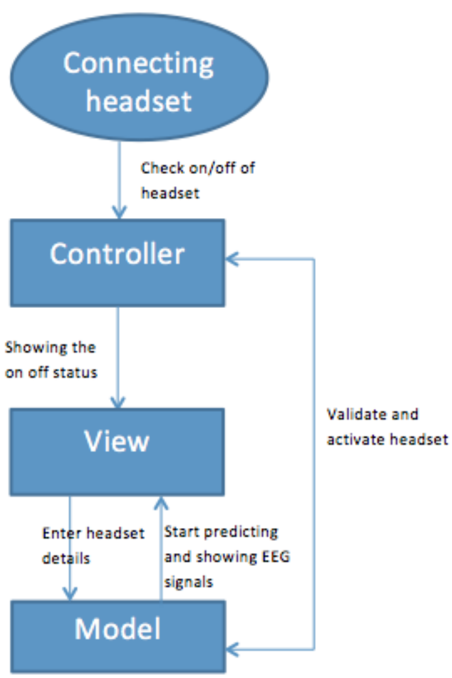


Figure 7: MVC Architecture for CONNECTING_HEADSET  module

## 4.2 DESIGN LEVEL DIAGRAMS

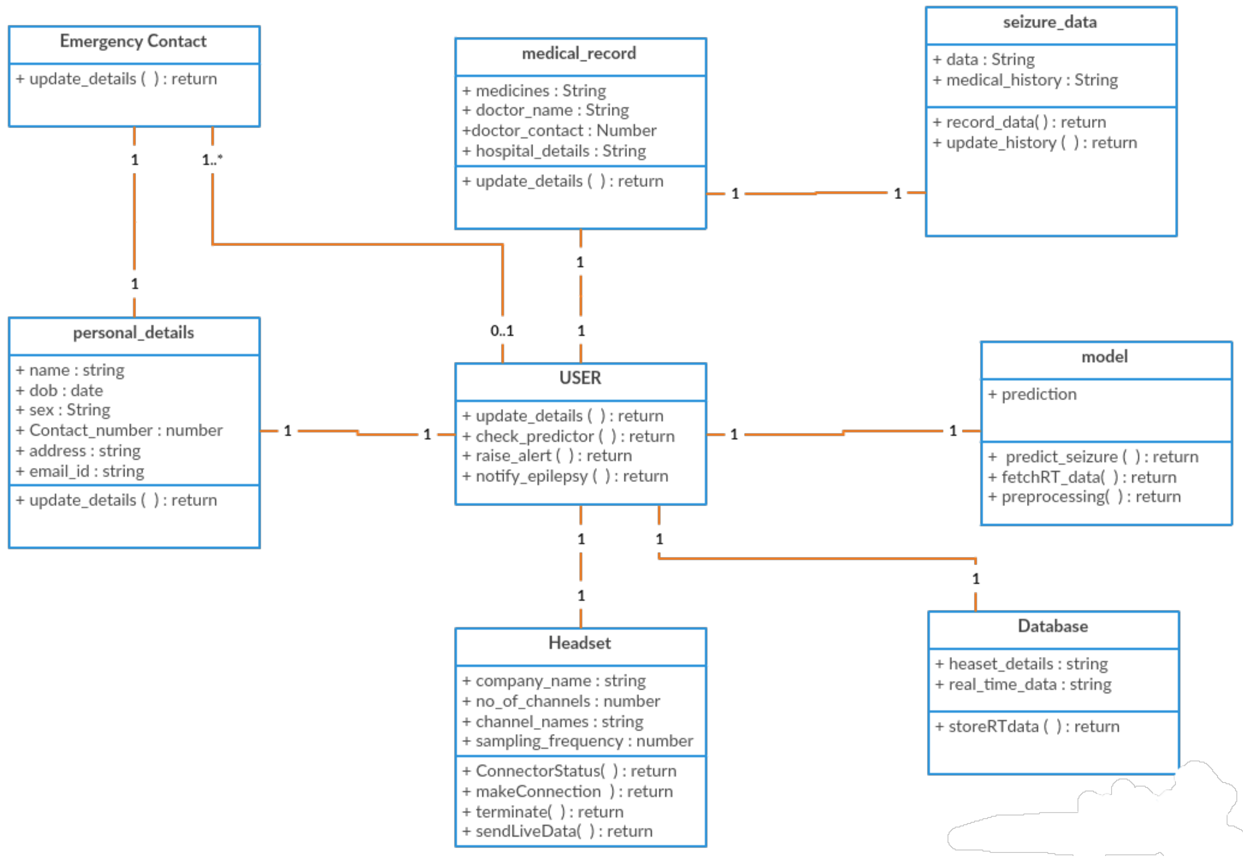


Figure 8: Class Diagram

## 4.3 USER INTERFACE DIAGRAMS

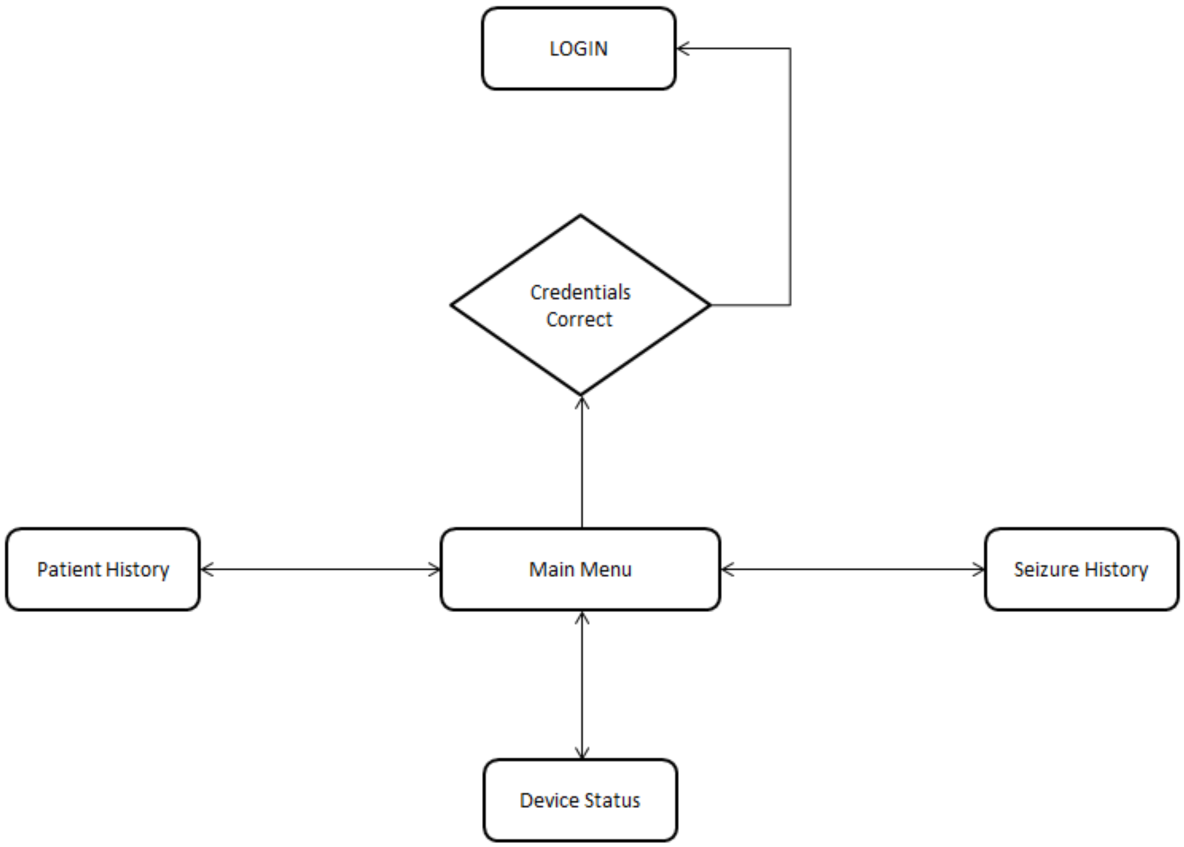


Figure 9: Component Diagram

## 4.4 SYSTEM SCREENSHOTS

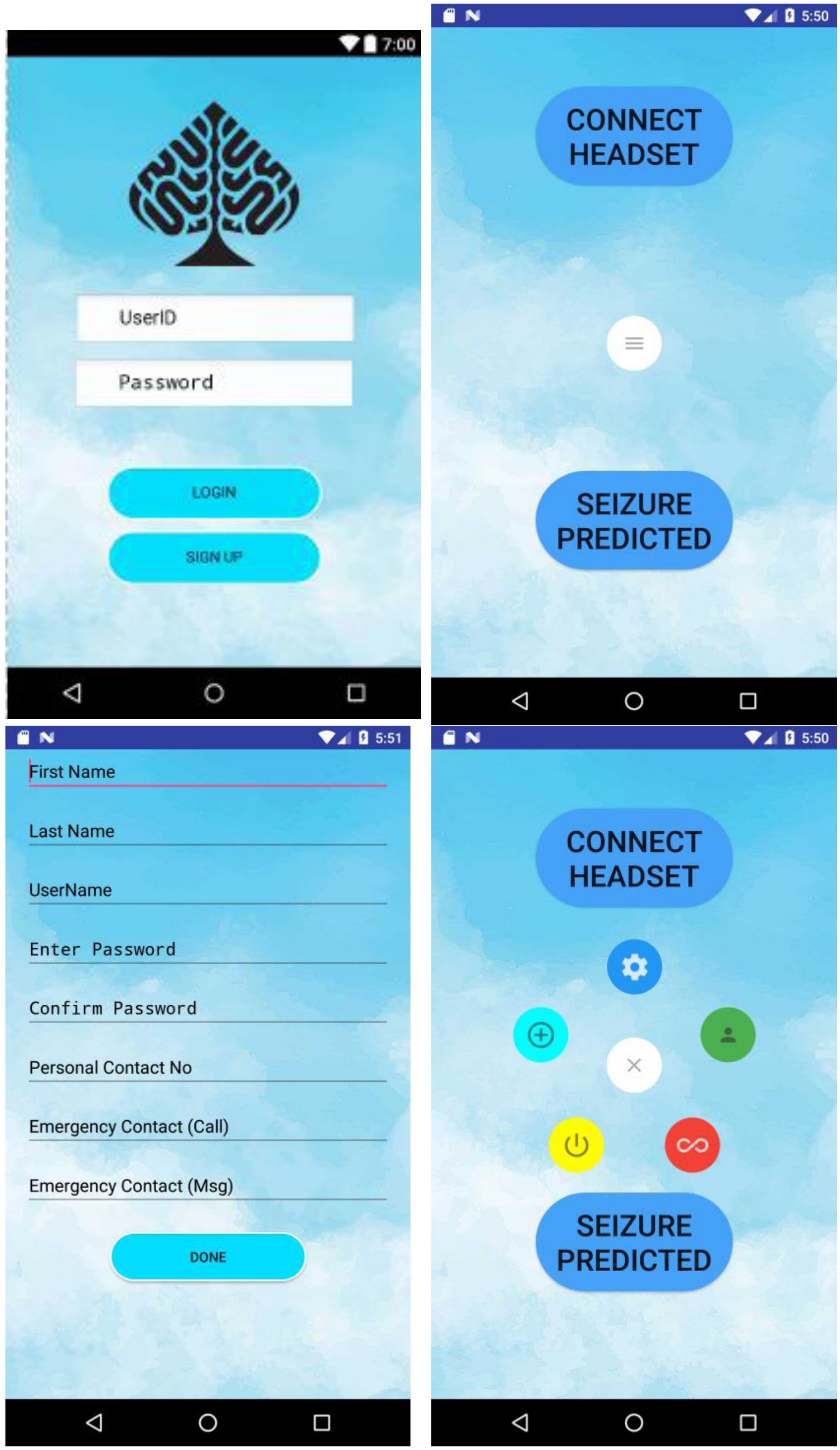


Figure 10: App ScreenShots

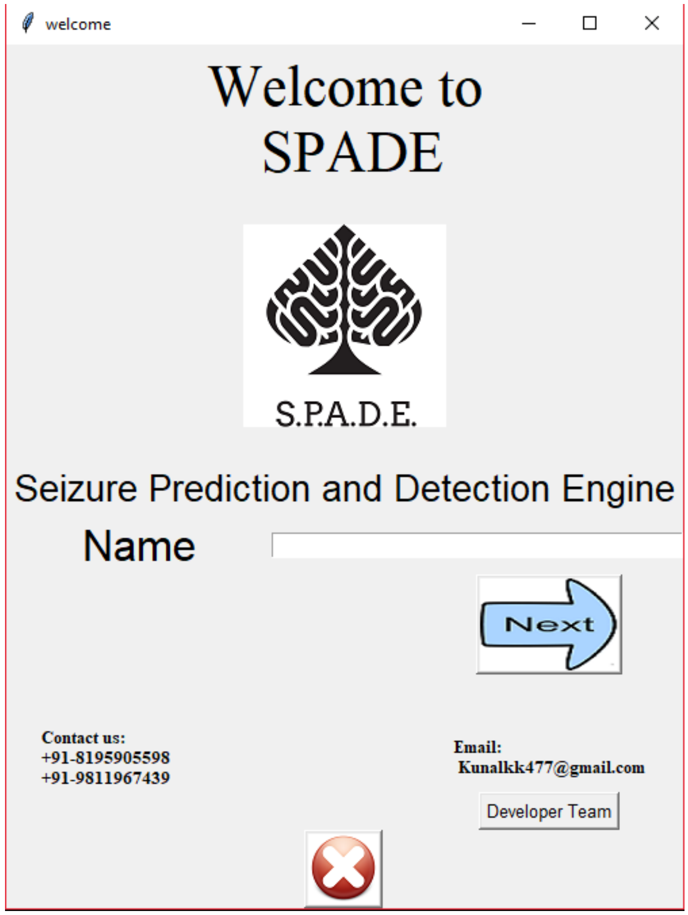


Figure 11: Welcome Page

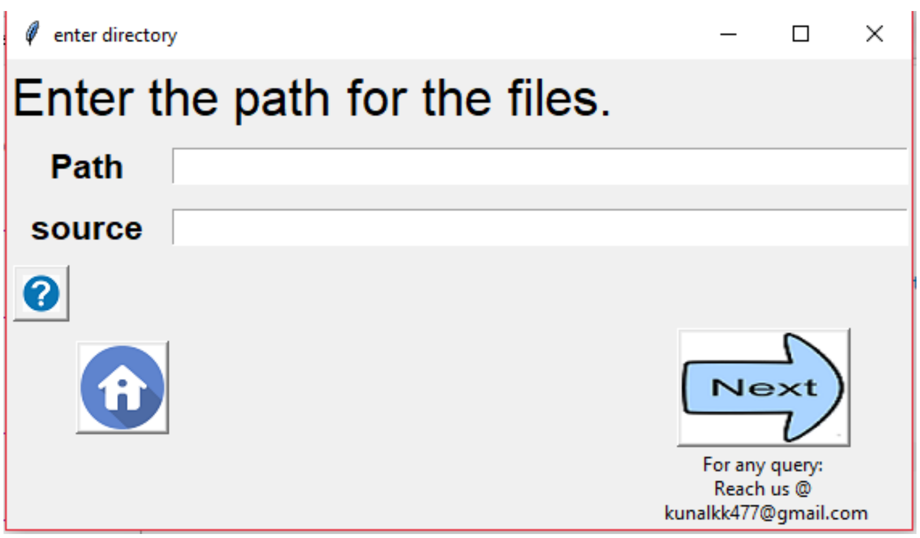


Figure 12: Enter Path Page

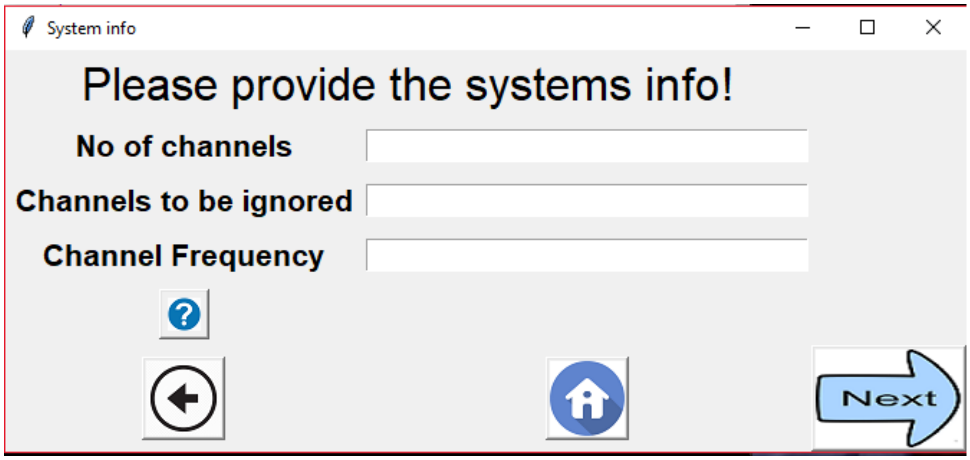


Figure 13: System Info Page

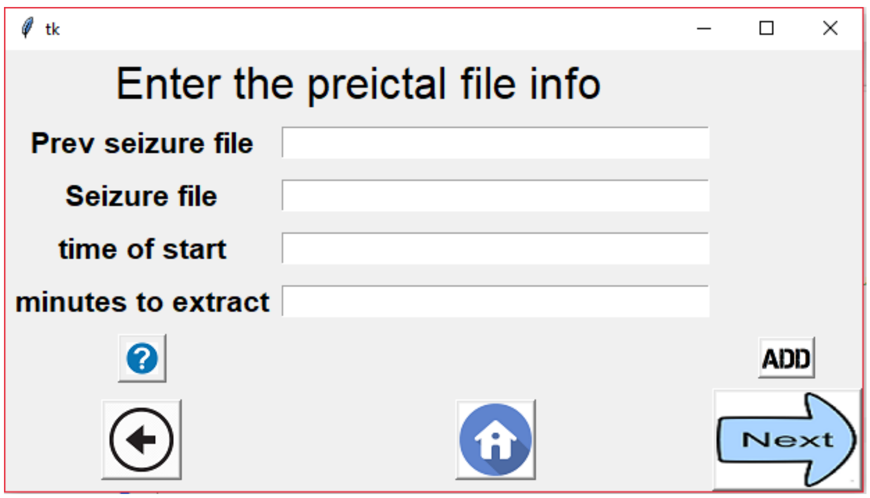


Figure 14: PreIctal File Upload Page

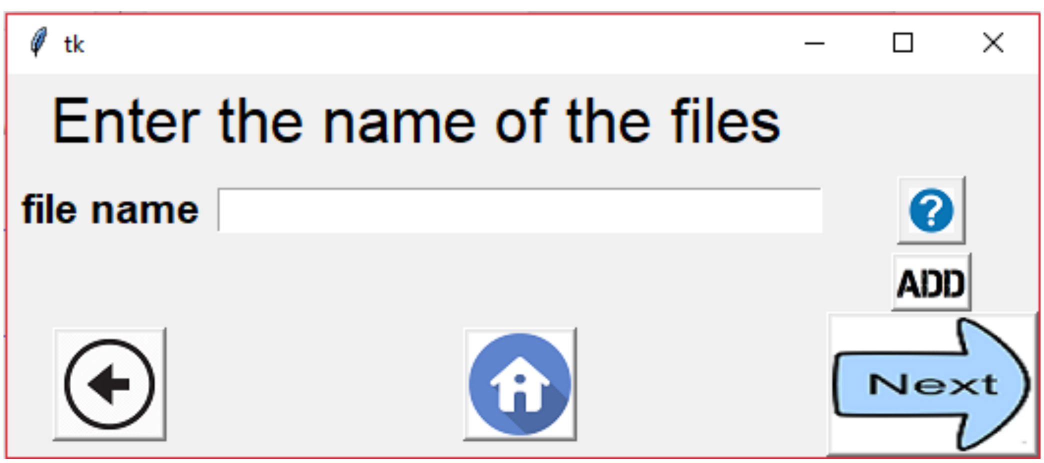


Figure 15: Enter File Name Page

# IMPLEMENTATION AND EXPERIMENTAL RESULTS

## 5.1 EXPERIMENTAL SETUP (OR SIMULATION)

Experimental setup consists of a computer software, a server (under development) and a mobile application. The app is connected to a server on which weights of the trained model are uploaded by the computer software.

## 5.2 EXPERIMENTAL ANALYSIS

The software takes the following input from the user :-

- Path of the folder containing previously recorded seizure data.
- Path where you want to save the trained model.
- File name of the seizure, file name of the data just before the seizure data, start time of the seizure and the time before the seizure which you want to take as pre-ictal data.
- File name of the inter-ictal data.

After feeding this information the application will call the core backend functions and libraries and train the model which will be saved on the above mentioned path. The essence of the trained model will uploaded on the server database (WIP) which will be downloaded by the mobile application. And based on the live EEG data fed to the app the prediction will be made.

### 5.2.1 DATA

Data used for training and testing consist of :-

- Seizure file in the '.edf' format

For training we have used the CHB-MIT Dataset.

- Time of start of seizure and extraction of pre-ictal data in 'seconds'.
- Channel numbers to be excluded or included are 'integer'.

### 5.2.2 PERFORMANCE PARAMETERS

1.Complete and successful execution of the training the model.

2.Proper extraction of essence of the model and errorless uploading to the server(WIP).

3.Accuracy of the system (i.e. prediction of seizure at an appropriate time).

4.Robustness and exception handling of the software and application.

5.Proper execution of the responses of the app when a seizure is predicted.

## 5.3 TESTING PROCESS

### 5.3.1 Test Plan

1.Features to be tested

2.Complete and successful execution of the training the model.

3.Proper extraction of essence of the model and errorless uploading to the server(WIP).

4.Accuracy of the system (i.e. prediction of seizure at an appropriate time).

5.Robustness and exception handling of the software and application.

6.Proper execution of the responses of the app when a seizure is predicted.

### 5.3.2 Test Strategy

1.Exception handling protocols in the software which will handle the wrong input entered and forward the input successfully to back processes for training the model.

2.Proper training of the model and testing its accuracy w.r.t. the angle of machine learning.

3.Secure and reliable connection of the mobile app with the server database and errorless downloading the weights of the model.

4.Connecting the headset to the app and receiving the real time EEG signals continuously and reliably.

5.Simultaneous combining the model weights and the input EEG signal and predicting the output (predicting the seizure in a time in which a proper action can be taken).

6.Based on the seizure predicted successfully executing the corresponding responses.

### 5.3.3 Test Cases

- The test cases shown below are made in the form of tables with column headers.
- Each table showcases the test cases for each window of the GUI of the software.
- Each column header in table is the input i.e. data to be entered in that corresponding window.
- Each row in the table is test case for the corresponding window containing the corresponding output.

ii.Window - “ENTER DIRECTORY”

Action - Press “NEXT” button.

Table 1: Test Cases for the First GUI window

| Path | Source | Output |
|---|---|---|
| - | - | Error, no forwarding |
| Random Wrong Input | Random Wrong Input | Error , no forwarding. |
| Random Wrong Input | Valid Input | No error , screen moves forward and is handled later. |
| Valid Input | Random Wrong Input | No error , screen moves forward and is handled later. |
| Valid Input | Valid Input | No error , program proceeds successfully. |

iii.Window - “SYSTEM INFO”

Action - Press “NEXT” button.

Note :- You will only be able to enter only natural number in these fields.

Table 2: Test Cases for the SYSTEM INFO window

| No of Channels | Channels to be ignored | Channel Frequency | Output |
|---|---|---|---|
| Greater than available in data | All the channels | Random natural number | All the channels in the data will be considered for training and error will be displayed to reduce the channels to be ignored. |
| Greater than available in data | Less than available | Random natural number | All the channels in the data will be considered for training and no error. |
| Less than available | All the channels | Random natural number | Only the initial channel numbers mentioned will be considered for training and error will be displayed to reduce the channels to be ignored. |
| Less than available | Less than available | Random natural number | Only the initial channel numbers mentioned will be considered for training and no error. |

iii. Window - “PRE-ICTAL INFO”

Action - Press “NEXT” button.

Note – You can only enter whole number in 3rd field and range of 5-60 minutes in 4th field.

Table 3: Test Cases for the PRE-ICTAL INFO window

| **Prev Seizure File** | **Seizure File** | **Time of start** | **Minutes to extract** | **Output** |
|---|---|---|---|---|
| Wrong Input | Wrong Input | Exceeds the file length | 5-60 | Error for Correction in 1st field |
| Wrong Input | Correct Input i.e. Existing file name | Exceeds the file length | 5-60 | Error for Correction in 1st field |
| Correct Input | Wrong Input | Exceeds the file length | 5-60 | Error for Correction in 2nd field |
| Correct Input | Correct Input i.e. Existing file name | Exceeds the file length | 5-60 | Error and program stops. |
| Correct Input | Correct Input i.e. Existing file name | In the range of file | 5-60 | Proper execution and program forwards. |

iv. Window - “INTER-ICTAL”
Action - Press “NEXT” button.

Table 4: Test Cases for the INTER-ICTAL window

| File Name | Output |
|---|---|
| Wrong Input | Error – “Please enter correct input” |
| Correct Input | No error and screen moves forward. |

v. Window - “START-END TIME”
Action - Press “NEXT” button.
Note :- You can only enter natural numbers in the range of 5-60 in both the fields.
Start time and end time are the minimum and maximum time (in the multiple of 5) respectively before seizure till which you want notification for seizure.
Error – “Incorrect time, Start time should be atleast 5 minutes smaller than end”.

Table 5: Test Cases for the START-END TIME window

| Start Time | End Time | Output |
|---|---|---|
| Greater than End time | Random | Error |
| Equal to End time | Random | Error |
| 5 min Less than end | Random | Accepted |

## 5.4 RESULTS AND DISCUSSIONS

**Results** :-

•Trained model stands to the accuracy of 99.3%.

•SPADE predicts the seizure on an average of 64 minutes before the arrival of the seizure.

**Discussion** :-

•This model trained is patient specific because the EEG signals are very specific to an individual just like a fingerprint.

•The trained model's accuracy can be further increased if we can get get more pre-ictal data with sufficiently large inter-ictal data.

## 5.5 INFERENCES DRAWN

The past concept that the seizures are completely random and unpredictable stands false. With the current advancements in Brain Computer Interfacing and Machine Learning Techniques have led to the successful prediction of seizures and controlling them. Thus helping people so as they are also able to lead a normal life.

## 5.6 VALIDATION OF OBJECTIVES

A non-invasive seizure prediction methodology is developed successfully to improve the quality of life of the patients with epilepsy.

The inter-ictal and pre-ictal data are correctly classified with the accuracy of 99.3 %.

Yes, the seizure is predicted a well time before the actual seizure occurs.

And the message to the emergency contact and the calls are made on time well before it's too late.

Hence Validated..

## 6.1 CONCLUSIONS

Before this project , it was a common thinking that the seizures cannot be predicted/detected or predetermined with naked eye or some normal physical experiments and tests. But with the development in Machine Learning Techniques this trend has changed.

Because, it is a concept in neurology that the EEG signals or we can say brain signals change their behavior much before the commencement of the seizure.

Our study and research focused in the pre-ictal data and the inter-ictal data. By applying the machine learning concepts we were able to predict the seizure 64 minutes before the seizure actually occurs.

Hence, validated the neuro science concept and predicted the seizure which will further help the epileptic patients.

## 6.2 ENVIRONMENTAL, ECONOMIC AND SOCIETAL BENEFITS

**Environmental Benefits**

By predicting the seizure prior to its happening, the amount of dead patients will be decreased and the amount of accidents will also decreased. The degree of a person's emotional, cognitive, social and spiritual experience of life is affected by his medcare. Epilepsy dection will help in increasing the one's quality of life and thus the level of social environment. A lot of people are denied job because of their epilepsy condition. If they are able to detect the epilepsy by 60 min before it actually happened there is no health issue or effectiveness issue for the hiring of the person.

**Economic Benefits**

In healthcare the consideration of Economy is gaining importance at an exponential rate. Healthcare providers are targeting limited resources. Epilepsy has imposed an economic burden on both the patient and the society. The sale of device will lead to a very high economic profit for both the healthcare company and also the knowledge of an upcoming seizure will lead to saving it. If the upcoming seizure is predicted before time it will lead to saving the hospital and treatment cost of the patient and also the patient will be able to save a lot of assets that could have been damaged while the patient was about to have seizure. In India there is a total of 6 Million registered Epileptic patients and for them there is only around 200 neurologists. So for 6 million patients the evenue by selling the device to even a 5% will be very huge.

Patients in India spent a lot of money on healthcare when they are treated, by detecting the epilepsy earlier patients will also be able to save a lot. If their healthcare expenses is less, they will take less loan from the banks and that will lead to a good economy as the amount of bad debts will also be less.

**Societal Benefits**

People with epilepsy have a higher prevalence of memory problems and learning disabilities and these can be caused by the brain damage. Attention deficit also occur during seizures, so if the prediction is done then the happening of seizure is highly unlikely as he will self-medicate or check up with a doctor. The less number of accident will also be a result of prediction of seizures.

A person's body is integral part of its odentity and self-percept and it decreases when he suffers from an epileptic attack. To reduce the stress of ever happening, non-timely, random happening seizures the detection of seizure using our app will be huge success. People around the patient will also behave more appropriately of the patient is sure that he is not going to have a mini or a major seizure.

## 6.3 REFLECTIONS

After doing the project, we learned a lot about a disease that we have no idea about beforehand. The number of people that are currently suffering from this disease only in India is about 6 million and for that there are only 2000 neurologists, the amount of patient to doctor ratio is very high.

By doing the project we learned about a lot of subjects and technologies that we have studied earlier but never applied in such a vast way. As in the case of our project we learn signal processing, data pre-processing, Machine learning, Model building using dump to save the models. Building vast GUI which can be operated on multiple systems. Talking to a lot of experts and learning how to do stuff, reading numerous research papers and websites for debugging and understanding the concept behind what we are doing.

We don't only learn about the disease and the patients but we also read about a lot of technologies and resources that are being used for solving this epilepsy dilemma. To create our project we increased our grasp on few of the topics that we have never studied that varied from Analog to android developing. The completion of the project will lead to solving the anxiety and the stress the patient and their family have. This also led us to know a lot about how an actual major project is made what is the documentation behind doing such a big project, how to work in groups when everyone is doing different things and at the end are combining not only their product but also the insights they have and gained by doing the project.

## 6.4 FUTURE WORK

1.A methodology or technique could be developed such that we require much less seizure data to train the machine learning model

2.Recent research in the field of deep learning techniques such as transfer learning and reinforcement learning holds immense possibility of a much less time consuming and less tiresome algorithm which can train and improve the model in real-time

3.A standalone product could be engineered which is much more comfortable, light weight and easy to wear

4.An app that will be able to communicate much further and predict the epilepsy even before an hour of the seizures.
5.To able to provide the exact location of the patient to the emergency contact in case of a sudden epilepsy.

## 7.1 CHALLENGES FACED

- Usability challenges

They express the limitations facing the user acceptance of BCI technology utilization. They include the issues related to the training process necessary for classes' discrimination. Information transfer rate (ITR) is one of the system evaluation metrics that combines both performance and acceptance aspects.

- Training process

Training the user is a time-consuming activity either in guiding the user through the process or in the number of recorded sessions. It takes place either in preliminary phase or in the classifier calibration phase. The user is taught to deal with the system as well as to control his\her brain feedback signals in the preliminary phase, while in the calibration phase, trained subject's signal has been used to learn the used classifier.

One of the commonly investigated solutions to this time-consumption problem is to employ single trial instead of multi-trial analysis, which is used for enhancing signal to noise ration, and placing the burden of small training size on subsequent BCI system components to handle.

- Technical challenges

They are issues related to the recorded electrophysiological properties of the brain signals which include non-linearity, non-stationarity and noise, small training sets and the companying dimensionality curse.

- Non-linearity

The brain is a highly complex nonlinear system in which chaotic behavior of neural ensembles can be detected. Thus EEG signals can be better characterized by nonlinear dynamic methods than linear methods.

- Non-stationarity and noise

Nonstationarity attribute of electrophysiological brain signals represents a major issue in developing a BCI system. It originates a continuous change of the used signals over time either between or within the recording sessions. The mental and emotional state background through different sessions can contribute in EEG signals variability. Also fatigue and concentration levels are considered part of internal nonstationarity factors. Noise is also a big contributor in the challenges facing the BCI technology and causing the nonstationarity issue. It includes unwanted signals caused by alterations in electrode placement, and environmental noise. A combination of movement artifacts, such as electrical activity produced by skeletal muscles electromyogram (EMG) and signals created by eye movements and blinking Electrooculogram (EOG), is also reflected in the acquired signals resulting in difficulties in distinguishing the underlying pattern.

- Small training sets

The training sets are relatively small, since the training process is influenced by usability issues. Although heavily training sessions are considered time consuming and demanding for the subjects, they provide the user with necessary experience to deal with the system and learn to control his\her neurophysiological signals. Thus a significant challenge in designing a BCI is to balance the trade-off between the technological complexity of interpreting the user's brain signals and the amount of training needed for successful operation of the interface.

- High dimensionality curse

In BCI systems, the signals are recorded from multiple channels to preserve high spatial accuracy. As the amount of data needed to properly describe different signals increases exponentially with the dimensionality of the vectors, various feature extraction methods have been proposed. They play an important role in identifying distinguishing characteristics. Thus the classifier performance will be affected only by the small number of distinctive traits instead of the whole recorded signals that may contain redundancy.

Generally, it is recommended to use, at least, five to ten times as many training samples per class as the number of dimensions. But this solution cannot be sustained in a highly dimensional environment as the BCI system, causing the expanding of the dimensionality curse

## 7.2 RELEVANT SUBJECTS

- Signal Processing
- Machine Learning
- Data Analytics
- Neuro-Science
- Software Engineering:

## 7.3 INTERDISCIPLINARY KNOWLEDGE SHARING

- Medical Sciences – Knowledge about Epilepsy such as - What is epilepsy? How it is diagnosed? What is EEG? What is the treatment? What is the medication? What are the symptoms? How it is therapized and cured? What are the potential threats? What are possible future treatments?

- Electronics and Communication – This discipline was explored for the knowledge of Signal Processing and it helped us to answer the questions like – What are the brain waves? what are the challenges with them? how to extract the features from the signals? How to preprocess them? How to handle the large dimensionality?

## 7.4 PEER ASSESSMENT MATRIX

| Aman | Keshav | Kunal | Sophie |
|---|---|---|---|
| Determination | 4 | 4.5 | 4 |
| Hardwork | 4 | 4 | 4.5 |
| Innovation | 4 | 4 | 4 |
| Teamwork | 4 | 3.5 | 4 |
| Involvement | 4 | 4 | 3.5 |

| Keshav | Aman | Kunal | Sophie |
|---|---|---|---|
| Determination | 4.5 | 4.5 | 4 |
| Hardwork | 4 | 4 | 4 |
| Innovation | 4 | 3 | 3.5 |
| Teamwork | 3.5 | 4.5 | 4 |
| Involvement | 4 | 4 | 4 |

| Kunal | Keshav | Aman | Sophie |
|---|---|---|---|
| Determination | 4.5 | 4 | 4 |
| Hardwork | 3.5 | 4 | 3.5 |
| Innovation | 4 | 4.5 | 4 |
| Teamwork | 4 | 4 | 4.5 |
| Involvement | 4.5 | 5 | 4 |

| Sophie | Keshav | Kunal | Aman |
|---|---|---|---|
| Determination | 4 | 4.5 | 4.5 |
| Hardwork | 4 | 4 | 4 |
| Innovation | 3.5 | 4 | 4.5 |
| Teamwork | 4 | 4 | 3.5 |
| Involvement | 4.5 | 4.5 | 4 |

Table 6: Peer Assessment Matrix

## 7.5 ROLE PLAYING

Table 7: Role Playing

| | Hardware Interfacing | Data Preprocess | Signal Preprocess | Feature extraction | Model training | App Development | Documentation |
|---|---|---|---|---|---|---|---|
| Aman | ★ | | ★ | | ★ | | |
| Keshav | ★ | | | ★ | | | ★ |
| Kunal | | ★ | | | ★ | ★ | |
| Sophie | | | | ★ | | ★ | ★ |

## 7.6 STUDENT OUTCOMES (A-K MAPPING)

Table 8: Student Outcomes

| | | |
|---|---|---|
| A | an ability to apply knowledge of mathematics, science and engineering | Yes |
| B | an ability to design and conduct experiments, as well as to analyze and interpret data | Yes |
| C | an ability to design a system, component, or process to meet desired needs within realistic constraints such as economic, environmental, social, political, ethical, health and safety, manufacturability, and sustainability | Yes |
| D | an ability to function on multidisciplinary teams | Yes |
| E | an ability to identify, formulate, and solve engineering problems | Yes |
| F | an understanding of professional and ethical responsibility | Yes |
| G | an ability to communicate effectively (3g1 orally, 3g2 written) | Yes |
| H | the broad education necessary to understand the impact of engineering solutions in a global, economic, environmental, and societal context | |
| I | a recognition of the need for, and an ability to engage in life-long learning | |
| J | a knowledge of contemporary issues | Yes |
| K | an ability to use the techniques, skills, and modern engineering tools necessary for engineering practice. | Yes |

### 7.7 work schedule

# REFERENCES

[1]Abdulhamit Subasi, M. Ismail Gursoy (2010). EEG signal classification using PCA, ICA, LDA and support vector machines. Expert Systems with Applications, Elsevier, Volume 37, Issue 12, pp.8659-8666.

[2] Alexandros T. Tzallas, Markos G. Tsipouras, Dimitrios I. Fotiadis (2009). Epileptic Seizure Detection in EEGs Using Time–Frequency Analysis. IEEE Transactions on Information Technology in Biomedicine, Volume 13, Issue 5, pp. 703 – 710.

[3] Keider Hoyos-Osorio, Jairo Castaneda-Gonzalez, Genaro Daza-Santacoloma (2016). Automatic epileptic seizure prediction based on scalp EEG and ECG signals. XXI Symposium on Signal Processing, Images and Artificial Vision (STSIVA).

[4] Lasitha S. Vidyaratne, Khan M. Iftekharuddin (2017). Real-time epileptic seizure detection using EEG. IEEE Transactions on Neural Systems and Rehabilitation Engineering, Volume 25, Issue 11, pp. 2146 – 2156.

[5] Mohammad Zavid Parvez, Manoranjan Paul (2015). Prediction and Detection of Epileptic Seizure by Analysing EEG Signals. Prediction and Detection of Epileptic Seizure by Analysing, In Biomedical Image Analysis and Mining Techniques for Improved Health Outcomes. IGI Global.

[6] Syed Muhammad Usman, Simon Fong (2017). Epileptic Seizures Prediction Using Machine Learning Methods. Computational and Mathematical Methods in Medicine, Volume 2017.

[7] Guo L, Rivero D, Pazos A (2010) Epileptic seizure detection using multiwavelet transform based approximate entropy and artificial neural networks. J Neurosci Methods 193(1):156–163

[8] Ghosh-Dastidar S, Adeli H, Dadmehr N (2008) Principal component analysisenhanced cosine radial basis function neural network for robust epilepsy and seizure detection. IEEE Trans Biomed Eng 55(2):512–518

[9] Kadappagari VK, Atul N (2008) SubXPCA and a generalized feature partitioning approach to principal component analysis. Pattern Recognit 41(4): 1398–1409

[10] Jaiswal, A.K. & Banka, H. Australas Phys Eng Sci Med (2018) 41: 81. https://doi.org/10.1007/s13246-017-0610-y

[11] Hussain, L. Cogn Neurodyn (2018) 12: 271. https://doi.org/10.1007/s11571-018- 9477-1