

Software Requirement Specification Document for Be Alert

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Table 1: Document version history

Version	Date	Reason for Change
1.0	22-Dec-2022	SRS First version's specifications are defined.

GitHub 1: <https://github.com/omarmoh26/BE-Alert>

GitHub 2: <https://github.com/Hussein1808/bealert>

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Abstract

Driving is one of the daily activities that requires concentration. Many road accidents are said to be caused by a driver's tiredness, drowsiness, inattention, or distraction. An electroencephalogram (EEG) is a recording of electrical activity in the brain made with electrodes inserted on the head. One of the most successful approaches for identifying drowsiness is the classification of electroencephalogram (EEG) signals. This project aims to alert drowsy drivers by utilizing a brain-computer interface comprised of a brain sensor and a mobile interface. Initially, the sensor's recorded brain signals will go through several phases, including feature extraction and classification using learning-based algorithms. The outcome will then be turned into visual and audible feedback via a mobile device.

1 Introduction

1.1 Purpose of this document

This document aims to explain in detail the requirements needed to develop a drowsy driver detection system. In addition, the document acts as a guide for developers and anyone involved in the system's development or maintenance. Also, it provides the algorithms and approaches used in the process of drowsiness detection. The system aims to detect drowsiness by using brain signals, which are acquired using a brain sensor. The mobile application will alert the driver according to his drowsiness level, which will be known due to the analysis of the brain signals.

1.2 Scope of this document

This document refers to systems that use EEG signals to detect the drowsiness of a driver, displays the overview, scope, and content of the Be Alert system design, and covers the mobile application's goals and target customer characteristics. This article also thoroughly examines Be Alert's functional and non-functional requirements, design restrictions, data design, and the application's fundamental class diagram. Finally, this article discusses the various working scenarios as well as the application's timetable.

1.3 Business Context

We are targeting automobile manufacturers, road transportation companies, and governments, which will assist them in reducing the percentage of accidents caused by drowsiness and fatigue. According to the National Safety Council (NSC), drowsy driving causes around 100,000 crashes each year, 71,000 injuries, and 1,550 fatalities. Furthermore, according to AAA Foundation for Traffic Safety research, drowsiness was a factor in up to 9.5 percent of all crashes and 10.8 percent of crashes involving airbag deployment, injury, or major property damage. Drowsy driving is extremely risky, and drivers must be aware of the dangers [1].

2 Similar Systems

2.1 Academic

- **Wei et al** [2] introduced that in order to get high-quality EEG while avoiding various technical restrictions, getting EEG from non-hair-bearing (NHB) areas is a convenient and comfortable alternative

Figure 2(a). Ten participants took part in the experiment that involved using a driving simulator and placing six electrodes on NHB regions Figure 2(b). He used three classification methods: Linear Discriminant Analysis (LDA), K Nearest Neighbors (KNN), and Support Vector Machine (SVM) to discriminate the EEG activity of a drowsy state from an alert state. Although SVM has the highest accuracy of the three classifiers in both NHB and Hair Covered (80% and 83.3%, respectively), there is no discernible difference between the NHB and Hair Covered in effectiveness.

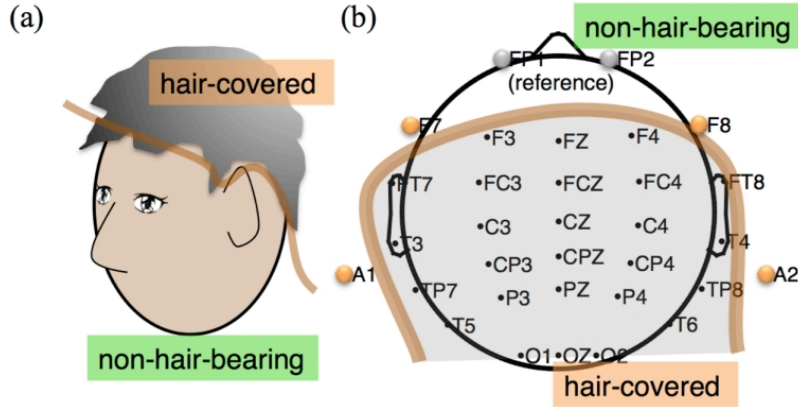


Figure 1: (a) The area with hair and the area without hair, separated by a brown line [2].

Figure 2: (b) The 32-channel recording system. [2].

- **Gao et al** mentioned in his paper that he employed eight competing techniques in addition to an EEG-based spatial-temporal convolutional neural network (ESTCNN) to identify driver fatigue[3]. He brought eight subjects and recorded the EEG of the subject who was driving when fatigued using a Neuroscan system with 40 electrodes and a sample frequency of 1000 Hz. The classification accuracy of ESTCNN is 97.37%, which is higher than that of the other techniques.
- **Zeng et al.** [4] constructed two mental state classification models called EEG-Conv and EEG-Conv-R for driver sleepiness identification. EEG data is obtained using a gUSBamp amplifier with 16 channels (g.Tec Medical Engineering GmbH) and is regularly sampled at 256 Hz. While gathering EEG data, the participant's count of eye blinks per minute and heart rate are also recorded. The CNN-based EEG classifier architecture includes eight layers: the

input layer, three convolutional layers, a pooling layer, a LRN (Local Response Normalization) layer, a fully connected layer, and the output layer. The EEG-CONv and EEG-Conv-R attained 91.788% and 92.682% classification accuracy, respectively. However, the inadequate number of samples for each intra-subject restricts the performance enhancement of EEG-Conv-R. Therefore, additional EEG data is required to be gathered to validate the EEG-Conv-R to a greater extent. It is also recommended to construct a multi-label classification of EEG signals by deep learning techniques instead of the present binary classification.

2.2 Business Applications

Lane Departure Warning system: This system is embedded in the car. The system provides visual and audio warnings to the driver when leaving the lane[5].

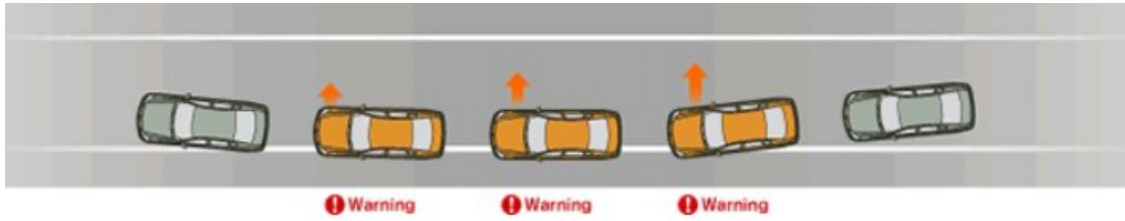


Figure 3: Lane departure system[6].

Lane keep assist system: The system is embedded in the car. The system corrects the steering of the car if it is going out of the lane and provides visual and audio warnings or vibration of the steering wheel[7].

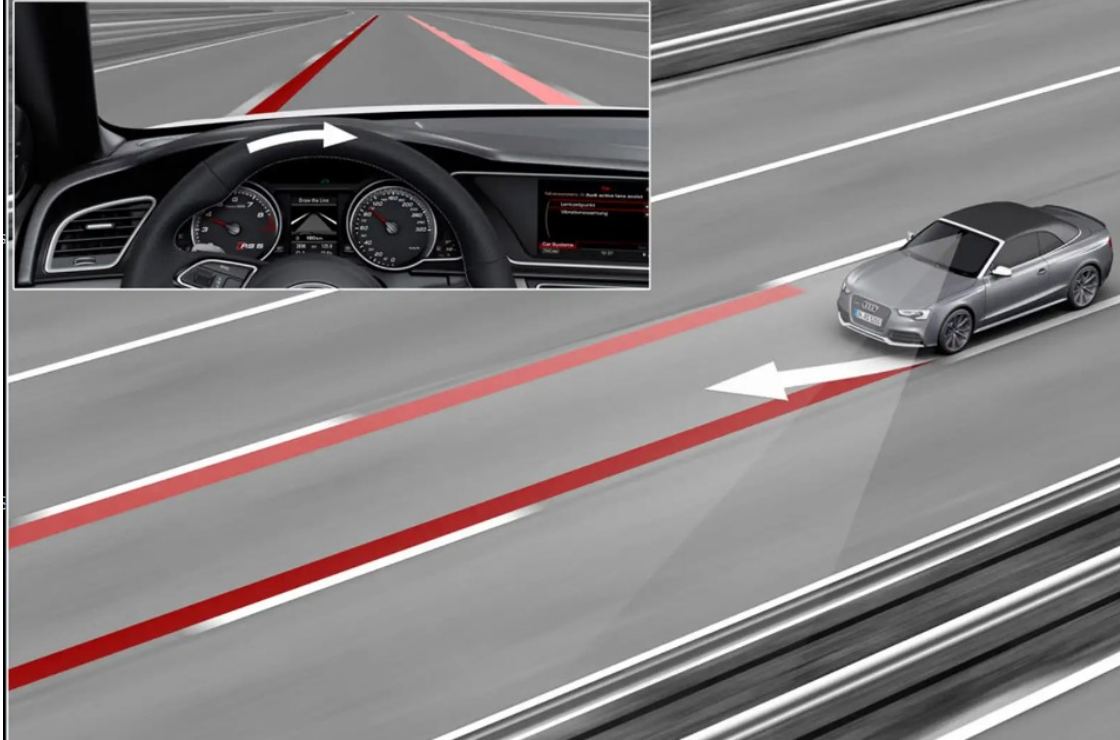


Figure 4: Lane keep assist system[8].

Lane cantering assist system: The system is embedded in the car. The system centers the car exactly at the center of the lane[5].

3 System Description

This section illustrates the system by showing the problem statement, system overview, system scope, system context, objectives, and user characteristics.

3.1 Problem Statement

Every accident happens because of drowsy driving. Innocent people die, and national properties get sabotaged. Drowsiness and distraction while driving can lead to highly catastrophic events that will affect people's lives, health, and businesses. Drowsy driving is more dangerous than drunk driving because the drunk driver can recognize that he or she is drunk, whereas the drowsy driver cannot recognize that he or she is drowsy unless he or she is alerted. So, if there is a device that can make the driver get alerted again by detecting if the driver is drowsy, this device can save many people's lives and health. This device can make people feel safer on the streets and help avoid catastrophic accidents.

3.2 System Overview

For the proposed system to be developed, it needs to follow certain procedures. For the input, needless to say is the signal acquisition; EEG signals from the driver will be obtained through the Brain Signal Sensor (Neurosky Mindwave EEG). During the data pre-processing data sampling, feature extraction, and dimensionality reduction methods will be employed. In feature extraction, each instance will have a collection of features once the dataset has been processed. Following that, feature selection is used to get a quick categorization.

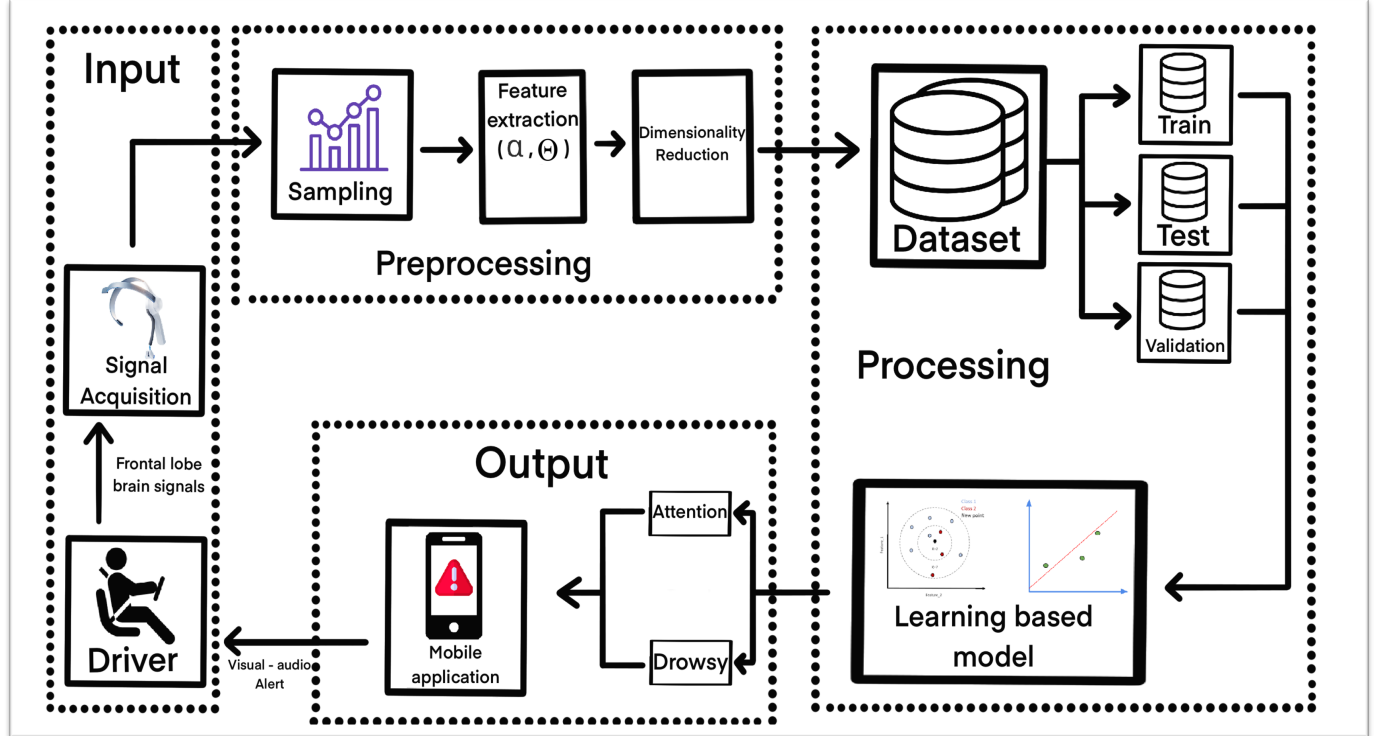


Figure 5:Project overview diagram.

In the processing phase, the dataset will be split into three sections for training, testing, and validation. Subsequently, a learning-based model will be utilized to predict the driver's drowsiness by injecting it with the testing dataset and assessing each model's correctness. Learning-based models using machine learning algorithms such as SVM, Decision trees, KNN, Linear regression, and Random forest. In addition to deep learning algorithms like Convolutional Neural Networks (CNNs), Long Short Term Memory Networks (LSTMs), and Recurrent Neural Networks (RNNs). Finally, the output of the mentioned algorithms will be a classification of whether the driver is drowsy or attentive. And based on the output, it will be displayed on their downloaded mobile application an audio/visual warning that they are drowsy or otherwise nothing will appear.

3.3 System Scope

BE-Alert aims to alert drowsy drivers according to their drowsiness level by recognizing and classifying EEG signals. Therefore, in order to achieve that, the system will contain:

- Dataset of the brain signals (alpha-theta) signals responsible for detecting drowsiness. Those signals are acquired using an EEG brain sensor, which measures the electrical activity of the cerebral cortex.
- Select the features needed and exclude unneeded features. This will help to minimize classification time and computation.
- To improve performance, experiment with various machine learning and deep learning methodologies.
- Using a hardware component, collect and preprocess an EEG dataset, then compare the two datasets.

3.4 System Context

The system will deal with a mobile application that will alert the user while driving if he gets drowsy by getting signals from the EEG headset.

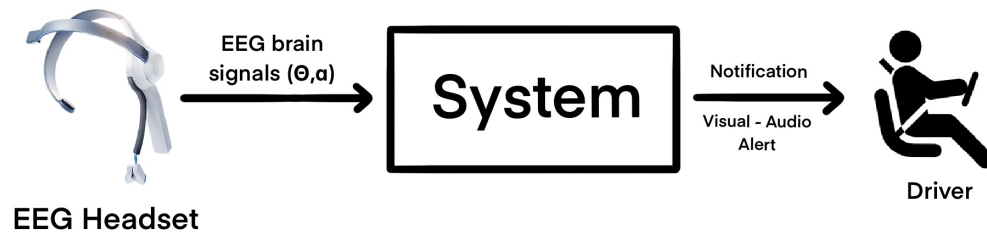


Figure 6: System Context.

3.5 Objectives

- Accurately identify drowsy drivers in order to avoid fatal vehicle accidents.
- Detect and classify sleepy drivers from their emitted EEG signals.
- Get high classification accuracy using one signal channel.
- Denoise raw EEG signals for improved signal processing.

3.6 User Characteristics

- The user reaches the age needed to drive a car or a motorcycle.
- The user must have a driving license.
- The user must have basic knowledge of how to use a mobile device.

4 Functional Requirements

This section depicts the requirements needed to develop the system.

4.1 System Functions

4.1.1 User

1. The user shall be able to Sign Up and Login.
2. The user shall enter his personal information.
3. The user shall enter vehicle information.
4. The user shall view the number of days he has been drowsy while driving.
5. The user shall view a statistical graph showing non-attentive driving time for each trip.
6. The user shall view a statistical graph showing non-attentive driving days in this week or month.
7. The user shall be able to view the history of his trips.
8. The user shall be able to edit his profile.
9. The user shall be able to log out.

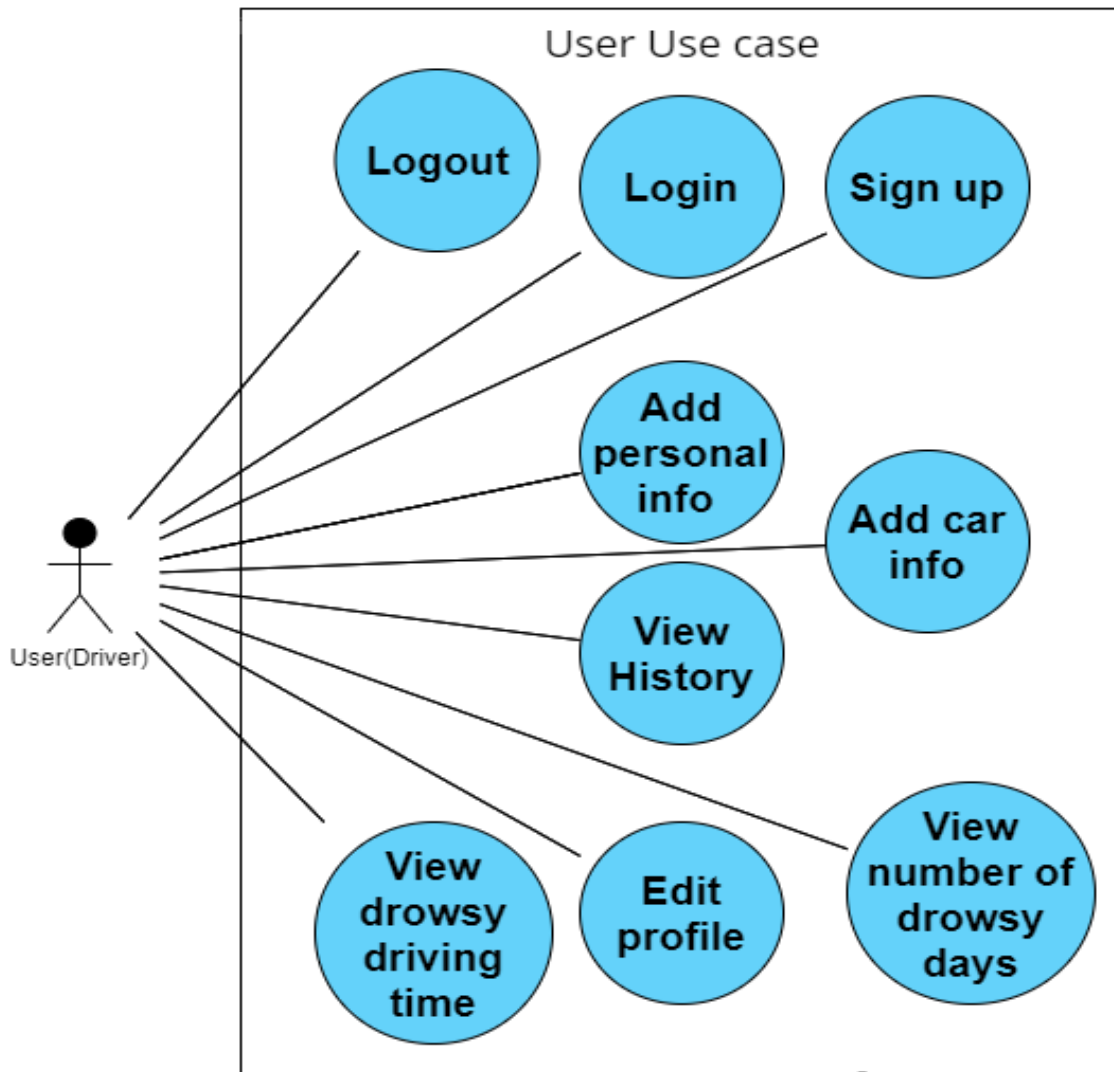


Figure 7:User use case diagram.

4.1.2 System

1. The system should give the user a simple description of how to use the mobile application.
2. The system shall acquire the brain signals using a brain sensor.
3. The system shall be able to perform machine learning and deep learning techniques on the acquired brain signals.
4. The system should notify the driver if he becomes drowsy on the same day in different weeks, so he can rest the day before.
5. The system shall alert the driver using audio-visual feedback according to the driver's drowsiness level.

6. The system shall contact the authorities that are responsible for the roads and provide the car's location if the driver is totally drowsy.

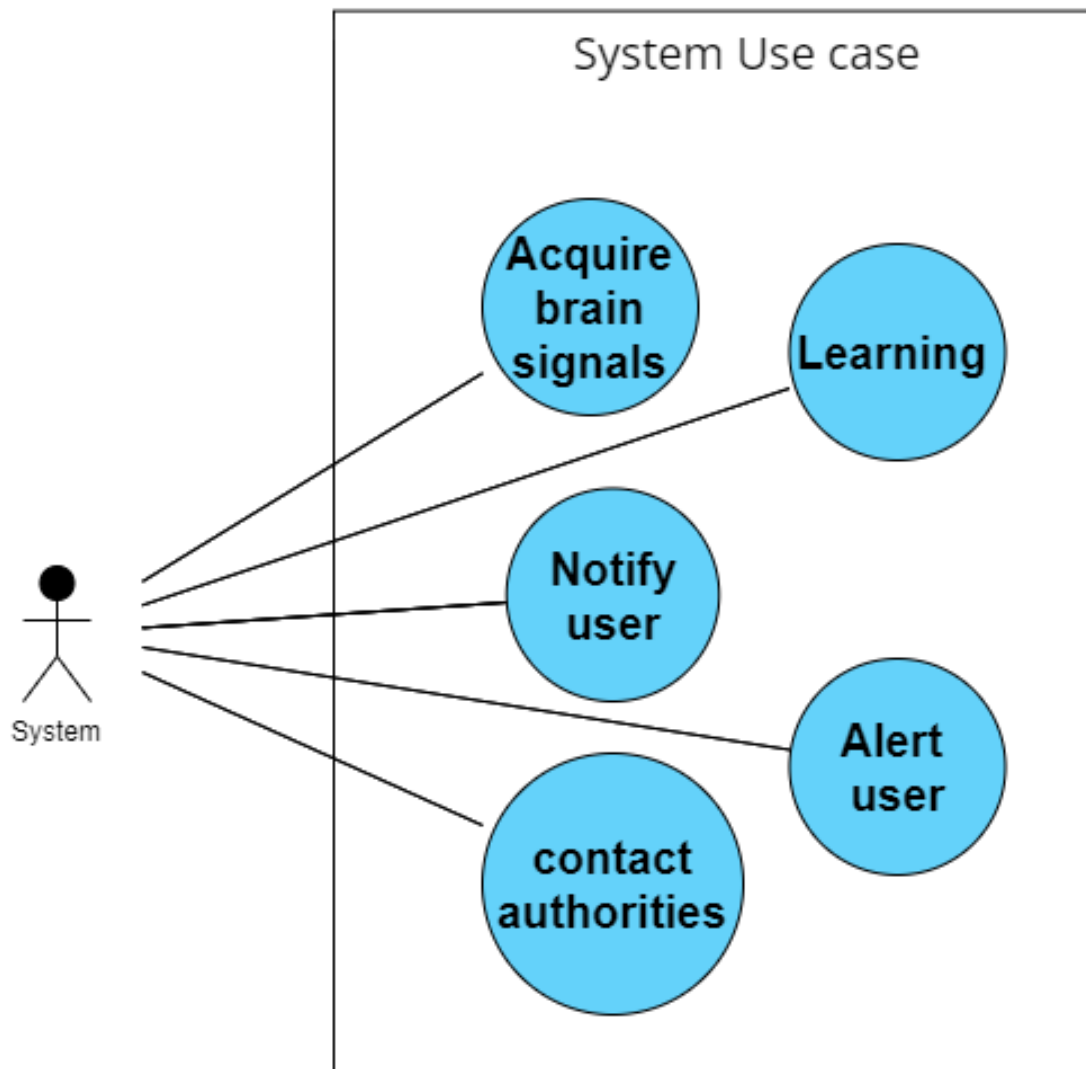


Figure 8: System use case diagram.

4.2 Detailed Functional Specification

Table 2: login function description

Name	login
Code	QR01
Priority	High
Critical	It's utilized for system login and needed to access all features of the system
Description	Checks email and password then redirects the user to the home page
Input	Email, Password
Output	None
Pre-condition	QR02
Post-condition	Navigate to home page
Dependency	signUp User has to be signed up in order to login
Risk	If the email and password don't match an existing user's credentials. The measure taken is to show an error message and prompt for correct email and password.

Table 3: signUp function description

Name	signUp
Code	QR02
Priority	High
Critical	Used for signing up into the system
Description	Checks if user has a unique email among other users then redirects them to the login page
Input	Name, Age, Email, Password, Mobile number, Car name, Car model, Car plate number
Output	Alert for successful sign up
Pre-condition	No existing users with the same email
Post-condition	Navigate to login page
Dependency	None
Risk	Email already exists or validations are broken. The action taken is showing an error message.

Table 4: logout function description

Name	logout
Code	QR03
Priority	Low
Critical	Logs the user out of the system
Description	Removes the user's session out of the device then redirects them to the login page
Input	None
Output	None
Pre-condition	QR01
Post-condition	Navigate to login page
Dependency	login User has to be logged in in order to logout
Risk	No internet connection. Course of action is displaying error message.

Table 5: connectSensors function description

Name	connectSensors
Code	QR04
Priority	Extreme
Critical	Used for connecting sensors to the system
Description	Sensors will be connected via bluetooth to the system
Input	None
Output	Alert for successful pairing of sensors
Pre-condition	None
Post-condition	Sensors are connected to the system
Dependency	Sensors have to be available and working
Risk	Sensors broken or hardware malfunction. Course of action is an error message display.

Table 6: getSignals function description

Name	getSignals
Code	QR05
Priority	Extreme
Critical	Acquires brain signals from the brain sensors
Description	Acquires brain signals from the brain sensors via bluetooth and inputs them into the system
Input	None
Output	Brain signals
Pre-condition	QR04
Post-condition	brain signals acquired and can be used within the system
Dependency	connectSensors Sensors has to be connected
Risk	Sensors connection failure or error transmission. Procedure taken is displaying error message.

Table 7: getInfo function description

Name	getInfo
Code	QR06
Priority	Low
Critical	Displays user's info
Description	Matches user's credentials with database and fetches their info to display it
Input	None
Output	User's Name, Age, Email, Password, Mobile number, Car name, Car model, Car plate number will be displayed
Pre-condition	QR01
Post-condition	User's info acquired and displayed for the user
Dependency	login User have to be logged in in order to fetch their data
Risk	User not logged in, session timeout, or no internet connection. Measure taken is to display error message

5 Design Constraints

In this section, the constraints and limitations of the system must be followed so it can function well.

5.1 Standards Compliance

The mobile application must be connected to the internet since it needs a server to store the data. In addition, the mobile device used must be a smartphone, as the application will only be available on Android and iOS.

5.2 Hardware Limitations

The smartphone must have a built-in GPS and be connected to the internet to provide accurate geolocation. In addition, the Raspberry Pi used for data processing must have a minimum of 4 GB of RAM. A single-channel wireless brain sensor must be used for signal acquisition.

6 Non-functional Requirements

This section will specify the quality attributes of a software system, such as security, usability, and reliability.

6.1 Availability

- The user must be able to access the system 99 percent of the time without failure.
- The user can depend on the system, as the mobile application will be running on an online server.

6.2 Reliability

- The system will be down for a maximum of six hours each month for maintenance.
- The system should not face any critical failures while being used.

6.3 Security

- To ensure the user's privacy, the system will encrypt all the user's critical data, such as passwords, license plates, and national IDs.
- The system must validate the user's data and prevent the types of data that may cause errors.
- The system must guarantee the integrity of the user data by requiring that each user only have access to his own data.
- The system must prevent commonly known cyberattacks, such as SQL injection.

6.4 Maintainability

- The system shall be well-refactored so it can be easily updated and expanded. Using the MVVM design pattern will facilitate the process of updating the code.

6.5 Usability

- The system shall provide a smooth, uncomplicated, and clear visualization to facilitate the process of using the application.
- Every form shall have clear validation messages and be clearly labeled.

6.6 Portability

- The system shall be connected to the Internet. so it can be accessed from anywhere and will operate on both Android and iOS, which can be easily done using Flutter.

7 Data Design

This section will describe the dataset used in the project.

7.1 Dataset Description

Confused student EEG brainwave data contains EEG signals from 10 college students to measure their confusion while watching online education videos. It consists of 12811 records and 13 features [9]. Features included are:

- Attention: Proprietary measure of mental focus.
- Meditation: Proprietary measure of calmness.
- Raw: Raw EEG signal.
- Delta: 1-3 Hz of power spectrum.
- Theta: 4-7 Hz of power spectrum.
- Alpha1: Lower 8-11 Hz of power spectrum.
- Alpha2: Higher 8-11 Hz of power spectrum.
- Beta1: Lower 12-29 Hz of power spectrum.
- Beta2: Higher 12-29 Hz of power spectrum.
- Gamma1: Lower 30-100 Hz of power spectrum.
- Gamma2: Higher 30-100 Hz of power spectrum.

- Predefinedlabel: whether the subject is expected to be confused.
- User-definedlabel: whether the subject is actually confused.

8 Preliminary Object-Oriented Domain Analysis

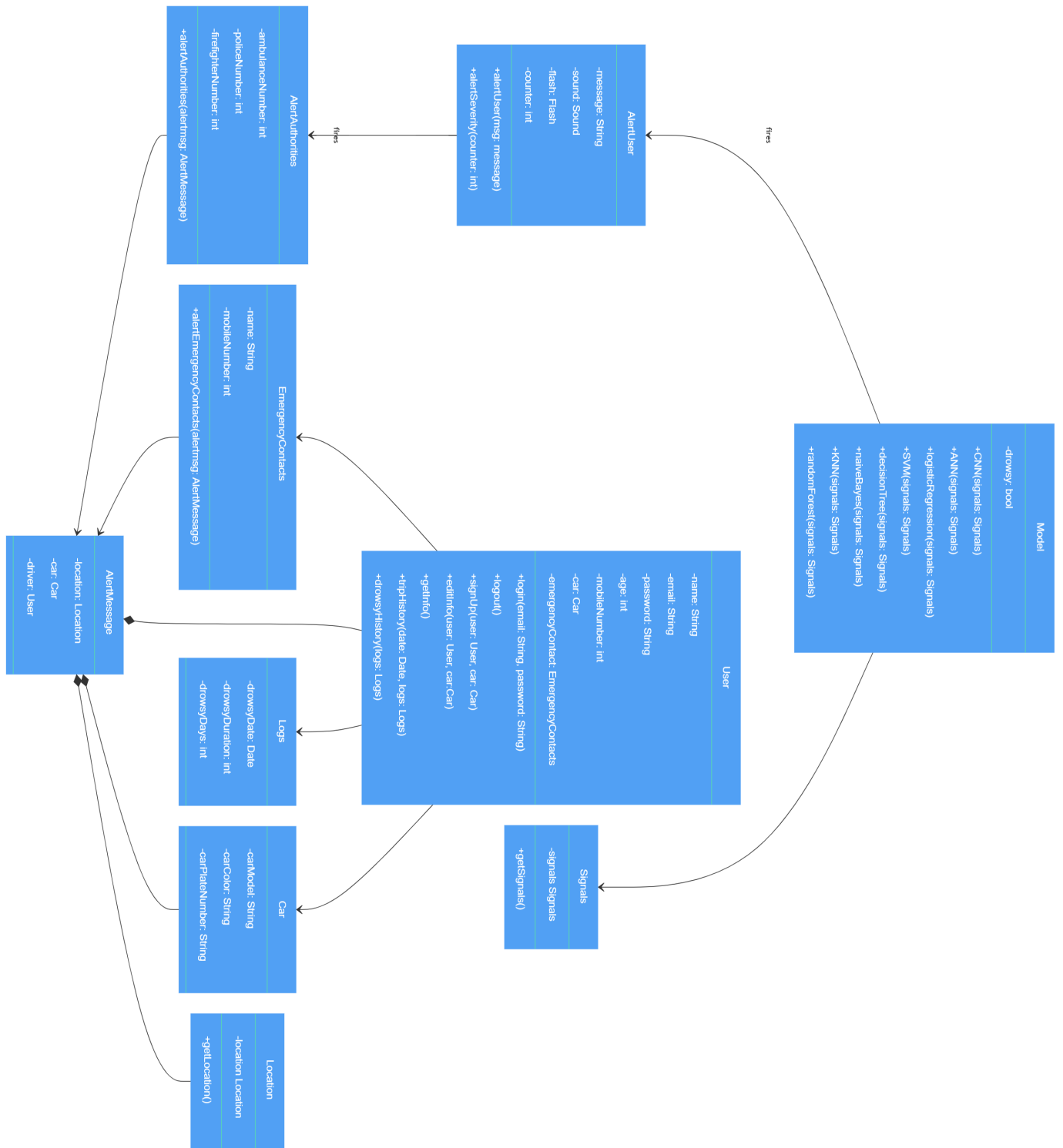


Figure 9:Class diagram.

9 Operational Scenarios

- **Scenario 1**

The driver will log in or sign up to gain access to the system to add, delete, or change his or her personal information and vehicle information.

- **Scenario 2**

The driver will log in and gain access to the application to activate the drowsiness detection mode. In addition, the driver will set up the hardware module (Brain Sensor), connect to the app, and start driving safely.

- **Scenario 3**

. The driver will log in and gain access to the application so, he/she can view the history of the day and time that he/she has been detected to be drowsy.

- **Scenario 4**

. The driver will be the actor in this scenario. The driver will be able to adjust the notification settings related to drowsiness detection.

- **Scenario 5**

The driver will log in and gain access to the application to activate the drowsiness detection mode. In addition, the driver will set up the hardware module (Brain Sensor), and connect it to the app. The application will alert the driver if he becomes drowsy using visual and audio alerts.

10 Project Plan

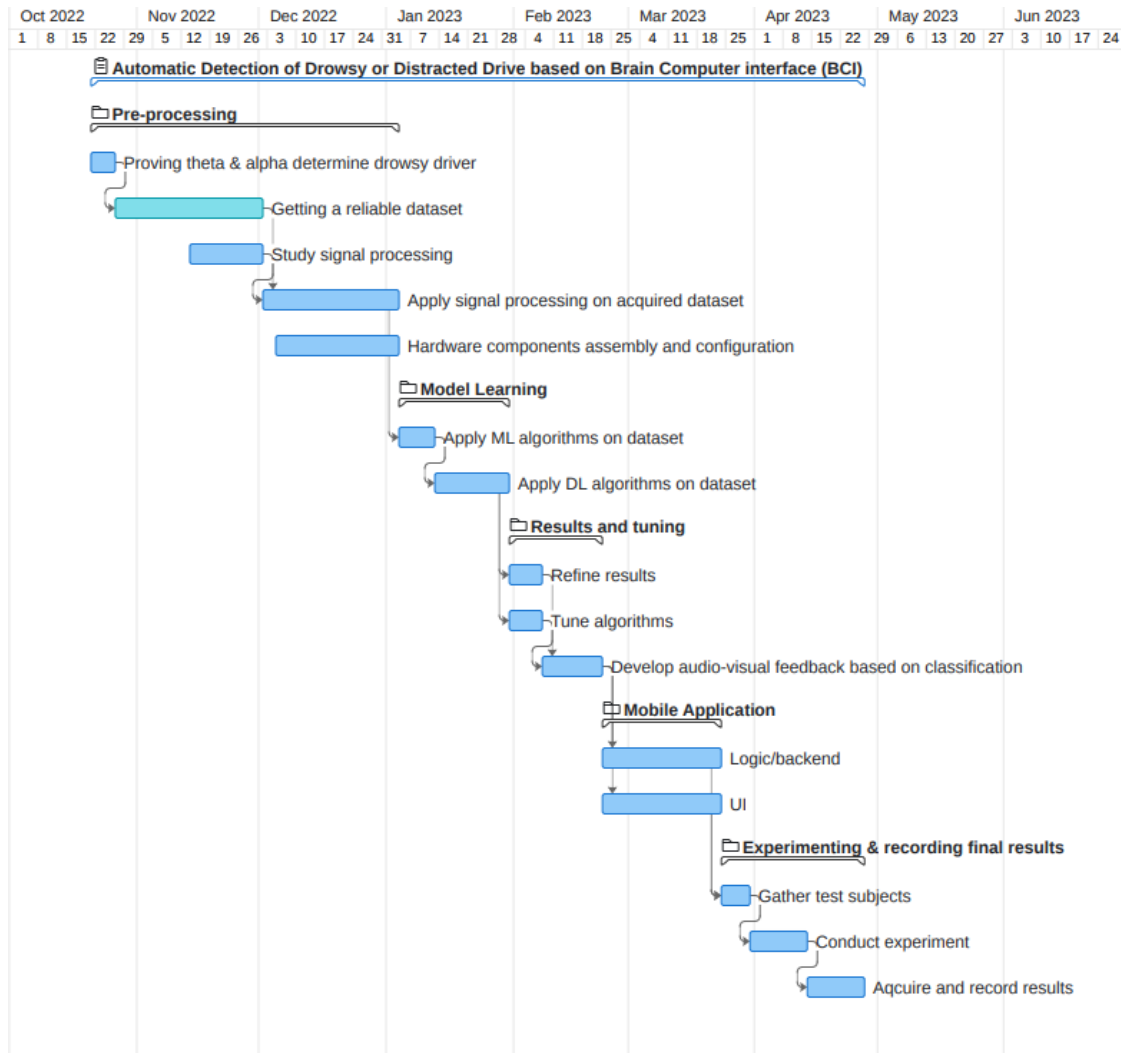


Figure 10: Proposed system time plan

11 Appendices

11.1 Definitions, Acronyms, Abbreviations

- EEG: Electroencephalogram.
- ESTCNN: Electroencephalogram-based Spatial-Temporal Convolutional neural network.

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