# Drowsiness Detection and Anti-Sleep Alarm System for Drivers

## ENG4702: Final Year Project - Final Report

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# 1 Executive Summary

Drowsy driving is a significant concern, leading to dangerous road accidents and fatalities. Queensland alone sees about 500 people severely injured or losing their lives annually due to drowsy driving accidents. Existing drowsiness detection methods lack reliability for standalone use, necessitating the development of a non-intrusive yet reliable drowsiness detection system.

The project aimed to develop a machine learning-based system that combines driver behavioural, physiological, and vehicular indicators to accurately detect drowsiness and alert the driver. Additionally, the team aimed to create a publicly available database with comprehensive data on drowsiness indicators for future research.

Two experiments were conducted to collect. The first involved a simulator experiment to collect physiological, vehicular and behaviour data used for neural network training for drowsiness detection. The second experiment collected data for tests on the feasibility and effectiveness of non-intrusive BCG and accelerometer breathing-rate devices for extracting ECG data.

Collected simulator data was pre-processed, including noise filtering and synchronization of data channels, to create a complete dataset for neural network training. Features were extracted from physiological, behavioural, and vehicular data. Techniques such as Pan-Tompkin's algorithm, EEG/EMG signal analysis, MediaPipe for facial landmarks, and lane detection for vehicular features were employed, yielding a total of 129 features.

The extracted features were analysed using t-tests to determine the features with statistically significant differences between awake and drowsy samples. Feature selection methods like MRMR and SelectKbest were used to ensure only the most important features were used as inputs to the neural networks.

A regression MLP model was trained using different numbers of selected features, with linearly interpolated KSS scores as target labels. The model achieved a 69.30% accuracy when 45 features were selected using the MRMR method showing promising results as a proof of concept, however the accuracy can be greatly improved in future works using a more complex model and better ways of labelling the data.

The project highlighted the complexity of drowsiness detection, emphasizing the need for a holistic approach that considers behavioural cues and vehicular data. Challenges in data collection and processing underscored the importance of accurate and reliable data. While the project was not taken to completion due to time constraints, it paves the way for further research in drowsiness detection to enhance road safety and reduce drowsiness related accidents.

# 2 Acknowledgement of Country

We wish to acknowledge the people of the Kulin Nations; on whose land we conducted this project. We wish to pay our respects to their Elders, past and present.

# Contents

# 3 Introduction

Drowsiness is a state of feeling sleepy and lethargic. This occurs often in drivers travelling on high-speed highways during late night or afternoons [1]. Drowsiness caused by sleep deprivation can result in significantly reduced reaction times as well as mental impairment effects like having a blood alcohol concentration (BAC) of 0.05-0.10% [2]. Furthermore, dozing off for just a few seconds is enough for vehicles to veer off uncontrollably at high speeds for over 100 metres. The combination of these factors causes a significant public safety concern, and it often results in devastating high-speed road accidents. According to investigations led by the Queensland Government, approximately 500 people a year are either severely injured or die because of accidents caused by drowsy driving just in Queensland [3]. Therefore, there is an urgent need for the research and development of a reliable system that detects drowsiness to prevent accidents.

Recent advances in technology, especially in machine learning methods, have led to an increased interest in research and development on drowsiness detection systems. There are three types of measures that are currently being used to monitor drowsiness. These include Vehicle-based measures, Behavioural measures, and Physiological measures [4]. Vehicle-based and behavioural measures are non-intrusive mostly and various methodologies have been adapted to analyse these measurements. Machine learning algorithms have been implemented in computer vision systems to monitor yawning and calculate Eye Aspect Ratio (EAR) in real-time [5] inside the car while the driver is driving. These methods work sometimes but are not reliable and robust enough to be used as a standalone system.

Continuing from prior research, this project will first focus on collecting data from a diverse set of participants using a selection of physiological and behaviour sensors which will then be analysed to extract features that correlate to drowsiness and then used to train a neural network model that is capable of detecting drowsiness in users in real-time.

# 4 Aims and Objectives

## 4.1 Hypothesis

**Current State**

The drowsiness detection and alert systems in cars are unreliable, inaccurate, and not widely used.

**Impact**

This results in an increased risk of accidents which are caused by the driver's impaired reaction time, attention, and judgement like having a BAC of 0.05-0.10% [2], as mentioned earlier. Drowsiness can lead to slower reflexes, decreased hazard perception, and reduced ability to make quick decisions while driving. These factors significantly increase the risk of accidents.

With no reliable way of being alerted while drowsy, severe drowsiness may cause them to fall asleep. This is extremely dangerous and can result in the loss of control over the vehicle, also leading to accidents.

**Desired State**

A reliable and accurate drowsiness detection and alerting system that is implemented or embedded in the cars or through a mobile application will reduce the probability of these accidents and make the drivers and other road users feel safer.

## 4.2 Aims

This project aims to create a system that utilizes a combination of driver behavioural and physiological indicators to detect drowsiness and alert the driver quickly and accurately.

## 4.3 Objectives

To accomplish this aim, several key milestones have been identified that must be achieved by the end of the year. These include:

1) Use the selected vehicle, behavioural, and physiological sensors to collect data from 20 participants of diverse backgrounds in two separate experiments:
    a) The first experiment will be conducted in a research laboratory where participants' data will be collected as they operate a virtual driving simulator in three different time periods:
        i) Morning sessions: **9-11 am**
        ii) Afternoon sessions: **3-5 pm**
        iii) Night sessions: **3-5 am**
    b) The second experiment will be conducted in a vehicle where the participant's data will be collected as they are being driven in the passenger seat.
2) Process and clean the collected data using conventional noise filtering methods.
3) Analyse the measurement data to extract features from the behavioural/physiological data that correlate to drowsiness.
4) Determine the relevance of the features to select the most important ones and implement algorithms to extract them.
5) Use the discovered features to train a Neural Network classifier that will be able to automatically detect drowsiness by analysing sensor data in real-time.
6) Implement a software system using a Raspberry Pi and relevant modules or a phone application to alert the driver when signs of drowsiness are detected.

# 5 Literature Review

## 5.1 Drowsiness Detection Methods

Drowsiness refers to an inclination of falling asleep. The state of being drowsy can lead to several impairments such as inhibited cognition, reaction speed and loss of control and driving while being in this state drastically increases the potential for accidents. However, drivers do not just suddenly become drowsy, there is a slow transition period where the sign of drowsiness becomes more and more prominent as the drowsiness level increases, therefore it is possible to develop a system capable of alerting the driver during early stages of drowsiness to prevent accidents.

A survey conducted by Nordebakke et al. [6] found that some signs common to all genders were:

- Difficulty in keeping eyes open.
- Yawning.
- More frequent blinking.

The above physical behavioural signs along with other physiological signs of drowsiness have been widely utilised by researchers to develop drowsiness detection systems. In general, most recent works have mainly adapted five categories of measures to determine driver drowsiness [4, 7].

The block diagram in figure 5.1.1 shows all the different types of detection measures that have been considered in driver drowsiness detection research.

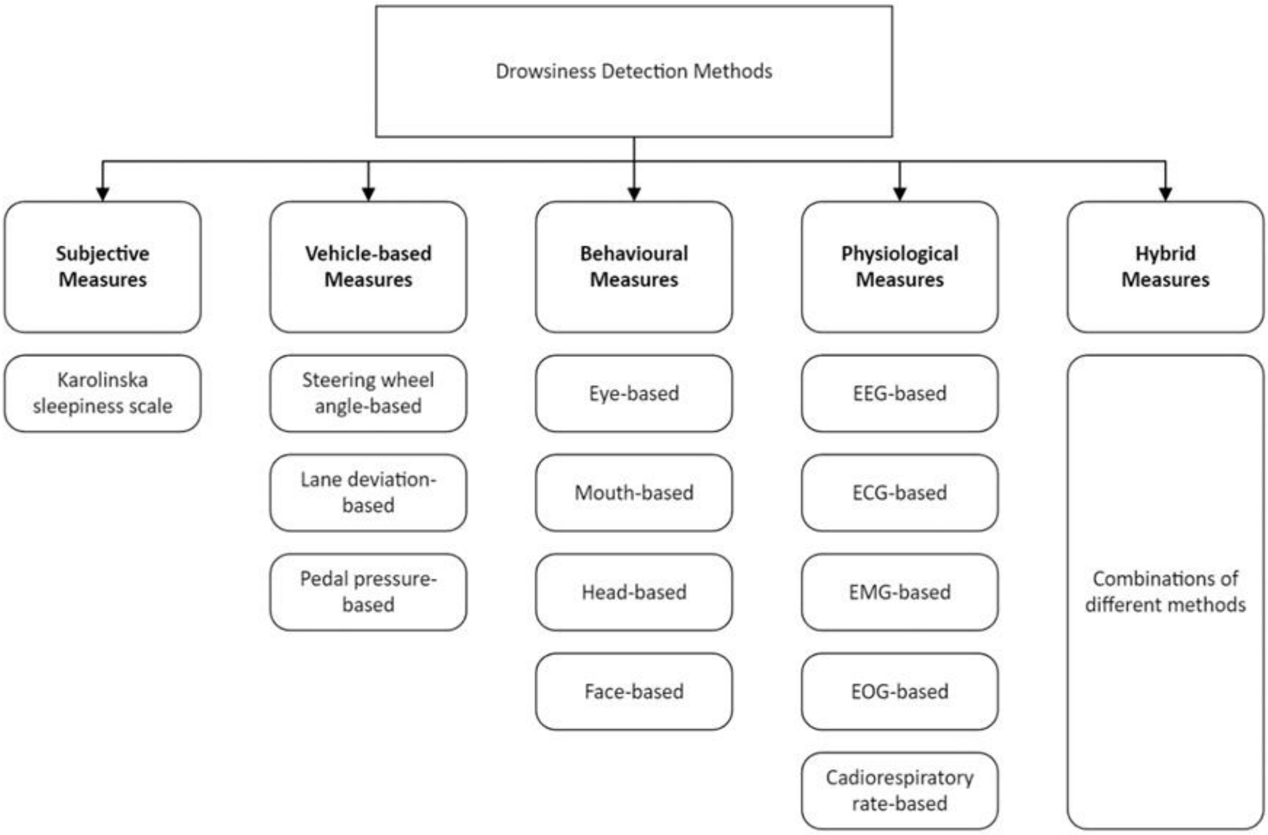


*Figure 5.1.1: Different types of methods for Driver Drowsiness Detection Systems*

### 5.1.1 Subjective Measures

Subjective measures refer to using the driver's personal estimation as an indication to the level of drowsiness that is being experienced by them. The most used scale is the nine-point Karolinska Sleepiness Scale which is elaborated in table 5.1.1.1 [4].

*Table 5.1.1.1: Karolinska Sleepiness Scale (KSS)*

| KSS Rating | Verbal descriptions |
|---|---|
| 1 | Extremely alert |
| 2 | Very alert |
| 3 | Alert |
| 4 | Fairly alert |
| 5 | Neither alert nor sleepy |
| 6 | Some signs of sleepiness |
| 7 | Sleepy, but no effort to keep alert |
| 8 | Sleepy, some effort to keep alert |
| 9 | Very sleepy, great effort to keep alert, fighting sleep |

A technique that uses this scale measures the KSS ratings of drivers every 5 minutes and compares it with measurements taken from all vehicle-based, behavioural, and physiological measure. It was found that there was no strong evidence of correlation between any of the measures with the KSS ratings of drivers [4]. The measurements were taken in 5-minute intervals and sudden variations in ratings cannot be detected. Additionally, the idea of rating themselves alerts the drivers and so the measurements cannot be relied upon since they do not match the conditions experienced by drivers in real driving situations. For these reasons, using subjective measures alone has been evaluated to be very unreliable and not conclusive enough to serve the purposes of this study.

### 5.1.2 Vehicle-based Measures

The monitoring points used for vehicle-based measures include measuring the steering wheel movements (SWM), standard deviation of lane position (SDLP), and, less commonly, pressure on acceleration pedals [4, 8]. These experiments are usually conducted in a simulator environment where various sensors are embedded into monitoring these.

When monitoring the SWM, small angle of rotations, usually between 0.5-5 degrees, are measured since it was found that when drowsy, drivers tend to make less micro-corrections on the driving wheel [8, 9]. This way, SWM can be used to monitor for driver drowsiness. However, car companies such as Nissan and Renault have attempted to adapt this technique into their cars and discovered that the system works in strict conditions as road structures and environmental differences are significant contributors to false positive results [10].

Similarly, the SDLP is monitored using cameras recording the lane in real driving situations or from the simulator itself if a simulator environment is used [11]. Drowsy drivers tend to find it difficult to remain centrally in lane while travelling along a curving road. There is evidence of positive correlation between KSS ratings provided by drivers and the SDLP, however, it was found that these varied significant on a participant-to-participant basis. The SDLP was also observed to vary when the driver is under influence of other condition excluding drowsiness, for example, depressants or alcohol [12].

Vehicle-based measures cannot be used as a standalone measure to detect drowsiness due to the limitations described above. Both the SWM and SDLP are inconsistent methods and must be used in conjunction with other measures to be discussed, so that the drowsiness can be reliably measured.

### 5.1.3 Behavioural-based Measures

Image based drowsiness detection techniques are used to detect behavioural changes that happen during the state of drowsiness. Recently researched work included yawning detection, thermal respiration detection, eye tracking/eyelid closure analysis, head posture detection and general face expression analysis [4, 13]. These behaviour detection methods often only require data from different types of cameras, and video and image analysis are performed to detect changes in facial features and driver posture. Due to the widespread use of smart phones and dash cams, video and image data are extremely accessible, which is beneficial to both development and deployment. Therefore, good behaviour detection-based systems are often very desirable especially because they are also non-intrusive and non-invasive.

Analysis of eye features is one detection method that has been extensively studied. One proposed method explored by Khan et al. [14] is to analyse curvature of the eyelid to determine whether the driver's eyes are closed or not. Although they achieved an average classification accuracy of 95% on simple scenes, the algorithm struggles with 70% accuracy on more complex scenes. Similar works on eye closure analysis include research by Horng et al. [15], where edge detection and pixel colour value matching were used to detect eye closure based on whether the eyeballs were visible. Both detection methods relied on checking for prolonged periods of eyelid closure, but this is often too late for effective accident prevention in high-speed situations.

An alternative ocular method that has been studied is blinking analysis. In early stages of drowsiness, both blinking frequency and blink duration are increased. This makes detection systems based on blinking analysis preferable for early drowsiness detection. Some relevant work include work done by Maior et al. [16] and Rahman et al. [17], where Eye Aspect Ratio (EAR) and corner detection were used respectively to determine eye state. Furthermore, blinking rate alone is often not conclusive enough due to possible outliers caused by conditions like dry eyes, and several other metrics such as change in blink velocity/duration could have been used in conjunction.

Another logical behavioural pattern that can be used for drowsiness detection is yawning detection. One popular method is performing face extract and mouth detection using computer vision techniques, and then performing classification using Support Vector Machine (SVM) [18]. Another notable method utilises thermal images to detect yawning by looking for temperature anomalies near the mouth region [19]. Although both works can detect the presence of an open mouth, the systems fail to detect gentle yawns with narrow mouth openings resulting in many false negatives. The works also only focus on solo drivers and does not account for the presence of talking and laughing, which may result in a lot of false positive detection in a real car environment.

Overall, behavioural analysis through image/video-based detection can achieve high detection accuracies. However, due to obvious limitations and performance drops due to factors such as, varying lighting conditions, presence of face wear and long facial hair, using these techniques as the standalone detection method is not ideal. Taking this into consideration, this project will take a more hybrid approach, focusing on detection of early signs of drowsiness, while matching it with other measurements to ensure reliability of detection.

### 5.1.4 Physiological Measures

Monitoring the physiological state of a driver is the most reliable method of identifying even the early signs of drowsiness. The main signals that researchers record is electrooculogram (EOG), electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG), and respiratory signals [13]. All these methods include attaching sensors at various parts of the participant’s body and measuring the signals while the participant is driving.

EOG uses electrodes placed at the outer corner of each eye and another one at the centre of the forehead to measure the electric field generated by a potential difference between the cornea and the retina. REM and Slow Eye Movements (SEM) that occur when a person is drowsy can be measured using this technique [20]. EOG is very rarely used due to the highly intrusive nature of the data collection and will not be used in this project for this reason as well.

The heart rate (HR) or the heart rate variability (HRV) are easily measured using the ECG electrodes and these can be used to determine the drowsiness of a driver since they vary greatly based on the different stages of drowsiness such as alertness and fatigue [21]. When using HRV, the low (LF) and high (HF) are measured which fall in the range of 0.04-0.15Hz and 0.15-0.4Hz respectively [22]. These are the beat-to-beat (R R intervals) changes in HR and the ratio of LF to HF decreases as a driver becomes drowsy [23]. These methods of monitoring the HR are intrusive and as such another non-invasive way to monitor HR is Ballistocardiograph (BCG). The technique involves measuring the degree of movement produced by a heartbeat by placing electrodes on the seat. While BCG works well in stationary systems [24], there are difficulties using it in cars due to the motion of the car and bumpy road creating noise, however, traditional filtering techniques have been used and are found to work well with BCG measurements. As such, both ECG and BCG techniques are adapted in this project due to their high reliability.

EEG is the most common physiological signal used to detect drowsiness. It measures the activity of the brain using electrodes. Mainly two different frequency bands are observed when determining drowsiness using this technique. There are the delta band between 0.5-4Hz that correspond to the sleep activity and the theta band between 4-8Hz that correspond to drowsiness. An increase in intensity of signals in these wavebands indicate drowsiness [25]. This technique will be significantly used in this project due to its accuracy and reliability.

EMG is the measure of the electrical activity generated by the body’s muscle during contraction. It was found that both the intensity and frequency of the signals generated by the contraction decrease when a driver is drowsy [26]. Thus, the changes in EMG signal intensity and frequency can serve as indicators of drowsiness.

Finally, the method of measuring the respiration rate measures the number of breaths taken per minute and it is also an important physiological parameter that indicates drowsiness. During drowsiness, respiration rate tends to decrease, indicating a reduction in the rate of breathing [27]. Breathing rate extraction via this method is challenging in a vehicle as the sensor picks up the vehicle's acceleration and deceleration rather than the breathing rate. Thus, filtering out these noises is necessary to obtain the driver's breathing rate. This filtering process will be explored in the project by using a reference sensor to perform noise cancellation.

Considering the described methods and their benefits, the utilization of physiological signals as an indicator of drowsiness has been assessed as considerably significant and valuable for the project's objectives.

Consequently, they will be utilized alongside other vehicle-based and behavioural measures detailed earlier, to develop a highly resilient and precise drowsiness detection system.

## 5.2 Feature Selection and Reduction Techniques

From the prior discussion, there are many features that can be extracted from each of the three measures, and this means that there is a need to select and reduce the number of features that would then be used to train neural networks. Having so many features being analysed at once by the neural network would be very costly computationally due to the high dimensionality of the data and as such the alert system may not be ‘real-time’ if it takes too long to predict whether the measured data correlates to drowsiness. There is also the possibility of some features being redundant and not providing useful information to the Neural Network.

Feature selection can be categorized into supervised and unsupervised techniques. Unsupervised means that there are no target labels that can be used and so correlation or clustering is usually used to only include relevant features. [28]

Supervised methods are classified into filter methods, wrapper methods, embedded methods, and Maximum Relevance Minimum Redundance (MRMR) [29]. Filter methods use univariate statistics of the features to determine the intrinsic properties of the features, and these are fast and less computationally expensive than others. Wrapper methods evaluate all possible subsets of the features in a specific machine learning algorithm and so usually selects more accurate features. Embedded methods utilize aspects of both filter and wrapper methods by including the statistics between the features while also only including features that contribute the most during each iteration in the training process. MRMR differs by trying to control for redundancy in the features during the selection process. [29, 30]

SelectKbest is a filtering feature selection which uses a score function such as ANOVA or chi2 [30], calculates the score of each feature, and returns k features with the highest scores. Depending on the score function used, the selected features can vary and, furthermore, depending on the classifier used, the accuracy would also vary.

MRMR is an algorithm that prioritizes features for predicting a target variable based on their relevance and redundancy components. Relevance is determined by the feature's correlation with the target (mutual information for categorical, F-statistic for continuous). Redundancy considers a feature's correlation with already selected features. The algorithm selects features iteratively by maximizing a score (relevance minus redundancy or relevance divided by redundancy). The first feature chosen is the most relevant, and subsequent features are chosen while considering redundancy.

Similarly, various other feature selection algorithms can be applied to select the one which meets the criteria. However, if the samples are changed randomly by adding in or removing samples from the dataset, it is seen that the selected features vary. [29] This is a problem as the results are not consistent which would mean that the selection algorithm is unstable. In this study both SelectKbest and MRMR are applied on features extracted using varying window sizes to find out which algorithm gives the highest accuracy in classification while also being stable and consistent

## 5.3 Classification Models for Drowsiness Detection

To successfully perform drowsiness detection, a reliable and appropriate classification model must be used at the final step of the process. The role of a classification model is to perform the decision-making step to determine whether a driver is in a state of drowsiness or not, by considering all the input parameters and information. However, depending on the input data type, some methods may be more suitable than others.

The most prominent classification models that have been used in recent drowsiness detection research include:

- Logistic Regression (LR)
- Support Vector Machine (SVM)
- (Deep) Convolutional Neural Network (CNN/DCNN)
- Artificial Neural Network (ANN)
- Long Short-Term Memory Networks (LSTM)

Logistic regression is a statistical model used for binary classification. It can find the ideal linear decision boundary within the data. In past research by Babaeian et al. [31], they utilised an LR classifier to differentiate between alert and drowsy ECG data. Although this type of model is simple, easy to understand and computationally inexpensive, a linear decision boundary may not be able to effectively separate complex data that have non-linear relationships. In comparison, the Support Vector Machine method also determines a decision boundary for the data but may be more suitable for non-linear relationships as it can use kernel functions to map input data into higher-dimensional feature space. In work by Kumar et al. [32], SVM was used to efficiently perform classification with 3 features, EAR, Mouth Opening Ratio (MOR) and Nose Length Ratio (NLR).

In terms of behavioural data from images, hand-crafted feature extractors like the ones used by Kumar et al. may be difficult to implement, which provides motivation for the use of state-of-the-art Convolutional Neural Networks for image and video data. CNNs use a series of convolutional layers to automatically learn spatial information and detect important features in images to maximise prediction accuracy. Various works showcase the effectiveness of CNNs in drowsiness detection [33, 34], demonstrating that this architecture often outperforms other methods. Although recent works using this architecture were able to achieve very high accuracies, training such a model requires a tremendous amount of labelled training image data, which may be very time-consuming to manually collect and annotate. Although CNNs perform well for behavioural analysis based on images, it is still unsuitable for classifying physiological and vehicular data that will be used for this project.

A more suitable method to classify numerical data such as physiological signals (EEG, ECG, EMG) and vehicular signals (SWM) is using Artificial Neural Networks such as Multi-Layered Perceptron (MLP). Hasan et al. [35] demonstrate the usage of ANNs for the classification of physiological signals, showing that it outperforms simpler classifiers such as LR and SVM. Furthermore, once facial features get quantified using EAR, MOR or NLR, these can also be classified using ANNs to achieve better results than using the SVM method [36].

In terms of drowsiness detection, a recurring problem is that it is often difficult to predict the drowsiness level of the driver based on just one instance of data, hence Recurrent Neural Networks like LSTM are often used to make predictions based on a sequence of data/image frames. Yarlagadda et al. in their work used LSTM in conjunction with CNN to perform classification across a consecutive number of frames, achieving 97.20% accuracy. [37] However, in their proposed method, only behavioural data in the form of face recording was considered, and their method does not consider the use of physiological and vehicular features to increase accuracy.

The above analysis suggests that for hybrid-based approaches like this project, it is often not enough to only use a single classification model. In this project, ANN will be primarily used for classification as it provides the ability to work with all the collected data, however, the LTSM-CNN based model will also be explored for behaviour analysis due to its effectiveness for video/image classification.

# 6 Methodology and Methods

## 6.1 Methodology

From the literature review conducted, this project falls into the category of quantitative research. Quantitative research refers to the collection of numerical data through standardized and structured tests, experiments, and simulations, and analysing it to test a hypothesis.

20 participants were recruited, and various Vehicle-based, Physiological and Behavioural signals were collected from them. A detailed description of what sensors were used to take the measurements is provided in section 6.2 and a combination of these measurements was used to make a detection system. All these measurements are quantifiable and, as discussed earlier, these methods generate quantitative data that were analysed statistically to determine patterns and trends within the data.

## 6.2 Methods

### 6.2.1 Participants

Participants were recruited through online advertisements and included 20 healthy adults aged 20 years old and onwards who hold a driver's licence (including probationary and international licences).

### 6.2.2 Procedure

Participants were asked to partake in two experiments:

1. Simulator experiment where participants are simulating driving in a virtual driving simulator, with various sensors (physiological, behavioural, vehicular) taking measurements while they drive.
2. Passenger seat experiment where participants had cardiorespiratory-related sensors attached that took measurements as they were being driven around.

A full explanation document was provided to participants that detailed the risks that are posed and guaranteed the confidentiality of personal data collected. They were requested to sign consent forms which were separated from the dataset to ensure anonymity. Participants were also asked to complete both a pre-experiment and a post-experiment survey that collected information about their sleep cycles and their experience with the experiment respectively.

#### *6.2.2.1 Simulator Experiment*

**Recording Data**

The simulator experiment was used to collect a complete set of data including ECG, EEG, EMG, Face recording, Simulator (dash cam) recording, Steering wheel angle and Pedal/Brake positions. These data were used for feature extraction and selection and served as training/validation data for the machine learning-based drowsiness detection system.

Participants were asked to record their data in 30-minute blocks in three sessions between:

- Morning sessions: **9-11 am**
- Afternoon sessions: **4-6 pm**
- Night sessions: **1-3 am**

Participants were also requested to remain in the laboratory to ensure they did not fall asleep from 11 pm until the late-night experiment.

The simulator used was Euro Truck Simulator 2 (ETS2) with a mod that changed the driving vehicle to a Toyota Corolla 2018 to have a more accurate immersive experience. This was changed from CARLA which was previously used by the previous researchers as a driving simulator. A perspective of the participant while driving in the simulator is shown in Figure 6.2.2.1.1.

*Figure 6.2.2.1.1: Simulator View*

In the new setup in ETS2, there was a pre-set destination 30 minutes away that the participants drove to by following the GPS map in the simulator. Participants operated the Logitech G29 Driving Force which has a steering wheel with gear change functionality, as well as acceleration and braking pedals. Many of the simulator settings were modified to improve realism, and the time in the simulator was changed to reflect the time of day of the session. A detailed list of the settings and their values is given in Appendix C: Simulator settings.

Unlike Carla, ETS2 does not provide vehicular data such as lane deviation, and thus, the software Open Broadcast Studio (OBS) was used to screen-record the simulator which allowed the lane position information to be determined after the recording. Five separate data recording sources were started one after another which were:

- recording of the simulator (i.e., dash cam),
- the webcam video,
- the Python script for the vehicular data,
- and the OpenBCI software for physiological signals.

A short 30-second video clip containing the times when each data source was initialised was recorded and used to synchronize the listed recording sources since it was not possible to start all the recordings simultaneously.

To obtain recordings of physiological signals, the participants had EEG, ECG and EMG sensors attached to them. The setup did not change from last year. The EEG hardware used was an OpenBCI electrode cap and the ECG/EMG hardware used were general ECG/EMG snap electrode cables and skin tact sticky electrodes. For EMG, the forearm muscles were used for the measurements. Figures 6.2.2.1.2 (a), (b), and (c) show the sensor setup for EEG, EMG and ECG respectively. These were interfaced with the OpenBCI Cyton Board + Daisy Board which connected to a Cyton Bluetooth USB dongle connected to a computer. The computer required the OpenBCI GUI software to be able to obtain the measurements from the dongle. A detailed guide on how to interface these sensors is provided by OpenBCI on their website [38].

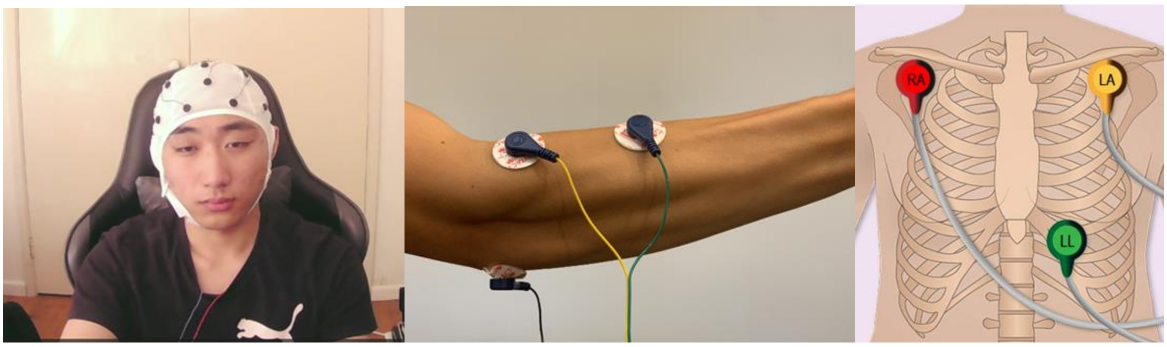


*Figure 6.2.2.1.2: (a) EEG cap (left), (b) EMG placement (middle), and (c) ECG placement (right)*

These programs and software were started before the participant began driving, and continuously collected data for 30 minutes after which point the programs were stopped manually. These processes were repeated for each session.

**Synchronising Data**

Using the 30-second clip, time differences between the different recording sources were calculated, and all the recordings were trimmed to match the latest starting recording source while having a duration of 29.5 minutes. The simulator experiment was usually run for a little longer, i.e., 31 minutes, to allow for the lost duration due to syncing. A Python program was created to automatically trim and synchronise the recordings based on the latest start time and the recording for the latest start time.

### *6.2.2.2 Passenger Seat Experiment Procedures*

**Recording Data**

The Passenger seat experiment was conducted to evaluate the practicality and effectiveness of a non-intrusive BCG seat and seat belt accelerometer for measuring cardiorespiratory signals.

Participants sat in the passenger seat of a car, on top of the BCG seat. The experiment collected 10 minutes of data from each of the data sources, which included, BCG signals using piezoelectric sensors, respiration rate using a pair of accelerometers and the heart rate using a separate handheld ECG device.

The participants were asked to assist with the calibration of the sensors as necessary (e.g., adjusting their seat position to accommodate the sensor placements) prior to driving. An accelerometer was attached to the seatbelt of the participant and another to the base of the seat and their measurements were used to determine the respiration rate of the participant.

There were seven piezoelectric sensors embedded into the BCG seat that were intended to measure the BCG signals of the participant. These measurements were used to determine their heart rate.

Lastly, the ECG device was used to measure ECG signals directly from the chest using the same setup shown in Figure 6.2.2.1.2 (c), which was used to obtain the ground truth cardiorespiratory signals for comparison.

The OpenBCI software was started first and then the accelerometer sensors, and the ECG module were started at the same time manually to keep at least two synchronized. This is because both the OpenBCI software and ECG module recorded the actual time with each data point and if the accelerometer is synced with any one of them, the data can be easily synchronized. The overall setup of the passenger seat is shown in Figure 6.2.2.2.1.

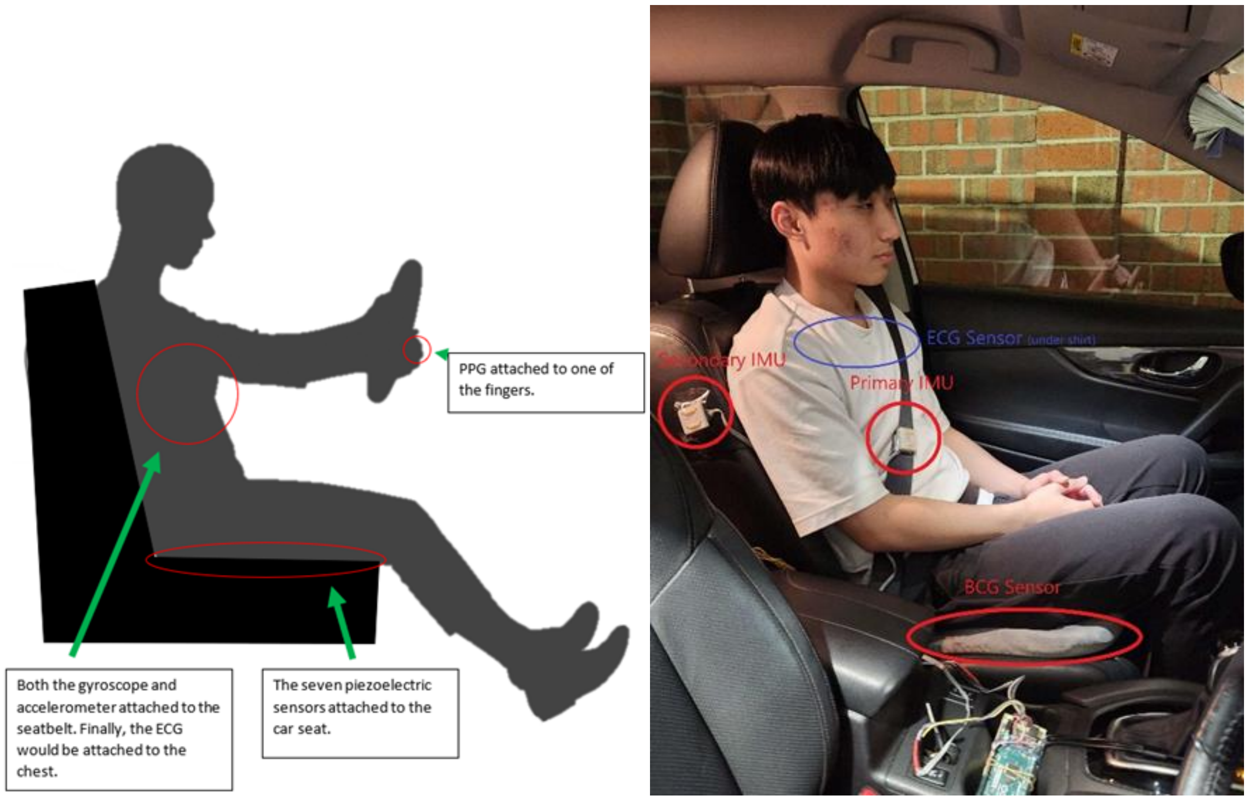


*Figure 6.2.2.2.1: Sensors for passenger seat experiment*

**Synchronising Data**

Since two of the measurements were synchronized, the time of recording was used to trim the accelerometer recording using a Python script. Additionally, there was a delay of 7 minutes and 42 seconds in the ECG measurement time, due to incorrect system time in the ECG device, and this system time offset was accounted for while syncing.

### 6.2.3 Feature Extraction

#### *6.2.3.1 Vehicular Features*

The screen recording of the simulator was used to determine lane position. This was done using a lane detection program using computer vision that had been adapted from a blog in Automatic Addison [39]. The general process is described as follows:

1. Applied binary thresholding to isolate the pixels that represent lane lines.
2. Applied perspective transformation to obtain Bird's Eye View.
3. Identified lane line pixels.
4. Filled in the lane line.
5. Overlayed lane line on original image.
6. Calculated lane line curvature.
7. Calculated centre offset.

This process was used to determine the mean offset and standard deviation in the offset.

The steering wheel rotation data was processed to filter out all rotations that are greater than 5 degrees since the area of interest was to check for micro-corrections between 0.5-5 degrees. After the filtering of the data, whenever there was a rotation of the steering wheel between 0.5-5 degrees in the dataset, a corresponding rotation in the opposite direction within the next few hundred milliseconds were searched for using a search algorithm. The frequency of this micro-correction was then measured to obtain a frequency domain plot of the micro-corrections.

Finally, only the values for the acceleration and brake pedals were used as standalone features.

#### *6.2.3.2 Behavioural Features*

Existing computer vision techniques were used to determine each of the features to be extracted from the webcam recording. A popular and well-explored face mesh extraction library, MediaPipe, was used to first extract the 478 3D facial landmark positions which were used to calculate various facial features such as EAR, MOR and NLR [33]. MediaPipe uses lightweight machine learning models to efficiently infer 3D face surfaces from just a single camera, which is critical for performing real-time drowsiness detection [40, 41]. A diagram of the facial landmarks is shown in Figure 6.2.3.2.1.

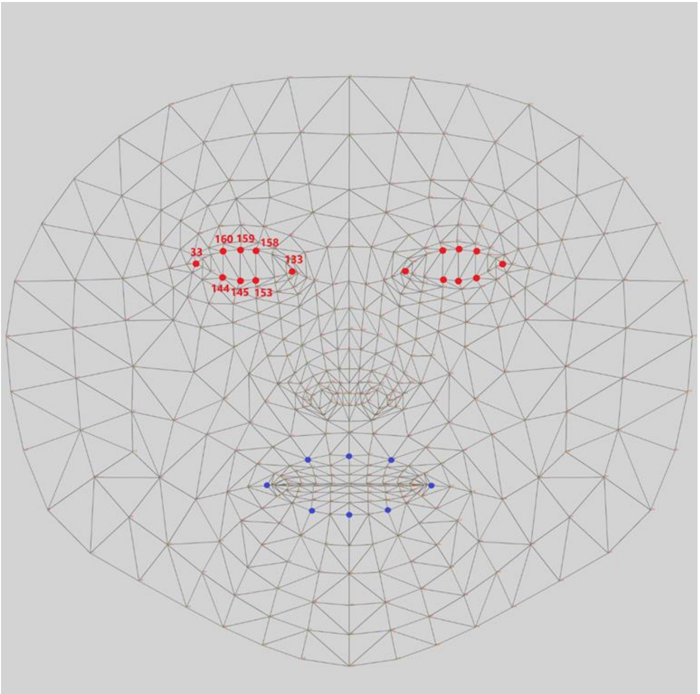


*Figure 6.2.3.2.1: Diagram of MediaPipe face mesh coordinates [42]*

From the obtained face mesh landmarks, hand-crafted features like EAR, MOR, pupil circularity (PuC) as well as head tilt and position were extracted. The method used was based on previous works such as ones by Rahman et al and Kumar et al [43, 44, 17, 32], and the equation used to calculate the EAR is shown in equations 1 and 2. Afterwards, several auxiliary features based on the EAR/MOR values were extracted for analysis, including average and change in blinking rate, change in eye closeness, blinking velocity/duration and yawning. These parameters were statistically analysed against independent variables such as time of recording (morning, afternoon, late night) and KSS drowsiness levels (1-10) and T-tests as well as F-tests were performed appropriately to evaluate the statistical significance and usefulness of these parameters in detecting drowsiness.

$$EAR = \frac{\|P2-P6\|+\|P3-P5\|}{2\|P1-P4\|} \tag{1}$$

$$Ear_{AVG} = \frac{1}{2}(EAR_{left} + EAR_{right}) \tag{2}$$

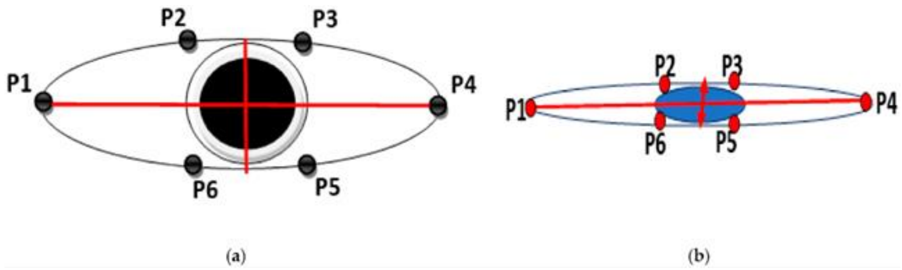


*Figure 6.2.3.2.2: EAR Calculation [43]*

Additionally, more abstract features were also extracted using existing pre-trained machine learning models like ResNet and VGGNet detailed by Dua et al and Anber et al [45, 46]. Transfer learning of these models was performed on our own collected dataset of face recordings to fine-tune it for improved accuracy. Publicly available drowsiness detection video datasets such as DROZY [47] and National Tsing Hua University (NTHU) [48] were also considered.  A summary of the extracted features is given in Table 6.2.3.2.1.

*Table 6.2.3.2.1: Summary of extracted behavioural features*

| Feature Type | List of features |
|---|---|
| Behavioural | **Low-level features:**<br>● MediaPipe 478 facial landmarks<br>● **EAR**: Eye aspect ratio<br>● **MAR**: Mouth aspect ratio<br>● **PuC**: Pupil Circularity<br>● **MOE**: Mouth over Eye ratio<br>● **HTilt**: Horizontal head tilt<br>● **VTilt**: Vertical head tilt<br>**High-level features:**<br>● **Blinking rate**<br>● **Blink duration**<br>● **Yawning rate** |

### *6.2.3.3 ECG Features*

Any ECG feature to be extracted from the signals primarily required the RR intervals throughout the signal. The RRI was determined via the Pan-Tompkins algorithm. The Pan-Tompkins Algorithm was utilized for identifying R waves within the QRS complex found in ECG signals, enabling the calculation of an individual's Heart Rate. This algorithm functions by examining the slope, amplitude, and width of QRS complexes within the filtered ECG signal. The ECG signal underwent filtration to reduce noise and lower detection thresholds, enhancing sensitivity for QRS complex detection. [49]

Using the RR-intervals, the Normal-to-Normal intervals (NNi) were obtained which were also then used to conduct heart rate variability analysis to extract several features. A summary of the extracted features is given in Table 6.2.3.3.1.

*Table 6.2.3.3.1: Summary of extracted ECG features*

| Feature type | List of features |
|---|---|
| ECG | **Time domain features** [50]**:**<br>● **Mean NNI**: The mean of RR intervals.<br>● **SDNN**: The standard deviation of the time interval between successive normal |

| | |
|---|---|
| | heartbeats.<br>● **SDSD**: The standard deviation of differences between adjacent RR intervals.<br>● **NN50**: Number of interval differences of successive RR intervals greater than 50ms.<br>● **pNN50**: The proportion derived by dividing NNI 50 (the number of interval differences of successive RR intervals greater than 50ms) by the total number of RR intervals.<br>● **NN20**: Number of interval differences of successive RR intervals greater than 20ms.<br>● **pNN20**: The proportion derived by dividing NNI 20 (the number of interval differences of successive RR intervals greater than 20ms) by the total number of RR intervals.<br>● **RMSSD**: The square root of the mean of the sum of the squares of differences between adjacent NN intervals.<br>● **Median_NN**: Median absolute values of the successive differences between the RR intervals<br>● **Range_NN**: Difference between the maximum and minimum NN intervals<br>● **CVSD**: Coefficient of variation of successive differences equal to the RMSSD divided by Mean NNI.<br>● **CV_NNI**: Coefficient of variation equal to the ratio of SDNN divided by Mean NNI.<br>● **Mean_HR**: The mean heart rate.<br>● **Max_HR**: Max heart rate.<br>● **Min_HR**: Min heart rate.<br>● **STD_HR**: Standard deviation of heart rate.<br><br>**Frequency domain features** [51]**:**<br>● **LF**: Variance in HRV in the low frequency (.04 to .15 Hz).<br>● **HF**: Variance in HRV in the high frequency (.15 to .4 Hz).<br>● **VLF**: Variance in HRV in the very low frequency (.003 to .04 Hz by default).<br>● **LH/HF ratio**: LF/HF is sometimes used by some investigators as a quantitative mirror of the sympathy/vegal balance.<br>● **LFnu**: Normalized LF power.<br>● **HFnu**: Normalized HF power.<br>● **Total_Power**: Total power density spectral.<br><br>**Non-Linear domain features:**<br>● **CSI:** Cardiac Sympathetic Index.<br>● **CVI:** Cardiac Vegal Index. |

#### *6.2.3.4 EMG Features*

For EMG features, there was a slight contamination from the ECG signal, and these had to be filtered out, otherwise there was no other pre-processing required before they could be extracted from the channel. A summary of the EMG features extracted is given in Table 6.2.3.4.1.

*Table 6.2.3.4.1: Summary of extracted EMG features*

| Feature Type | List of features |
|---|---|
| EMG | **Time domain features** [52]**:**<br>● **VAR**: Variance of the signal.<br>● **RMS**: Root mean square of the signal. |

| | |
|---|---|
| | • **IEMG**: Integral.<br>• **MAV**: Mean Absolute Value.<br>• **WL**: Wavelength.<br>• **AAC**: Average Amplitude Change.<br>• **DASDV**: Difference Absolute Standard Deviation Value.<br>• **ZC**: Zero-Crossing.<br>• **WAMP**: Willison Amplitude.<br>• **MYOP**: Myopulse Percentage Rate.<br><br>**Frequency domain features:**<br>• **FR:** Frequency Ratio.<br>• **MNP:** Mean Power.<br>• **TOT**: Total Power.<br>• **MNF**: Mean Frequency.<br>• **MDF**: Median Frequency.<br>• **PKF**: Peak Frequency.<br><br>**Time-Frequency domain features:**<br>• **H wavelet:** Haar wavelet. |

#### *6.2.3.5 EEG Features*

EEG features were extracted using existing python libraries for EEG feature extraction and analysis. Since the EEG signals were collected from 3 separate at different positions on the head, the channels were assumed to be independent of each other and features were extracted for each channel.

The "eeglib" library was used to extract the frequency band powers as well as the different complexity and dimensional features, while "Neurokit2" was used to obtain the many entropy features. Popular MATLAB extensions like EEGLAB were also explored but were not selected as the primary feature extractor.

A summary of the EEG features extracted is given in Table 6.2.3.5.1.

*Table 6.2.3.5.1: Summary of extracted EEG features*

| Feature Type | List of features |
|---|---|
| EEG | **Time domain features** [53]**:**<br>• **Hjorth Parameters**: Variance of the derivatives of the EEG signal. Mobility, activity, and complexity are the first three derivatives of the signal and the most-used Hjorth parameters.<br>• **EEG mean**: Mean of the EEG signal.<br>• **EEG median**: Median of the EEG signal.<br>• **EEG std**: Standard Deviation of the EEG signal.<br>• **EEG kurtosis**: Kurtosis of EEG signal.<br>• **EEG skew**: Skewness of the EEG signal.<br><br>**Frequency domain features:**<br>• **Delta band power:** Power in the band 0.5–4 Hz.<br>• **Theta band power:** Power in the band 4–8 Hz.<br>• **Alpha band power:** Power in the band 8–12 Hz.<br>• **Beta band power:** Power in the band 12–30 Hz. |

| | |
|---|---|
| | **Non-linear features:**<br>● **DFA:** Detrended Fluctuation Analysis.<br>● **PFD**: Petrosian fractal dimension.<br>● **LZC**: Lempel-Ziv complexity.<br>● **HFD**: Higuchi fractal dimension.<br>● **Sample Entropy**: Entropy of recurrence plot.<br>● **Shannon Entropy:** Entropy calculated based on Shannon's information theory.<br>● **Approximate Entropy**: Entropy derived from Kolmogorov's entropy that addresses the irregularity of a time-series.<br>● **Fuzzy Entropy**: Entropy based on the concept of Fuzzy sets.<br>● **Multiscale Entropy:** Generalization of an entropy measure to different time scales.<br>● **Spectral Entropy**: Calculated with the expression for Shannon's entropy based on the normalized PSD of the EEG signal.<br>● **Wave entropy**: calculated based on the coefficients of the wavelet decomposition of the given time-series. |

### 6.2.4 Feature Selection and Analysis

Due to the nature of the experiment, it was possible that a lot of the features extracted from the different signals were redundant and it was necessary to conduct statistical tests to determine if the features were relevant and to reduce the number of features to be used for the neural network. As such, a statistical significance test, the t-test, was conducted to test whether the features were relevant, and then feature selection techniques such as Maximum Relevancy Minimum Redundancy (MRMR) and SelectKbest were used, and their performances were compared to select the best features.

#### *6.2.4.1 Statistical Significance Test*

The chosen test was the T-test, however, for T-tests to work, the data must be normally distributed and, so, the Kolmogorov-Smirnov test was used to check whether the features were normally distributed. Afterwards, T-tests were conducted between features using the following different comparisons:

- Morning vs. Afternoon features
- Morning vs. Night features
- Afternoon vs. Night features
- Awake (i.e., KSS <7) vs. Drowsy (i.e., KSS>=7) features

For the KSS T-tests, since KSS drowsiness values were only recorded at the very beginning and end of the sessions, only samples within in first and last 1.5 minutes were used for statistical analysis, as it would have the strongest reliability.

The feature samples used were also extracted by averaging using different window sizes and step sizes and then analysed to choose the best window size. Some parameters tested include:

- Window size = 15s, Step size = 5s
- Window size = 30s, Step size = 20s
- Window size = 45s, Step size = 30s

#### *6.2.4.2 Feature Selection*

The chosen Feature Selection methods were MRMR and SelectKbest, however, there must be a target label provided. From the literature, it was seen that EEG signals had the most potential to be the most relevant and reliable way to determine the drowsiness of the driver to use as the target label. However, due to project time constraints, the KSS values from the pre-experiment and post-experiment survey were linearly interpolated and used as the target labels instead. As such for both MRMR and SelectKbest, the most relevant features were determined and then the results were compared.

### 6.2.5 Regression Neural Network

A machine learning-based predictive regression model was trained from the selected features in section 6.2.4.2. As reviewed in section 5.3, the most accurate architectures used in recent work utilize ANNs to classify physiological data and numerical hand extract features like EAR, and CNNs to perform prediction directly on the face image frames. Therefore, an architecture that utilized a combination of the two was chosen. A Multi-layered Perceptron (MLP) was used to perform regression on the numerical features, and the element of time was introduced by extracting the features using large window sizes of up to 1 minute, with some overlap. The MLP consists of 2 hidden layers with the Relu non-linear activation function. The first hidden layer consists of two-thirds of the input layer nodes, the second hidden layer has a third of the input layer nodes, and the output layer consists of a single node for the regression value for the drowsiness level (1-10), 1 being alert and 10 being drowsy. This value can be used to perform classification by selecting a threshold value (i.e., >= 6.5 being classified as drowsy).

The entire process/architecture is shown in the diagram in Figure 6.2.5.6.1.

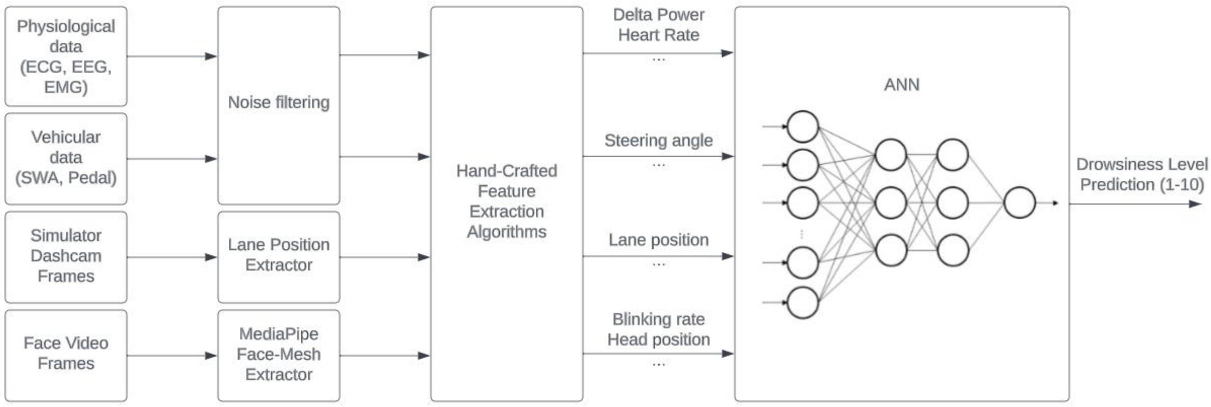


*Figure 6.2.5.6.1: Proposed process and architecture diagram*

#### *6.2.5.1 Neural-Network Training*

The MLP regression neural network training was done with PyTorch as it provides easy-to-use functions and objects. The number of input features used was varied and the results were compared. A learning rate of 5e-4 was chosen, and this was reduced by 10 times after training 60% of the 500 epochs. The loss function used was the Mean Squared Error loss and the Adam optimiser was chosen.

For training, the dataset was split into three different categories, training, validation and testing, and the data split chosen was 60:20:20 respectively. The data points were shuffled before the data was split, and the model weights were only trained on the training set, while the best model was selected based on the validation accuracy. The testing set was used after training the model to evaluate the performance of the model.

# 7 Results and Discussion

## 7.1 Data Collection and Preprocessing

From the procedure described in section 6.2.2, a sizeable set of simulator experiment data as well as passenger seat experiment data has been collected and pre-processed. In total, the following were collected:

Simulator: **13 participants (16 sets)** x 3 sessions x 30 minutes session length

Passenger Seat: **20 participants (30 sets)** x 10 minutes session length

The simulator data has been synchronised and cleaned, while the passenger seat data has only been synchronised. This data will be made available as a free public database containing all physiological, vehicular, and behavioural data, in hopes of promoting and assisting other researchers in innovating solutions for drowsiness detection. Currently, no such database complete with all the different types of data are publicly available.

Figure 7.1.1 shows the noise filtered ECG data compared to the original raw ECG data.

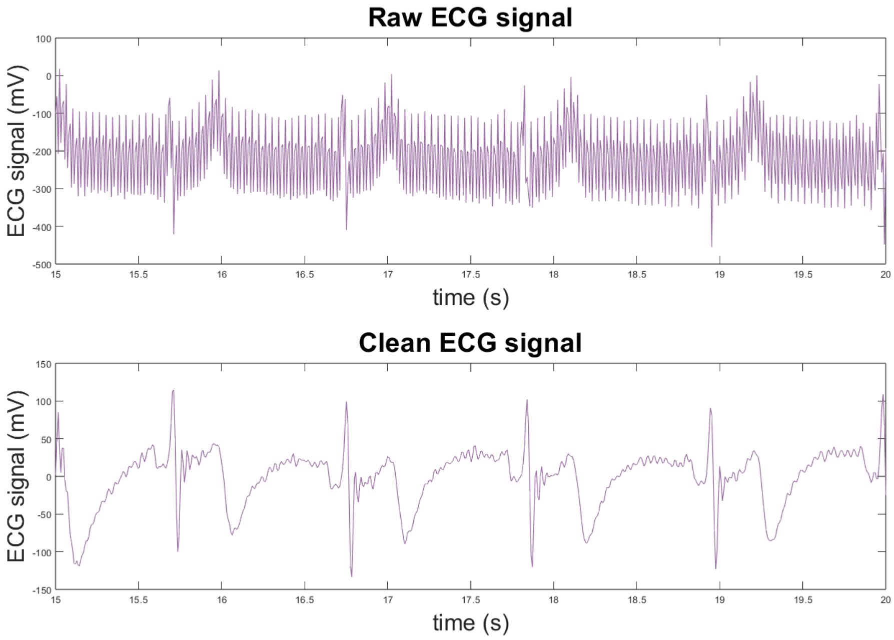


*Figure 7.1.1: Raw vs clean ECG data*

The noise filtering performed has been very effective in removing the high frequency noise at 50-60Hz. This filtered data facilitates much easier feature extraction from the data.

## 7.2 Feature Extraction

### 7.2.1 Vehicular Features

The program with the algorithm described in section 6.2.3.1 was performed on the simulator videos captured from the simulator experiment. An example of the input simulator capture frame is shown in figure 7.2.1.1 while the results from the algorithm are shown in figure 7.2.1.2.

*Figure 7.2.1.1: Original simulator capture*

(a) (b)

*Figure 7.2.1.2: Lane estimation (a) incorrect, (b) correct.*

The green area highlighted in the image is the estimated lane that the car is driving in. The detected lane in figure 7.2.1.1 (a) is very inaccurate.

This inaccuracy is because the simulator is recorded from the driver's point of view, and the lane region was extracted through cropping the original image greatly reducing the image quality. The lane markers are also not white enough to be captured properly by the program.

However, after the image has been processed with various parameters such as increasing the brightness, contrast, brilliance, saturation, sharpness, definition, and black point while reducing the shadows and noise, the lane can be captured accurately as shown in figure 7.2.1.2 (b).

An example of the lane deviation throughout the experiment from a participant with KSS drowsiness rating of 10, where multiple crashes were recorded is shown in figure 7.2.1.3.

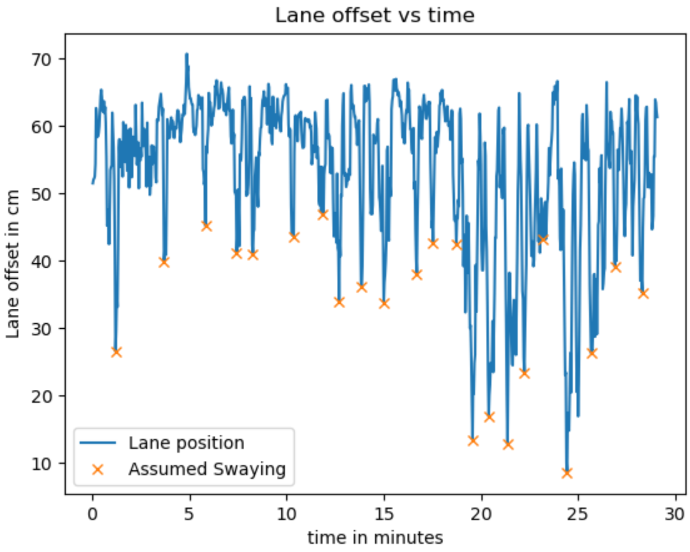


*Figure 7.2.1.3: Variation of lane offset per frame over time*

An average offset of 60cm exists due to the lane being recorded from the driver's seat and not at the center of the vehicle. The program used is not very resilient which is why there seems to be a lot of noise. The video has also been clipped slightly to only show recording for when the driver is on the highway. The average lane deviation increases towards the end of the experiment, which corresponds to when there were multiple crashes due to microsleeps in the participant.

### 7.2.2 Behavioural Features

As described in section 6.2.3.2, the face mesh coordinates are first extracted from the face recordings using the MediaPipe library in Python. From these 3D landmark positions, various features such as Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), Pupil Circularity (PuC) and Head Tilt were calculated. The face mesh extracted from each frame from the videos are shown in Figure 7.2.2.1, where (a) depicts a frame in which the eyes are open, and (b) depicts one with eyes closed.


**(a)** **(b)**

*Figure 7.2.2.1: Face mesh extracted using MediaPipe (a) eye open, (b) eye closed*

From the extracted EAR values, instances of blinks were successfully determined using a peak finding algorithm. As shown in Figure 7.2.2.2, blinks can be identified by a sharp drop and rise in the EAR value. Using this method, the average blinking rate over a period can be calculated by the total amount of blinks divided by time. Additionally, by removing these dips/blinks, the average eye openness can also be obtained.

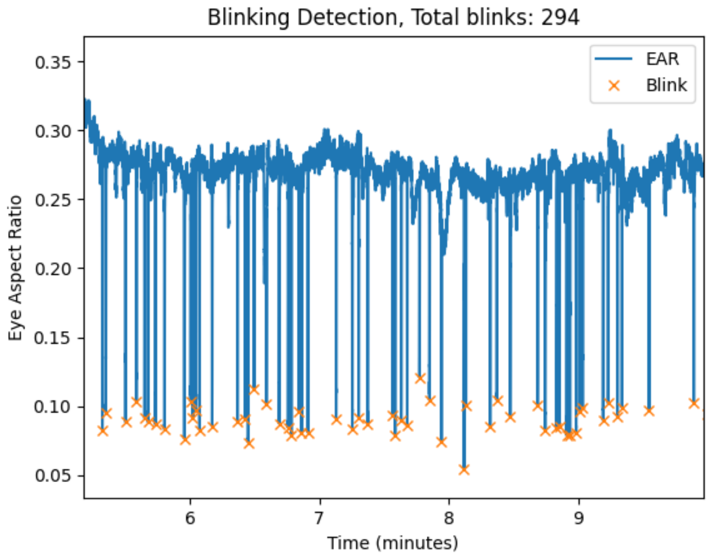


*Figure 7.2.2.2: Example of blinking detection from EAR Plot*

From manual validation, the number of blinks detected were extremely accurate with occasional false detections when some participants are looking downwards.

### 7.2.3 Physiological Features

Following the methods Pan-Tompkins algorithm for RR intervals as described in section 6.2.3.3, the heart rate along with 24 other features were extracted from the ECG data. Figure 7.2.3.1 shows the detected RR peaks.

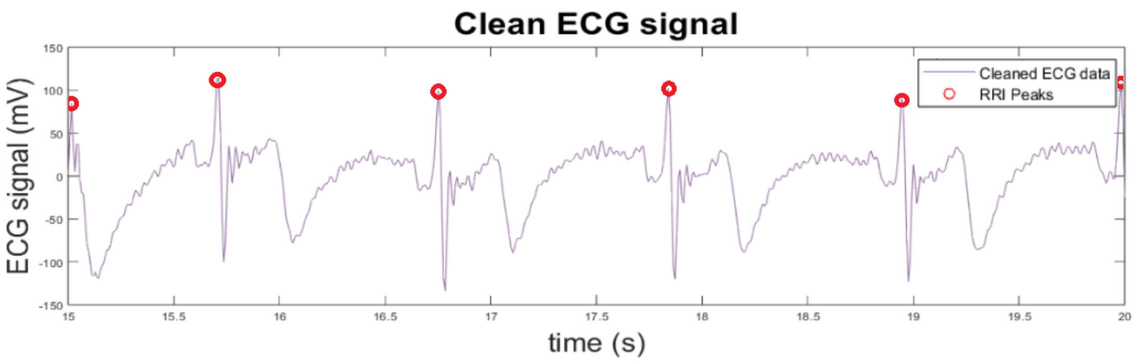


*Figure 7.2.3.1: Detected RRI peaks in ECG data*

Similarly, the EEG band powers were successfully extracted from the cleaned EEG data using band pass filters. The different bands for 4 seconds of data are shown in figure 7.2.3.2.

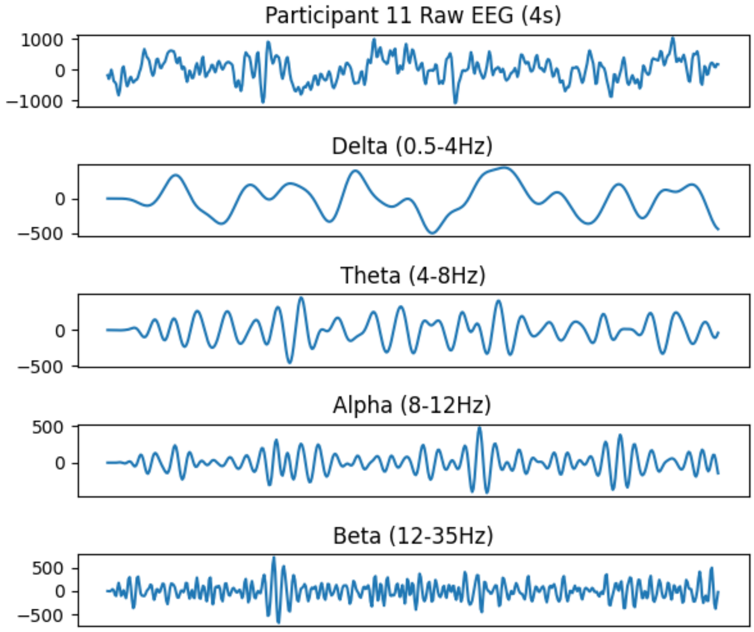


*Figure 7.2.3.2: EEG band powers*

The delta, theta, alpha, and beta band waves are 4 of the 21 or so features extracted from the EEG signals. This signal is from a participant that has a KSS score of 6-7, which corresponds to some signs of drowsiness. This is reinforced by the signs of some delta and theta waves since those are the main features correlating to drowsiness.

## 7.3 Feature Analysis

In section 6.2.3, a summary of all the features extracted from the data collected from the simulator recordings was provided and in total there are 129 features. These features were extracted using several methods, i.e., by varying windows sizes, overlap and then not using these windows at all as well. This section discusses the effectiveness of these methods by looking at the results obtained from the analysis work done.

The chosen method of analysis was using t-test. The t-test is a parametric test of difference that compares the means of two groups of data. T-tests assume the data is:

- Independent.
- (Approximately) normally distributed.
- Have similar variance within each group being compared.

To verify normality, a Kolmogorov-Smirnov test was used on each feature in the dataset and all the features were determined to be normally distributed. It was concluded that the entire dataset was valid for conducting t-tests.

For a t-test, the null hypothesis ($H_0$) is the claim that that there is no significant difference between the means of two groups being compared. The null hypothesis typically states that the population means of the two groups are equal. There was a lot of data, and it could be interpreted and analysed in various ways. The following sections describe the different methods and the results obtained.

### 7.3.1 KSS and Time of day

The first t-test conducted was using the pre-experiment and post-experiment KSS values against the time of the recording of the experiment. The KSS values were sorted for each session time, i.e., morning, afternoon, and night and then each pair was tested. Figures 7.3.1.1 and 7.3.1.2 show a box plot of the KSS values against the time of day.

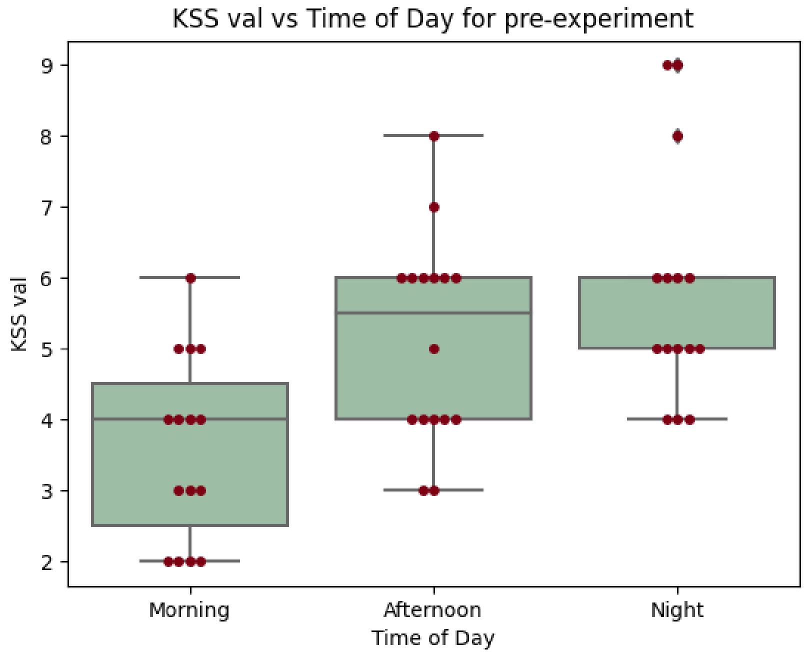


*Figure 7.3.1.1: KSS against Time of Day for pre-experiment*

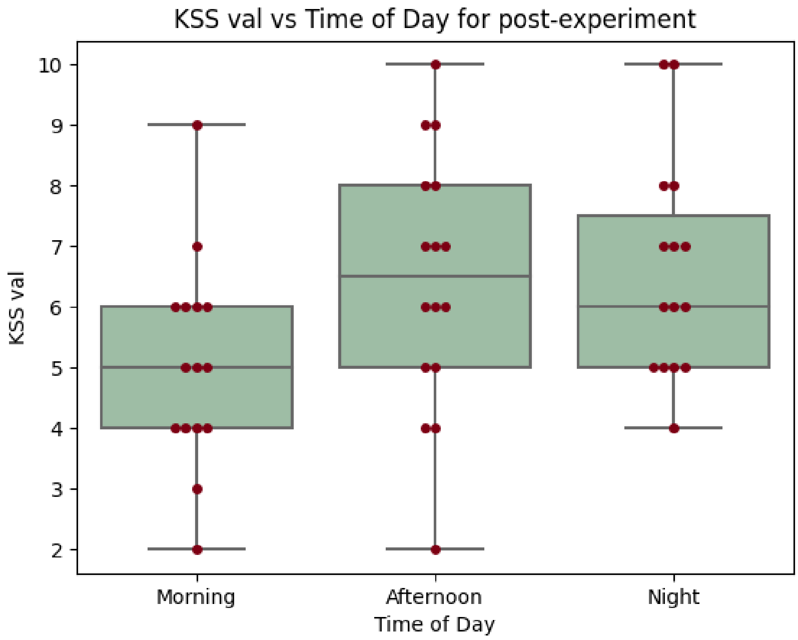


*Figure 7.3.1.2: KSS against Time of Day for post-experiment*

Since the data was being compared to different times of day, a two-sample t-test was conducted, i.e., independent t-test. The null hypothesis would therefore be stated as:

$$H_0: \mu_1 = \mu_2 \quad (3)$$

It was also decided to one one-tailed t-test since we wanted to determine whether the means of the KSS for one session were less than or greater than the other. Table 7.3.1.1 and 7.3.1.2 show the results obtained for the pre and post experiment KSS values respectively.

*Table 7.3.1.1: Pre-experiment KSS vs time of day t-test results*

| | Session 1 | Session 2 |
|---|---|---|
| | **Morning** | **Afternoon** |
| **Number of Samples** | 15 | 16 |
| **Mean** | 3.6 | 5.125 |
| **Standard Deviation** | 1.254325848 | 1.408678459 |
| **t-value** | -3.071388855 | |
| **p-value** | 0.002299121 | |
| | **Morning** | **Night** |
| **Number of Samples** | 15 | 15 |
| **Mean** | 3.6 | 5.8 |
| **Standard Deviation** | 1.254325848 | 1.6 |
| **t-value** | -4.04889471178206 | |
| **p-value** | 0.000184262833841091 | |
| | **Afternoon** | **Night** |
| **Number of Samples** | 16 | 15 |
| **Mean** | 5.125 | 5.8 |
| **Standard Deviation** | 1.408678459 | 1.6 |
| **t-value** | -1.20757387287518 | |
| **p-value** | 0.118483986592122 | |

From the results seen in table 7.3.1.1, the null hypothesis is rejected for the morning and afternoon pair and the morning and night pair. The KSS values are seen to have statistically significance between these two pairs of sessions. There does, however, not seem to be any significant difference in the means of the KSS values in the afternoon and night sessions.

*Table 7.3.1.2: Post-experiment KSS vs time of day t-test results*

| | Session 1 | Session 2 |
|---|---|---|

| | Morning | Afternoon |
|---|---|---|
| **Number of Samples** | 15 | 16 |
| **Mean** | 5.06666666666666 | 6.4375 |
| **Standard Deviation** | 1.65193489244851 | 2.06060519022931 |
| **t-value** | -1.96857812800233 | |
| **p-value** | 0.0293129066659999 | |
| | **Morning** | **Night** |
| **Number of Samples** | 15 | 15 |
| **Mean** | 5.06666666666666 | 6.6 |
| **Standard Deviation** | 1.65193489244851 | 1.74355957741626 |
| **t-value** | -2.38866093838837 | |
| **p-value** | 0.0119457472432915 | |
| | **Afternoon** | **Night** |
| **Number of Samples** | 16 | 15 |
| **Mean** | 6.4375 | 6.6 |
| **Standard Deviation** | 2.06060519022931 | 1.74355957741626 |
| **t-value** | -0.228511191391286 | |
| **p-value** | 0.410426290953113 | |

From the results seen in table 7.3.1.2, the null hypothesis is again rejected for the morning and afternoon pair and the morning and night pair and there does not appear to be any relation between the afternoon and night pair.

From these results it would indicate that people are in general sleepier in the afternoon or the night when compared to the morning, however, it varies from person to person whether they are sleepier in the afternoon compared to the night. This difference in the afternoon and night KSS could be due to difference in individual person’s circadian rhythm or difference in the exhaustion experienced.

### 7.3.2 KSS pre and post experiment

In this test, a paired t-test is conducted since the groups are from the same population. Similarly, a one-tailed t-test is conducted once again. Figure 7.3.2.1 shows a boxplot for the KSS values against Survey time and table 7.3.2.1 show the results obtained from this analysis.

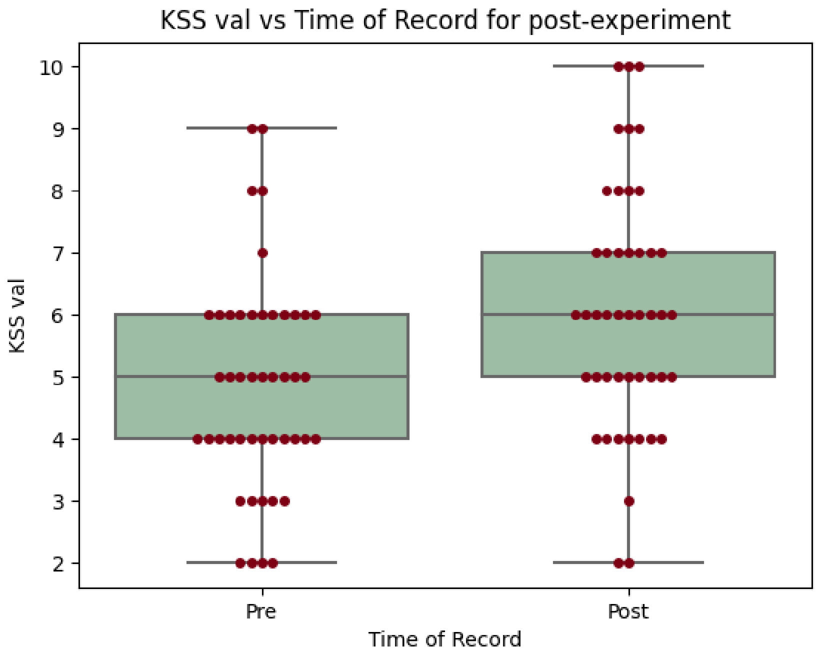


*Figure 7.3.2.1: KSS against Survey time*

*Table 7.3.2.1: Pre-exp KSS vs post-exp KSS*

| | Pre-experiment | Post-experiment |
|---|---|---|
| **Mean** | 4.84782608695652 | 6.04347826086956 |
| **Standard Deviation** | 1.69356058291846 | 1.95555531687382 |
| **t-value** | -3.10043038897029 | |
| **p-value** | 0.0012899808461804 | |

From the result of the test, it is evident that people are generally sleepier after the experiment than before proving that long drives get most people sleepier.

### 7.3.3 Feature X awake vs Feature X drowsy

This was one of the two main t-tests conducted for the analysis work done. As mentioned earlier, the features were extracted using varying window sizes and overlaps. Additionally, the definition for awake and drowsy was carried from before as KSS≤7 and KSS>7 respectively. The main results have been summarized in table 7.3.3.1.

*Table 7.3.3.1: Number of features rejecting null hypothesis for each method*

| Method | n(features(p-val<0.05)) |
|---|---|
| Window: 15s, Overlap: 10s (a) | 7 |
| Window: 15s, Overlap: 10s (b) | 111 |
| Window: 30s, Overlap: 15s | 64 |

| | |
|---|---|
| Window: 45s, Overlap: 15s | 29 |

There were two further methodologies used for t-testing the 15s window size features. In (a), a mean value for the feature was calculated for each recording and so there would have been just 46 total values in total for each feature. Due to this low sample size for each feature, it was difficult to ascertain statistical significance and hence the very small number of features rejecting the null hypothesis. In (b), however, the number of samples for each feature was very high coming to about 6000 on average. This was because each feature value for the 15s window was used as its own sample, and this resulted in the p-vals for most of the features being close to 0. Ideally, t-tests work best for a sample size of about 100.

From the previous observations, a larger window size was attempted to reduce the number of samples. With a window size of 30s, there were about 200 samples for each feature. This was more appropriate and gave 64 statistically significant features.

One last test was conducted using a window size of 45s for this method and it analysed 29 features to be significant.

For visualization, a box plot for the Normal-Normal Interval (ECG feature) and the test results is shown in figure 7.3.3.1.

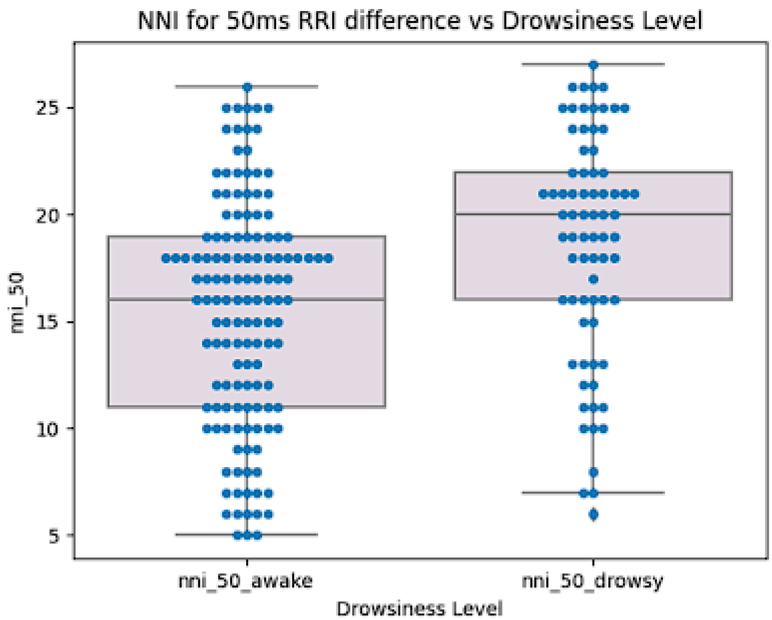


*Figure 7.3.3.1: Boxplot for NNI_50 against KSS*

As an example, for one of the features, NNI_50 (as described in section 6.2.3.3), the values were seen to be higher for drowsy groups (M = 18.6, SD = 5.28) compared to awake groups (M = 15.5, SD = 5.27).

$$t(207) = -4.10, p = 2.95e - 05 \quad (4)$$

These results indicate that this feature is suitable for detecting signs of drowsiness. This would also make sense because this meant that drowsy people had a higher amount 50ms interval difference between successive RRi which would results in a lower HR.

The features selected from these t-tests of all the instances were recorded to be used in feature reduction and selection methods along with training the neural network model.

### 7.3.4 Feature X morning vs Feature X afternoon vs Feature X night

This was the other main test carried out using the varying window sizes methodology. Features were separated into the morning, afternoon and night sessions and the statistical significance between the three pairs were determined. The results are summarised in table 7.3.4.1.

*Table 7.3.4.1: Number of features rejecting null hypothesis for each method*

| **Morning vs Afternoon** | |
|---|---|
| **Method** | **n(features(p-val<0.05))** |
| Window: 15s, Overlap: 10s (a) | 7 |
| Window: 15s, Overlap: 10s (b) | 109 |
| Window: 30s, Overlap: 15s | 61 |
| Window: 45s, Overlap: 15s | 74 |
| **Morning vs Night** | |
| **Method** | **n(features(p-val<0.05))** |
| Window: 15s, Overlap: 10s (a) | 8 |
| Window: 15s, Overlap: 10s (b) | 110 |
| Window: 30s, Overlap: 15s | 59 |
| Window: 45s, Overlap: 15s | 57 |
| **Afternoon vs Night** | |
| **Method** | **n(features(p-val<0.05))** |
| Window: 15s, Overlap: 10s (a) | 8 |
| Window: 15s, Overlap: 10s (b) | 111 |
| Window: 30s, Overlap: 15s | 62 |
| Window: 45s, Overlap: 15s | 48 |

The results were interesting when the features were analysed using this methodology. Even though the number of samples between the different session for the 30s and 45s window size varied greatly, the number of features that appeared statistically significant remained in the same order between the two methods. Upon further inspection, it was found that the important features in both methodologies were mostly the same as well.

Again, the features selected from these t-tests of all the instances were recorded to be used in feature reduction and selection methods along with training the neural network model.

## 7.4 Neural Network

The method described in section 6.2.5 was used to train a regression MLP model which predicts the drowsiness level (1-10) of the given numerical sample with a window size of 30 seconds. Values above the threshold of 6.5 was chosen to be classified as drowsy.

The accuracies for varying number of input features selected from both MRMR and SelectKBest methods are shown in table 7.4.1.

*Table 7.4.1: Model Accuracies*

| Number of Input Features | MRMR | SelectKBest |
|---|---|---|
| 15 | 64.56% | 63.12% |
| 30 | 68.44% | 67.86% |
| 45 | 69.30% | 67.58% |
| 60 | 68.58% | 68.44% |

45 features selected using MRMR method provided slightly better results (69.30%) than the other combinations. With 15 features, the results were much worse, most likely because the model does not have enough features to learn a correlation to drowsiness. Whereas with 60 features, the accuracy also begins to drop, most likely due to the model starting to overfit on the training set due to some irrelevant features. On average, MRMR feature selection method seems to slightly outperform the SelectKBest method for any number of input features.

Overall, the model results could be further improved. The model complexity could be increased to have more learning power, while a CNN could be used on the video face capture as a feature extractor before passing through the classifier. Additionally, better ways of labelling the data may be required to obtain better results as the drowsiness of a participant does not linearly increase during the experiment, unlike our linearly interpolated labels due to limitation of time.

## 7.5 Findings

The data collection and preprocessing has yielded a substantial dataset, consisting of both the simulator experiment data, which can be used for drowsiness detection research, and the passenger seat data for determining feasibility of non-intrusive BCG and accelerometer based breathing rate devices. In this area, the initial objects in collecting a complete dataset to eventually make publicly available has mostly been achieved. However, there were some shortcomings in terms of the number and variety of participants which is discussed further in section 7.6.

From the t-tests performed against the KSS values, it was found that participants were generally sleepier in the late-afternoon and night compared to early morning, and pre-experiment vs. post-experiment sleepiness surveys demonstrated consistent increased drowsiness after the drive, which is consistent with our hypothesis. More importantly, through analysis of the 129 extracted features, it was determined that a decent number of features had strong correlation with drowsiness and have the potential to be used for drowsiness detection, which is was significant step and a major success towards achieving our aim of creating a drowsiness detection system utilising all the different indicators.

A simple neural network model (MLP) was developed for drowsiness detection using MRMR and SelectKBest as the feature selection methods. It achieved promising results of 69.30%, however, it is still far from achieving our aims of developing a model to accurately detect drowsiness in drivers, as too many false positives or false negatives makes the system not yet suitable for real world use, especially in a vehicle where reliability is key. However, it serves as a proof of concept and demonstrates that future works can be done to greatly improve the model, which is further discussed in section 7.6.

## 7.6 Limitations and Future Work

### 7.6.1 Vehicular Data

Due to an error in the vehicular data recording program, the vehicular data for most of the initial participants were corrupted and unable to be used. Some vehicular data was later captured due to some participants who were willing to re-do the simulator experiment, however there were not enough data for any significant analysis or neural networks work to be done. Future works could try to capture more data with vehicular features and utilise them as another indicator of drowsiness.

### 7.6.2 Simulator Participant Variety

The collected simulator data mostly contained young adults around the age of 21. Additionally, the experiments contained far more male participants than female participants. These all may affect the performance of the classification model as not only does men and women have slightly different physiological features, but they may also differ for different ages. Future works can work on acquiring more simulator data from female participants and older participants to improve the generalisation of the data.

### 7.6.3 Data Labelling

As discussed in section 7.3, due to time limitations, the method of labelling the data used for machine learning was simply linearly interpolated between the pre-experiment and post-experiment surveyed drowsiness level. Since the real drowsiness level of participants often fluctuate significantly during the 30-minute drive, this method of labelling may have introduced a lot of incorrect labels, causing the machine learning model to be unable to effectively learn the correlations between the input features and the drowsiness level. Future works can find better ways of labelling, one method could be utilising the EEG data to generate the true labels while using the remaining features for training. This method may provide better results as literature has shown that EEG data is often the most common and accurate indicator of drowsiness [25].

### 7.6.4 Lane Deviation Extraction

The current lane deviation algorithm shown in 7.2.1 was not reliable enough throughout the entire simulator recording to be used as an input feature for the neural networks. Due to simulator resolution, and different simulator weather conditions like rain, the lane position was not always able to be successfully extracted. Future works can develop better lane detection algorithms or find better pre-trained neural network models to perform this task and use it to improve the model accuracy.

### 7.6.5 Behavioural Feature Extraction

In most scenarios, the behavioural features were able to be successfully extracted, however, in certain cases, such as when sun-glasses are being worn, the eyes are not able to be detected properly, hence EAR related features would have significant error. Furthermore, in low-light situations (in some participant night recordings), the face could not be detected properly, which caused a few of the data samples to not be useable in our analysis. Future works could investigate other face extraction algorithms to extract general features such as head tilt, even in low light environments. This may be beneficial for real-life situations, as the lighting is often very dim inside the vehicle during nighttime.

# 8 Conclusion

This research has provided a crucial step forward in achieving our aims of developing an accurate drowsiness detection system. By collecting and pre-processing a complete dataset encompassing all the different indicators including physiological, vehicular, and behavioural, we've laid the groundwork for future research.

The extraction of the features from all the different types of data along with the statistical significance tests performed demonstrated that many features have correlation with drowsiness, highlighting the potential of a hybrid drowsiness detection system utilising all the different indicators to achieve highly accurate predictions.

Our simple neural network model, while showing promise, highlights the challenges of drowsiness detection. Although this falls short of our initial objective of developing an accurate model, it provides a solid baseline for the path forward, which involves refining this model, possibly with an expanded feature set including vehicular and more behavioural features and developing a more accurate data labelling method.

Our team managed to collect, analyse and utilise the data to develop the foundation for a neural network model Further work is required to fulfill our initial vision of real-time drowsiness detection. Future endeavours should use the recommendations provided earlier and build upon the results gained from this research and develop a system for accurately detecting drowsiness.

# 9 Reflection on Project Management

## 9.1 Project Scope

The revised scope of the project includes:

- Using the selected sensors for the simulator experiment to collect data from 20 participants at various times of the day.
- Using the selected sensors for the real driving experiment to collect data from 20 participants.
- Preprocessing all the collected data to prepare them for any analysis work.
- Extract all features as determined from the literature review conducted.
- Analyse the extracted features to determine the statistical significance of each feature.
- Use feature selection/reduction techniques to select relevant features for determining drowsiness.
- Use selected features to create and train Neural Network model that can be used to predict drowsiness from real-time measurements.

The project will not include:

- Implementing the Neural Network(s) in a mobile application that can send out alerts to the driver (at this stage).
- Interfacing the mobile application with the sensors that collect data (at this stage)
- Integrating the sensors into a physical vehicle.
- Releasing the mobile application on an app store.
- Developing EEG, ECG, EMG, and EOG sensors.
- Investigate the suitability of sensors.
- Improving the circuits and the hardware already existing.
- Testing the final system on a physical vehicle.

## 9.2 Project Plan & Timeline

### 9.2.1 Project Plan

The project aims to create a drowsiness detection and alert system for drivers and as such, the work breakdown has been divided into four phases:

- Phase 1: Research and Preparation
- Phase 2: Data Collection
- Phase 3: Data Analysis
- Phase 4: Detection System

#### *9.2.1.1 Phase 1: Research and Preparation*

The Research and Preparation phase consists of two main steps which are the Preparation and Project Proposal.

Preparation refers to catching up on the work completed, preparing the simulator and then the sensors. This will be considered complete when a complete set of recording of the investigators are retrieved.

The Project Proposal step refers to doing literature review, determining the methods and methodologies to be adapted for the project, and establishing the OHS and non-OHS risk assessments. This will be considered complete when the project proposal is approved.

#### *9.2.1.2 Phase 2: Data Collection*

The data collection phase consists of three main steps which are participants recruitment, simulation data collection and car seat sensors data collection.

The participants recruitment include advertising, obtaining gift cards and scheduling the data recordings. This step will be complete when all the participants schedule has been made and gift cards are arranged.

The simulator data collection consists of getting measurements from the vehicular, physiological, and behavioural sensors and is considered complete when the simulator experiment measurements are retrieved for all the participants.

The passenger seat data collection consists of getting the BCG and accelerometer measurements and is considered complete when it is retrieved from all the participants.

#### *9.2.1.3 Phase 3: Data Analysis*

The three steps making up the data analysis is noise filtering, simulator data analysis and passenger seat data analysis.

Noise filtering refers to pre-processing the measurements taken so that they can be ready to be inputted into machine learning algorithms to identify and extract features from the data. Simulator and Passenger seat data analysis refers to using the pre-processed data and extracting features from them. Data Analysis will be completed when the features identified in literature review are able to be extracted.

#### *9.2.1.4 Phase 4: Detection System*

The two steps that make up the Detection system phase are the Neural network implementation and the Software Implementation.

The Neural Network implementation refers to determining the architecture of the network, creating the datasets and training/optimization parameters and the software implementation refers to making the mobile app and the vehicle system software. This final phase will be completed when the mobile app and vehicle software system is able to detect drowsiness accurately in the driver and alert them.

### 9.2.2 Revised Timeline

The following Gantt chart in figure 9.2.2.1 shows the revised proposed timeline for the project.

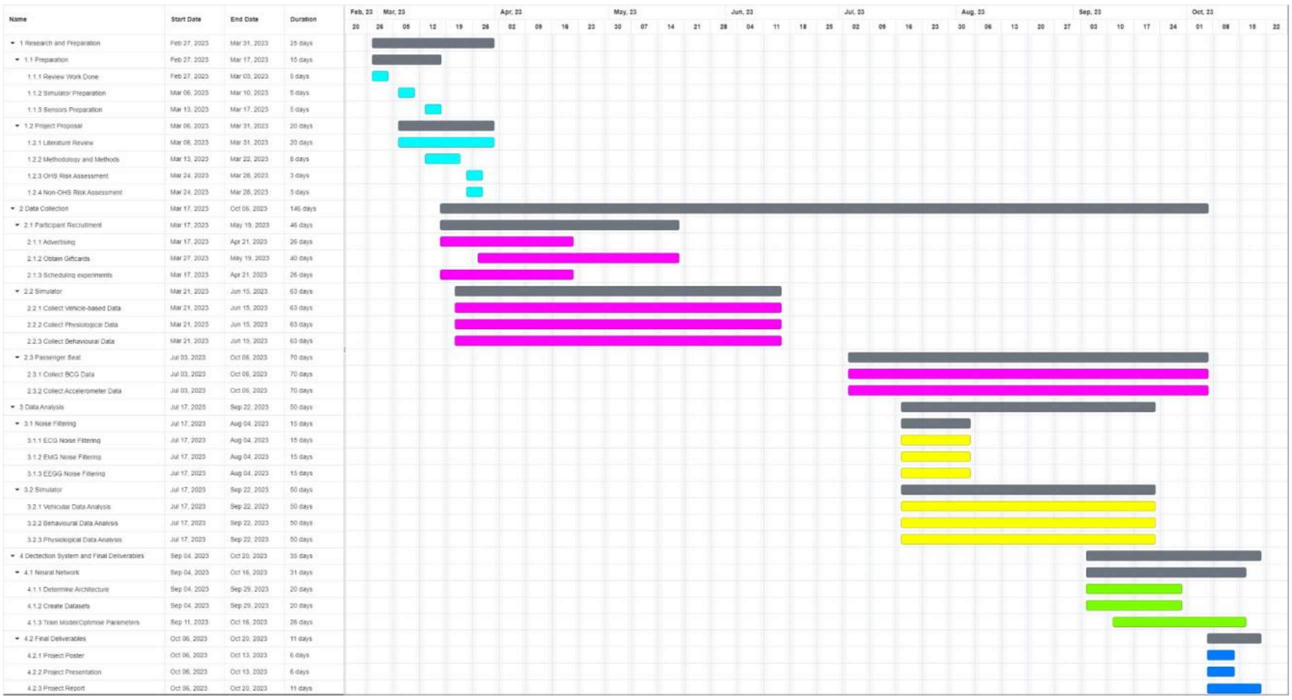

*Figure 9.2.2.1: Revised Gantt chart*

A link to a higher quality Gantt chart including the original one is provided in Appendix F.

Several deliverables and timeline for the phases have changed. The major change is in the Neural Network phase which was estimated to start at the beginning of the second semester, however, was not started until week 8 in the second semester. Similarly, recording the passenger seat experiments took much longer than expected. Analysis work also had not begun until much later towards the start of semester 2.

## 9.3 Reflection on Project

### 9.3.1 Umar Abedin

This FYP has been the one of most challenging projects I have undertaken in my academic career. It was a project primarily focused on data collection, processing and analysis and every step was more difficult than the former.

Both Chen and I took on very reasonable shares of the total work and I feel that both of us contributed significantly to each step and were able to complement each other's weaker fields. Setting goals for each week and establishing standards were the key factors that enabled us to perform exceptionally well as a team.

The project has progressed significantly from the progress made last year. From the hardware and software setup that we received from last year students, we were able to create a public database, extract all drowsiness related features and analyse them. We were also able to make a start on the neural network architecture that would become the product.

However, it must be noted that there were quite a few setbacks. The major setback was the error in the vehicular data measurement program which caused us to lose a lot of the vehicular measurements which we initially thought we had. Due to a lack in this category of data, we were forced to remove the features extracted from the few we properly collected later so that the model is trained properly.

Regarding our timeline, our original one was ambitious, and we were not able to foresee or plan for a lot of the setbacks we experienced including difficulties in obtaining night recordings, OpenBCI module breakdown and so on. We had to change our approach so that we could at least finish phase 3 of our planned timeline and have it in optimal condition for handing it over to whoever continues.

Although we were not able to see this project through to the end in the time that we had, I am eager to see what kind of form the work we have done takes. I am satisfied with my performance and all the learning opportunities I have had with this project.

#### 9.3.2 Ling Chen

This Final Year Project for me has been a very challenging yet rewarding experience. Throughout this project, I was able to learn and gain experience on the entire machine learning process. From data collection to data analysis, data labelling, data selection and reduction, to finally the neural network model development, this project encompassed the entire package, which provided me with a very good insight into this area of study.

Overall, our performance as a team was very good, and the responsibilities were divided well. I was more familiar with Python, computer vision and neural networks, whereas Umar was more familiar with MATLAB and data analysis. We were able to both learn from each other in various areas. The quality of work was also kept very high as we each strived to match each other's standard of work.

The project overall achieved several successes, including creating a dataset to be published publicly to assist other researchers, extracting various features, and performing analysis on them, and then finally beginning to use our data to perform neural network classification.

In general, we were on time with our timeline as we allocated 2 days every week to work solely on this FYP, which ensured that we met the 12 hours of recommended work every week, so we always had some progress every week. However, one of the key factors we underestimated was the amount of time required to collect data. For the simulator data alone, 90 minutes of data were collected from each participant spread out across specific times of the day. Since we strived for 20 participants, this meant over 30 hours of data collection, excluding all the set-up time required. Realistically, only data 2-3 participants every week were able to be collected. This compounded with the fact that some of the sensors broke multiple times and were required to be re-soldered, dragged out our initial timeline allocated for data collection.

This meant that after data analysis was finished, we were only left with a very short amount of time (3-4 weeks) to finish our overly ambitious goal of developing a good neural network model and a mobile application. In the end we had to remove the mobile application, and only trained a very simple classification model with rushed data labelling with results that could be further improved.

Improvements that could be made upon this project include better data labelling and extracting more features from behavioural data and vehicular data.

Overall, I am very satisfied with the progress of this project and the learning experience it provided. I am excited to see where this project ends up next year building upon what we have done this year.

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# 11 Appendices

## 11.1 Appendix A: Project Risk Assessment

| | RISK DESCRIPTION | STATUS | TREND | CURRENT | RESIDUAL |
|---|---|---|---|---|---|
| 53058 | ECSE_FYP_2023_S1_LingChen_UmarAdullahAlAbedin_DrowsinessDetectionAndAnti-SleepAlarmSystemForDrivers | Draft | | High | Medium |

| RISK TYPE |
|---|
| 1. Activity or Task Based Risk Assessment |

| RISK OWNER | RISK IDENTIFIED ON | LAST REVIEWED ON | NEXT SCHEDULED REVIEW |
|---|---|---|---|
| LING CHEN | 01/10/2023 | | |

| RISK FACTOR(S) | EXISTING CONTROL(S) | CURRENT | PROPOSED CONTROL(S) | TREATMENT OWNER | DUE DATE | RESIDUAL |
|---|---|---|---|---|---|---|
| An ergonomic risk arises from prolonged sitting or working in a poorly designed workstation with incorrect posture and ergonomics. | Control: Using an adjustable ergonomic chair<br>Control Effectiveness:<br>__________<br>Control: It is advisable for both the FYP team members and participants conducting experiments to take frequent breaks from their workstations.<br>Control Effectiveness:<br>__________<br>Control: Keep a safe distance from the computer screen to promote healthy habits.<br>Control Effectiveness:<br>__________<br>Control: Follow the ergonomic guidelines detailed on the Monash ergonomics page www.monash.edu/ohs/info-docs/ergonomics<br>__________<br>Control: Every hour take a few minutes to change the point your eyes are focusing on to somewhere in the distance | Medium | Review and adhere to Safe Work Australia's guide for setting up a home workstation for optimal ergonomics and safety while working from home. | LING CHEN | 10/10/2023 | Low |
| Electrical shock from hardware prototyping and benchtop testing. | Control: Inspect all electrical connections and circuitry before commencing any tests | High | Use electrical insulation over any exposed electrical wiring during hardware development | UMAR ABDULLAH AL ABEDIN | 10/10/2023 | Medium |

 

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| | Control Effectiveness:<br>__________<br>Control: Only adjust circuitry or other relevant prototype configurations with the power supply disconnected or turned off<br>Control Effectiveness:<br>__________<br>Control: When working in ECSE labs, if you suspect someone is being electrocuted do not touch them, hit the big red emergency power shut off button on the wall near the door<br>Control Effectiveness: | | Use RCD protection when using benchtop power supplies while prototyping and bench testing | Umar Abdullah Al Abedin | 10/10/2023 | |
| Risk of getting infected with and/or spreading COVID-19 in areas where social distancing is not possible. | Control: Wearing face masks as per the Victorian Government guidelines, or as per the COVID safe plan of the applicable venue.<br>Control Effectiveness:<br>__________<br>Control: Regularly sanitising shared workstations and/or equipment.<br>Control Effectiveness:<br>__________<br>Control: Social distance when possible<br>Control Effectiveness:<br>__________<br>Control: Please follow the latest recommendations from Monash University www.monash.edu/news/coronavirus-updates and the state government www.coronavirus.vic.gov.au | Medium | Stay home if unwell and get tested. Maintain 1.5m physical distance if possible, if not wear a mask | UMAR ABDULLAH AL ABEDIN | 10/10/2023 | Medium |
| Risk of tripping over cables, wires, or other loose items from the workstation or | Control: Ensure cables and/or wires are neatly arranged away from high traffic areas where | Medium | Keep loose items (e.g. bags, coats, etc.) stowed away from high traffic areas | LING CHEN | 10/10/2023 | Medium |

 

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| hardware prototype. | possible, and secured down to the floor with tape if required<br>Control Effectiveness: | | | | | |
| Risks of minor self-inflicted damage (cuts, eye damage) resulting from use of pliers, side cutters etc. | Control: Wear enclosed shoes<br>Control Effectiveness:<br>_______________<br>Control: Keep the workspace clean and tidy at all times.<br>Control Effectiveness:<br>_______________<br>Control: Long/loose hair must be contained or restrained.<br>Control Effectiveness: | Medium | Wear safety glasses when necessary | LING CHEN | 10/10/2023 | Medium |
| Sleep deprivation from conducting tests around midnight | Control: Do not consume caffeinated, sugary or alcoholic substances roughly 6 hours before sleep.<br>Control Effectiveness:<br>_______________<br>Control: Do not exercise approximately two hours before sleep<br>Control Effectiveness:<br>_______________<br>Control: Do not eat large meals approximately two hours before sleep<br>Control Effectiveness: | Low | Plan a time throughout the day of the late night tests to have a 90 minute nap. | UMAR ABDULLAH AL ABEDIN | 10/10/2023 | Low |
| Crashing car from lack of sleep | Control: Use other form of transport (uber, train or bus)<br>Control Effectiveness: | Medium | The researcher will update their procedure document with a note to advise caution to participants before returning to their own vehicle post-study. Sim controls and experience will feel significantly different from real world vehicle so participants needs to be aware that they should take a break before driving home, particularly if they experience any confusion or disorientation.<br>- Participants will be encouraged to contact the researcher upon returning home to advise of their safe arrival.<br>- At the end of each drive participants will be asked to fill in the Well being | LING CHEN | 10/10/2023 | Medium |



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| | | | questionnaire (attached). Participants who indicated that they are feeling unwell (even slightly) will be monitored by the researcher and will be asked to remain on-site until they feel well enough to leave.<br>- An incident report will be completed via the online hazard report system (S.A.R.A.H.).<br>- The MUARC Safety Officer and a First Aider will be notified of the event as soon as possible.<br>- The researcher will seek medical attention for the participant/visitor as soon as possible if required. | | | |
| Risk of a car accident while testing the car seat heart rate sensor. | Control: Follow road rules<br>Control Effectiveness:<br>_______________<br>Control: Do not drive while drowsy/sleepy<br>Control Effectiveness:<br>_______________<br>Control: Use the passenger seat instead of the driver seat to collect heart rate data.<br>Control Effectiveness:<br>_______________<br>Control: Vehicle operators are suitably licensed and competent to operate the vehicle for the terrain and conditions that may reasonably be encountered.<br>Control Effectiveness:<br>_______________<br>Control: Drive on roads with low speed limits and limited traffic | Medium | Drive in a location that will not be too busy or dangerous whilst conducting the test | LING CHEN | 10/10/2023 | Medium |
| Risk of lead exposure when using the soldering station. | Control: Solder only in a well-ventilated environment to mitigate lead fumes.<br>Control Effectiveness:<br>_______________ | Medium | Use lead-free solder | UMAR ABDULLAH AL ABEDIN | 10/10/2023 | Medium |

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| | Control: Wash hands after soldering.<br>Control Effectiveness:<br><br>Control: Use lead free solder where possible.<br>Control Effectiveness:<br><br>Control: Wear a mask (if necessary) when soldering.<br>Control Effectiveness:<br><br>Control: Wear safety glasses when soldering.<br>Control Effectiveness: | | | | | |
| Risk of burning when working at a soldering station. | Control: Only operate the soldering iron from the handle - always assume the tip is hot.<br>Control Effectiveness:<br><br>Control: Clean the soldering tip regularly with steel wool/sponge at the workstation as required, to prevent excess solder build up on the tip.<br>Control Effectiveness:<br><br>Control: Wear safety glasses while soldering to protect eyes from hot solder.<br>Control Effectiveness:<br><br>Control: Wear close fitting, protective clothing.<br>Control Effectiveness:<br><br>Control: Wear enclosed footwear.<br>Control Effectiveness: | Medium | Always dock the soldering iron on the soldering iron stand when not in use, and turn off the iron when not using the workstation. | LING CHEN | 10/10/2023 | Medium |
| Risk of developing headache/migraine from | Control: Adjust and loosen cap into a comfortable position | Low | Ensure the cap is only worn for the shortest amount of time possible. | UMAR ABDULLAH AL ABEDIN | 10/10/2023 | Low |



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| wearing EEG cap | before starting the tests.<br>Control Effectiveness: | | | | | |
| Risk of electrical shock from EMG sensor | Control: Ensure wires are properly covered/insulated and apply electrical tape if necessary<br>Control Effectiveness:<br><br>Control: Use only when necessary and ensure wires are clearly visible and untangled<br>Control Effectiveness:<br><br>Control: Ensure all power outlets are RCD protected<br>Control Effectiveness: | Medium | When working in ECSE labs, if you suspect someone is being electrocuted do not touch them, hit the big red emergency power shut off button on the wall near the door | LING CHEN | 10/10/2023 | Medium |
| Participant becomes unwell (sim sickness) or distressed during study. | Control: - The researcher will follow a set of criteria for assessing whether participants are safe to continue driving, which will include procedures for withdrawing participants should<br>they feel unwell.(See Well Being Questionnaire' attached. This is a validated tool for measuring simulator sickness).<br>- An incident report will be completed via the online hazard report system (S.A.R.A.H.).<br>- The researcher will follow a set of criteria for assessing whether participants are safe to continue the study, which will include standard procedures for withdrawing<br>participants should they feel unwell anxious or upset.<br>- In the event a participant becomes unwell or distressed the researcher will provide water and dry biscuits. The participant will also be offered a cab charge for their trip home (or an Uber will be arranged).<br>- Disposable sick bags and buckets will be kept in the sim | Medium | - List of defibrillator locations/first aiders are made available in each sim lab.<br>- All researchers who will be using the facilities have completed training in the use of the simulator, as well as the OHS local area induction and online module.<br>- The temperature in the sim lab is maintained at a suitable level so as not to impact the electronic equipment.<br>- Participants will be advised to dress appropriately. | LING CHEN | 10/10/2023 | Medium |

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| | lab and/or in the first aid kit located in room G06.<br>- The MUARC Safety Officer and a First Aider will be notified of the event.<br>Control Effectiveness:<br>______________<br>Control: - Participants will be excluded from the study if they have a history of conditions which could put them at risk of simulator sickness including previous simulator sickness, motion sickness or epilepsy, or if they are pregnant.<br>- Participants will be rescheduled for the study if they are normally fit and healthy but are unwell on the day of testing.<br>- Any participant who turns up to the study and reports that they are feeling unwell prior to getting into the simulator or if their responses to the Well being questionnaire (attached) prior to getting into the simulator indicate that they are unwell (even if slightly) will not be allowed to continue with the study on that day.<br>-To prevent simulator sickness escalating to nausea or vomiting, participants will be continuously monitored for signs of impending simulator sickness which include sweating, yawning, turning pale, or rubbing the face. Any participant exhibiting these signs will be carefully monitored or advised to stop the study.<br>Control Effectiveness:<br>______________<br>Control: - Participants will read and sign the MUARC explanatory statement (which | | | | | |



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| | outlines the exclusion criteria for simulator sickness and the risks involved) and consent form before participating in the study.<br>Control Effectiveness: | | | | | |
| Monash staff member/student is assaulted by participant. | Control: - In the event of verbal and/or physical aggression the researcher will leave the room immediately and contact security or emergency services if necessary.<br>Control Effectiveness:<br>______________<br>Control: - Participant will have been spoken to during eligibility screening; if exhibiting aggression or any level of impairment that would affect their ability, the participant will be withdrawn from the study.<br>Control Effectiveness:<br>______________<br>Control: - The researcher will carry with them a list of emergency contacts and a mobile phone at all times.<br>- An incident report will be completed via the online hazard report system (S.A.R.A.H.).<br>- The MUARC Safety Officer and a First Aider will be notified of the event as soon as possible.<br>- The researcher will seek medical attention as soon as possible if required.<br>Control Effectiveness:<br>______________<br>Control: A senior staff member will be supervising and security will be made aware of the experiments.<br>Control Effectiveness: | Low | - Data collection will generally occur on-site at MUARC during business hours when other staff are available.<br>- Where after-hours data collection is required the experimenter will comply with the MUARC after-hours work procedure.<br>- Where after-hours data collection is required then either a second experimenter will be present or Monash security will be advised that the simulator is being used.<br>- Participants will read and sign the MUARC explanatory statement and consent form before participating in the study.<br>- List of defibrillator locations/first aiders are made available in each sim lab.<br>- All researchers who will be using the facilities have completed training in the use of the simulator, as well as the OHS local area induction and online module. | UMAR ABDULLAH AL ABEDIN | 10/10/2023 | Low |
| Damage/theft of equipment | Control: - An incident report will be completed via the online | Low | - The researcher will inspect the equipment prior to running each | LING CHEN | 10/10/2023 | Low |

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| | hazard report system (S.A.R.A.H.).<br>- Damage/theft will be reported to security and the police (if required).<br>- Insurance services will be contacted to ensure any actions for replacing/ repairing equipment comply with the relevant insurance policies (if required).<br>- The Primary Supervisor for the sim facilities will be advised of the event.<br>Control Effectiveness:<br>————————<br>Control: - The researcher will ensure the area is made safe / access is restricted if hazard is present.<br>- Researcher will be on-site with the participant at all times.<br>- Access to the sim lab is restricted to authorised Monash staff/students only.<br>Control Effectiveness: | | participant to ensure it is intact and operational.<br>- All researchers who will be using the facilities have completed training in the use of the simulator, as well as the OHS local area induction and online module.<br>- The temperature in the sim lab is maintained at a suitable level so as not to impact the electronic equipment. | | | |
| Participant/staff/students/visitors are injured/hurt while on the premises | Control: - The researcher will install tape over any cables that are exposed and within the areas to be accessed during the study (by either the researcher or participants).<br>- The researcher will ensure the area is made safe / access is restricted if hazard is present.<br>Control Effectiveness:<br>————————<br>Control: - Researcher will be on-site with the participant at all times.<br>- Access to the sim lab is restricted to authorised Monash staff/students only.<br>- Covers will be installed around base of the sim to protect participant from getting foot/hand caught/pinched in the motion | Medium | - Participants will read and sign the MUARC explanatory statement and consent form<br>before participating in the study.<br>- List of defibrillator locations/first aiders are made available in each sim lab.<br>- Workplace safety inspections are completed twice yearly to identify and address any<br>potential hazards.<br>- Ergonomics reviews are conducted on the workspace as required.<br>- Step ladders and trolleys are available for manual handling tasks, and researchers are encouraged to seek assistance for more difficult tasks (BEIMS requests to be submitted as required).<br>- All researchers who will be using the facilities have completed training in the use of the simulator, as well as the OHS local area induction and online. | UMAR ABDULLAH AL ABEDIN | 10/10/2023 | Medium |



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| | base/equipment/etc. Cover also hides cables that could be trip hazard.<br>- Electrical equipment is tested and tagged annually.<br>Control Effectiveness: | | | | | |
| Participant has an infectious condition (e.g. flu or nor virus) that could be exposed to the researcher/s if the participant vomits or sweats excessively due to simulator sickness, or in the cases that the collection of bodily fluids or an alcohol breath test is required for the study (i.e. saliva) | Control: - Research staff having contact with participants will have on hand a bucket to contain any vomit, and procedures in place for safely disposing of vomit (down the toilet) and cleaning vomit spills including a spill kit<br>- Contaminated material will be disposed of in an approved biohazard bin.<br>Arrangements for the collection and appropriate disposal of the biohazard bin will be arranged when the bin is nearing full (a replacement bin will be provided), or at the conclusion of the study (whichever occurs first).<br>Control Effectiveness:<br>————————<br>Control: - Equipment used during the study including head caps, phones, tablets, etc will be wiped down with alcohol swabs prior to each use.<br>Control Effectiveness: | Low | - Research staff cleaning up vomit will use PPE including gloves, eye glasses and a coverall suit to minimize the risk of potential infection.<br>- Research staff involved in the collection/testing of bodily fluids will use PPE including gloves, eye glasses and where required, a coverall suit. | UMAR ABDULLAH AL ABEDIN | 10/10/2023 | Low |
| Eye stress or visual discomfort from prolonged use of monitor screens | Control: Every 20 minutes, take a 20-second break and focus on something that is 20 feet away.<br>Control Effectiveness:<br>————————<br>Control: Position the monitor so that the top of the screen is at or slightly below eye level, and make sure it is at a comfortable distance from your eyes.<br>Control Effectiveness: | Medium | Use an anti-glare screen filter or adjust the lighting in your workspace to minimize glare on the monitor screen. | UMAR ABDULLAH AL ABEDIN | 10/10/2023 | Low |
| Data breaches or loss of | Control: Use strong passwords | Medium | Connect to virtual private networks to | UMAR ABDULLAH AL | 10/10/2023 | Low |

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| sensitive information due to hacking, malware, or other cyber threats | and 2-factor authentication to reinforce security<br>Control Effectiveness:<br>______________<br>Control: Restrict access to sensitive information only to those who need it, and implement strong access controls and authentication protocols.<br>Control Effectiveness: | | ensure secure browsing and data transmission | ABEDIN | | |
| Failure of equipment or technology, leading to loss of data or inability to complete the experiment | Control: Before starting an experiment or data collection, test all equipment and technology to ensure they are working properly and to identify any potential issues.<br>Control Effectiveness: | Medium | Have a backup plan in place in case of equipment or technology failure. Could include having spare equipment available, backing up data regularly, or having alternative methods for data collection. | LING CHEN | 10/10/2023 | Low |
| Psychological distress or trauma experienced by participants due to the experimental conditions or procedures | Control: Provide participants with all relevant information about the experiment, including potential risks and benefits, and obtain their informed consent before conducting the experiment.<br>Control Effectiveness: | Medium | Provide participants with access to support resources like mental health professionals if they experience distress or trauma. | LING CHEN | 10/10/2023 | Low |
| Development of vibration syndrome from operating the simulator steering wheel, due to vibrations. | Control:<br>Control Effectiveness: | Low | Reduce vibration significantly in the settings of the simulator steering wheel<br>. | LING CHEN | 10/10/2023 | Low |

## 11.2 Appendix B: Risk Management Plan

A comprehensive risk assessment plan is a critical document that helps to identify, evaluate, and prioritize risks that would inhibit the success and deliverance of the project. Failure to complete any of the predecessor tasks will result in delays to subsequent tasks' completion. It is, therefore, imperative to ensure timely completion and to make them robust to potential failure. Table 11.2.1 details the non-OHS risks that should be considered.

*Table 11.2.1: Non-OHS Risk Assessment*

| **Project Risk** | **Risk** | **Likelihood** | **Consequence** | **Risk level** | **Mitigation** | **Residual Risk** |
|---|---|---|---|---|---|---|
| Communication errors between team members and supervisor | Tasks may be incorrectly done due to misunderstanding expectations | Possible | Serious | M | Clarify with supervisor on points of confusion of the project.<br>Maintain a clear communication channel between team members that is always open.<br>Conduct regular meetings with all team members and supervisor to prevent confusion. | Delayed project deliverables and progressing work |
| Skewed workload distribution due to improper scheduling/timelining. | May cause dissatisfaction of team members and delay the work allocated to them | Possible | Minor | M | Produce a realistic and proper Gantt chart and assign task responsibilities.<br>Maintain communication between teammates and work together to ensure everyone knows the deadline of tasks. | Delayed completion of workload distribution and Gantt chart preparation |
| Loss/damage to personal devices due to improper handling leading to loss to project files and data. (Physical damage and software damage from malware) | Delayed analysis of participant data and may need to recollect data | Unlikely | Serious | M | Backup the files in Google Drive to prevent the loss of data.<br>Avoid downloading files or clicking on links from untrustworthy websites, and to maintain secure and up-to-date passwords. | Must have stable internet connection to be able to use the data stored in Google Drive |
| Loss/damage of sensor equipment due to improper handling | Unable to collect required data for analysis on time | Unlikely | Disastrous | M | Keep equipment within a protective bag/case when moving it around.<br>Use appropriate power supply so electronics do not get damaged.<br>Contact unit coordinators for replacements immediately to prevent further project delays. | May have additional costs related to transporting and storing the sensors and that may strain the budget to be spent on other parts. |
| Some team members getting sick, therefore unable to work | Delayed completion of tasks allocated to | Likely | Minor | M | Make sure everyone on the team understands all components of the project, so that if one person is unable to work, the | May have a lack of expertise in certain areas that are critical to the project's success may cause the need to rely on |

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| | sick team members | | | | completion of the project isn’t significantly affected.<br><br>Achieve this through regular group meetings and communication. | external resources, which could result in delays. |
| Inability to recruit enough participants for data collection | Delayed collection and analysis of data | Possible | Serious | M | Post ads into FYP forums to try and recruit people and offer then vouchers for volunteering to participate | People may still be unwilling to volunteer |
| Inability to find suitable noise filtering techniques for data | Delayed analysis of data or incorrect analysis of data | Unlikely | Serious | M | Work with knowledgeable people to create a novel filtering method.<br><br>Research filtering methods to expand our knowledge of available filters | Unable to still create a high-quality filter that works properly leading to spending more time to get the system to work in the real world |
| Inability to find suitable machine learning methods for the data | Delayed creation of software system for drowsiness detection | Possible | Serious | M | Research mentions of proper and working Neural Network architectures in literature | May require expert math knowledge which may also require more time to be invested into learning algorithms, in turn, delaying project |

## 11.3 Appendix C: Sustainability Plan

Sustainable engineering refers to the practice of designing and developing engineering solutions that meet present needs without compromising the ability of future generations to meet their own needs. This uses a concept that is called the triple bottom line which emphasizes the consideration of three connected dimensions which are economic viability, environmental protection, and social equity.

This project of detecting drowsiness in drivers and creating an alarm system strongly relates to the UN SDG 3 which is Good Health and Well-being. More specifically, it enforces target 3.6 of this goal which is: 'By 2020, halve the number of global deaths and injuries from road traffic accidents.' The key indicator for this target is measuring the number of road traffic accidents per 100,000 population. The leading cause of death for people between 15 and 29 years of age is road traffic accidents. By developing a system that can detect drowsiness in drivers, the project can help reduce the number of accidents caused by fatigue-related incidents, thereby improving road safety. It helps prevent injuries and saves lives, aligning with the goal of reducing the global burden of injuries and deaths.

The project plan, process, outcomes, and implications, hence, should bear sustainable engineering considerations at its core. For example, the use of environment friendly technologies such as energy-efficient rechargeable batteries and can help ensure accessibility, affordability, and sustainability of the system to benefit a wide range of users. By enhancing road safety, the system contributes to a more sustainable transportation system. Additionally, if the system is designed to be affordable and accessible, it can reach a broader population, including low-income communities, making road safety advancements more equitable. Finally, by reducing road traffic accidents and injuries, the project contributes to the conservation of human life, an essential aspect of sustainability.

When looking at the environmental consequences, the positive impacts include reducing the number of road traffic accidents caused by drowsy driving. The negatives would include the impact of producing the drowsiness detection system, including resource extraction, energy consumption, and waste generation.

For the social consequences, the project aims to enhance road safety, which has significant social benefits. It can prevent injuries, fatalities, and the associated physical and emotional trauma for drivers, passengers, and pedestrians. However, privacy concerns may arise as the project involves monitoring and analysing personal data to detect drowsiness and to address these, transparency, consent, and strong data protection measures are in place to address potential social implications and maintain public trust.

Finally, when analysis the economic consequences, the project can have positive economic impacts by reducing the financial burden associated with road accidents. Fewer accidents mean reduced costs related to healthcare, emergency services, vehicle repairs, insurance claims, and productivity losses. Conversely, implementation of the drowsiness detection system would involve initial costs, including research and development, system integration, and infrastructure requirements.

The stakeholders for this project are the road users, the local communities, transportation authorities and policymakers, and automobile manufacturers and technology providers. They must also be considered for sustainability, and this can be done by promoting inclusive engagement, transparent communication, and long-term partnerships. By considering these stakeholder groups and incorporating their perspectives into the project's design, implementation, and evaluation, the sustainability of the project can be enhanced.

The project on detecting drowsiness in drivers and an alarm system exemplifies a sustainable approach by considering the triple bottom line and actively incorporating environmental, social, and economic considerations. By promoting road safety, minimizing environmental impact, prioritizing stakeholder engagement, and fostering economic value, the project works towards a more sustainable and resilient future for all.

## 11.4 Appendix D: Generative AI Statement

26/05/2023, 18:37 Monash University Mail - Generative AI use in FYP A (ENG/FIT4701)

MONASH University

**Umar Abedin <uabe0001@student.monash.edu>**

**Generative AI use in FYP A (ENG/FIT4701)**
1 message

**Google Forms** <forms-receipts-noreply@google.com> 26 May 2023 at 16:33
To: uabe0001@student.monash.edu

Thanks for filling in Generative AI use in FYP A (ENG/FIT4701)

Here's what was received.

Edit response

# Generative AI use in FYP A (ENG/FIT4701)

The responses to this form will need to be copied and put into an appendix in your Progress Report.

Email *

uabe0001@student.monash.edu

Name *

Umar Abdullah Al Abedin

Are you part of a team? If you are please add your team mates names below, if not, please answer 'No'

Ling Chen

https://mail.google.com/mail/u/1/?ik=a7c7e70c21&view=pt&search=all&permthid=thread-f:1766937364972159418&simpl=msg-f:1766937364972… 1/3

Campus

- (●) Clayton
- ( ) Malaysia

Host Department

- ( ) Chemical and Biological Engineering
- ( ) Civil Engineering
- (●) Electrical and Computer Systems Engineeing
- ( ) Materials Science Engineering
- ( ) Mechanical and Aerospace Engineering
- ( ) Software Engineering
- ( ) Robotics and Mechatronics Engineering

Supervisor

Faezeh Marzbanrad

This project has been conducted using AI tools *

- (●) In this project, there will be no use of generative artificial intelligence (AI). All content in relation to the assessment task has been produced by the authors.
- ( ) In this project, the following generative AI will be used for the purposes nominated in part 2. (Please note: any use of generative AI must be appropriately acknowledged - see Learn HQ)
- ( ) In this project, AI writing assistants (e.g., Grammarly, Writesonic, Quillbot, Microsoft Editor) will be the only form of Generative AI used.
- ( ) This project involves the development or authoring of Unique Generative AI, Unique operation of commercially available Generative AI OR Unique non-generative AI (Machine Learning, Artificial Neural Network, Logistic Regression, etc.)

Permissions

The use of Generative AI has been discussed with and approved by my academic supervisor. *

Yes

No

End

Thank you for completing this form - your responses will be emailed to you for your Progress Report

Create your own Google Form
Report Abuse

## 11.5 Appendix E: Simulator Settings

### 11.5.1 Config.ctg

uset s_reverb_world "1"

uset s_reverb_cabin "1"

uset s_noise_aero "1"

uset s_noise_windows "1"

uset s_rumble_enabled "1"

uset s_reverse_enabled "1"

uset s_cb_radio_beep_type "roger01"

uset s_cb_radio_beep_own "0"

uset s_cb_radio_beep_enabled "1"

uset s_cb_radio_noise_enabled "1"

uset g_mp_name_tags "1"

uset g_chat_fade_out_timer "5"

uset g_chat_partial_fade_out "0"

uset g_chat_on_navigation "1"

uset g_chat_activate "1"

uset g_chat_close_automatic "0"

uset g_disable_beacons "0"

uset g_show_game_blockers "1"

uset g_show_game_elements "1"

uset g_hmd_no_3d_background "0"

uset g_hmd_no_special_menu "0"

uset g_hmd_reduced_cabin_movement "1"

uset g_hmd_no_artifical_movement "0"

uset g_eye_pause_gaze "3000"

uset g_eye_pause "0"

```
uset g_cam_blinker "0"

uset g_cam_physics_value "1.0"

uset g_cam_physics "1"

uset g_blinker_auto_off "1"

uset g_cruise_control_smart "5.0"

uset g_cruise_control_grid "5.0"

uset g_adaptive_shift "0.0"

uset g_fuel_simulation "0"

uset g_hardcore_simulation "0"

uset g_reg_setting ""

uset g_brake_light_all "0"

uset g_use_speed_limiter "1"

uset g_hud_speed_warning "-1"

uset g_hud_speed_limit "1"

uset g_axle_drop_auto "1"

uset g_engine_start_auto "1"

uset g_motor_brake_auto "0"

uset g_retarder_auto "0"

uset g_cabin_suspension_stiffness "0.75"

uset g_suspension_stiffness "0.74"

uset g_trailer_stability "0.5"

uset g_truck_stability "0.5"

uset g_mpg "0"

uset g_gallon "0"

uset g_fahrenheit "0"

uset g_pounds "kg"

uset g_mph "0"
```

```
uset g_road_events "0.45"

uset g_detours "0.3364"

uset g_name_localization_secondary "0"

uset g_name_localization "1"

uset g_lang_set "1"

uset g_lang "en_us"

uset g_cutscenes "0"

uset g_phys_mirrors "0"

uset g_world_map_zoom "7"

uset g_cargo_load_require_park_brake "0"

uset g_cargo_load_require_engine_off "1"

uset g_show_always_wotr_event "0"

uset g_last_wotr_event_start "0"

uset g_multiplayer_backup_index "-1"

uset g_force_load_selector "-1"

uset g_autoload_ignore_autosave "0"

uset g_start_in_truck "0"

uset g_park_brake_init "0"

uset g_trailer_advanced_coupling "0"

uset g_parking_difficulty "1"

uset g_simple_parking_doubles "1"

uset g_speed_warning "0"

uset g_voice_navigation_pack ""

uset g_voice_navigation "0"

uset g_job_distance "0.2"

uset g_job_distance_limit "-1.0"

uset g_income_factor "5"
```

```
uset g_currency "0"
uset g_bad_weather_factor "0.41"
uset g_truck_analysis_fold "0"
uset g_desktop_rnd "0"
uset g_desktop_bcg "config"
uset g_save_idx "1"
uset g_ui_map_align "1"
uset g_gps_routing_mode "0"
uset g_gps_navigation "3"
uset g_heavy_cargo_popup "0"
uset g_mirrors "1"
uset g_adviser_eta "1"
uset g_adviser_running_message "1"
uset g_adviser_auto_parking "0"
uset g_adviser_keep_hidden "0"
uset g_adviser "1"
uset g_desktop_tutorial "0"
uset g_tutorial "0"
uset g_fatigue "0"
uset g_time_zones "0"
uset g_police "0"
uset g_subtitles "0"
uset g_clock_24 "1"
```

### 11.5.2 Config_local.cfg

```
uset s_cbeffects_mute "0"
uset s_voiceover_mute "0"
uset s_intro_music_mute "0"
```

```
uset s_ui_music_mute "0"

uset s_ui_mute "0"

uset s_navigation_mute "0"

uset s_music_mute "0"

uset s_radio_mute "0"

uset s_interior_mute "0"

uset s_ambient_mute "0"

uset s_world_mute "0"

uset s_traffic_mute "0"

uset s_trailer_mute "0"

uset s_truck_noise_mute "0"

uset s_truck_effects_mute "0"

uset s_truck_turbo_mute "0"

uset s_truck_exhaust_mute "0"

uset s_truck_engine_mute "0"

uset s_master_mute "0"

uset s_cbeffects_volume "0"

uset s_voiceover_volume "0"

uset s_intro_music_volume "0"

uset s_ui_music_volume "0"

uset s_ui_volume "0"

uset s_navigation_volume "0.26"

uset s_music_volume "0"

uset s_radio_volume "0"

uset s_interior_volume "0.25"

uset s_ambient_volume "0.26"

uset s_world_volume "0.25"
```

```
uset s_traffic_volume "0.25"
uset s_trailer_volume "0.24"
uset s_truck_noise_volume "0.24"
uset s_truck_effects_volume "0.23"
uset s_truck_turbo_volume "0.22"
uset s_truck_exhaust_volume "0.22"
uset s_truck_engine_volume "0.23"
uset s_master_volume "0.29"
uset i_oculus_eye_protrusion "0.09"
uset i_oculus_eye_height "0.15"
uset i_hmd_max_prediction "0.1"
uset i_hmd_min_prediction "0.0"
uset r_interior "1"
uset r_steering_wheel "1"
uset g_eye_preset_5 ""
uset g_eye_preset_4 ""
uset g_eye_preset_3 ""
uset g_eye_preset_2 ""
uset g_eye_preset_1 ""
uset g_eye_enable "0"
uset g_cam_window_block "0.0"
uset g_toy_physics "1"
uset g_cam_steering_reverse "1.0"
uset g_cam_steering_value "1.26"
uset g_cam_steering "1"
uset g_pedal_clutch_range "1.0"
uset g_brake_intensity "1.33061"
```

```
uset g_steer_anim_range "900"
uset g_steer_autocenter "1"
uset g_clutch_brake "0.0"
uset g_hshifter_synchronized "1"
uset g_hshifter_split "3"
uset g_hshifter_layout_shifting "1"
uset g_hshifter_layout "splitter"
uset g_trans "3"
uset g_baked_vehicle "1"
uset g_force_economy_reset "0"
uset g_input_configured "1"
```

## 11.6 Appendix F: Link to Gantt Chart

https://docs.google.com/spreadsheets/d/1LKkt1m0CYXNPv2mchKFDkc2smKJqXzzwLHMDv3-0zFA/edit?usp=sharing

## 11.7 Appendix G: Team Contract

ITP METRICS

**Team Contract**

*Teams are responsible to fill out any and all areas of the contract in blue below.*

**Team Name:** Drowsiness Detection Team

**Team Member Names:**

| | |
|---|---|
| Ling | Chen |
| Umar Abdullah Al | Abedin |
| | |

**1. Document Purpose**

The purpose of this team contract is to outline the standard operating practices and team norms of the above named team and individually listed members for the remaining duration of the team lifespan. The guidelines outlined in this document are agreed to by all team members as indicated by their signature at the end of the contract. Any amendments to the contract must be discussed and agreed to by all signing members. Failure to abide by the outlined standard operating practices of this contract could harm the team's overall functioning and result in penalizing action as detailed in the contract.

**2. Rules and Regulations**

The team agrees to the following guidelines regarding general procedures, practices, and behaviours that are deemed acceptable.

**A. Expectations**

*i.* ***Project Expectations***

- Detail the goals, level of quality, and acceptable outcome(s) for the project.
- Outline the expected procedure of overall project deadlines set as a team and self-imposed deadlines or milestones set by individual members.
- Describe how the team will distribute contribution to the project equally among members and how to address inequality of member contribution throughout the project.

*ii.* ***Member Expectations***

- Detail the expected level of effort and the standard of work that is expected from each member.
- Outline the expected weekly time commitment for each member.
- Describe the academic integrity and honesty policies team members are expected to adopt and adhere to (e.g., plagiarism, pirating, false reports, citations, etc.).

*iii.* ***Role Expectations***

- Outline the role titles and role descriptions within the team. Include the tasks and responsibilities that each role is accountable for.
- Detail the agreed upon role assignment within the team. In instances where there are multiple individuals assigned to a role, assign a lead member to be responsible for accountability.

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## B. Communication

***i. Communication Medium***

- Describe the preferred medium for communication regarding the project.

***ii. Communication Timelines***

- Outline the agreed upon acceptable hours of communication delivery (e.g., weekdays only, 9-5, etc.).
- Detail the expected timeliness of responding (e.g., within 24-hours except on weekends) and if this expectation changes across the group project (e.g., quicker response times closer to project deadline).

***iii. Communication Code of Conduct***

- Outline the expected standard of respectful and professional communications both internal (i.e., between members) and external (e.g., mentors) to the team.

## C. Team Meetings

***i. Scheduling***

- Outline the agreed upon meeting schedule and how this schedule is changed if unanticipated time conflicts arise.

***ii. Involvement***

- Detail how the team will ensure all team members are involved in team meeting discussions and decisions.
- Outline the expectation of team members in regards to preparation for team meetings.

***iii. Attendance & Notice***

- Detail expectations regarding meeting attendance, tardiness, absences, and make-up sessions regarding team meetings.
- Outline procedures (e.g., amount of notice, contact medium, make-up meetings, etc.) team members are expected to follow if they anticipate being late or absent from a scheduled team meeting.

## D. Team Conflict & Decision Making

***i. Conflict Code of Conduct***

- Outline the expected code of conduct when team members experience disagreements about the project, processes, or interpersonal differences.

***ii. Initial Conflict & Conflict Escalation***

- Detail the steps that team members are expected to follow in order to work through an initial conflict.
- Outline escalation procedures for team members to follow if initial conflicts cannot be resolved, including individuals who will have ruling and authoritative decisions in the conflict (e.g., team leader, mentor*, etc.).
  **If this individual is external to the team, their signature is also required to acknowledge they understand their role as an impartial judge within a conflict situation.*

***iii. Decision-Making***

- Outline how the team plans to come to an agreed upon decision.
- Outline procedures to follow when sub-groups (i.e., not including all team members) make project decisions.
- Detail what the team will do when one or two team members have a different view of a decision.

- Detail the steps the team will take if a decision cannot be reached including individuals who will have ruling authority in a final decision (e.g., team leader, mentor*, etc.). **If this individual is external to the team, their signature is also required to acknowledge they understand their role as an impartial judge within a decision-making situation.*

## E. Stress Management

*i.* ***Monitoring & Assistance***

- Outline how team members will reduce stress, manage their workload, and prevent burnout. Include how members will monitor one another and provide assistance when needed to help a fellow team member who is struggling.

*ii.* ***Resources***

- Outline at least three resources available for team members to reduce stress, manage their workload, and prevent burnout.

## F. Contract Code of Conduct

*i.* ***Contract Breaches***

- Outline the agreed upon procedure for handling individuals who are in breach of the team contract. Specifically, outline how the team will identify and track breaches, discuss the breach, and inform the member in question (e.g., verbal warning, written warning, three strikes, etc.).

*ii.* ***Penalties***

- Detail the agreed upon procedure for deciding any penalization for members in breach of this contract (e.g., allocation of peer feedback marks). Consider how you would want the situation handled if you were the one in breach of the contract.

## 3. Declaration

By signing below, team members acknowledge and agree to be bound by the guidelines outlined above.

| | |
|---|---|
| | 03/04/2023 |
| Team Member Signature | Date |
| UMAR ABDULLAH | 03/04/2023 |
| Team Member Signature | Date |
| Team Member Signature | Date |
| Team Member Signature | Date |
| Team Member Signature | Date |
| Team Member Signature | Date |

## 11.8 Appendix H: Work Breakdown Structure