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# Masters Project Final Report

# (MCS)

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# Driver Drowsiness Detection System Towards Accident Prevention

**A dissertation submitted for the Degree of Master of Computer Science**

**W. D. T. Priyath**

**University of Colombo School of Computing**

**2020**

## Declaration

The thesis is my original work and has not been submitted previously for a degree at this or any other university/institute.

To the best of my knowledge it does not contain any material published or written by another person, except as acknowledged in the text.

Student Name: W.D.T. Priyath

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This is to certify that this thesis is based on the work of W.D.T. Priyath under my supervision. The thesis has been prepared according to the format stipulated and is of acceptable standard.

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# ABSTRACT

Drowsiness and driver fatigue are the main factors of the road accidents. It is very important to identify driver drowsiness in early stages for minimizing the damage and preventing accidents but it is a very complex and challenging task. It is possible to detect the state of driver fatigue with the development of the technology of computer science. A variety of techniques has been introduced to detect driver drowsiness in the past.

In this work, we proposed a novel approach to detect real-time driver fatigue by monitoring behavioral measures on facial expressions, human physiological signals and vehicular parameters. The study addresses the feature extraction methodologies with preprocessing, filtering and normalizing. Facial expressions such as eye features, yawning have been captured and analyzed via computer vision techniques that are based on deep learning algorithms. In this research used built-in sensors of modern wearable devices like smart watches, to extract the signals. Other sensory information such as grip pressure, heart rate, speed of the vehicle, steering wheel behavior has been collected from using specific sensors and simulators. This system designed client-server architecture and that includes several client application modules and main server application. Client modules such as vision application, smart watch app, and grip pressure reader module capture the data from various sensors and send it to the server. These inputs are received at its corresponding server and processed using a drowsiness detection model.

That model has been developed with fuzzy rules with modern computer science concepts. The model includes fuzzy rules based on input parameters according to biomedical theories and expert knowledge. The proposed model classify driver drowsiness state into four levels based on input sensory data. Experimental results shows the multi-sensory data and fuzzy model provide valuable contribution for drowsiness detection.

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This project would not be successful without the efforts of many dedicated personals. I would like to thank them all.

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# CHAPTER 1 - INTRODUCTION

## 1.1 Problem Definition

In general traffic accidents occur due to several reasons such as high speed, drunk driving, night driving, bad weather conditions etc. Drowsiness of driving has been identified as a major problem and that is the root cause of most road accidents. That dangerous behavior increases the amount of deaths and injuries in every year. The National Highway Traffic Safety Administration estimates [17] that 100,000 police-reported crashes involve drowsy driving annually. Virginia Tech Transportation Institute (VTTI) reported that 65% road accidents have occurred due to drowsy driving. Apart from that NHTSA's fatality analysis report estimated 396,000 accidents related to drowsy driving in the 2011 and 2015 period.

Many people drive vehicles with tiredness and fatigue after leaving their workplaces. Also this problem can be seen among most taxi drivers because they are driving day and night without frequent rest periods. Many studies and experiments have proven that driving performance decreases due to the fatigue and lack of sleep. According to these statistics, drowsy driving is critical for people and is a leading cause of road accidents. The aim of this research is to build an application to detect behaviors of drivers and predict the driver's drowsiness to prevent road accidents.

## 1.2 Motivation

As discussed earlier, drowsy driving is a critical problem and people follow up various strategies to control this unsafe behavior using both technical and non-technical methods. Here we can express the non-technical methods such as listening to the radio programs, drinking caffeinated beverages and taking frequent driving breaks etc. Using these methods we can expect some effective results, but the main problem is not completely resolved. For that reason, many scientists and researchers have proposed several ways to analyze the driver's drowsiness and build a variety of applications using modern technology. As a result of those experiments, new safety systems and equipment have been introduced with advanced concepts to avoid the road accidents. Most of these applications are based on detecting unsafe driving in real time and several actions have been taken to minimize the damage. Nowadays there are huge improvements in IOT application development and mobile based applications. There are a variety of sophisticated equipment introduced to detect driving drowsiness, such as “STEER wearable device”, “Stop Sleep electronic ring” including multi sensors and those are used several methods to alert and refresh the driver. Along with development of drowsiness detection applications, several intelligent techniques are integrated with high end cars to prevent road accidents. As examples scientists and automobile companies have focused on building autonomous vehicles, driver assistance systems and driver supporting systems etc. and improving their performance with high accuracy. As an example Tesla automobile company introduced a driver assistance system which is capable of identifying the driver fatigue by modern technology and keeping the driving auto-pilot mode.

In this research, an accurate prediction model is introduced using the modern artificial intelligence techniques to overcome the drawbacks of the current applications.

As we discussed in the previous section, these days we can see the latest technology and computer science theories are applied to identify the drowsiness. When studying researches and experiments based on the driver drowsiness recognition, we can see several approaches have been proposed with computer science domain. They tend to solve this problem using different computer science concepts combined with biomedical theories and equipment. According to that, researchers [3], used three main techniques to identify driver fatigue in currently implemented applications. One of the techniques is analyzing the behaviors of the driver such as facial expression[7], eye blinking[1], yawning frequency[17],[18] based on video processing with computer vision. Second approach is based on monitoring physical conditions of vehicles [14] such as steering wheel movement, lane keeping, and driving patterns. In Third approach, multi-sensors are used to track human biological measures[2] like heart rate, pulse rate, blood pressure etc. and that information is used to find out the drowsy driving.

By considering concepts of modern science and technology those are having thorough capability to solve these types of real world problems with higher success rate.  Different machine learning algorithms and modern artificial intelligent techniques can be applied to analyzing these data and predicting the results. We can see in most of the applications used to limited sources as inputs and focused only one or two factors to predict drowsy level of the driver. As an example some applications used only eye blinking behavior as an input to identify the drowsiness. Due to that reason accuracy of the prediction will be reduced. In this research, multiple sensory data and computer vision techniques are used to feature extract to identify driver’s drowsiness with high accuracy rather than already existing applications.

## 1.3 Scope

Here we proposed a system that has the ability to capture the data through different types of sensors and analyze them to predict the drowsiness level of the driver in early stages. The proposed system can be divided into two parts. The first part includes the feature extraction processes using the appropriate sensors and software modules. The facial behaviors such as blinking rate, yawning, eyelid closure etc. are captured through the computer vision techniques. Other human physiological data such as grip force of the hand and heart rate have been captured through relevant sensors and electronic devices. For the prototype of the system vehicular parameters such as speed of the vehicle and steering wheel behaviors have been extracted via relevant hardware devices and software components like simulators.

The main purpose of the second part of the system is to provide the novel model to predict the drowsiness level of the driver by analyzing collected input parameters with accuracy. As the initial scope collected sensory data has been analyzed through a fuzzy model. This model incorporates expert knowledge including the biomedical theories which are related to drowsiness identification. By considering the success rate of that model, the system will be enhanced with building neural network models using deep learning methods as the next step.

## 1.4 Objectives

The main objective of this research is to provide the solution for identifying driver exhaustion to prevent harmful road accidents. In other words, this work aims to build an application to capture behaviors of drivers in different ways and predict the driver's drowsiness before a fatal accident. The specific goals and objectives of this work can be described as follows.

1. To identify the most significant parameters from the human body those are reflecting a level of fatigue through literature reading.

   The one of the most important parts of this research is the identification of significant input psychological parameters that can be captured by specific sensors. When studying medical theories we can find out the most relevant characteristic changes on physiological parameters in the human body such as heart rate, pressure, brain waves etc. Modern technology supports capturing these measurements via sensors in real time. Facial expressions can be defined as another critical measurement of the drowsiness recognition process. By considering these we focused on selection of most suitable parameters to implement a novel model.

2. To find out the relevant environmental behaviors and vehicular parameters through literature review which related to the drowsiness identification while driving.

   When considering the driving scenario, it is very important to capture the vehicular parameters such as steering wheel behavior, speed of the vehicle etc. Those parameters have capability of identifying unsafe driving and within this research we discuss the significant importance of each parameter with proper reasons.

3. To design a classification model to detect the drivers' drowsiness with high accuracy.

   This is the main objective of our research that can be considered as the brain of the project. This part involves converting the different types of sensory inputs to effective outputs after the complex evaluation process. In this context we state the threshold values of each of these input parameters with logical perspective including the medical and science theories. Finally our major goal is introducing an expert system to evaluate drowsy driving.

4. Assess the effectiveness and effectiveness of the proposed model when predicting the results

   Within this objective we are trying to build up the effective application with quick responses.  It is very essential detection drowsy in early stages and that helps to prevent accidents or minimize the damage.

5. To Implement a proof of concept prototype with computer science methods and modern technology

   The main purpose of this objective is proposing a driver comfortable approach to detect the drowsiness that can be implemented practically in real driving scenarios. It is essential to build the application with low cost materials and it should be applied to any type of vehicle without any more complexity. Our aim is to build a system with modern technology including mobile devices such as wristbands.

6. Validate the prediction results by evaluating the implemented model through usability testing.

   The other objective is to measure the usability of the result of the proposed model with the expected results according to the feedback of the participants.

## 1.5 Contribution

The main contribution of the research project is to develop a model to estimate drowsiness level of the driver by analyzing combinations of factors such as video stream, images and sensor data in real time. In order to produce predictions, more parameters are used as inputs to the system. The fuzzy model including novel algorithms is introduced considering the importance of each of the parameters to evaluate these input parameters. This system facilitates the alert in the early stage and that helps to reduce the road traffic accidents by avoiding drowsy driving. The sensors which have been used in the application are comfortable to the driver and consuming low power. As an example here wearable devices (smart watches) are used to capture data such as heart rate, speed of the vehicle etc. Apart from that our experiment is supported by drowsiness detection under the different conditions to build the adaptive system.

## 1.6 Thesis Outline

This report is organized as follows. In the introductory section, we discuss the overview of the current study with problem definition, key objectives, contributions etc.

In chapter 2, we discuss about the previous approaches used by the other researchers to detect the drowsy driving. In other words complete overview of existing applications and previous studies were described with focusing on important points such as advantages, drawbacks, accuracy, limitations.

Chapter 3 presents full details about the theoretical basis for detecting drowsiness and the techniques used to solve this problem. Apart from that it describes the novelty of the methodology used in the research.

Chapter 4 elaborates on the detailed description of the design of the system. That section provides information about the modules such as the notification module, the processing module, the object detection module etc. and how they interact with each other.

In Chapter 5 we discuss about the technical and implementation details of the application including the methodology of data collection, sensor information, algorithms and other information of the hardware equipment.

Chapter 6 describes the experimental and evaluation methods used to test both performance and functionality aspects to achieve the objectives of this study.

Chapter 7 describes about the further improvements and feature works according to the evaluation results of the application.

# CHAPTER 2 - LITERATURE REVIEW

This section describes the summarization of previous approaches proposed by researchers to deal with driver drowsiness identification. In order to improve accuracy and performance of drowsiness detection, various methods have been used which are related to different areas such as computer vision, machine learning and deep learning etc.

There are three main techniques that can be used for analyzing driver exhaustion. One technique is to place sensors on standard vehicle components such as steering wheel, gas pedal etc. for analyzing sensor input data. Second one is the measurement of physiological signals such as heart rate, pulse rate, and blood pressure, etc. through relevant sensors. The third method is to detect drowsiness by analyzing the driver's facial movements and behavior using computer vision and machine learning algorithms.

## 2.1 Feature Extraction Methods

There are so many computer vision techniques, sensors and algorithms which are used by the researchers to extract the physiological, behavioral and vehicular features to detect the drowsiness of the driver. From those techniques, image/video processing with texture matching and image classification can be considered as the most powerful feature extraction method to identify the facial behaviors. There have been several attempts to identify the drowsiness and most of them are focused on detecting eye blinking and yawning analysis.

When considering image processing, it is important to identify areas of the face and facial objects such as eyes, and mouth etc. Most researchers used a combination of various methods to identify face regions and objects. Researches [12], [5] proposed a method called as “Ada Boost” algorithm (adaptive boosting) with regression analysis to extraction of facial landmarks. According to research, [1] the adaptive boosting algorithm causes some difficulties in detecting the eyes. Due to that reason they used “Ada Boost” algorithm combining with “Blob Detection” algorithm to identify face regions and eyes accurately and they used the validation process to verify the eye recognition. Also they used NIR filters to reduce the feature extraction errors due to the variation of environment conditions such as lighting. In research [10] Ensemble of Regression Trees (ERT) algorithm is used for facial landmarks localization process which is robust and very powerful. Research [1] proposed a technique of feature extraction of eye state classification that uses both eyes to extract the features separately and then combine those results with the normalization process.

When studying facial detection we can see the researchers tend to use modern technology to improve the accuracy of the driver status monitoring. Research [4] proposed a depth camera instead of using a normal camera to monitor the driver's face in 3 dimensional view with CANDIDE-3 face model. That model has the ability to capture the locations of facial components and head movement with a 3D coordinate system. Microsoft Kinect sensors provide facility to capture depth of objects and color image sequences with high accuracy and Kinect SDK can be supported for the feature tracking process.

After identifying facial objects, another important process is the extraction of their facial features. In research [1] proposed well-known two machine learning approaches which are PCA (Principal Component Analysis), LDA(Linear Discriminant Analysis) used for eye classification. Those techniques can detect the eye opened or closed using the values of the sparseness and kurtosis of the projected histogram. According to their findings the open eye has a larger sparseness and kurtosis than the closed eye. Most researchers [6], [7], [19] used an eye blinking based method called "PERCLOS" to measure drowsiness. Generally PERCLOS describes the percentage of eye closure. Apart from that research [7] extract 18 features such as blinking frequency, blinking duration, energy of blinking and eye closure speed etc. by processing facial videos. When studying eye feature extraction concept we can see most common methods used by researchers as mentioned previously. Apart from those methods some experiments have been done with the complex features such as detection of eyeball positioning and eye movements [20].

In [3] their own dataset is built to identify the drowsiness by eye features, head movements and facial behaviors including different subjects such as ethnic groups, gender etc. That dataset provides the ability to identify subtle cases of drowsiness signs with different external conditions. In that research, four models (Baseline-4 Model, Baseline-2 Model, Compressed-2 Model, Benchmark model) are introduced to detect facial behaviors by changing the number of input streams. The main purpose of Proposition 4 models to detect drowsiness is to find the most efficient and accurate method in practice.

SMI eye tracking glasses are used to analyze the eye movement with different parameters such as blink durations, start time, and end time etc. Those glasses facilitate the extraction of information efficiently and accurately rather than traditional cameras. Eye blinking is detected from Vertical Electro Oculogram (VEO) and saccade is extracted from Horizon Electro Oculogram (HEO).

Many researchers used Yawning analysis to detect driver drowsiness with different techniques. In research [16] Histogram of Oriented Gradients (HOG) and The Local Binary Patterns (LBPs) descriptor are used to identify the human mouth behaviors and extract the yawning information. In [17] they proposed to capture mouth openness and internal zone of the mouth by calculating a spatio-temporal descriptor based on the tracking of the lips. Head nodding frequency [7] is another measurement that has been extracted from computer vision techniques.

Apart from the facial feature extraction there is another important area that focuses on the driver's physiological status using different sensors to detect drowsiness. Some researchers [2] used only multi sensor data to detect driver drowsiness instead of computer vision techniques. Most of the researchers tend to use heart rate variability as a parameter for identifying drowsiness. There are several sensors such as Heart rate sensors, Pulse rate sensor, ECG etc. that have been used to capture the heart rate of the driver.

Apart from that another important area for the driver drowsiness detection is analyzing brain waves of the person. EEG sensors [2] are most often used to monitor key brain areas and analyze the neurophysiological signals of the electrical activity of the brain by recording from electrodes placed on the head. They used only 12 EEG channels (CP1, CPZ, CP2, P1, PZ,P2, PO3, POZ, PO4, O1, OZ, and O2) capture the brain signals and extract important features called power spectral density (PSD) and differential entropy (DE) to detect driving fatigue.

Modern researchers introduced new techniques to collect data through the latest technology and smart wearable devices. Some Wristbands include multiple sensors such as Photoplethysmogram, GRS(Galvanic Skin Response sensor) and heart rate sensors. Research [9] used GSR sensors to extract the stress level of the driver and that is included as an input to evaluate the driver fatigue. Apart from that EOG sensors have been used to identify physiological signals such as eye movement. In research [2] three sensors such as Pulse oximeter, Blood oxygen saturation meter, Pressure sensor etc. are used to track physiological information of the driver.

Some studies [4], [5], [6] used steering behavior of the vehicle as input data to detect drowsiness. In research [7] proposed use GPS signals to measure the information of vehicle speed and [8] proposed to use modern vehicle dynamics in laboratory environments to capture vehicle kinematics, traffic information etc. The most easy way to capture properties like acceleration, motion of the vehicle using built-in sensors in smart mobile devices such as accelerometer and gyroscope.

Some researchers proposed pre-processing and post processing steps to improve the accuracy of the feature extraction process and reduce the complexity of the inputs. In research [6] performed two preprocessing techniques before presenting to the Artificial neural network that are discretizing and coding steering signals, normalizing the road curvature with steering angle. Research [1] features are extracted from left eye and right eye and then optimized the data separately before input to the classifier. There are some score fusion methods used to increase the accuracy of the calculation process. They apply different weights to each eye to calculate the fused score. And also it used different numbers of subjects and different types of conditions when training neural network models such as time (day or night), type of the glasses or no glasses etc. The peculiarity of the research paper [1] is that they calculate the user-specific threshold for each driver, rather than using the fixed threshold value for all drivers to detect drowsiness of the driver. They also selected the most suitable features to train network models for error reduction.

## 2.2 Analyzing Techniques for Drowsiness Detection

When it comes to analyzing techniques to detect drowsy driving, we can see several approaches have been used by researchers with adequate accuracy and reliability. When studying the latest research papers and experiments, most of them use modern computer science techniques such as artificial intelligence methods, algorithms, fuzzy logic and deep learning etc. to detect the drowsy driving.

Most of the studies [1], [2], [5], [9] used a support vector machine (SVM) classifier to train data models for detecting driver drowsiness. SVM is the popular supervised machine learning method that has been used to classification by finding the hyper-plane that has capability to differentiate data sets to the two or more classes by maximizing the distances between the support vectors. When it comes to drowsy detection scenarios SVM classifiers have been trained according to the different types of collected input data which are related to driving behaviors. In research [1] the SVM trained model has capability to classify the eyes as opened or closed. In experiment [9] uses the trained classifier to evaluate the drowsiness level of the participant. Some researchers introduced novel models by combining SVM models with other popular algorithms and deep learning methods. In study [5] introduced the model with combination of SVM and Gaussian Radial Basis Function (RBF) to determine the drowsy and non-drowsy features. In [2] experiment, the comparative study is done with a support vector machine method and graph regularized extreme learning machine (GELM) to find out the performance of both methods and they concluded GELM is more powerful than SVM.

The major disadvantage of using an SVM learning model to detect drowsiness is that the model does not support the time series of data. To avoid this drawback some researchers proposed the long short-term memory (LSTM) network model for detection drowsy driving. LSTM network is an artificial recurrent neural network (RNN) architecture that is capable of consuming the sequence of data and learning with long term dependencies. In other words the LSTM has the ability to remember data series for long periods of time while training. When considering driving scenarios, different types of long-term driving-related information such as facial expressions, physiological measures etc. should be collected and trained through the LSTM network model. According to the study [13] they proposed the novel model called a "two-level attention bidirectional LSTM network"(TLABiLSTM ). The main importance of the proposed model is that it is capable of combining both short-term memory attention and long-term temporal attention for spatial-temporal fusion. This model captures short-term drowsiness-related information with temporal dependencies and outputs captures long-term drowsiness score of each frame. The research[14] proposed Stacked - LSTM model with form "many-to-one" architecture which analyzes the behavior of driving according to the 9 fused sensor data and classifies into 3 classes that are "Normal" ,"Aggressive" and "Drowsy".

When studying about the different experiments, we can see several algorithms and analyzing techniques have been used to recognize the drowsiness of the driver. Research [4] use three-class pattern classification with synchronized multi-sensory data and scaled conjugate gradient (SCG) algorithm and Levenberg–Marquardt (LM) algorithm have been evaluated. Experiment [7], mainly focused to measure drowsiness using different statistical analyzing techniques such as Bravais-Pearson correlation coefficient, Spearman correlation coefficient, Fisher-metric MDA etc. and various visual representation methods have been used. Apart from that the researcher used dimension reduction techniques such as Principal Component Analysis (PCA) and Fisher transform (LDA) to misleading data and improve the accuracy of neural network model. Research [10] used different type deep learning neural networks such as VGG-Face, FlowImageNet, 8-layered AlexNet etc. to training the datasets with five different conditions(Bareface, with glasses, with sunglasses etc.) and computed the final rate of the drowsiness. According to the study [2] focusing on different deep learning techniques for analyzing drowsiness by combining them using standard ensemble strategies such as feature level fusion (FLF) and decision level fusion (DLF).

In addition to the use of deep learning techniques to analyze sleepless driving, some of the other major artificial intelligence techniques like Fuzzy logic models have been introduced by researchers. Mainly fuzzy logic attempts to solve real world problems by obtaining possible conclusions based on the degree of truth value according to the given rule set. In study [20] proposed fuzzy model to evaluate the input parameters from then in-build vehicle sensors. The main advantage of the using fuzzy logic model is that it provides capability for designing a control system based on expert knowledge. Most of the researchers used a combination of the other common algorithms to improve the fuzzy results. In study [20] used the Edit-distance method to enhance the results of the fuzzy rule evaluation to recognize drowsy driving with high accuracy. In study [21] the Employ Gaussian type membership functions have been generated according to the input parameters. And also they enhanced their results with the use of a Real-coded Genetic algorithm that has capability to solve real-world optimization problems.

The following diagram illustrates a taxonomy of deep learning techniques used by other researchers.

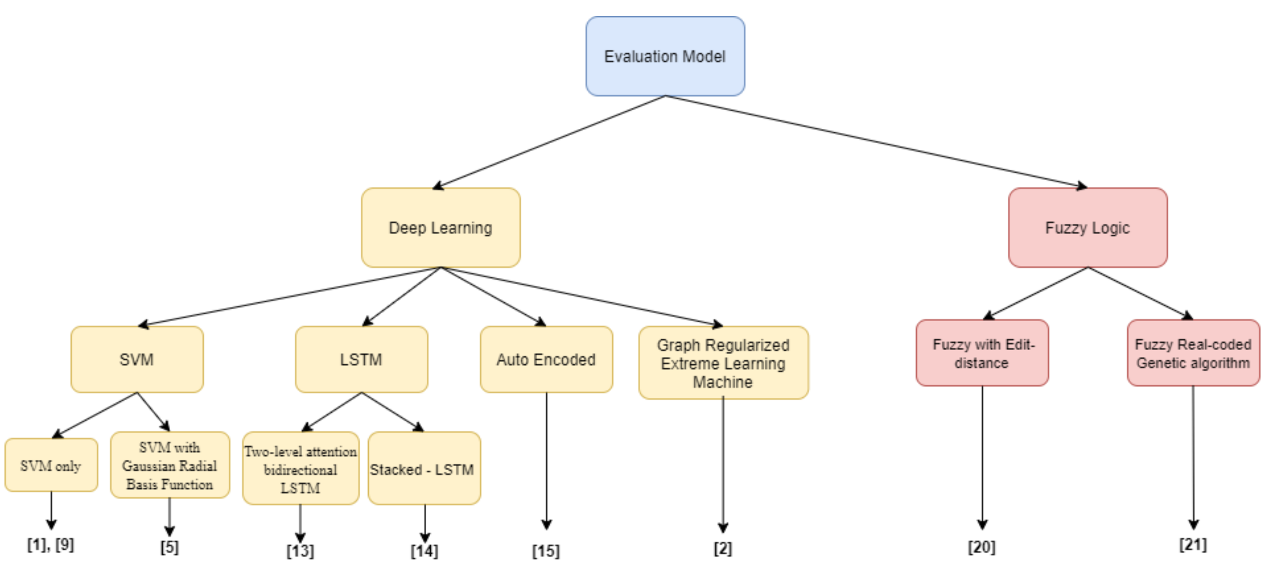


Figure 2.1: Taxonomy for Drowsiness Detection Methods

## 2.3 Drawbacks of Existing Systems

Identification the driver's drowsiness has been a topic of research for many years and several approaches have been studied to date. Most of the researchers have used small amount of inputs to detection of the driver drowsiness. As example, [1], [3] mainly focus on eye detection (Eye

Aspect Ratio, blinking behavior, etc.) to evaluate the drowsiness predictions. Some researches [2] proposed to identify driver fatigue based on tracking the study on monitoring and recognizing physiological signals only through different sensors such as EEG and EOG.

As considering about datasets, some researchers used datasets with general human expressions which are not included drowsiness detection qualities. These type datasets are not usable for training neural network model. The research with DROZY dataset [3] is included various types of time-synchronized data but those are regarding to small amount of (14) subjects. According to these facts the accuracy of the prediction results will be reduced.

There are several equipment that can be found regarding the driver drowsiness detection such as "STEER wearable device", "Stop Sleep electronic ring" etc. That equipment is using some type of sensor and focusing only one factor to detect the fatigue and drowsiness of the driver.

## 2.4 Summary of Related Works

Following Table describes summarization of related works done by the other researchers.

| Resea rch Paper | Data collection and Feature extraction | Methods used for improve the accuracy | Training/Analyzing Techniques |
|---|---|---|---|
| [1] | • Video Camera<br>• Four methods - PCA, LDA, Sparseness, and kurtosis to extracting the features | • Extract the features separately from eyes and combine those results with normalization process<br>• "Ada Boost" and "Blob Detection" - identify face regions<br>• Calculate the user-specific threshold for each driver | • SVM & MAP classifiers<br>• PERCOLS, EDC<br>• Modeling the user specific pattern of normal blinking based on 2D Gaussian PDF |
| [2] | • SMI eye tracking glasses are used for track eye movements<br>• EEG, EOG sensors are used to detect heart rate, pulse rate, brain waves etc. | • NIR filter to reduce the feature extraction errors | • Combining machine learning Algorithm using standard ensemble strategies - feature level fusion (FLF) & decision level fusion (DLF)<br>• Graph regularize extreme learning machine (GELM) and support vector machine (SVM) |

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| [3] | ● Kinect sensor - Facial feature tracking - Microsoft Kinect SDK<br>● Pulse oximeter<br>● Steering angle sensor<br>● Blood oxygen saturation meter<br>● Pressure sensor | ● Multi sensor inputs for improving accuracy<br>● Data sets of different sensors are synchronized on the same time | ● Scaled conjugate gradient (SCG) algorithm<br>● Levenberg–Marquardt (LM) algorithm<br>● CNN (Convolution Neural Network) |
| [5] | ● facial expression<br>feature extraction, steering wheel feature extraction | ● Video stream convert it to grayscale and use histogram equalization | ● SVM classifier with Gaussian Radial Basis Function (RBF)<br>● Take the average of the values of the facial feature for training data |
| [7] | ● IR-Camera unit<br>(640×480 pixels) and two IR-pods for illumination<br>● GPS signals – measure vehicle speed<br>● Eye detection and head angle - 18 Features(Blinking Amplitude/duration, Head nodding, Mean Eye Opening, etc) | ● IRpods were mounted to minimize the reflections on the glasses<br>● Both eye signals are combined weighting and normalization with the confidence values<br>● Special feature extraction methods/filters used for night drive(PERCLOS) | ● Bravais-Pearson correlation coefficient, Spearman correlation coefficient and the Fisher-metric MDA<br>● Visual impression of the features(Scatter plots, class histograms and boxplots)<br>● Dimension reduction techniques - Principle Component Analysis (PCA) and Fisher transform (LDA)<br>● Select the most promising features for a classifier - Sequential Floating Forward Selection (SFFS) algorithm |
| [10] | ● Eyes of each face are detected using the Ensemble of Regression Trees (ERT) algorithm<br>● Enhanced covariance metrics using texture descriptors and Pyramid-Multi Level (PML) face representation | ● Preprocessing - Aligned and cropped face. | ● Supervised feature selection method - Fisher scoring<br>● Results compared with deferent neural network models(VGG-Face, FlowImageNet, 8-layered AlexNet) |

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| [6] | • Track behaviors of steering wheel (Angle)<br>• Eye closure measuring system with digital camera<br>• Vehicle kinematics, traffic information | • Experiment conducted with variations(morning/night sessions)<br>• Discretizing and Coding steering signals<br>• Normalize the road curvature with steering angle | • Eye Closure Measure (PERCLOS)<br>• Error-propagation supervised learning algorithm |
| [8] | • Infrared camera<br>• EMG sensor (Myoware) to acquire myoelectric signals of the neck muscles<br>• ECG sensor - collect the pulse signal from the neck<br>• Pressure sensor (TeKscan Flexiforce) and captures the driver's grip force | • Preprocessing Eyeball positioning - Grayscale processing, Linear enhacement, Sharpening | • Principal component analysis (PCA)<br>• Fuzzy Comprehensive evaluation algorithm<br>• Region segmentation method and PERCLOS |
| [9] | • Wristband with sensors – wearable device<br>• Photoplethysmogram sensor – Heart rate, pulse rate<br>• Galvanic Skin Response sensor – Stress level<br>• Motion sensors - accelerometer and gyroscope sensors ( mobile device built-in sensors) | • Collect multiple sensor data with latest technology | • Support Vector Machine (SVM) |
| [13] | • Video camera - Facial expression, head pose and illumination condition | • Use MTCNN detector to coordinate of driver's face<br>• Use Kernelized Correlation Filter (KCF) [57] and Kalman Filer (KF) to extract occluded face region through prior knowledge. | • 3D Conditional GAN and Two-level Attention Bi-LSTM |
| [14] | • GPS sensor -Vehicle speed<br>• Camera - Distance to ahead vehicle, Number of vehicles<br>• Acceleration along z, y, z axis, Roll angle, Pitch angle, Yaw angle | • Synchronize sensor data with timestamp by Up-sampling technique<br>• Normalizing – Use mean values and standard deviation | • Stacked-LSTM |

Table 2.1: Summary of Related Works

## 2.5 Summary

According to the previous studies, many approaches have been proposed for the feature extraction process and drowsiness identification. Most of them used deep learning methods and some other researchers used fuzzy classification and statistical analysis techniques to recognize drowsy driving. The major drawback of the deep learning methods is lack of standard data sets. Finding large datasets, including multiple subjects is essential for training deep learning models to make accurate predictions. There are many video sets available but that are not provided sensitive data such as heart rate, pressure etc. In our research we used several types of sensors to capture the behaviors of the driver and parameters of the vehicle. According to that we decided to develop a fuzzy classification model for drowsiness detection that is similar to the method used by some other researchers [20], [21].

# CHAPTER 3 - METHODOLOGY

## 3.1 Overview

In this chapter, an overview of the current research aspects and theories associated in the development of driver drowsiness detection is discussed. It summarizes current technologies, algorithms, and design challenges associated with existing systems in this area in order to deliver a brief understanding about how its key components such as feature extraction and Fuzzy logic rules work. Further, Imaging processing techniques, and novelty of the proposed model will be discussed in the latter part of this chapter.

## 3.2 Data Collection

In this research, various types of drowsiness-related data has been identified and used to analyze the driver's drowsiness. These parameters are collected through monitoring physiological and physical conditions.

Following Sensors and combinations of factors are used to analyze and extract features. (Table 3.1)

| **Sensor** | **Information / risk factors** |
|---|---|
| Heart Rate sensor | Heart rate |
| Accelerometer & gyroscope | Track movements and position information<br>(Replace with Carlar Simulator software - Speed of vehicle) |
| Camera | Eye blinking/eye closure/Yawning |
| Grip force sensor | Captures the driver's grip force on steering wheel |
| Steering Wheel Angle Sensor | Angle of steering wheel<br>(Replace with Carlar Simulator software - steering wheel angle) |

Table 3.1 : Sensor Information with Data Collection

Facial expression and behaviors of face, eyes and mouth have been captured through camera. Physiological information of the driver such as heart rate is captured through built-in sensors of the smart watch like Pulse Rate sensor, Heart Rate sensor etc. Motion data is extracted using the motion sensors like accelerometer and gyroscope which are also built-in smart watch. The steering wheel sensor captures the information of the steering wheel pattern like angle of the steering wheel movement. The grip force sensor is used to detect the pressure on the steering wheel by the hands.

## 3.3 Feature Extraction

### 3.3.1 Capture Facial Expression

When it comes to detecting drowsiness, there are several aspects we can evaluate looking at the physical appearance of a particular person. Furthermore, facial expressions alone play an important role in whether a person can be identified as if he or she is going through tiredness and fatigue based on medical and psychological theories. With the advancement of modern video processing and computer vision, now it is getting possible to digitally identify drowsiness.

The concept of video processing consists of a variety of areas where image processing is taken into consideration as a key pillar for computer vision. The only language that a computer can understand data is binary. In order to see, a computer should be fed with nothing but in binary (bits). Therefore, if we need the computer to see and understand something and process something, that should be in the form of binary. That is where image processing comes in handy, more likely the base element of Computer Vision. It allows the computer to understand an image or a sequence of images (a video) in binary form so that it can interpret with the help of logics and algorithms.

As we already know, drowsiness can accurately be identified using a facial expression of a person. But when the face is contained in an image along with a lot of other details such as background and other objects, it is challenging to identify the face straightway and proceed with identifying eyes and mouth subsequently. To achieve that, common image operations such as edge finding and morphological operations are used. Further, Object detection tools like frontal face detection and object pose estimation are used in this case.

Face alignment and position is a crucial factor in reading the facial behaviors such as eye movement, mouth movement (yawning tracking), and blink detection in order to identify the drowsiness. according to Vahid K. and Josephine S. in their ‘One Millisecond Face Alignment with an Ensemble of Regression Trees’ study they suggest the possibility of using regression trees to estimate the face's landmark positions [18] directly from a sparse subset of pixel intensities.

As drowsiness recognition in facial behavior input parameters amount of Eyelid Closure, amount of open mouth, Blinking Frequency/Blink Duration is most commonly used. In Eye Aspect Ratio of both eye signals are combined in weighting and norming with the confidence values in which it detects both left eye and right eye separately and calculates average eye aspect ratio to improve the accuracy. The Figure 3.1 and Equation 3.1 represents the points of eye that are used to calculate the Eye Aspect Ratio.

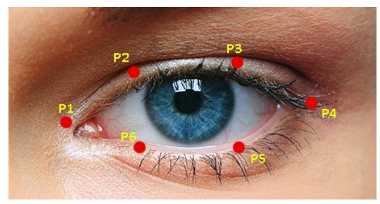


Figure 3.1: Extraction of Eye Area [31]

$$\text{EAR} = \frac{||P2-P6|| + ||P3-P5||}{2\,||P1-P4||} \qquad \textbf{(3.1)}$$

In conventional blink measures, including: PERCLOS [16], blinking frequency, indicates the proportion of time that the driver closes his/her eyes per unit time and blink duration is the average time required to perform a complete blink. To calculate these upper and lower eyelid positions were first identified from the face video, and blinks were detected from brief changes of the eyelid positions.

In order to build a yawning detection approach, we extracted a set of features from mouth behavior and that is essential to manage to detect the yawning states. In fact, after the identification of the lips, we will be able to calculate the amount of openness (Mouth Aspect Ratio) based on the tracking of the lips surface evolution and the internal zone of the mouth. The Equation 3.2 is used to calculate the Mouth Aspect Ratio and Figure 3.2 shows the points of lips surface.

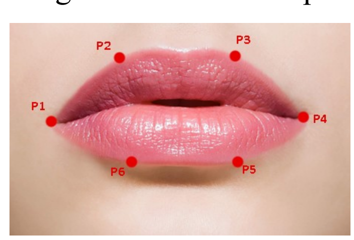


Figure 3.2: Extraction of Mouth Area [32]

$$\text{MAR} = \frac{||P2-P6|| + ||P3-P5||}{2\,||P1-P4||} \qquad \textbf{(3.2)}$$

### 3.3.2 Physiological Signals Extraction

This extraction is focused on the driver’s physiological status which is the other most important area in order to detect drowsiness apart from facial expressions. This area itself has more proven and stable research findings in drowsiness detection. Here we mainly focus on the driver's heart rate and steering wheel holding grip (pressure).

An individual's heart rate can vary depending on many variables both psychological and physiological. Therefore, in this case we would be using pre-evaluated normal heart rate range as normal heart-rate range (fuzzy rule) for fuzzy logic using age and gender as inputs which is one of the widely used methods.

However, in order to overcome this drawback, we are implementing a learning model that can maintain a normal heart rate range specific to the driver. Furthermore, decreased heart rate from wakefulness(fully awaken) to non-rapid eye movement (NREM) sleep reflects relatively increased parasympathetic influences, and the increased heart rate and heart rate variability during rapid eye movement(REM).

Steering wheel holding grip is crucial for detecting drowsiness since there is a tendency to release the steering wheel holding grip gradually once a person slowly enters to sleep. In order to identify this, an inbuilt pressure sensor is used to collect grip pressure data. The pressure sensor is a varistor (variable resistor) and the output data is a voltage value upon the pressure applied on it, where one pressure data is collected every 1s.

### 3.3.3 Vehicle Behaviors Extraction

As per the findings of previous research in drowsiness detection, steering wheel feature extraction shows a solid relationship between steering wheel movement and the decrement of vigilance while driving. In normal state, the driver keeps making small frequent adjustments to the steering wheel angle to keep the vehicle in the track without getting into sudden significant adjustments to the current trajectory. But when the driver is tired and drowsy, significant adjustments may start to occur which can be used as vehicle behavior inputs. Average of steering variability for given time window is extracted.

## 3.4 Fuzzy Evaluation Algorithm

The fuzzy classification system is built with suitable programming language using set of fuzzy rules to evaluate the collected physiological parameters like heart rate, pressure value, blinking rate, vehicle speed etc.

### 3.4.1 Introduction to Fuzzy Logic

Fuzzy Logic has the capability to resemble the human decision-making methodology. It deals with vague and imprecise information. This is a higher cognitive process of solving the real-world problems and based on degrees of truth rather than usual Boolean logic like true or false.

Fuzzy logic concepts help to solve a real world problem after considering all offered knowledge. Then it takes the best possible decision for the given input. The fuzzy logic methodology imitates the way of decision making in a human brain which considers all the intermediate possibilities between true and false.

The process of fuzzy logic evaluation can be represented as following diagram.

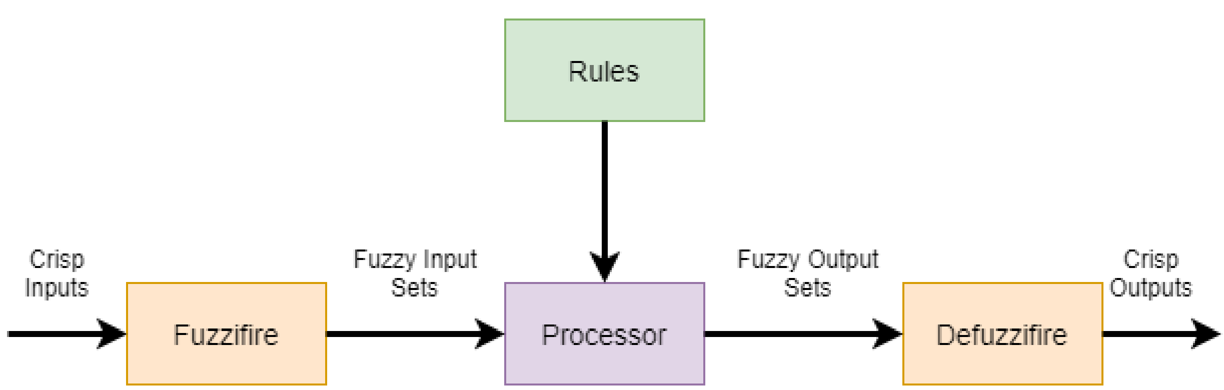


Figure 3.3: Fuzzy Evaluation Process

This fuzziness is best characterized by its membership function. In other words, we can say that membership function represents the degree of truth in fuzzy logic. Membership functions can be defined as a technique to solve practical problems by experience rather than knowledge.

## 3.5 Fuzzy Model for Drowsiness Detection

The fuzzy classification system is built with programming language using a set of fuzzy rules to evaluate the collected physiological parameters like heart rate, pressure value, blinking rate, vehicle speed etc.

### 3.5.1 Fuzzification

Fuzzification is a process of transforming a crisp set to a fuzzy set. Basically, this operation translates accurate crisp input values into linguistic variables. In here we have used s-fuzzification method to translate the crisp input values to linguistic variables. In this method fuzzified set can be defined as following Equation 3.3 as the mathematical representation.

$$\check{A} = \mu_1 Q(x_1) + \mu_2 Q(x_2) + \cdots + \mu_n Q(x_n) \tag{3.3}$$

$Q(x_1)$- Kernel of fuzzification.

$\check{A}$– Fuzzy Set

This method is implemented by keeping $\mu_i$ constant and $x_i$being transformed to a fuzzy set$Q(x_1)$.

### 3.5.2 Fuzzy Membership Function

Membership functions are generated using specific ranges of parameter values. Each of these parameters is divided into 3 membership functions based on the range of the value. As an example value of the parameter heart rate can be divided into levels as shown as below.

- Low heart rate
- Moderate heart rate
- High heart rate

We finally classify these results into 4 levels of outputs as described below (Table 3.2).

| Level | Fuzzy Status | Description |
|---|---|---|
| Level 1 | Low | No risk and driver behavior is normal |

| | | |
|---|---|---|
| Level 2 | Medium | It shows some signs of drowsy but not sleepy |
| Level 3 | High | It shows that in a short period of time the driver may be at risk of drowsy driving |
| Level 4 | Highest | This is a condition where the driver has severe drowsiness or fatigue and needs to rest immediately. |

Table 3.2: Status of Driver Drowsiness Level

Following figure represent the Membership function of parameter types.

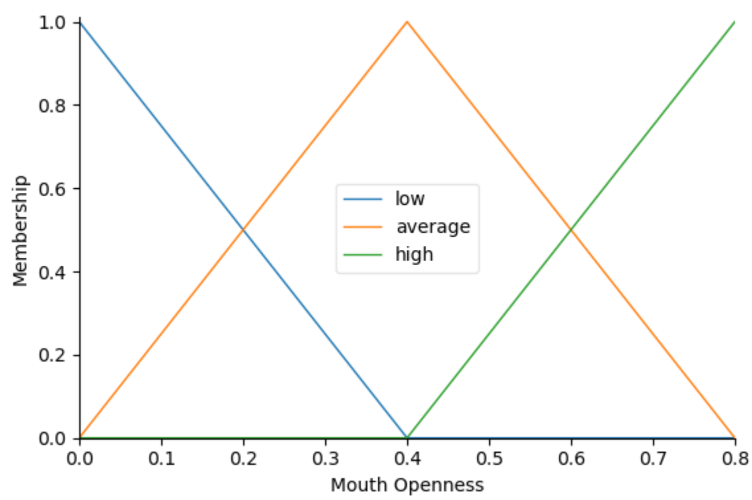


Figure 3.4: Membership Function for Mouth Openness

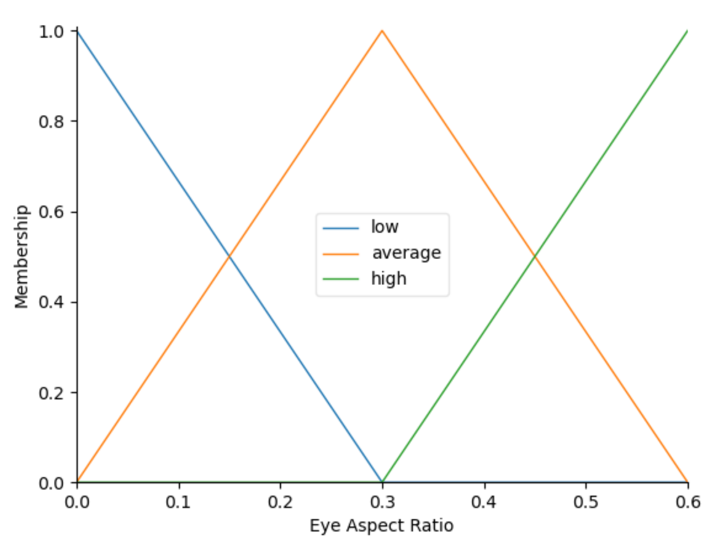


Figure 3.5: Membership Function for EAR

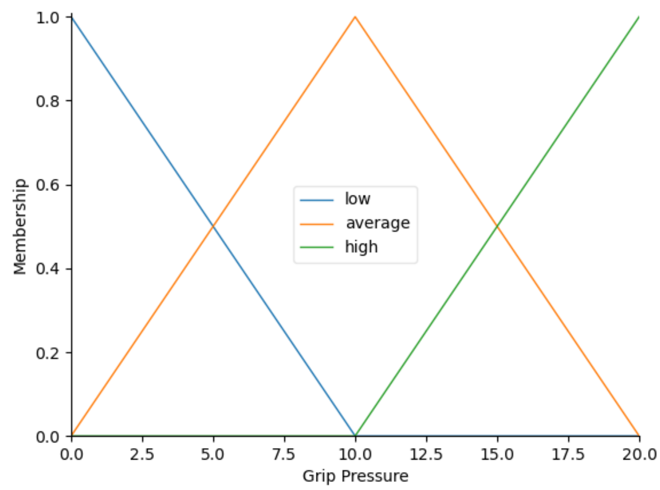


Figure 3.6: Membership Function for Grip Pressure

### 3.5.3 Defuzzification

Defuzzification is a process of translating a fuzzy set into a crisp set. In other words that is a conversion of fuzzy members into crisp parameters. There are several methods that can be found for defuzzification in fuzzy theory such as Centroid, Lambda-cut, Weighted average etc. In our fuzzy model we used the Centroid method to defuzzification and that can be represented as following Equation 3.4.

$$x^* = \frac{\int \mu_{\tilde{A}(x)}.\ xdx}{\int \mu_{\tilde{A}(x)}.\ dx} \tag{3.4}$$

x∗ - Defuzzified output

### 3.5.4 Fuzzy Rules & Results

In this research we defined the set of fuzzy rules including the combination of our fuzzy variables to evaluate the drowsy state of the driver. The levels of each parameter as mentioned in Table 3, are included in the fuzzy rules. Following table shows the sample fuzzy rules which are defined in our model.

| Variable Combination of Rule | Fuzzy Result |
|---|---|
| (**Yawning Duration:** ‘High’ AND **Eye Close Duration:** ‘High’)<br>AND<br>**(Grip Pressure:** ‘Low' AND **Heart Rate:** ‘Low')<br>AND<br>**Steering Variability:** ‘Low’ | Highest |
| (**Mouth Openness:** ‘High’ AND **Yawning Duration:** ‘High’)<br>AND<br>(**Eye Aspect Ratio:** ‘Low’ AND **Eye Close Duration:** ‘High’) | Highest |
| (**Yawning Duration:** 'High' AND **Eye Close Duration:** ‘High')<br>AND<br>**(Grip pressure:** ‘Average' OR **Heart rate:** ‘Average') | High |
| (**Mouth openness**: 'Average' OR **Eye Aspect Ratio:** ‘Average')<br>AND<br>**Grip Pressure:** ‘Average'<br>AND<br>**Heart rate:** ‘Average' | Medium |
| (**Mouth Openness**: 'Low' OR **Eye Aspect Ratio:** ‘High')<br>AND<br>**Grip Pressure:** ‘High'<br>AND<br>**Heart Rate:** ‘High'<br>AND<br>**Steering Variability:** ‘High’ | Low |

Table 3.3: Sample of Fuzzy Rules

Following diagrams shows in Figure 3.7 represent the visualization of the results provided by the fuzzy evaluation model. The fuzzy results have been collected during the 30 seconds time period and final drowsiness state has been calculated based on the probability of the fuzzy classification states.

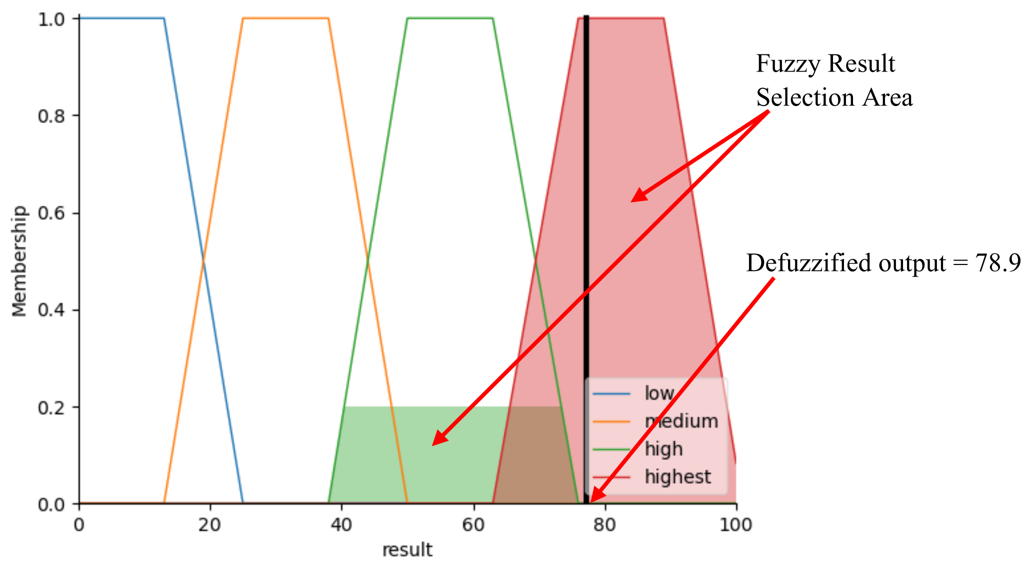


Figure 3.7: Graphical Representation of Fuzzy Output Values

## 3.6 Summary

In this chapter presented a proposed feature extraction methodologies and fuzzy model approach used for detecting drowsiness. Here we discussed the theoretical background behind collecting input parameters and fuzzy rule evaluation with mathematical terms including visual representations. These theories are applied inside the different modules of the proposed system and which are explained in detail in the next chapters.

# CHAPTER 4 - DESIGN

## 4.1 Design Overview

In this chapter we discuss the main idea behind our approach, which is to automatically detect drowsy and fatigue driving conditions of the driver and to alert them accordingly in order to avoid possible accidents. Further, the architecture of the application and individual module of the application and their integrity will also be discussed in detail.

The application is based on client-server architecture, where the client side interacts and requests for the support of services from its corresponding backend servers. Considering the infrastructure limitations and high speed mobility, the initial proposed design is improved that the application contains both client and server sides in the same local processor that it could perform as a stand-alone application without being interrupted by infrastructure like network connectivity which is a crucial factor in a real-time application where continuous client-server communication is required.

In the simulation setup we are using a video camera to monitor the driver's face continuously starting right after the vehicle begins to move. The video feed is forwarded as the input for the image processing module where it gets preprocessed before using as actual inputs to obtain the facial features recognition of the driver. Along with that, two other independent inputs from the heart rate sensor and the steering wheel holding grip pressure signal retrieved respectively from the smart wearable in hand and dedicated pressure sensor in the steering wheel are used to evaluate the driver's fitness to drive. If the final evaluation based on the inputs is showing that the driver is not in a suitable condition (drowsy/fatigue) to continue driving, the system will instantly alarm the driver and try to get his attention so that he could decide whether to continue or rest for a while starting again.

Here in this proposed model a vehicle simulator will be used as a vehicle simulator instead of a real vehicle in the implementation.

## 4.2 Application Design Architecture

According to the previous explanation, application architecture is a client-server architecture. Both the Client and the Server side will be present in the same processor which will deliver better performance and faster responses. The adapted architectural change for the initial proposed cloud based server is mainly taken into consideration due to the plausible mobile network related issues that could have caused possible challenges to the application in order to work in real-time. Figure 4.1 shows the initial proposed design of the system. The necessity of the application to work in real-time is because the warning alarms should not be lagging behind since every second is crucial from an accidents point of view. Even with the latest mobile networks such as 5G capabilities, the chances of connection issues remain considerable which led us having to move the server side into the application itself. The challenge we faced with this change of architecture is the lower processing power of the mobile device that we designed to use only for the Client-side of the application. But with adequate optimizations, it is convenient to bring the server-side and client-side together making the application, so it delivers better performance compared to network issues we might have faced with a cloud Server-side.

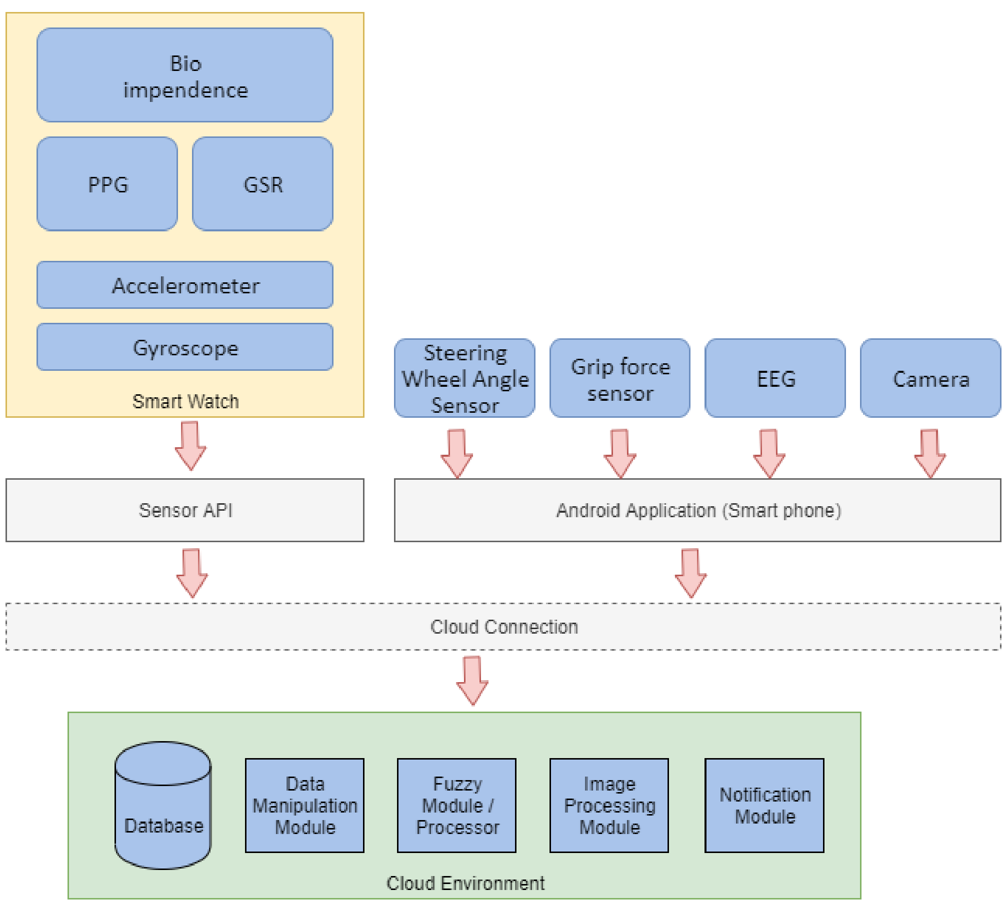

Figure 4.1: System Overview

### 4.2.1 Client Application

The main two sensor data sources are driver's heartbeat sensor data and Steering wheel grip holding sensor data which are obtained by a smart wearable watch and a generic grip force sensor respectively. Apart from that continuous camera feed is obtained using a dedicated camera. Input preprocessing is mainly used for the camera feed which needs more accuracy and precision in image data that is fed to the image processing module. Also image compression is used without losing the important data to minimize the unnecessary usage of processing power which will improve processing speed. This explains the process of forwarding the retrieved inputs to the corresponding services.

### 4.2.2 Server Application

Receiving multiple input data streams, and grouping them according to their type and time stamp is done server-side. Each input is received at its corresponding server and processed accordingly in order to be used as an input rule in the Fuzzy model which is implemented in the server-side itself. Based on the input rules (input data) Fuzzy model will provide the results to the notification system.

## 4.3 Final Design & Application Modules

As per the discussion in Application Design Architecture (4.2) section we decided to continue our project without using cloud computing. Different sensors and a video stream are used to read driver's condition inputs and forward them to the server-side which will return results so the notifications can be delivered in real-time. These input data streams will be sent to their corresponding server-side modules to be processed accordingly. Following diagram in Figure 4.2 shows the final version of the high level architecture of the application and how to build an interconnection between the modules.

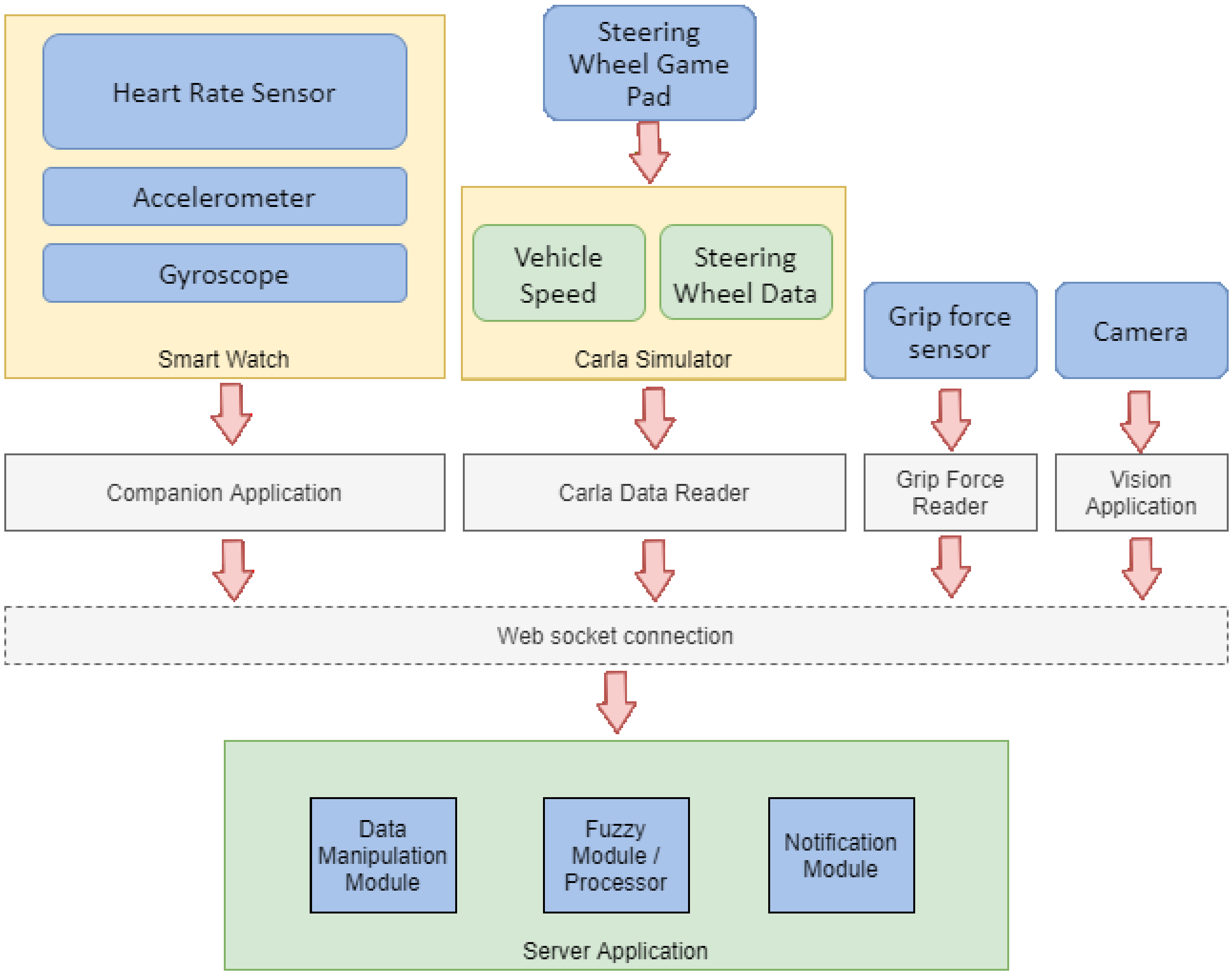


Figure 4.2: High Level Architecture of the Implemented System

### 4.3.1 Video Processing Module

This module uses the image processing algorithm to classify facial images into different drowsiness levels by percentage of eye closure, blinking rate and yawning analysis.

The image processing part of the system, dealing with monitoring driver's eyes to estimate fatigue levels, must essentially perform the following functions:

- Detecting driver's face in all input frames,
- Provide the eye location for both eyes, mouth,
- Representing eyes, mouth state using a feature extraction method.

### 4.3.2 Smart Watch Application Module

This module is deployed in smart-watch and captures data regarding the built- in sensors like heart rate sensor, accelerometer etc. In our prototype, we used this module to read the heart rate of the driver and send the data to the server application through the companion.

### 4.3.3 Grip Force Sensor Module

This module captures the grip pressure of the driver on the steering wheel and sends the data to the server after performing some normalization processes.

### 4.3.4 CARLA Simulator Module

Read steering wheel data and speed of the vehicle. This module is used only in prototype. This will be replaced with a steering wheel angle sensor and smart watch (read speed from accelerometer in smart watch).

### 4.3.5 Data Manipulation Module

Server application which collects data via web socket from different sources. Data manipulation module can be considered as the main module of the processing system. This module connects with different sources (vision app, smart watch API) to collect the information and process with a fuzzy model.

### 4.3.6 Fuzzy Model

The sensory data and results of the image processing module are retrieved from this module and that data is evaluated through fuzzy classification. When the system predicts some drowsiness of the driver, the signals are sent to the notification system.

### 4.3.7 Notification Module

Notification module facilitates sending the alerts to different sources according to the results of the fuzzy module.

## 4.4 Summary

The proposed system has been designed with main server application and several independent client modules. The major advantage of this architecture is that new modules such as sensor reader modules can be plugged to the whole system without affecting other modules. According to the design aspect, server applications provide the common interconnection method to communicate with client modules which is not specific for any programming language or any platform. The technologies, internal structures and implementation details of these modules will be discussed in the next chapter.

# CHAPTER 5 - IMPLEMENTATION

## 5.1 Introduction

This chapter is all about describing sensors, software, technology, algorithms, code segments that are used for this implementation. For deep analyzing and classification purposes some third party libraries have used implementing the models. Practical implementation and experiment setup details of every module mentioned in the design chapter.

## 5.2 Hardware Equipment

As hardware equipment mainly steering wheel attached grip force sensor (Flexiforce Sensor) with ESP32 microprocessor to measure grip force pressure of the driver hand on steering wheel, Smart watch with Built-in heart rate sensor and steering wheel gamepad to create driver simulated environment by reading steering wheel angle with connection to the simulator app via computer. Detection process for facial behavior; webcam is used. As other equipment Core I3 laptop with 8 GB memory is used to connect all hardware (gaming steering wheel/sensors) and for installing all the client server applications including Carla simulator software. Due to high performance of CARLA simulator this is the minimum specs that needs to be included in the selected computer to build a simulated environment. Without the Carla simulator other software applications can be deployed in Raspberry PI device in real world scenarios. Figure 5.1 shows the experimental driving environment with related components.


Figure 5.1: Experimental Environment with Simulator and Hardware Components

## 5.3 Software Applications

### 5.3.1 Server Application

Gathered measurements which are done by above mentioned hardware equipment needs to be evaluated using a server application. For this server implementation developed a python application using Django framework including all evaluation logics and Fuzzy model. Web socket is opened to receive parameters of sensor data from client applications. Following diagram in Figure 5.2 shows the major processes of the server application.

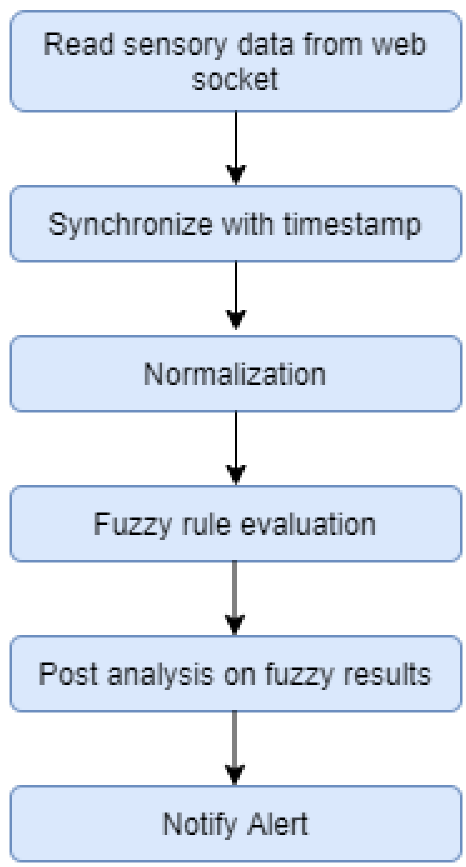


Figure 5.2: Flow Chart for Process of Server

### 5.3.2 CARLA Vehicle Simulator

Measured parameters such as speed, steering wheel angle by Carla Simulator Software and which are sent to the server application to evaluate. Although smart watch contains an accelerometer, gyroscope sensors to capture above mentioned information; in a simulated environment there might be an accuracy issue of the data. For the prototype, the Carla simulator chose to capture these parameters.

Python API that uncovered by CARLA permits clients to manage all aspects identified with the reenactment, including sensors, vehicle data like increasing speed. CARLA has been created starting from the earliest stage to help development, preparing, and approval of self-sufficient driving frameworks. Other than protocols and open source code, it gives open advanced resources (urban designs, vehicles, buildings) that were made for this reason and can be utilized uninhibitedly. The recreation stage adaptable to sensor suite determination, natural conditions, controlling entirely both static and dynamic actors, generating maps and substantially more. Figure 5.3 shows the screenshot of Carla simulator software.


Figure 5.3: Carla Simulator Software

### 5.3.3 Vision Application

Also a python application developed with dlib library that captures facial behaviors by reading video stream through camera. The application capable of detecting left/right eyes, mouth (Shape Predictor 68 features) and aware of the eye aspect ratio, blinking duration and mouth opening (yawning) patterns. Those gathered data and parameters sent to the server application via web socket. Figure 5.4 represents the interface of vision application.

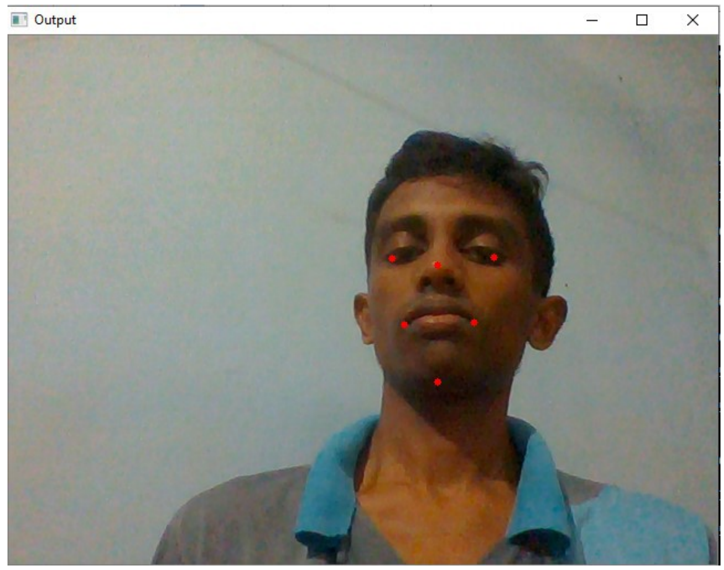


Figure 5.4: Facial Expression Detection in Vision App

### 5.3.4 Smart Watch App and Companion App

For the task of reading heart rate sensor data; a Fitbit application is developed using java script language (run on FitBit OS). This application sends the data to the companion mobile app via the Fitbit messaging framework. Companion app follows the same procedure as the vision application by sending data to the server application via web socket. Figure 5.5 shows the emulator of the smart watch and sensor application.

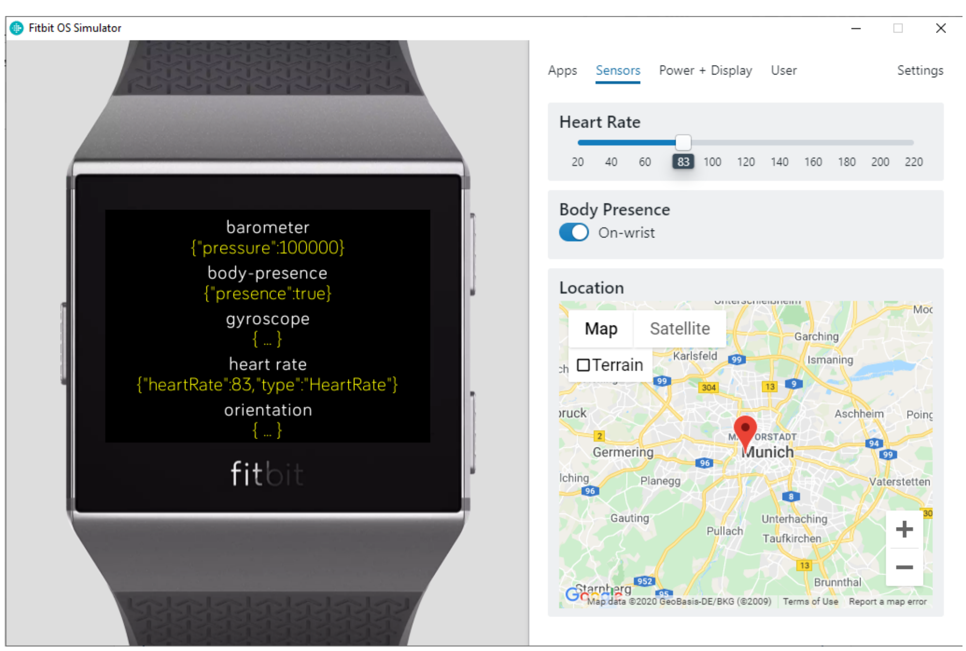


Figure 5.5: Smart Watch Application

### 5.3.5 Grip Force Reader

Grip force reader is an Arduino application that has been deployed on micro controller (ESP 32 development board) to read the hand grip force data from the Flexiforce pressure sensor. The grip pressure value on the steering wheel has been converted into numerical value according to the variability of the resistance of the sensor.

## 5.4 Implementation of Fuzzy Model

For the task of developing a fuzzy model, Python library called Scikit-fuzzy is used. Library contains its own fuzzy rule sets and logic algorithms as a substitute for SciPy Stack written in python language.

Following code segment is used to generate membership function according to the given range.

```
heart_rate = ctrl.Antecedent(np.arange(60, 81, 1), 'heart_rate')
eye_closure = ctrl.Antecedent(np.arange(0, 0.7, 0.1), 'eye_closure')
eye_close_dur = ctrl.Antecedent(np.arange(0, 101, 1), 'eye_close_dur')
mouth_openness = ctrl.Antecedent(np.arange(0, 0.9, 0.1), 'mouth_openness')
yawning_dur = ctrl.Antecedent(np.arange(0, 101, 1), 'yawning_dur')
grip_pressure = ctrl.Antecedent(np.arange(6, 20, 1), 'grip_pressure')
steering_variability = ctrl.Antecedent(np.arange(0, 101, 1), 'steering_variability')

result = ctrl.Consequent(np.arange(0, 101, 1), 'result')

# Auto-membership function generation
heart_rate.automf(3, variable_type='quant')
eye_closure.automf(3, variable_type='quant')
eye_close_dur.automf(3, variable_type='quant')
mouth_openness.automf(3, variable_type='quant')
yawning_dur.automf(3, variable_type='quant')
grip_pressure.automf(3, variable_type='quant')
steering_variability.automf(3, variable_type='quant')
```

Following code segments is used to define fuzzy rules and ranges of fuzzy results.

```
result[O_LOW] = fuzz.trapmf(result.universe, [-1, 0, 13, 25])
result[O_MEDIUM] = fuzz.trapmf(result.universe, [13, 25, 38, 50])
result[O_HIGH] = fuzz.trapmf(result.universe, [38, 50, 63, 76])
result[O_HIGHEST] = fuzz.trapmf(result.universe, [63, 76, 89, 101])

rule1h = ctrl.Rule(
    mouth_openness[I_HIGH] & yawning_dur[I_HIGH] & eye_closure[I_LOW] & eye_close_dur[I_HIGH], result[O_HIGHEST])
rule2h = ctrl.Rule(
    grip_pressure[I_LOW] & heart_rate[I_LOW] & steering_variability[I_LOW], result[O_HIGHEST])
rule3h = ctrl.Rule(
    yawning_dur[I_HIGH] & eye_close_dur[I_HIGH] &
```

```
    grip_pressure[I_LOW] & heart_rate[I_LOW] & steering_variability[I_LOW], result[O_HIGHEST])
rule4h = ctrl.Rule(
    (mouth_openness[I_HIGH] | yawning_dur[I_HIGH]) & (eye_closure[I_LOW] | eye_close_dur[I_HIGH]), result[O_HIGHEST])
```

For high level data manipulation and calculation, a tool called panda is developed by Wes McKinney. Here it is used as a python library for data manipulations and calculation processes. It is based on the Numpy package and DataFrame is its key data structure. DataFrames permit users to store and control tabular information in rows of observations and columns of variables.

## 5.5 Summary

When it comes to implementation of the system we need to choose the most suitable tools and technologies according to their capabilities. Here we implemented our application as client-server architecture with independent software modules which have the ability to communicate with each other through socket API.

Programming language is the most important factor in the success of a project when developing these types of systems. There are various programming languages available and commonly used for research based projects such as Fortran, Python, Matlab etc. Among these languages we choose Python for implementing our main model of the system considering the capability of that language. Python is the most powerful language that supports scientific computation including numerical analysis, visualization, machine learning algorithms etc. Not only the evaluation model development, our server and vision modules are completely written in python. Python has high capability to work with I/O operations such as real-time streaming and that functionality is most useful when capturing facial expressions of the driver in real time via the camera. As well as that includes. Python frameworks such as Django provide flexibility to build server applications with APIs and that feature is especially useful when migrating this system for a cloud based environment. Apart from that Carla Simulator is used to build our prototype which provides python API to communicate with other integrated applications. In addition to that we used Java script language for develop smart watch application that also very light weight programming language and supports the fitbit operating system.

# CHAPTER 6 - EVALUATION

This research project is a proposed new model to identify drowsy levels of the driver using multiple sensory data with high accuracy rather than existing applications. This document explains the evaluation methods that will be used to test our proposed drowsiness detection model.

According to biological phenomena, there is a link between human heart rate and grip force pressure with drowsiness. Within this research we conduct an evaluation for identifying the relationship between drowsiness of the driver with heart rate and grip pressure on the steering wheel and discuss how to vary the behaviors of the vehicle such as speed, acceleration, steering angle etc.

In this project we will conduct usability evaluation and capture two types of data which are qualitative data and quantitative data. Quantitative data will be collected from the output of the application and qualitative data will be collected through the feedback of participants.

## 6.1 Usability Evaluation

Usability evaluation is a core concept for research and which is an assignment of the user experience to identify the usability issues. It also focuses on measuring product quality and coverage of the research objectives.

The drowsiness detection model was tested and evaluated using simulated driving environment. Following items were used to build up a simulated environment and capture the input parameters.

- Laptop computer was used to process the input data. All sensors were connected to the computer and software applications such as processing software, runtime environments, hardware drivers, vehicle simulator software (Carla) will be installed.
- Gaming steering wheel was used to simulate the real driving environment.
- Web Camera, Smart watch, Grip Sensor attached proper places to capture behaviors of the participants.
- Carla Simulator Software which displays the driver's view of a car through a computer terminal and that was used to capture the parameters such as speed, acceleration, steering wheel angle etc. (Smart watch contains an accelerometer, gyroscope sensors and those are supported to capture this information. But in a simulated environment it is not possible to

get this information from a smart watch. Because of that we plan to use the Carla simulator to capture these parameters)

The usability tests take place at the laboratory in a controlled environment with participants of different age groups. The users were requested to sit in front of the camera and drive a vehicle in the simulated environment using a steering wheel gamepad. The grip sensors were attached to the steering wheel and that capture the grip pressure of the participant's hand.  During the experiment, participants worn the smart watch that is communicated with the drowsiness detection system in order to receive the heart rate of the person. All the facial expressions were monitored and noted throughout the experiment for analysis.

The purpose of the usability evaluation is to identify the problem areas and potential opportunities to improve the overall effectiveness and efficiency of the system.

## 6.2 Participants and Conditions

To evaluate the application participants were selected randomly to acting as drivers with following variations.

i. Driver characteristics
    - Gender men and women
    - Different age ranges such as 18-30, 30-45, 45-65…
    - After taking meals

ii. Environment characteristics
    - Various light conditions including: daylight, nightlight
    - Different time conditions: Morning, afternoon, night

The duration of the tests varied from one person to another and usually is in the range of 20 or 30 minutes. The participants were selected according to their age, gender to evaluate proposed system. Following Table 6.1 shows sample of combinations.

| Gender | Age | Taking meals |
|---|---|---|
| Male | 18-30 | No |
| Male | 31-45 | No |
| Male | 46-65 | No |
| Male | 65 < | No |
| Female | 31-45 | No |
| Female | 46-65 | No |
| Male | 18-30 | Yes |
| Male | 31-45 | Yes |
| Male | 46-65 | Yes |
| Female | 18-30 | Yes |
| Female | 31-45 | Yes |
| … | … | … |

Table 6.1: Parameter Combination of Participants

After the experiment, self-evaluation about their drowsiness level will be collected from each participant. We asked to mark their drowsiness level according to the Karolinska Sleeping Scale (KSS). Table 6.2 represents the mapping between KSS levels and drowsiness level of our model.

| KSS Level | Level of Proposed Model | Fuzzy Result |
|---|---|---|
| 1 - Extremely alert | 1 – Non Drowsy | Low |
| 2 - Very alert | | |
| 3 - Alert | 2 - Little Drowsy | Medium |
| 4 - Rather Alert | | |
| 5 - Neither alert nor sleepy | 3 - Drowsy | High |
| 6 - Some signs of sleepiness | | |
| 7 - Sleepy, but no difficulty remaining awake | | |
| 8 - Sleepy, some effort to keep alert | 4 - Extremely Drowsy | Highest |
| 9 - Extremely sleepy, fighting sleep | | |

Table 6.2: Mapping of KSS Rate with Drowsiness Level of Proposed System

These self-evaluation results of the drowsiness level of participants will be compared with the results of our drowsiness detection model.

## 6.3 Validation of Parameters

During the experiments, the several parameters such as EAR, mouth openness, heart rate, steering wheel angle, grip pressure etc. have been used for monitoring fatigue and validated them individually. This section represents the continuous measurement of the parameters over time in graphically.

### 6.3.1 Mouth Openness

The following Figure 6.1 represents the test measurement of mouth openness with a 40 seconds duration of where the user simulated both drowsy and non-drowsy behavior. According to this graph, mouth openness of drowsy participant is higher than general participant that indicate a yawning.

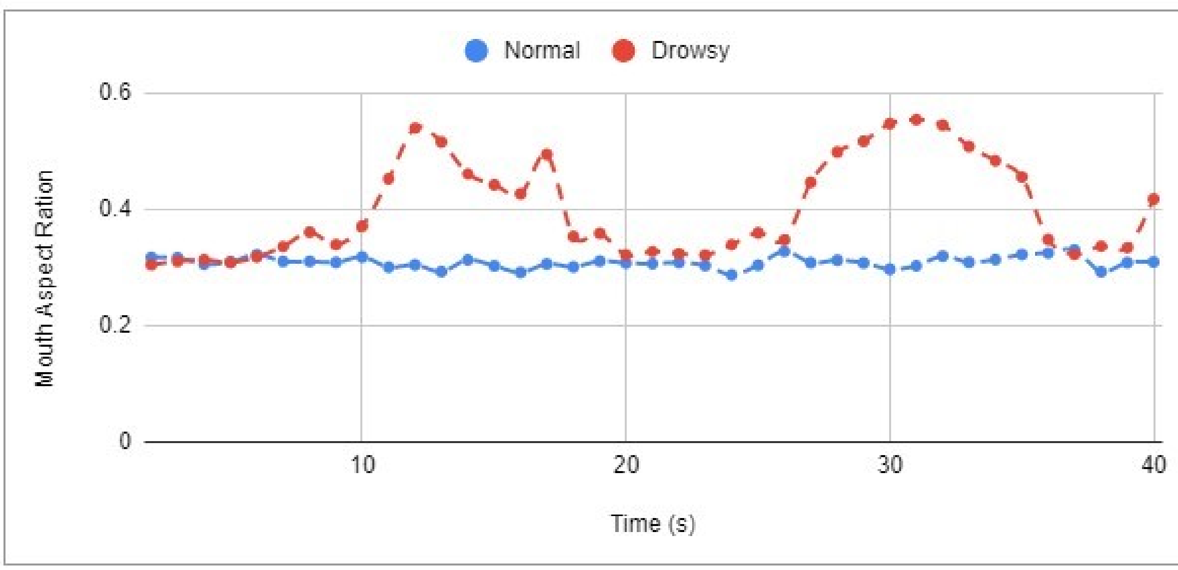


Figure 6.1: Mouth Openness Over Time

### 6.3.2 Eye Aspect Ratio

The following Figure 6.2 represents sample results of Eye Aspect Ratio at drowsiness and non-drowsiness time. The value of EAR becomes lower range for drowsy participant.

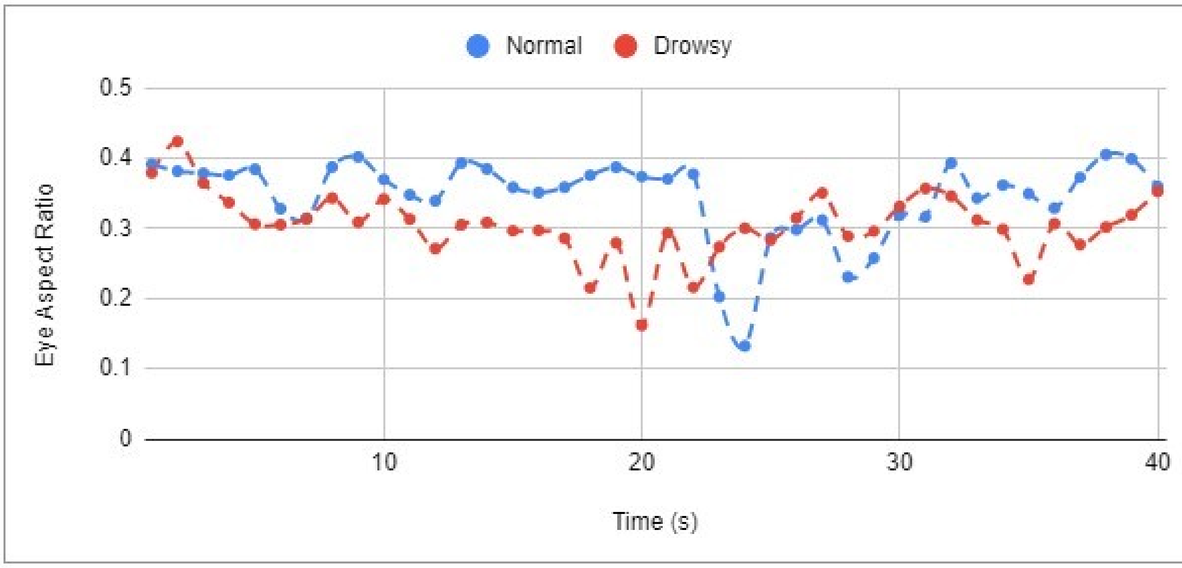


Figure 6.2: EAR Variability Over Time

### 6.3.3 Heart Rate Variability

The following Figure 6.3 shows the heart rate variability over time in both drowsy state and non-drowsy state for same person in 18-30 age range. Person is becoming sleepy heart rate getting decrease.

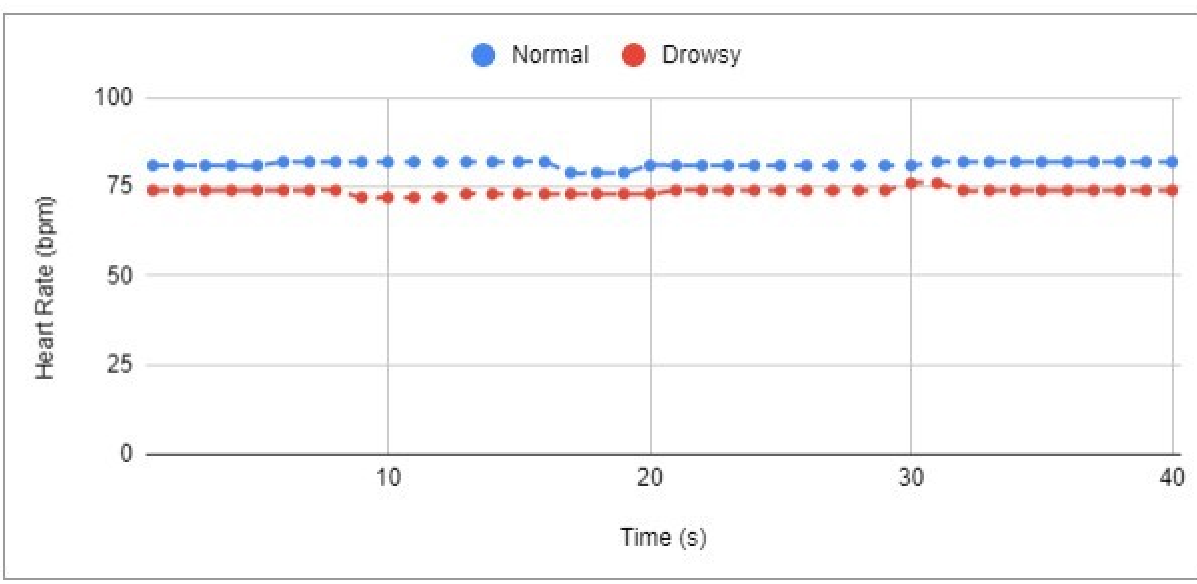


Figure 6.3: Heart Rate Variability Over Time

### 6.3.4 Steering Wheel Angle

The steering wheel movement is very active and frequently changed with small amount for the alert user to maintain the stability of the vehicle. When user becomes drowsy, the small corrections of steering may be reduced and degree of the steering variability close to zero. Figure 6.4 shows the graph of steering wheel variability over time.

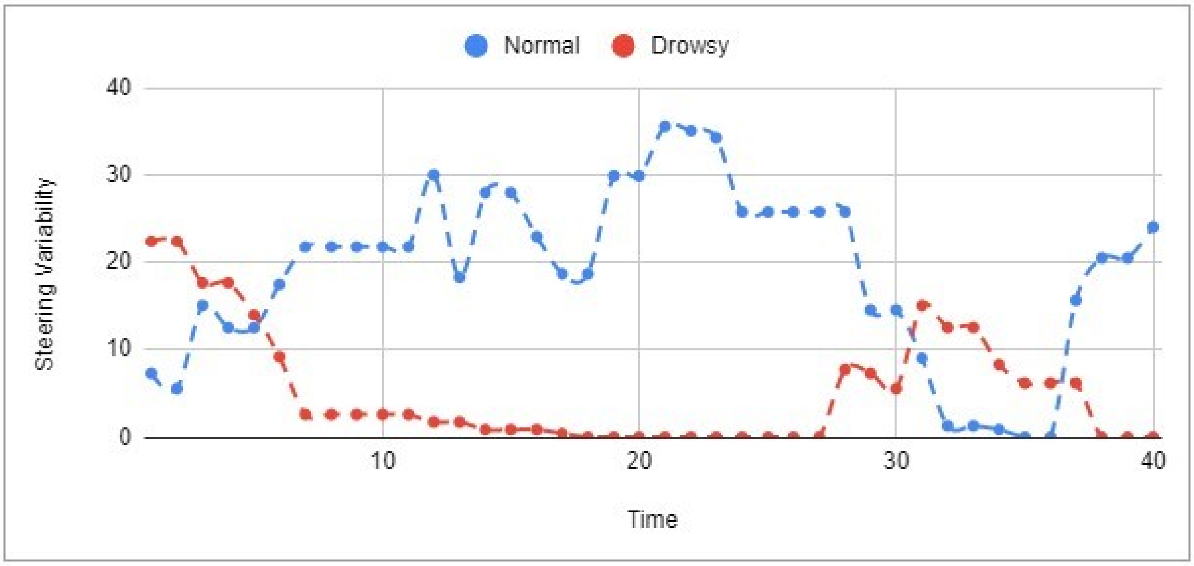


Figure 6.4: Steering Wheel Variability Over Time

### 6.3.5 Grip Pressure Variability

The following Figure 6.5 represents the variability of resistance measured from grip sensor according to the pressure on steering wheel by participant hand. That shows the grip force value of sleepy participant decreases frequently.

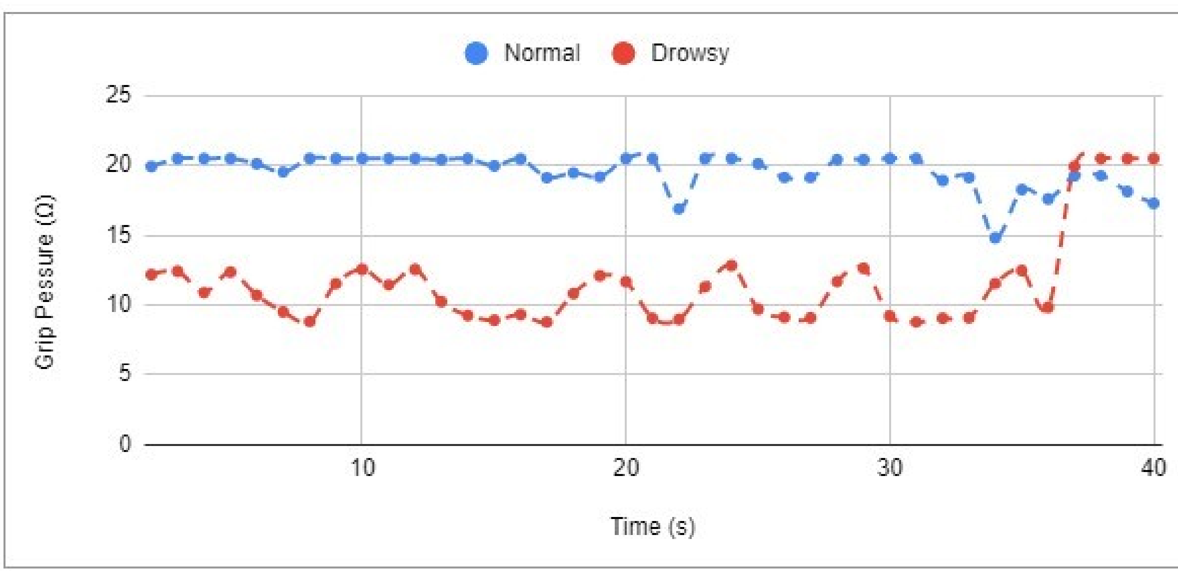


Figure 6.5: Grip Pressure Variability Over Time

## 6.4 Evaluation Results

The multiple sensory data including 7 features were entered to the fuzzy classification model and results were carried out through the experiment. The sample results of the fuzzy model can be illustrated with following Figure 6.6, Figure 6.7 and Figure 6.8.

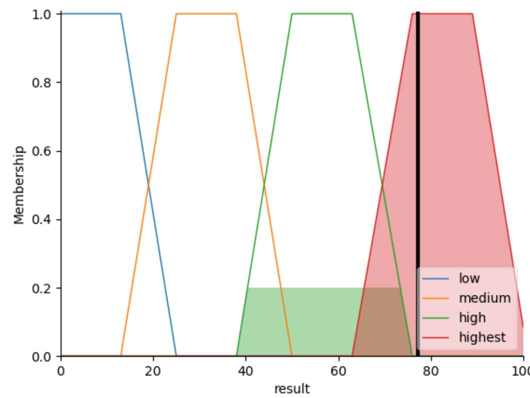


Figure 6.6: Fuzzy Result with Highest Level

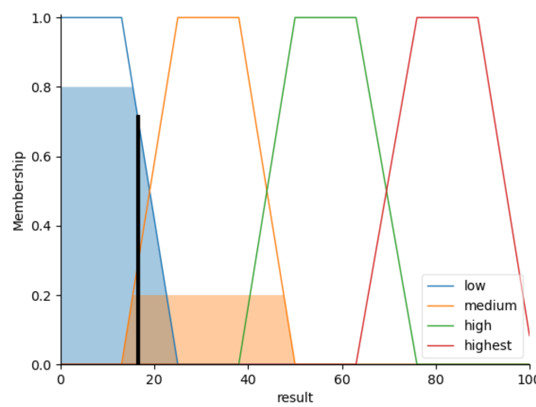


Figure 6.7: Fuzzy Result with Low Level

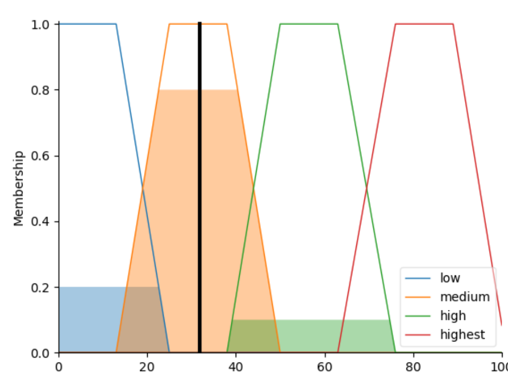


Figure 6.8: Fuzzy Result with Medium Level

Behaviors and sensory data of these 5 peoples were evaluated through application and results will be collected. The following Table 6.2 shows the comparison of user self-evaluation drowsiness rate (KSS) with the drowsiness level evaluated from the classification model. The fourth column of the table represents the expected drowsiness level defined in our system according to the KSS level.

| Participant | Attempt | Drowsy level of Self Evaluation | | Predicted level of Fuzzy Model |
|---|---|---|---|---|
| | | KSS Level | Expected | |
| **1** | 1 | KSS Level 1 | Level 1 | Level 1 |
| **1** | 2 | KSS Level 8 | Level 4 | Level 4 |
| **2** | 1 | KSS Level 1 | Level 1 | Level 1 |
| **2** | 2 | KSS Level 5 | Level 3 | Level 2 |
| **3** | 1 | KSS Level 1 | Level 1 | Level 1 |
| **3** | 2 | KSS Level 6 | Level 3 | Level 2 |
| **4** | 1 | KSS Level 3 | Level 2 | Level 3 |
| **4** | 2 | KSS Level 8 | Level 4 | Level 4 |
| **5** | 1 | KSS Level 1 | Level 1 | Level 1 |
| **5** | 2 | KSS Level 6 | Level 3 | Level 3 |

Table 6.3: Experimental Results

## 6.5 Performance Evaluation

After implementing the entire application performance testing was done for introduced algorithm and hardware devices. Python applications and algorithms were tested using profiler tool called "cProfile". The performance of hardware devices and data transfer methods was monitored using testing tools.

# CHAPTER 7 - CONCLUSION AND FUTURE WORKS

## 7.1 Conclusion

As described in previous chapters drowsiness causes a major reason for automobile accidents. It is very essential to identify driver fatigue states in early stages for preventing road accidents or minimize the dangerous situations. In this work, we tended to drive state classification dependent on facial behaviors and various sensory data collected through the specific sensors.

After performing comprehensive subject review we recommend most significant parameters as heart rate variability, grip pressure of hand, eye features and yawning behavior that are reflecting directly to level of drowsiness. Among these parameters facial expression plays a major role in drowsiness recognition and those have been captured through computer vision-based expression analysis. Through the process of vision based approach some potential challenges that have been identified due to deviation of the intensity of light, maintaining the accuracy of computer vision algorithms and managing image resolution when the face/head moves out of the camera view etc. When considering the vehicular parameters we identified steering wheel variability is the major factor that may be related to the drowsy driving according to the literature review. Based on our experiment human physiological parameters are more powerful than vehicular parameters in order to identify the drowsiness state of the driver. The discussing about another the main objective of over research, use of fuzzy model to detection drowsy driving and that facilitate to include expert knowledge related to the biological area. The proposed model can detect fatigue levels according to the input parameters based on the pre-defined knowledge base. Design and implementation chapters demonstrates the prototype of drowsiness detection system that has been built including the modern devices, sensors and software components. To enhance the model with deep learning techniques, the main challenge we faced is not being able to find a proper standardized data set. From the evaluation results, the system able to predict drowsy and non-drowsy states properly but it is hard to classify the intermediate states which are level 2 and level 3. According to feedback the usability evaluation the proposed system was implemented with comfortable sensors and user friendly manner. Based on these information the proposed system able to identify the drowsy driving in early stage to prevent the road accidents.

## 7.2 Future Works

It's a crucial requirement to enhance current implementation to the next level. In the current implementation it is only concerned about avoiding tragic accidents during drowsy driving by looking at the driver's perspective. In the next level, the system is going to evolve as a fully car automation system based on these perspectives. Which are suitability of vehicle components and functionalities, outside environment except driver and the vehicle and behavioral and mental status of the driver.

By concerning behavioral and mental status of the driver these are the possible approaches need to be taken in future implementation. Evaluation and improvement of existing algorithms for varied lighting conditions, more precisely, real in-vehicle lighting conditions especially during night time is necessary. To avoid the inconsistencies due to intensity of the lighting issues, if the face detection camera unable to read the exact face impression of the driver system going to keep track and maintain several impression analyzing and prediction modules in different lighting scenarios. So system going to keep track drivers face using selected module for a particular lightning intensity. Crucial enhancements need to be done for considering fusing more visual cues, such as face touches, wearing glasses and sunglasses etc.

Researchers have found in stressed situations such as crowded areas with high traffic jam may causes to unexpected accidents. Using heart & pulse rate increment in same route in a same time in every day for a daily traveler, system going to keep track those details and wish to implement a specific module to mitigate and reduce stress level of driver (e.g. turn on the music radio & adjust a/c level of the vehicle).

Integration of several sensors with latest technology takes a main endorsement in enhancing the current system. High functional PIR sensors (Pyroelectric Infrared Sensors) can be used to increase detecting accuracy of human behavior. These sensors mainly consider direction, position, shape and speed of the human movement.

As initial step we used the fuzzy model to evaluate the drowsy driving and in the next step machine learning techniques can be used to build a model for high accurate predictions. The fuzzy model can be enhanced using genetic algorithms to find the range of values of the membership functions. The deep learning methodologies like LSTM can be used to determine the drowsy state of the driver with higher accuracy.

Necessary security mechanism will be added as additional feature for people with serious medical conditions, if system detects this kind of a symptoms from the driver AI is going to keep track about vehicle speed, distance to whatever the front object, gaps between road sides and taking control of the vehicle according to above mentioned deep learning standards.

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# APPENDIX

## Appendix A: Evaluation Survey

**Information Sheet for Research Participants**

**Name of the experiment:** Driver drowsiness detection for preventing accidents

We would like to invite you to take part in an experiment. Here, you will find relevant information about the study which will help you decide whether to take part or not. You may choose whether or not to participate. Before getting involved in our experiment you can ask any questions you have and you should be able to obtain satisfactory answers from them. In addition, you may withdraw without giving any reason and without consequences.

Please understand that your participation is voluntary and you have the right to withdraw your consent or discontinue participation at any time in any experiment without penalty. You have the right to refuse to answer particular questions. Your individual privacy will be maintained in all published and written data resulting from the studies. If you are dissatisfied at any time with any aspect of the studies, you may contact anonymously, through the email tpriyath@gmail.com or by phone 0766967479) directly.

1. **What is the purpose of the research?**

The main objective of this research is to provide highly accurate solution for identifying driver drowsiness to prevent harmful road accidents. In other words, this work aims to build an application to capture behaviors and biological measures of driver with different sensors and predict the driver's drowsiness in early stage before fatal accident.

2. **Why have I been invited?**

You have been chosen because we need to select people with different variations like age ranges( 18-30, 30-45, 45-65,…) gender (male, female), professional drivers and non-professional drivers etc. You are able to represent the some combination of these variations.

3. **Do I have to take part?**

It is up to you to decide whether to participate or not. If you decide to attend, you will. If you do decide to take part you will be able to keep a copy of this information sheet and you should indicate your agreement to the online consent form. You can still leave at any time without giving any reason.

4. **What will the study involve?**

This study is included computer vision part, video processing IOT, Fuzzy rule evaluation model to identify the drowsy driving. You will be able to participate the driving using simulated environment. Facial expressions and sensory data of will be captured through camera and sensors which are evaluated by artificial intelligent model.

5. **Are there any risks in taking part in this study?**

In this research we use various type of sensors such as EEG, PPG etc. to capture physiological data but there are not any biological risk from those sensors. And we stored these video information and sensor data in database securely and we never use that data for any other purposes.

**6. Are there any benefits from taking part in this study?**

There are no immediate benefits to the project participants, and this work is expected to have a beneficial impact on the prevent road accidents by identifying the drowsiness driving. Results are shared with participants to inform their professional work.

**7. Who has reviewed this study?**

The project is a supervised by Dr. G.D.S.P.Wimalaratne from University of Colombo School of Computing (UCSC). This project has been reviewed by the examiners of UCSC according to the standard review procedure.

**8. Who is organizing and funding the research?**

The project is a done by Tharindu Priyath (Post graduate student) and supervised by Dr. G.D.S.P.Wimalaratne (Senior lecturer) from University of Colombo School of Computing (UCSC).

**9. What will happen to the results of the research?**

When the results are likely to be published, where they can obtain a copy of the published results. Apart from that you will not be identified in any report or publication.

**10. Who will know that I am taking part in this research?**

All information we collect about you during the research period will be kept confidential. You will not be identified or identified in any report or publication. Any data you collect about yourself which are stored in cloud database with secure form with passwords and other relevant security procedures and technologies.

**11. What if something goes wrong?**

If you have any complaints about this research project in the first instance you can contact any member of the research team. If you feel your complaint has not been handled to your satisfaction you can contact the University of Colombo School of Computing (UCSC) Registrar and Secretary to take your complaint further.

**PARTICIPANT CONSENT FORM**

**Name of the study:** Driver drowsiness detection using computer vision and artificial intelligence techniques

**Purpose of the study:** The aim of this research is to build an application to detect behaviors of drivers and predict the driver's drowsiness to prevent road accidents.

**Researcher:** Tharindu Priyath

**Supervisor:** Dr. G.D.S.P.Wimalaratne

1. I confirm that I have read and understand the information sheet dated ______________________ concerning participation in experimental studies conducted in the ___________, have had the opportunity to ask questions, and have had satisfactory answers to any questions.
   Yes No

2. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving any reason, and without any adverse consequences.
   Yes No

3. I understand that the information I provide in questionnaires may be looked at by responsible individuals running the experiments. I give permission for these individuals to have access to the information provided for the research project (thesis), and to store anonymized data for further analysis and academic publishing.
   Yes No

4. 4. I understand that this project has been reviewed by, and received ethics clearance through, the Imagineering Institute Research Ethics Committee, and understand how to raise a concern and make a complaint.
   Yes No

5. I understand the potential risks of participating and the support that will be available to me should I become distressed during the course of the research.
   Yes No

6. I understand that the data will not be made available to any commercial organizations but is solely the responsibility of the researcher(s) undertaking this study.
   Yes No

I agree to participate in this study.

________________________ ___________________ _________________

Name of Participant Signature Date

________________________ ___________________ _________________

Researcher Signature Date

# Drowsiness Measurement Survey

**Name** : ______________________________________

**Age** : ☐ 18-30 ☐ 31-45 ☐ 46-45 ☐ 66+

**Sex** : ☐ Male ☐ Female

**Date** : ______________________________________

**Time** : ______________________________________

1. How many hours have you been on the alert?

   ------------------------------------------------------------

2. How many hours of sleep have you gotten in the past 24 hours?

   ------------------------------------------------------------

3. How many hours ago did you last eat?

   ------------------------------------------------------------

4. In the past 2 hours have you consumed any of the beverage like Tea/Coffee, etc.?

   ☐ Yes ☐ No

5. Have you ever driven a vehicle?

   ☐ Yes ☐ No

6. Did you take alcohol in past 24 hours?

   ☐ Yes ☐ No

**Karolinska Sleeping Scale (KSS)**

| Rate No | Level Definition |
|---|---|
| 1 | Extremely alert |
| 2 | Very alert |
| 3 | Alert |
| 4 | Rather Alert |
| 5 | Neither alert nor sleepy |
| 6 | Some signs of sleepiness |
| 7 | Sleepy, but no difficulty remaining awake |
| 8 | Sleepy, some effort to keep alert |
| 9 | Extremely sleepy, fighting sleep |

According to the Karolinska Sleeping Scale as a reference, what is your current degree of drowsiness?

**Rate No:** ☐

**User Feedback about the experiment**

1. Experiment organized and well planned

   ☐ Strongly Disagree ☐ Disagree ☐ Neutral ☐ Agree ☐ Strongly Agree

2. Sensors are comfortable

   ☐ Strongly Disagree ☐ Disagree ☐ Neutral ☐ Agree ☐ Strongly Agree

3. Similar experience of actual driving

   ☐ Strongly Disagree ☐ Disagree ☐ Neutral ☐ Agree ☐ Strongly Agree

**Other Comments:**

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# Appendix B: Evaluation Results

| Participant | Attempt | Age | Gender | Date | Time | KSS Level | Hours have you been on the alert | How many hours of sleep (in past 24 hours) | How many hours ago did you last eat | Consumed any of the beverage in past 2h | Have you ever driven a vehicle | Did you take alcohol in past 24 hours | Experiment organized and well planned | Sensors are comfortable | Similar experience of actual driving |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| No 1 | 1 | 27 | Male | 2020-06-12 | 7:30 AM | 1 | | 6 | 10 | NO | YES | NO | YES | YES | NO |
| No 1 | 2 | 27 | Male | 2020-06-12 | 11:30 PM | 8 | | 6 | 0.25 | NO | YES | NO | YES | YES | NO |
| No 2 | 1 | 32 | Male | 2020-06-16 | 11:10 AM | 1 | | 8 | 4 | YES | YES | NO | YES | YES | NO |
| No 2 | 2 | 32 | Male | 2020-06-16 | 2:15 PM | 5 | | 8 | 0.25 | NO | YES | NO | YES | YES | NO |
| No 3 | 1 | 31 | Female | 2020-06-16 | 11:45 PM | 1 | | 9 | 4.5 | YES | YES | NO | YES | YES | NO |
| No 3 | 2 | 31 | Female | 2020-06-16 | 3:00 PM | 6 | | 9 | 0.5 | NO | YES | NO | YES | YES | NO |
| No 4 | 1 | 69 | Male | 2020-06-12 | 8:15 AM | 3 | | 7 | 11 | NO | YES | NO | YES | YES | NO |
| No 4 | 2 | 69 | Male | 2020-06-12 | 10:00 PM | 8 | | 7 | 1 | NO | YES | NO | YES | YES | NO |
| No 5 | 1 | 67 | Female | 2020-06-12 | 10:25 AM | 1 | | 7 | 3 | NO | NO | NO | YES | YES | NO |

# Appendix C: Code Snippets

```
from collections import Counter

import numpy as np
import skfuzzy as fuzz
import time
from skfuzzy import control as ctrl
import pandas as pd
import threading

from base.process import data_store

I_HIGH = 'high'
I_AVG = 'average'
I_LOW = 'low'

O_HIGHEST = 'highest'
O_HIGH = 'high'
O_MEDIUM = 'medium'
O_LOW = 'low'

heart_rate = ctrl.Antecedent(np.arange(60, 81, 1), 'heart_rate')
eye_closure = ctrl.Antecedent(np.arange(0, 0.7, 0.1), 'eye_closure')
eye_close_dur = ctrl.Antecedent(np.arange(0, 101, 1), 'eye_close_dur')
mouth_openness = ctrl.Antecedent(np.arange(0, 0.9, 0.1), 'mouth_openness')
yawning_dur = ctrl.Antecedent(np.arange(0, 101, 1), 'yawning_dur')
grip_pressure = ctrl.Antecedent(np.arange(6, 20, 1), 'grip_pressure')
steering_variability = ctrl.Antecedent(np.arange(0, 101, 1), 'steering_variability')

result = ctrl.Consequent(np.arange(0, 101, 1), 'result')

# Auto-membership function generation
heart_rate.automf(3, variable_type='quant')
eye_closure.automf(3, variable_type='quant')
eye_close_dur.automf(3, variable_type='quant')
mouth_openness.automf(3, variable_type='quant')
yawning_dur.automf(3, variable_type='quant')
grip_pressure.automf(3, variable_type='quant')
steering_variability.automf(3, variable_type='quant')

# Custom membership functions can be built interactively with a familiar,
# Pythonic API
result[O_LOW] = fuzz.trapmf(result.universe, [-1, 0, 13, 25])
result[O_MEDIUM] = fuzz.trapmf(result.universe, [13, 25, 38, 50])
result[O_HIGH] = fuzz.trapmf(result.universe, [38, 50, 63, 76])
result[O_HIGHEST] = fuzz.trapmf(result.universe, [63, 76, 89, 101])

rule1h = ctrl.Rule(
    mouth_openness[I_HIGH] & yawning_dur[I_HIGH] & eye_closure[I_LOW] & eye_close_dur[I_HIGH], result[O_HIGHEST])
rule2h = ctrl.Rule(
    grip_pressure[I_LOW] & heart_rate[I_LOW] & steering_variability[I_LOW], result[O_HIGHEST])
rule3h = ctrl.Rule(
    yawning_dur[I_HIGH] & eye_close_dur[I_HIGH] &
    grip_pressure[I_LOW] & heart_rate[I_LOW] & steering_variability[I_LOW], result[O_HIGHEST])
rule4h = ctrl.Rule(
    (mouth_openness[I_HIGH] | yawning_dur[I_HIGH]) & (eye_closure[I_LOW] | eye_close_dur[I_HIGH]), result[O_HIGHEST])
rule5h = ctrl.Rule(
    yawning_dur[I_HIGH] & eye_close_dur[I_HIGH] &
```

```
    (grip_pressure[I_LOW] | heart_rate[I_LOW]) & steering_variability[I_LOW], result[O_HIGHEST])

rule1m = ctrl.Rule(
    mouth_openness[I_HIGH] & yawning_dur[I_AVG] & eye_closure[I_LOW] & eye_close_dur[I_AVG], result[O_HIGH])
rule2m = ctrl.Rule(
    mouth_openness[I_AVG] & yawning_dur[I_AVG] & eye_closure[I_AVG] & eye_close_dur[I_AVG], result[O_HIGH])
rule3m = ctrl.Rule(
    yawning_dur[I_HIGH] & eye_close_dur[I_HIGH] &
    grip_pressure[I_AVG] & heart_rate[I_AVG] & steering_variability[I_LOW], result[O_HIGH])
rule4m = ctrl.Rule(
    yawning_dur[I_AVG] & eye_close_dur[I_AVG] &
    (grip_pressure[I_AVG] | heart_rate[I_LOW]) & steering_variability[I_AVG], result[O_HIGH])
rule5m = ctrl.Rule(
    yawning_dur[I_AVG] & eye_close_dur[I_AVG] &
    (grip_pressure[I_LOW] | heart_rate[I_AVG]) & steering_variability[I_LOW], result[O_HIGH])

rule1l = ctrl.Rule(
    mouth_openness[I_AVG] & yawning_dur[I_LOW] & eye_closure[I_AVG] & eye_close_dur[I_LOW], result[O_MEDIUM])
rule2l = ctrl.Rule(
    mouth_openness[I_AVG] & yawning_dur[I_AVG] & eye_closure[I_AVG] & eye_close_dur[I_LOW], result[O_MEDIUM])
rule3l = ctrl.Rule(
    yawning_dur[I_AVG] & eye_close_dur[I_AVG] &
    grip_pressure[I_AVG] & heart_rate[I_AVG] & steering_variability[I_AVG], result[O_MEDIUM])
rule4l = ctrl.Rule(
    yawning_dur[I_AVG] & eye_close_dur[I_AVG] &
    (grip_pressure[I_AVG] | heart_rate[I_HIGH]) & steering_variability[I_HIGH], result[O_MEDIUM])
rule5l = ctrl.Rule(
        yawning_dur[I_AVG] & eye_close_dur[I_AVG] &
        (grip_pressure[I_HIGH] | heart_rate[I_AVG]) & steering_variability[I_AVG], result[O_MEDIUM])
    rule6l = ctrl.Rule(
        (yawning_dur[I_AVG] & eye_close_dur[I_AVG] &
         grip_pressure[I_AVG] & heart_rate[I_AVG]) | steering_variability[I_AVG], result[O_MEDIUM])

    rule1n = ctrl.Rule(
        mouth_openness[I_LOW] & yawning_dur[I_LOW] & eye_closure[I_HIGH] & eye_close_dur[I_LOW], result[O_LOW])
    rule2n = ctrl.Rule(
        yawning_dur[I_LOW] & eye_close_dur[I_LOW] &
        grip_pressure[I_HIGH] & heart_rate[I_HIGH] & steering_variability[I_HIGH], result[O_LOW])
    rule3n = ctrl.Rule(
        yawning_dur[I_LOW] & eye_close_dur[I_LOW] &
        (grip_pressure[I_AVG] | heart_rate[I_AVG]) & steering_variability[I_HIGH], result[O_LOW])
    rule4n = ctrl.Rule(
        yawning_dur[I_LOW] & eye_close_dur[I_LOW] &
        grip_pressure[I_HIGH] & heart_rate[I_HIGH] & steering_variability[I_AVG], result[O_LOW])

    result_ctrl = ctrl.ControlSystem(
        [rule1h, rule2h, rule3h, rule4h, rule5h, rule1m, rule2m, rule3m, rule4m, rule5m, rule1l, rule2l, rule3l, rule4l,
         rule5l,
         rule6l,
```

```
         rule2n, rule3n, rule4n])
    process_model = ctrl.ControlSystemSimulation(result_ctrl)


    def calculate_final_state(result_list):
        res_dic = Counter(result_list)
        print(res_dic)


    def process_data():
        print("Process Data...")
        result_list = []
        while True:

            if data_store.facial_exp_data and data_store.wrist_band_data and data_store.grip_pressure_data and data_store.vehicle_data:
                wrist_band_data_temp = sorted(data_store.wrist_band_data.copy(), key=lambda k: k['timeStamp'])
                df_wrist_band_data = pd.DataFrame(wrist_band_data_temp)
                facial_exp_data_temp = sorted(data_store.facial_exp_data.copy(), key=lambda k: k['timeStamp'])
                df_facial_exp_data = pd.DataFrame(facial_exp_data_temp)
                grip_pressure_data_temp = sorted(data_store.grip_pressure_data.copy(), key=lambda k: k['timeStamp'])
                df_grip_pressure_data = pd.DataFrame(grip_pressure_data_temp)
                vehicle_data_temp = sorted(data_store.vehicle_data.copy(), key=lambda k: k['timeStamp'])
                df_vehicle_data = pd.DataFrame(vehicle_data_temp)

                param_list_df_1 = pd.merge(df_wrist_band_data, df_facial_exp_data, on='timeStamp')
                param_list_df_2 = pd.merge(param_list_df_1, df_grip_pressure_data, on='timeStamp')
                param_list_df = pd.merge(param_list_df_2, df_vehicle_data, on='timeStamp')
                print(param_list_df)
                for ind in param_list_df.index:
                    try:
                        process_model.input['heart_rate'] = int(param_list_df['heartRate'][ind])
                        process_model.input['eye_closure'] = int(param_list_df['EAR'][ind])
                        process_model.input['eye_close_dur'] = int(param_list_df['eyeClosureDur'][ind])
                        process_model.input['mouth_openness'] = int(param_list_df['mouthOpenness'][ind])
                        process_model.input['yawning_dur'] = int(param_list_df['mouthOpenDur'][ind])
                        process_model.input['grip_pressure'] = int(param_list_df['gripPressure'][ind])
                        process_model.input['steering_variability'] = int(param_list_df['steerVariability'][ind])

                        process_model.compute()
                        res = process_model.output['result']
                        if 0 < res <= 20:
                            result_level = 1
                        elif 20 < res <= 40:
                            result_level = 2
                        elif 40 < res <= 60:
                            result_level = 3
                        else:
                            result_level = 4

                        result_list.append(result_level)
                        if len(result_list) == 10:
```

```python
                        result_list.remove(0)
                    calculate_final_state(result_list)

                except Exception as e:
                    print(e)

            for p in facial_exp_data_temp:
                data_store.facial_exp_data.remove(p)
            for p in wrist_band_data_temp:
                data_store.wrist_band_data.remove(p)
            for p in grip_pressure_data_temp:
                data_store.grip_pressure_data.remove(p)
            for p in vehicle_data_temp:
                data_store.vehicle_data.remove(p)

        time.sleep(2)
        # print(param_list)


class FuzzyThread(threading.Thread):
    def __init__(self):
        threading.Thread.__init__(self)

    def run(self):
        print("Starting Thread")
        process_data()
        print("Exiting Thread")


def init():
    print("Init Fuzzy Processor")
    try:
        # _thread.start_new_thread(process_data, ("Thread-Process",))
        thread = FuzzyThread()
        thread.start()
    except Exception as ex:
        print(ex)
        print("Error: unable to start thread")


def test_model():
    process_model.input['heart_rate'] = 80
    process_model.input['eye_closure'] = 0.6
    process_model.input['eye_close_dur'] = 1
    process_model.input['mouth_openness'] = 0.2
    process_model.input['yawning_dur'] = 5
    process_model.input['grip_pressure'] = 10
    process_model.input['steering_variability'] = 9
    process_model.compute()
    result.view(sim=process_model)
    res = process_model.output['result']

    process_model.input['heart_rate'] = 62
    process_model.input['eye_closure'] = 0.6
    process_model.input['eye_close_dur'] = 60
    process_model.input['mouth_openness'] = 0.6
    process_model.input['yawning_dur'] = 60
    process_model.input['grip_pressure'] = 18
    process_model.input['steering_variability'] = 10
    process_model.compute()
    result.view(sim=process_model)
    res = process_model.output['result']

test_model()
```