REAL-TIME DRIVER DROWSINESS DETECTION USING OPENCV WITH KERAS CONVOLUTIONAL NEURAL NETWORK

A Thesis Presented to
the Graduate Program
College of Engineering and Technology
Pamantasan ng Lungsod ng Maynila

In Partial Fulfillment of the Requirements for the Degree
of Bachelor of Science in Computer Engineering

By
Alim, Andrea Gail M.
Dalangin, John Rey G.
Fajel, Kenneth Q.
Racelis, Glorie Alynna C.
Robles, John Joe Rimuel P.
Siochi, Jamie Anne S.

Engr. Eufemia A. Garcia
Engr. Maria Rizette H. Sayo
Thesis Advisers

August 2022

APPROVAL SHEET

The thesis hereto titled

REAL-TIME DRIVER DROWSINESS DETECTION USING OPENCV WITH KERAS CONVOLUTIONAL NEURAL NETWORK

prepared and submitted by Alim, Andrea Gail M., Dalangin, John Rey G., Fajel, Kenneth Q., Racelis, Glorie Alynna C., Robles, John Joe Rimuel P. and Siochi, Jamie Anne S. in partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Engineering has been examined and is recommended for acceptance and approval for **ORAL EXAMINATION**.

Engr. Eufemia A. Garcia Adviser 1	Engr. Maria Rizette H. Sayo Adviser 2

PANEL OF EXAMINERS

Approved by the Committee on Oral Examination
with a grade of _________ on _______.

____
Panel Chair
Chairman

________________________ Panel Member Member	________________________ Panel Member Member

Accepted and approved in partial fulfilment of the requirements for the degree of Bachelor of Science in Chemical Engineering.

________________________ Dr. Denvert C. Pangayao Director Graduate Program	________________________ Dr. Clydelle M. Rondaris Dean College of Engineering and Technology

ABSTRACT

Accidents can be triggered by Drowsiness. Drowsiness reduces the attention of drivers, hinders quick reactions and impacts a driver's capacity for decision-making while driving. This Real-time Driver Drowsiness Detection using OpenCV with Keras Convolutional Neural Network uses digital image processing, machine learning object detection algorithms, and model training methods to monitor the driver's facial movements, reducing the need for human intervention and helping to reduce accidents and fatalities.

This driver drowsiness detection system can assess whether the driver's eye is closed by utilizing a Python-based Anaconda Jupyter Application and can inform the driver by sounding an alarm. The system was tested using the following variables, which produced correct results: Drowsiness Level, Face Angle, Lighting Conditions, Eye Coverage, Eye Accessories, and Eye Shape.

The system made was able to input an image from the camera, was able to classify a face and the eyes, was able to create Region of Interest, was able to feed the image to the classifier that identifies if the eyes are open nor close and was able to calculate the time to check of the person is drowsy or not using Keras Convolutional Neural Network with PERCLOS method.

A pre-trained Inception V3 model was used for the training algorithm. The model training algorithm was also used since it uses transfer learning that reduces the time for the model to train. This was implemented using the TensorFlow application for the convenience that it takes an input as a multidimensional array.

ACKNOWLEDGEMENTS

The researchers would like to acknowledge Engr. Perferinda Caubang, Engr. Evangeline Lubao, Engr. Evelyn Carolino, Engr. Eufemia Garcia and all the Computer Engineering Department Faculty.

This Thesis would not be possible without the support of all the researchers' family, friends, and mentors. Deepest gratitude to their professors, Engr. Eufemia A. Garcia and Engr. Maria Rizette Sayo generously provided knowledge, expertise, and guidance throughout the process of making this Paper. The researcher couldn't have done it without your help.

The researchers would like to give their special thanks to their parents and loved ones, as their belief and trust kept the researcher's spirits and motivation high during this process.

The researchers would like to acknowledge the Computer Engineering Department Chairperson, Engr. Perferinda Caubang for the endless support through their College years.

Lastly, thanks to anyone who wasn't mentioned above but instrumental in this project. The researchers will always be glad and humbled with all your generosity.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Accidents can occur anytime, anyplace, but one of the most typical places they occur is on the road. Accidents occur for a variety of reasons, including the high volume of moving vehicles, people and/or animals crossing the road, nearby buildings, infrastructure on the road and on the sidewalk, drowsiness driving, and many other factors. One specific example is a long travel, especially at night, can be risky because tired or nodding-off drivers are more common. In fact, drowsiness is one of the primary reasons why drivers make mistakes, according to the American Automobile Association (LeBeau, 2018). As reported by the UK Department of Transport, twice as many accidents as those caused by speeding, one in ten incidents are caused by drivers falling asleep behind the wheel. In a recent study by the US Centers for Disease Control and Prevention (CDC) that was reported in the Morbidity and Mortality Weekly Report (Buban, 2013), researchers discovered that snoring and short sleep duration were both independently linked to an increased risk of drowsy driving. Driving while fatigued might be just as risky as drinking and driving.

In the Philippines, driving drowsiness or the steady decline in attention that results in sporadic dozing off and eventually sleep cause hundreds of auto accidents each year. While it may be difficult to pinpoint which of the roughly 90,000 traffic accidents that take place in the nation each year could be linked to road fatigue and drowsiness (Buban, 2013), data from the Public Works Department, Metropolitan Manila Development Authority, and the Philippine National Police-Highway Patrol Group revealed that in 2011, there were 85,820 traffic accidents that were recorded, resulting in close to 2,000 fatalities and nearly 29,000 injuries. Despite the fact that, unlike with alcohol, it is still impossible to determine whether a driver who was involved in an accident was fatigued or drowsy, the British Royal Society for the Prevention of Accidents estimates that driver fatigue accounts for up to 20% of traffic accidents and up to 25% of fatal and serious accidents (Buban, 2013). It's interesting to note that Cardiff University researchers in the UK discovered that driver fatigue after a few hours has a similar impact to driving when intoxicated (Buban, 2013).

According to a 2010 study, three hours behind the wheel at night might make drivers behave as though they are drunk. Furthermore, the same study discovered that even two hours of nighttime driving can have the same negative effects on performance as a few drinks. Driving while sleep deprived is risky in the Philippines. "While the majority of individuals are aware of the risks associated with drunk driving, many are unaware that drowsy driving can be just as deadly. Sleepiness, like alcohol, slows reaction times, reduces awareness, clouds judgment, and raises the danger of a collision, according to Daisy Jacobo, director of the Land Transportation Office's Traffic Safety Division (Buban, 2013).

When traveling at 100 kph, even a brief time of dozing off can be exceedingly dangerous since it can cause the driver to lose control and go roughly 30 meters. This is more than enough space to cause the driver to crash into a ditch, hit a tree, an approaching car, or even worse, a pedestrian. In a separate study, 14 healthy young men between the ages of 21 and 25 were recruited to determine the extent to which fatigue impairs driving performance (Soleimanloo et al., 2017). The study was carried out by researchers at Utrecht University in the Netherlands. Each driver, under supervision, was required to maintain a steady speed of 129 kph on the highway and stay in the center of the traffic lane for two, four, or eight hours at a period during the night.

The findings, which were reported in the Journal of Sleep Research, demonstrated that after just two hours behind the wheel, the drivers were already engaging in behaviors according to blood alcohol concentrations of 0.05 percent, which is already more than twice the legal limit for driving in the UK. However, it should be interesting to note that law for professional truck and public transport drivers in Europe requires them to not drive without a break—driving time should not exceed 9 hours per day or 56 hours per week. The maximum number of hours to safely drive per day varies from driver to driver and situation to situation. It's crucial to keep drowsy drivers off the road, but it can be challenging. One solution to deal with this problem is to be able to identify drowsy drivers and warn them to drive carefully and take a rest if they feel sleepy. By detecting drowsiness, accidents caused by microsleep, tiredness, and inattentiveness can be avoided. A Driver Drowsiness Detection System in most cases is a tool or component of advanced driver assistance systems (Wessel, 2022). These are technologies and systems aimed at making driving safer and reducing the likelihood of catastrophic road traffic accidents being caused by human error. These may include automatic emergency braking, a warning if something is in the driver's blind spot, alert systems such as alarms, and the like.

Driver Drowsiness Detection systems use cameras, eye or facial tracking sensors, and other hardware to measure visual indicators and parameters. Drowsiness can be identified by yawning frequency, eye blinking frequency, eye gaze movement, head movement, and facial expressions. These systems have the ability to watch driving input behavior, alert the driver to errant lane changes, pedal use, steering movements, and detect facial movements, and alarms (Wessel, 2022). Some of the current systems and various technologies that can be used to detect driver's drowsiness are the following: steering pattern monitoring, vehicle position in lane monitoring, driver eye and face monitoring, physiological measurement, and digital image recognition and sensor.

Advanced Driver Assistance Systems (ADAS) Technology, such as systems that detect driver drowsiness, is quickly becoming the norm. Many different forms of ADAS equipment will be standard on US automobiles, as technology becomes more and more practical for supporting drivers and enhancing road safety (Benson et al., 2018). Another example is the 2018 Cadillac CT6. The Cadillac Super Cruise system, an infrared camera the size of a gumdrop mounted on the steering wheel column can precisely ascertain the driver's level of attentiveness. Under a wide range of daytime and nighttime driving conditions, a precise measurement of head orientation and eyelid movements is used to ascertain the driver's attention status. A light bar built into the steering wheel will flash to draw the driver's attention back to the road if they glance away from it or close their eyes for longer than a few seconds. The system will deploy a series of escalating visual, audio, and seat vibration alerts if it decides that the driver is continuing to purposefully or unintentionally neglect the road, culminating in an automatic safety stop if the driver is unable to do so (Shenouda, 2017).

In a proposed study, using the Image Processing Drowsiness Detection System, to gauge one's state of sleepiness, drowsiness-related factors including eye movements are noticed and examined (Poursadeghiyan et. al., 2018). The visual signs of intoxication could be picked up by taking a picture of the driver and using image processing (Khan & Mansoor, 2008). The eyes are comparatively more significant than other facial features, and numerous studies on how to process eye health have been done. For instance, the IR Illuminator used variables like PERCLOS (Percentage of Eye Closure), duration of eyes closure, and frequency of blinks to assess the level of attentiveness (Bergasa, et.al. 2006). The only basis for the detection of sleepiness was PERCLOS. A tiny camera was used to conduct the observation test, which had a 98% accuracy rate for identifying the degree of drowsiness (Liu et al., 2010).

In the Philippines, a study on Driver Drowsiness Detection based on Eye Movement and Yawning Using Facial Landmark Analysis study used a 300W dataset and the application of API Based Histogram of Oriented Gradients and Linear Support Vector Machine approach. This makes it possible to recognize faces and classify them, perform Random Forest Regression on each tree with two node splits to identify facial landmarks and extract Euclidean Distance points from the eyes and mouth to determine tiredness based on eye closure and yawning. The findings demonstrated that in both of the study's two different camera angle configurations, eye closure consistently gave a 100% detection rate. However, there are several limitations to the detection and recognition of yawning and the combination of mouth and ocular drowsiness actions (Ramos et.al., 2019). Quiroz et al., (2020) state that the system was able to detect drowsiness correctly and precisely due to the application of a pre-trained facial landmarks detector, the computation of eye aspect ratio using Euclidean distance, and the appropriate value of the eye aspect ratio threshold. The most crucial parameter in this system is the eye aspect ratio threshold. If it is set too low, the system won't be able to detect drowsiness, and if it is set too high, it may be excessively sensitive to it.

Influenced by the existing devices and the desire to create a Drowsiness Detection System here in the Philippines, the Armada team proposes to develop a system that determines whether the driver’s eyes are closed through Real-time Driver Drowsiness Detection using OpenCV with Keras Convolutional Neural Network. This will assess whether the person is drifting off when their eyes are closed for at least 5 seconds. The system will sound a repeated warning to startle the subject if it recognizes the earlier scenarios. The researchers will create instances such as eye shapes, eye accessories, and other factors to compare results and ensure that the data is accurate. Through this, there is a chance to lessen road accidents caused by driver’s sleepiness or drowsiness and may save the driver’s life and other possible casualties.

1.2 Statement of the Problem

The study on Real-time Driver Drowsiness Detection using OpenCV with Keras Convolutional Neural Network seeks to determine whether a system can contribute to the reduction of accidents and fatalities that occur every year by introducing modern technology-based software that decreases human intervention and monitors every driver's movement. Specifically, it intends to measure the project capabilities by answering the following question:

1. How can the system utilize machine learning object detection algorithms to identify driver drowsiness status?
2. Can the system operate effectively under different scenarios that may possibly affect the recognition capability of the system?
3. How accurate are the facial and eyelid detection capability of the system?
4. Can the system be deployed commercially?

1.3 Objective of the Study

This section offers a comprehensive explanation and a concise understanding of the general and specific objectives of this project entitled, Real-time Driver Drowsiness Detection using OpenCV with Keras Convolutional Neural Network.

1.3.1 General Objective

The goal of this research is to create a system for detecting Real-time Driver Drowsiness Detection using OpenCV with Keras Convolutional Neural Network. It determines whether the driver's eyes close and creates an alarming sound to wake them up. In order to compare and evaluate whether the algorithm produces accurate results, the researchers will also develop scenarios in which various eye shapes, eye accessories, and other variables are trained in the database. This will reduce the likelihood of a traffic collision and the frequent fatalities brought on by drowsy driving. The system will be developed using a Python-based Anaconda Jupyter application.

1.3.2 Specific Objectives

1. To input an image from the camera;
2. To detect face and eyes in the image;
3. To create a Region of Interest (ROI), for both detected face and eyes;
4. To feed the image to the classifier (model), which will categorize whether eyes are open or closed; and
5. To calculate the time to check if the person is drowsy or not.

1.4 Significance of the Study

This research is proposed with the goal of providing crucial information and knowledge regarding any related issues in concern with the chosen title; Real-time Driver Drowsiness Detection using OpenCV with Keras Convolutional Neural Network. Benefiting the study are the various sectors as follows:

The Traffic Monitoring Authority. As this research revolves around traffic monitoring, this industry will be the direct recipient of this study. Any improvement brought by the output of this project can be used to lessen road accidents caused by driver drowsiness. This can also serve as an additional reinforcement to prevent the upwards trajectory of this cause of death every year.

The Car Companies or Businesses. In the business aspect, drowsiness detection will be an additional function in car safety technology. Through this, consumers will be guaranteed that when they purchase a car, it has a feature to keep them extra safe and secured.

The Future Researchers. The majority of forthcoming researchers undertaking comparable and connected studies regarding traffic accidents and driver drowsiness would greatly benefit from the results of this study.

The General Public. Although this study was created with the intention of assisting the traffic monitoring authorities, it will also be useful as a caution to consumers that these incidents are real and will serve as an example of how to avoid being in one of the accidents.

1.5 Scope and Limitations

The goal of this study is to identify Real-time Driver Drowsiness Detection using OpenCV with Keras Convolutional Neural Network. The system will be developed using a Python-based Anaconda Jupyter application. The project will determine whether the subject's eyes are closed when drowsy, yawning, or they're simply nodding off. When the system detects the previous scenarios, it will produce a recurring alarm to startle the subject. The research will also take into account various eye shapes, eye accessories, and other factors that may hinder drowsiness detection. Instances will be produced by the researchers in order to compare outcomes and verify the accuracy of the data. This study will simply examine how the eyes move, excluding any other elements that can contribute to driver drowsiness.

CHAPTER TWO

REVIEW OF RELATED LITERATURE

2.1 Driver Drowsiness Issue

Road accidents have become a major source of concern as they cause a significant number of injuries and fatalities. The World Health Organization (2020) reports that 1.25 million people die worldwide annually as a result of road accidents, an issue that is both predictable and avoidable. In the Philippines, according to the Philippines Statistics Authority (2022), there were 6,440 fatalities related to road accidents between January and September of 2021. Comparing it to the same period in 2020 wherein there are 6,179 deaths, it can be seen that there was an increase of 4.2 percent. With that, in the given period in 2021, road accidents were responsible for 1.4 percent of all fatalities in the country causing road accidents to be ranked as the 15th leading cause of death among Filipinos in 2021.

According to Rafid, et. al. (2020), it is a proven truth that driving while inattentive accounts for a significant portion of road accidents. Driver fatigue and drowsiness have been identified to be contributing factors to inattentive driving. Driver drowsiness is frequently induced by four major factors: sleep, work, time of day, and physical exhaustion. People sometimes strive to do a lot in a day, which causes them to lose important sleep. People frequently stay awake by consuming caffeine or other stimulants. Over the course of several days, the lack of sleep worsens until the body ultimately gives out and falls asleep. Quite a lot of times, the body is affected by the time of day. The human brain is conditioned to believe that occasionally the body ought to be sleeping. They are frequently connected to seeing the dawn and sunset. The brain tells the body to sleep between the hours of 2 AM and 6 AM. The body will eventually crash if the awake duration is prolonged. The last aspect to consider is a person's physical condition. People occasionally take medications that induce sleepiness or suffer from physical conditions that result in these problems. Being physically unfit, either underweight or overweight, will lead to exhaustion. Additionally, the body will become weary more quickly when under mental stress (ROSPA, 2020).

As Sasikala et al. (2018) said, driver drowsiness is one of the major safety hazards now affecting the road transportation sector, and falling asleep behind the wheel is its most dangerous expression. It lacks a triggering event and is instead characterized by a gradual loss of focus on the road and traffic demands. Saini & Saini (2014) stated that fatigue causes sleep and affects response time, both of which are critical elements of safe driving. Additionally, it lowers attentiveness, alertness, and concentration, which makes it harder to execute attention-demanding tasks like driving. Being sleepy slows down how quickly information is processed and it may also affect decision-making standards (Sasikala et al., 2018). The NHTSA (National Highway Traffic Safety Administration) in America conducted a census of fatal crashes and found that drowsy driving accounts for 1.6% of all fatalities in 2020. It is responsible for one out of every eight crashes that result in hospitalization, 71,000 injuries, and almost 100,000 collisions per year (Stewart, 2022).

2.2 Conventional Driver Drowsiness Detection

According to Saini & Saini (2014), a major challenge in the realm of accident avoidance systems is the development of technologies for detecting or preventing drowsiness while driving. One of the devices that have been continuously developed over the years is a drowsiness detector in an automobile which can help to prevent numerous accidents. Accidents can happen as a result of a brief spot of negligence, hence a real-time driver monitoring system is important. This detector should operate with high accuracy and be deployable to an embedded device (Reddy et al., 2017).

Several authors have put forth several methods for drowsiness detection systems, the majority of which use vehicle-based methods and ECG. First is the Steering Wheel Movement (SWM). Driving patterns can be estimated by detecting steering wheel movement, deviation from the lane, or lateral position. To keep the car in a specific lane while driving, micro steering wheel adjustments are necessary. Based on correlations between micro adjustments and drowsiness, one study reached an accuracy of 86 % in drowsiness detection. In the other situation of driving pattern recognition, lane position deviation is used. This tracks the vehicle's position in relation to the lane and evaluates any deviations. However, driving skills, road conditions, and vehicle feature all play a significant role in the driving pattern-based strategies (Jabbar et al., 2018). It is also possible to measure the driver's steering behavior by mounting an angle sensor on the steering column. When driving while drowsy, fewer micro-corrections are made to the steering wheel than when driving normally. According to Sahayadhas et al. (2014), drivers who lack sleep turn the steering wheel less frequently than usual. The researchers only took into account tiny steering wheel motions (between 0.5° and 5°), which are required to alter the lateral position inside the lane, in order to minimize the consequence of lane changes.

Numerous researchers have also thought of using the electrocardiogram (ECG) and electroencephalogram (EEG) as physiological signals to identify drowsiness. Also, there are significant differences in heart rate (HR) between alertness and fatigue and other stages of drowsiness. As a result, drowsiness can also be detected using heart rate, which the ECG signal makes it easy to determine. Others have evaluated drowsiness using Heart Rate Variability (HRV), with low (LF) and high (HF) frequencies in the 0.04-0.15 Hz and 0.14-0.4 Hz ranges. On the other hand, the Electroencephalogram (EEG) is the most often utilized physiological signal to assess drowsiness. The EEG signal has several frequency bands, including the beta band (13-25 Hz), which corresponds to alertness, the alpha band (8-13 Hz), which represents relaxation and creativity, and the theta band (4-8 Hz), which is related to drowsiness, and the delta band (0.5-4 Hz), which corresponds to sleep activity. Drowsiness is indicated by a rise in the theta frequency band and a decrease in the power changes in the alpha frequency band (Ngxande et al., 2017).

In fact, the current approach for addressing drowsy driving is classified as either intrusive systems or nonintrusive systems. The most accurate system is intrusive because it measures physiological signals, but drivers complain that it is annoying because it requires wearing sensors, like the Advance Safety Vehicle (ASV) created by Toyota, Nissan, and Honda that uses a wristband to monitor drowsiness based on the pulse rate. On the other hand, non-intrusive systems concentrate on changes in facial features caused by various lighting conditions, angles of the face, and expressions, such as the observation of eye closure in drowsiness detection because it is considered to be the first and most crucial sign to consider when analyzing the drowsiness of the driver (Ramos, 2019).

2.3 Eye Behavior-based Driver Drowsiness Detection

The most important aspect of drowsiness detection is the eyes and eye region. The majority of drowsiness detection systems compare eye condition and eyelid movement to identify drowsiness. More than any other indicator, the condition of the eyes—whether open or closed—helps detect driver drowsiness. Subconsciously, the eyelid muscles gravitate to hasten the process of getting to sleep (Manu, 2016). The rate of eye blinking and the duration of eye closure are assessed to detect driver drowsiness. Drivers can easily be identified as being drowsy since their eyes blink and stare between their eyelids differ from usual situations. In this technique, the position of the irises and the states of the eyes are tracked over time to estimate the frequency and length of blinking. Additionally, it uses a remotely located camera to capture video, after which computer vision techniques are used to successively localize the positions of the face, eyes, and eyelids in measuring the ratio of closure. One can tell if a driver is drowsy by watching their eyes closed and how often they blink (Sasikala et al., 2018).

According to Han et al. (2019), eyelid movements must first be accurately recognized and represented before features can be extracted from them. A sequence of values that describe the degree of eyelid openness at each sample point can be used to illustrate eyelid movements across time. However, the majority of previous studies, only identified two levels of eyelid openness, which is insufficient for modeling eyelid motions because it is unable to determine the pace of change. There have been some attempts to directly calculate the percentage of eyelid opening from the geometry of the eyes. Moreover, the eye aspect ratio threshold is the most key parameter in this system; if it is too low, the system will not be able to detect drowsiness; if it is too high, the system will be very sensitive to detecting drowsiness (Quiroz et al., 2020).

CHAPTER THREE

THEORETICAL FRAMEWORK

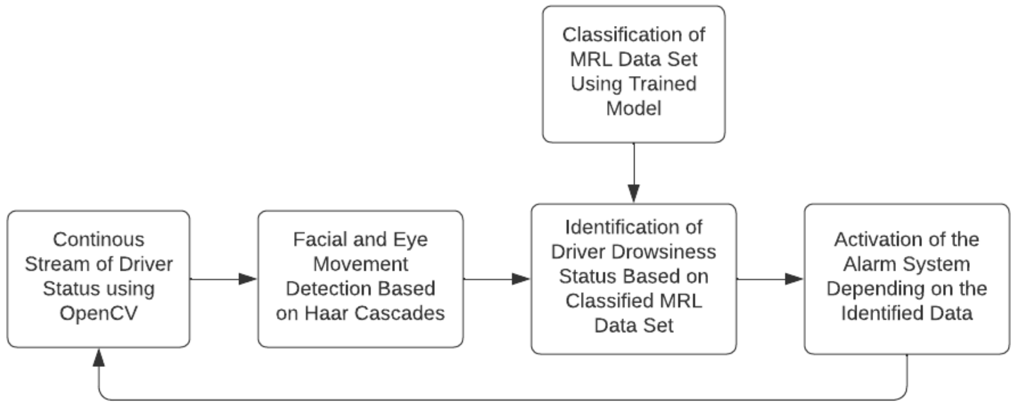


Figure 3.1 Theoretical Framework

The theoretical framework of the study was created on the premise of the application of a trained model algorithm. The trained model algorithm of the system is responsible for the classification of the MRL data set using data selection to identify which images have opened or closed eyes, the resulting classification will then be used to classify the incoming video stream from the image acquisition device to identify the driver drowsiness status. The resulting drowsiness status will be used as a parameter for the activation of the alarm system which can only be activated if the driver reached the predetermined parameters.

3.1 Face and Eye Movement Recognition

The system's facial detection capability is due to the use of machine learning object detection algorithms specifically, haar cascades. Haar cascades algorithms were used to identify positive images, the part of the image which the proponent wants, and the negative images, which is everything else on the image apart from the positive image. With this, the face is set to be a positive image, then, using the acquired space, the eyes are identified.

3.2 Classification of Data Set Using Trained Model Algorithm

A training model or a machine learning model is an algorithm that has the capability to categorize given data using labels. It seeks to relate the given data with each of their labels, as the human brain does. Models that are trained on a high amount of data are more accurate.

3.3 Identification of Drowsiness Level using PERCLOS

Percentage of eyelid closure or PERCLOS is the measure of alertness level of a person based on the percentage of their eyelid closure over a set period of time. Among the drowsiness-detection measures and technologies currently available, PERCLOS was among the most reliable and valid determination of a driver's alertness level. A driver is considered drowsy when the measurements of their eyelid are more than 80% closed in a set period of time.

CHAPTER FOUR

METHODOLOGY

This chapter describes the techniques utilized in data collection and analysis that are pertinent to the research. The approaches will include topics that were used in the creation of the system such as data set, data selection, and technology used.

4.1 Data Set

One of the things needed when it comes to modeling is the data set used for the model's training. The data set for the building model for the system comes from the MRL website, which contains a large-scale data set of human eye images. This collection comprises low-resolution infrared photos from exactly thirty-seven individuals acquired under various lighting situations and with multiple instruments. The dataset is appropriate for testing a variety of features or trainable classifiers. The following are the sample images included in the data set.

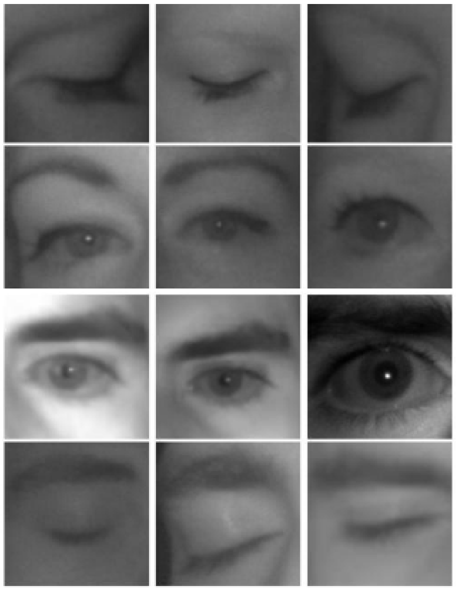


Figure 4.1 Sample images of the Data set

4.2 Data Identification

For the sake of convenience, the attached images within the data set are annotated based on the properties of each image: subject ID, image ID, gender, glasses, eye state, reflections, lighting condition of the image, and sensor ID.

1. Subject ID - the data set is gathered from thirty-seven individuals and this section serves as their identification from subjects 1 to 37.
2. Image ID - it serves as the identification number for each image.
3. Gender - the annotation allocated for this property is defined as 0 for males, and 1 for females.
4. Glasses - some of the subject individuals wear glasses therefore we need to identify them using 0 and 1 where: 0 is for without glasses and 1 is for with glasses.
5. Eye state - this property is the most important property of the image in this study because it will define whether the eyes are closed or not. The 0 represents close and 1 represents open.
6. Reflections - some of the images have reflections and this annotation is addressing certain reflections whether there is a big, small, or no reflection at all. They were represented by 2, 1, and 0 respectively.
7. Lighting condition - each image has two states, bad and good. This is clearly represented by 0 and 1 respectively.
8. Sensor ID - The collection comprises photos from three separate sensors (Intel RealSense RS 300 sensor with 640 x 480 resolution, IDS Imaging sensor with 1280 x 1024 resolution, and Aptina sensor with 752 x 480 resolution). The real sense sensor is represented by 01, the IDS is represented by 02, and Aptina is represented by 03.

The annotation for each image is important to speed up the processing of the images during the model training. With all of the properties, the most vital part of the image is the eye state for the reason of identifying whether the driver is drowsy or not.

The following are the sample image annotations from the data set.

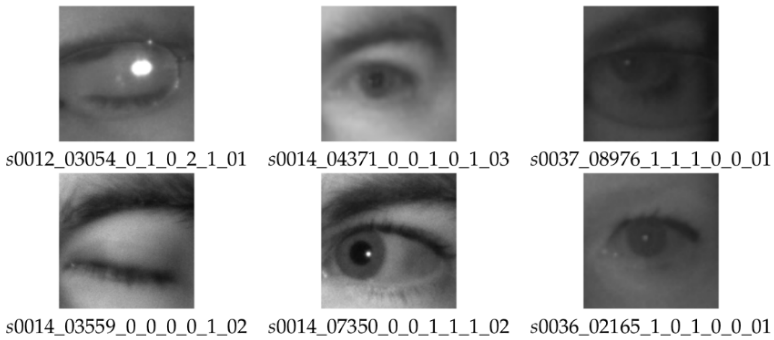


Figure 4.2 Sample Image Annotations of the Data Set

4.3 Data Selection

Based on the gathered image from the data set, the proponents categorized each image as whether it is in a closed or open eyes state. This can be determined based on the annotation stated on each image. From the same path as the downloaded data set, the classification of each image into a different folder may take place to smoothen out the path directory during the implementation. The following diagram will represent the data selection and classification.

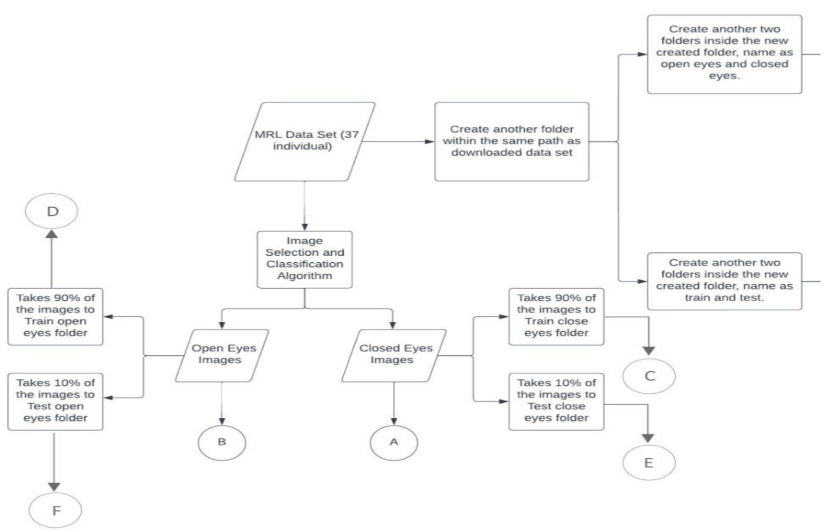


Figure 4.3 Flowchart for Data Selection Part 1

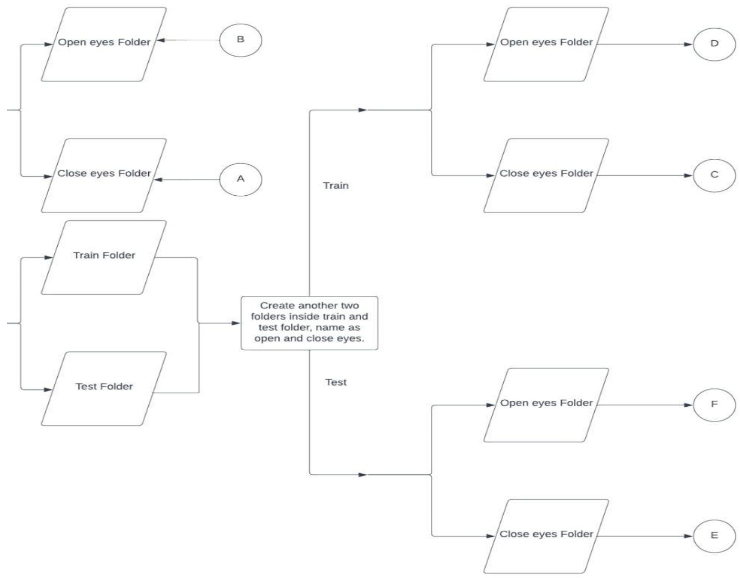


Figure 4.4 Flowchart for Data Selection Part 2

Based on the diagram represented above, the data from the downloaded MRL data set needs to be categorized based on its eye state property. The classified images need to be stored inside the open and close eyes folder using some image selection and classification algorithm. After grouping the images, train and test folders need to be created and each of these folders has open and closed eyes folders inside. The train folder needs to have 90% of the images from the closed and open eyes folder created earlier where each eye's state-based images are stored. On the other hand, the test folder needs only 10% of the open and closed-eye images.

4.4 Model Training Algorithm

The model we used is built with Keras using Convolutional Neural Networks (CNN). A convolutional neural network is a special type of deep neural network which performs extremely well for image classification purposes. A CNN basically consists of an input layer, an output layer and a hidden layer which can have multiple layers. A convolution operation is performed on these layers using a filter that performs 2D matrix multiplication on the layer and filter. The CNN model architecture consists of the following layers:

- Convolutional layer; 32 nodes, kernel size 3
- Convolutional layer; 32 nodes, kernel size 3
- Convolutional layer; 64 nodes, kernel size 3
- Fully connected layer; 128 nodes

For the training algorithm, the proponents decided to use a pre-trained Inception V3 model. This model is an image recognition model and has been proven to achieve higher than 78.1% accuracy on the ImageNet dataset, another Keras application model architecture. Convolutions, average pooling, max pooling, concatenations, dropouts, and fully linked layers are among the symmetric and asymmetric building blocks used in the model. Batch normalization is done to activation inputs and is utilized extensively throughout the model. Softmax is used to compute loss. The following image is the diagram of the model.

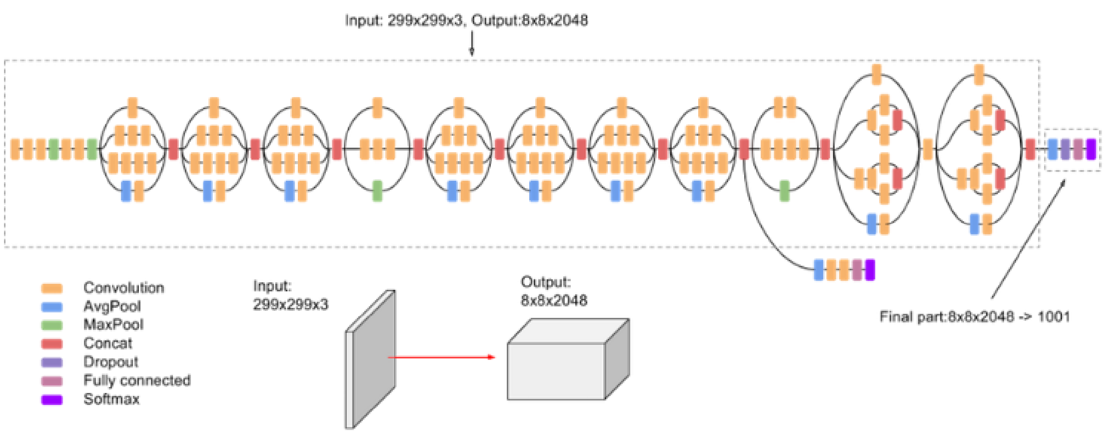


Figure 4.5 Inception V3 Diagram

Based on the figure above the model is composed of input and output layers. The proponents decided to use the InceptionV3 model to apply transfer learning to the model needed for the study. In context, the input layer or the knowledge of the said architecture is the only needed layer for the training of the model and the output layer is being disregarded.

MODEL	Size	Top-1 Accuracy	Top-5 Accuracy
Inception V3	92 MB	77.9%	93.7%

Table 4.1 Evaluation of Inception V3 based on its size and accuracy

The proponents decide to use this model because of different factors such as the size of the model. The InceptionV3 model is more efficient in terms of file size than other Keras application models like VGG 16 and Resnet 152 where sizes range from 100 to 500 MB. Another factor is the time, since this study is limited in time, they tend to choose this model due to its minimum effort in the implementation process compared to other models which have a more complex structure.

4.5 Transfer Learning

The implementation of the pre-trained model from Keras is necessary to reduce the time allocated for the model to be trained. Because training a model from scratch takes time and may be longer than the time span needed for the study to be finished, Based on the model training algorithm, uses transfer learning to reduce the time for the model to train. This transfer learning is also part of machine learning but in a different approach from the traditional machine learning setup. In transfer learning, the learning method built within the model to perform a specific task is reused within another model to perform another task. The following diagram shows the difference between traditional machine learning and transfer learning.

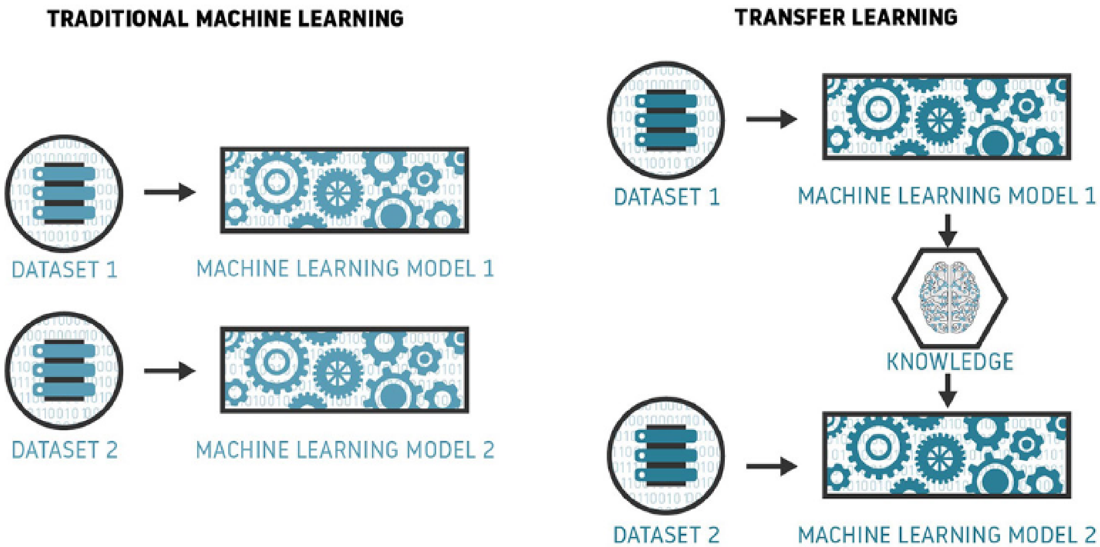


Figure 4.6 Traditional Machine Learning vs Transfer Learning

The figure shows the difference between the processes of traditional machine learning and transfer learning. In traditional machine learning, the model training process starts from scratch to perform a specific task, and another model needs to be trained from scratch without reusing pre-trained data from other sources to do a specific task. Transfer learning, on the other hand, can reuse and incorporate existing knowledge from another model to improve its own performance.

4.6 Tensorflow Application

To implement the model training algorithm and the transfer learning to the custom model for the system, the proponents used the TensorFlow application. Tensorflow is an application focusing on machine learning algorithm implementation, which takes an input as a multi-dimensional array. These multi-dimensional arrays are called tensors, which flow through different kinds of operations present within the system and come out as an output on one end. All of the processes to create, train, and evaluate the custom model for the system built within the tensor flow, gives the proponents convenience in terms of creating the model.

CHAPTER FIVE

RESULTS AND DISCUSSION

The results of the created system's test implementation are presented in this chapter. The proponents test the system under various conditions through a set of parameters that may affect the performance of the project. The drowsiness level, face angle, lighting conditions, eyes covered, eye accessories, and eye shape are all factors.

5.1. Drowsiness Level

Figure 5.1 Testing of Drowsiness Level: open, quarter closed, and close eyes

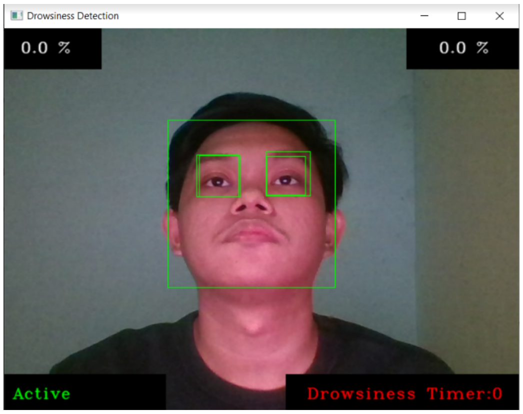
Figure 5.1 depicts different scenarios which identify the drowsiness level of the subject. Based on the images, the created system can recognize the state of the eyes, whether they are in an active state or not. The system interface is capable of showing the eye states, the drowsiness level of each eye, and the drowsiness timer.

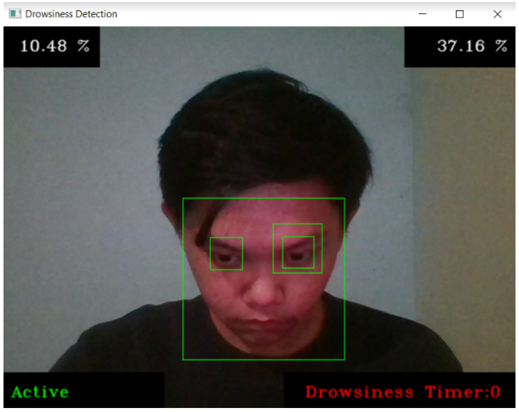
Drowsiness Level			
	Open Eyes	Quarter Closed Eyes	Close Eyes
Left	0.05%	64.92%	96.01%
Right	0.04%	17.38%	98.50%

Table 5.1 Data gathered from the testing of Drowsiness Level

The data gathered from the experiment are shown in table 5.1, which comprises the drowsiness level of the subject based on the distance of the eyelids. In the first image, the eyes of the subject are widely open, thus resulting in an active eye state. The left eye shows a 0.05 percent drowsiness level and a 0.04 percent drowsiness level for the right eye. In the second image, the eyes of the subject are quarter closed and show 64.92 percent of drowsiness level on the left eye and 17.38 percent on the right eye. And for the last image, the subject's eyes are fully closed, thus showing a result of 96.01 percent drowsiness level for the left eye and 98.50 percent for the right eye.

5.2 Face Angle





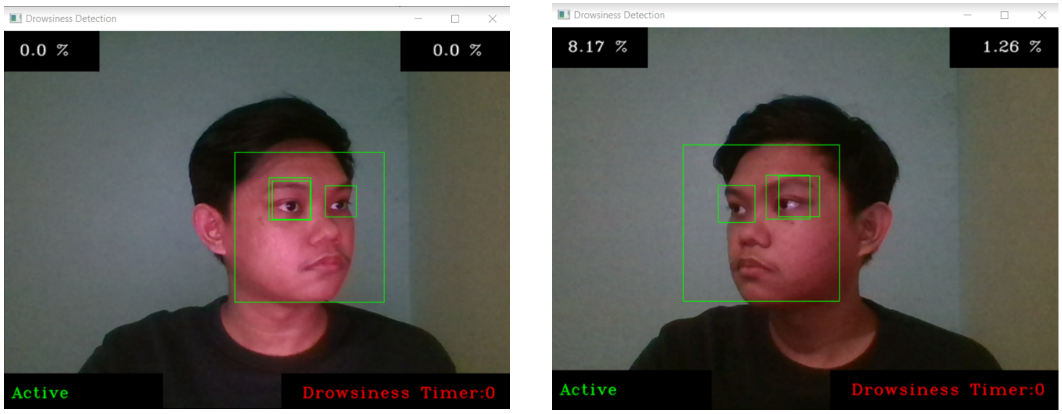


Figure 5.2 Testing of different Face Angles: up, down, left, and right

Figure 5.2 above shows the different scenarios when the subject is facing the camera at various face angles. Under these situations, the system can still recognize the face and the eyes of the subject, together with the eye state and drowsiness level.

FACE ANGLE				
	Up Angle	Down Angle	Left Angle	Right Angle
Left	0.00%	10.48%	0.00%	8.17%
Right	0.00%	37.16%	0.00%	1.26%

Table 5.2 Data gathered from the testing of different Face Angles

The data gathered from the experiment based on face angle is shown in table 5.2. The proponents defined the face angle parameters as up angle, down angle, left angle, and right angle. The first image in figure 5.2 depicts the up angle and detects the eye state as active, resulting in a 0.00 percent drowsiness level on the left and right eyes. In the second image, the subject is at a downward angle and still recognizes the face and eye of the subject, yielding a 10.48 percent of drowsiness level on the left eye and 37.16 percent on the right eye. The third image shows the left angle and still detects the face and the eyes of the subject. The image gives a result of a 0.00 percent drowsiness level in both eyes. And lastly, the face angle is the right angle. It still detects the face and the eyes of the subject, yielding 8.17 percent for the left eye and 1.26 percent for the right eye.

5.3 Light Conditions

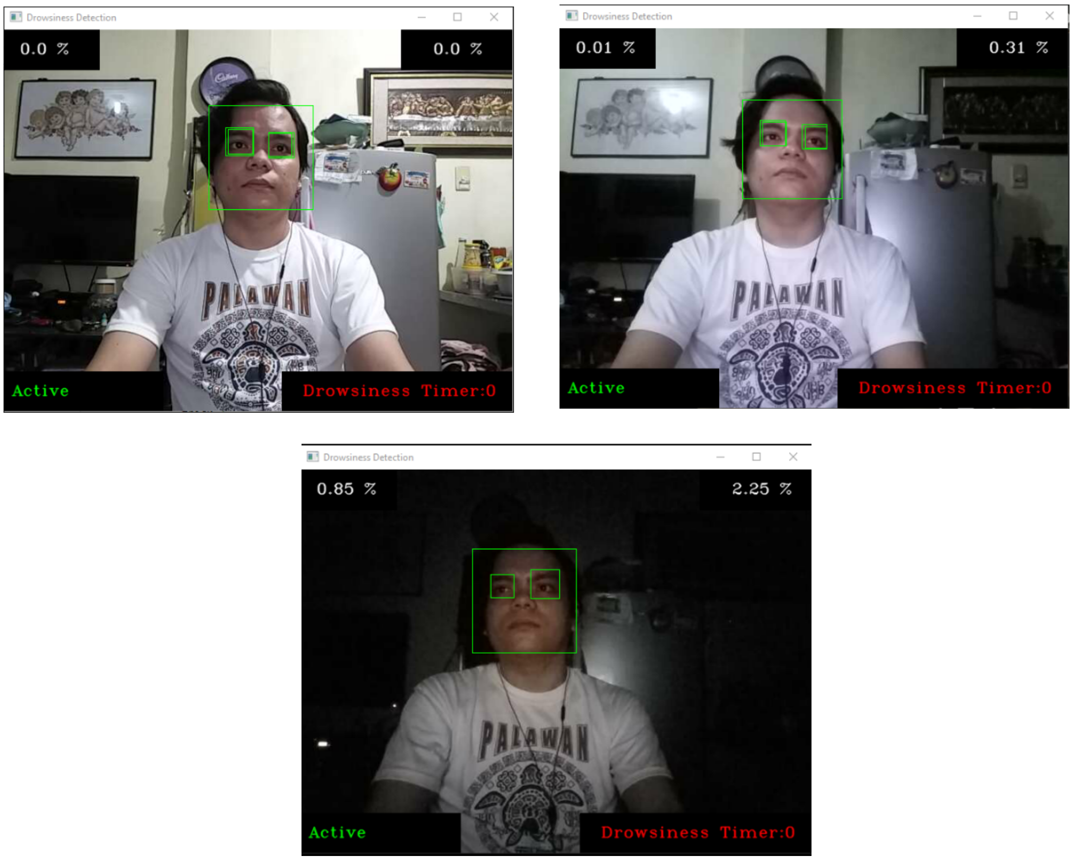


Figure 5.3 Testing of different Light Conditions: high, mid, and low lighting

The system also tests under different lighting conditions to test whether the image lighting quality affects the detection of the face and the eyes of the subject. Figure 5.3 above shows the different lighting conditions in the subject. Under these various situations, the system still detects the face and the eye of the subject and indicates the eye state and drowsiness level.

Lighting			
	High Lighting	Mid Lighting	Low Lighting
Left	0.00%	0.01%	0.85%
Right	0.00%	0.31%	2.25%

Table 5.3 Data gathered from the testing of different Lighting Conditions

Table 5.3 above shows the data gathered from the test of the subject under different lighting conditions. The proponents define the lighting parameters as high lighting, mid-lighting, and low lighting. The first image in figure 5.3 shows the subject under high lighting conditions and gives a result of 0.00 percent drowsiness level for the left and right eyes. In the second image, the subject is under mid-lighting conditions and the system still recognizes the face and the eye of the subject, yielding a 0.01 percent drowsiness level for the left eye and a 0.31 percent for the right eye. And in the last image, the subject is under low lighting conditions and can still detect the face and the eyes of the subject. The data gathered from the last image shows a 0.85 percent drowsiness level for the left eye and 2.25 percent for the right eye.

5.4 Eye Cover

Figure 5.4 Testing the system's accuracy when one eye is covered

The system also tested whether it can still detect each of the eyes when each of the eyes is blocked. Figure 5.4 shows the subject covering each eye and the system can still identify each eye, which can be seen by the green boxes in the images. The system can still also recognize the eye state and drowsiness level of the subject.

	Eye Cover	
Left	8.38%	-
Right	-	11.38%

Table 5.4 Data gathered from the testing when one eye is covered

Table 5.4 shows the data gathered from the test of the subject after blocking each eye. In the first image seen in figure 5.4, the subject blocks its right eye and still recognizes the left eye. The eye state is in an active state and gives an 8.38 percent drowsiness level. On the other hand, the second image blocks its left eye and still yields an active eye state and an 11.38 percent drowsiness level.

5.5 Eye Accessory

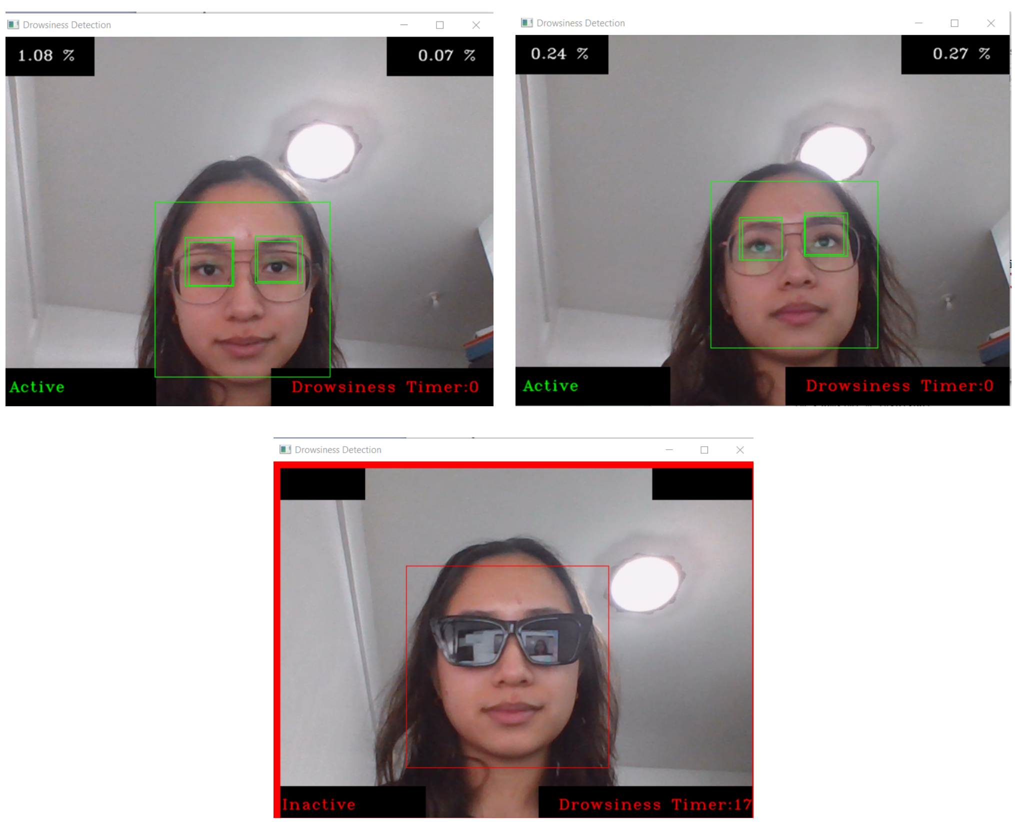


Figure 5.5 Testing the system's accuracy when the subject is wearing eye accessories: glasses, blocked by reflection, and sunglasses

The proponents also considered the eye accessory that a subject may use during driving such as eyeglasses and sunglasses. This is an important parameter to discuss since it can greatly affect the eye detecting function of the system. The second image in figure 5.5 also shows reflection in the eyeglasses. The gathered data from this test can be shown in the table below.

Eye Accessory			
	Glasses	**Blocked by Reflection**	**Shades**
Left	1.08%	0.24%	Not Detected
Right	0.07%	0.27%	Not Detected

Table 5.5 Data gathered from the testing when the subject is wearing eye accessories: glasses, blocked by reflection, and shades

Table 5.5 shows the data gathered from the test subject under the condition of wearing eye accessories. The parameters, according to the proponents, are: wearing eyeglasses, eyeglasses blocked by reflection, and shade (sunglasses). Based on the images from figure 5.5, the first image shows a subject wearing eyeglasses without the interference of a reflection. It gives a result of 1.08 percent for the left eye and 0.07% for the right eye. In the second image, the eyeglasses of the subject were blocked by reflections that resulted in 0.24 percent for the left eye and 0.27 percent for the right eye. In the last image, the subject wears sunglasses, which can totally block the eyes. Having this, the system automatically shows an inactive eye state and it is not detected by the system

5.6 Eye Shape

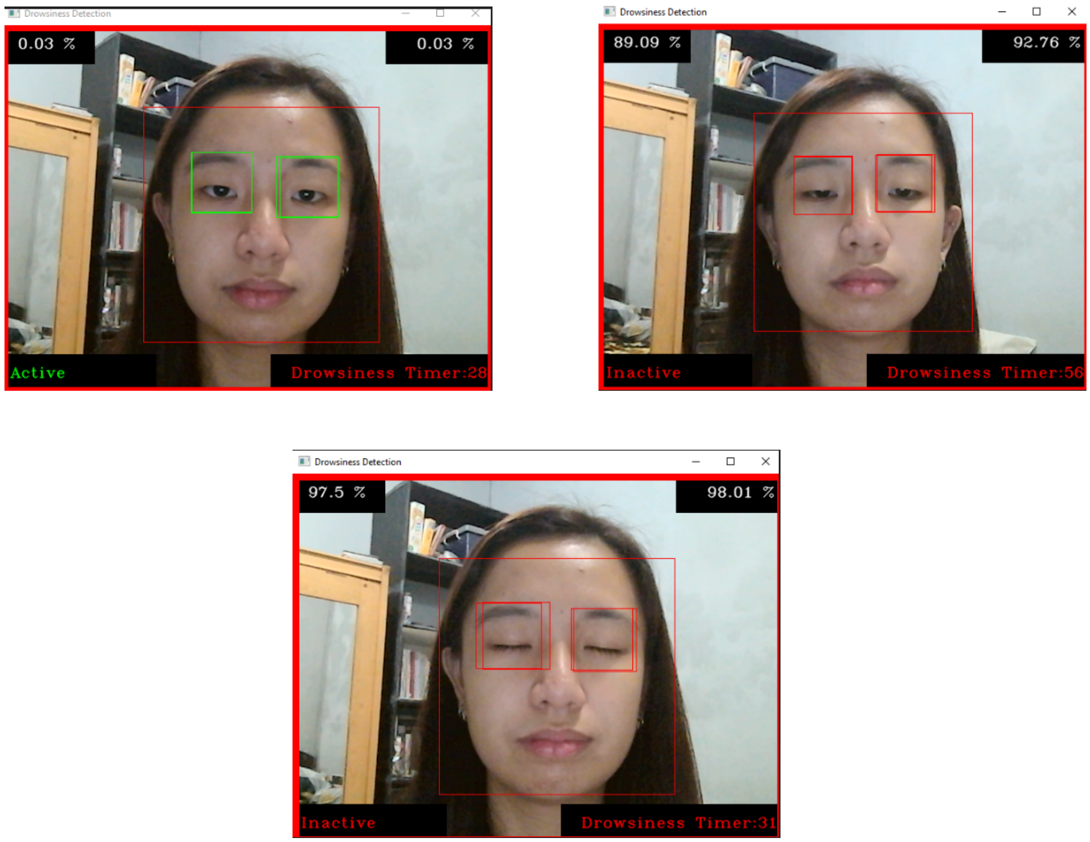


Figure 5.6 Testing the system's accuracy through the subject's eye shape

The proponents still considered other factors that may affect the system, such as the eye shape of the subject. Figure 5.6 above shows a subject that has Asian eyes, which somehow affects the eye detecting function of the system. When the eye of the subject is in an open and closed state, the detection of the active and inactive status of the eye is still working. But when the eye is a quarter closed, the system automatically detects the subject as drowsy and has an inactive eye state. The table below shows the data gathered for this test.

Eye Shape			
	Open Eyes	Quarter Closed Eyes	Close Eyes
Left	0.03%	97.50%	89.09%
Right	0.03%	98.01%	92.76%

Table 5.6 Data gathered from the testing of the system's accuracy through the subject's eye shape

Table 5.6 shows the data gathered from the subject based on its eye shape under different eye states. The proponents define the parameters as open eyes, quarter closed eyes, and closed eyes. The first image in figure 5.6 shows the open-eye state of the subject, resulting in a 0.03 percent drowsiness level for both eyes. In the second image, the subject is in quarter closed eyes and shows an inactive eye state having a 97.50 percent of drowsiness level for the left eye and 98.01 percent for the right eye. In the last image, the subject totally closed her eyes, yielding an 89.09 percent drowsiness level for the left eye and 92.76 percent for the right eye.

5.7 Detection Capability

Detection Capability			
Identifiable	**In Optimal Condition**	**With Eye Accessories**	**Under Poor Lighting Condition**
Face	Detected with no issue	Detected with no issue	Detected as long as visible
Left Eye	Detected with no issue	Depending on the accessories	Detected as long as visible
Right Eye	Detected with no issue	Depending on the accessories	Detected as long as visible
Eyelid Open	Detected with no issue	Depending on the accessories	Detected as long as visible
Eyelid Close	Detected with no issue	Depending on the accessories	Detected as long as visible

Table 5.7 Data gathered from the testing of detection capability in optimal conditions, with eye accessories, and under poor lighting conditions.

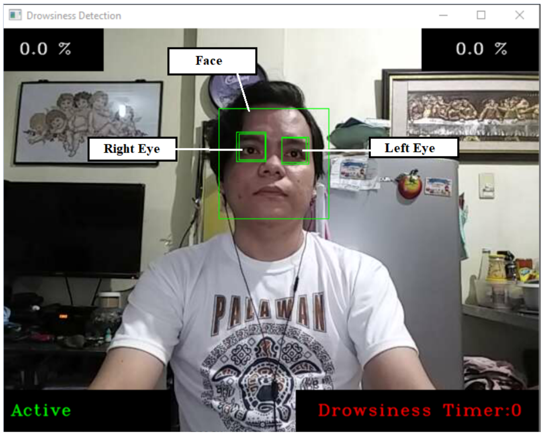


Figure 5.7 Testing of the system's detection capability in optimal conditions, with eye accessories, and under poor lighting conditions.

The detection capability of the system was checked by operating under various conditions. The proponents set a list of identifiable on which the system must detect in order to function properly, namely, face, left eye, right eye, eyelid open, and eyelid close. The system then was tested if it was capable of detecting the identifiable. The proponents were able to observe that in optimal condition, the system function without any problem. In identifying if the system can see through eye accessories, it is observed that it can identify the facial structure with no issues but the eyes and eyelid movements can only be detected provided that the system has a clear view of the eyes. In poor lighting conditions, the system will work as long as the light is adequate and the subject could still be seen through minor detection fluctuations observed.

CHAPTER SIX

CONCLUSION AND RECOMMENDATION

6.1 Conclusion

The proponents of the study seek to know how machine learning object detection algorithms can be used to identify driver drowsiness status if the system can operate under various scenarios, the accuracy of the facial and eyelid detection system, and if the system can compete against commercially available driver drowsiness detection systems. After thorough testing and observation, the proponents concluded that the creation of a Real-time Driver Drowsiness Detection using OpenCV with Keras Convolutional Neural Network was possible using machine learning object detection algorithms and model training algorithms. Specifically, the system was created using the implementation of convolutional neural networks to classify eyes as open or closed wherein drowsiness was determined based on the frequency of closed eyes over a set period of time, this method is called PERCLOS, percentage of eyelid closure, which is found to be the most reliable and valid determination of driver's alertness level. With that established, the system undergoes testing on various scenarios and conditions particularly, on scenarios that are most likely to happen namely, lighting condition, eye accessories, face angle, and eye shape. Upon examination of the gathered data on various testing, the proponents concluded that the system can operate normally in some scenarios provided that the main input, which is the face and eyelid movements, are still visible. The system detection capability was also checked under different conditions. In an optimal scenario, in which lighting is adequate and there's no hindrance of accessories, the detection capability encounters no issue; however, when accessories were added, issues arise depending on what kind of glasses were used. Eye detection with clear glasses or prescription glasses experiences no issue unless reflection from a light source blocks the system's view of the eyes. Sunglasses, on the other hand, serve as a hindrance to the system, in fact, it blocks the system from identifying the eyes and eyelid movement but it does not affect the detection of the face itself. Based on all the data provided by the system and the observation of the proponents, the system performs properly for academic use but poorly for commercial deployment. There exist studies that are highly advanced and use far better algorithms than the system but the system potential and scalability are worth noting.

6.2 Recommendation

Upon completion of the prototype, testing, and observation by the proponents of this study, the proponents found out that the system suffers from several drawbacks that could be improved through refining various algorithms that were used by the system. The said drawbacks include; the detection of objects which resembles a human face, failure of the alarm to activate upon detection of two human faces, minor inaccuracy to detect eye movement when presented with eye accessories, and failure to identify unfamiliar eye structure of different ethnic groups and video streams that have low frame rates creating false-positive scenarios. In addition, it is worth noting that the time and resource constraints that the proponents are subjected to directly affects the technical quality of the system as image processing technologies along with model training algorithms require time and large data sets. With that said, the proponents recommend the following:

- Improvement of facial detection algorithm
- Refinement of eye movement detection algorithm
- Inclusion of large data set that encompass various ethnicity
- Improvement of real-time computer vision for continuous streaming
- Inclusion of other facial features that indicates drowsiness
- Additional facial recognition feature to recognize the driver

LIST OF REFERENCES

Advanced Guide to Inception v3 | Cloud TPU |. (2022). Google Cloud. https://cloud.google.com/tpu/docs/inception-v3-advanced

Albadawi, Y., Takruri, M., & Awad, M. (2022). A Review of Recent Developments in Driver Drowsiness Detection Systems. Sensors, 22(5), 2069. https://doi.org/10.3390/s22052069

Benson, A., Tefft, B.C., Svancara, A.M. & Horrey, W.J. (2018). Potential Reduction in Crashes, Injuries and Deaths from Large-Scale Deployment of Advanced Driver Assistance Systems (Research Brief). Washington, D.C.: AAA Foundation for Traffic Safety.

Bergasa LM, Nuevo J, Sotelo MA, Barea R, Lopez ME. (2006). Real-Time system for monitoring driver vigilance. IEEE trans Intell Transp Syst, 7 (1): 63–77.

Buban, C. E. (2013, September 13). Lack of sleep a public health epidemic. INQUIRER.net. Retrieved August 10, 2022, from https://business.inquirer.net/142773/lack-of-sleep-a-public-health-epidemic

Dong, Y., Hu, Z., Uchimura, K., & Murayama, N. (2011). Driver Inattention Monitoring System for Intelligent Vehicles: A Review. IEEE Transactions on Intelligent Transportation Systems, 12(2), 596–614. https://doi.org/10.1109/tits.2010.2092770

Jabbar, R., Al-Khalifa, K., Kharbeche, M., Alhajyaseen, W., Jafari, M., & Jiang, S. (2018). Real-time Driver Drowsiness Detection for Android Application Using Deep Neural Networks Techniques. Procedia Computer Science, 130, 400–407. https://doi.org/10.1016/j.procs.2018.04.060

Khan MI, Mansoor AB. (2008). Real Time Eyes Tracking and Classification for Driver Fatigue Detection, ICIAR 2008, LNCS 5112, Image Analysis and Recognition, pp: 729–738

Kim, C. (2021, October 6). *Car Accidents in The Philippines: Causes, Facts & Latest Statistics*. Philkotse. Retrieved August 9, 2022, from https://philkotse.com/safe-driving/road-accidents-in-the-philippines-causes-facts-latest-statistics-5455

Liu D, Sun P, Xiao YQ, Yin Y. (2010). Drowsiness Detection Based on Eyelid Movement. Proc. the 2nd International Workshop on Education Technology and Computer Science (ETCS), Wuhan, China, 12–13; pp. 49–52.

Manu, B. N. (2016). Facial features monitoring for real time drowsiness detection. 2016 12th International Conference on Innovations in Information Technology (IIT). https://doi.org/10.1109/innovations.2016.7880030

MRL Eye Dataset | MRL. (2021). MRL. Retrieved August 12, 2022, from http://mrl.cs.vsb.cz/eyedataset

Ngxande, M., Tapamo, J.-R., & Burke, M. (2017). Driver drowsiness detection using Behavioral measures and machine learning techniques: A review of state-of-art techniques. Retrieved August 12, 2022, from https://researchspace.csir.co.za/dspace/bitstream/handle/10204/10018/Ngxande_20148_2017.pdf?sequence=1&isAllowed=y

Ordinario, C. (2022, January 11). *Amid NCR pandemic curbs, road mishaps kill 345 people everyday | Cai Ordinario*. BusinessMirror. Retrieved August 9, 2022, from https://businessmirror.com.ph/2022/01/11/amid-ncr-pandemic-curbs-road-mishaps-kill-345-people-everyday/#:%7E:text=Based%20on%20data%20from%20the,the%20same%20period%20in%202020.

Overview of Motor Vehicle Crashes in 2020. (2022). https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/813266

Philippine Statistics Authority | Republic of the Philippines. (n.d.). Psa.gov.ph. Retrieved August 12, 2022, from https://psa.gov.ph/press-releases/id/164052

Poursadeghiyan, M., Mazloumi, A., Nasl Saraji, G., Baneshi, M. M., Khammar, A., & Ebrahimi, M. H. (2018). Using Image Processing in the Proposed Drowsiness Detection System Design. Iranian journal of public health, 47(9), 1371–1378.

Quiroz, F. E., Madeja, R. J. S., & Jaro, C. R. A. (2020). Vision-based Drowsiness Detection and Alarm System. Journal of Industrial Electronics and Applications, 3(1), 140–1

Rafid, A.-U.-I., Niloy, A., Islam Chowdhury, A., & Sharmin, N. (2020). A Brief Review on Different Driver's Drowsiness Detection Techniques [Review of A Brief Review on Different Driver's Drowsiness Detection Techniques]. International Journal of Image, Graphics and Signal Processing. https://doi.org/10.5815/ijigsp.2020.03.05

Ramos, A. L. A., Erandio, J. C., Enteria, E. M., Del Carmen, N., Enriquez, L. J., & Mangilaya, D. H. (2019). Driver Drowsiness Detection Based on Eye Movement and Yawning Using Facial Landmark Analysis. International Journal of Simulation: Systems, Science & Technology. https://doi.org/10.5013/ijssst.a.20.s2.37

Ramzan, M., Khan, H. U., Awan, S. M., Ismail, A., Ilyas, M., & Mahmood, A. (2019). A Survey on State-of-the-Art Drowsiness Detection Techniques. IEEE Access, 7, 61904–61919. https://doi.org/10.1109/access.2019.2914373

Reddy, B., Kim, Y.-H., Yun, S., Seo, C., & Jang, J. (2017). Real-time Driver Drowsiness Detection for Embedded System Using Model Compression of Deep Neural Networks [Review of Real-time Driver Drowsiness Detection for Embedded System Using Model Compression of Deep Neural Networks]. 2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW). https://doi.org/10.1109/CVPRW.2017.59

Road Accidents in the Philippines: Top 9 Causes to Avoid. (2022, June 13). Moneymax. Retrieved August 9, 2022, from https://www.moneymax.ph/car-insurance/articles/road-accidents-causes

Road Safety. (n.d.). WHO | Regional Office for Africa. Retrieved August 12, 2022, from https://www.afro.who.int/health-topics/road-safety#:~:text=Key%20Facts%201%20About%201.25%20million%20people%20die

Road safety leaders commit to reducing road traffic deaths and injuries in the Philippines. (2019, May 10). World Health Organization. Retrieved August 9, 2022, from https://www.who.int/philippines/news/detail/10-05-2019-road-safety-leaders-commit-to-reducing-road-traffic-deaths-and-injuries-in-the-philippines

Sahayadhas, A., Sundaraj, K., Murugappan, M. (2012). Detecting Driver Drowsiness Based on Sensors: A Review. Sensors. 12(12):16937-16953. https://doi.org/10.3390/s121216937

Saini, V., & Saini, R. (2014). Driver Drowsiness Detection System and Techniques: A Review [Review of Driver Drowsiness Detection System and Techniques: A Review]. International Journal of Computer Science and Information Technologies, 5(3).

Sasikala, R., Suresh, S., Chandramohan, J., & Valanrajkumar, M. (2018). Driver Drowsiness Detection System using Image Processing Technique by the Human Visual System. International Journal of Emerging Technologies in Engineering Research (IJETER), 6(6). https://www.ijeter.everscience.org/Manuscripts/Volume-6/Issue-6/Vol-6-issue-6-M-01.pdf

Sept 8, 2020 Law Enforcement Units to Reduce Road Accidents in MM. (2020, September 8). Metropolitan Manila Development Authority. Retrieved August 9, 2022, from https://mmda.gov.ph/72-news/news-2020/4362-sept-8-2020-law-enforcement-units-to-reduce-road-accidents-in-mm.html

Shekari Soleimanloo, S., White, M. J., Garcia-Hansen, V., & Smith, S. S. (2017). The effects of sleep loss on young drivers' performance: A systematic review. PLOS ONE, 12(8). https://doi.org/10.1371/journal.pone.0184002

Shenouda, S., (2017, October 23). 2018 Cadillac CT6 utilizes seeing machines' technology in Super Cruise Driver Assistance System. DBusiness Magazine. Retrieved August 11, 2022, from https://www.dbusiness.com/daily-news/2018-cadillac-ct6-utilizes-seeing-machines-technology-in-super-cruise-driver-assistance-system/

Sikander, G., & Anwar, S. (2019). Driver Fatigue Detection Systems: A Review. IEEE Transactions on Intelligent Transportation Systems, 20(6), 2339–2352. https://doi.org/10.1109/tits.2018.2868499

Stewart, T. (2022, March). Overview of motor vehicle crashes in 2020 (Report No. DOT HS 813 266). National Highway Traffic Safety Administration.

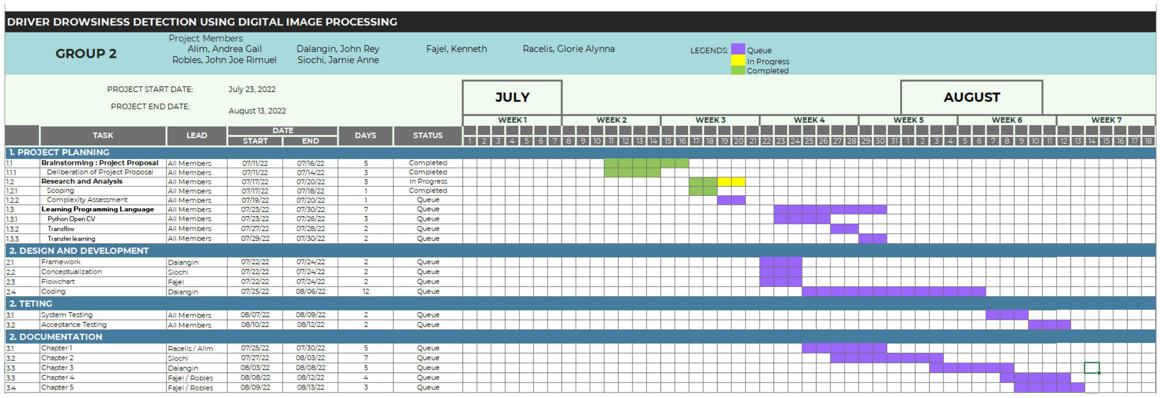
The Royal Society for the Prevention of Accidents Driver Fatigue and Road Accidents Factsheet. (2020). https://www.rospa.com/media/documents/road-safety/driver-fatigue-factsheet.pdf

Wessel, R. (2022, February 23). What are driver drowsiness detection systems?: Tomtom blog. TomTom. Retrieved August 10, 2022, from https://www.tomtom.com/blog/automated-driving/driver-drowsiness-detection-systems/

Yse, D. (2022). Introduction to Transfer Learning. Pinecone.

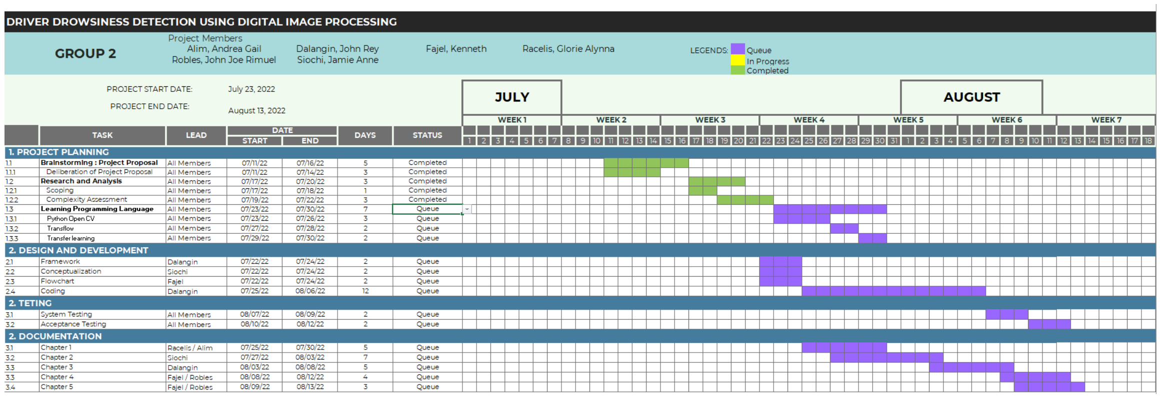
https://www.pinecone.io/learn/transfer-learning/

APPENDIX A: GANTT CHART



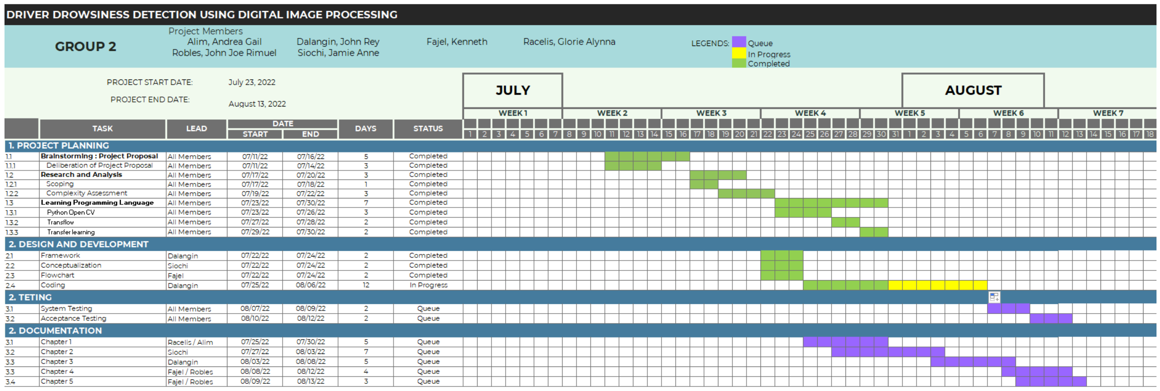
	TASK	LEAD	DATE START	DATE END	DAYS	STATUS
1. PROJECT PLANNING						
1.1	**Brainstorming : Project Proposal**	All Members	07/11/22	07/16/22	5	Completed
1.1.1	Deliberation of Project Proposal	All Members	07/11/22	07/14/22	3	Completed
1.2	**Research and Analysis**	All Members	07/17/22	07/20/22	3	In Progress
1.2.1	Scoping	All Members	07/17/22	07/18/22	1	Completed
1.2.2	Complexity Assessment	All Members	07/19/22	07/20/22	1	Queue
1.3	**Learning Programming Language**	All Members	07/23/22	07/30/22	7	Queue
1.3.1	Python Open CV	All Members	07/23/22	07/26/22	3	Queue
1.3.2	Transflow	All Members	07/27/22	07/28/22	2	Queue
1.3.3	Transfer learning	All Members	07/29/22	07/30/22	2	Queue
2. DESIGN AND DEVELOPMENT						
2.1	Framework	Dalangin	07/22/22	07/24/22	2	Queue
2.2	Conceptualization	Siochi	07/22/22	07/24/22	2	Queue
2.3	Flowchart	Fajel	07/22/22	07/24/22	2	Queue
2.4	Coding	Dalangin	07/25/22	08/06/22	12	Queue
2. TETING						
3.1	System Testing	All Members	08/07/22	08/09/22	2	Queue
3.2	Acceptance Testing	All Members	08/10/22	08/12/22	2	Queue
2. DOCUMENTATION						
3.1	Chapter 1	Racelis / Alim	07/25/22	07/30/22	5	Queue
3.2	Chapter 2	Siochi	07/27/22	08/03/22	7	Queue
3.3	Chapter 3	Dalangin	08/03/22	08/08/22	5	Queue
3.3	Chapter 4	Fajel / Robles	08/08/22	08/12/22	4	Queue
3.4	Chapter 5	Fajel / Robles	08/09/22	08/13/22	3	Queue

Figure 1 Week 1



	TASK	LEAD	DATE START	DATE END	DAYS	STATUS
1. PROJECT PLANNING						
1.1	**Brainstorming : Project Proposal**	All Members	07/11/22	07/16/22	5	Completed
1.1.1	Deliberation of Project Proposal	All Members	07/11/22	07/14/22	3	Completed
1.2	**Research and Analysis**	All Members	07/17/22	07/20/22	3	Completed
1.2.1	Scoping	All Members	07/17/22	07/18/22	1	Completed
1.2.2	Complexity Assessment	All Members	07/19/22	07/22/22	3	Completed
1.3	**Learning Programming Language**	All Members	07/23/22	07/30/22	7	Queue
1.3.1	Python Open CV	All Members	07/23/22	07/26/22	3	Queue
1.3.2	Transflow	All Members	07/27/22	07/28/22	2	Queue
1.3.3	Transfer learning	All Members	07/29/22	07/30/22	2	Queue
2. DESIGN AND DEVELOPMENT						
2.1	Framework	Dalangin	07/22/22	07/24/22	2	Queue
2.2	Conceptualization	Siochi	07/22/22	07/24/22	2	Queue
2.3	Flowchart	Fajel	07/22/22	07/24/22	2	Queue
2.4	Coding	Dalangin	07/25/22	08/06/22	12	Queue
2. TETING						
3.1	System Testing	All Members	08/07/22	08/09/22	2	Queue
3.2	Acceptance Testing	All Members	08/10/22	08/12/22	2	Queue
2. DOCUMENTATION						
3.1	Chapter 1	Racelis / Alim	07/25/22	07/30/22	5	Queue
3.2	Chapter 2	Siochi	07/27/22	08/03/22	7	Queue
3.3	Chapter 3	Dalangin	08/03/22	08/08/22	5	Queue
3.3	Chapter 4	Fajel / Robles	08/08/22	08/12/22	4	Queue
3.4	Chapter 5	Fajel / Robles	08/09/22	08/13/22	3	Queue

Figure 2 Week 2



	TASK	LEAD	DATE START	DATE END	DAYS	STATUS
1. PROJECT PLANNING						
1.1	**Brainstorming : Project Proposal**	All Members	07/11/22	07/16/22	5	Completed
1.1.1	Deliberation of Project Proposal	All Members	07/11/22	07/14/22	3	Completed
1.2	**Research and Analysis**	All Members	07/17/22	07/20/22	3	Completed
1.2.1	Scoping	All Members	07/17/22	07/18/22	1	Completed
1.2.2	Complexity Assessment	All Members	07/19/22	07/22/22	3	Completed
1.3	**Learning Programming Language**	All Members	07/23/22	07/30/22	7	Completed
1.3.1	Python Open CV	All Members	07/23/22	07/26/22	3	Completed
1.3.2	Transflow	All Members	07/27/22	07/28/22	2	Completed
1.3.3	Transfer learning	All Members	07/29/22	07/30/22	2	Completed
2. DESIGN AND DEVELOPMENT						
2.1	Framework	Dalangin	07/22/22	07/24/22	2	Completed
2.2	Conceptualization	Siochi	07/22/22	07/24/22	2	Completed
2.3	Flowchart	Fajel	07/22/22	07/24/22	2	Completed
2.4	Coding	Dalangin	07/25/22	08/06/22	12	In Progress
2. TETING						
3.1	System Testing	All Members	08/07/22	08/09/22	2	Queue
3.2	Acceptance Testing	All Members	08/10/22	08/12/22	2	Queue
2. DOCUMENTATION						
3.1	Chapter 1	Racelis / Alim	07/25/22	07/30/22	5	Queue
3.2	Chapter 2	Siochi	07/27/22	08/03/22	7	Queue
3.3	Chapter 3	Dalangin	08/03/22	08/08/22	5	Queue
3.3	Chapter 4	Fajel / Robles	08/08/22	08/12/22	4	Queue
3.4	Chapter 5	Fajel / Robles	08/09/22	08/13/22	3	Queue

Figure 3 Week 3

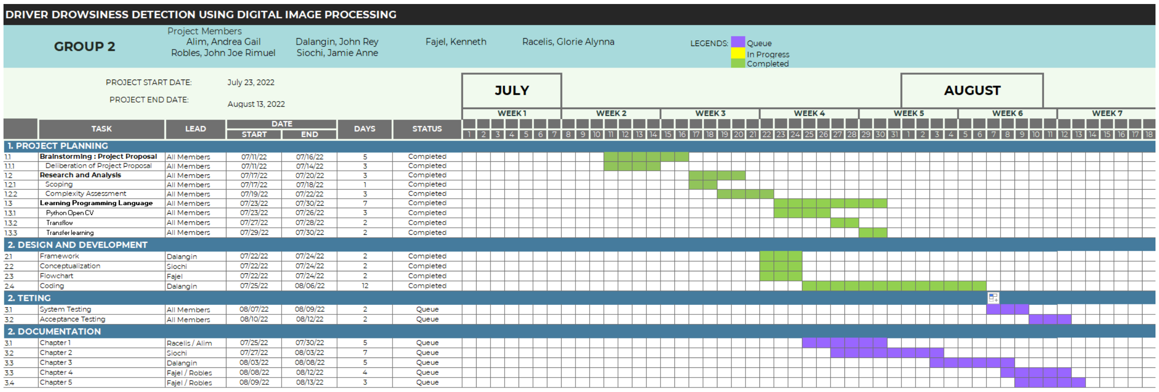


Figure 4 Week 4

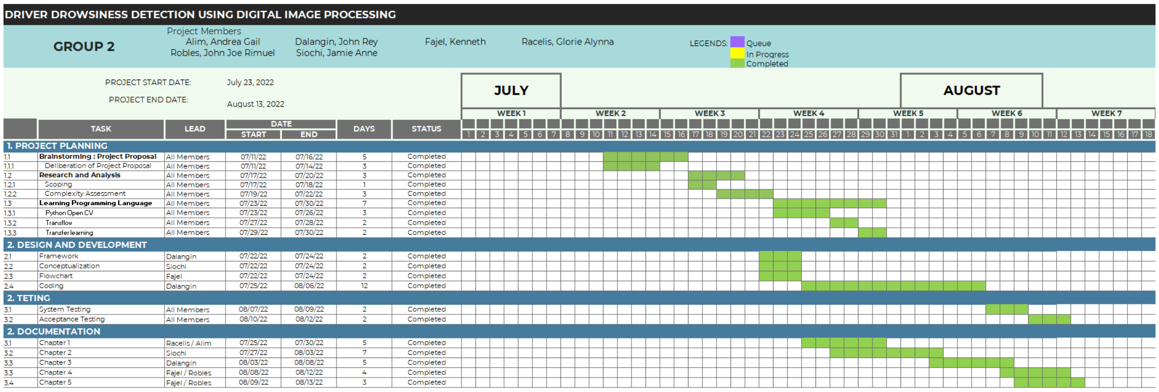


Figure 5 Week 5