Development of drowsiness detection system using machine learning and image processing techniques

DENZEL OMONDI (101033)

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Institute of Mathematical Sciences
Strathmore University
Nairobi, Kenya

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Declaration

I declare that this work has not been previously submitted and approved for award of a degree by this or any other University. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

Name: **Denzel Omondi**

Signature:

Date: January 24, 2024

Approval

The proposal of Denzel Omondi was reviewed and approved by the following:

Dr. Evans Omondi

Supervisor, January 26, 2024

Institute of Mathematical Sciences, Strathmore University.

Abstract

Since drowsy driving is a major problem in Kenya, which has led to multiple fatal accidents, it has raised discussions that seek for a set of solutions. Several fatalities and injuries resulting from road accidents caused by drowsy driving have been recorded and it has been identified to be a significant problem. Studies that have been conducted in this field have identified interventions in terms of detection and alert systems that can offer solutions to this problem. This study mixes these categories to come up with a machine learning algorithm that records the driver, analyses their condition, processes the information and gives feedback to get the driver back to normal. The data used in training the machine learning model used for this study was extracted from secondary sources, including the internet. The data was then cleaned before use. However, the accuracy of the model determines its application. The model developed for this study generated a weighted average precision of 86% with a recall of 83%, an 84.5% accuracy and an F1-score of 83%. These results are relatively high compared to many models that have been used by previous researchers. This shows how applicable the model is in real situations and how much the other models need to be improved. However limitations like small size of training data and low processing power of the equipment used should be addressed in future studies for better outcomes.

Table of contents

List of figures

List of abbreviations

AI	Artificial Intelligence	CNN	Convolutional Neural Networks
FHWA	Federal Highway Administration	GSM	Global System for Mobile communication
GSM	Global System for Mobile communication	GLONASS	Global Navigation Satellite System
GPS	Global Positioning System		
HOG	Histogram Oriented Gradients	IRD	Injury Related Death
ML	Machine Learning	NHTSA	National Highway Traffic and Safety Administration
PSV	Public Service Vehicles	RNN	Recurrent Neural Networks
SVM	Support Vector Machines	US	United States

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Dedication

I dedicate this thesis to every individual affected by drowsy driving-related accidents in Kenya together with their friends and families. I hope that my machine learning model will have a significant contribution to the prevention of such accidents and their consequences. I also dedicate this paper to the memory of individuals who have lost lives through involvement in road accidents caused by drowsy driving. Such phenomena trigger a reminder of how important road safety is and how much we need to develop innovative solutions to combat drowsy driving. I finally dedicate this paper to my loved ones who have given me constant and unwavering support and encouragement which have inspired me throughout this journey.

Chapter 1

Introduction

1.1 Background to the study

Road accidents have increased over the past few years and it is an emerging public health problem with about 1.3 million deaths recorded annually (WHO, 2022). This is because of various reasons such as the increased use of cars on the roads, compromised impairment, failure of drivers to obey the set traffic rules, drinking while driving, overpopulation in the cities, and poor roads especially in the rural setup but the leading reason today is drowsy driving. In Kenya, for instance, approximately 3000 lives are lost and over 5,000 are left disabled yearly as a result of road accidents (Muguro and Njeri, 2020). It also happens to impact negatively on the economy of developing countries, Kenya for example, is estimated to cost about 1.3% to 3% of the country's gross national product (GNP) per annum (Muguro and Njeri, 2020). The majority of people losing their lives to road accidents in Kenya is made group of those aged between 15-49 years resulting in financial strains to the remaining family members since this age constitutes the most productive group of society (Muguro and Njeri, 2020). Road accidents have been on the rise due to a number of factors such as;

- Increased use of cars on the roads.
- Compromised impairment.
- Failure of drivers to obey the set traffic rules.
- Drinking while driving.
- Overpopulation in the cities.
- Poor roads especially in the rural setup.

- Drowsy driving

Today drowsy driving has become the leading cause of most road accidents accounting for a larger percentage compared to the other causes (Saleem, 2022). In the US, over the years there are high estimates of drowsy driving-related road accidents. NHTSA, on average annually reports several crashes about 80,000 that are attributed to drowsy driving, with about 755 fatalities with these being approximated numbers (Venkatraman, 2021). In the US, insufficient sleep contributes to about 2.5% of the fatal accidents and it is mostly experienced by young and inexperienced drivers, truck drivers who have long journeys, people with sleeping disorders, and business drivers (Venkatraman, 2021). Such statistics can change for the better with technological intervention using machine learning and artificial intelligence. Coupled with database management, artificial intelligence becomes important in identifying drowsiness during deriving and making necessary decisions. Chan (2021) reports that AI is able to perform facial recognition like humans. This characteristic makes it more suitable for application in the motor vehicle industry to identify the facial cues of drivers in real-time. Drowsy driving comes with notable changes in the eyes of the driver, that AI can identify and send signals to a processor programmed to interpret the signals and give necessary feedback (Alicandri, 1994).

1.2 Drowsy Driving

A study conducted by NHTSA in 2002, illustrates that about 37% of drivers have confirmed being drowsy while driving at some point in their lives (Royal, 2003). There is also an approximate number of two-thirds of American adults who get less than 6 hours of sleep and this is somehow associated with drowsy driving (Al-Lawati, 2018). Sleep deprivation to an extent can contribute to fatigue for mostly long-distance drivers. Report that road accident fatalities in low income or developing nations form at least 93% of the global road accident fatalities (Al-Lawati, 2018). Both in the US and Kenya, distracted driving is a significant cause of traffic accidents. Drowsy driving causes at least 2.5% of all collisions in the US, resulting in more than 72,000 collisions and 44,000 injuries each year, according to the Federal Highway Administration (FHWA). According to data from National Highway Traffic Safety Administration (NHTSA), driver weariness is thought to be a major contributing factor in 20–30% of all collisions around them (Zhang and Qiu, 2014). According to Soares and Ferreira (2020) drowsy driving has been linked to a number of factors, including driver traits like age and gender, job schedules, and the use of specific drugs. Young male drivers, shift workers, and people who take sedative drugs are at a higher risk for sleepy driving-related crashes, according to studies (Muguro and Njeri, 2020). The US and Kenya have both established a number of treatments and legislation to address the issue of sleepy driving. The employment of in-vehicle technologies like driver fatigue warning systems is one of them. Others include public awareness campaigns, legislation that control the hours of duty for commercial drivers, and public education efforts (Muguro and Njeri, 2020). Improving road safety in the US and Kenya requires evaluating the efficacy of various treatments and regulations. In the US, a number of studies have been done to determine how sleepy driving-related crashes are affected by interventions including public education campaigns and hours of service laws. These research' findings have been inconsistent, with some reporting a considerable decline in crashes caused by fatigued driving and others reporting no change at all. The effects of sleepy driving and the effectiveness of measures to decrease it have received substantially less research in Kenya (Muguro and Njeri, 2020). But according to a recent NTSA study, increased traffic law enforcement and public awareness programs were linked to a decline in accidents caused by fatigued driving (Otieno, 2022). Ultimately, it is evident that driving while fatigued is a serious issue in both the US and Kenya, and further research is required to fully comprehend its prevalence and the effects it has on traffic safety in these nations. It is imperative for reducing drowsy driving that effective interventions and policies are created and evaluated. For a period of four years (1989-1993), NHTSA estimated drowsy driving contributed to road accidents around 100,000 in the US. With around 1500 people were killed annually in the four years as reported by the police Knipling and Wang (1994) Kenya on the other hand has a high number of road accidents attributed to drowsy driving with an average of 3,000 lives. In the country, the PSVs contribute a good percentage due to carrying passengers more than the limits, careless driving, and driving unworthy vehicles. This is also attributed to poor enforcement of road regulations As a result, road accidents caused by drowsy driving lead to an economic loss of about 14 billion shilling annually.Drowsy driving is however due to a number of factors which includes;

1.2.1 Factors attributing to drowsy driving

The driver at the time of drowsy driving can reportedly be unwell or must have been undergoing certain medication that can cause fatigue resulting in drowsiness. Medically, the human body needs an uninterrupted sleep of about 7-8 hours per day in order to function optimally. Similarly, the drivers that operate on long distance tend not to adhere to this requirement thus can cause malfunction of the body resulting in fatigue with the end result being drowsiness. There are also various medical conditions that interrupt the normal sleeping patterns resulting in not adhering to the recommended sleeping time resulting in fatigue. Such includes insomnia or narcolepsy. Truck drivers are the other group of people more prone to drowsy driving as they happen to do long distance drives, maybe from one country to another ferrying goods and products. This can be on monotonous roads or even in deserted highways, this itself can induce sleep resulting in drowsy driving. Additionally, most drivers tend to use alcohol and other drugs like marijuana especially truck drivers to help keep them awake or to feel good. Such can lead to drowsiness causing many road accidents. Lastly, in the present world today, people are often stressed for a reason or another. Stress can prevent sleep during the night and thus disrupting sleeping patterns thus can result in fatigue causing drowsy driving.

1.2.2 Failure of alco blow in reducing drowsy driving caused by alcoholism

Walter (2017) reports that there exists a group of motorists who have a higher capacity of alcohol and can drink more than expected without intoxication. Arvin and Khattak (2020) found that the most common factor in drowsy driving and auto accidents is alcohol impairment. To combat this issue, a number of nations have passed laws requiring the installation of "alco-blows," also known as alcohol interlock devices, in the vehicles operated by those who have been found guilty of drunk driving (Nelidov and van de Ven, 2021). Before starting the car, the driver must deliver a breath sample to these devices, which stops the car from starting in situations where the driver has a blood alcohol content (BAC) is too high. Alco-blows are frequently utilized, although there is conflicting information regarding how well they work to prevent drunk driving. According to certain research, the usage of alco-blows is linked to a decrease in accidents involving alcohol and recurrent DUI (Driving Under Influence) crimes (Muguro and Njeri, 2020). For instance, a study discovered that using alcohol blows was linked to a decrease in recurrent offenses among high-risk offenders (Munro and Snijder, 2022). Alco-blows, however, may only be partially beneficial in reducing drunk driving, according to other studies. Alco-blows were found to be beneficial in reducing drunk driving crimes in the near term, but their effectiveness waned with time, according to a study of multiple studies conducted in the United States. Alco-blows were linked to a slight decrease in drunk driving crimes, but they had no effect on crashes involving alcohol, according to a different Canadian study. Alco-blows might not be 100% successful in reducing drunk driving due to a number of factors. One hypothesis can be that people who continue to drive after drinking may be more likely to figure out how to get around the device, say by having a sober person give a breath sample for them. Alco-blows also fail to address the individual's alcohol use, which is what is really causing the issue. Even if they are utilizing an alco-blow, people may continue to drive when fatigued if underlying alcohol consumption issues are not addressed. Alco-blows may be successful in lowering drunk driving crimes in the short term, but they may not be as successful in preventing alcoholism-related drowsy driving in the long run. It may be essential to use additional interventions and tactics, such as alcohol treatment programs and greater enforcement of laws against driving while intoxicated.

1.3 Signs of drowsy driving

A driver cannot easily know when he/she is about to fall asleep especially when there is no other person in the vehicle. There are several ways that drowsy driving can include;

i In a case of drowsy driving, the driver's head may become heavy leading to not keeping the head straight while on the wheels resulting in nodding off the head.

ii There are various lanes on the roads ranging from the service lanes, when a driver is constantly missing the right lanes, inappropriately shifting lanes even when it is not necessary, it can be a warning of drowsy driving.

iii Yawning severally while on the wheels can be a sign of hunger but on a higher percentage it is associated with fatigue. In a case of two drivers, at these points the driver is always advised to leave and take a rest since it can result in a road accident in an extreme case.

At all times, especially on busy roads drivers are always expected to be so attentive while driving. In any case of an emergency, a driver is expected to respond quickly. For instance, with drowsy driving a driver is seen to have delayed responses thus can claim a lot of lives on the roads even the innocent pedestrians. Therefore, AI can identify the signs of drowsy driving like the position of the head, eye configuration, reflex and other facial cues like yawning. The primary objective is to minimize the probability of accident occurrence by identifying drowsiness and automatic response by warning and/or breaking safely. This feature can be more effective in auto-piloted vehicles that can park the vehicle in a safe spot to reduce accident probability.

1.4 Problem of Study

Drowsy driving is a significant contributing factor to road accidents in the United States of America (USA) and Kenya. According to the Federal Highway Administration (FHWA), drowsy driving is estimated to be a factor in at least 2.5% of all crashes in the USA, resulting in more than 72,000 crashes and 44,000 injuries each year. In Kenya, data from the National Transport and Safety Authority (NTSA) indicates that drowsy driving is a leading cause of accidents, with an estimated 20-30 % of all accidents being attributed to driver fatigue. Despite the significant impact of drowsy driving on road safety, there is a lack of research on the prevalence and effects of drowsy driving in these countries, particularly in Kenya. There is a need to study the effects of drowsy driving on road accidents in the USA and Kenya in order to understand the extent of the problem and develop strategies to address it. The aim of this project is to develop a drowsy detection system using machine learning and image processing techniques to be used in predicting road carnage in Kenya and USA.

The objectives of this study include; to build a model that can alert the driver if drowsiness is detected from the driver while driving; to develop an algorithm that can classify the face from an image and be able to detect areas of interest around the eye. Therefore, they lead to the following research questions; can an image processing technique be used to detect drowsiness in a driver? Which techniques are available and used for detecting drowsiness on drivers? Are there existing technologies that can be used to implement these techniques? This research focuses on building a machine-learning algorithm that's able to detect drowsiness in a driver. While in Kenya there's a high risk of road accidents caused by drowsiness, it's been identified there's a lack of cars that are able to detect drowsiness in drivers, and if they're there they're unaffordable for the majority. The government and media have both given the issue of sleep-related accidents a great deal of attention. As a result of this project, low-income people now have access to affordable systems; the nation's drowsiness-related accidents are decreased; income loss is decreased; the dependency ratio is increased as a result of traffic accidents; and, finally, pertinent technologies are introduced to address this issue.

Road accidents due to drowsiness are increasing at an alarming rate, being able to build and use ML that can detect drowsiness can become handy. The system is able to as early as possible detect any symptoms associated with drowsiness before the driver loses his /her concentration on the road, therefore sending a warning to the driver of their incapability to operate the vehicle on the road. This is both helpful for commercial and private vehicles.

When this objective is achieved, there is likely to be a significant improvement of safety on highways and other roads.

Chapter 2

Literature review

2.1 Introduction

In Kenya and many other countries around the world, drowsiness and fatigue have become a menace by creating several road accidents, resulting in numerous injuries and fatalities. The current world is moving towards using technology as a solution to many problems and this is not an exception. Specifically, the use of machine learning and image processing, can offer a solution by minimizing or eliminating the risks of drowsiness-related accidents. This literature review highlights previous studies that have been conducted in the field of machine learning techniques and the use of image processing to build drowsiness detection systems. It focuses on addressing the specific objectives that include: developing an algorithm that can classify the face from an image and detect the area of interest around the eye, ensuring that the model can classify the state of the eye and building a model that can alert the driver if drowsiness is detected while driving.

2.2 Algorithm for face detection and area of interest detection

The advent of technology has seen various machine learning models and image processing techniques that humanity has used in identification of facial detail, most importantly, the detection and classification of facial features. For example, Haar Cascade classifier is an object detection algorithm that has been common for detection of images and faces. AL-Anizy and Razooq (2015) conducted a study that applied a Haar Cascade classifier coupled with support vector machines to detect fatigue among drivers. This method worked by analysing the driver's facial and eye regions in real-time. The results of the study showed that Haar Cascade classifiers coupled with support vector machines had an 99.45% detection accuracy (AL-Anizy and Razooq, 2015).

Apoorva and Rakesh (2020) also conducted a study in this field that compared different drowsiness detection systems based on facial and eye features using various algorithms. In one of the systems that involved "Real-Time Drowsiness Detection using Eye Blink Monitoring" which used AdaBoost, Viola Jones and Haar classifier algorithms, the accuracy was 94% (Apoorva and Rakesh, 2020). Their facial detection system also utilized Haar Cascade classifier as a tool for facial and eye detection in the image input followed by the support vector machines and AdaBoost algorithms to identify whether the driver is drowsy or not. As opposed to the other system used AL-Anizy and Razooq (2015), this system yielded a lower drowsiness detection accuracy rate. There are more deep learning algorithms that have been used in drowsiness detection, which may be challenging to cover in a single literature. Besides the ones mentioned already, other such algorithms are those based on the convolutional neural networks (CNN). This algorithm has also been highly explored for use in detection of facial and eye features. In another study by Zhao and Zhang (2020), there was a proposition of a fatigue detection system for drivers, which applies both CNN and Haar Cascade features. Even though the other systems registered significantly high accuracies, this system was able to register an accuracy of 93.6% in detecting fatigue in drivers.

2.3 Eye state classification

In order for this study to be successful, a system with image processing capabilities must also be able to classify the eyes' state, determining whether they are closed or open (Kim, 2017). Several studies in this field have investigated and tried a variety of methods of tracking and monitoring the eye (Kim, 2017). Some of these methods include measurement of the distance between the eyelids as well as applying computer vision techniques to detect variations in the properties of the eyelids at different states (Kim, 2017). Another method that has been applied for this purpose is the use of infrared sensors in eye movement detection (Narejo and Kulsoom, 2016). These methods are considered accurate at different levels in terms of identification of the state of the eyes, which is used in the determination of whether the driver is drowsy or alert. The classification part gets completed by the use of deep learning algorithms and neural networks, which have shown promising results in accurate classification of the state of the eyes. Before a model gets applied in drowsiness detection, the developer must ensure that the model can classify the state of the eye – whether it is closed or open (Kim, 2017). Almost every machine learning technique and image processing method mentioned in the previous sub-section work by classifying the state of the eye as part of the eye detection. These methods and techniques are feature-based approaches that analyse the characteristics of the eye, which include the pupil size, durations of blinks, and eyelid movements.Hu (2017), in their study, proposed fuzzy entropy feature extractor and AdaBoost-based algorithms for a drowsiness detection system, which is based on features shown by the eye. The system used the characteristics of the eye to classify its state, registering an accuracy of 97.5% drowsiness detection (Hu, 2017). Another way that an algorithm can be designed to classify the state of the driver's eye is by using methods that focus on appearance and analyse the eye's visual appearance. Based on another study by Chirra and Kolli (2019) proposed a drowsiness detection system based on eye appearance using CNN classifier and Viola Jones detection algorithm. Some of the visual appearances that the system analysed for classification include eye closure and movement, to classify the state of the eye. This system was 96.42% accurate in drowsiness detection (Chirra and Kolli, 2019).

2.4 Drowsiness alert system

A good detection system is that which is able to provide feedback after completion of the process to be considered to have completely performed its function. Therefore, developers tend to build models that can alert the driver in case it detects signs of drowsiness while driving. Researchers in this field have proposed a variety of methods to help in alerting drivers whenever they become drowsy. The simplest and the most notable ways that such systems provide feedback is through the use of audio output devices like alarms, that get triggered whenever drowsiness gets detected.Biswal and Yang (2021) studied this topic and reached a conclusion to propose a driver fatigue detection system audio alarm as its feedback output. The accuracy of this system depended on its ability to trigger the alarm system at the right moment – when the system had truly detected drowsiness. Out of the samples tested, the system could accurately trigger the alarm 97.1 % of the times that fatigue or drowsiness was detected in the driver (Biswal and Yang, 2021). Another approach that has been used in alerting drivers is the application of haptic feedback, which is like a gesture, such as vibrating the steering wheel or seat. This type of feedback and concluded that haptic feedback is the fastest to alert the driver compared to other alert systems. The system worked by using different image classification methods and triggered haptic feedback when there was positive feedback for drowsiness. In accordance with a reference based on video simulations, the suggested system Li and Chung (2020) obtained a 91.25% accuracy for an alert class, 83.78% when tested for early-warning, and 91.92% accuracy when tested for a full warning, according to a study on the usage of wearable devices as alert systems. Based on a probabilistic assessment of the systems' efficacy, these categories were formed. These findings suggest that the suggested combination of the commercial-grade smart wristwatch and the SVM-based system constitutes an efficient, practical, and cost - effective wearable technology that can help notify the driver in the event of drowsiness.

2.5 Eye and face detection using machine learning algorithms

According to Rahmad and Muhiqqin (2020), face detection systems that use HOG are more accurate than those that use the popular Haar Cascade algorithm. However, Haar Cascade is faster than HOG in facial detection. The discipline of computer vision and pattern recognition has paid a lot of attention to the detection of faces and eyes using machine learning methods. In order to detect and identify eyes and faces in photos and videos, machine learning algorithms must be able to learn from and adapt to new data. Eye and face detection has been tackled by a variety of machine learning algorithms, including convolutional neural networks (CNNs), support vector machines (SVMs), and Haar cascades. For the task of face detection, CNNs in particular have demonstrated promising results, with numerous research proving the capacity to reach high accuracy rates in testing conditions. The requirement for substantial quantities of annotated training data presents one difficulty in the use of machine learning algorithms for eye and face detection. The development of face detection algorithms based on machine learning has been made easier by the availability of huge datasets like the Labeled Faces in the Wild (LFW) dataset (Schofield and Carvalho, 2019). In addition to conventional machine learning algorithms, deep learning methods for face and eye recognition have also been studied recently. Deep learning algorithms based on artificial neural networks are capable of finding complex patterns in data and have yielded state-of-the-art results for a range of computer vision tasks. Human-computer interaction, security, and surveillance are just a few of the contexts in which the use of algorithms based on machine learning for face as well as sight recognition could potentially to be employed. Overall, the application of these algorithms has produced encouraging results. However, more investigation is required to boost the precision and robustness of these algorithms, especially in difficult situations like dim lighting and the presence of occlusions. Therefore, internet giants like Google and Facebook for data. For instance, Google's most recent face recognition method used eight million unique identities together with 200 million images in training of models.

2.6 Electrooculogram (EOG), electromyogram (EMG), electroencephalography (EEG) and algorithm

Budak and Sengur (2019) Developed a drowsy-driving detection system using the EEG technique designed using components which include wavelet transform algorithm, VGGNet method and AlexNet method. This process is responsible for the effective analysis of drowsiness by analyzing indicator signals from the brain, sensors and a camera which apply machine learning in alerting the driver of drowsiness while driving (Budak and Sengur, 2019). Electrooculography (EOG), electromyography (EMG), and electroencephalography

(EEG) are non-invasive techniques for measuring the electrical activity of the eye, muscles, and brain, respectively (Budak and Sengur, 2019). These techniques have a wide range of applications, including the diagnosis and treatment of neurological disorders, the assessment of cognitive function, and the development of brain-computer interfaces. EOG measures the electrical activity of the eye muscles, which can be used to determine the direction of eye movements and to assess various aspects of eye function. EOG has been used in the diagnosis and treatment of disorders such as strabismus, amblyopia, and nystagmus, as well as in the evaluation of visual acuity and the development of visual prosthetics (Budak and Sengur, 2019). EMG measures the electrical activity of muscles, which can be used to assess muscle function and to diagnose disorders such as muscle weakness, nerve damage, and myasthenia gravis (Hudson and ones, 2022). EMG has a variety of clinical and research applications, including the assessment of muscle function in stroke patients and the development of assistive devices for individuals with paralysis. Brain electrical activity (EEG) can be used to diagnose neurological conditions like sleep disorders, brain tumours, and epilepsy, as well as to evaluate brain function. Many clinical and research applications of EEG exist, such as the examination of neural activity while on sleep, the creation of brain-computer user interfaces, and assessment of brain function. The application of algorithms for the analysis and interpretation of EEG, EMG, and EOG data has gained popularity in the last few years (Hudson and ones, 2022). These algorithms can be used to extract relevant features from the data, classify patterns of activity, and make predictions about various aspects of eye, muscle, and brain function. A number of different algorithms have been applied to the analysis of EOG, EMG, and EEG data, including machine learning algorithms such as support vector machines (SVMs) and decision trees, and signal processing techniques such as independent component analysis (ICA) and power spectral density (PSD) analysis. The use of EOG, EMG, and EEG in combination with algorithms has the potential to improve the diagnosis and treatment of a wide range of neurological disorders and to advance our understanding of brain function. However, additional research is needed to further develop and validate these techniques and algorithms.

2.7 GPS location and tracking

GEOTAB (2020) states that the accuracy of GPS depends on the openness of the location of a GPS device. Other factors like atmospheric conditions and artificial interferences also affect the accuracy of the location system. These setbacks act as the primary disadvantages likely to be encountered in any system that relies on GPS for geolocation. GPS (global positioning system) location and tracking technology has the potential to be used as a tool for preventing drowsy driving, a leading cause of road accidents. Drowsy driving is often characterized by a decrease in driving performance, including lane drifting, slower reaction times, and difficulty maintaining a consistent speed (Xia and Xu, 2021). By tracking a vehicle's location and movement, GPS technology can be used to detect patterns of drowsy driving behavior and to alert the driver or take other appropriate action to prevent an accident. Several studies have explored the use of GPS location and tracking data for detecting drowsy driving behavior. For example, a study by Driessen and de Winter (2022) used GPS data to identify lane drifting as a potential indicator of drowsy driving, and developed an algorithm to detect lane drifting based on GPS data. Another study by Freed and Stavrinos (2021) used GPS data to analyze the relationship between driving speed and drowsy driving, finding that slower driving speeds were associated with an increased risk of drowsy driving-related crashes. In addition to detecting drowsy driving behavior, GPS location and tracking technology can also be used to prevent drowsy driving through the use of alert systems and other interventions (Khan and Nayyar, 2020). For example, GPS-based alert systems can be used to notify the driver when they are at a high risk of drowsy driving, or to automatically alert a designated contact or emergency services if the vehicle is involved in a crash. Overall, GPS location and tracking technology has the potential to be a valuable tool for preventing drowsy driving and improving road safety. However, additional research is needed to further develop and validate algorithms for detecting drowsy driving behavior based on GPS data, and to evaluate the effectiveness of GPS-based alert systems and other interventions in reducing drowsy driving-related accidents.

2.8 eCall technology

eCall Technology is a European based autonomous call technology used in motor vehicles to call for emergency services hypothesized to reduce the emergency response time by 40% in urban areas and 50% in rural areas (Bonyár A., 2017). eCall technology is a system that automatically initiates a call to emergency services in the event of a vehicle crash. By using sensors to detect a crash, eCall technology can quickly alert emergency services and provide them with the location of the crash, potentially reducing response times and improving the chances of survival for crash victims. In recent years, there has been a growing interest in using eCall technology in combination with algorithms that monitor drowsy driving behavior (Ortiz and Detyniecki, 2022). Drowsy driving is a leading cause of road accidents, and can be characterized by a decrease in driving performance, including lane drifting, slower reaction times, and difficulty maintaining a consistent speed. By using sensors and other data sources to monitor driving behavior, algorithms can be developed to detect patterns of drowsy driving and to alert the driver or take other appropriate action to prevent an accident. One potential use of eCall technology in combination with drowsy driving monitoring algorithms is to automatically initiate a call to emergency services in the event of a drowsy driving-related crash. By detecting a crash and immediately alerting emergency services, eCall technology can potentially reduce response times and improve the chances of survival for crash victims. Another potential use of eCall technology in combination with drowsy driving monitoring algorithms is to provide the driver with alerts or other interventions to prevent a drowsy driving-related crash from occurring. For example, as proposed by Ortiz and Detyniecki (2022) mentioned that an algorithm could use data from sensors and other sources to detect when the driver is at a high risk of drowsy driving, and could initiate an alert to the driver or automatically initiate a call to a designated contact or emergency services if the risk of a crash is deemed to be high. Generally, the use of eCall technology in combination with algorithms that monitor drowsy driving behavior has the potential to improve road safety and reduce the number of drowsy driving-related accidents. However, additional research is needed to further develop and validate algorithms for detecting drowsy driving behavior, and to evaluate the effectiveness of eCall technology and other interventions in reducing drowsy driving-related accidents. The eCall technology is currently unavailable in Kenya leading to more response time to road accidents hence more deaths.

2.9 GSM technology and raspberry Pi

Kumaran and R.Dhanyasri (2021), assure that Raspberry Pi 3 can be used as a processor for input and output devices like sensors and alarm systems to achieve an alert system. GSM (Global System for Mobile Communications) technology is a widely-used standard for mobile communication that allows for the transmission of data and voice over a network of cell towers (Chinnasami Sivaji and Soundharaj, 2022). GSM technology has a range of applications, including the development of telematics systems for vehicles. Raspberry Pi is a small, low-cost computer that is popular among hobbyists and educators for its versatility and ease of use. Raspberry Pi can be used to build a variety of different systems and devices, including those that use GSM technology. One potential use of GSM technology and Raspberry Pi in combination with drowsy driving monitoring algorithms is to develop a telematics system that can transmit data on driving behavior and vehicle location to a remote server or other device (Janani and Muthukumaran, 2022). This data could be used to monitor drowsy driving behavior in real-time and to provide the driver with alerts or other interventions to prevent a drowsy driving-related crash. Application of GSM technology and Raspberry Pi in combination with algorithms that monitor drowsy driving behavior has the potential to improve road safety and reduce the number of drowsy driving-related accidents. However, additional research is needed to further develop and validate algorithms for detecting drowsy driving behavior, and to evaluate the effectiveness of telematics systems and other interventions in reducing drowsy driving-related accidents.

2.10 Gaps in existing study

Most of the literature reviewed focuses on the accuracy of different models and systems. However, Kenya still has a high prevalence of road accidents caused by drowsy driving.

Therefore, this study applies these approaches but considering the special context of Kenya. It uses a combination of these techniques to come up with a more accurate system to correctly classify drowsiness and send feedback to lower the prevalence of accidents in Kenya.

2.11 Summary

The use of machine learning techniques and image processing methods is easily manipulatable according to the requirements of the end user and the expected accuracy. However, in the transportation and automobile industry, the highest possible accuracy is desired because of the potential losses at stake. Therefore, these algorithms play a crucial role in developing a drowsiness detection system that can solve the problem of increased road accidents in Kenya. Previous studies like those referred to in this section have shown that the use of Haar Cascade classifiers, support vector machines, AdaBoost, CNN, and other algorithms have registered high rates of accuracy in detecting drowsiness through image classification. Additionally, researchers have proposed various methods that would alert drivers when they find themselves in a position of drowsiness using audio alarms and haptic feedback. However, further study is recommended to develop optimized versions of these systems and to ensure these systems stay effective in performing their intended purpose in real-world scenarios.

Chapter 3

Methodology

3.1 Introduction

The primary aim of this study is to develop a machine learning algorithm that would assist in detecting drowsy driving and give necessary feedback, which includes an action to make the driver alert. To achieve this goal, this process involves model development, data collection, model training and testing followed by optimization. To achieve an acceptable accuracy and validity of outcomes and results, this process must be carefully considered with keen attention on how the model works.

3.2 Study Design

This thesis uses simulation study which involves creating a simulated environment in which to test the algorithm's performance. This can be useful when it is not practical or ethical to test the algorithm on real data. For example, a simulation study could be used to test a self-driving car algorithm's ability to navigate different road conditions. Drowsy driving is a major contributor to road accidents, leading to fatal injuries and in many cases, deaths (Saleem, 2022). However, machine learning can help detect drowsy driving and provide feedback to drivers to help prevent such accidents (Sajid Hasan and Weiss, 2022). This project aims to develop a system that uses a machine learning algorithm developed by latex to detect drowsy driving and respond with feedback. The data required to achieve this objective can be sourced for this project from secondary sources available over the internet. This study design section outlines the approach that is used to achieve the study objectives. Some of the important questions that would help in achieving the study objectives are based on;

the accuracy of machine learning models in detecting drowsy driving; the ability of the feedback from the system to assist in preventing accidents caused by drowsy driving; and the effectiveness of the system in detecting drowsy driving and providing feedback (Sajid Hasan and Weiss, 2022).This study involves collection of data from publicly available secondary sources. The data gets labeled to indicate whether the driver was drowsy or not. The criteria that was used to label the data include:

i Drowsy driving – The driver shows signs of slow eye movements, difficulty in keeping their head up, and slow reaction times.

ii Not drowsy driving - The driver shows signs of being alert, focused, and has normal reaction times.

In order to process the data, the collected video footage was split up into frames, from which aspects like eye movement, head position, and reaction time was extracted and converted into numerical features (Akshay and Anuvaishnav, 2021). Data cleaning was also a part of this procedure necessary to be used in the removal of any noise or inaccuracies that may be visible in the data. A few machine learning algorithms – including neural networks, random forests, decision trees, and logistic regression – were analyzed after the data collection and processing stages (Akshay and Anuvaishnav, 2021). Following this, various models were trained and tested on the labeled data to identify the most accurate and effective model to be utilized for drowsy driving. Once the machine learning model detects drowsy driving, the feedback system gets triggered to alert the driver as an accident prevention measure. The feedback system is set to use visual and auditory signals in alerting the driver (Gumaei and Fortino, 2020). These signals include a warning sound, flashing lights, or a vibration on the steering wheel. As mentioned before, the effectiveness of the whole system was evaluated by the performance of the machine learning models. This was achieved by using metrics such as accuracy, precision, and recall. This study also evaluated the effectiveness of the feedback system by analyzing how fast the driver responds to the alerts produced by the feedback system.

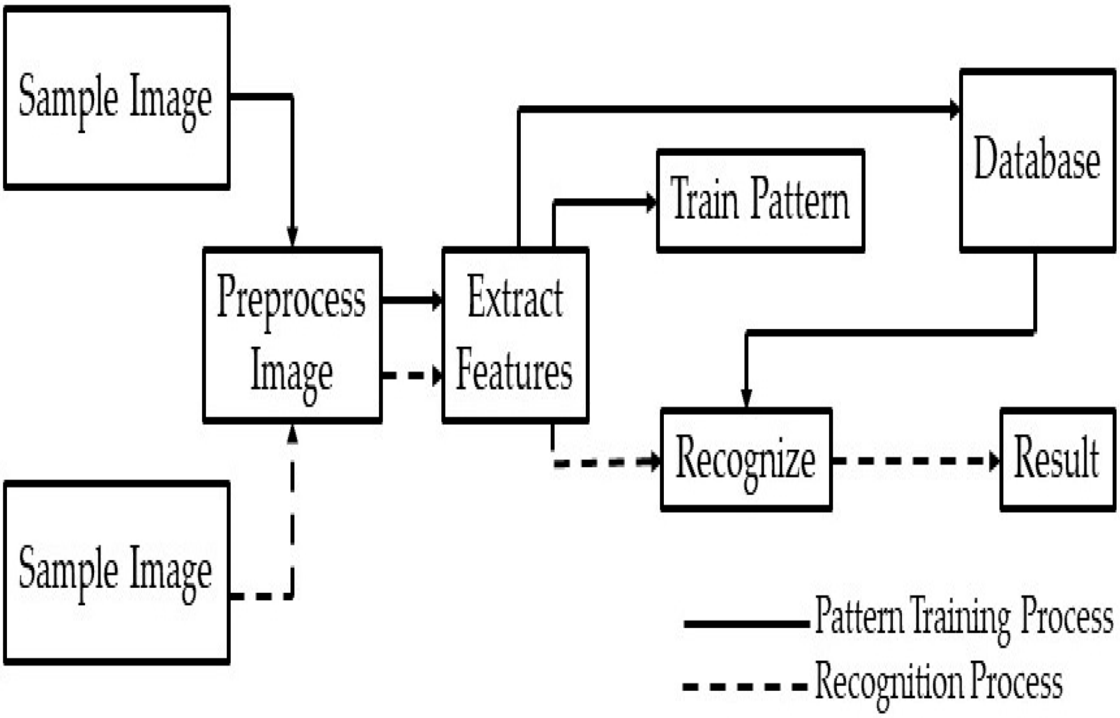

Figure 3.1: Machine Learning Process Flow. Source: (Patel and Gilkey Jr, 2020)

3.3 Data Collection

As a result, the quality and amount of the data used in the model training process have a significant impact on the model's ability to operate successfully. The data used in this study is based on US-based subjects, with applicability on other countries like Kenya. For this study, the dataset used was mainly applied for training the model, because the elements under consideration are similar and show no difference from one country to another. To ensure that the data is sufficient in terms of reflecting the real-world scenarios, the data for this project was collected from internet-based public sources (Gumaei and Fortino, 2020). The many forms of data that were gathered for this study include electroencephalography (EEG) data, dash-cam recordings, and driving behavior data. Dash-cam videos feature a variety of driving situations, including those on freeways, city streets, and country roads. The data in these situations includes head and facial movement, as well as eye and lip motions (Gumaei and Fortino, 2020). The datasets contained data on speed, steering behavior, braking, and acceleration in terms of driving behavior. On the other hand, EEG data involves invisible activity. This kind of data involves brain activity, and alterations in the brain can be utilized to identify drowsy driving. Following collection, the data was cleaned to remove any noise or errors that might be present in the datasets, such as inaccurate labels or missing values.

3.4 Data Preprocessing

This step involves transformation of the raw data into a format that can be used in training and testing the selected machine learning model for this project. Therefore, the data collected from various sources, including dash-cam videos, driving behavior datasets, and EEG data, required different preprocessing techniques to extract meaningful features that can be effective for the training of the model. This step involved other steps like video data processing, driving behavior data processing, EEG data processing, data cleaning, feature scaling, followed by feature selection at the end.

3.4.1 Video data preprocessing

This step involves conversion of the video data into frames and extraction of relevant features like eye movements, head position, and reaction time (Chang and Gupta, 2022). This process can be achieved using computer vision techniques to detect facial landmarks – such as the eye position – and track their movements over time. Also, the algorithms can assist in estimating the driver's reaction time by analyzing the speed and direction of their movements.

3.4.2 EEG data preprocessing

The EEG data was converted into numerical features – such as frequency bands and amplitude – using signal processing techniques (Zhdanov and Hoffmann, 2022). This can still be achieved using machine learning algorithms like the principal component analysis (PCA), to assist in reducing the data dimensionality and to extract relevant features.

3.4.3 Data cleaning

Data cleaning was performed on the datasets that were collected to eliminate errors and noises. For instance, this project used imputation techniques to fill in the missing values or remove samples having incorrect labels.

3.4.4 Feature scaling

Feature scaling was conducted to ensure that all features are on the same scale and exist within a similar range. This process is expected to prevent some features from dominating the others, which may highly affect the performance of the machine learning model.

3.4.5 Feature selection

This step of the project involved selection of the most relevant features to be used in machine learning model training. The main objective of this step is minimization of the data dimensionality as well as to improve the performance of the model.

3.5 Machine Learning Model Selection

This project aims to apply machine learning algorithms in classification of drivers as drowsy or non-drowsy. This classification is based on the drivers' driving behavior, facial expressions, and EEG data. The selection process began by exploration of different types of machine learning models. The main models that were considered include logistic regression, decision trees, random forests, deep learning models – like convolutional neural networks (CNN), recurrent neural networks (RNN) and support vector machines (SVM). The main aspect of these models that were considered as the basis of selection is their performance (Gumaei and Fortino, 2020). The performance went through an evaluation using measures like model recall, model precision, model accuracy and F1-scores of the models. A cross-validation was used to select the best machine learning model so as to ensure that the model does not over-fit to the training data. Another process that was included in this stage is tuning of the hyper-parameters of each model using grid search or random search as an approach to optimize their performance. Once the best model gets selected, it proceeds to the training stage with the preprocessed dataset. This was then followed by evaluation of the model performance on a separate test set. This is aimed at assessing the model generalizability to new data. The suitability of the selected model was based on its performance as compared with the performance of other existing models.

This project uses CNN model to build the image classifier, based on the assumption that you can train the model on noisy images and the model will be capable of learning how to map the noisy image (Sharma, 2023) to correspond to denoised versions, that is once the model is trained the CNN is capable of denoising the images through the network therefor ending up obtaining the constructed images.

3.6 Evaluation Metrics

Evaluation metrics are important in measurement of the machine learning model performance. This project applied the receiver operating properties, F1- score, recall, precision, accuracy, and confusion matrix as evaluation metrics to determine the effectiveness of our model.

3.6.1 Accuracy

As a percentage of all predictions made by the machine learning model, accuracy is a frequently used evaluation statistic that assesses the percentage of correct predictions made by the model. It is determined as a percentage based on the ratio of samples that were correctly identified to all samples in the test set.

$$\frac{(\text{True Positive } + \text{True Negative})}{(\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative})}$$

3.6.2 Precision

In this case, precision measures the proportion of true positives among all the samples predicted by the model as drowsy. True positives are those samples that are correctly classified as drowsy. Therefore, according to Huilgol (2020), precision can be defined as "the ratio of the number of true positives to the number of true positives plus false positives". False positives are those samples that are incorrectly classified as drowsy.

$$\frac{\text{True Positive}}{(\text{True Positive} + \text{False Positve})}$$

3.6.3 Recall

Recall quantifies the number of genuine positive samples among all the positive samples. This includes both true positives and false negatives. "The ratio of the frequency of true positives to the sum of the true positives and false negatives" is what gets used in computation of recall or samples that are incorrectly classified as non-drowsy (Huilgol, 2020).

$$\frac{\text{True Positive}}{(\text{True Positive} + \text{False Negative})}$$

3.6.4 F1-score

This is a measure that measures a model's accuracy as a derivative of both recall and precision. It is calculated as 2 times the product of precision and recall divided by their sum. This measure is important especially because the datasets involved in this project contain unevenly distributed classes.

$$F1 = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2 * \text{TP}}{2 * \text{TP} + \text{FP} + \text{FN}}$$

3.6.5 Receiver Operating Characteristic (ROC) Curve

ROC curve refers to “a graphical representation of the performance of a binary classifier at different thresholds”. This measure involves plotting the true positive rate (TPR) against the false positive rate (FPR) for different threshold values. The measure of the ability of the model to differentiate between negative and positive samples is provided by the area under the ROC curve.

3.6.6 Confusion matrix

This refers to a table that gives a summary of how a machine learning model performs by showing the outcomes of the model in terms of “the number of true positives, true negatives, false positives, and false negatives” (Huilgol, 2020).

		Prediction outcome		
		p	**n**	**total**
	p′	True Positive	False Negative	P′
actual value	**n′**	False Positive	True Negative	N′
	total	P	N	

Figure 3.2: Confusion matrix. Source: (Pettersson Ruiz and Angelis, 2022).

3.7 Conclusion

This chapter discusses the project design based on the aims of using machine learning to detect drowsy driving and respond with feedback. It explains the data collection techniques as well as the applications for these datasets. Other specifications made in this section include the machine learning models that were evaluated to find the best one suitable for application in this project. Similarly, the evaluation metrics that were applied are discussed. As much as machine learning models can be trained adequately, their effectiveness in performing their designed function must be tested to ensure minimal chances of failure. This project can however, be further developed and enhanced through application of more advanced techniques and approaches. This can ultimately contribute to enhancing road safety and reducing the prevalence of drowsy driving related accidents.

Chapter 4

Analysis, Results and Interpretation

4.1 Introduction

The goal of this study was to create a machine-learning model that is able to detect drowsy driving using image processing and give feedback based on the results of the image processing. For the success of developing the system a flow was designed and this flow was about Data pre-processing, feature extraction, training and testing the system. Dataset used to create the model for this study included four image categories: open-eye images, closed-eye images, yawning images, and non-yawning images. The dataset was partitioned in a 7:3 ratio that is 70% of the data being set for training and the remaining 30% getting used for testing the model. Data augmentation was additionally employed in order to expand the training dataset without overfitting the model.Keras "Deep learning API" was used to train the model, which produced an accuracy of 84.5%. This report provides the findings as well as a discussion of the process used in the development of this model.

4.2 Algorithm

For face detection and eye tracking, the Haar-Cascade algorithm is employed, and EAR is then used to identify sleepiness. OpenCV is used in the programming, which is done in Python. Many pre-trained classifiers for faces, eyes, smiles, etc. are already available in OpenCV. For the pre-trained classifiers this project uses; Haarcascadefrontalfacedefault.xml to enable classify yawn and no yawn from an image and Haarcascade.xml to enable classify open and closed eye from an image.

4.2.1 Eye Aspect Ratio (EAR)

This attractive technique uses a fairly uncomplicated computation based on the ratio of lengths between the eyes' facial landmarks. Six (x, y)-coordinates are used to represent each eye, starting at the left-corner and rotating clockwise around the remaining part of the area.

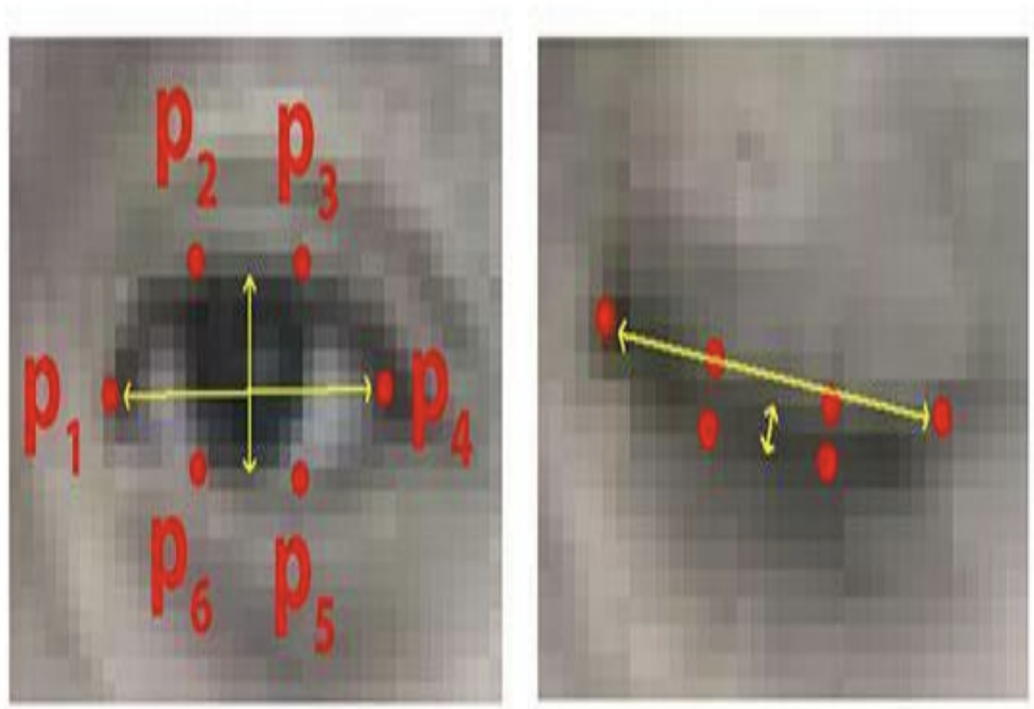

Figure 4.1: Coordinate of EAR

The formula below is use to calculate the EAR

$$\mathbf{EAR} = \frac{||p_2 - p_6|| + ||p_3 - p_5||}{2||p_1 - p_4}$$

Haar-Cascade algorithm in conjunction with EAR algorithm is achieved through a series of steps. In the first step, the required XML classifiers get loaded through the use of openCV function CascadeClassifier(). In the second step, the input image gets converted intograyscale colorscheme. For the third step, the algorithm looks for faces in the image. In this step, whenever faces get discovered, their positioning gets registered in the form of Rect (x,y,w,h). This step is followed by getting the location of specific features while creating an ROI

(Region of interest). For the EAR algorithm, the first step is to use the region of the eye that has been detected from the above algorithm, followed by a computation of the Eye Aspect Ratio. This determines if the eyes are closed. The third step involves an execution of a condition that tests if EAR satisfies the category of drowsiness. If this is true it proceeds to end. For any other feedback, the alarm gets triggered.

Figure 4.2: System flow

4.3 Findings

4.3.1 Drowsiness classifying algorithm

For the driver's safety and security, this system combines two distinct models: drowsiness detection and face recognition. Below on Figure 4.3 a snippet of video that was captured without the classification model being applied and on Figure 4.4 is a snippet of video after the classification has been applied. From Figure 4.4 the model is able to detect the face and the eye hence the blue on the face and orange boxes on the eye.

Figure 4.3: Video capture without algorithm applied

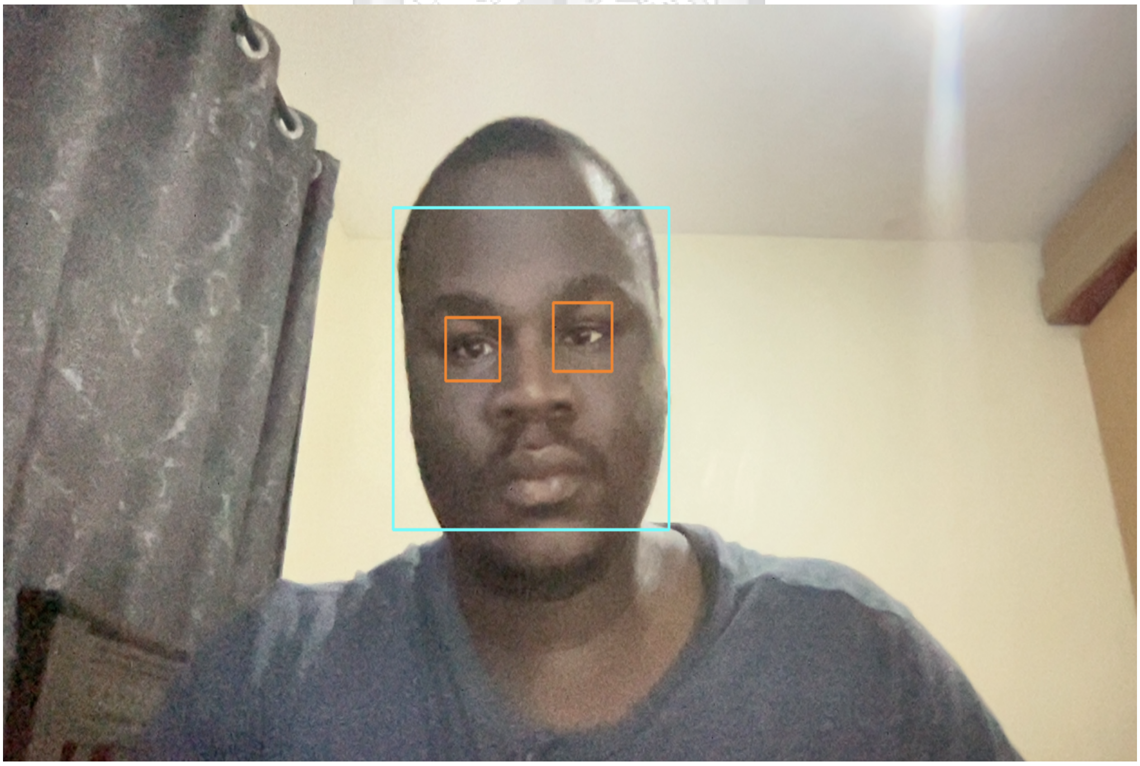

Figure 4.4: Video capture with algorithm applied

Test Condition	System Behaviour	Expected Results
Straight Face, Good Light with glasses	Not Drowsy	Not Drowsy
Tilted Face, Good Light no glasses	Drowsy	Drowsy
Tilted Face, Good Light with glasses	Drowsy	Drowsy

Table 4.1: Test cases test results

4.3.2 Alert System

Once the image has been determined to be a drowsy image, the alert system should be redirected as a result. This information must be continuously supplied from the camera, which uses bounding boxes to recognize the driver's face and eyes. If the driver closes his eyes for three to four seconds, an alarm goes off.

4.4 Performance testing

The train and test accuracy of the machine learning model developed for detecting drowsy driving through image processing was found to be 84.5% and 83.2% respectively. This indicates that the model can correctly classify images with a high level of precision. Other metrics such as precision, recall, and F1-score for the model were also considered to determine its performance comprehensively. These metrics provide a more accurate assessment of the model's effectiveness by measuring the number of false positives, false negatives, and true positives. Three averages were computed for each metric and Figure 4.2 shows the results. Generally, the model showed a relatively high precision compared to a number of algorithms that have been used in drowsy driving detection like Random Forest, Logistic Regression, and Naive Bayes.

The training dataset's size was increased through the use of data augmentation, producing a more accurate model. To artificially expand the dataset, this method generates new data from pre-existing images. This method was used to lessen overfitting and improve the generalizability of the model. However, the original dataset's quality is crucial in determining the effectiveness of data augmentation; as a result, the original datasets was confirmed to have excellent quality before utilizing data augmentation. A sequential training model was established for this project using Keras, a high-level neural network API. In general, this API makes experimenting with machine learning models simple and effective. It is thus regarded as the ideal choice for developing machine learning models, particularly for those meant to perform image processing functions. This is due to its user-friendly design and flexible interface. To achieve the best results, this study ensured that the hyper-parameters used to train the model were properly calibrated.

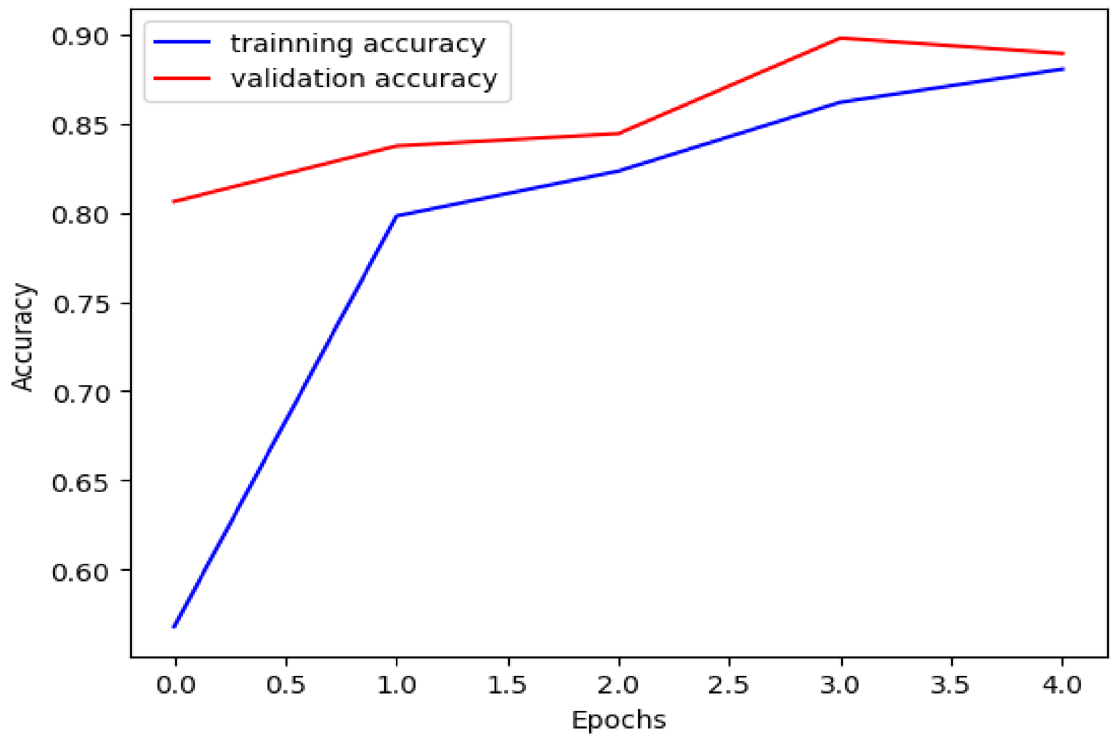

Figure 4.5: Model accuracy from the model testing

The plot above Figure 4.5 shows a graph of the model accuracy from the testing plotted against the epochs. The training accuracy shows a fast rise with respect to epochs to 80% in the first trial. However, the subsequent tests show that the training accuracy rises to more than 85%. On the other side, the validation accuracy begins at 80%, meeting the training accuracy at the last epoch.

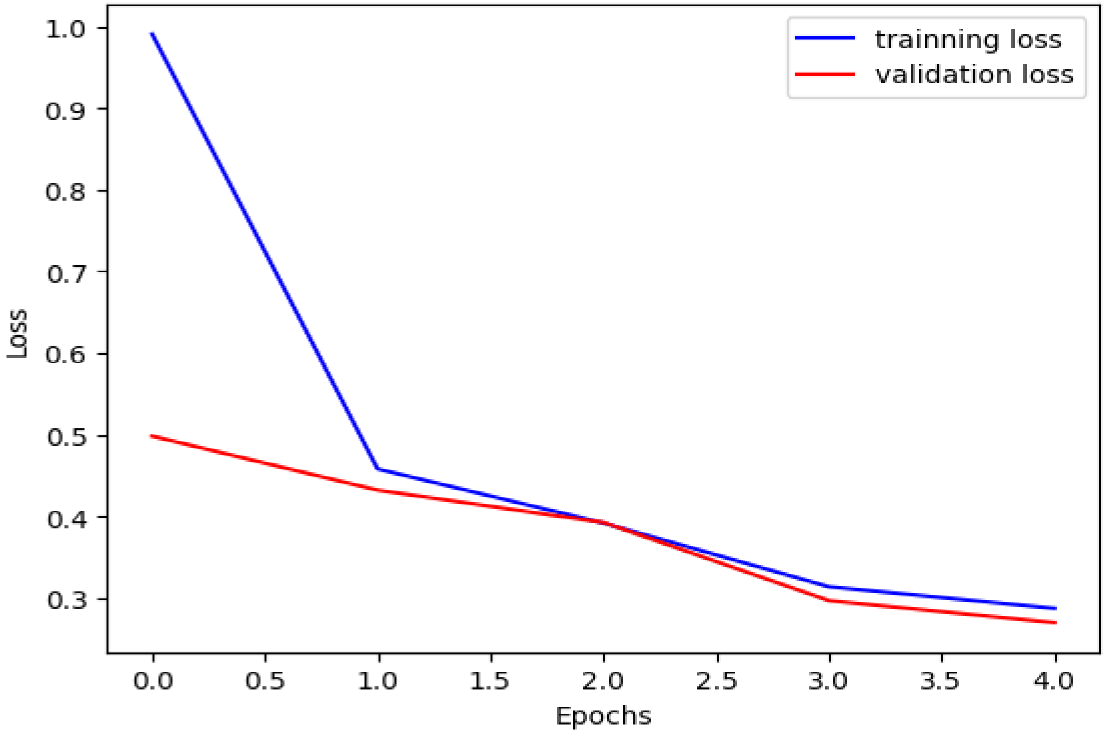

Figure 4.6: Model accuracy from the model testing

The plot above Figure 4.6 While the training and validation accuracy increase, the subsequent training and validation loss drops in almost a similar manner. After the first test, the training loss drops to less than 50%, continuing to 30% after the susequent epochs. Obn the other hand, the validation loss begins at 50%, dropping to less than 30% after the last testing.

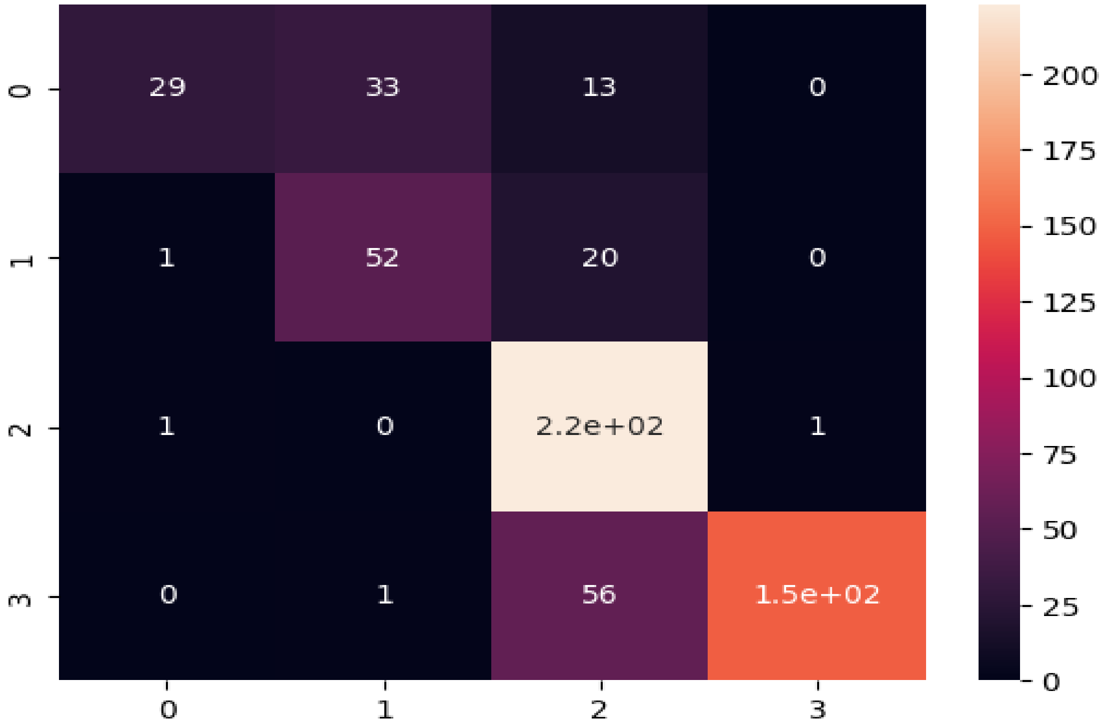

Figure 4.7: Confusion matrix

In Figure 4.7, with 0 representing yawn, 1 representing no-yawn, 2 representing Closed and 3 representing open, we are able to see that 29 yawn images were predicted correct out of 31 with 1 wrongly classified as no-yawn and 1 wrongly classified as closed, 52 no-yawn images were predicted correct out of 86 with 33 wrongly classified as yawn and 1 wrongly classified as open, which is quite a performance for the model.

	Precision	**Recall**	**F1-Score**	**Support**
Yawn	0.97	0.51	0.67	75
No-Yawn	0.67	0.85	0.75	75
Closed	0.78	0.99	0.87	225
Open	0.99	0.77	0.87	205
Micro Average	0.83	0.83	0.83	578
Macro Weighted average	0.85	0.78	0.79	578
Weighted average	0.86	0.83	0.83	578
Sample average	0.8	0.83	0.83	578

Table 4.2: Model accuracy derived from the model testing

Precision: Out of all the images the model predicted 97% of the images are Yawn, 67% No-Yawn image, 78% Closed eye image and 99% Open eye Image.

Recall: Out of all the images tested in the model only 51% of the images are correctly predicted to be Yawn, 85% are correctly predicted to be No-Yawn image, 99% are correctly predicted to be Closed eye image and 77% are correctly predicted to be Open eye Image.

F1-score: Since 67% is slightly above average 50% the model here performed moderately in predicting whether or not the image gets classified to be Yawn. For 75% No-Yawn image, 87% Closed eye image and 87% Open eye Image they are close to 100% which means the model did a good job predicting whether or not the images get classified as No-Yawn, Closed, Open eye respectively.

Support:These values tell us more about how many images belonged to each class group of the test dataset.75 are Yawn images, 75 No-Yawn image, 225 are Closed eye images and 205 are Open eye Image.

Chapter 5

Discussion, Conclusions and Recommendations

5.1 Introduction

This chapter highlights the discussion of the results, the conclusion drawn from these results and the recommendations for the application of this study. The information in this chapter depends on the results outlined in the previous chapter in conjunction with previous studies on drowsy driving and its control to discuss the outcomes of this project. The supporting information from the previous studies used in this section assist in drawing conclusions, which also influence the recommendation section.

5.2 Discussion

The model performance evaluation was done in different condition areas with low and enough light, the results were interesting to explore, and this had a great impact on the model performance. Light as a factor has a great impact on the performance of the model, that is when the model is tested in different lighting conditions there is intense variation in the results due to the level of available external illumination. The model performed high with up-to 84.5% accuracy of drowsiness detection when exposed to high illumination, unlike when there is less illumination, the drowsiness detection goes down up-to about 70%, these adjustments in drowsiness detection are due to lighting conditions. Even though this algorithm produced a relatively high accuracy of 70% to 84.5% with different conditions, it was not able to achieve the level of accuracy achieved by (AL-Anizy and Razooq, 2015) and (Apoorva and Rakesh, 2020). These researchers used the Haar Cascade classifier together with other frameworks like Viola Jones, which may be the reason for their high accuracy results. However, as defined by (Kim, 2017) in the second chapter of this report, a system that is able to perform image processing must also classify the state of the eyes to identify whether they are open or closed. This study has been able to meet this definition by being able to process images in different conditions like varying lighting. This is a simulation of the typical driving scenario at night and day time.

Another factor that was notable was the frame rate, it also had an impact on the performance of the model, pictures and videos had high frame rate and had several advantages to the model, the model accuracy was high as a result of high quality video thereby being able to detect eye properties accurately. With a high frame rate the model is able to capture blink frequency and blink duration. Increasing the frame rates would mean need for high memory and processing power which impacts the environment for training the model.Most embedded systems however have low computational capabilities hence may not be able to handle very high frame rates, in this the number of frames used in drowsiness computation should be reduced to avoid the system taking too long before it arrives at decisions. The number of frames used in the computation should be limited in this situation to prevent the system from taking too long to reach choices because the majority of embedded systems, on the other hand, have minimal computational resources and may not be able to handle very high frame rates. (You, 2013), (Kim, 2017), and (Narejo and Kulsoom, 2016) used different algorithms that work by monitoring eye movements that are unique to different states of alertness. These algorithms mainly monitor distinct features of the eyes, which depend on the image quality. Therefore, the quality of images captured for this study are attributed to the high frame rate used in the capturing of images.

The model developed for this study has a high level of precision in diagnosing drowsy driving through image processing and a good level of accuracy. Other metrics, such as precision, recall, and F1-score, also display comparatively superior results to other models created to carry out the same purpose. These metrics generally track the number of false positives, false negatives, and true positives to provide a more detailed assessment of the performance of this model. Since the accuracy of the original dataset determined the efficiency of data augmentation in this project - which helped to increase the training dataset - the original dataset's excellent quality was confirmed before the data augmentation operation got applied. The implications of this project indicate that drowsy driving is a major cause of road accidents worldwide but it is possible to prevent such accidents through the development of a reliable machine-learning model. The model developed in this project has proven to have the potential to provide a solution in real-world scenarios, such as in cars, to alert drivers who are experiencing drowsiness, thus preventing road accidents. This project can also get extended to include other forms of impairment affecting drivers and to make the roads in Kenya safer. Even though the accuracy results were considered for the general dataset, (**?**) recommended that these results be considered for different eye states, which have been used in this study as image classifications. Other metrics, such as precision, recall, and F1-score, also display comparatively superior results to other models created to carry out the same purpose. For example, (You, 2013) report values of recall and precision at 75% and 83% respectively. Similarly, (Papakostas, 2020) generated an average recall of 82%, which is still a percentage lower than this study's average recall of 83%. .

5.3 Conclusion

This project was successful in developing a machine learning model using an algorithm that can successfully detect drowsy driving through image processing at least nine of the ten times it gets used. This has been proven by the model's ability to achieve an accuracy of 84.5%, which is high when compared to other recently developed models. This is an indicator of a high level of precision in classifying images. More studies to be conducted in this field should focus on extending the project to include other forms of impairments that lead to road accidents. They should also seek to optimize parameters used in the recently developed models in order to improve their performance. Overall, this project demonstrated the effectiveness of machine learning in detecting drowsy driving through image processing and the potential of this algorithm in improving road safety through the use of artificial intelligence.

5.4 Recommendation

5.4.1 Further study

Lack of enough dataset to conduct testing for the model, researchers should consider creating a database with testing dataset for future research to make the research more effective when testing the models. More study is needed to make the system/ model to perform better at night or in places where there is low light, an active method of video can be embraced. That is, the use of infrared cameras. In the future, research should also be advanced to include more complex user behavior, far beyond closed, and open eyes, yawning and non yawning faces. More study is additionally needed in order to improve the model accuracy. It is suggested that the model works best when there is only enough illumination, in order for this model to work in low illumination a team of great data scientist and software engineers need to work together with the aim of developing a device that can consume much light even in the dark for the model to work effectively.

5.4.2 Policy making

Government to implement a law that encourages and even offers subsidies to importation of cars fitted with cameras that can detect drowsiness, this could prevent accidents.

5.5 Limitations of study

In future research it will be great to develop a test database for many researchers, making a great step towards technological advancements in research.

Limited processing power, training the model through deep learning requires a lot of processing power, the devices used were limited thereby opting for online resources which the model ran but slowly.
It is clear that the method has limits with just 84.5% accuracy. The biggest drawback is that persons with a really dark complexion cannot use it. This is clear since the algorithm that underlies the system is based on binarization at its heart. Binarization does not function for those with dark skin.
There cannot be any reflective materials behind the driver, which is another restriction. The system becomes more reliable as the background becomes more homogenous. To solve this issue for testing purposes, a black sheet was placed up behind the test participant.

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Appendix A

Python Code

This Python code with the help of Keras was used to build an image classifier that can detect drowsiness Chapter 4 and Chapter 5.

A.1 Python(Keras) Drowsiness Detection code

```
import numpy as np # linear algebra
import pandas as pd # data processing
import os
import cv2 #OpenCV image processing module

#visualization
import matplotlib.pyplot as plt
import seaborn as sns

#machine learning
#training and testing dataset
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelBinarizer
#to split dataset into train and test
from sklearn.model_selection import train_test_split


#Disable warnings
```

```
import warnings
warnings.filterwarnings("ignore")

#Depenencies
import tensorflow as tf
import keras
from tensorflow.keras.models import Model
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Input, Lambda, Dense, \
Flatten, Conv2D, MaxPooling2D, Dropout
from keras.preprocessing.image import ImageDataGenerator

#model accuracy
from sklearn.metrics import accuracy_score, confusion_matrix, \
classification_report

#get the names of folder
labels = os.listdir("drive/MyDrive/MScProject/train")
labels

def face_for_yawn(direc="drive/MyDrive/MScProject/train", \
face_cas_path="drive/MyDrive/MScProject/haarcascade_frontalface_default.xml"):
yaw_no = []
IMG_SIZE = 145
categories = ["yawn", "no_yawn"]
for category in categories:
path_link = os.path.join(direc, category)
class_num1 = categories.index(category)
print(class_num1)
for image in os.listdir(path_link):
```

```
image_array = cv2.imread(os.path.join(path_link, image), cv2.IMREAD_COLOR)
face_cascade = cv2.CascadeClassifier(face_cas_path)
faces = face_cascade.detectMultiScale(image_array, 1.3, 5)
for (x, y, w, h) in faces:
img = cv2.rectangle(image_array, (x, y), (x+w, y+h), (0, 255, 0), 2)
roi_color = img[y:y+h, x:x+w]
resized_array = cv2.resize(roi_color, (IMG_SIZE, IMG_SIZE))
yaw_no.append([resized_array, class_num1])
return yaw_no


yawn_no_yawn = face_for_yawn()


def get_data(dir_path="drive/MyDrive/MScProject/train/", \
face_cas="haarcascade_frontalface_default.xml", eye_cas="haarcascade.xml"):
labels = ['Closed', 'Open']
IMG_SIZE = 145
data = []
for label in labels:
path = os.path.join(dir_path, label)
class_num = labels.index(label)
class_num +=2
print(class_num)
for img in os.listdir(path):
try:
img_array = cv2.imread(os.path.join(path, img), cv2.IMREAD_COLOR)
resized_array = cv2.resize(img_array, (IMG_SIZE, IMG_SIZE))
data.append([resized_array, class_num])
except Exception as e:
print(e)
```

```
return data

data_train = get_data()

extend the datasets
def append_data():
#total_data = []
yaw_no = face_for_yawn()
data = get_data()
yaw_no.extend(data)
return np.array(yaw_no)

new_data = append_data()

Sparate labels and features
X = []
y = []
for feature, label in new_data:
X.append(feature)
y.append(label)

X = np.array(X)
X = X.reshape(-1, 145, 145, 3)

Label Binarization
label_bin = LabelBinarizer()
y = label_bin.fit_transform(y)

Train and test split
X_train, X_test, y_train, y_test = train_test_split(X, y, \
```

```
random_state=100, test_size=0.3) #split test to 30%

train_generator = ImageDataGenerator(rescale=1/255,\
 zoom_range=0.2, horizontal_flip=True, rotation_range=30)
test_generator = ImageDataGenerator(rescale=1/255)

Data Augmentation
train_generator = train_generator.flow(np.array(X_train), y_train, shuffle=False)
test_generator = test_generator.flow(np.array(X_test), y_test, shuffle=False)

Keras model
model = Sequential()

model.add(Conv2D(256, (3, 3), activation="relu", input_shape=X_train.shape[1:]))
model.add(MaxPooling2D(2, 2))

model.add(Conv2D(128, (3, 3), activation="relu"))
model.add(MaxPooling2D(2, 2))

model.add(Conv2D(64, (3, 3), activation="relu"))
model.add(MaxPooling2D(2, 2))

model.add(Conv2D(32, (3, 3), activation="relu"))
model.add(MaxPooling2D(2, 2))

model.add(Flatten())
model.add(Dropout(0.5))

model.add(Dense(64, activation="relu"))
model.add(Dense(4, activation="softmax"))
```

```
model.compile(loss="categorical_crossentropy", \
metrics=["accuracy"], optimizer="adam")

model.summary()

history = model.fit(train_generator, epochs=5, validation_data=test_generator, \
shuffle=True, validation_steps=len(test_generator))

#Get train accracy
_, accuracy = model.evaluate(X_train, y_train)
print(f"Train Accuracy: %.2f {accuracy*100}")

#Get test  accuracy
X_test1 = X_test
prediction = model.predict(X_test1).round()
prediction5 = prediction
accuracy_score(y_test, prediction)

#creating confusion matrix
X_test3 = X_test
prediction1 = model.predict(X_test3) # for building CM
y_pred=np.argmax(prediction1, axis=1)
y_test=np.argmax(y_test, axis=1)

accuracy = history.history['accuracy']
val_accuracy = history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(len(accuracy))
```

```
plt.plot(epochs, accuracy, "b", label="trainning accuracy")
plt.plot(epochs, val_accuracy, "r", label="validation accuracy")
plt.legend()
plt.show()

plt.plot(epochs, loss, "b", label="trainning loss")
plt.plot(epochs, val_loss, "r", label="validation loss")
plt.legend()
plt.show()

Predictions
labels_new = ["yawn", "no_yawn", "Closed", "Open"]
IMG_SIZE = 145
def prepare(filepath, \
face_cas="drive/MyDrive/MScProject/haarcascade_frontalface_default.xml"):
img_array = cv2.imread(filepath, cv2.IMREAD_COLOR)
img_array = img_array / 255
resized_array = cv2.resize(img_array, (IMG_SIZE, IMG_SIZE))
return resized_array.reshape(-1, IMG_SIZE, IMG_SIZE, 3)

model = tf.keras.models.load_model("./drowiness_new6.h5")

prediction = model.predict(\
[prepare("drive/MyDrive/MScProject/train/yawn/113.jpg")])
np.argmax(prediction)
```

Appendix B

Turnitin Report