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Driver drowsiness detection in the freight industry.

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DRIVER DROWSINESS DETECTION IN THE FREIGHT INDUSTRY

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ABSTRACT
Driver drowsiness has over the years become a key concern to everyone involved in long distance travels especially in the freight industry. Year in, year out, the number of deaths and fatalities globally as a result of driver drowsiness keep increasing significantly. Thus, ensuring the road safety of people is of uttermost importance. One of the safety measures employed against driver drowsiness is the use of a dashboard camera.

Despite the widespread adoption and growing numbers of installations of dashboard cameras (Dashcams) across the globe with even evolved technology, current dashcams are still incapable of learning how to identify different postures or gestures that indicate that a driver seems to be either distracted, drowsy or asleep while driving. Even though they have the capability of recording anything happening on the road or in the vehicle in the event of an accident, they are still unable to provide real-time warnings or triggers to the drowsy driver attempting to possibly prevent an accident from happening. They also require continuous monitoring which is ineffective due to a human's inability to maintain sufficient attention to discern significant events, a gap that the proposed enhancement aims to fill. The proposed Machine Learning Aided Drowsiness Detection System intends to cater for the fundamental flaws in today' dashcams.

Machine learning incorporates aspects of artificial intelligence that empower systems with the ability to continuously learn and improve automatically with experience without being explicitly programmed. It triggers a new way of thinking about the current dashcams. It offers new features, such as real-time conscious monitoring and gives an alert to the driver in the case of drowsiness being detected, in addition to the pre-existing systems' features – a visual system that not only 'sees', but also 'understands' what it's 'seeing'. It is an undeniable fact that the use of dash cams integrated with machine learning will offer new robust capabilities. The Drowsiness Detection System comprises co-working components of a computer vision, camera, and a special type of machine learning model based on Deep Learning using Neural Networks which excels in object detection and recognition tasks via image analysis achieving an accuracy of 96.19%.

The drowsiness detection system is thus highly efficient in the identification of drowsiness from different facial features such as eyes and mouth, send out a warning or alert in the event that drowsiness is detected and be continuously trained and improved with better and more datasets. The proposed system is convenient due to its improved performance and efficiency.

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LIST OF ABBREVIATIONS

3-D	Three Dimensional
AEB	Automatic braking system
AI	Artificial Intelligence
CNN	Convolutional Neural Network
DVR	Digital Video Recorder
FCW	Forward Collision Warning
GPS	Global Positioning System
GRU	Gated Recurrent Unit
PERCLOS	Percentage of Eyelid Closure

CHAPTER ONE
INTRODUCTION

1.1 INTRODUCTION OF STUDY

Driver drowsiness is a key factor in the development of the mechanisms we use to ensure safety when navigating vehicles. This led to the invention of devices and methods that allowed people to know what to pay attention to in order to prevent accidents from occurring (Titare, Chinchghare & Hande, 2021).

Essentially, one of the key contributing factors to both professional and traffic accidents is a driver's incapacity to maintain appropriate levels of awakeness. This is due to the increased likelihood of the driver dozing off. Due to their lack of alertness, the driver makes poor decisions and may even daydream, all of which are linked to stress and inadequate sleep. Weariness and tiredness will cause a number of mistakes, including bad distance estimation, poor distancing, and steering off the road according to Dr. Geoffrey Wango (Wango, 2023).

According to brake in the UK (Brake, 2023), 10 to 20% of road accidents of all road accidents was contributed to by driver fatigue and according to them drivers are most likely to fall asleep around 6am. They further stated that 1 in 8 would admit to falling asleep behind the wheel. According to Brake (Brake, 2023) between 10% and 20% of all traffic accidents are thought to be caused by weariness globally. Due to the lack of driver stimulation and the monotonous road conditions, highways and dual carriageways are the sites of the majority of sleep-related crashes.

Dash cams were introduced in the late 1930s and saw an increase in utility and demand. Almost every truck considered safe has some way to monitor the vehicle, and it's most likely through a camera on the dashboard. Dash cams use a system of interconnected cameras to capture images and save them to the Digital Video Recorder (DVR). Data on the DVR can be stored on an SD card for reuse and review. It is usually placed on the dashboard or mounted right next to the rearview mirror on the vehicle's windshield and can monitor the road ahead or the vehicle's interior. The camera on the dashboard can record inside the vehicle, thereby monitoring the driver or the road ahead from a wide angle while doing both at the same time (Titare, Chinchghare & Hande, 2021).

Despite the good adoption of this technology, there are still some challenges in this area. Most of these dash cams are only useful after incidents such as accidents, to conduct an investigation to find the probable cause but by then the damage has already been done. What if we could find a way to detect drowsiness in real time while the driver is on the move. This is possible by applying machine learning and artificial intelligence (AI) to video and modeling to identify patterns and movements consistent with sleepiness and perform an action such as warn the driver promptly (Samira, Saad, Yilin, Haiman, Yudong, Maria, Mei-Ling, Shu-Ching & Iyengar, 2019). This can be done using neural networks with extremely complex models consisting of many layers used in deep learning algorithms. They are capable of automating the feature extraction process. This is the recommended implementation to detect drowsiness.

1.2 PROBLEM STATEMENT

Driving in a drowsy state causes one in every four accidents involving vehicles, and one in every 25 drivers would admit to feeling drowsy behind the wheel in the last 30 days (Aziz, 2022). The point that is frightening is that driving in a drowsy state is more than just falling asleep behind the wheel. Driving in a drowsy state can be termed as a very short state of not being conscious caused by the driver's inattention while being on the road. It is estimated that each year, drowsy driving causes over 71,000 injuries, 1,500 deaths, and $12.5 billion in financial losses and damages according to research paper by Sara Aziz (Aziz, 2022). Due to the importance of this issue, it is critical to come up with a solution to detect cases of drowsiness, in particular at the initial stages, in order to avoid accidents.

1.3 OBJECTIVES

1.3.1 MAIN OBJECTIVE

To develop a system for driver drowsiness detection, based on an intelligent algorithm, to perform detection and recognition of drowsiness and issue an alert.

1.3.2 SPECIFIC OBJECTIVES

i. To design and develop an intelligent visual system that detects patterns and movements of drowsiness.

ii. To develop a system that correctly recognizes patterns and indications of drowsiness taken by a camera.

iii. To notify via making a sound alert to the driver at the point of drowsiness being detected.

1.4 RESEARCH QUESTIONS

i. What are the most effective features and parameters in intelligent algorithms for driver drowsiness detection?

ii. How does the real-time responsiveness and accuracy of drowsiness detection algorithms impact the effectiveness of alert systems in preventing driver fatigue-related incidents?

iii. How effectively can one be alerted when in order to mitigate drowsiness and call for corrective action?

1.5 SIGNIFICANCE

The proposed Intelligent Drowsiness Detection System is highly proficient in identification of drowsiness and has a remarkable ability to sound an alert on drowsiness being detected based on driver facial features. The Drowsiness detection system should significantly reduce accidents caused by drowsy drivers in operation of freight vehicles and generally contribute towards road safety.

1.6 SCOPE OF STUDY

Upon implementation of this dissertation, a camera is used as the source of input where the data collected is passed to a machine learning algorithm for purposes of detection and recognition. Machine Learning used follows Neural Networks which excels in object detection and recognition tasks via image analysis. Due to its feature extraction ability, it can differentiate the patterns worth noting as drowsiness by tracking eye movement such as the eyelids. It also tracks the mouth movements such as excessive yawning. By monitoring and tracking all these movements an alert via sound will be triggered to the driver.

CHAPTER TWO

LITERATURE REVIEW

2.1 INTRODUCTION

The literature gives a background of how drowsiness detection evolved and its importance. This chapter discusses the literature on Related Works, Drowsiness when driving, Dashboard Cameras, Collision Avoidance Warning Systems, Lane Departure Warning Systems, Facial Recognition, Video Image Processing, Feature Extraction, Eye detection and tracking, Head Tilt Technology, CNN (Convolutional Neural Network) and Drowsiness Detection in the industry.

2.2 Related Works

Physiological-based systems: These systems use sensors or electrodes to capture and analyze the driver's physiological signals, such as electroencephalogram (EEG), electrocardiogram (ECG), electrooculogram (EOG), electromyogram (EMG), skin conductance, blood pressure, heart rate, or respiration rate. These signals are considered to be direct and accurate indicators of the driver's drowsiness, as they reflect the changes in the driver's brain activity, autonomic nervous system, and muscular activity. However, these systems also have some drawbacks, such as being intrusive, uncomfortable, expensive, sensitive to noise and artifacts, and requiring calibration and individualization. (Albadawi, Takruri, & Awad, 2022; Nasri, Karrouchi, Kassmi, & Messaoudi, 2022)

Vehicle-based systems: These systems use sensors or devices to capture and analyze the driver's driving behavior or vehicle dynamics, such as steering wheel angle, lane deviation, speed variation, braking force, or gas pedal pressure. These features are considered to be indirect and coarse indicators of the driver's drowsiness, as they reflect the changes in the driver's driving performance and control. These systems have the benefits of being non-intrusive, simple, and compatible with existing vehicle systems. However, these systems also have some limitations, such as being influenced by road conditions, traffic situations, driving styles, or vehicle types. (Albadawi, Takruri, & Awad, 2022; Nasri, Karrouchi, Kassmi, & Messaoudi, 2022)

2.3 Drowsiness when driving

Driving while in a sleepy state is known as drowsy driving is a situation that can affect anyone who gets behind the wheel and drives. Drowsy driving increases the risk of an accident significantly, resulting in an alarming number of injuries and deaths each year (Suni, 2022).

Driving while in a drowsy state significantly increases the chances of getting into a car accident. Microsleeps happen when a person nods off for a few seconds, and when they happen while driving, the car is in danger of running off the road or colliding with another vehicle. When these crashes happen at high speeds, the damage they cause increases.

Insufficient sleep can cause drowsiness. The average human being is recommended and in need of 7 to 8 hours of sleep per night. If you have been awake for more than 18 hours, your chances of being involved in an accident are significantly increased (Chowdhary, 2018). Long distances alone on long, boring stretches of road can lead to a driver falling asleep easily on the commute.

2.4 Dashboard Cameras

A dashboard camera is a real-time camera that records different points of a vehicle mainly the road, the inside facing the driver and occupants or 360-degree view of the vehicle. Users can view the video recordings when driver safety events such as over speeding, emergency braking, aggressive acceleration, and harsh cornering occur when the videos are linked to fleet management software (Navman, 2022).

Dashboard cameras can be more advanced when there is an inclusion of AI capabilities that utilizes the aspect of computer vision to give interpretations of videos and provide insights into distracted driving and unsafe driving behaviors (Navman, 2022). The majority of businesses use video footage to develop a safety program that commends positive behaviors such as collision avoidance.

The Dashboard works when the engine is started, the dashcam system begins by recording and continues until the engine ignition is switched off. The AI processor analyzes the recordings based on an analysis of over 3 billion minutes of driving footage, computer vision is used to identify dangerous and positive driver behaviors (Navman, 2022).

Fleet safety is critical to running a successful and profitable business. It gives alerts in real-time for driver behavior and then monitors the conditions of the road to prevent accidents, AI dash cams ensure and improve safety. Drivers are also kept up to date on external conditions in real time, allowing them to plan ahead of time and avoid potential hazards (Netradyne, 2022). Acquiring behavior-based alerts in real-time is especially useful when drivers must travel long distances and complete deliveries late at night.

2.5 Collision Avoidance Warning Systems

There is an important aspect of safe driving known as collision avoidance. Collision Avoidance Warning Systems uses radar or other sensors (such as laser and camera) to detect an impending collision and then warns the driver or takes direct braking/steering action (Wu, 2016). To detect an impending collision, some systems employ AI machine vision technology, while others rely on dash cam images and GPS location data. There are different types of collision avoidance systems (Samsara, 2022):

- Forward collision warning system (FCW): A forward collision warning system (FCW) is a cutting-edge that checks a vehicle's speed, the speed at which the vehicle ahead of it is going, and the gap between the vehicles are all monitored by safety technology, if a vehicle gets too close to another due to the pace of the vehicle, the system will display and sound an alert to the driver of an impending collision.
- Automatic braking system (AEB): An AEB is a technology for vehicles when it detects an impending object, it automatically engages the vehicle's braking system. Certain AEB systems will only exert a bit of the pressure on the brakes to provide the driver with ample time to act accordingly to salvage the situation, whereas other systems will slowly get on the brakes until the vehicle comes to a standstill.

2.6 Lane Departure Warning Systems

This is a type of collision avoidance system that warns drivers when their vehicle starts to veer off its lane, and it can be especially useful for real-time drowsiness detection. According to the Ministry of Transport in China, vehicles that deviate from the usual driving lane cause approximately 50 percent of automobile traffic accidents. The most common cause is that drivers are distracted or tired. At least one-quarter of the drivers driving had fallen asleep at least once a month; 66 percent of truck drivers dozed off while driving; and 28 percent of truck drivers dozed off while being behind the wheel within one month. Such a startling stats demonstrates the significance of putting a stop to veering off the lane. The use of lane departure warning systems together with technology for automated driving to improve road safety is an important innovative technology that can significantly reduce the number of traffic accidents (Weiwei, Wang, Wang, & Li, 2020).

Lane departure warning systems checks the status of the indicator signal for turning and issues lane departure alerts only if the driver fails to use the indicator signal for turning in the direction of the lane change. If the driver does not take action after the warning, the most advanced systems apply an anti-steering torque applied to the steering wheel, either through the vehicle's electronic steering system or by delivering braking power to a steerable road wheel, causing the vehicle to go back to a secure position (Clemson, n.d.).

Current applications and research centered on LDWS are based on image processing and machine vision. The system primarily gathers and statistically analyzes road data using visual sensors, and it extracts lines of a lane inside the roadway, and completes the assisted driving functionality under all road circumstances, including lane line recognition, lane holding, and preceding vehicle following (Gopalan & Hong, 2012). It can minimize driver weariness, lower the incidence of traffic accidents, and increase road safety to some level.

2.7 Facial Recognition

Facial recognition is a type of software that makes comparisons and does and analysis of patterns based on a person's face features in order to uniquely identify or authenticate the individual. Although facial recognition is mostly used to provide security, Other uses are gaining popularity. In fact, facial recognition technology has gotten a lot of attention because it has the potential for a great variety of applications in the tech industry for recognizing a face with precision. (Omoyiwola, 2018).

The majority of facial recognition systems are based on the various distinguishing node points that are on a human face. There are figures measured against variables associated with points on an individual's face that assist in verifying the person. Systems can use data depicted from faces to accurately and swiftly identify specific people using this technique (Omoyiwola, 2018). Facial recognition methods are rapidly evolving, with new kinds of ways such as 3-D modeling assisting in the resolution of problems with existing techniques.

Facial recognition can be described as a process with four different steps that begins with face detection, then goes on to doing face alignment, feature extraction, and the last part being face recognition (Brownlee, 2019).

- Face Detection - Mark single or numerous faces represented in form an image bounding box.

- Alignment of the Face - Normalize the face so that it matches the database in terms of geometry and metrics of a photo.
- Feature Extraction - Get facial features that can be utilized for the task of recognition.
- Recognition of faces – Get a match for the face in contrast with single or multiple faces which are known in the database that has been prepared.

A system may include a module that is separate for every step, as was previously the case, or it may merge a few or all of the steps into a one process.

Machine Learning has simplified many processes and provided efficient face-recognition algorithms and systems. It is still a developing field, but the beginnings of face recognition with machine learning have been quite beneficial.

2.8 Video Image Processing

Computers can generate still or moving images from digital signals that form pictures for a variety of purposes. Video, which is basically a series of still images, gives the impression of an action that is moving. The handling of these digital or analog signals by direct alteration of the video picture itself is referred to as video image processing. It is concerned with the computer-aided digitization of visual information.

There are two types of video image processing: real-time and postprocessing, also known as postproc. Computer and machine vision, optical sorting, and augmented reality are examples of real-time applications. For more practical uses, video segmentation is a technique that allows a computer to follow minute differences between still pictures and concentrate on a moving object within a frame (Baxter, 2023).

In the case of drowsiness detection, the video image processing will process the drivers image and face to allow for utilization of facial recognition in order to extract features used to identify the attributes of drowsiness. The will used to determine the state of the face using features like eyes being open and closed.

2.9 Feature Extraction

Extraction of features is one of the facial recognition processes whereby facial components which include: the eyes, mouth and other required features from a human face image are extracted from a person’s face. Feature Extraction is a form feature retrieval that will acquire the analyzed value for the process coming after. Feature extraction examines and modifies the input data held in a parameter pattern (Fitrianingsih, Setyati, & Zaman, 2018). The objectives are to minimize number computations, eliminate duplicate information, increase accuracy recognition, and speed up calculation.

The localization and detection of the eye is important among all facial features because it allows the position of all other facial features to be identified.

2.10 Eye tracking

Eye-tracking technology is the process that involves tracking of the eye and measuring the user's eye movements and focus point. Many fields, including marketing, medicine, psychology, gaming on computers, and cognitive science, use eye tracking. As a result, eye tracking is becoming more popular in computer science fields, where it uses features of the eyes to implement certain processing tasks (Rayner, 2009). A sensor for tracking the eyes or a camera can be used to measure and obtain eye-tracking data. The data has multiple features and can be used for a variety of classification tasks. Eye-tracking technology is extremely beneficial, and it has the potential to be widely utilized and implemented in the future because it only requires a device for capturing images and videos like a camera to collect the necessary data. Eye Tracking can help determine the driver's attention by monitoring the movements of the eyes and pick up indications of drowsiness.

2.11 Percentage of Eyelid Closure

A method that is widely utilized for detecting drowsiness is the percentage of eyelid closure (PERCLOS). It mathematically defines the time in percentage when the eyes are closed from 80% to 100%. It detects the slow closure of an eyelid rather than the fast closing and opening of the eyes (Nguyen & Chew, 2015).

The driver's level of fatigue S=H/L, where the term H is the driver's height and L is the length of the driver's eye. Each frame in the input from the video is classified based on the S value being the measure. The PERCLOS value is then computed as

$$\text{PERCLOS} = \frac{Number\ of\ frames\ of\ \text{"}closed\text{"}\ eye}{3min\ interval\ of\ all\ frames - blinking\ time}$$

Threshold 1	Threshold 2	Threshold 3	Threshold 4	Threshold 5
S≤3.75%	3.75%<S≤7.5%	7.5%<S≤11.25%	11.25%<S≤15%	15%<S
Low drowsiness	Low drowsiness	Moderate Drowsiness	Moderate Drowsiness	Severe Drowsiness

Figure 2.1. PERCLOS thresholds. Source:

https://www.researchgate.net/publication/283018835_Eye_tracking_system_to_detect_driver_drowsiness#pf3

When the level of fatigue gets to the severe point, the system sounds the alarm, alerting the driver to take initiative actions to prevent a potential accident from happening (Nguyen & Chew, 2015).

2.12 Head Tilt Technology

Head tilt or posture can give states of the driver's condition of being either alert or showing signs of falling asleep behind the wheel. A driver is either sleepy or inattentive if he frequently looks in other directions for an extended period of time. In studies on sleep and sleepiness on flights that were long and took up a lot of time, inclinometers were used to measure how the head moves. It showed that there was activity during wakefulness but no activity during sleep (Teyeb, Jemai, Zaied, & Amar, 2014). Fatigue is estimated using the posture of the head for analysis. When the driver's head inclination exceeds a certain time T and a predefined angle X, it indicates that he is not focused and his gaze is diverted away from the steering wheel (Teyeb, Jemai, Zaied, & Amar, 2014).

2.13 CNN (Convolutional Neural Network)

A Convolutional Neural Network (CNN) is a Deep Learning method that can take an input picture, give priority to distinct aspects in the image (learnable weights and biases), and differentiate one from the other. CNN requires not much pre-processing as compared to other techniques used for classification. CNN is able to gain information on these characteristics with sufficient training (A Comprehensive Guide to Convolutional Neural Networks — the ELI5 way, 2018).

2.14 Drowsiness Detection in the industry

Volvo has a system called DAC (Driver Alert Control). DAC is designed to draw the driver's attention when he or she begins to drive less consistently, such as when the driver becomes distracted or falls asleep. The goal of DAC is to detect driving ability that is deteriorating gradually, and it is intended primarily for safety on major roads.

There is a camera that detects the side markings which are painted on the roadway and makes a comparison of the road section to the inputs of the driver on the steering. If the truck is not in line with the roadway evenly, the driver gets notified. Despite driver fatigue, driving ability is not affected in some cases. In that case, no warning will be issued to the driver. As a result, In regard to whether or not DAC issues a warning, it is fundamental to pull over and take a break if you notice any signs of driver fatigue (Volvo, 2023).

Mercedes has created the ATTENTION ASSIST system, in order to detect when drivers become drowsy and alerts them to take a break. ATTENTION ASSIST monitors the driver's behavior and creates a profile that is unique to the driver at the start of each trip, which is then compared with current data at the sensor continuously. The monitoring is continuous since it is critical for detecting the point at the driver being awake to being drowsy and alerting the driver with time to spare. The system goes on to operate at a range of speeds from 80 to 180 km/h (Mercedes, 2008).

A highly sensitive sensor that is the most important component of this Mercedes system allows for extremely precise checking of the movements on the steering. ATTENTION ASSIST calculates an individual behavioral pattern based on these data during the first few minutes of each trip. The vehicle has an electronic control unit that compares this pattern to the current steering inputs given by the driver and the situation of the driver on a continuous basis. This process enables the system to detect the usual attributes of drowsiness and gives a warning to the driver by making an audible sound and flashing an unmistakable instruction on the instrument cluster display (Mercedes, 2008).

2.15 Conclusion

Drowsiness detection systems for truck drivers is an important topic because fatigue is a major cause of accidents in the transportation industry. Drowsiness in truck drivers can be detected using a variety of methods, including physiological measures such as eye-tracking, heart rate, and EEG signals, as well as behavioral measures such as lane departure, steering angle, and acceleration. The proposed way of doing it is by using Computer vision-based approaches which uses a camera that tracks the driver's face and eye movements, then using machine learning techniques and algorithms can analyze the data collected from these methods to accurately detect drowsiness. Overall, truck driver drowsiness detection systems are an important safety feature that can help reduce the risk of accidents and ensure that drivers remain alert and attentive during long hauls.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This research looks at how drowsiness for truck drivers can be detected for purposes of road safety to avoid accidents. The requirement is to design, implement and test the system required for drowsiness detection using the agile methodology. In this chapter, the methodology of the research is used to answer the research questions.

3.2 Agile Methodology

This methodology is appropriate for rapid development cycles and allows for specification changes during the design and build process. It is adaptable and strives for iterative incremental product improvement. In short words Agile is to plan, build, test, learn, repeat (Ng, 2020).

Reasons for considering agile is:

- The changes in requirements should be accommodated throughout the development process.
- It ensures a consistent rate of development.
- Simplicity in seeking a solution

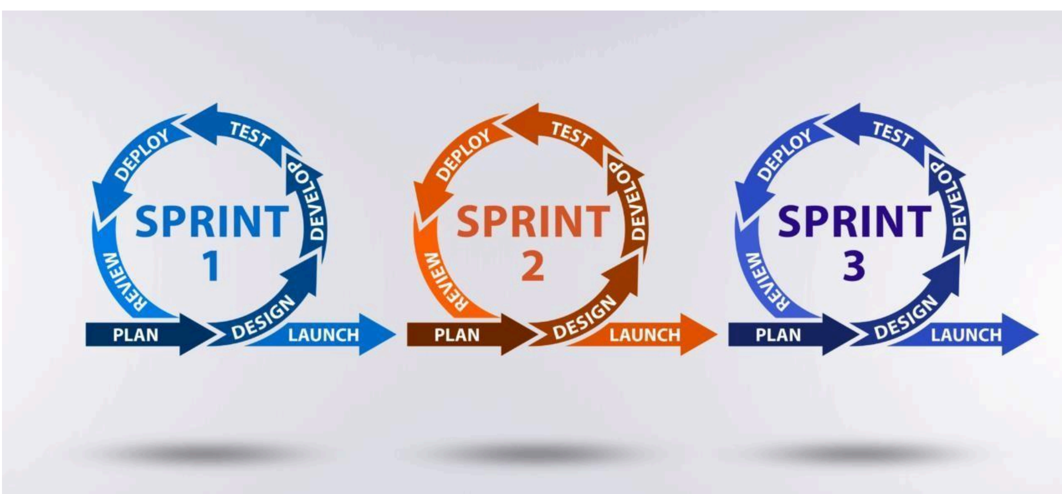

Figure 3.1. Agile Methodology. Source: https://kruschecompany.com/agile-software-development/

3.2.1 Planning phase

This is the first step of the methodology which involves identifying the problem the project is trying to solve. The major target is to outline the scope of the project (Adam, 2022). In the case of truck driver drowsiness detection, the main problem is drowsiness behind the wheel when the truck driver is driving out on the road. The outcome is to develop a system that detects facial attributes of being drowsy and sends an alert to the driver before it is too late.

i) Data Collection

The data collection method that is viable would be the use of a camera for the primary data as well as secondary data obtained from an online source. The main source of data was secondary, gathered from Kaggle by an Author named Dheeraj Perumandla which is openly available for download and use. This was collected in the form of images that will monitor the driver's physical state on his face. The data collected are the eye movements showing whether open or closed. It also has images of yawning and no yawning. This information can be used to detect drowsiness symptoms such as drooping eyelids and yawning.

ii) Sprint

The sprint is defined as the time limit during which specific work must be completed and also ready for review (Brunksill, 2019). During a sprint, new features are developed based on the user stories and backlog. After the current sprint concludes, a new sprint begins.

3.2.2 Designing Phase

The design phase begins after the need for the software has been validated and the initial scope, requirements, and resources expected to be required have been established during the analysis and planning phase.

An agile design process enables you to deliver design to your user in an iterative and incremental manner. Divide your required functionality into small iterations so that at the end of each iteration, you can share your design with the user for feedback. The stages of the agile design process run concurrently. You start by breaking down the functionality into different smaller parts that can be delivered independently. This allows for faster design and faster feedback on your work (Minhas, 2019).

For the design we can use these approaches:

Use case Analysis: It is easier to know what the user wants sooner rather than providing him with a complete prototype and then asking for feedback. In this step we do a use case analysis and by creating a use case diagram. It simulates how an external user interacts with the system in order for it to function (Walker, 2023). Use case diagrams are in charge of visualizing how the system interacts with external entities.

Process Modeling: Providing small chunks of design for development allows for faster implementation. In structured analysis and design, the process model is a fundamental diagram or the data flow diagram(DFD). It depicts how the information flows in the system. Each process converts inputs to outputs. There are flow lines which represent how data flows between nodes, which can include processes, external entities and data stores (Process Model, n.d.).

Data Modeling: This is the process where a diagram representing the software system is created and the components of data it includes, how it is represented by text and symbols, and how it flows (Stedman, 2021). This can be done using an Entity relationship diagram

3.2.3 Development Phase

This is the phase in which the system was built on the architectures created during the design phase.

Dataset: The dataset includes images captured under various lighting conditions and contains 2900 images belonging to 4 classes which are no yawn, yawn, closed and open. The dataset was divided into 2 subsets: a training set being 70%, and a validation set 30% of the data to facilitate model training and evaluation.

Data Preprocessing: All images are resized to a standardized dimension of 145*145 to reduce computational complexity. Data augmentation was used by rescaling the pixel values of the images. The pixel values range from 0 to 255, where 0 represents black, and 255 represents white. The scaling down of these pixel values to a range between 0 and 1 was applied. This is done to ensure that the pixel values are within a suitable range for neural network training, as it can help improve convergence during training.

Use of the HAAR algorithm for face detection. It is one of the few object detection methods capable of detecting faces. Paul Viola and Michael Jones created this method (Murdeshwar, Salian, & Kotari, 2019). Below is the HAAR algorithm.

$f(x, y) = \sum_{i=1}^{n} w_i \cdot h_i (x, y) < T_i$ where,

- $f(x, y)$ represents the strong classifier's output for a given input x, y.
- n is the total number of weak classifiers.
- w_i are the weights associated with each weak classifier $h_i (x, y)$.
- $h_i (x, y)$ represents the output of the i th weak classifier for input x, y.
- T_i is the threshold associated with the i th weak classifier.

This equation essentially combines the outputs of multiple weak classifiers weighted by their importance (weights) and compares the combined output to their respective thresholds.

Modeling: Once the face detection input has been done, The CNN (Convolutional Neural Network) will be used for feature extraction which is used for the learning phase of the model. SoftMax Layer in the CNN is used to determine whether the driver is awake or falling asleep. The flattening layer is important since it flattens the output from the previous layers into a one-dimensional vector. This step is necessary to connect the convolutional layers to the fully connected (Dense) layers. The dropout layer helps prevent overfitting, and soft-max activation in the final layer provides class probabilities. (Chirra, Uyyala, & Kolli, 2019). There is a Gated Recurrent Unit layer integrated into the model which the potential justification for using a GRU layer in a deep CNN is to leverage both the spatial feature extraction capabilities of the CNN layers and the temporal modeling capabilities of the GRU layer. This can be particularly useful in tasks such as video analysis, action recognition, or sequential data processing where both spatial and temporal information are crucial according to Khatun(Khatun, Mohammad & Mohammad, 2023). The loss function is specified as categorical cross-entropy which is used for multi-class classification. Below is the loss function

$L(y, p) = \sum_{i} y_i log(p_i)$

Where:

- $L(y, p)$ is This denotes the cross-entropy loss between the true label distribution y and the predicted probability distribution p
- $\sum_i$ symbolizes a summation over all classes or categories in the classification task.
- y_i This represents the true probability or label for class i It's typically a one-hot encoded vector where $y_i = 1$ for the true class $y_i = 0$ for all other classes.
- p_i denotes the predicted probability assigned to class i by the model. It represents the model's confidence in predicting each class.

$log(p_i)$ This computes the natural logarithm of the predicted probability for class i.

The Adam optimizer is an optimization algorithm commonly used for training deep neural networks. This optimizer combines the concepts of momentum and adaptive learning rates to efficiently update model parameters during training. It helps overcome challenges such as slow convergence and poor generalization in deep learning tasks according to Kingma(Kingma,2014).

$$m_t = \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t$$

$$v_t = \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2$$

$$m_t^{corrected} = \frac{m_t}{1-\beta_1^t}$$

$$v_t^{corrected} = \frac{v_t}{1-\beta_2^t}$$

$$\theta_t = \theta_{t-1} - \frac{\alpha}{\sqrt{v_t^{corrected}+\epsilon}} \cdot m_t^{corrected}$$

In the equation:

- m_t represents the exponentially decaying average of past gradients.
- v_t represents the exponentially decaying average of past squared gradients.

- $m_t^{corrected}$ and $v_t^{corrected}$ are bias-corrected estimates of m_t and v_t.
- θ_t represents the updated parameters of the model.
- β_1 and β_2 are the exponential decay rates for the first and second moment estimates.
- g_t is the current gradient of the parameters with respect to the loss function.
- α is the learning rate, controlling the step size during optimization.
- ϵ is a small constant added to prevent division by zero, typically set to 10^{-8}.

The Gated Recurrent Unit (GRU) is a type of recurrent neural network (RNN) architecture that is designed to address the vanishing gradient problem encountered by traditional RNNs (Kostadinov, 2017). It is composed of gates that regulate the flow of information within the network. The formula for the GRU layer can be broken down into several components:

1. Update Gate(z): The update gate helps in determining how the past information is going to be passed into the future

   $z_t = \sigma(W_z \cdot [h_{t-1}, x_t])$

   Where:

   - z_t is the output of the update gate at time step t.
   - σ is the sigmoid activation function.
   - W_z is the weight matrix associated with the update gate.
   - h_{t-1} is the hidden state from the previous time step.
   - x_t is the input at time step t.
2. Reset Gate(r): It is used to decide how the information from the past should be forgotten.

   $r_t = \sigma(W_r \cdot [h_{t-1}, x_t])$

   Where:

   - r_t is the output of the reset gate at time step t.
   - σ is the sigmoid activation function.
   - W_z is the weight matrix associated with the reset gate.

- h_{t-1} is the hidden state from the previous time step.
- x_t is the input at time step t.

3. Candidate Activation: It introduces a new content which is used by the reset gate to store the relevant information that is from the past.

$$\overline{h}_t = tanh(W \cdot [r_t \odot h_{t-1}, x_t])$$

Where:

- $\overline{h}_t$ is the candidate activation at time step t.
- $tanh$ is the hyperbolic tangent activation function.
- W is the weight matrix.
- r_t is the output of the reset gate at time step t.
- h_{t-1} is the hidden state from the previous time step.
- x_t is the input at time step t.
- $\odot$ denotes element-wise multiplication.

4. Hidden State(h_t): It determines what to collect from the Candidate state.

- $h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \overline{h}_t$
- Where:
- h_t is the hidden at time step t
- z_t is the output of the update gate at time step t.
- $\overline{h}_t$ is the candidate activation at time step t.
- h_{t-1} is the hidden state from the previous time step.
- $\odot$ denotes element-wise multiplication.

The model applied begins with a series of convolutional layers designed to extract features from input images. These convolutional layers are followed by max-pooling layers, which reduce the spatial dimensions of the feature maps while retaining the most important information.

After the convolutional layers, the output is reshaped to prepare it for input to the recurrent layers. This reshaping step organizes the features into a format suitable for sequential processing.

Next, two gated recurrent unit (GRU) layers are added. The first GRU layer has 256 units and returns sequences, allowing it to process sequential data. A dropout layer is inserted after this GRU layer to prevent overfitting by randomly dropping out a fraction of the units during training.

Following the dropout layer, a second GRU layer with 128 units is added. Unlike the first GRU layer, this layer does not return sequences, effectively summarizing the sequence information.

After the GRU layers, the output is flattened to prepare it for input to the dense layers. Flattening collapses the multi-dimensional output into a one-dimensional vector.

A dropout layer with a dropout rate of 0.5 is then added for further regularization before passing the output to two dense layers. The first dense layer has 64 units and uses the ReLU activation function to introduce non-linearity into the model. The final dense layer has 4 units, corresponding to the number of classes in the classification task, and uses the softmax activation function to output class probabilities.

Finally, the model is compiled with categorical cross-entropy loss, accuracy as the evaluation metric, and the Adam optimizer. This completes the construction of the model, which is ready for training and evaluation on image classification tasks.

The choice of the model was decided upon building different neural networks from the normal CNN, the combined CNN with a GRU layer and Adjusted CNN with GRU layer and a transfer learning model. The decision was influenced by the model's ability to effectively handle sequential data, which is critical for tasks requiring an understanding of temporal relationships. Unlike traditional CNNs that excel in processing spatial data like images, the inclusion of recurrent units like GRU enabled the model to learn long-term dependencies, thereby reducing the risk of overfitting while enhancing generalization.

System development: The system will be developed using Python. This system will enable the users to interact with the system where input of the user’s face will be used to give the results, which is detecting the state of alertness of the driver (being awake or drowsy).

3.2.4 Testing Phase

Once the system is built it will be deployed in a testing environment. The testing is done to ensure that the entire application works as expected.

Unit Testing: At the first instance of testing, the system is put through evaluations that examine certain components of software in order to check if they are completely functional. The most significant advantage of this phase of testing is that it can be run whenever a portion of code is changed, allowing the underlying issues to be resolved as quickly as possible. The primary goal of this endeavor is to determine whether the system is functioning as intended (Pearson, 2015).

Integration Testing: Integration testing is used to bring together all of the units in the system and test them together in a group. This level of testing is initiated to detect issues between modules/functions. This is especially useful due to the fact that it determines how well the different parts work together (Pearson, 2015).

System Testing: It involves testers who haven't taken a hand in developing the system. This testing is carried out in a production-like environment. The system is tested to ensure the technical and functional requirements are met (Pearson, 2015).

Acceptance Testing: It is carried out in order to ascertain whether the system is all set for release. In this phase, the system is tested by the user to verify whether the system meets the requirements of its usability to the driver. After this process is completed and the system has been approved, the program will be deployed (Pearson, 2015).

3.2.5 Deployment Phase

The model is then deployed using the Visual Studio Code environment via the terminal. A separate python file with system objectives is then run in the terminal and loads a python application window utilizing the camera via computer vision libraries and thus getting the real time video in image frames using the HAAR algorithm.

3.2.6 Review Phase

This is the last step of Agile development. Once all previous stages of development are completed, the system is presented with the results achieved in meeting the requirements to the user (Pearson, 2015).

3.3 Conclusion

In conclusion, this chapter provides a detailed description of the methodology used to analyze, design and build the drowsiness detection system for freight drivers. The agile methodology is an extremely effective method for developing driver drowsiness detection systems. It allows delivering high-quality solutions that meet the needs of end-users and stakeholders by encouraging flexibility, collaboration, and continuous improvement.

CHAPTER FOUR

SYSTEM DESIGN AND ARCHITECTURE

4.1 Introduction

In the context of road safety, the significance of a well-structured Machine Learning (ML) Data Analytics framework for driver drowsiness detection cannot be overstated. The system's success is intricately tied to its design and architecture, forming the bedrock for accurate and efficient identification and prevention of driver fatigue. This chapter is dedicated to delineating the critical components, elucidating the decision-making processes, and unveiling the overall structural framework of the system.

The paramount objective is to harness the power of advanced analytics to proactively detect signs of driver drowsiness, thereby mitigating potential accidents and enhancing overall road safety. By delving into the intricacies of the system's design, a comprehensive understanding of its inner workings is achieved, laying the groundwork for its effective implementation.

4.2 System Design

The design process enables you to deliver design to your user in an iterative and incremental manner. Divide your required functionality into small iterations so that at the end of each iteration, you can share your design with the user for feedback.

4.2.1 Use Case Analysis

The use case diagram below simulates how the driver interacts with the system and gets alerts

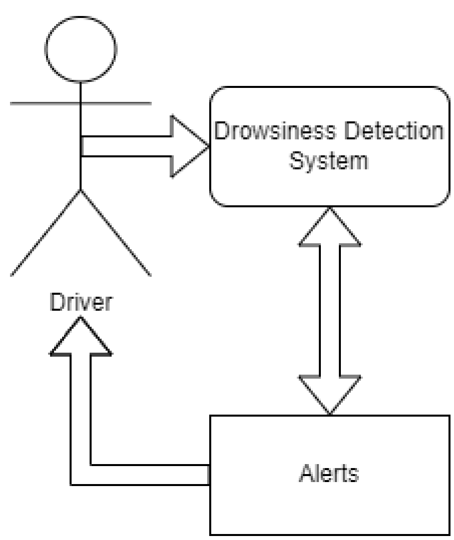

Figure 4.1. Use case Analysis.

4.2.2 Data Flow

The data flow diagram below depicts how the information flows in the system. Each process converts inputs to outputs.

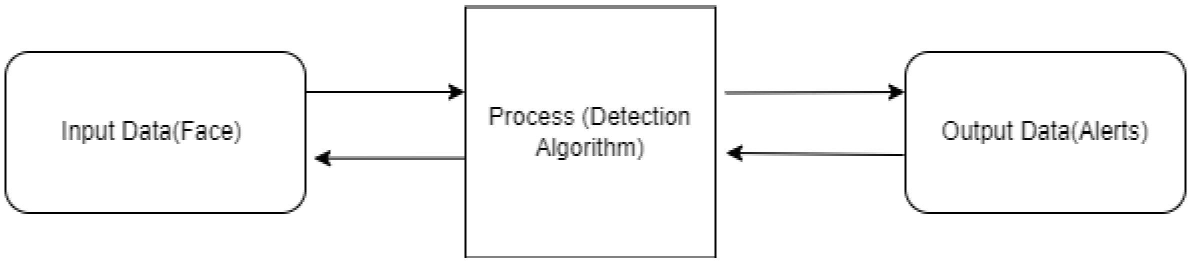

Figure 4.2. Data Flow diagram.

4.2.3 Entity Relationship

The entity relationship diagram below represents the relationships between various entities in the driver drowsiness detection system

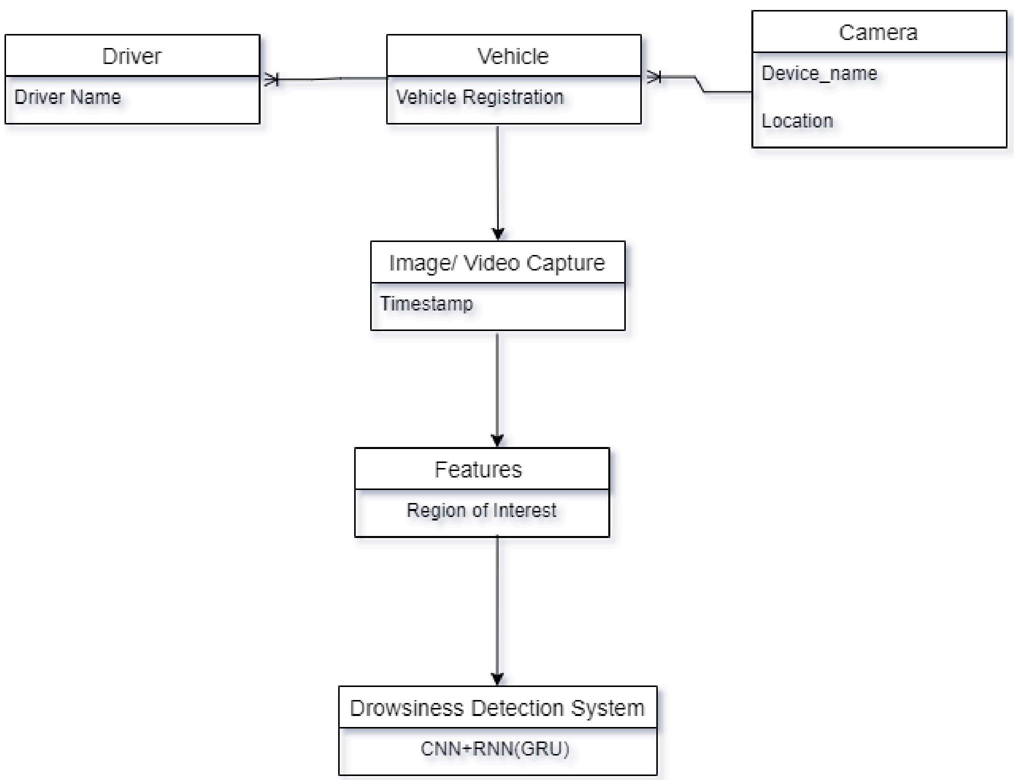

Figure 4.3. Entity Relationship Diagram.

4.3 Overall System Architecture

The architecture of the system shows its adaptability and scalability, addressing the intricate challenges posed by real-world scenarios. By embracing a modular framework, the system accommodates the multifaceted aspects of drowsiness detection within the dynamic context of driving. Each module is carefully designed to synergize with others, creating a cohesive structure that harmonizes with the complexities inherent in vehicular environments. The proposed architecture is shown in figure 4.4.

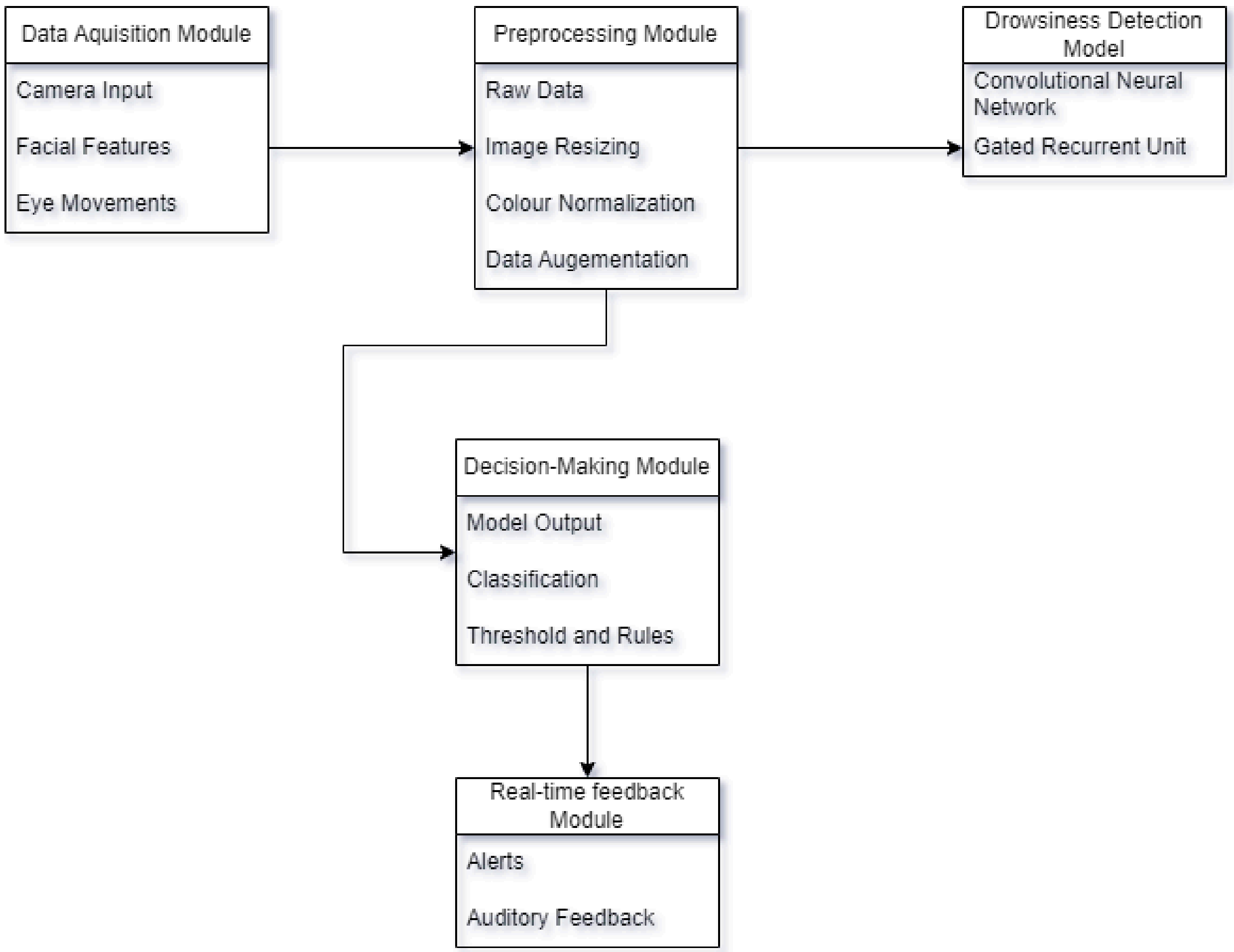

Figure 4.4. Overall System Architecture.

4.3.1 Data Acquisition Module

The initial phase of the system, the Data Acquisition Module, serves as the sensory gateway, capturing real-time data from a camera monitoring the face. This module acts as the system's eyes, focusing primarily on facial features and eye movements, which serve as pivotal indicators for drowsiness detection.

4.3.2 Preprocessing Module

The Preprocessing Module, cleans, augments, and normalizes the raw data. Employing sophisticated techniques such as image resizing, color normalization, and data augmentation, this module ensures that the data fed into the subsequent stages is refined and optimized for the highest degree of model generalization and robustness.

4.3.3 Drowsiness Detection Model

The Drowsiness Detection Model serves as the cornerstone of the entire system, responsible for accurately identifying signs of drowsiness in individuals. This model embodies a sophisticated blend of Convolutional Neural Network (CNN) architecture coupled with Gated Recurrent Unit (GRU) layers, a combination chosen for its efficacy in capturing both spatial and temporal features from input data.

Convolutional Layers: The model commences with several convolutional layers aimed at extracting spatial features from the input images. Each convolutional layer is followed by a max-pooling operation, facilitating spatial downsampling and feature extraction.

The chosen filter sizes and activation functions are tailored to enhance the network's ability to discern relevant features indicative of drowsiness, such as eye closure and facial expressions associated with fatigue.

Reshaping for GRU Input: Following the convolutional layers, the features extracted are reshaped to conform to the input requirements of the subsequent GRU layers. This reshaping operation ensures compatibility between the convolutional and recurrent layers.

Gated Recurrent Unit (GRU) Layers: GRU layers are introduced to capture temporal dependencies within the input data sequence, thereby incorporating the temporal aspect crucial for drowsiness detection.

The GRU architecture is chosen over traditional recurrent layers due to its ability to retain long-term dependencies while mitigating the vanishing gradient problem.

The addition of multiple GRU layers enables the model to learn complex temporal patterns associated with drowsiness, such as the progression of eyelid movements and changes in facial expressions over time.

Flattening and Regularization: Following the GRU layers, the output is flattened to prepare for subsequent fully connected layers. Additionally, dropout layers are strategically incorporated to prevent overfitting and improve the model's generalization ability.

Fully Connected Layers: The flattened output is fed into fully connected layers, facilitating higher-level feature abstraction and enabling the model to make predictions regarding the drowsiness state.

The choice of activation functions and the number of neurons in these layers are optimized through experimentation to achieve the desired predictive performance.

Model Compilation and Training: The model is compiled with the categorical cross entropy for loss functions, and an Adam optimizer, and evaluation metrics tailored to the specific task of drowsiness detection.

During the training phase, the model is fine-tuned using a diverse dataset encompassing various scenarios and individuals to ensure robustness and generalization.

Model Summary:

Upon compilation, the model summary provides insights into its architecture, including the number of parameters, layer configurations, and output dimensions. This summary serves as a comprehensive overview of the model's structure and complexity, aiding in understanding its capabilities and potential areas for optimization.

Below is a summary of the model showing how each layer and parameters were configured.

Layer (type)	Output Shape	Param #
conv2d_8 (Conv2D)	(None, 143, 143, 256)	7,168
max_pooling2d_8 (MaxPooling2D)	(None, 71, 71, 256)	0
conv2d_9 (Conv2D)	(None, 69, 69, 128)	295,040
max_pooling2d_9 (MaxPooling2D)	(None, 34, 34, 128)	0
conv2d_10 (Conv2D)	(None, 32, 32, 64)	73,792
max_pooling2d_10 (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_11 (Conv2D)	(None, 14, 14, 32)	18,464
max_pooling2d_11 (MaxPooling2D)	(None, 7, 7, 32)	0
reshape_1 (Reshape)	(None, 49, 32)	0
gru_2 (GRU)	(None, 49, 256)	222,720
dropout_2 (Dropout)	(None, 49, 256)	0
gru_3 (GRU)	(None, 128)	148,224
flatten_2 (Flatten)	(None, 128)	0
dropout_3 (Dropout)	(None, 128)	0
dense_4 (Dense)	(None, 64)	8,256
dense_5 (Dense)	(None, 4)	260

Total params: 773,924 (2.95 MB)
Trainable params: 773,924 (2.95 MB)
Non-trainable params: 0 (0.00 B)

Figure 4.5. Model Summary.

4.3.4 Decision-Making Module

The Decision-Making Module acts as the point of decisiveness of the system, interpreting the nuanced output from the Drowsiness Detection Model. It classifies the driver's state into categories such as 'Alert' or 'Drowsy,' employing predefined thresholds and rules that encapsulate the severity of detected drowsiness. This module serves as the gatekeeper, deciding when and how to intervene based on the model's output.

4.3.5 Real-Time Feedback Module

The Real-Time Feedback Module serves as the system's auditory section, delivering immediate warnings to the driver based on the detected drowsiness. This module operates solely through auditory cues, ensuring a streamlined and non-intrusive approach to alerting the driver of their current state. The module emits alarm sounds to capture the driver's attention during critical drowsiness episodes. The alarm sounds are designed to be attention-grabbing yet non-startling, ensuring they effectively penetrate the driver's consciousness without causing undue stress.

4.4 System Flow

The system orchestrates a symphony of operations to ensure not only real-time responsiveness but also a high degree of accuracy in drowsiness detection. The sequential flow delineates the journey of data from acquisition to feedback:

1. **Data Acquisition:** The data is meticulously collected from a camera, with a keen focus on facial features and eye movements.
2. **Preprocessing:** The data undergoes a transformative process, ensuring standardization and augmentation for optimal performance in subsequent stages.
3. **Drowsiness Detection:** The preprocessed data finds its way into the intricate layers of the Drowsiness Detection Model, which, like a discerning artist, outputs the likelihood of drowsiness based on learned features.
4. **Decision Making:** The Decision-Making Module then takes the reins, interpreting the model output and making informed classifications of the driver's state, ready to trigger appropriate warnings if necessary.
5. **Real-Time Feedback:** Finally, the detected drowsiness states are communicated to the driver in real-time, utilizing visual, auditory, or haptic feedback mechanisms to ensure swift and corrective action.

4.4 Scalability and Adaptability

The foresight embedded in the system's architecture manifests in its Scalability and Adaptability. Designed to evolve with technological advancements and diverse user preferences, the system readily accommodates additional sensors, features, and feedback mechanisms. Its modular design not only simplifies integration but also positions the system to seamlessly embrace future innovations in both Machine Learning and sensor technologies.

4.5 Conclusion

In conclusion, the system's design and architecture, detailed in this chapter, provide more than a mere framework; they offer a comprehensive blueprint for deploying an exceptionally robust Machine Learning Data Analytics system for driver drowsiness detection. The modular approach, coupled with real-time responsiveness, forms the backbone of a solution poised to significantly enhance road safety by proactively mitigating the risks associated with driver fatigue. As this chapter unfolds the intricate layers of the system, it becomes evident that the synergy between components is not just technical; it's a strategic harmony aimed at preserving lives on the road.

CHAPTER FIVE
SYSTEM IMPLEMENTATION AND TESTING

5.1 Introduction
This chapter presents the implementation details and testing procedures for the driver drowsiness detection system tailored for the freight industry. The system aims to enhance safety and mitigate risks associated with drowsy driving among freight drivers. This chapter outlines the key components of the system, the technologies employed, and the testing methodologies used to evaluate its effectiveness.

5.2 System Architecture
The system architecture comprises several interconnected modules designed to detect and alert drivers of drowsiness in real-time. These modules include data acquisition, pre-processing, feature extraction, drowsiness detection algorithm, and alert mechanism. The architecture ensures seamless integration of hardware and software components to achieve robust performance.

5.3 Implementation Details
The implementation of the system involves the deployment of a camera device utilizing computer vision to capture relevant data such as eye movements. The collected data undergoes pre-processing to remove noise and artifacts, followed by feature extraction to identify drowsiness-related patterns. After the preprocessing, the building comparison of the 4 different implementations of the model is done to choose the best performing one. The decision was on the customized drowsiness detection model with the CNN and Additional GRU layers.

The customized drowsiness detection algorithm is then applied to the extracted features to classify the driver's alertness level. The algorithm utilizes machine learning techniques with deep neural networks with a GRU layer to accurately predict drowsiness states based on the input data. Additionally, an alert mechanism in the form of an alarm is implemented to notify the driver and relevant stakeholders in case of detected drowsiness. The images below show an overview of how the system works.

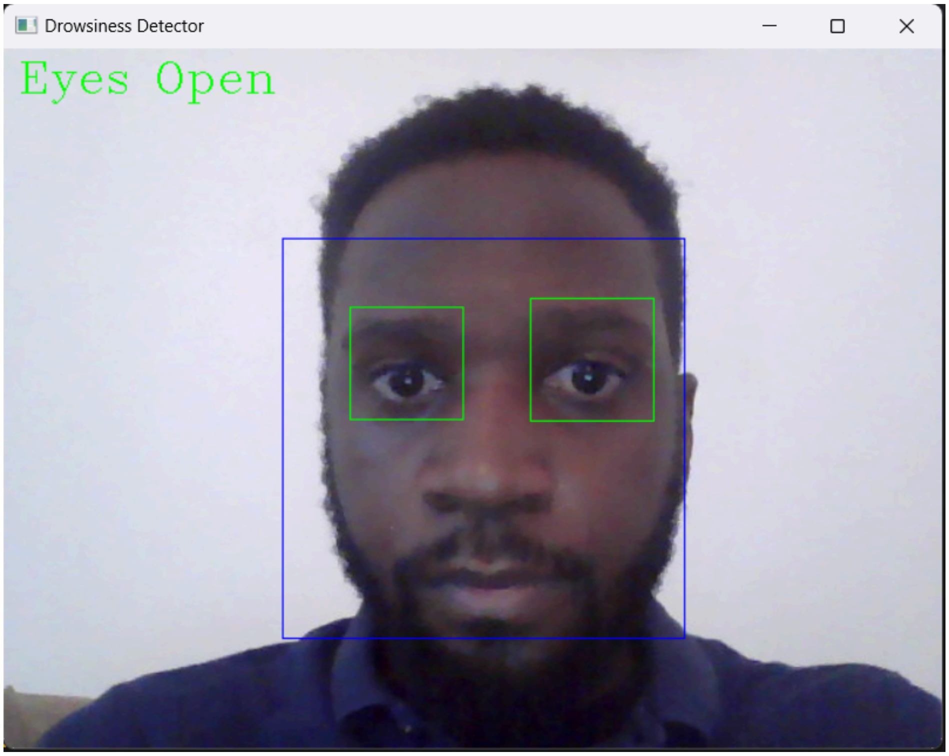

Figure 5.1. Eyes Open.

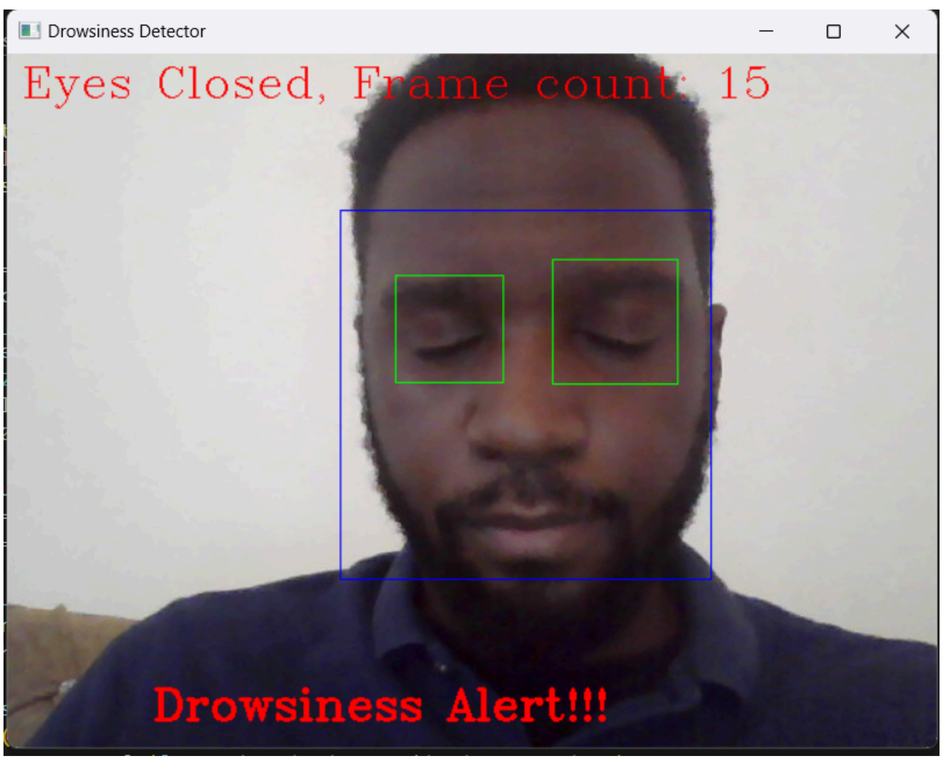

Figure 5.2. Eyes Closed, Drowsiness Alert.

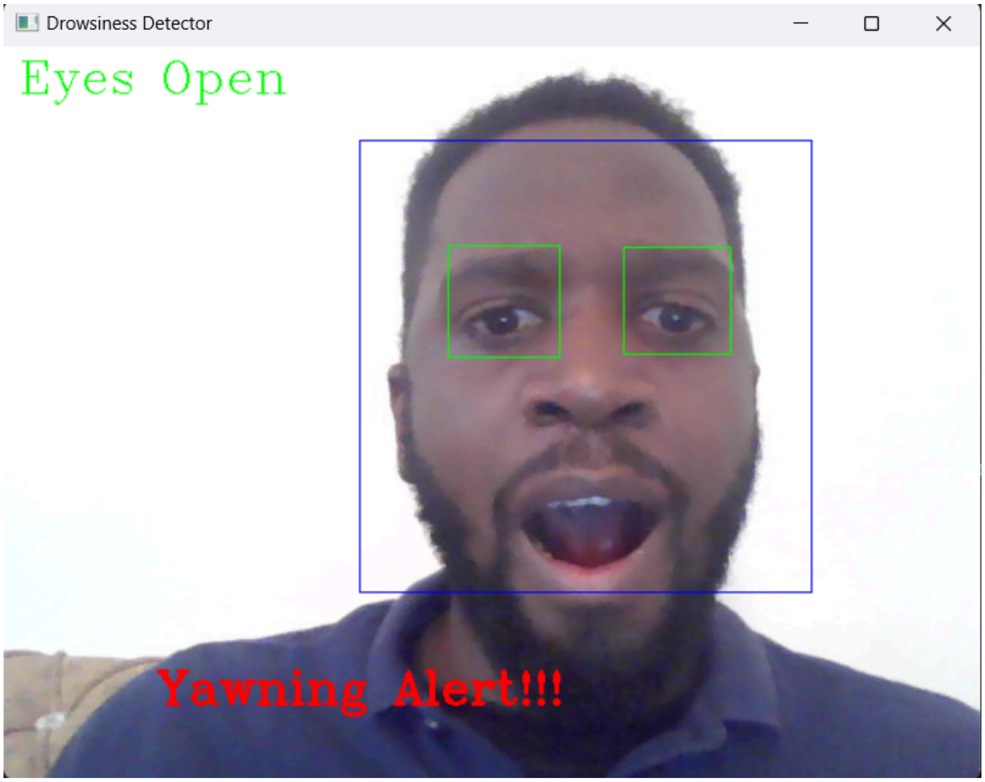

Figure 5.3. Yawning.

5.4 Testing Methodology

The testing of the drowsiness detection system involves both offline and online evaluations to assess its performance under various conditions. Offline testing utilizes historical data and simulated scenarios to validate the accuracy and reliability of the system's algorithms. Real-world testing, conducted in controlled environments to evaluate the system's effectiveness in detecting drowsiness in real-time.

The system is subjected to diverse scenarios, including different lighting conditions, driver behaviors, and environmental factors, to evaluate its robustness and adaptability.

5.5 Results and Analysis

The results of the system implementation and testing provide insights into its performance and effectiveness in detecting driver drowsiness in the freight industry.

High Detection Accuracy: The system demonstrates high accuracy in detecting drowsiness, with low false alarm rates and fast response times.

Robust Performance: The system performs well under diverse conditions, including varying lighting conditions, driver behaviors, and environmental factors.The analysis highlights the strengths and limitations of the system, identifies areas for improvement, and informs future enhancements and optimizations.

5.6 Conclusion

This chapter concludes with a summary of the system implementation and testing outcomes, emphasizing the significance of drowsiness detection technology in enhancing safety and reducing accidents in the freight industry. Recommendations for further research and development are also provided to advance the capabilities of the system and address emerging challenges in driver monitoring and safety.

Overall, the implementation and testing of the driver drowsiness detection system represent a crucial step towards improving road safety and ensuring the well-being of freight drivers.

CHAPTER SIX
DISCUSSION OF RESULTS

6.1 Model Training and Evaluation

The developed Convolutional Neural Network (CNN) for driver drowsiness detection was trained on a diverse dataset consisting of 2900 driver images with four classes: 'no_yawn,' 'yawn,' 'Closed,' and 'Open.' The model was implemented using TensorFlow and Keras libraries. The objective was to enhance the detection of drowsiness in drivers and subsequently reduce the number of road accidents caused by fatigue.

6.1.1 Training Process

The training process involved data augmentation and preprocessing using the ImageDataGenerator from Keras. The dataset was split into training (70%) and validation (30%) sets, and the images were rescaled to improve training stability. The chosen CNN model architecture was designed with multiple convolutional layers, max-pooling, and recurrent layers (GRU). The model was compiled using categorical cross-entropy as the loss function and the Adam optimizer.

6.2 Model Performance

The trained model exhibited promising results in terms of accuracy and loss during both training and validation phases.

6.2.1 Training Accuracy

The training accuracy of the model steadily increased over the 50 epochs, reaching an accuracy of 0.9619%. This indicates that the model successfully learned and adapted to the features present in the training dataset. This is shown in figure 6.1 below.

Figure 6.1. Training and Validation Accuracy

6.2.2 Validation Accuracy

The validation accuracy also demonstrated a commendable performance, peaking at 96.20%. This suggests that the model generalizes well to unseen data, confirming its ability to detect drowsiness effectively.

6.2.3 Loss Trends

The training and validation loss steadily decreased throughout the training process, reaching 0.0877 and 0.1497, respectively. This indicates that the model effectively minimized the error during training, showcasing its capability to make accurate predictions. This is shown in figure 6.2.

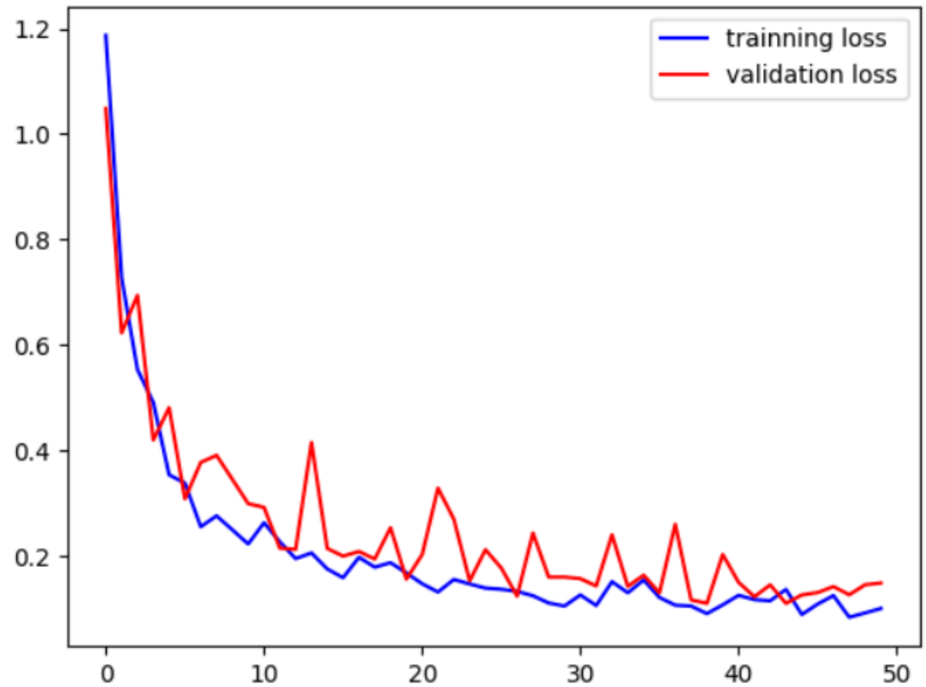

Figure 6.2. Training and Validation Loss

6.3 Model Evaluation and Discussion

6.3.1 Model Robustness

The model's robustness was assessed by evaluating its performance on diverse images, considering various lighting conditions and facial orientations. The assumption made at the beginning, stating that different lighting conditions and image orientations would not significantly affect the model's quality, was validated through the consistent performance across the dataset. The model gave a Test Loss: 0.1497 and Test Accuracy: 0.9619 after doing a test evaluation.

6.3.2 Detection of Drowsiness Attributes

The model successfully detected drowsiness by analyzing different attributes of facial features, such as yawning and closed eyes. The functions implemented for the HAAR algorithm for eye close and yawn detection using landmarks provided valuable insights into the driver's state. The classes were categorized as 0-yawn, 1- no_yawn, 2-Closed and 3-Open. As shown from figure 6.3 below random images were loaded from the different classes and the model was able to accurately predict the different attributes.

Prediction

0-yawn, 1-no_yawn, 2-Closed, 3-Open

```
prediction = model.predict([prepare(r"train/no_yawn/1067.jpg")])
np.argmax(prediction)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 432ms/step
1
```

```
prediction = model.predict([prepare(r"train/Closed/_101.jpg")])
np.argmax(prediction)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 91ms/step
2
```

```
prediction = model.predict([prepare(r"train/Closed/_104.jpg")])
np.argmax(prediction)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 65ms/step
2
```

```
prediction = model.predict([prepare(r"train/yawn/12.jpg")])
np.argmax(prediction)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 65ms/step
0
```

Figure 6.3. Prediction results.

CHAPTER SEVEN

CONCLUSION, RECOMMENDATIONS AND FUTURE WORKS

7.1 Conclusion

In conclusion, the results of our machine learning-based drowsiness detection model are promising, with exceptional performance on both the training and validation datasets. The model exhibits robustness in identifying drowsy drivers, making it a valuable component for road safety.

The integration of real-time drowsiness detection systems represents a significant stride toward proactive road safety. The combination of advanced technologies and data-driven insights not only enhances the effectiveness of traditional safety measures but also establishes a foundation for intelligent, preventative solutions in the evolving landscape of transportation safety.

The ever-changing landscape of both road safety and technology demands a dedication to ongoing innovation. To further increase and strengthen the capabilities of sleepiness detection systems, research and development efforts should consistently investigate new methods, better algorithms, and improved sensor technologies.

In order to ensure that drowsiness detection is a common feature of vehicle safety in the future, we must think carefully about how best to implement it. To ensure widespread adoption and effectiveness across a variety of vehicle types, standardizing and mandating these systems will require cooperation between technology developers, automobile makers, and regulatory organizations.

The research has yielded significant findings and achievements in the realm of drowsiness detection within the freight industry, leveraging the innovative CNN-GRU model. One notable accomplishment is the precision exhibited by the CNN-GRU model in detecting subtle indicators of drowsiness. These indicators include phenomena such as eyelid closure and yawning, which can often be overlooked or misinterpreted. By amalgamating spatial and temporal features derived from input data, our system attains a nuanced comprehension of the driver's alertness level, thereby enhancing the accuracy of drowsiness detection.

Furthermore, the integration of real-time feedback mechanisms, prominently featuring auditory warnings, has facilitated immediate interventions upon detecting drowsiness. This proactive strategy empowers drivers to swiftly address their alertness levels, thereby mitigating the risk of potential accidents and ensuring the uninterrupted flow of operations within the freight industry. Such timely interventions underscore the efficacy of our approach in enhancing safety standards and preserving operational continuity in real-world scenarios.

7.2 Recommendations

For maximum efficiency, it's crucial that the drowsiness detection system seamlessly integrates with the telematics and fleet management platforms already in use within the freight industry. This integration is essential as it enables a unified approach to monitoring and intervention capabilities across fleets. By integrating with existing systems, the drowsiness detection system can leverage the data and infrastructure already in place, minimizing disruption and maximizing interoperability. This comprehensive integration ensures that fleet managers have access to real-time drowsiness alerts and intervention tools, allowing them to proactively address driver fatigue and maintain operational efficiency.

Continuous refinement and optimization of the model are paramount to enhance its accuracy and adaptability over time. Ongoing efforts to refine the model based on real-world feedback and additional data collection endeavors are imperative. Regular updates to the model's architecture and training methodologies enable it to better capture subtle indicators of drowsiness and adapt to changing environmental conditions. By continuously refining and optimizing the model, its performance and reliability can be elevated, ensuring that it remains at the forefront of drowsiness detection technology within the freight industry.

While the drowsiness detection system provides real-time feedback to drivers, investing in comprehensive driver training programs and awareness campaigns is essential. These programs play a vital role in educating drivers about the significance of alertness and the role of technology in enhancing safety on the road. By raising awareness about the dangers of drowsy driving and the capabilities of the drowsiness detection system, drivers can develop a greater understanding of the importance of remaining vigilant behind the wheel. This fosters a culture of responsibility and encourages drivers to proactively address any signs of fatigue, ultimately enhancing overall safety within the freight industry.

7.3 Limitations and Future Work

While the developed model shows promising results, there are some limitations and areas for improvement:

1. **Dataset Size:** The model's performance could be further enhanced with a larger and more diverse dataset.
2. **Real-Time Implementation:** The model's applicability in real-time scenarios, such as in-vehicle systems, needs to be tested for responsiveness and efficiency.
3. **External Factors:** Factors like external lighting conditions and driver-specific characteristics could impact real-world performance.

In conclusion, the developed hybrid CNN-GRU model for driver drowsiness detection demonstrates substantial accuracy and robustness, laying a foundation for future improvements and real-world applications in road safety.

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APPENDICES

Ethics Review Clearance:

Strathmore UNIVERSITY

5th April 2024

Mr Okero Michael,
michael.okero@strathmore.edu

Dear Mr Okero,

RE: Driver Drowsiness Detection in the Freight Industry

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** research proposal. Your application reference number is **SU-ISERC2045/24.** The approval period is from 5th **April 2024 to 4th April 2025.**
This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, MTA) will be used.
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification.
iv. Any changes anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours.
v. Clearance for the export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

Mr Ambrose Rachier,
Chairperson; SU-ISERC

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