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**ABSTRACT**

Across the globe, there is an increasing number of accidents and injuries (both fatal and non-fatal) occurring daily. Most of these accidents are attributed to drivers’ drowsiness because of many factors like exhaustion, long driving hours, medication, disease etc. this in part can be attributed to the substantial changes in the way that people manage their time in modern times, which has altered their sleep cycle. People that have irregular sleep habits and inadequate rest can fall asleep at various times of the day. Driving is an activity that requires a sound and functional state of mind and with sleep cycle altered because of demanding work schedules may result in drowsy driving. As there is an increase in demand for mobility, safety measures need to be put in place to reduce the occurrence of these incidents.

Detecting driver drowsiness is a crucial aspect of addressing driver fatigue, a significant contributor to road accidents. The identification of drowsiness allows for timely interventions and preventive measures, enhancing road safety. In this research, we will be using convolutional neural networks and two of the best deep learning frameworks, TensorFlow and Keras to develop a model that detects driver drowsiness. TensorFlow serves as the foundation for modeling intricate neural networks, and Keras, with its intuitive interface, makes it easier to quickly develop and test these models.

An essential component of processing and evaluating real-time video data to identify indicators of driver drowsiness is OpenCV, a potent computer vision library. The programming language, Python, which is well-known for its ease of use and adaptability, works in unison with these technologies to facilitate the effective management of data and model training procedures. The system's utilization of state-of-the-art tools not only enables it to precisely detect initial indications of driver fatigue but also guarantees prompt and dependable alert systems, thereby making a substantial contribution to the prevention of accidents and road safety.

**CHAPTER ONE**

**1.0 INTRODUCTION**

Accidents occurring daily on our roads have been on the increase globally. This can be attributed to the increase in the number of vehicles plying the roads, creating not only gridlocks, but also making the occurrence of accidents on our roads more likely. In today's fast-moving world where roadways serve as a vital means of transportation, ensuring the safety of both drivers and passengers is very crucial. Drowsy driving has been identified as the second most key factor that causes accidents after alcohol, (Verwey and Zaidel, 1999: Wang et al., 2017). This has led to single and multiple accidents on our roads, that often resulted in significant fatalities, injuries (Bhandayker, 2019; Satish et al., 2023), serious financial setbacks, and substantial property damage globally. (Shaik, 2023).

Tiredness at the wheel is a major public concern globally (Singh et al., 2023), as this has been found to be a major contributing factor in road accidents. The world health organization (WHO, 2020) reported that globally more than 1.35 million people (about the population of Maine) were fatally injured in road traffic accidents with 20-50 million people sustaining non-fatal serious injuries. Cai et al., (2020), observed in their study that in the United States, 21% of fatal motor vehicle crashes was attributed to drowsiness while driving and 13% of severe injury was also a result of drowsy driving as obtained from the AAA foundation data. This has been on the increase thereby necessitating the need to conduct research on techniques that reliably identify and forecast drowsy driving early enough to enhance safety in transportation. (Shaik, 2023).

Drowsiness, also commonly referred to as sleepiness or tiredness, often results in falling asleep in an inappropriate situation and time (Arunasalam et al.,2020). Drowsy driving, also referred to as driver fatigue or tired driving, refers to the action of operating a motor vehicle while experiencing fatigue or sleepiness (Moradi, Nazari and Rahmani, 2019: Czeisler et al., 2016). This can be caused by job related stress, sleep deprivation, long driving hours, alcohol consumption, medication, medical illnesses, etc. Driver drowsiness detection is a technology designed to identify the extent of tiredness or drowsiness exhibited by a driver during vehicle operation. The objective of this technology is to notify the driver or implement precautionary actions, such as reducing speed or halting the vehicle, with the aim of averting accidents resulting from driver fatigue.

Some symptoms of driver drowsiness include yawning, blinking frequently, inability to focus like drifting from lane, difficulty keeping eyes open, difficulty concentrating, nodding, unjustifiable variations in speed, poor judgement, delayed reaction time etc. The combined impacts of these factors significantly impair performance, alertness, memory, focus, and reaction times. (Dernocoeur, 2000; Mahowald and Bornemann, 2006). Researchershave categorized driver drowsiness based on the followingfactors: Physiological, Vehicle-based, and Behavioral parameters (Dua et al., 2021).

In physiological measurement of drivers’ drowsiness, sensors, and electronic gadgets are attached to the drivers’ bodies or skin to measure their heart rate, pulse rate, brain activity, body temperature, and other physiological variables. Three signals used in this evaluation will include electroencephalography, electrooculography, and electrocardiography to evaluate the state of the driver (Barua et al., 2019). Despite their ability to provide highly accurate results, these devices face limited acceptability due to their practical constraints.

Vehicle based drowsy detection relies on vehicle control system incorporating indicators like steering wheel actions, braking behaviors, the vehicles position on a lane etc. monitoring of car movement pattern is done through sensors installed to measure various vehicle and street parameters like steering wheel angle, speed, or deviation from the lane. Of the various methods listed, steering wheel measurements typically offer superior outcomes compared to alternative vehicle-centric approaches. Though the vehicle-based techniques are non-intrusive, their accuracy in detecting drowsiness varies and is dependent on factors like the condition of the road and how good a driver is.

Behavioral detection, on the other hand, is more dependable than vehicle-based measures because it centers on the individual rather than the vehicle. It detects drowsiness by monitoring head movements and facial parameters such as the eyes, face expression, eyebrows etc. Head movement is captured by using a camera (Bamidele et al., 2019, Kiashari et al., 2019).

The huge negative impact caused by drowsy drivers has made researchers explore various methods of identifying drowsy driving. Many studies have explored various detection techniques for identifying drowsy drivers. Garcia et al., (2012), developed a non-intrusive approach to driver drowsiness detection using an IR camera positioned in front of the driver’s dashboard to detect his face and obtain drowsiness clues from their eyes closure. This system comprises of three stages; preprocessing, pupil position detection and use of PERCLOS to calculate eye closure information.

Chakraborty and Avon suggested a fatigue detection system that utilizes Behavioral Studies with Computer Vision. It aims to offer a quick and straightforward detection technique. The system works by initially detecting faces, then locating eyes to analyze the existence of eye pupils and measureblink rate. Based on these parameters, the system determines the driver's fatigue level.

This research describes a simple, non-intrusive and affordable system to detect drowsy drivers in real-time using a webcam. It works by using image processing to locate the driver's face, then tracking the eyes when the face has been found and then checking for signs of drowsiness by analyzing features of the eyes (like how closed they are). The face is detected in each frame by employing image processing techniques using PERCLOS. Eyelid ratio is thenused to determine drowsiness and trigger warnings to alert the driver to avoid accidents, thereby saving lives and properties.

In addition to the introduction, the research paper will be structured into different sections. Chapter two will consist of an elaborate literature review, while chapter three will outline the methodology used in this study. Chapter four will present the results and analysis of our findings and chapter five will not only summarize the findings of the research but also discuss the contributions of this study to driver drowsy detection.

**1.1 RESEARCH AIMS**

To design and develop an efficient and accurate driver monitoring system using convolutional neural networks (CNNs) and deep learning techniques, leveraging webcam-based face detection, with the primary objective of enhancing road safety through real-time assessment of driver attentiveness. This research aims to explore the capabilities of CNNs in facial recognition and classification, optimizing model architecture, training procedures, and data augmentation techniques to achieve robust performance in detecting various states of driver alertness, including drowsiness, distraction, and impairment.

Furthermore, the study aims to investigate the feasibility and effectiveness of integrating the developed model into existing vehicle safety systems or deploying it as a standalone application for personal vehicles. Through empirical evaluation and analysis of collected data, this research seeks to contribute insights into improving road safety measures and reducing the incidence of accidents caused by driver fatigue or distraction.

**1.2 OBJECTIVES**

* To identify the key factors that lead to drowsiness among drivers.
* To highlight the impact of the increased cases of driver’s drowsiness on road safety.
* To find an automated approach for the detection of driver’s drowsiness.
* Extensive review of literature to analyze previous works in a bid to select the most appropriate technique in tackling the problem
* Data collection and preprocessing
* Feature extraction and selection
* Model design with AI-based technique convolutional Neural network and deep learning
* Model training and validation
* Implementation of designed model
* Testing of the designed model
* Evaluation of the model to ascertain if design objectives were met

**1.3 JUSTIFICATION**

In the contemporary world, where fatigue often leads to accidents causing fatalities and severe injuries, it becomes imperative to implement measures to mitigate this hazard. This can be achieved through research aimed at developing technologies that can reduce road accidents, thus bolstering road safety. Constructing a driver detection system utilizing a convolutional neural network (CNN) in tandem with webcam-based face detection facilitates continuous real-time assessment of the driver's alertness without the need for specialized hardware, thereby cutting costs.

Furthermore, CNN's precision in detecting faces, coupled with the analysis of gathered data to discern patterns and trends, contributes to the enhancement of road safety. This model presents a sturdy, effective solution for bolstering road safety that is also economically viable. A CNN-driven system can be educated to recognize various levels of driver attentiveness, including drowsiness, distractions, or impairment from substances like alcohol or drugs. This flexibility enables the system to issue appropriate alerts or interventions based on the identified state.

**CHAPTER TWO**

**2.0 LITERATURE REVIEW**

Drowsiness behind the wheel can be caused by several factors and is extremely dangerous. some of these factors include lack of sleep, exhaustion, medication, shift work etc. and a mixture of these can severely affect the driver's performance, alertness, memory concentration and reaction times (Dernocoeur, 2000). in their study, Zhang, and Chang, (2014) noted that the real extent of the sleep problem is underestimated, since sleepiness causes greater loss than what is estimated.

Drowsy detection can be classified as physiological, vehicular, and behavioral. This can be further described as intrusive if equipment like sensors is attached or non-intrusive. Some of the intrusive methods include ECG, EOG and Head motion (Viola and Jones, 2004). some of the intrusive methods involve wearing of headgear while driving which the drivers find uncomfortable most times. other intrusive methods like the use of detectors attached to the steering wheel and in the back of the seat were unreliable most time.at is why this technique was not much adopted for common people (Furman and Baharav, 2010)

Previous drowsiness detection methods used complex models, but Jabber et al. (2020) created a simpler and more accurate system using facial landmarks and a special learning technique (Convolutional Neural Network). Their method works well even on phone cameras and is small enough to fit on devices like smartphones. This innovation paves the way for real-time drowsiness detection in cars, making driving safer for everyone. This method provides a simpler and more efficient alternative to existing models, achieving over 88% accuracy for drivers without glasses and over 85% accuracy for night-time driving without glasses. Overall, the model maintains an accuracy of over 83% across all categories.

Sharma et al., (2020), in their paper proposed an innovative approach using deep learning for real-time driver drowsiness and distraction detection through object recognition. The method employs a vision-based, cost-effective system that utilizes 68-point facial landmarks to determine aspect ratios for the eyes and mouth—specifically, Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR), as these features are most affected by drowsiness. The system integrates object recognition using various deep learning algorithms simultaneously to optimize results in identifying distracting objects.

The research by Kundinger et al., (2020), builds on the idea that traditional methods of detecting drowsy drivers based on driving behavior become less useful in self-driving cars. The study explores using wrist-worn sensors to measure physiological signals, a promising and comfortable approach. To ensure accuracy in a car's dynamic environment, they focused on non-intrusive methods. Their wrist-worn sensor system achieved high accuracy (over 92%) compared to medical-grade equipment in a driving simulator test, making it a viable option for monitoring driver alertness in self-driving cars.

Dua et al., (2020), in their paper, introduced a driver drowsiness detection system utilizing four distinct deep-learning models: AlexNet for handling background and environmental variations, VGG-FaceNet for extracting facial features such as gender and ethnicity, FlowImageNet for analyzing behavioral features and head gestures, and ResNet for focusing on hand gestures, known for its high detection accuracy. These models process RGB driver videos, identifying four levels of drowsiness: non-drowsy, eye blinking, yawning, and nodding. The individual outputs of these models are combined through an ensemble algorithm utilizing a SoftMax classifier, providing a final prediction of either "drowsy" or "not drowsy". The model achieved 85% accuracy. The main disadvantage of this method of measuring drowsiness is that it can lead to biased and inaccurate self-reporting.

Biju and Edison, (2020), introduced a real-time driver drowsiness detection system using a deep learning technique called Convolutional Neural Networks (CNNs). The system treats drowsiness detection as a two-step process: Object detection and localization: The system uses a pre-trained algorithm called YOLOv3 to identify and locate the driver's face in the video frame. Once the face is located, another pre-trained network called Inception-v3 classifies the face as "drowsy" or "non-drowsy". “The system was trained and tested using three standard datasets: Closed Eyes in the Wild (CEW) database, National Tsuing Hua University (NTHU) Driver Drowsiness Detection database, and a custom database. An accuracy of 80.32%, 79.34%, and 89.90% were recorded on these three databases, respectively. Also, the proposed system can process video streams in real-time without requiring high-end hardware like GPUs, thereby saving costs.

Kaggle, comprising 2000 images depicting opened and closed eyes. To assess model performance, multiple evaluation metrics including accuracy, precision, recall value, and f1 score were computed. The proposed model achieved an accuracy of 99.67% and demonstrated a recall, precision, and f1-score of 100%, surpassing the performance of relevant drowsiness detection models.

Rajamohana, et al., (2021), proposed a system that adopts a hybrid approach combining CNN (Convolutional Neural Network) and BiLSTM (Bidirectional Long-Term Dependencies) to detect driver drowsiness. A video camera wasused in monitoring the driver's facial image and eye blinks. The system operated in three primary phases: in the first stage, the driver's facial image is identified and monitored using a web camera. This is followed by extraction of the features of the eye image utilizing the Euclidean algorithm. the third and last phase involves continous monitoring of eye blinks. This final stage determines whether the eye square measurement indicates a closed or open state using both Both CNN and BiLSTM . If the system detects the driver falling asleep, a warning message is triggered to alert the driver and mitigate the risk of road accidents.

Rajamohana et al. (2021), proposed a system, using a hybrid approach of Convolutional Neural Network and Bidirectional Long-Term Dependencies to detect the driver’s drowsiness. A video camera is used to track the facial image and eye blinks of the driver. The proposed system works in three main phases: In the First phase, the driver's face image is Identified and observed using a webcam. In the Second phase, the eye image features are extracted using the Euclidean algorithm. During the third phase, the eye blinks are continually monitored. The final stage decides whether the measure in the eye square is a closed state or open state. When a driver falls asleep, there will be a warning message to alert the driver to prevent road accidents.

Quddus et al., (2021), proposed a new approach that uses a regular camera to capture images instead of expensive eye tracking equipment. They employed a type of neural network called long short-term (LSTM) network to analyse the images to detect drowsiness. Two types of LSTMs were employed: 1-D LSTM (R-LSTM) which is used as baseline and the convolutional LSTM (C-LSTM) which facilitates using 2-D images directly. The proposed network was trained using data obtained from simulated driving experiment that monitored participant’s brainwaves to determine their level of alertness. 38 subjects were used in the study with results that displayed high efficacy of the proposed system outperforming existing eye-tracking based methods. R-LSTM based approach resulted in accuracy around 82 % and C-LSTM based approach resulted in accuracy in the range of 95%–97%.

Some studies have been undertaken in detecting driver drowsiness using the various methods parameters. Chang et al., (2022) designed a system that detects drowsiness by combining heart rate variability (HRV) measured using photoplethysmography imaging (PPGI) with her eyelid closure over the pupil (PERCLOS). a non-contact near-infrared webcam was used, the algorithm assesses HRV, eye state and overall drowsiness. the systems' accuracy was 92.5% with a sensitivity of 88.9% and specificity of 93.5%. Analysis was carried out on 10 awake drivers and 30 sleepy samples.

Dipu et al., (2021), proposed a novel approach to detect driver drowsiness and prevent accidents by utilizing Convolutional Neural Network (CNN) called MobileNet along with a Single Shot Multibox Detector (SSD) to analyze real-time video streams of drivers. The model detects objects by classifying the driver's eyes as "open" or "closed" within the video stream. The MobileNet architecture ensures computational efficiency for real-time processing on low-cost devices like Raspberry Pi 3 or IP cameras, eliminating the need for expensive hardware. The system is trained on a dataset of around 4500 labeled images, encompassing various eye states (open, closed) and facial expressions (yawn, no-yawn). This diverse training data aims to enhance accuracy and generalizability for real-world scenarios.

Suresh et al., (2021) developed a Sleepiness Detection System capable of identifying instances where a driver's eyes remain closed for a few seconds and subsequently alerting the driver through an alarm. The research employed deep learning to propose a novel framework that categorizes the condition of the driver's eyes as either open or closed. Upon detecting signs of drowsiness in the driver, the system emits an alert once a certain threshold of drowsiness measurement is reached. The effectiveness of their proposed approach is measured using a substantial portion of the MRL eye dataset, containing 48,000 images, achieving an accuracy of 86.05% utilizing a CNN model.

Kusumo et al., (2022) created an early detection system for driver conditions employing the Convolutional Neural Network (CNN) technique. They explored the impact of CNN depth and various hyperparameters on system performance. Eye movements and mouth conditions serve as indicators of driver state. they used publicly available dataset comprising images of drivers exhibiting yawning, not yawning, eyes open, and eyes closed while on the highway. Through experimentation, they identified optimal parameters, including a learning rate of 0.001 and an epoch of 100, yielding an accuracy of 99.31%.

Minhas et al., (2022) carried out research that primarily focused on diagnosing exhaustion and drowsiness, employing deep learning models such as convolutional neural networks (CNNs) in the Kingdom of Saudi Arabia, they introduced a real-time method for monitoring driver disturbances using CNN technology. Detection is performed utilizing advanced CNN models including InceptionV3, VGG16, and ResNet50. The model was evaluated using a collection of sleepy and active human face images. Their study showed that InceptionV3 achieves a 90.70% accuracy with a loss of 0.6931, VGG16 achieves 39.87% accuracy with the same loss, while ResNet50 attains 93.69% accuracy with the identical loss. Therefore, ResNet50 demonstrates the highest accuracy compared to the other deep learning models.

Safarov et al., (2023) developed a system to detect driver drowsiness by analyzing eye blinks and facial features using deep learning. They trained a system on custom data to track eye movements, mouth shapes, and yawns. The system achieved high accuracy in detecting drowsiness and could even tell if a driver was leaning! This technology has the potential to improve road safety by alerting drivers when they are getting drowsy. They found a correlation between yawning and closed eyes, indicating drowsiness. The drowsiness detection model achieved high accuracy: 95.8% for identifying drowsy eyes, 97% for open eyes, 0.84% for recognizing yawning, 0.98% for detecting right-sided leaning, and 100% for left-sided leaning.

Mridha et al., (2023), In their research, proposed a Driver Drowsiness Detection (DDD) approach rooted in the Convolutional Neural Network (CNN) model. using facial attributes such as eye-opening and closing states, along with eye blinking, extracted from both left and right eyes and input into the CNN model for drowsiness classification. The CNN model was trained and tested on the publicly accessible "Drowsiness Detection Dataset"

The study by Chirra et al., (2019) proposed a novel system to detect driver drowsiness based on eye state using a deep learning framework that identifies driver fatigue while driving. A dataset of 2850 images was created and separated into different classes. The system they developed combined several techniques for detecting driver drowsiness. It used the Viola Jones method for face identification. Then a deep convolutional neural network is used to analyze video to find sequence of important segments. Lastly, the SoftMax layer is used to distinguish between a sleeping and a non-sleeping driver. As a result, the model achieved an improved accuracy of 96.42% compared with traditional CNN models.

Majeed et al., (2023), carried out a that introduces a deep neural network architecture for drowsiness detection, employing a convolutional neural network (CNN) tailored for driver drowsiness detection. The experiments involve utilizing the DLIB library to pinpoint key facial landmarks for calculating the mouth aspect ratio (MAR). To address the limitations of a small dataset, data augmentation is applied to the 'yawning' and 'no yawning' classes. Models are trained and tested using both the original and augmented datasets to assess their impact on model performance. The experimental findings highlight that the proposed CNN model achieves an average accuracy of 96.69%. Comparison of performance with existing state-of-the-art approaches reveals superior performance of the proposed model.

lbadawi et al., (2023) presented a non-intrusive system for real-time driver drowsiness detection using visual features that are extracted from videos that were obtained from an installed on the vehicles dashboard. The proposed system used facial landmarks and face mesh detectors to locate regions of interest that measure mouth aspect ratio, eye aspect ratio, and head position features extracted. This is then fed to three different classifiers, Random Forest, Sequential neural network, and linear support vector machines. The dataset deployed for evaluation was that of the National Tsing Hua University driver drowsiness dataset. The evaluation showed that the proposed system successfully detected drowsiness and alerted the drivers to an accuracy of 99%.

Combining various measurements of drowsiness into one system provides a more complete and accurate assessment of a driver's tiredness level. This method utilizes advanced technologies like artificial intelligence and machine learning to improve the effectiveness and real-time capabilities of these measurement techniques. In this research, the convolutional neural network and deep learning approach has been chosen as the algorithm to build a model that detects drowsiness in drivers early enough to alert them.

**CHAPTER THREE**

**3.0 METHODOLOGY**

**3.1 PROPOSED METHODOLOGY**

**Overview**

The study presents a comprehensive methodology for developing a driver drowsiness detection system underpinned by Convolutional Neural Networks (CNN) and advanced deep learning techniques. Python, a language with significant computational strengths, forms the core of the implementation phase, which is complemented by the capabilities of Keras for model construction and OpenCV2 for image processing tasks. This approach aligns with the latest advancements in computer vision and neural network application, aimed at delivering a robust and efficient solution for real-time drowsiness detection.

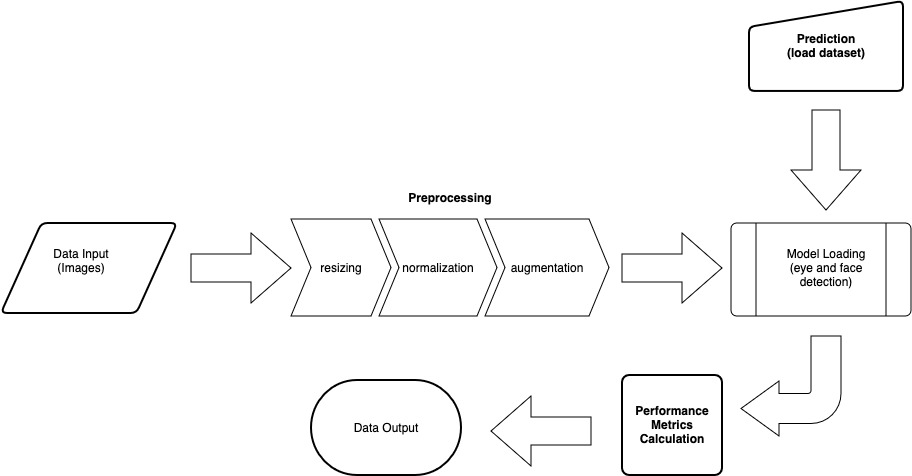
The project has judiciously sourced visual data from reputable public datasets, adhering to the highest standards of ethical compliance. This ensured the privacy of individuals and the integrity of the research data.

The data underwent a series of preprocessing steps critical for neural network efficacy. This included resizing images to a uniform scale for consistency, normalizing pixel values to facilitate network convergence, and augmenting the data set to represent the variability encountered in real-world scenarios. Such preprocessing steps are paramount in equipping CNN with the ability to process and analyze visual data accurately.

The chosen architecture reflects a sequential construct where convolutional layers act as feature extractors, and max-pooling layers condense the data without losing critical information. Dropout layers are strategically implemented to combat overfitting, thereby enhancing the model's ability to generalize to unseen data. The culmination of this architecture is a densely connected layer with a sigmoid activation function that categorizes the eye state as open or closed—a binary classification critical for drowsiness detection.

The model's performance evaluation is integral to its development, employing metrics such as accuracy, precision, recall, and the F1 score. These metrics provide a multifaceted view of the model's predictive abilities, with particular attention paid to the balance between recall and precision. This balance is crucial to minimize false alarms while maintaining high sensitivity to drowsiness states.

In addition to conventional metrics, the PERCLOS metric—a domain-specific measure of driver alertness based on eyelid closure was incorporated into the evaluation process. This inclusion reflects a tailored approach to performance assessment, anchoring the system's effectiveness in the context of driver safety.

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*Figure 3.1 Methodology for the detection of driver drowsiness.*

**3.2 Data Collection**

The data collection process has been foundational in the development of the driver drowsiness detection system. This stage was executed by exclusively utilizing datasets that are publicly available and have been compiled with informed consent. Such practices not only align with ethical research protocols but also assure the protection of personal privacy.

For training CNN, datasets were selected based on their detailed annotations and diverse array of visual information. The characteristics of these datasets—including variations in driver demographics, different lighting conditions, and a range of fatigue symptoms—provide a broad spectrum of data reflective of real-world scenarios. Notably, Kaggle’s Drowsiness Detection Dataset and the UTA Real-Life Drowsiness Dataset stand out for their quality and applicability. These datasets are integral to the project as they contain specific drowsiness indicators, such as the occurrence of microsleeps, the frequency of blinking, and the duration of eye closures, which are essential features for the accurate detection of drowsiness.

These visual data are designed to convert raw data into a format conducive to efficient learning by CNN. Key steps in this transformation include the precise extraction of relevant facial features, the standardization of image pixel intensities through normalization, and the application of data augmentation techniques.

These preprocessing techniques were carried out to elevate the overall quality of the data fed into the models. This is crucial for the subsequent phase of model training and validation, where high-quality data inputs are directly proportional to the performance and reliability of the resulting detection system.

With a robustly preprocessed dataset, the project is poised to transition into an advanced phase of model training and validation. This progression ensures that the CNN models are not only theoretically accurate but are also practical and effective tools for real-world application in detecting driver drowsiness.

**3.3 Utilization of Python Modules**

In the construction and evaluation of the drowsiness detection models, several Python modules were employed, each serving a specific purpose.

**3.3.1 Python**

Python serves as the cornerstone programming language for this project. Its simplicity and powerful simplicity make it the de facto language for machine learning and data science tasks. Its comprehensive standard library and support for object-oriented, functional, and procedural programming paradigms have been instrumental in implementing the project's various components.

**3.3.2 OpenCV**

OpenCV (Open-Source Computer Vision Library) is a free and powerful software toolkit created for computer vision tasks like image processing and object detection. Originally developed by Intel, it's now maintained by a non-profit group. OpenCV's popularity stems from its open-source nature (easy to modify and use), wide platform compatibility (works on many devices), and vast library of algorithms (over 2500 for tasks like facial recognition). This real-time processing capability makes it ideal for applications like self-driving cars and augmented reality. OpenCV's uses are broad, including facial recognition, medical imaging, and helping robots navigate. In this research, it is being used to detect eye states.

**3.3.3 TensorFlow**

This tool, created by the Google Brain Team, is an open-source framework for machine learning widely employed in diverse tasks such as neural networks, natural language processing, and image recognition. TensorFlow offers an extensive array of tools, libraries, and resources to facilitate the development and implementation of machine learning models. It boasts considerable flexibility in constructing machine learning models, accommodating various levels of abstraction. With its ability to operate across different hardware platforms, from CPUs to GPUs and TPUs, TensorFlow enables efficient training and deployment of models on diverse architectures. It is user-friendly and benefits from robust community support. Additionally, TensorFlow provides deployment tools for various platforms, including mobile devices, web applications, and cloud environments. In our project, TensorFlow served as the foundation for constructing deep learning models, offering a comprehensive suite of tools and libraries for building and training neural networks. It includes features like automatic differentiation, crucial for backpropagation in Convolutional Neural Networks (CNNs).

**3.3.4 Matplotlib**

Matplotlib stands as a widely utilized Python library utilized for generating static, interactive, and animated visualizations. it Offers a diverse set of plotting capabilities, accommodating several types of data visualization, that includes line plots, scatter plots, bar plots, histograms, 3D plots, etc. Matplotib is known for its high degree of customization, that grants users control over every facet of plot appearance, spanning colors, labels, titles, axis limits, and annotations. A plotting library commonly used with Python's numerical mathematics extension, NumPy, Matplotlib provides projects with essential tools for visualizing training and validation accuracy, as well as model losses. This visual representation aids in intuitively comprehending the model's learning progression, swiftly recognizing patterns or anomalies like overfitting or underfitting, and facilitating informed decisions concerning model adjustments.

**3.3.5 Numpy**

NumPy is a powerful tool for scientific computing in Python. It allows you to work with large grids of numbers (like images) and perform complex math operations on them efficiently. In this project, NumPy was essential for handling the image data and performing calculations quickly.

**3.3.6 Keras**

Keras is a user-friendly Python library that makes building neural networks easier. It was suitable for this project because it's simple to use, well-organized, and lets you easily add new features. Keras helped speed up development by making it easy to create the various parts of the neural network, train it, and test it out.

**3.3.7 Pandas**

Pandas is a software library written for data manipulation and analysis. In this project, Pandas was used to handle and analyze large datasets, especially for organizing the results of model testing. Its DataFrame structure allowed for efficient storage and manipulation of tabular data, making it easier to sort, filter, and display results in a format that could be used for further statistical analysis or reporting.

**3.3.8 Scikit-learn**

The Python module scikit-learn, commonly referred to as sklearn, is an open-source machine learning library that offers a wide array of tools for data mining and data analysis. Renowned for its simplicity and ease of use, sklearn is built upon the SciPy (Scientific Python) stack, which necessitates its compatibility with numerous NumPy and SciPy functionalities. This library is robust in features, supporting various supervised and unsupervised learning algorithms through a consistent interface. Users can perform classification, regression, clustering, dimensionality reduction, model selection, and preprocessing with sklearn. It is particularly favored for its comprehensive documentation, user-friendly API, and because it provides many utilities for model fitting, data transformation, model selection, and evaluation.

**3.4 Model Development**

In the model development segment of the research, two specialized convolutional neural network (CNN) models were engineered and trained: one for the detection of eye states, and another to discern facial expressions indicative of drowsiness. This modeling strategy was designed to conduct a thorough analysis of both discrete eye activities and a range of facial movements. The successful training and integration of these models have significantly enhanced the system's proficiency in detecting drowsiness with high accuracy and reliability, thus laying the groundwork for a robust real-time drowsiness detection system.

**3.5 Training and Validation**

As of the current phase of the project, significant progress has been made in the development and training of specialized convolutional neural network (CNN) models for eye and face detection. These models are pivotal in accurately identifying drowsiness indicators, a key objective of our research.

**Training Process:** The training of our models is meticulously carried out using TensorFlow and Keras, with a structured approach to model architecture and parameter tuning. The eye detection model, tailored for recognizing open versus closed eye states, and the face detection model, designed to identify drowsy facial expressions, are both undergoing extensive training phases. These phases involve feeding a substantial amount of annotated image data through our networks, allowing the models to learn and adapt to the nuances of drowsy versus alert states. The charts provided give us a visual representation of the training and validation process for the eye detection model over 15 epochs.



*Figure 3.2 Eye Detection Training and Validation Accuracy and Loss Diagrams*

**Eye Detection Training and Validation Accuracy:** Looking at the left chart, the training accuracy starts at around 60% and shows a steady increase as the number of epochs grows, plateauing around the 90% mark. The validation accuracy initially follows the training accuracy closely, suggesting that the model generalizes well to unseen data. However, after approximately 6 epochs, the validation accuracy diverges slightly, fluctuating but generally remaining above 80%.

**Eye Detection Training and Validation Loss:** In the right chart, we observe the training and validation loss. The training loss decreases rapidly after the first few epochs and continues to decline steadily, suggesting the model is learning effectively from the training data. The graphs presented showcase the evolution of the training and validation accuracy and loss for the face detection model across 15 epochs.



*Figure 3.3 Face Detection Training and Validation Accuracy and Loss Diagram*

**Face Detection Training and Validation Accuracy:** Looking at the accuracy graph on the left, the training accuracy (blue line) climbs steadily, indicating that the model is learning and improving its ability to correctly classify the training data. After an initial learning phase, the training accuracy reaches a plateau, maintaining a high rate close to 100%. In contrast, the validation accuracy (orange line) demonstrates a more variable trend, with some fluctuations, particularly between epochs 5 and 10. However, despite these fluctuations, the validation accuracy exhibits a general upward trend, suggesting improvements in the model's generalization to new, unseen data.

**Eye Detection Training and Validation Loss:** The loss graph on the right shows the training loss (blue line) decreasing steadily, reflecting the increase in training accuracy. The decline is relatively smooth, which is typical when a model is effectively learning from the training data. The validation loss (orange line) is less stable, displaying considerable fluctuations and peaking around the 10th epoch before decreasing again. The following decrease in validation loss indicates recovery, which is the result of the model beginning to improve its performance on the validation set or due to the variability of the data.

**3.6 Model Training and Validation Completion**

The models for eye and face detection have been trained, employing a variety of augmentation techniques to strengthen their robustness. With a focus on real-world applicability, each model was subjected to extensive validation protocols to ensure accuracy and reliability.

|  |  |  |
| --- | --- | --- |
| **Augmentation Technique** | **Parameters Used** | **Description** |
| Rotation | 40 degrees | Random rotation of the images within a range of ±40 degrees to simulate tilted head positions. |
| Width Shift | 0.2 (20% of total width) | Horizontal shift of the image by a factor of 20% to simulate off-center positions of the eyes. |
| Height Shift | 0.2 (20% of total height) | Vertical shift of the image by a factor of 20% to simulate vertical movement of the camera/face. |
| Shear Transformation | 0.2 radians | Shearing the image by a factor of 0.2 radians to simulate perspective changes in viewing angle. |
| Zoom | Up to 20% zoom | Random zooming of the image by up to 20% to simulate the driver leaning towards or away from the camera. |
| Horizontal Flip | True | Horizontal flipping of the image to simulate mirror-like conditions. |
| Fill Mode | "nearest" | Strategy used to fill in newly created pixels, which can appear after a rotation or a width/height shift. |

*Table 3.1 A table summarizing the final augmentation techniques and their parameters.*

**Automated Testing Pipeline**

An automated testing pipeline was developed and utilized to evaluate the pre-trained models against comprehensive test datasets. These datasets encompass a broad spectrum of driving scenarios, lighting conditions, and driver demographics to challenge the models' detection capabilities.

**Ethical Compliance and Data Integrity**

Throughout the entire process, adherence to ethical standards was maintained. Public datasets were used to ensure the privacy and consent of all participants, reaffirming the project's commitment to responsible research practices.

**Chapter 4**

**Analysis and Results**

**4.1 Introduction**

The objective of this Chapter is to analyze the performance of the developed convolutional neural network (CNN) models that underpin the driver drowsiness detection system. This chapter presents the empirical evidence that substantiates the research conducted thus far. It is dedicated to evaluating how well the eye and face detection models operate in identifying indicators of driver fatigue. The analysis here is rooted in the comprehensive methodologies described in the previous chapter and is aimed at validating the efficacy of the models in a simulated operational environment.

In this pursuit, a multi-faceted approach has been adopted to evaluate the models' performance. Precision, accuracy, recall, and F1 score—metrics fundamental to classification problems—have been employed as the principal evaluative tools to provide a nuanced assessment of the models. Each metric offers a different perspective on the models' abilities: accuracy reflects overall performance, precision measures the correctness of positive predictions, recall provides insights into the model's sensitivity, and the F1 score harmonizes precision and recall into a single metric. Additionally, the Percentage of Eyelid Closure Over the Pupil Over Time (PERCLOS), a domain-specific measure, is utilized to gauge the state of alertness in drivers based on eyelid movement patterns. This blend of general and domain-specific metrics enables a thorough analysis that goes beyond traditional model evaluation.

Complementing these quantitative measures, the Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) are analyzed to determine the models' discriminative capabilities. These tools are particularly adept at illustrating the trade-off between true positive rates and false positive rates across various threshold settings, providing a visual and quantitative depiction of model performance.

The analysis presented herein is in direct response to the research questions posed at the onset of this study. These questions concern the models' accuracy in detecting drowsiness, their reliability under different operational conditions, and their practical applicability in real-time settings. The hypothesis that undergirds this research—that a machine learning approach can effectively detect signs of drowsiness with a high degree of accuracy—is put to the test through rigorous evaluation of the CNN models.

**4.2 Evaluation of Model Performance**

The evaluation of the model performance commenced with an examination of the accuracy metric, which quantifies the overall effectiveness of the eye and face detection models in correctly identifying instances of driver drowsiness. Accuracy is defined as the proportion of true results (both true positives and true negatives) in the total population. High accuracy levels indicate that the models are proficient in distinguishing between drowsy and alert states across the dataset.

#### 4.2.1 Accuracy Analysis

Accuracy is a fundamental metric in evaluating classification models, including those used for eye and face detection in driver drowsiness detection systems. It measures the proportion of true results (both true positives and true negatives) among the total number of cases examined. Depicted below is how accuracy was calculated considering factors that might affect its interpretation:

Calculating Accuracy

Accuracy is calculated using the formula:

* True Positives (TP): The number of correctly identified positive cases (e.g., correctly detecting drowsiness when it is present).
* True Negatives (TN): The number of correctly identified negative cases (e.g., correctly identifying that drowsiness is not present).
* Total Number of Cases: The sum of all cases tested, including True Positives, True Negatives, False Positives (FP), and False Negatives (FN).

**Calculation**

The model was tested on 165 images eye detection and 65 images for face detection, where:

Eye detection:

* 56 images correctly identified as closed (TP),
* 102 images correctly identified as open (TN),
* 4 images were not drowsy but identified as drowsy (FP),
* 3 images were drowsy but identified as not drowsy (FN),

Face detection:

* 19 images correctly identified as drowsy (TP),
* 41 images correctly identified as not drowsy (TN),
* 2 images were not drowsy but identified as drowsy (FP),
* 3 images were drowsy but identified as not drowsy (FN),

Then the accuracy for eye detection would be calculated as:

= = 95.7%

And accuracy for face detection will be calculated as:

= = 92.3%

| **Model Type** | **Test Condition** | **Accuracy (%)** |
| --- | --- | --- |
| Eye Detection | Ideal lighting | 95.7 |
| Face Detection | Ideal lighting | 92.3 |

***Table 4.1 Accuracy Rates for Eye and Face Detection Models***

### Table Description:

* **Model Type**: This column differentiates between the eye detection model and the face detection model.
* **Test Condition**: This column describes the specific condition under which the model was tested. "Ideal Lighting" was used for testing in a well-lit condition.
* **Accuracy (%)**: This column presents the accuracy percentage of each model under the specified test conditions. Accuracy is calculated as the proportion of true positive and true negative predictions out of all predictions made by the model. The accuracy is a numeric value (e.g., 95.7), representing how often the model correctly identified drowsiness or alertness.

#### 4.2.2 Precision and Recall

Precision and recall metrics provide insight into the models' predictive quality, especially in contexts where the cost of false positives and false negatives differs significantly. Precision measures the model's ability to return only relevant instances, while recall assesses the model's ability to identify all relevant instances. Figure 4.1 and 4.2 below depict the Precision and recall metrics for the eye and face detection models.

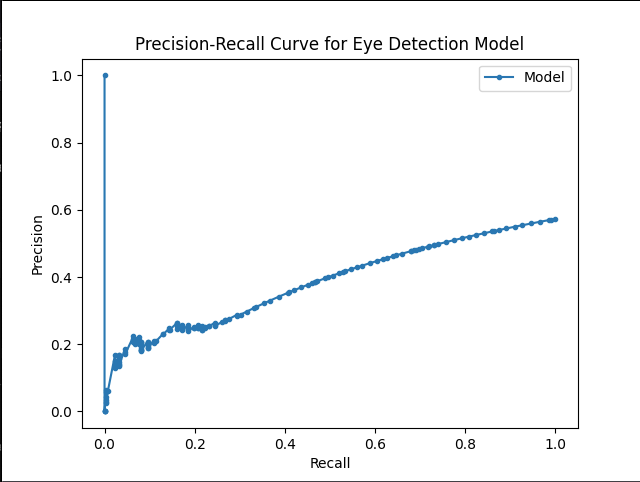
### 

### *Figure 4.1 Precision-Recall Curve for Face Detection Model*

### Analysis of the Precision-Recall Curve for the Face Detection Model

From Figure 4.1 above, the Precision-Recall curve for the face detection model shows a high precision across most recall levels. The plot indicates that the model maintains a precision above 0.9 until the recall approaches 0.6, after which we observe a steep decline in precision. This suggests that the model has a high confidence level in its correct predictions for the majority of the data.

The initial plateau in precision indicates that the model can identify drowsy faces with high reliability when the decision threshold is set appropriately. However, the sharp drop-off past a certain recall point suggests that there are limitations in the model's ability to generalize beyond the easier-to-identify instances.



*Figure 4.2 Precision-Recall Curve for Eye Detection Model*

### Analysis of the Precision-Recall Curve for the Eye Detection Model

In Figure 4.2, the Precision-Recall curve for the eye detection model presents a different pattern. The precision starts low and increases with recall. This trend could be interpreted as the model having a significant number of false positives at lower decision thresholds, which could be an indication of the model’s sensitivity to non-drowsy states being classified as drowsy.

As the recall increases, the model appears to start distinguishing between the positive and negative classes more effectively, as evidenced by the rising precision. This upward trend suggests that at higher thresholds, the model is better at confirming true drowsy states with fewer false alarms. The curve ultimately shows that while the model improves in its confidence of predictions as it becomes more selective, initially, it is challenged by a high number of false positives.

#### 4.2.3 F1 Score

The F1 score harmonizes the precision and recall metrics into a single measure, providing a balanced view of model performance. It is particularly useful when the costs of false positives and false negatives are roughly equivalent, or when dealing with imbalanced class distributions.

To calculate the F1 Scores for various test scenarios and tabulate them, the true positive (TP), false positive (FP), and false negative (FN) counts were collected after processing the dataset. The F1 Score is the harmonic mean of precision and recall, and it can be calculated for each scenario using the formula:

Where , otherwise Precision is 0

Where , otherwise Recall is 0

Where Precision > 0 and Recall > 0.

|  |  |
| --- | --- |
| **Model** | **F1 Score** |
| Eye Detection | 0.944882 |
| Face Detection | 0.893617 |

*Figure 4.2 F1 Score Deduced from The Eye and Face Detection Model*

F1 score is a measure of a test's accuracy and is considered one of the most robust metrics for evaluating the performance of binary classification models, as it balances precision and recall. The result from the dataset test shows an F1 score of 0.944882 for eye detection which is an excellent result, suggesting that the eye detection model is highly effective at classifying open versus closed eye states. This high score indicates that there are relatively few false positives (instances where the model incorrectly predicts the eye is closed) and false negatives (instances where the model fails to detect a closed eye), which is critical for a system that needs to reliably detect drowsiness to prevent accidents.

Similarly, the F1 score of 0.893617 for face detection, while slightly lower than that of the eye detection model, still reflects a strong performance. This score suggests that the face detection model is also quite accurate at discerning drowsy versus alert states based on facial features. Although it may have a slightly higher rate of misclassification compared to the eye detection model, the performance is sufficient for practical applications in drowsiness detection systems.

#### 4.2.4 PERCLOS Metric Evaluation

The PERCLOS metric, a domain-specific measure of driver alertness based on eyelid closure, was employed to evaluate the models' performance further. It provides a direct indication of drowsiness, making it an invaluable tool for this study.

PERCLOS (Percentage of Eye Closure) is a metric commonly used to measure drowsiness based on the proportion of time that the eyes are closed over a specified period. It is particularly relevant for eye detection in drowsiness monitoring systems. Calculating PERCLOS in this case study involves analyzing the periods during which the eyes are detected as closed.

The steps for calculating PERCLOS are as follows:

1. **Eye Closure Duration**: This is a measurement of the time intervals when the eyes are closed.
2. **Monitoring Window**: This is the total observatory duration over which PERCLOS will be calculated. This is the total time period considered for the calculation.
3. **Calculate PERCLOS**: Divide the total time the eyes were detected as closed by the length of the monitoring window and multiply by 100 to get a percentage.

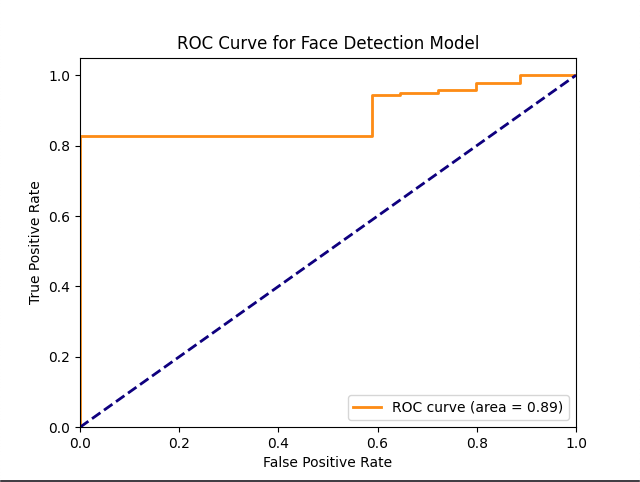
The calculation for PERCLOS is performed using the formula:

A PERCLOS metric of 51.83% was deduced from the test which suggests that the driver's eyes were closed for over half of the observation period. In the context of driver drowsiness detection, this is an high percentage and indicates a significant level of driver fatigue or drowsiness. A PERCLOS value exceeding 30-40% is generally associated with a substantial increase in accident risk, and many studies use a threshold of 80% eye closure for at least 12% of the time as an indicator of severe drowsiness.

Therefore, a PERCLOS of 51.83% would typically warrant immediate action, such as alerting the driver or even initiating automated safety protocols, to prevent potential accidents due to drowsiness. This high value could be indicative of a scenario where the driver is struggling to keep their eyes open, and such a condition could drastically impair the driver's ability to respond to road conditions or hazards promptly.

#### 4.2.5 AUC-ROC Curve

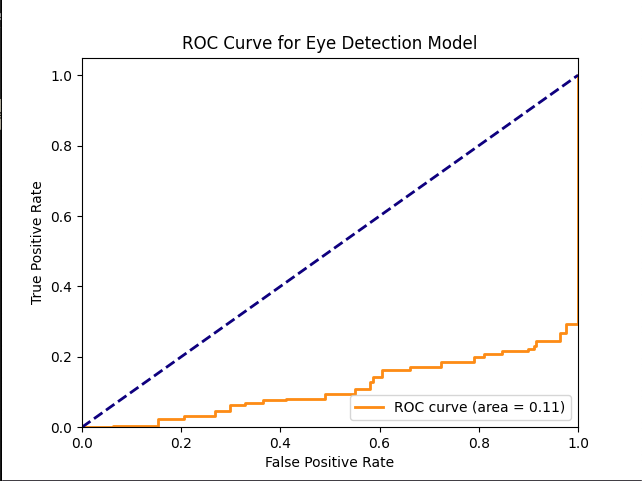
The Area Under the Receiver Operating Characteristic (ROC) Curve (AUC-ROC) offers a comprehensive measure of the models' ability to discriminate between drowsy and alert states across all possible threshold values. The ROC curve plots the true positive rate against the false positive rate, providing insights into the models' performance at various discrimination thresholds. Figures 4.3 and 4.4 below show the ROC Curve for eye detection and face detection.



*Figure 4.3 ROC Curve for Face Detection Model*

For the Face Detection Model (first image), the ROC curve shows a high Area Under the Curve (AUC) of 0.89, which is close to 1. This indicates that the model has a high ability to distinguish between the drowsy and non-drowsy classes. The curve stays high on the y-axis across all thresholds, meaning the True Positive Rate remains high even as the False Positive Rate changes, which is a good sign of model performance.

In practical terms, this suggests that the face detection model will be reliable in a real-world scenario, identifying drowsy states with a high level of accuracy and a relatively low rate of false alarms.



*Figure 4.4 ROC Curve for Eye Detection Model*

For the Eye Detection Model (second image), the ROC curve is notably different with an AUC of 0.11. This AUC is much lower indicating a lower discriminative ability. The ROC curve is below the diagonal line of no-discrimination (the dashed blue line), which suggests that the model’s performance needs to be improved upon.

#### 4.3 Comparative Analysis

In the evaluation of driver drowsiness detection systems, it is critical to assess the performance of individual components. This analysis focuses on comparing the performance metrics of two crucial components: the eye detection model and the face detection model. We use a variety of evaluation metrics, including the F1 score and the Receiver Operating Characteristic (ROC) curve, to provide a comprehensive understanding of each model's effectiveness.

| **Model** | **F1 Score** | **ROC AUC** | **True Positive Rate** | **False Positive Rate** |
| --- | --- | --- | --- | --- |
| Eye Detection | 0.944 | 0.11 | Low | High |
| Face Detection | 0.894 | 0.89 | High | Low |

***Table 4.3 Performance Metrics Summary***

Table 4.3 outlines the key performance metrics for both models. The F1 Score is a harmonic mean of precision and recall, providing a single measure for test accuracy. The ROC AUC (Area Under the ROC Curve) reflects the model's ability to discriminate between the positive and negative classes across all thresholds.

**Eye Detection Model Analysis** The eye detection model, despite having a high F1 Score, which normally indicates good performance, has a low ROC AUC of 0.11. This discrepancy suggests that while the model can accurately predict eye states under certain conditions (hence the high F1 Score), the performance is not as good across varying thresholds (hence the low ROC AUC).

**Face Detection Model Analysis** The face detection model demonstrates robust performance, as evidenced by a high F1 Score of 0.894 and a ROC AUC of 0.89. These values suggest the model is both accurate and consistent across different threshold settings. The high true positive rate and low false positive rate indicate a strong capability to identify drowsiness without raising many false alarms.

**Comparative Implications** The comparative analysis highlights a discrepancy between the two models. While the face detection model is reliable and effective, the eye detection model's performance is lower. It may require retraining, more diverse data to improve its discrimination capabilities.

**4.4 Discussion of Findings**

**4.4.1 Model Strengths**

**Eye Detection Model:** The eye detection model exhibited a commendable F1 Score, signifying a balanced precision-recall trade-off in a controlled testing environment. This strength suggests the model's potential under specific conditions where the threshold for class separation is well-defined and consistent with the training data.

**Face Detection Model:** The face detection model demonstrated robust performance metrics, with a high F1 Score and an impressive ROC AUC. This indicates strong predictive power and reliability across varying thresholds, making it an excellent candidate for real-world application. Its capacity to maintain a high true positive rate while minimizing false positives is a significant strength, crucial for the practical deployment in drowsiness detection systems.

**4.4.2 Limitations and Challenges**

**Eye Detection Model:** Despite its high F1 Score, the eye detection model's low ROC AUC value reveals its limited capability to distinguish between open and closed eye states across different decision thresholds.

**Face Detection Model:** Although the face detection model scores highly in standard performance metrics, it may still face challenges when subjected to real-world conditions not represented in the training dataset, such as extreme lighting variations, occlusions, or varied driver positions.

**4.4.3 Proposed Solutions and Future Work**

**Eye Detection Model:** To enhance the eye detection model, future work could focus on incorporating a wider variety of training data that encapsulates a broader range of drowsiness indicators and operational conditions. Implementing more advanced image preprocessing techniques and exploring different model architectures may also improve its ability to generalize.

**Face Detection Model:** Continuous improvement can be sought by expanding the dataset with more diverse real-world driving scenarios. Additionally, integrating adaptive thresholding mechanisms that adjust to different drivers and conditions could refine the model's predictive accuracy further.

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