

# **DROWSY DRIVER ALERT SYSTEM**

## **MINI PROJECT REPORT**

*Submitted by*

**Hayagriv Koushik S**

**210701081**

**Hirthik Mathesh GV**

**210701084**

*in partial fulfillment for the award of the degree of*

**BACHELOR OF ENGINEERING**

*in*

**COMPUTER SCIENCE AND ENGINEERING**



**RAJALAKSHMI ENGINEERING COLLEGE, CHENNAI**

**ANNA UNIVERSITY :: CHENNAI 600 025**

**APRIL 2024**

**RAJALAKSHMI ENGINEERING COLLEGE,  
CHENNAI**

**BONAFIDE CERTIFICATE**

Certified that this Report titled “**Drowsy Driver Alert System**” is the bonafide work of “**Hayagriv Koushik S (210701081)**” and “**Hirthik Mathesh GV (210701084)**” who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

**SIGNATURE**

**Rahul Chiranjeevi. V**

**Assistant Professor,**

Department of Computer Science and Engineering,

Rajalakshmi Engineering College,

Chennai – 602015

Submitted to Mini Project Viva-Voce Examination held on \_\_\_\_\_

**Internal Examiner**

**External Examiner**

## ABSTRACT

The drowsy driver alert system presented in this project leverages the integration of computer vision and machine learning techniques to detect and mitigate driver fatigue in real-time. Utilizing the OpenCV library, facial and ocular features are identified through a haar cascade classifier (uses AdaBoost algorithm), enabling the system to track the driver's face and eyes. Ensuring robust detection of pertinent facial landmarks crucial for detecting drowsiness. Following face and eye detection, a Convolutional Neural Network (CNN) model is employed to predict the driver's alertness status. Trained on a dataset encompassing a diverse range of facial expressions and eye behaviors indicative of drowsiness, the CNN model learns to accurately classify the driver's state in terms of wakefulness or drowsiness. Utilizing the powerful ability of deep learning, the CNN model provides a reliable assessment of the driver's condition, enabling timely intervention to prevent potential accidents caused by drowsy driving. The system's implementation offers versatility, allowing integration into various automotive platforms and environments. Whether embedded within vehicles or integrated into existing driver assistance systems, the drowsy driver alert system enhances safety on the road by consistently monitoring the driver's level of alertness. Real-time alerts prompt corrective actions, such as auditory or visual alerts, to mitigate the risks associated with drowsy driving. Overall, this project demonstrates the potency of combining computer vision with machine learning to create an intelligent system capable of detecting and addressing driver fatigue, contributing to the enhancement of road safety and the prevention of accidents caused by drowsiness-induced impairments.

## ACKNOWLEDGEMENT

Initially we thank the Almighty for being with us through every walk of our life and showering his blessings through the endeavor to put forth this report.

Our sincere thanks to our Chairman **Mr. S. MEGANATHAN, B.E, F.I.E.,** our Vice Chairman **Mr. ABHAY SHANKAR MEGANATHAN, B.E., M.S.,** and our respected Chairperson **Dr. (Mrs.) THANGAM MEGANATHAN, Ph.D.,** for providing us with the requisite infrastructure and sincere endeavoring in educating us in their premier institution.

Our sincere thanks to **Dr. S.N. MURUGESAN, M.E., Ph.D.,** our beloved Principal for his kind support and facilities provided to complete our work in time. We express our sincere thanks to **Dr. P. KUMAR, Ph.D.,** Professor and Head of the Department of Computer Science and Engineering for his guidance and encouragement throughout the project work. We convey our sincere and deepest gratitude to our internal guide, **Rahul Chiranjeevi. V** Assistant Professor, Department of Computer Science and Engineering. Rajalakshmi Engineering College for his valuable guidance throughout the course of the project.

**Hayagriv Koushik S : 210701081**

**Hirthik Mathesh GV : 210701084**

**TABLE OF CONTENTS**

<b>CHAPTE RNO.</b>	<b>TITLE</b>	<b>PAGE NO.</b>
	<b>ABSTRACT</b>	<b>ii</b>
	<b>ACKNOWLEDGEMENT</b>	<b>iii</b>
	<b>LIST OF FIGURES</b>	<b>vii</b>
	<b>LIST OF TABLES</b>	<b>viii</b>
	<b>LIST OF ABBREVIATIONS</b>	<b>ix</b>
<b>1.</b>	<b>INTRODUCTION</b>	<b>10</b>
	1.1 GENERAL	10
	1.2 OBJECTIVE	11
	1.3 EXISTING SYSTEM	11
	1.4 PROPOSED SYSTEM	14
<b>2.</b>	<b>LITERATURE SURVEY</b>	<b>16</b>
<b>3.</b>	<b>SYSTEM DESIGN</b>	<b>22</b>
	3.1 GENERAL	22

3.2	DEVELOPMENT ENVIRONMENT	22
3.2.1	HARDWARE SPECIFICATIONS	22
3.2.2	SOFTWARE SPECIFICATIONS	22
3.3.1	ARCHITECTURE DIAGRAM	23
3.3.2	PROCESS FLOW DIAGRAM	24
<b>4.</b>	<b>PROJECT DESCRIPTION</b>	<b>26</b>
4.1	MODULES DESCRIPTION	26
4.1.1	OPEN CV	26
4.1.2	HAAR CASCADE CLASSIFIER	26
4.1.3	KERAS	26
4.1.4	CONVOLUTIONAL NEURAL NETWORKS	26
<b>5.</b>	<b>IMPLEMENTATION AND RESULTS</b>	<b>28</b>
5.1	IMPLEMENTATION	28
5.2	OUTPUT SCREENSHOTS	29
<b>6.</b>	<b>CONCLUSION AND FUTURE</b>	<b>31</b>

## **ENHANCEMENTS**

6.1 CONCLUSION 31

6.2 FUTURE ENHANCEMENTS 31

**LIST OF FIGURES**

<b>S.NO</b>	<b>NAME</b>	<b>PAGE NO</b>
3.3.1	FACE DETECTION USING HAAR CASCADE CLASSIFIER	23
3.3.2	DROWSINESS DETECTION USING CNN	24
5.2.1	RESULT WHEN EYES ARE OPENED	29
5.2.2	RESULT WHEN EYES ARE CLOSED	30



## LIST OF TABLES

<b>S.NO</b>	<b>NAME</b>	<b>PAGE NO</b>
3.2.1	HARDWARE SPECIFICATIONs	22
3.2.2	SOFTWARE SPECIFICATIONS	22
5.2.1	PRECISION TABLE AFTER APPLYING SYSTEM ON DATASET	29
5.2.2	CLASSIFICATION ACCURACY	29

## LIST OF ABBREVIATIONS

**CV** Computer Vision

**CNN** Convolutional Neural Networks

**SVM** Support Vector Machine

**RoI** Region of Interest

**EAR** Eye Aspect Ratio

**MAR** Mouth Aspect Ratio

# CHAPTER 1

## INTRODUCTION

### 1.1 GENERAL

In recent years, road safety has become a critical area of focus due to the increasing number of traffic accidents. One significant factor contributing to these accidents is driver drowsiness, which impairs judgment, reduces reaction time, and increases the likelihood of severe collisions. To mitigate this risk, the development of a Drowsy Driver Alert System has emerged as a pivotal solution. Leveraging advancements in computer vision and machine learning, this system aims to detect and alert drowsy drivers in real-time, potentially saving countless lives. This project combines the power of OpenCV, Haar Cascade Classifier, and Convolutional Neural Networks (CNNs) to create an effective and reliable alert mechanism.

OpenCV (Open Source Computer Vision Library) is a fundamental tool for building a Drowsy Driver Alert System. As a robust and versatile library, OpenCV provides comprehensive support for image and video processing tasks, enabling the development of sophisticated computer vision applications. In this project, OpenCV plays a crucial role in capturing video frames from a camera, preprocessing these frames, and performing initial face and eye detection. The process begins by capturing real-time video feed using a webcam or any camera module. Each frame of the video is then converted to grayscale to simplify the computational process, as color information is not necessary for initial face and eye detection. Grayscale conversion reduces the complexity and enhances the performance of the subsequent steps.

The Haar Cascade Classifier is employed to detect facial features such as the face, eyes, and mouth within the video frames. Developed by Paul Viola and Michael Jones, the Haar Cascade Classifier is known for its speed and accuracy in object detection tasks. It uses a machine learning approach where a cascade function is trained with positive and negative images to detect objects of interest. In the context of the Drowsy Driver Alert System, pre-trained Haar Cascade Classifiers for face and eye detection are utilized. These classifiers quickly and efficiently identify the regions of interest (ROI) in the video frames, which include the driver's face and eyes. The detection process involves scanning the entire frame with the trained classifiers to locate and highlight the facial features. Once the face and eyes are detected, these ROIs are cropped and forwarded to the next stage for further analysis.

While Haar Cascade Classifiers provide a good starting point for detecting facial features, they are limited in their ability to assess the state of drowsiness accurately. This is where Convolutional Neural Networks (CNNs) come into play. CNNs are a class of deep learning models specifically designed for image recognition tasks, making them ideal for analyzing eye states (open or closed) and

other signs of drowsiness. In this project, a CNN model is trained on a labelled dataset containing images of open and closed eyes. The CNN architecture typically consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. These layers work together to automatically extract and learn hierarchical features from the input images. The trained model can then classify the state of the eyes in real-time with high accuracy.

When a video frame is processed, and the eyes are detected, the cropped eye images are fed into the CNN model. The model predicts whether the eyes are open or closed. If the eyes are detected to be closed for a consecutive number of frames, indicating that the driver might be drowsy, an alert is triggered. This alert can be in the form of an audible alarm or a visual warning, prompting the driver to take a break or take necessary actions to avoid accidents. The integration of OpenCV, Haar Cascade Classifier, and CNNs results in a comprehensive Drowsy Driver Alert System that operates in real-time. The system continuously monitors the driver's face and eye states, processes the data using advanced algorithms, and provides immediate feedback if drowsiness is detected. This real-time capability is crucial for the effectiveness of the alert system, as it ensures timely intervention before a potential accident occurs.

In conclusion, the Drowsy Driver Alert System represents a significant advancement in road safety technology. By combining the strengths of OpenCV for image processing, Haar Cascade Classifier for efficient feature detection, and Convolutional Neural Networks for accurate state classification, this system provides a robust solution to a critical problem. The implementation of such a system can greatly reduce the incidence of drowsiness-related accidents, ultimately saving lives and enhancing road safety.

## **1.2 OBJECTIVE**

The primary objective of the Drowsy Driver Alert System project is to develop an advanced, real-time monitoring and alert system that can effectively detect signs of driver drowsiness and issue timely warnings to prevent potential accidents. Utilizing the powerful capabilities of OpenCV for image processing, Haar Cascade Classifier for efficient facial feature detection, and Convolutional Neural Networks (CNNs) for accurate state classification, this system aims to enhance road safety by reducing the risk of accidents caused by driver fatigue.

One key objective is to leverage OpenCV's comprehensive suite of image processing tools to capture and preprocess video frames in real-time. By converting these frames to grayscale, the system simplifies the computational complexity, thereby improving the speed and efficiency of subsequent processes. This preprocessing step ensures that the input data is optimized for accurate detection and analysis of facial features. Another crucial objective is to employ Haar Cascade Classifiers for the rapid and reliable detection of facial features such as the face, eyes, and mouth within the video frames. By using pre-trained

classifiers, the system can quickly identify regions of interest (ROIs) where further analysis is necessary. The goal is to achieve high detection accuracy while maintaining real-time performance, ensuring that the system can continuously monitor the driver without significant delays.

The integration of Convolutional Neural Networks (CNNs) is a core objective, aimed at enhancing the system's ability to accurately assess the driver's state of alertness. CNNs are trained on a large dataset of labelled images depicting open and closed eyes, allowing the model to learn and recognize patterns associated with drowsiness. The objective is to develop a CNN model that can reliably classify the state of the driver's eyes in real-time, providing a robust mechanism for detecting drowsiness. If the model detects that the driver's eyes remain closed for a predefined number of consecutive frames, it should trigger an alert, thereby preventing potential accidents.

Ensuring seamless integration of these components to create a cohesive and effective system is another primary objective. The project aims to combine the strengths of OpenCV, Haar Cascade Classifiers, and CNNs to develop a holistic solution capable of operating in real-time. This involves not only the technical integration of different algorithms and models but also the optimization of their performance to ensure that the system runs efficiently on available hardware.

Furthermore, the project seeks to design an intuitive and user-friendly alert mechanism. When the system detects signs of drowsiness, it should promptly issue a clear and immediate alert to the driver. This alert could be an audible alarm, a visual warning, or a combination of both, designed to effectively capture the driver's attention and prompt them to take necessary action, such as pulling over to rest.

In summary, the Drowsy Driver Alert System project aims to create a real-time, accurate, and efficient monitoring system that enhances road safety by detecting and alerting drowsy drivers. By harnessing the capabilities of OpenCV for image processing, Haar Cascade Classifiers for feature detection, and CNNs for state classification, the project strives to develop a reliable solution that can significantly reduce the risk of accidents caused by driver fatigue. This comprehensive approach ensures that the system not only performs well in detecting drowsiness but also operates seamlessly in real-world driving conditions, ultimately contributing to safer roads.

### **1.3 EXISTING SYSTEM**

The development of Drowsy Driver Alert Systems has been an active area of research in recent years, driven by the urgent need to reduce road accidents caused by driver fatigue. Various systems leveraging machine learning and computer vision have been developed, each incorporating different methodologies and

technologies to detect drowsiness. Understanding the landscape of these existing systems provides valuable insights into the advancements and limitations in this domain.

One prevalent approach in existing systems involves the use of eye-tracking technology. These systems typically utilize infrared cameras to monitor the driver's eye movements and blink patterns. By analyzing parameters such as blink duration, blink frequency, and the percentage of eyelid closure over time, these systems can estimate the driver's level of alertness. Machine learning models, particularly Support Vector Machines (SVM) and Decision Trees, are often employed to classify these eye movement patterns and predict drowsiness. Despite their effectiveness, these systems can be intrusive and expensive due to the specialized hardware required, limiting their widespread adoption. Another common method focuses on head position and facial expression analysis. These systems use cameras to track the driver's head movements and facial landmarks. Techniques such as the Viola-Jones algorithm for face detection, along with various machine learning models like Random Forests and Neural Networks, are used to analyze deviations in head position, yawning frequency, and other facial expressions associated with drowsiness. While these systems can be implemented using standard cameras, their accuracy can be affected by variations in lighting conditions, occlusions, and the diversity of drivers' facial features.

In addition to visual monitoring, some existing systems integrate physiological signals to enhance drowsiness detection. Wearable devices such as smartwatches and fitness trackers can monitor parameters like heart rate variability (HRV) and electroencephalography (EEG) signals. Machine learning models are trained on these physiological data to predict fatigue levels. Although these systems can provide accurate and early detection of drowsiness, they require the driver to wear additional sensors, which may not be convenient or feasible for all users.

Recent advancements have also seen the integration of convolutional neural networks (CNNs) and deep learning techniques into drowsiness detection systems. CNNs, with their ability to automatically extract and learn hierarchical features from images, have shown promise in analyzing facial features and eye states. For instance, some systems use CNNs to classify images of open and closed eyes, combined with recurrent neural networks (RNNs) to track temporal sequences and better understand the context of drowsiness over time. These deep learning-based systems have demonstrated high accuracy in controlled environments but still face challenges in real-world applications due to varying lighting conditions and driver behaviors. Furthermore, some innovative approaches employ multimodal systems that combine visual, physiological, and behavioral data to improve the robustness of drowsiness detection. These systems utilize data fusion techniques to integrate information from different sources, providing a comprehensive assessment of the driver's state. For example, combining facial analysis with steering behavior and lane-keeping performance can enhance the reliability of drowsiness detection. However, such systems can be complex and computationally intensive, requiring sophisticated algorithms and powerful hardware to operate effectively in real-time.

In summary, existing Drowsy Driver Alert Systems in machine learning encompass a wide range of methodologies, from eye-tracking and head position analysis to physiological monitoring and deep learning techniques. Each approach has its strengths and limitations, often balancing between accuracy, intrusiveness, and practicality. While significant progress has been made, challenges such as variability in environmental conditions, driver diversity, and the need for non-intrusive, cost-effective solutions remain. These existing systems provide a foundation upon which further advancements can be built, aiming to create more reliable and accessible drowsiness detection solutions for enhancing road safety.

## 1.4 PROPOSED SYSTEM

The proposed Drowsy Driver Alert System aims to address the limitations of existing systems by combining the strengths of OpenCV, Haar Cascade Classifier, and Convolutional Neural Networks (CNNs) to create a robust, non-intrusive, and real-time drowsiness detection solution. This system is designed to enhance road safety by accurately monitoring the driver's state and issuing timely alerts to prevent accidents caused by drowsiness.

The foundation of the proposed system is built on OpenCV, a powerful and widely used open-source computer vision library. OpenCV's extensive functionalities allow for efficient image and video processing, which is essential for real-time applications. In this system, OpenCV is utilized to capture video frames from a camera, typically mounted on the dashboard of a vehicle. These frames are then converted to grayscale to simplify subsequent processing steps, as grayscale images reduce computational load without losing critical information required for feature detection. For detecting facial features such as the driver's face and eyes, the system employs Haar Cascade Classifiers. Developed by Paul Viola and Michael Jones, Haar Cascade Classifiers are known for their rapid and reliable object detection capabilities. The classifiers are trained on positive and negative samples to detect the regions of interest (ROIs) in the video frames. In this case, pre-trained Haar Cascade Classifiers for face and eye detection are used. The classifiers scan the grayscale frames to locate the face and eyes, providing the coordinates of these features. Once detected, these ROIs are cropped and prepared for further analysis by the CNN model.

The core innovation of the proposed system lies in the integration of Convolutional Neural Networks (CNNs) for drowsiness detection. CNNs are highly effective for image recognition tasks due to their ability to learn and extract hierarchical features from input images. In this system, a CNN is trained on a dataset containing images of open and closed eyes. The architecture of the CNN typically includes multiple convolutional layers, pooling layers, and fully connected layers, which work together to classify the state of the driver's eyes accurately. When the system detects the eyes using the Haar Cascade Classifier, the cropped eye images are fed into the trained CNN model. The CNN processes these images and predicts

whether the eyes are open or closed. If the model consistently detects closed eyes over a series of frames, it indicates that the driver might be drowsy. To ensure reliability, the system uses a temporal analysis method, monitoring the eye state over several consecutive frames before issuing an alert. The alert mechanism in the proposed system is designed to be immediate and effective. If drowsiness is detected, the system triggers an audible alarm or a visual warning on the dashboard, prompting the driver to take corrective actions such as taking a break or pulling over safely. This real-time feedback is crucial for preventing accidents caused by driver fatigue.

In addition to its technical strengths, the proposed system emphasizes user-friendliness and non-intrusiveness. By using a standard camera and avoiding the need for wearable devices, the system ensures comfort and convenience for the driver. Furthermore, the use of OpenCV and Haar Cascade Classifiers ensures that the system can operate efficiently on various hardware platforms, making it accessible and cost-effective.

In conclusion, the proposed Drowsy Driver Alert System leverages the capabilities of OpenCV for image processing, Haar Cascade Classifiers for efficient feature detection, and CNNs for accurate state classification to create a reliable, real-time drowsiness detection solution. This system addresses the limitations of existing methods by providing a non-intrusive, cost-effective, and highly accurate mechanism for enhancing road safety, ultimately contributing to the reduction of accidents caused by driver drowsiness.



## CHAPTER 2

### LITERATURE SURVEY

In [1] To address the issue of drowsy driving in the automobile sector, a machine learning-based drowsy monitoring system using the GS1 standard is proposed. The GS1 standard language is used to model vehicle motion data for prediction purposes. We present optimal algorithms for real-time contexts, such as KNN, Naïve Bayes, Logistic Regression, and RNN-LSTM. Integration is accomplished using the Raspberry Pi and an open-source machine learning software framework. The system prioritizes the readability and utility of motion data, with a focus on real-time environmental parameters. The rapid prototyping process for connected automobile systems is demonstrated without the use of additional sensor devices.

In [2] The author is exploring ways to use deep learning to predict drivers' cognitive states using EEG data. They've come up with new algorithms like Channel-Wise Convolutional Neural Networks (CCNN) and its variant, CCNN-R, as well as Restricted Boltzmann Machines. They've also applied deep learning hidden units-based bagging classifiers. The testing was carried out on a large EEG dataset from three driver fatigue studies, which included 70 sessions from 37 participants. The results suggest that CCNN and CCNN-R perform better than DNN, CNN, and other non-deep learning algorithms. Additionally, deep learning using raw EEG inputs performs better than using ICA-transformed features for predicting across different sessions.

In [3] This project is all about spotting tired drivers early to prevent accidents. The focus is on telling the difference between an alert driver and one who's starting to feel a bit drowsy. We're looking at things like body signals, behavior, and how well someone drives using data from a driving simulator and monitor. We're crunching 32 pieces of info in a 10-second window and using machine learning tools like logistic regression, support vector machine, k-nearest neighbor, and random forest to sort it all out. The random forest method is giving us up to 81.4% accuracy in telling the difference between an alert driver and someone who's starting to feel a bit drowsy.

In [4] The suggested system aims to prevent accidents by monitoring the driver's gaze using video capturing and facial recognition techniques. A camera captures video frames in order to detect faces using the Histogram of Oriented Gradients (HOG) and Support Vector Machine (SVM). SVM identifies video components, particularly pupils, to detect fatigue indicators. Facial markers such as eye locations are identified, and the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio

(MAR) are measured. Machine learning algorithms, particularly SVM, estimate driver weariness and issue alarms if drowsiness is identified, with an accuracy of 92.85% and improved crash prevention capabilities.

In [5] This work is devoted to driver drowsiness detection by non-invasive image processing means. It uses a camera to capture real-time images of a driver's face and analyzes the ratio of eye and mouth openness, alerting in case of drowsiness. The mechanism has a hallmark of not interfering with the driving. Drowsiness detection was done by measuring the values of eye closure, classifying drivers into a sleepiness level if they were above a predefined threshold. The accuracy through offline testing in machine learning methods such as Support Vector Machine-based classification gives great sensitivity of 95.58% and specificity of 100%, which are quite enough to accurately detect and prevent drowsy driving incidents.

In [6] The goal of this study is to detect drowsy driving by analyzing Heart Rate Variability (HRV), which measures drowsiness, exhaustion, and stress levels using ECG signals. Twelve features are monitored in the time and frequency domains to detect HRV changes, which have typically been used to predict epileptic seizures. Machine Learning (ML) and Deep Learning approaches, notably 1D CNNs, are used to identify drowsiness, and they outperform 2D CNNs due to their applicability for one-dimensional signals such as biological data. The suggested approach consists of four layers: convolutional, batch normalization, max pooling, and fully connected layers. This technique, which uses bioelectric signals and advanced neural network designs, shows promise in preventing accidents caused by drowsy driving.

In [7] Driver drowsiness detection is critical for preventing accidents caused by weariness or drunk driving. Recognizing drowsiness is difficult because drivers frequently fail to recognize the transition from exhaustion to sleepiness. To overcome this, a system based on metrics such as eye blink frequency is proposed. If drowsiness is identified while continuously monitoring eye movements, a warning alarm is triggered. The implementation uses the OpenCV library and machine learning methods. This method promises to save lives by reducing accidents caused by driver drowsiness, addressing a major issue in road safety.

In [8] To address the rise in traffic accidents, a non-intrusive, real-time technology that combines sleepiness and alcohol detection has been developed. An MQ-3 sensor detects alcohol, while a Support Vector Machine and Histogram of Oriented Gradient identify tiredness based on facial features. Raspberry Pi 3 with Arduino UNO merge both technologies to provide a low-cost solution. The technology achieves an accuracy of 86%, indicating a viable strategy to reducing accidents

caused by weariness and alcohol intoxication, hence filling a gap in existing safety measures.

In [9] To combat drowsy driving accidents, a low-cost, real-time sleepiness detection device based on a camera is developed. Image processing techniques examine driving frames, calculating the eye aspect ratio (EAR) and mouth opening ratio (MOR) for each. Drowsiness is identified by comparing computed values to predefined criteria. This methodology, in comparison to existing methods, provides a convenient and cost-effective solution to the need for accessible sleepiness detection devices to improve road safety and avoid accidents.

In [10] An alert system to drowsy drivers has been offered that has remained one of the top problems of drowsy driving accidents, which is still OpenCV. Facial features are assessed by computer vision algorithms to detect tiredness and the driver is informed the same through visual and auditory signals. This system layout involves a camera, microcontroller, sensors, computer vision algorithms, an alarm system, and a customizable interface. The operation process is outlined in detail, including the image processing and feature extraction procedures used for the detection of drowsiness.

In [11] To address the growing worry about road accidents caused by driver drowsiness, a system based on computer vision and image processing technologies is presented. This technology continuously examines the driver's facial expressions, particularly eye and lip movements, for indicators of tiredness or emotional changes. When the system detects such changes, it sends timely alerts to the driver, assisting in accident prevention. This approach provides a cost-effective and resource-efficient solution by using facial landmark analysis to evaluate driver performance without the need for extra sensors or equipment, hence improving road safety measures.

In [12] This study addresses drowsy driving accidents by introducing a machine learning approach for detecting tiredness. It consists of three stages: face detection, eye detection, and drowsiness detection. Face detection uses image processing to find the driver's face, whereas eye tracking leverages templates from discovered eye regions in consecutive frames. Drowsiness is identified by evaluating monitored eye pictures for indicators of exhaustion, which are assessed using the Eye Aspect Ratio (EAR). The LSTM-KNN approach obtains an average eye localization and tracking accuracy of 81.5% on test footage. This approach provides a realistic and cost-effective alternative for real-time driver sleepiness monitoring, hence improving road safety measures.

In [13] The Driver Drowsiness Detection model addresses a key issue: drowsy driving accidents, which account for a considerable portion of global road fatalities. While purposeful errors like reckless driving can be avoided by adhering to traffic laws, incidental errors like driver fatigue necessitate technology assistance. There are several approaches for detecting drowsiness, the most common of which is based on facial features. This model focuses on detecting tiredness using face traits, namely eyes, and use algorithms to improve accuracy. This model uses technology to decrease accidents caused by drowsy driving, delivering an effective answer to a significant road safety issue.

In [14] This work covers a real-time visual-based driver sleepiness detection approach that filters eye aspect ratio (EAR) characteristic. To begin with face region localization and eye detection are applied to video frames from a sleepiness detection dataset. The EAR values are calculated, evaluated, and recorded for each frame. The three classifiers—linear support vector machine, random forest, and sequential neural network—are intended to increase the detection accuracy. Data is categorized to look for eye closure, which sounds an alarm to warn drowsy drivers if it lasts for a certain period of time. This gadget aims to minimize the number of crashes resulting from a tired driver and offers a preventive road safety approach.

In [15] This work addresses the essential issue of drowsy driving by introducing a lightweight, real-time detection system implemented as a web application. The technology uses video data from dashboard-installed cameras to identify face landmarks and calculate measures such as Eye Aspect Ratio (EAR) and Eye Closure Ratio (ECR). Unlike intrusive or expensive approaches, this strategy provides a non-intrusive and cost-effective alternative. Integration of machine learning technologies, notably the YOLOv5 classifier, improves detection accuracy to 91%. The system's efficiency demonstrates YOLOv5's ability to improve driver safety by efficiently identifying drowsiness and therefore reducing road accidents caused by driver weariness.

In [16] Road accidents are often caused by driver drowsiness these days. Drowsiness is when the driver is in a state between sleeping and being awake. In addition to identifying the causes of these accidents, this research offers a solution to this problem. Therefore, in order to prevent road accidents, it's crucial to create a system that can detect the signs of drowsiness well in advance. These signs could be physical or psychological. The main focus of our research is to determine how to develop and implement our dlib shape indicator on facial images and real-time video. Specifically, we're concentrating on the eye region; the system identifies this area and then calculates the eye aspect ratio. Subsequently, if the eyes remain

inactive for 36 consecutive frames, the system issues an alert. This alert helps the driver regain focus. To achieve our goal, we've created the application in OpenCV using the Python language. The results demonstrate a high level of accuracy in detecting driver drowsiness, reaching 92.57%.

In [17] The automotive industry is focused on enhancing driving safety and preventing accidents. Unfortunately, some people don't always follow traffic laws, leading to potential accidents. It's important to note that most accidents are not intentional, often caused by factors like fatigue. To address this, a Driver Safety Aid System has been developed to improve comfort and security for drivers, including the elderly. By incorporating a human-machine interface, this system aims to enhance overall traffic safety by reducing accidents caused by human error. Unlike traditional safety features like seat belts and airbags, this system can also alert drivers to potential issues like drowsiness and potential collisions, contributing to vehicle stability in critical situations.

In [18] According to the National Highway Traffic Safety Administration (NHTSA), drowsy driving leads to over 71,000 injuries, 1,500 deaths, and \$12.5 billion in monetary losses each year. One of the main problems that needs fixing is giving drivers a heads-up well before they get too drowsy. This paper suggests a bold fix for the issue: creating a system that can spot when the driver is getting drowsy and give a timely warning. The paper talks about a non-invasive method that looks at the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) to measure drowsiness by keeping an eye on and analyzing both the eyes and mouth, even in the dark. The real-time EAR is compared with the initial EAR of the driver, and the MAR is compared with a set threshold of 20. The system alerts the user by sending text and audio warnings. We also offer a clever alarm system that can be turned off by recognizing a hand gesture. We collect data from the user in real-time to test the system. This system accurately predicted 9 out of 10 cases, in both dark and light conditions, with different facial features, including glasses.

By blending this system with user prompts, the goal is to enhance the text to resonate more with readers while staying true to the original content's purpose and factual accuracy.

In [19] Driving while tired is a big problem that puts a lot of lives at risk, so it's important to take action right away. That's why scientists and engineers have been working hard to create reliable devices that can detect when a driver is getting sleepy. This paper takes a close look at the latest techniques and technology for spotting sleepiness, focusing on how artificial intelligence and sensor tech can be combined. The system uses cutting-edge computer vision, machine learning, and

sensor data fusion to keep track of the driver's condition in real-time. It assesses sleepiness levels by looking at a range of physical and behavioral signs, like facial expressions, eye movements, body signals, and how the vehicle is being driven. The paper also looks at the challenges of detecting sleepiness, including the need for diverse sets of data, real-world testing, and the risk of getting false results. By tackling these challenges, the proposed system aims to minimize mistakes and give drivers accurate and timely warnings, reducing the chances of accidents caused by fatigue. The main goal of this research is to make roads safer by offering a smart and comprehensive way to fight drowsy driving. The advances in sleepiness detection are set to make driving safer for everyone and save countless lives.

In [20] The advancements in technology are really making a huge difference in saving lives. Back in the day, it was tough to diagnose illnesses, but now, thanks to the latest developments in science and tech, we can pinpoint exactly what's wrong. We can even predict and prevent accidents before they happen using stuff like machine learning, deep learning, CNN, and more. In our study, we put together a model to spot potential accidents caused by drowsy driving. It's shocking to hear that around 1.5 lakh people lose their lives every year in India. So, we came up with a system to alert drivers who are feeling too drowsy. Previous studies only checked things like how often someone blinks and the ratio of their eye, but in our research, we took it a step further. We looked at the eye and mouth aspect ratios, as well as the driver's posture. This combo of the system and user prompts is all about making sure the technology can really help in a more natural and relatable way.

## **CHAPTER 3**

### **SYSTEM DESIGN**

#### **3.1 GENERAL**

System design involves the formulation and creation of systems that meet the specific needs of users. Fundamentally, the essence of studying system design lies in comprehending the individual elements and how they interact with each other.

#### **3.2 DEVELOPMENT ENVIRONMENT**

##### **3.2.1 HARDWARE SPECIFICATIONS**

This document offers a comprehensive overview of the hardware and its implementation, detailing the key components, their interactions, and the necessary requirements for seamless connectivity to utilities and installation.

**Table 3.2.1** Hardware Specifications

<b>PROCESSOR</b>	Intel Core i5
<b>RAM</b>	4GB or above (DDR4 RAM)
<b>GPU</b>	Intel Integrated Graphics
<b>HARD DISK</b>	6GB
<b>PROCESSOR FREQUENCY</b>	1.5 GHz or above

##### **3.2.2 SOFTWARE SPECIFICATIONS**

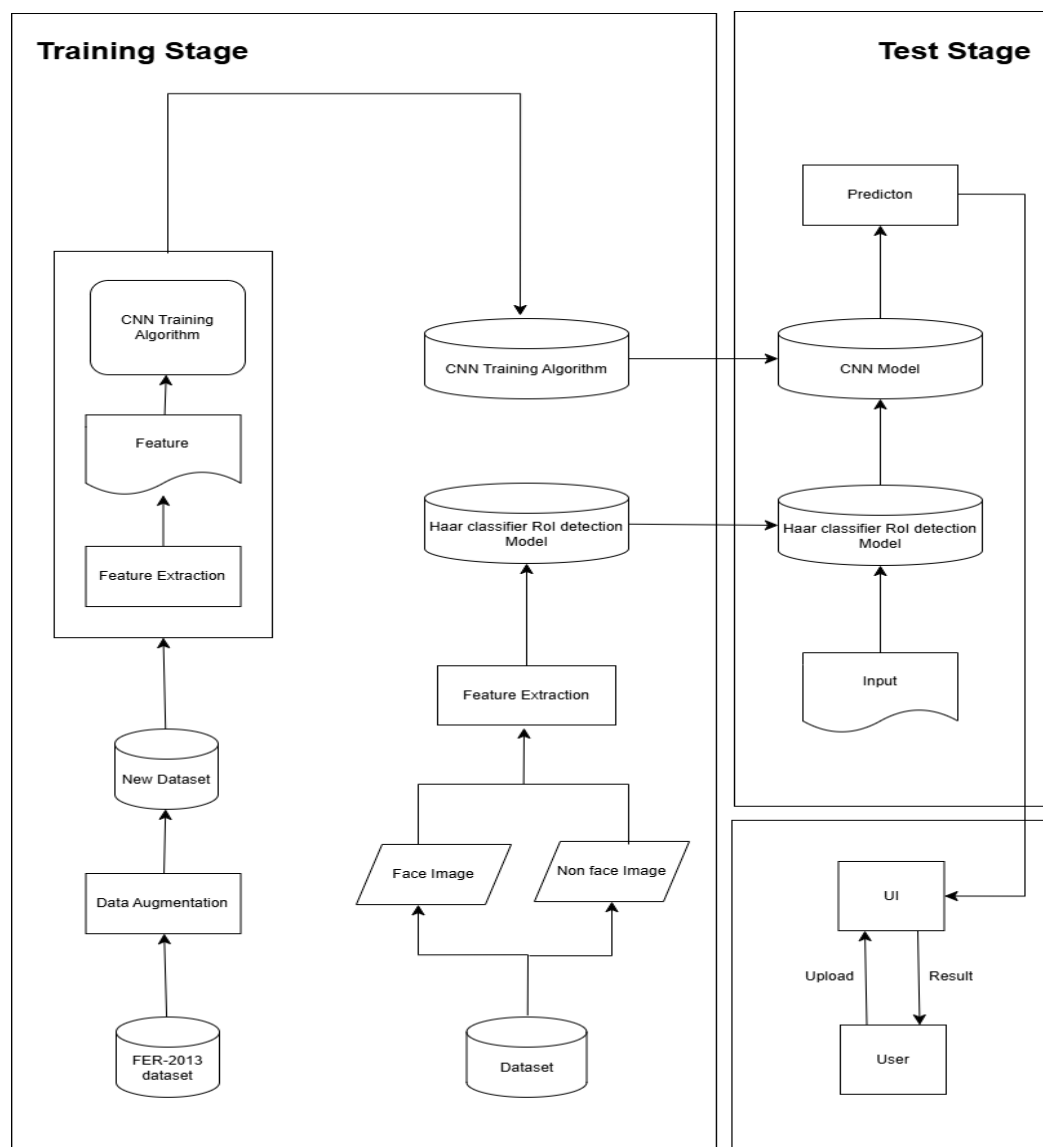
The below table constitutes a thorough evaluation of requirements that precedes the more detailed phases of system design, aiming to minimize the need for subsequent revisions. Furthermore, it should offer a practical foundation for estimating product expenses, potential risks, and project timelines.

**Table 3.2.2** Software Specifications

<b>FRONT END</b>	Python
<b>BACK END</b>	Python
<b>CODE EDITOR</b>	Visual Studio Code, Jupyter Notebook
<b>FRAMEWORKS</b>	TensorFlow

### 3.3 SYSTEM DESIGN

#### 3.3.1 FACE DETECTION USING HAAR CASCADE CLASSIFIER

**Fig 3.3.1** Face detection using haar cascade classifier



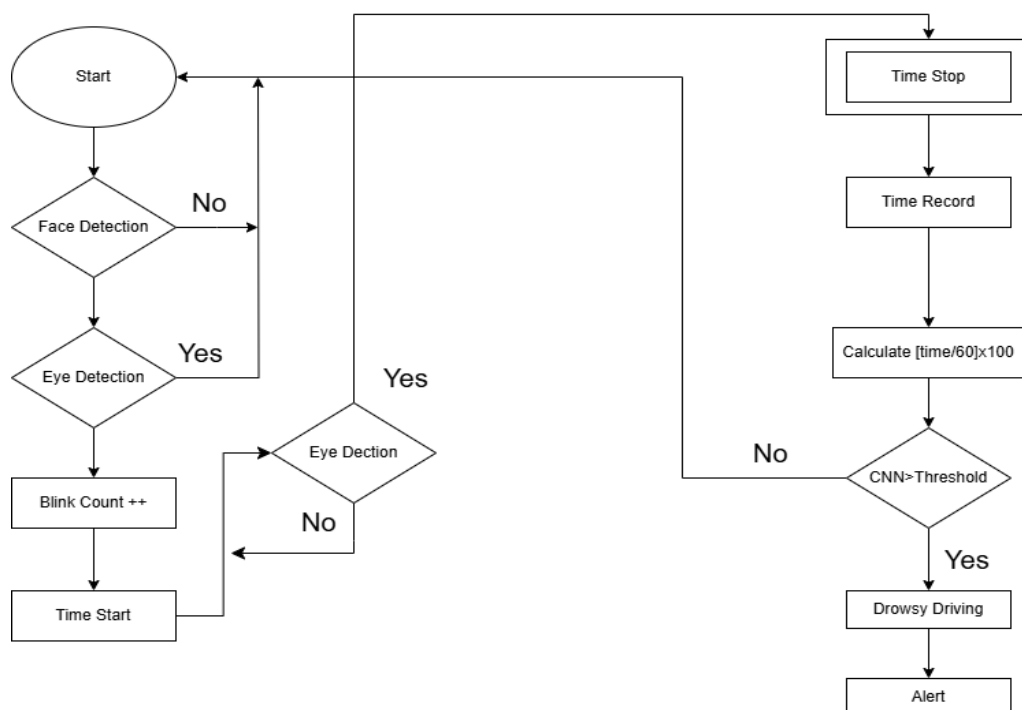
Face detection using Haar cascade classifier involves several steps. Firstly, the classifier is trained on a large dataset of positive and negative images. Positive images contain the object to be detected (in this case, faces), while negative images contain other objects or backgrounds.

Once trained, the classifier works by sliding a window over the input image at different scales and positions. At each window position, the classifier calculates a feature vector using Haar-like features, which are simple rectangular filters. These features are computed by subtracting the sum of pixel intensities in certain areas of the window from the sum of pixel intensities in other areas.

Next, the classifier evaluates the feature vector using a set of pre-defined weak classifiers, which are simple decision trees. These weak classifiers determine whether the current window contains a face or not based on the features' values.

During the detection phase, the classifier moves the sliding window across the input image, resizing it at each step, and applies the weak classifiers to classify each window. If a window is classified as containing a face based on the threshold set during training, it is considered a positive detection. Finally, post-processing techniques may be applied to refine the detections and remove false positives.

### 3.3.2 DROWSINESS DETECTION USING CNN



**Fig 3.3.2 Face detection using Haar cascade classifier**

Detecting drowsiness and alerting using Convolutional Neural Networks (CNNs) involves several steps. Initially, a dataset containing images or video frames of individuals exhibiting various states of drowsiness is collected. These images serve

as input data for training the CNN. The CNN is then trained to extract relevant features from the images that are indicative of drowsiness, such as eye closure, head position, or facial expressions. This training process involves passing the images through multiple convolutional layers, which apply filters to detect patterns and features at different spatial scales. Once trained, the CNN is deployed to analyze real-time video streams or images. Frames from the video feed are passed through the CNN, and the extracted features are analyzed to determine the likelihood of drowsiness. For instance, if the CNN detects closed eyes or a drooping head, it may infer that the individual is drowsy. Finally, if the CNN detects signs of drowsiness above a certain threshold, an alerting mechanism is triggered. This could involve sounding an alarm, sending a notification to the individual, or activating safety systems in vehicles. Overall, CNNs enable automated drowsiness detection by learning to recognize relevant features from visual input, thereby enhancing safety in various contexts such as driving or operating machinery.

## **CHAPTER 4**

### **PROJECT DESCRIPTION**

#### **4.1 MODULE DESCRIPTION**

##### **OpenCV**

OpenCV, or Open Source Computer Vision Library, is a powerful open-source library that provides tools for various computer vision tasks. Developed in C++, OpenCV offers extensive support for Python and other programming languages. It includes a wide range of functionalities such as image processing, feature detection, object recognition, machine learning, and more. OpenCV facilitates the development of applications in fields like robotics, augmented reality, medical imaging, and surveillance. Its comprehensive documentation, active community, and cross-platform compatibility make it a popular choice for both academic research and industrial projects, empowering developers to create advanced computer vision solutions efficiently.

##### **Haar Cascade Classifier**

The Haar cascade classifier module is a feature-based object detection algorithm used primarily for face detection. It works by sliding a window over an image at various scales and positions, computing Haar-like features within each window, and classifying them using pre-trained weak classifiers. These weak classifiers are combined into a strong classifier, enabling efficient detection of objects like faces. The module's effectiveness lies in its ability to rapidly scan images and identify regions containing the target object. It's widely utilized in computer vision applications due to its speed and accuracy in detecting objects within images.

##### **Keras**

Keras is a high-level neural networks API written in Python, designed for fast experimentation with deep learning models. It provides a user-friendly interface for building, training, and deploying deep learning models, hiding the complexity of neural network implementation details. With Keras, developers can easily construct neural networks using intuitive building blocks like layers and models, allowing for rapid prototyping and iteration. Keras also supports both CPU and GPU acceleration, making it suitable for a wide range of machine learning tasks.

##### **Convolutional Neural Networks**

Convolutional Neural Networks (CNNs) are a class of deep neural networks designed to process structured grids of data, such as images. They consist of multiple layers of interconnected neurons, including convolutional layers, pooling layers, and fully connected layers. CNNs leverage convolutions, which apply filters to input data to extract meaningful features. These features are then

progressively combined and abstracted through pooling layers to form hierarchical representations. CNNs excel at tasks like image classification, object detection, and image segmentation, due to their ability to automatically learn spatial hierarchies of features from raw input data, making them a cornerstone technology in computer vision and beyond.

## CHAPTER 5

### IMPLEMENTATION AND RESULTS

#### 5.1 IMPLEMENTATION

The implementation of drowsiness detection and alerting using OpenCV, Haar cascade classifier, and Convolutional Neural Networks (CNNs) typically involves a combination of techniques to achieve accurate and robust detection.

**5.1.1 Face Detection with Haar Cascade Classifier:** Initially, the system uses the Haar cascade classifier to detect faces within a video stream or images. This involves sliding a window over the input frames and applying a pre-trained Haar cascade classifier specifically designed for face detection. Detected faces are then extracted for further analysis.

**5.1.2 Eye Detection:** Once faces are detected, regions of interest (ROIs) corresponding to the eyes are identified within the face bounding boxes. This step is crucial for monitoring eye behavior, a key indicator of drowsiness.

**5.1.3 Feature Extraction with CNNs:** CNNs are employed to extract features from the eye regions, such as eyelid closure, eye movement, or gaze direction. A CNN model is trained on a dataset containing images of eyes in various states of alertness and drowsiness. During inference, the trained CNN analyzes the eye images and extracts relevant features indicative of drowsiness.

**5.1.4 Drowsiness Classification:** The extracted features are then fed into a drowsiness classification model, which could be a simple rule-based system or a more sophisticated machine learning classifier. This model analyzes the features and determines whether the individual is drowsy or alert based on predefined criteria or learned patterns.

**5.1.5 Alerting Mechanism:** If the classification model detects signs of drowsiness above a certain threshold, an alerting mechanism is triggered to notify the individual. This could involve sounding an alarm, displaying a warning message, or activating safety systems such as vibrating seats or steering wheel feedback in vehicles.

By combining the capabilities of OpenCV for face detection, Haar cascade classifier for eye localization, and CNNs for feature extraction and classification, this implementation offers an effective solution for drowsiness detection and alerting in various applications, including driver monitoring systems, surveillance, and workplace safety.

## 5.2 OUTPUT SCREENSHOTS

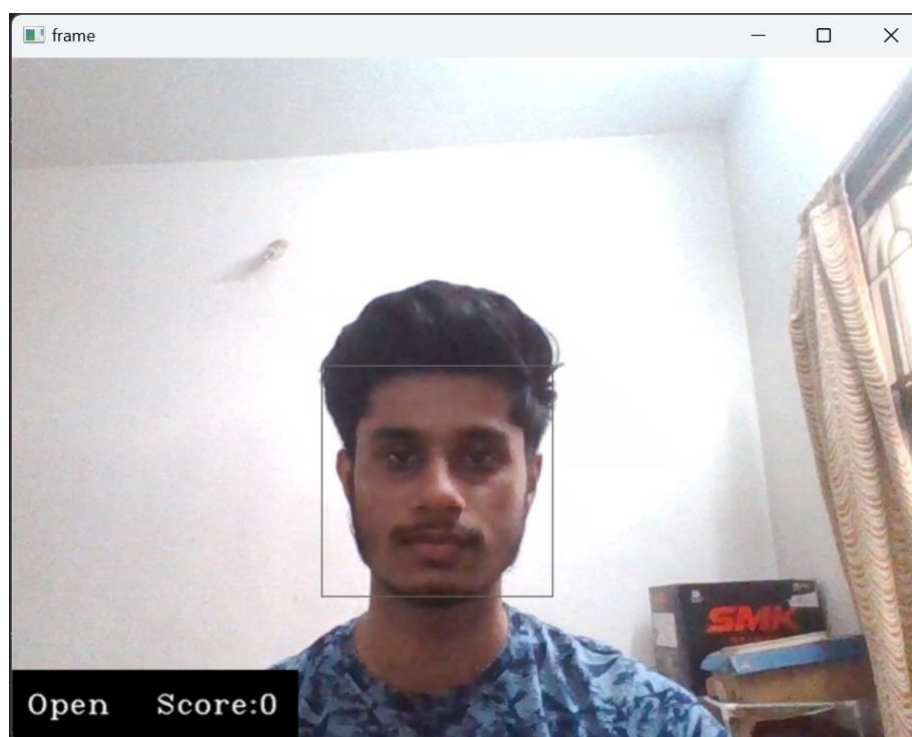
**Table 5.2.2 Precision Table After Applying System On Dataset**

State	Precision	Recall	F1-Score
Closed	0.95	0.95	0.95
Open	0.93	0.93	0.93

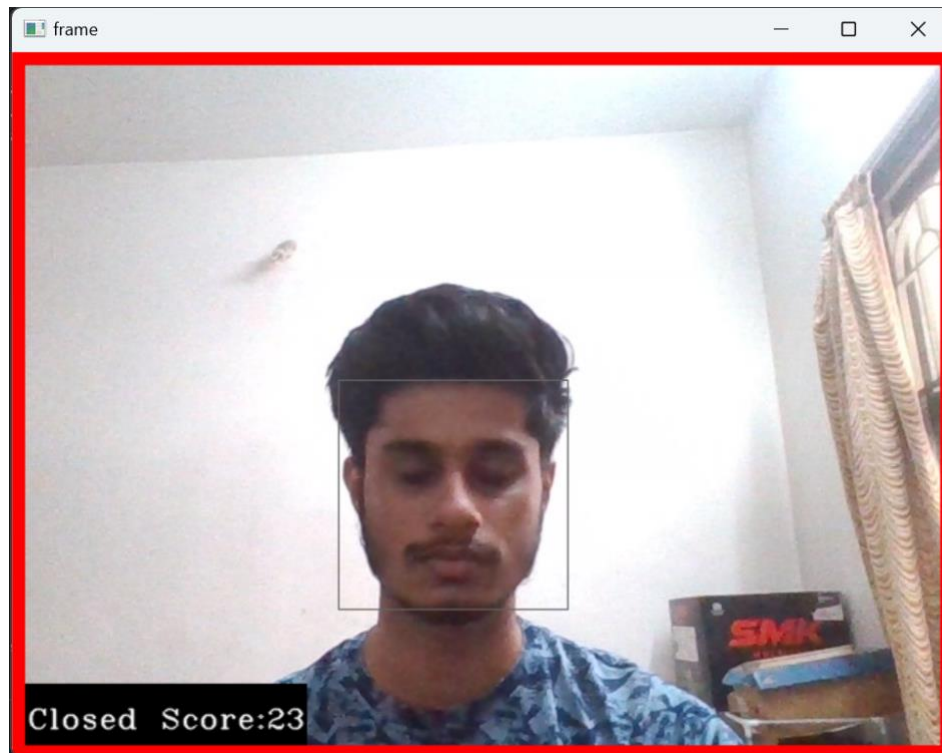
**Table 5.2.2 Classification Accuracy Table**

Method of Evaluation	Accuracy
Training Accuracy	98.1
Test Accuracy	94

**Fig 5.2.1 Result when eyes are opened**



**Fig 5.2.2 Result when eyes are closed**



## **CHAPTER 6**

### **CONCLUSION AND FUTURE ENHANCEMENTS**

#### **6.1 CONCLUSION**

In conclusion, the Drowsy Driver Alert System project successfully harnesses the power of OpenCV, Haar cascade classifiers, and Convolutional Neural Networks (CNNs) to enhance road safety by detecting driver drowsiness in real-time. By utilizing OpenCV for image processing and Haar cascade classifiers for facial feature recognition, the system effectively identifies key facial landmarks associated with drowsiness, such as eye closure and yawning. The integration of CNNs further refines the detection accuracy by analyzing subtle facial expressions and movements that indicate fatigue. This multi-faceted approach ensures a robust and reliable alert system, capable of significantly reducing the risk of accidents caused by driver drowsiness. The project's outcomes demonstrate the feasibility and effectiveness of combining traditional computer vision techniques with advanced deep learning models, paving the way for future advancements in intelligent vehicle safety systems. Through continuous improvement and real-world testing, this system has the potential to become an indispensable tool for promoting safer driving practices.

#### **6.2 FUTURE ENHANCEMENTS**

Future enhancements for the Drowsy Driver Alert System project could include integrating additional sensors such as infrared cameras to improve detection accuracy in low-light or nighttime conditions. Expanding the dataset with more diverse facial expressions and varying lighting conditions would further train the Convolutional Neural Networks (CNNs) for better performance. Incorporating head pose estimation and gaze tracking could provide a more comprehensive analysis of driver attentiveness. Implementing real-time adaptive learning could allow the system to personalize detection based on individual driver behaviors. Additionally, integrating the system with vehicle control mechanisms, such as adaptive cruise control or lane-keeping assist, could enable proactive safety



measures. Enhancing the system's user interface with voice alerts and vibration signals would ensure that drivers receive timely and clear warnings. Finally, conducting extensive field tests and collaborations with automotive manufacturers would facilitate the development of a robust, market-ready product, contributing to broader road safety initiatives.

## REFERENCES

- [1] Drowsy Driving Warning System Based on GS1 Standards. (2017, June 1). IEEE Conference Publication | IEEE Xplore. <https://ieeexplore.ieee.org/document/8029337>
- [2] Prediction of driver's drowsiness and alert states from EEG signals. (2015, December 1). IEEE Conference Publication | IEEE Xplore. <https://ieeexplore.ieee.org/document/7383844>
- [3] Early Detection of Drowsiness in drivers, Utilizing ML based on Physiological Signals, Behavioral Measures, and Driving Performance. (2018, November 1). IEEE Conference Publication | IEEE Xplore. <https://ieeexplore.ieee.org/document/8569493>
- [4] Driver's Drowsiness Detection System Using Machine Learning. (2023, November 23). IEEE Conference Publication | IEEE Xplore. <https://ieeexplore.ieee.org/document/10465952>
- [5] Drowsy Driver Monitoring Using Machine Learning and Visible Actions. (2022, March 16). IEEE Conference Publication | IEEE Xplore. <https://ieeexplore.ieee.org/document/9751890>
- [6] Machine Learning Algorithms For Heart Rate Variability Based Drowsiness Detection. (2021, October 1). IEEE Conference Publication | IEEE Xplore. <https://ieeexplore.ieee.org/document/9587733>
- [7] Application of Machine Learning in Driver Drowsiness Detection. (2023, April 21). IEEE Conference Publication | IEEE Xplore. <https://ieeexplore.ieee.org/document/10169668>
- [8] An Integrated Framework for Driver Drowsiness Detection and Alcohol Intoxication using Machine Learning. (2021, October 25). IEEE Conference Publication | IEEE Xplore. <https://ieeexplore.ieee.org/document/9655979>
- [9] Driver Drowsiness Monitoring System Using Visual Behavior and Machine Learning. (2022, November 26). IEEE Conference Publication | IEEE Xplore. <https://ieeexplore.ieee.org/document/10029275>

- [10] Drowsy Driver Alert System Using OpenCV. (2023, June 1). IEEE Conference Publication | IEEE Xplore. <https://ieeexplore.ieee.org/document/10266278>
- [11] Automated Driver Drowsiness Detection System using Computer Vision and Machine Learning. (2023, March 23). IEEE Conference Publication | IEEE Xplore. <https://ieeexplore.ieee.org/document/10104942>
- [12] Driver Drowsiness Monitoring and Detection using Machine Learning. (2023, January 5). IEEE Conference Publication | IEEE Xplore. <https://ieeexplore.ieee.org/document/10053497>
- [13] Driver Drowsiness Detection using Machine Learning Algorithms. (2022, February 12). IEEE Conference Publication | IEEE Xplore. <https://ieeexplore.ieee.org/document/9760618>
- [14] Realtime Driver Drowsiness Detection Using Machine Learning. (2022, February 21). IEEE Conference Publication | IEEE Xplore. <https://ieeexplore.ieee.org/document/9734801>
- [15] Machine Vision for Driver Safety: YOLOv5-powered Real-time Drowsiness Detection. (2023, December 21). IEEE Conference Publication | IEEE Xplore. <https://ieeexplore.ieee.org/document/10452555>
- [16] Automatic Driver Alertness Detection using Machine Learning. (2021, October 26). IEEE Conference Publication | IEEE Xplore. <https://ieeexplore.ieee.org/document/9651420>
- [17] An Assistance System for Driver's Safety based on YOLO Algorithm. (2023, May 26). IEEE Conference Publication | IEEE Xplore. <https://ieeexplore.ieee.org/document/10170480>
- [18 ] Real-time Drowsiness Detection using Adaptable Eye Aspect Ratio and Smart Alarm System. (2021, March 19). IEEE Conference Publication | IEEE Xplore. <https://ieeexplore.ieee.org/document/9441756>
- [19 ] Machine Learning Approach for Real-Time Drowsiness Detection: Aware Drive. (2023, December 14). IEEE Conference Publication | IEEE Xplore. <https://ieeexplore.ieee.org/document/10448831>
- [20] System for Detecting Drowsiness in Drivers. (2023, December 13). IEEE Conference Publication | IEEE Xplore.

## ORIGINALITY REPORT

13%

SIMILARITY INDEX

8%

INTERNET SOURCES

7%

PUBLICATIONS

6%

STUDENT PAPERS

## PRIMARY SOURCES

1	Submitted to University of Hertfordshire Student Paper	2%
2	Sandeep Bhatia, Bharat Bhushan Naib, Amit Kumar Goel, Lalit Kumar, Kritesh Singh. "Drowsy Driver Alert System Using OpenCV", 2023 3rd International Conference on Pervasive Computing and Social Networking (ICPCSN), 2023 Publication	1%
3	www.ijraset.com Internet Source	1%
4	ijsret.com Internet Source	1%
5	ieeexplore.ieee.org Internet Source	1%