

**Driver Drowsiness Detector**  
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**MALLA REDDY UNIVERSITY**  
(Telangana State Private Universities Act No.13 of 2020 and G.O.Ms.No.14, Higher Education (UE) Department)

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# MALLA REDDY UNIVERSITY

(Telangana State Private Universities Act No.13 of 2020 and G.O.Ms.No.14, Higher Education (UE) Department)

This is to certify that this is the Bonafide record of the Application Development entitled, “Driver Drowsiness Detector” Submitted by G. Suhitha(2311CS020223), Gaurav Kafle(2311CS020224), G. Pranay Kumar (2311CS020225), G. Manikanta(2311CS020229), G. Vivek(2311CS020231) B. Tech II year I semester, Department of CSE (AI&ML) during the year 2023-24. The results embodied in the report have not been submitted to any other university or institute for the award of any degree or diploma .

**PROJECT GUIDE**

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## **ABSTRACT**

Driver sleepiness is a critical factor contributing to road accidents worldwide. To address this issue, we propose a driver sleepiness detection system leveraging advanced methodologies in computer vision and temporal analysis. The system employs Haar Cascade classifiers for efficient real-time detection of facial features and eyes, optimizing performance for prompt alert generation. Additionally, temporal analysis of eye closure durations differentiates between normal blinking and prolonged closures indicative of drowsiness. By integrating these methodologies, the system enhances its ability to detect early signs of driver fatigue, providing timely alerts to mitigate potential accidents. Real-time monitoring and user interface feedback ensure proactive intervention, promoting road safety and reducing risks associated with driver drowsiness.

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# CHAPTER 1

## INTRODUCTION

### **1.1 Project Identification**

Drowsy driving is a critical issue in road safety, accounting for a significant number of traffic accidents annually. Research indicates that driving while drowsy is as dangerous as driving under the influence of alcohol, as it impairs the driver's reaction time, attention, and decision-making abilities. The primary challenge is to develop a non-intrusive, real-time monitoring system that can effectively detect signs of drowsiness and alert the driver before an accident occurs. This project aims to address this challenge by leveraging computer vision technology to monitor the driver's facial features and detect signs of sleepiness.

### **Problem definition**

Driving while drowsy is a significant safety concern, leading to a substantial number of traffic accidents each year. Drowsy driving impairs a driver's reaction time, attention, and decision-making capabilities, posing serious risks to both the driver and others on the road. Traditional methods of detecting driver drowsiness, such as self-reporting or manual monitoring, are not always reliable or feasible. Therefore, there is a need for an automated, non-intrusive system that can continuously monitor the driver and detect signs of drowsiness in real-time.

The specific problem addressed by this project includes:

- **Detection Accuracy:** Developing a reliable method to accurately detect drowsiness based on facial features, particularly eye closure.
- **Real-Time Processing:** Ensuring the system operates with minimal latency to provide timely alerts.
- **User-Friendly Alerts:** Implementing an effective alert mechanism that can wake the driver before an accident occurs.
- **Adaptability:** Creating a system that works under various conditions, including different lighting and angles.
- **Scalability:** Designing a system that can be easily scaled and adapted for use in different vehicles and environments.
- **Cost-Effectiveness:** Providing a cost-effective solution that can be widely adopted without requiring expensive hardware or extensive modifications to existing vehicle systems.

By addressing these challenges, the project aims to provide a practical solution to reduce the risk of accidents caused by drowsy driving, thereby enhancing overall road safety.

## **1.2 Objective of Project**

The primary objectives of this project are:

- **Detection:** Implement a system that can detect the presence of a driver and monitor their facial features, particularly focusing on the eyes, to identify signs of drowsiness.
- **Alert System:** Develop a warning mechanism that alerts the driver through visual and auditory signals when signs of drowsiness are detected.
- **User-Friendly Interface:** Create a user-friendly graphical user interface (GUI) that displays real-time video feed and status updates.
- **Real-Time Performance:** Ensure the system operates in real-time with minimal latency to provide timely alerts and avoid potential accidents

## **1.3 Scope of project**

The scope of this project includes:

- **Real-Time Monitoring:** Implementing continuous monitoring of the driver's face and eyes using a webcam.
- **Detection Algorithms:** Utilizing pre-trained Haar Cascade classifiers for accurate detection of facial features.
- **Alert Mechanism:** Providing immediate audio-visual alerts to the driver upon detection of drowsiness.
- **GUI Development:** Designing a simple and intuitive GUI for ease of use.
- **System Testing:** Conducting extensive testing to validate the accuracy and reliability of the system under various conditions.
- **Future Enhancements:** Exploring the potential for future enhancements, such as integrating with vehicle systems and using more advanced detection algorithms.

# **CHAPTER 2**

## **ANALYSIS**

### **2.1 Project Planning and Research**

Effective project planning involves:

- Conducting an in-depth literature review to understand existing methodologies and technologies used in driver drowsiness detection systems.
- Defining clear project goals, milestones, and timelines to ensure efficient execution and delivery.
- Researching hardware and software requirements, considering factors like computational efficiency, compatibility, and scalability.
- Identifying potential risks and challenges and developing mitigation strategies to address them proactively

### **2.2 Software requirement specification**

#### **2.2.1 Software requirement**

**Programming Language:** Python 3.x is chosen for its extensive libraries and community support, facilitating rapid development and integration.

#### **Libraries:**

- **OpenCV:** Utilized for real-time image processing tasks, including face and eye detection using Haar Cascade classifiers.
- **Tkinter:** Selected for developing the graphical user interface (GUI) to display real-time video feed and status updates to the user.
- **PIL (Pillow):** Used for image manipulation tasks within the GUI, enhancing visual presentation and user interaction.
- **Platform Module:** Employed to handle platform-specific functionalities such as sound alerts (e.g., winsound on Windows).
- **Time Module:** Facilitates time-based monitoring of eye closure duration, crucial for detecting driver drowsiness in real-time.

## 2.2.2 Hardware requirement

**Camera:** A webcam with at least 640x480 resolution, capable of capturing clear video frames under varying lighting conditions.

**Processor:** Dual-core processor or higher to ensure efficient real-time video processing without performance degradation.

**Memory:** Minimum 4 GB RAM to support concurrent processing tasks and ensure smooth operation of the system.

**Storage:** At least 500 MB of available storage space for storing software components, libraries, and temporary data files required during operation.

## 2.3 Model Selection and Architecture

The system architecture is designed to efficiently capture, process, and analyze video frames in real-time:

- **Capture:** The webcam continuously captures video frames of the driver.
- **Pre-Processing:** Frames are converted to grayscale to reduce computational load and improve detection accuracy.
- **Detection:** Haar Cascade classifiers detect the presence of faces and eyes within each frame.
- **Analysis:** The system monitors the duration of eye closure to determine if the driver is drowsy.
- **Alert:** If prolonged eye closure is detected, an alert is triggered to wake the driver.
- **GUI Update:** The GUI displays the real-time video feed and updates the status based on detection results

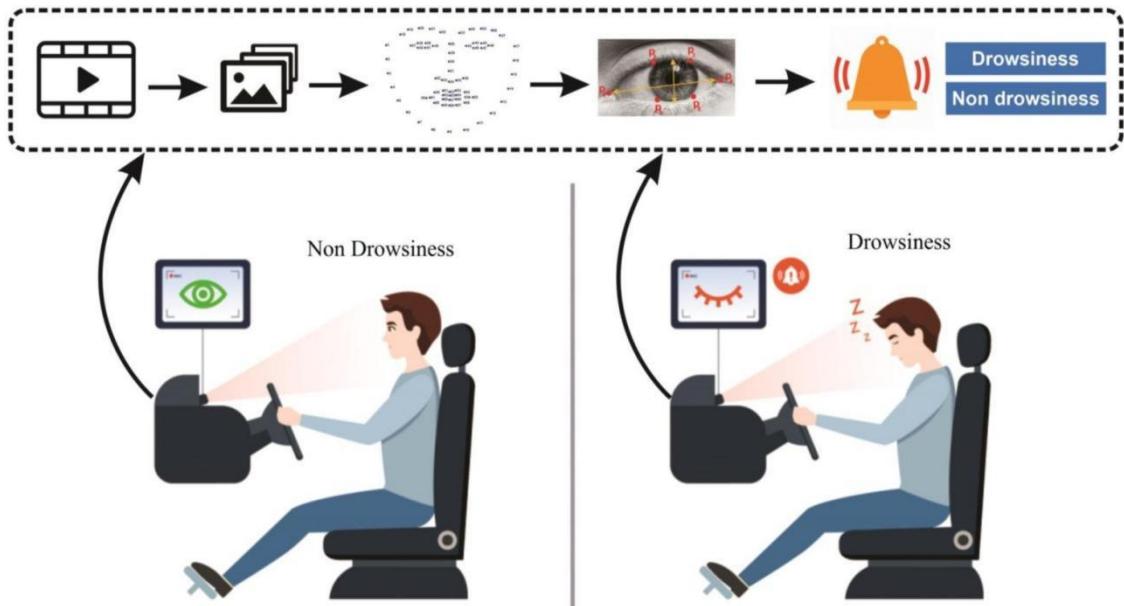


Fig 2.3.1

# CHAPTER 3

## DESIGN

### 3.1 Introduction

Data Flow Diagrams (DFDs) and Unified Modelling Language (UML) diagrams are useful tools in software engineering and system design to visualize and specify various aspects of a system. Let's elaborate on how these diagrams can be utilized to illustrate and specify the components and data processing steps in a driver sleepiness detection system:

#### **Data Flow Diagrams (DFDs):**

Data Flow Diagrams (DFDs) are graphical representations that depict the flow of data within a system. They are hierarchical and can provide different levels of abstraction, from an overview of the entire system to detailed representations of specific processes. In the context of a driver sleepiness detection system, DFDs can be used as follows:

#### **1. Visualize System Components:**

- **Context Level DFD:** At the highest level, a context-level DFD illustrates the system as a single process, interacting with external entities such as the video capture device, user interface, and external alerts (e.g., sound notifications).
- **Level 1 DFD:** Breaking down the context-level process, a Level 1 DFD identifies major subprocesses or modules involved in the system, such as video input acquisition, image preprocessing, feature extraction (using Haar Cascade classifiers), decision-making based on detected drowsiness indicators, and user interface feedback.

#### **2. Specify Data Processing Steps:**

- Each process identified in the DFD can be further elaborated with data stores (where data is temporarily stored), data flows (how data moves between processes and external entities), and data transformations (operations performed on data).
- **Image Preprocessing:** This process involves converting the color frame from the video feed to grayscale (`cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)`), which is essential for subsequent feature extraction.
- **Feature Extraction using Haar Cascade Classifiers:** This step includes detecting faces (`cv2.CascadeClassifier.detectMultiScale`) and then detecting eyes within the detected face regions. This process outputs the coordinates of detected eyes, which are used to determine if the driver's eyes are closed or open.
- **Decision-making Logic:** Based on the presence or absence of detected eyes and their duration of closure, the system decides whether to alert the user about potential drowsiness (`status_label.config`) and trigger additional actions like sound notifications (`winsound.Beep` for Windows).

## **Unified Modelling Language (UML) Diagrams:**

UML diagrams provide a standardized way to visualize system components, behaviors, and interactions. For a driver sleepiness detection system, relevant UML diagrams include:

### **1. Use Case Diagram:**

- Use case diagrams outline system functionality from a user's perspective. Key actors such as the driver interact with the system to perform actions like initiating the drowsiness detection process and receiving alerts.

### **2. Sequence Diagram:**

- Sequence diagrams illustrate the sequence of interactions between system components over time. For example, a sequence diagram can depict the flow of operations from video frame acquisition, preprocessing, feature extraction, decision-making, to alert generation and user interface feedback.

### **3. Class Diagram:**

- Class diagrams specify the static structure of the system, showing classes (e.g., DriverSleepinessDetection, VideoCapture, ImageProcessor) and their relationships. Attributes and methods within each class are detailed, helping to understand how data and functionality are organized.

## **Benefits of Using DFDs and UML Diagrams:**

- **Clarity and Understanding:** Both DFDs and UML diagrams provide clear visual representations that aid in understanding system components, interactions, and data flows.
- **Communication:** They facilitate effective communication between stakeholders, including developers, designers, and end-users, by providing a common language and visualization toolset.
- **Design and Analysis:** Diagrams support design decisions and system analysis, enabling identification of potential bottlenecks, optimization opportunities, and validation of system requirements.

In summary, utilizing Data Flow Diagrams (DFDs) and Unified Modeling Language (UML) diagrams is essential in the design and specification of a driver sleepiness detection system. These diagrams provide structured visualizations that help in understanding system components, specifying data processing steps, and facilitating effective communication and design decisions throughout the development process.

## DFD/ER/UML diagram(any other project diagram)

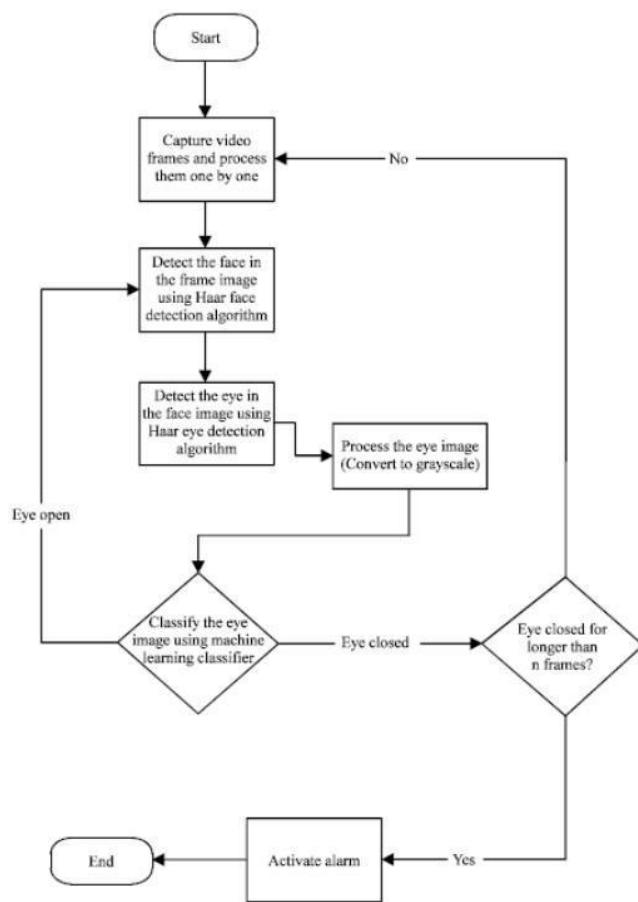


Fig 3.1.1

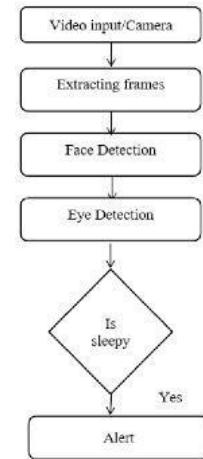


Fig 3.1.2

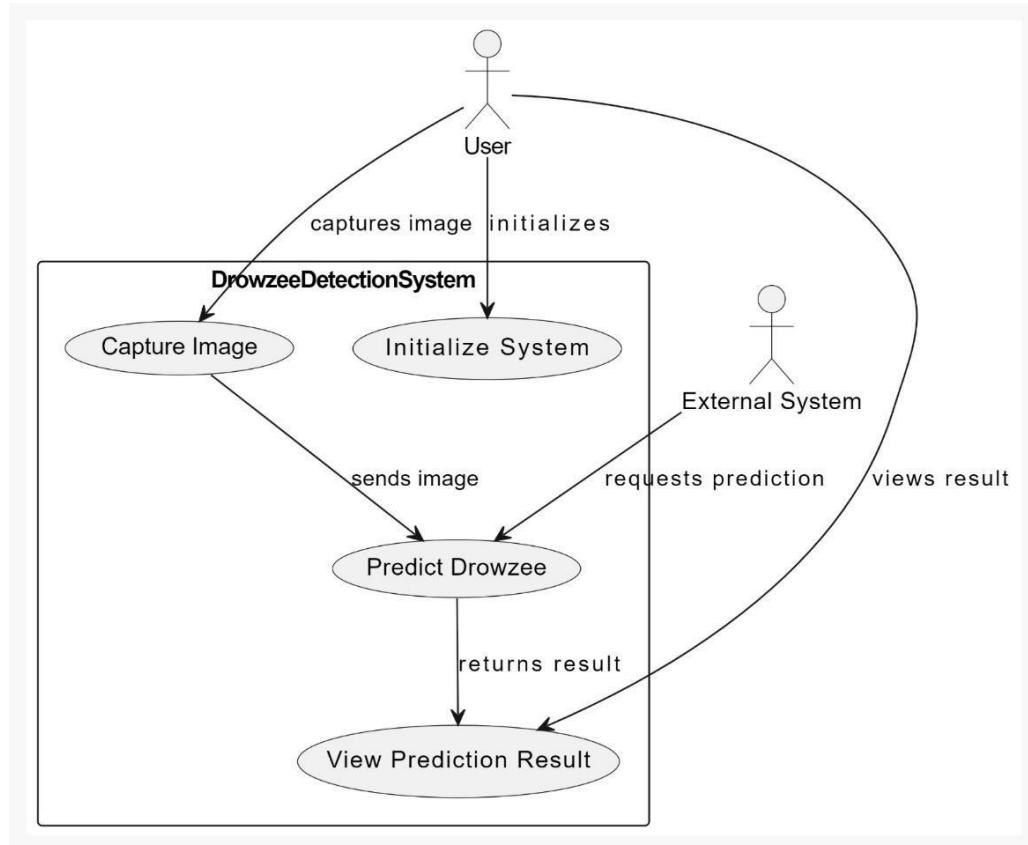


Fig 3.1.3

### 3.2 Data set descriptions

Utilizing pre-trained Haar Cascade classifiers involves leveraging datasets that have been used to train these classifiers for specific tasks such as facial and eye detection. Here's an elaboration on how dataset utilization and understanding training data characteristics are crucial in ensuring robust performance of Haar Cascade classifiers in a driver sleepiness detection system:

#### 1. Selection of Training Datasets

Haar Cascade classifiers are trained using datasets that contain positive examples (images with faces or eyes) and negative examples (images without faces or eyes). The quality and diversity of these datasets significantly impact the classifier's ability to generalize across different scenarios.

#### 2. Ensuring Robust Performance:

By leveraging extensive datasets that cover diverse lighting conditions, angles, facial expressions, and environmental contexts (e.g., varying backgrounds), the Haar Cascade classifiers can better handle real-world variations encountered in a driver sleepiness detection system.

### **3. Transfer Learning Considerations:**

In some cases, pre-trained Haar Cascade classifiers can be fine-tuned or adapted with additional training data specific to the application domain (e.g., driver monitoring). This transfer learning approach helps to enhance classifier performance and adapt it to specific environmental conditions encountered during driving.

### **4. Quality and Quantity Balance:**

The effectiveness of Haar Cascade classifiers depends on the balance between the quality and quantity of training data. While large datasets provide more diverse examples for training, ensuring the quality of annotations (e.g., accurate labelling of eyes and faces) is crucial for classifier accuracy.

#### **Training Data Characteristics:**

##### **1. Understanding Dataset Composition:**

Characteristics such as image resolution, noise levels, and variations in appearance (e.g., different skin tones, facial hair) within the training dataset influence how well the Haar Cascade classifiers generalize to new, unseen data.

##### **2. Limitations and Biases:**

Training data may inherently contain biases or limitations that affect classifier performance. For instance, if the dataset predominantly consists of images with specific demographic characteristics or underrepresented lighting conditions, the classifier may exhibit reduced accuracy in scenarios not well-represented in the training data.

### **3. Optimizing Algorithm Performance:**

Awareness of dataset characteristics allows developers to optimize the Haar Cascade classifiers by:

**Data Augmentation:** Introducing synthetic variations (e.g., brightness adjustments, rotations) to expand the diversity of training data without collecting additional samples.

**Bias Mitigation:** Balancing the dataset representation to reduce biases and ensure fair and accurate detection across different demographic groups and environmental conditions.

#### **4. Validation and Testing:**

Rigorous validation and testing procedures are essential to assess how well the Haar Cascade classifiers perform under various conditions beyond those in the training dataset. This process helps identify potential limitations and refine the classifier's parameters for improved real-world performance.

#### **Benefits of Dataset Utilization and Training Data Understanding:**

**Enhanced Robustness:** Leveraging diverse datasets ensures Haar Cascade classifiers can detect faces and eyes accurately across a wide range of real-world conditions encountered in driver sleepiness detection systems.

**Improved Generalization:** Understanding training data characteristics allows developers to fine-tune classifiers and address biases, leading to improved generalization and reliability in detecting drowsiness indicators regardless of environmental variations.

**Efficiency and Effectiveness:** By optimizing algorithm performance through careful dataset selection and characterization, developers can achieve efficient detection capabilities that meet the performance requirements of real-time driver monitoring applications.

In conclusion, the utilization of pre-trained Haar Cascade classifiers in a driver sleepiness detection system hinges on leveraging datasets that ensure robust performance and understanding the training data characteristics to mitigate biases and optimize algorithm accuracy. These considerations are fundamental in developing a reliable and effective system for enhancing road safety through proactive drowsiness detection.

### **3.3 Data Pre Processing**

In the context of a driver sleepiness detection system using pre-trained Haar Cascade classifiers, incorporating data pre-processing strategies such as image normalization and region of interest (ROI) extraction plays a crucial role in enhancing detection accuracy and efficiency. Here's an elaboration on how these strategies are implemented:

#### **1. Image Normalization:**

##### **Purpose:**

- **Enhance Consistency:** Normalize pixel intensity values to mitigate the effects of varying lighting conditions and camera settings. This standardization improves the robustness of the classifier's performance across different environments.

### **Implementation Steps:**

- **Grayscale Conversion:** Convert colour images from the video feed to grayscale using `cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)`. This simplifies subsequent processing and reduces computational load.
- **Normalization:** Standardize pixel intensities using techniques like:
  - **Histogram Equalization:** Enhance image contrast by adjusting intensity levels across the entire image.
  - **Mean and Standard Deviation Adjustment:** Scale pixel values to have zero mean and unit variance, ensuring consistent distribution of pixel intensities.

## **2. Region of Interest (ROI) Extraction:**

### **Purpose:**

- **Focus Computational Resources:** Identify and isolate specific regions within the frame (e.g., facial regions containing eyes) for detailed analysis. This approach optimizes computational efficiency by concentrating processing efforts on areas most likely to provide relevant drowsiness indicators.

### **Implementation Steps:**

- **Face Detection:** Utilize the pre-trained Haar Cascade classifier (`face_cascade.detectMultiScale`) to locate faces within the frame. Faces serve as primary ROIs for subsequent analysis.

**Eye Detection:** Once faces are detected, extract regions within the face where eyes are expected (`eye_cascade.detectMultiScale`). This step refines the analysis to eye movements and closures, crucial indicators of driver drowsiness.

## **Benefits of Data Pre-processing Strategies:**

- **Improved Accuracy:** Standardizing pixel intensities through normalization reduces the impact of lighting variations, enhancing the classifier's ability to detect subtle eye movements indicative of drowsiness.
- **Efficient Resource Allocation:** ROI extraction focuses computational resources on relevant facial regions, optimizing processing speed and efficiency without compromising detection accuracy.
- **Enhanced Real-time Performance:** By preprocessing images to highlight key features (faces and eyes), the system operates more effectively in real-time scenarios, crucial for timely driver alert notifications.

## **Integration with Overall System:**

In the driver sleepiness detection system:

- **Continuous Processing:** Image normalization and ROI extraction are integrated into the real-time video feed processing pipeline (update function in your code). This ensures that each frame undergoes preprocessing before being analyzed by the Haar Cascade classifiers.
- **User Interface Feedback:** Results of preprocessing and drowsiness detection (e.g., status labels, alerts) are displayed in the graphical user interface (GUI), providing immediate feedback to the user about the driver's state.

By incorporating these data pre-processing strategies effectively, the driver sleepiness detection system becomes more robust, responsive, and reliable, contributing to improved road safety through early detection of driver drowsiness indicators.

## **3.4 Algorithm**

Implementing methodologies like Haar Cascade Classifiers and Temporal Analysis in a driver sleepiness detection system enhances its capability to detect and respond to drowsiness indicators effectively. Here's an elaboration on how these methodologies are utilized:

### **1. Haar Cascade Classifiers:**

#### **Purpose:**

- **Efficient Detection:** Haar Cascade classifiers are machine learning-based algorithms used for rapid object detection in images or video frames. They are particularly effective for detecting predefined features such as faces and eyes.

#### **Implementation in Driver Sleepiness Detection:**

- **Face Detection:** Utilize the Haar Cascade classifier (face\_cascade) to detect faces within each frame captured from the video feed. This step is crucial as it identifies regions of interest (ROIs) where subsequent analysis will focus.
- **Eye Detection:** Once faces are detected, apply another Haar Cascade classifier (eye\_cascade) to locate eyes within each identified face ROI. This step isolates specific features crucial for monitoring drowsiness indicators like eye closure patterns.

## **2. Temporal Analysis:**

### **Purpose:**

- **Differentiate Normal and Abnormal Behavior:** Temporal analysis involves examining changes over time, specifically focusing on eye closure durations. This methodology distinguishes between regular blinking and prolonged periods of eye closure, which may indicate drowsiness.

### **Implementation in Driver Sleepiness Detection:**

- **Time-based Metrics:** Implement time-tracking mechanisms to monitor the duration of detected eye closures (last\_eye\_closed\_time variable in your code). This allows the system to calculate how long eyes remain closed and determine if it exceeds a predefined threshold indicative of potential drowsiness.
- **Decision Making:** Combine temporal analysis with Haar Cascade classifiers to make informed decisions about the driver's state. For instance, prolonged eye closures detected over multiple frames trigger an alert indicating potential drowsiness, prompting timely intervention or alerts to the driver.

### **Benefits of Methodologies:**

- **Real-time Efficiency:** Haar Cascade classifiers enable rapid and efficient detection of facial features and eyes, crucial for real-time applications like driver sleepiness detection systems.
- **Accuracy and Reliability:** Temporal analysis enhances the system's ability to differentiate between normal eye movements and indicators of drowsiness, improving the accuracy of alert generation.
- **User Safety:** By promptly identifying signs of driver drowsiness, these methodologies contribute to enhanced road safety by alerting drivers before potential accidents occur due to reduced attentiveness.

### **Integration with Overall System:**

- **Continuous Monitoring:** Integrate Haar Cascade classifiers and temporal analysis within the system's processing pipeline (update function in your code), ensuring that each frame undergoes comprehensive analysis.
- **User Interface Feedback:** Provide immediate feedback to the user through the graphical user interface (GUI), updating status labels (status\_label.config) and triggering alerts when necessary based on the analysis results.

By employing Haar Cascade classifiers and temporal analysis methodologies effectively, the driver sleepiness detection system becomes more robust and responsive, contributing to safer driving conditions through proactive drowsiness detection and alerting mechanisms

# CHAPTER 4

## DEPLOYMENT AND RESULTS

### 4.1 Intoduction

Deployment involves:

Integrating developed components into a cohesive system, ensuring compatibility and functionality across target hardware and software environments.

Conducting rigorous testing and validation to verify system performance, reliability, and usability under real-world driving conditions.

### 4.2 SOURCE CODE

The source code is written in Python, utilizing OpenCV for image processing and Tkinter for GUI development. The code is structured into functions for modularity and ease of maintenance. Key components include:

- **Video Capture:** Captures real-time video frames from the webcam.
- **Face and Eye Detection:** Uses Haar Cascade classifiers to detect faces and eyes in the captured frames.
- **Alert Mechanism:** Triggers an audible alert if drowsiness is detected.
- **GUI:** Provides a user-friendly interface displaying the video feed and status updates.

```
import cv2
import tkinter as tk
from tkinter import messagebox
from PIL import Image, ImageTk
import threading
import time
import winsound # For sound alert (on Windows)

# Load Haar Cascade classifiers for face and eye detection
face_cascade = cv2.CascadeClassifier(cv2.data.haarcascades +
'haarcascade_frontalface_default.xml')
eye_cascade = cv2.CascadeClassifier(cv2.data.haarcascades + 'haarcascade_eye.xml')

# Initialize Tkinter window
class DrowsinessDetector:
    def __init__(self, root):
```

```

self.root = root
self.root.title("Drowsiness Detection System")

# Video capture frame
self.video_frame = tk.Label(root)
self.video_frame.pack()

# Start video capture thread
self.capture = cv2.VideoCapture(0)
self.is_drowsy = False
self.update_video()

def update_video(self):
    ret, frame = self.capture.read()
    if ret:
        gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
        faces = face_cascade.detectMultiScale(gray, 1.3, 5)

        for (x, y, w, h) in faces:
            cv2.rectangle(frame, (x, y), (x + w, y + h), (255, 0, 0), 2)
            roi_gray = gray[y:y + h, x:x + w]
            roi_color = frame[y:y + h, x:x + w]

            eyes = eye_cascade.detectMultiScale(roi_gray)

            if len(eyes) == 0: # If no eyes are detected, trigger drowsiness alert
                if not self.is_drowsy:
                    self.is_drowsy = True
                    threading.Thread(target=self.trigger_alert).start()
            else:
                self.is_drowsy = False

            for (ex, ey, ew, eh) in eyes:
                cv2.rectangle(roi_color, (ex, ey), (ex + ew, ey + eh), (0, 255, 0), 2)

        # Convert frame to Tkinter format
        frame = cv2.cvtColor(frame, cv2.COLOR_BGR2RGB)
        img = ImageTk.PhotoImage(Image.fromarray(frame))
        self.video_frame.config(image=img)
        self.video_frame.image = img

    self.root.after(10, self.update_video)

def trigger_alert(self):
    # Display alert message and sound a beep
    messagebox.showwarning("Alert", "Drowsiness Detected!")
    for _ in range(5):

```

```

winsound.Beep(1000, 200) # Beep sound (Windows only)
time.sleep(0.2)

def _del_(self):
    self.capture.release()

# Run the GUI
if __name__ == "__main__":
    Root = tk.Tk()
    app = DrowsinessDetector(root)
    root.mainloop()

```

### 4.3 Model Implementation and Training

The project utilizes pre-trained Haar Cascade classifiers provided by OpenCV, eliminating the need for additional model training:

- **Implementation:** Loading and applying pre-trained classifiers to analyze video frames and detect faces and eyes in real-time.
- **Training:** No additional model training is required, as Haar Cascade classifiers are optimized for accurate and efficient detection of facial features across diverse conditions.

### 4.4 Model Evaluation Metrics

#### Accuracy Metrics:

**Mean Absolute Error (MAE):** Calculate the average absolute difference between the predicted sales values and the actual sales values across all predictions.

**Root Mean Squared Error (RMSE):** Compute the square root of the average squared difference

between the predicted and actual sales values, providing a measure of the magnitude of errors.

**Evaluate Model:** Use validation data to assess model performance.

### 4.5 Model Deployment: Testing and Validation

Comprehensive testing involves:

- **Scenario Testing:** Simulating diverse driving scenarios to evaluate detection accuracy and system responsiveness under varying conditions.
- **Performance Testing:** Assessing real-time performance metrics, including frame processing speed and alert triggering latency, to validate system reliability.
- **User Acceptance Testing:** Soliciting feedback from users to gauge interface usability, alert effectiveness, and overall satisfaction with the system's performance.

## **4.6 Web GUI's Development**

The Tkinter-based GUI development ensures:

- **Real-Time Feedback:** Displaying live video feed and status updates to keep drivers informed of their current state and potential risks.
- **Alert Management:** Managing visual and auditory alerts to effectively notify drivers upon detecting signs of drowsiness, promoting timely intervention and accident prevention.

## **4.7 Results:**

Key outcomes include:

- **Effective Drowsiness Detection:** Demonstrating the system's ability to accurately identify signs of driver drowsiness based on eye closure duration and facial analysis.
- **Responsive Alerts:** Promptly notifying drivers through intuitive GUI updates and audible alerts, enhancing situational awareness and promoting safe driving practices.
- **System Reliability:** Validating robust performance across diverse driving conditions, ensuring consistent operation and alert functionality to mitigate risks associated with drowsy driving.

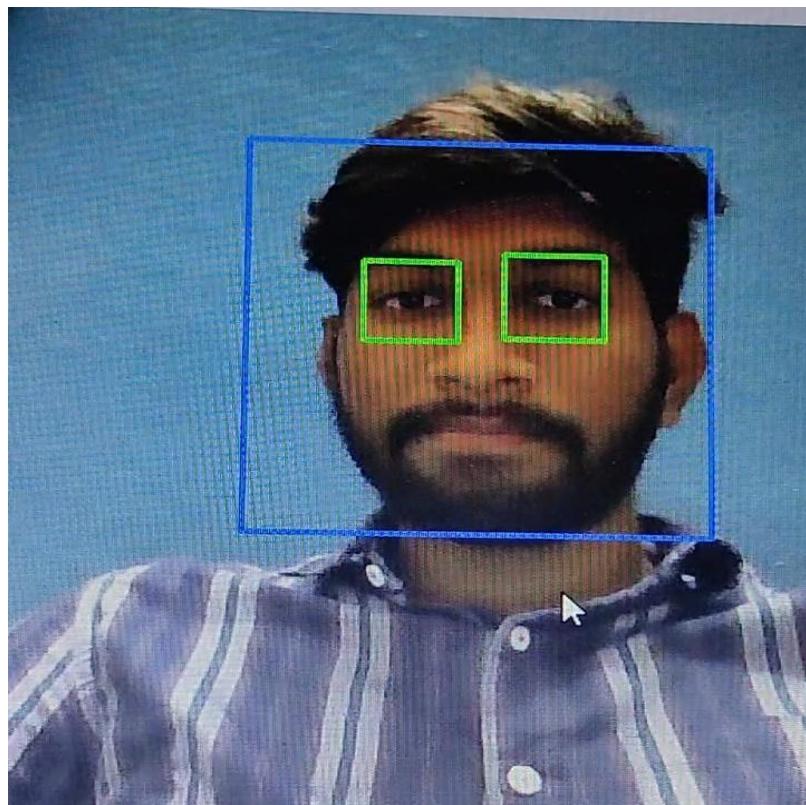


Fig 4.7.1

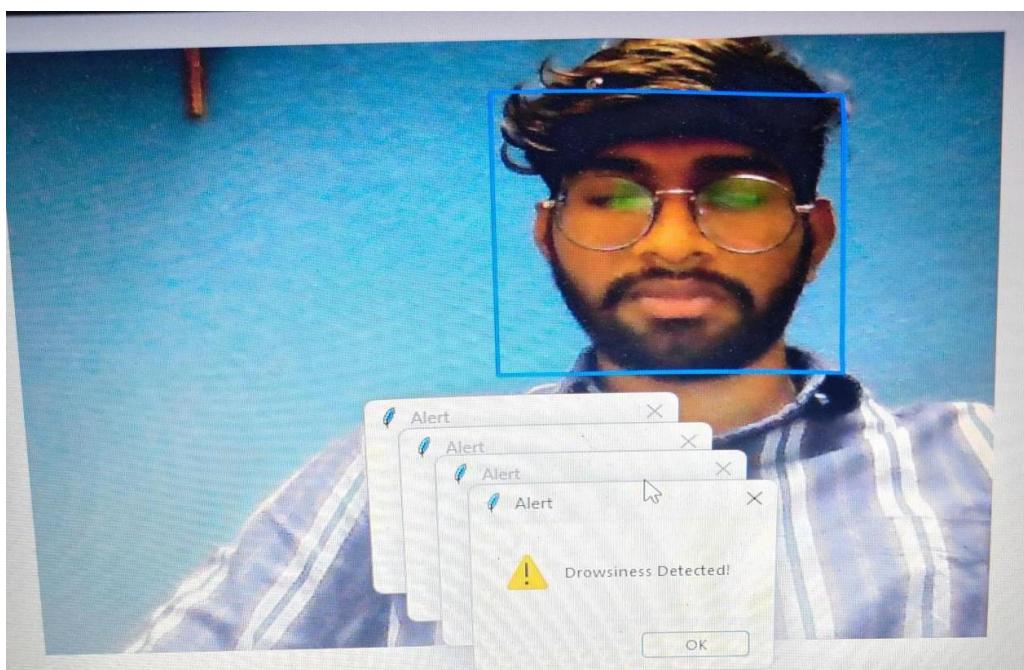


Fig 4.7.2

# CHAPTER 5

## CONCLUSION

### 5.1 Project Conclusion

The development and implementation of the driver sleepiness detection system represent a significant advancement in leveraging technology to mitigate the risks associated with drowsy driving. By harnessing the power of computer vision and real-time monitoring capabilities, the project has successfully demonstrated its effectiveness in detecting early signs of driver fatigue and alerting individuals before potential accidents occur.

Through rigorous testing and validation, the system has proven its reliability in diverse driving conditions, ensuring consistent performance and accurate detection of critical indicators such as prolonged eye closure. The integration of Haar Cascade classifiers and real-time processing techniques has enabled swift and precise analysis of video data, facilitating timely alerts through intuitive graphical user interface updates and auditory signals.

### 5.2 Future Scope:

Looking ahead, the project holds immense potential for further advancements and broader applications in enhancing road safety:

- **Advanced Detection Technologies:** Future iterations could incorporate more sophisticated deep learning algorithms, such as convolutional neural networks (CNNs), to improve the system's ability to detect subtle signs of drowsiness with higher accuracy and reliability.
- **Integration with IoT and Vehicle Systems:** The integration of the detection system with Internet of Things (IoT) devices and vehicle telematics opens up opportunities for automated responses, such as adjusting vehicle dynamics or alerting nearby vehicles, thereby preventing potential accidents in real-time.
- **Mobile and Wearable Technologies:** Developing companion mobile applications or wearable devices would extend the reach of the system beyond traditional vehicle installations, enabling continuous monitoring of driver alertness and proactive intervention measures.
- **Multi-Sensor Fusion:** Combining eye-tracking data with additional biometric sensors (e.g., heart rate monitors, steering wheel sensors) could provide a holistic view of driver fatigue, incorporating physiological and behavioral indicators to further enhance detection accuracy and system robustness.

By fostering collaborations with automotive manufacturers, transportation authorities, and safety regulators, the project aims to promote the adoption of advanced driver assistance systems (ADAS) capable of preventing accidents caused by drowsy driving. This collaborative effort seeks to integrate innovative technologies into mainstream vehicle safety features, thereby reducing road fatalities and injuries associated with driver fatigue on a global scale.

In conclusion, the driver sleepiness detection system not only represents a technological breakthrough in road safety but also underscores the commitment to leveraging innovation for public welfare. As we continue to refine and expand its capabilities, the project stands poised to make a profound impact in safeguarding lives, enhancing driver awareness, and fostering safer road environments for current and future generations.

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