Drowsy Driver Detection System Using Deep Learning

A Project Report

Submitted by

ANKITHA G ***20232MCA0012***

Under the guidance of

Mr. Sakthi S

Assistant Professor, Presidency School of Computer Science and Engineering

in partial fulfilment for the award of the degree

of

MASTER OF COMPUTER APPLICATIONS

At

SCHOOL OF INFORMATION SCIENCE

PRESIDENCY UNIVERSITY

BENGALURU

MAY 2025

MASTER OF COMPUTER APPLICATIONS

SCHOOL OF INFORMATION SCIENCE

PRESIDENCY UNIVERSITY

GAIN MORE KNOWLEDGE
REACH GREATER HEIGHTS

CERTIFICATE

This is to certified that the University Major Project report "**Drowsy Driver Detection System Using Deep Learning**" being submitted by **Ankitha G**, bearing roll number **20232MCA0012**, in partial fulfilment of requirement for the award of **Master in Computer Applications** is a Bonafide work carried out under my supervision.

Mr. Sakthi. S
Assistant Professor,
Presidency School of CSE,
Presidency University.

Dr. W Jaisingh
Head of the Department (SOIS),
Presidency School of CSE & IS,
Presidency University.

Dr. R Mahalakshmi
Associate Dean,
Presidency School of IS,
Presidency University.

Dr. Md. Sameeruddin Khan
Pro-VC & Dean,
Presidency School of CSE & IS,
Presidency University.

ABSTRACT

Drowsy driving is recognized as one of the leading causes of traffic accidents globally, often resulting in serious injuries, fatalities, and significant economic losses. Drivers experiencing fatigue typically show physical signs such as prolonged eye closure, frequent yawning, and reduced reaction time, all of which compromise road safety. To combat this issue, this paper presents a real-time driver drowsiness detection system that combines computer vision techniques with facial landmark analysis to monitor the driver's alertness continuously. The system primarily relies on two biometric indicators: The Eye Aspect Ratio (EAR) and the Mouth Aspect Ratio (MAR). The EAR measures the degree of eye openness, and when it falls below 0.22 for more than three consecutive frames, it suggests the eyes are closed for an extended period. Similarly, the MAR detects yawning by calculating how widely the mouth opens; a value above 0.7 indicates a possible sign of fatigue. These thresholds help identify early symptoms of drowsiness. The implementation uses OpenCV for real-time video capture and image processing, Dlib for accurate facial landmark detection, and the Pygame mixer module to produce an immediate audio alert when signs of drowsiness are detected. This alarm serves to wake the driver and prevent potential accidents. The system is designed to be lightweight, cost-efficient, and easily deployable in various vehicle types. It performs reliably in different lighting conditions and is adaptable to a wide range of facial features, making it a practical solution for enhancing road safety through non-intrusive, real-time driver monitoring

ACKNOWLEDGEMENT

The completion of project work brings with great sense of satisfaction, but it is never completed without thanking the persons who are all responsible for its successful completion. First and foremost, we indebted to the GOD ALMIGHTY for giving us the opportunity to excel our efforts to complete this project on time. We wish to express our deep sincere feelings of gratitude to our Institution, Presidency University, for providing us opportunity to do our education.

We express our sincere thanks to our respected dean **Dr. Md. Sameeruddin Khan,** Pro-Vice Chancellor, School of Engineering, and Dean, Presidency School of CSE and IS, Presidency University for getting us permission to undergo the project.

We record our heartfelt gratitude to our beloved professor **Dr. R Mahalakshmi**, Associate Dean, Presidency School of Information Science, **Dr W. Jaisingh**, Professor and Head, Presidency School of Information Science, Presidency University for rendering timely help for the successful completion of this project.

We sincerely thank our project guide, **Mr. Sakthi S**, Assistant Professor, Presidency School of CSE for his guidance, help and motivation. Apart from the area of work, we learnt a lot from him, which we are sure will be useful in different stages of our life. We would like to express our gratitude to Faculty Coordinators and Faculty, for their review and many helpful comments.

We would like to acknowledge the support and encouragement of our friends.

ANKITHA **20232MCA0012**

TABLE OF CONTENTS

LIST OF FIGURES

CHAPTER-1

INTRODUCTION

Driver fatigue is a significant factor in road accidents, especially during long-distance or night-time driving. Traditional monitoring methods that rely on vehicle-based data, such as steering behavior or lane deviation, often lack the accuracy and responsiveness needed to detect early signs of drowsiness. In contrast, vision-based systems provide a more precise and non-invasive solution by analyzing facial behaviors directly. This study introduces a drowsiness detection system that monitors visual cues such as prolonged eye closure, yawning, and head movement in real time. By identifying these early indicators of fatigue, the system can issue immediate alerts to the driver, helping to prevent accidents caused by reduced alertness and delayed reaction times.

Driver fatigue is a major cause of road accidents globally, contributing to 20–30% of motor vehicle crashes and posing a serious public safety concern by impairing reaction time, attention, and decision-making. It significantly increases the risk of driving errors and delayed responses. Real-time monitoring systems provide a proactive solution by detecting early signs of drowsiness, such as eyelid movement, head position, and in some cases, abnormal steering patterns. These systems issue timely alerts to the driver, enabling them to respond before fatigue leads to dangerous situations. Early intervention through such technology can play a critical role in reducing accidents and ultimately saving lives.

1.1 Challenges in Driver Fatigue Detection Systems

Despite the promising potential of driver fatigue detection systems, several challenges must be addressed for effective real-world deployment. One major issue is lighting variability inside the vehicle, where poor or changing lighting conditions—such as night-time driving or glare from sunlight—can hinder accurate facial detection. Occlusion is another problem, as objects like sunglasses, hats, or even hands can obstruct key facial landmarks, particularly the eyes and mouth. The effectiveness of detection also heavily depends on the proper positioning of the camera, as an incorrect angle or limited visibility can reduce accuracy.

Moreover, individual differences in facial features, such as skin tone, facial hair, and expressions, introduce variability that can impact system performance. False positives and negatives are a common concern; normal behaviors like blinking or looking sideways may be wrongly interpreted as drowsiness, while genuine fatigue signs might go undetected. Additionally, real-time processing is essential for timely alerts, requiring the system to be computationally efficient, especially when deployed on low-cost hardware. User acceptance is another factor, as drivers may find the system intrusive or annoying if it triggers frequent or unnecessary alerts. Finally, successful implementation also requires seamless integration with various vehicle models and onboard systems, which can be technically complex and resource-intensive.

1.2 Objectives of the Study

1. **To develop a real-time, non-intrusive drowsiness detection system** that uses facial landmark analysis to identify signs of driver fatigue such as eye closure and yawning.
2. **To implement Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR)** as key indicators for detecting drowsiness, enabling accurate identification of symptoms like prolonged eye closure and yawning.
3. **To design an early warning system** that triggers immediate auditory alerts when drowsiness is detected, helping drivers take timely action to prevent accidents.
4. **To create a cost-effective and adaptable solution** that performs reliably under varying lighting conditions and across diverse driver profiles, without the need for wearable devices or intrusive sensors.
5. **To integrate a real-time auditory alert system using Pygame** that activates immediately when drowsiness symptoms are detected, warning the driver to regain focus or take a break.
6. **To build a non-intrusive and cost-effective solution** that does not rely on physical sensors or wearable technology, making it practical for everyday drivers and commercial use.
7. **To ensure system adaptability and reliability** across varying lighting conditions, facial structures, and driver postures, enabling accurate detection in diverse real-world environments.
8. **To evaluate system performance through testing** in both controlled environments and real-world scenarios to measure accuracy, response time, and effectiveness in detecting fatigue.

1.3 Significance and Applications

The Driver Drowsiness Detection System is highly significant in promoting road safety by identifying early signs of fatigue in drivers and providing timely alerts to prevent accidents. Fatigue is a leading cause of road mishaps, especially during night-time or long-distance driving. Traditional systems often rely on physiological sensors or vehicle movement data, which can be intrusive or delayed in detection. In contrast, this system uses computer vision techniques with facial landmark analysis to monitor visual fatigue indicators such as eye closure and yawning through Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR). This non-invasive and real-time approach ensures that drivers receive immediate feedback through an audio alert, prompting corrective action before their drowsiness leads to dangerous outcomes. The system is also cost-effective, lightweight, and adaptable to various lighting conditions and user profiles, making it suitable for practical deployment.

This project has a wide range of applications across different domains. In private vehicles, it can help individual drivers maintain alertness on long or late-night trips. In commercial transport fleets, logistics companies can use the system to monitor driver alertness, enhancing operational safety and reducing liability. Public transportation services can install the system in buses and taxis to protect passengers and improve service safety. The technology can also be valuable in driver training programs, offering real-time feedback and education on fatigue awareness. Furthermore, it can be integrated into modern vehicles as part of advanced driver-assistance systems (ADAS). The system is particularly beneficial for long-haul truck drivers, night-shift workers, and professionals in high-risk roles such as emergency responders and military personnel. By helping prevent fatigue-induced accidents, this project offers practical and life-saving applications across diverse sectors.

CHAPTER-2

LITERATURE SURVEY

The growing concern over driver fatigue and its contribution to road accidents has motivated significant research into real-time, non-intrusive monitoring systems. Modern driver drowsiness detection systems focus on analyzing visual cues from the face to identify signs of fatigue. This literature review is organized into four main sections: Feature Extraction, Feature Selection Techniques, Challenges, and Future Directions.

2.1. Feature Extraction

Feature extraction is the foundation of any driver drowsiness detection system. It involves identifying and isolating facial features or behavioral patterns that are indicative of fatigue. Among the most widely adopted techniques are those that focus on the eyes and mouth, as these are the most expressive parts of the face when it comes to detecting sleepiness.

The **Eye Aspect Ratio (EAR)** is a popular feature used to determine the openness of a person's eyes. It is computed using six facial landmarks around the eye. A decrease in EAR over consecutive frames indicates prolonged eye closure, which is a primary sign of drowsiness. Similarly, the **Mouth Aspect Ratio (MAR)**, calculated from the vertical and horizontal distances between specific mouth landmarks, is used to detect yawning.

Several research studies have confirmed the reliability of these features. For instance, Soukupová and Čech introduced the EAR metric, showing its robustness in detecting eye closure in real-time video. Similarly, MAR has been proven effective in identifying yawns in natural settings. Dlib's 68-point facial landmark detector is commonly used for this purpose due to its precision and efficiency.

OpenCV is the preferred tool for video capture and pre-processing tasks such as grayscale conversion, histogram equalization, and frame resizing. These pre-processed frames are passed to Dlib for landmark extraction. Libraries like SciPy are used for computing Euclidean distances between landmarks, which form the basis of EAR and MAR.

Some advanced systems also extract secondary features such as **head pose**, **blink rate**, and **gaze direction**, which help refine the system's ability to assess fatigue. These features are particularly useful in scenarios where the eyes or mouth may be partially obstructed.

2.2. Feature Selection Techniques

Feature fusion techniques are also being explored, where multiple features (EAR, MAR, head tilt, etc.) are combined to make a more informed decision. This approach Once features are extracted, the next step is selecting the most relevant ones for classification and decision-making. In simpler systems, threshold-based techniques are used—EAR and MAR values are compared against predefined thresholds to determine if the driver is drowsy. For example, an EAR value below 0.22 for more than three consecutive frames is typically used to detect closed eyes, while a MAR value above 0.7 is often used to detect yawning.

Although threshold-based methods are easy to implement and require minimal computational resources, they can be sensitive to noise and individual variation. Therefore, recent research has focused on **machine learning-based feature selection** methods. Techniques such as **Support Vector Machines (SVM)**, **Random Forests**, and **K-Nearest Neighbors (KNN)** have been used to classify the state of the driver based on multiple features.

More sophisticated approaches involve the use of **deep learning**, particularly **Convolutional Neural Networks (CNNs)**. These networks can automatically learn hierarchical feature representations from facial images, eliminating the need for manual feature engineering. For instance, Thejas et al. proposed a CNN-based model that achieved high accuracy in eye state classification. Smith et al. developed a multi-stream CNN that combined features like head pose, eye movement, and facial expression for robust detection. is particularly effective in reducing false positives and negatives, making the system more reliable in diverse driving conditions.

2.3. Challenges

Despite significant advancements, there are still multiple challenges that affect the accuracy and practicality of driver drowsiness detection systems.

One of the biggest challenges is **lighting variability**. Since most systems rely on regular webcams, their performance can degrade significantly in low-light or overly bright conditions. Night driving or changing sunlight angles can cause shadowing or reflection, leading to incorrect landmark detection.

Another major issue is **facial occlusion**. Drivers may wear sunglasses, face masks, or have facial hair that obstructs key facial landmarks. Even temporary occlusions, such as a hand near the face or turning the head, can disrupt detection.

User variability also poses a problem. Differences in facial structure, age, skin tone, and expression across individuals can affect the consistency of EAR and MAR values. Older adults, for example, may have naturally smaller eye openings, leading to higher false positives.

Maintaining **real-time performance** is another technical challenge. Fatigue detection systems must operate at high frame rates with minimal latency to be effective. This requires optimized algorithms that can process video streams and perform computations quickly, even on low- to midrange hardware such as in-vehicle computers.

Furthermore, **false positives and false negatives** are still a concern. Blinking or speaking may be wrongly interpreted as signs of drowsiness. Conversely, quick eye closures or subtle yawns may be missed altogether, reducing system reliability.

2.4. Future Directions

One promising direction is the use of **infrared (IR) cameras** or **night vision** technology, which can improve detection accuracy in low-light or night-time conditions. These sensors can be used to enhance facial feature visibility without disturbing the driver.

Another approach is to implement **adaptive thresholding** using machine learning. By personalizing the EAR and MAR thresholds based on the driver's behavior over time, the system can reduce false alerts and improve accuracy. This would allow the system to adjust dynamically to each user.

The integration of **multi-modal sensors** such as combining visual cues with steering behavior, heart rate, or seat pressure can significantly improve detection reliability. This multisensory fusion approach provides a broader context for decision-making.

Research is also focusing on developing **deep learning models trained on large and diverse datasets**, which can generalize better across different demographic groups and real-world conditions. Transfer learning and domain adaptation techniques can further help apply these models across different vehicle environments.

Finally, the incorporation of drowsiness detection into **Advanced Driver Assistance Systems (ADAS)** and semi-autonomous vehicles is a growing trend. These systems can not only alert the driver but also take corrective actions such as slowing down the vehicle, sending emergency signals, or switching to autonomous mode.

CHAPTER-3

REQUIREMENT ANALYSIS

Requirement analysis is a fundamental phase in any software development process. It involves identifying the needs and expectations of stakeholders to ensure the system fulfils its intended purpose. For the **Driver Drowsiness Detection System**, the aim of requirement analysis is to define what the system must do (functional requirements), how it should behave (non-functional requirements), and what resources are needed to implement it (hardware and software requirements). This section provides a detailed analysis to guide the design and development of a reliable, real-time fatigue monitoring system.

3.1. Introduction to Requirement Analysis

The primary goal of requirement analysis is to identify, document, and validate the needs and expectations of stakeholders, and then translate those into specific system functionalities and technical constraints. In the case of a drowsiness detection system, the core stakeholders include drivers, transportation safety authorities, automotive companies, and software developers. This system must operate in real-time to track facial landmarks, process facial behavior such as blinking and yawning, and immediately alert the driver upon detecting fatigue symptoms.

An accurate requirement analysis ensures the developed system is user-friendly, highly responsive, adaptable to various conditions, and able to operate efficiently on standard computing hardware. It also helps identify potential risks, technical challenges, and the scope for future enhancements such as the integration of deep learning or additional behavioral parameters like head tilt and gaze tracking.

3.2. Functional Requirements

Functional requirements define the specific tasks and services that the system is expected to perform These functionalities ensure the system achieves its primary objective detecting driver drowsiness accurately and efficiently using facial landmarks.

- **Live Video Feed Capture**: The system must initiate and maintain a continuous stream of video input from a webcam. This feed is the primary source of data for monitoring facial behavior in real time.
- **Face Detection and Tracking**: The application must be able to detect the presence of a human face in the video stream. If no face is detected, the system should continuously monitor until one is found. Once detected, the face should be tracked consistently across frames.
- **Facial Landmark Extraction**: Using Dlib's pre-trained 68-point facial landmark model, the system should identify key facial regions such as the eyes and mouth. These landmarks are crucial for calculating EAR (Eye Aspect Ratio) and MAR (Mouth Aspect Ratio).
- **EAR and MAR Calculation**: The system must calculate EAR by analyzing distances between vertical and horizontal eye landmarks. Similarly, MAR must be computed using landmarks around the inner lips. These values serve as indicators of drowsiness (eye closure and yawning).
- **Threshold Comparison Logic**: The application must implement logic to compare the calculated EAR and MAR against predefined thresholds. EAR values below 0.22 for at least 3 consecutive frames must be treated as prolonged eye closure. MAR values exceeding 0.7 are considered yawning events. Both indicate potential drowsiness.
- **Auditory Alert Generation**: Upon detecting a valid drowsiness event, the system should immediately trigger an audible alert using Pygame's mixer module. This is intended to warn the driver and prompt corrective action.
- **Real-time Display Feedback**: The current EAR and MAR values must be displayed on the screen for user awareness, along with a warning message like "DROWSINESS DETECTED!" if fatigue is identified.
- **Alert Reset Mechanism**: If the driver's eyes reopen or mouth closes (values return to normal range), the alarm must stop automatically. This ensures that the alert is context-sensitive and does not annoy the driver unnecessarily.
- **Program Termination**: The system must provide an easy and accessible way to terminate its execution, typically through a keystroke (e.g., pressing 'q'), ensuring user control over system operation.

3.3. Non-Functional Requirements

Non-functional requirements describe the system's overall behavior and constraints that influence the user experience, system performance, and operational reliability. These are critical for long-term success and real-world usability.

- **Real-Time Performance**: The system must process video input at a minimum of 20–30 frames per second (FPS) to enable smooth and accurate detection without noticeable lag. Delayed detection of drowsiness could render the system ineffective.
- **Accuracy and Precision**: The EAR and MAR detection algorithms must be precise, achieving high true positive rates (correct detection of drowsiness) while minimizing false positives (wrongly identifying drowsiness) and false negatives (missing actual fatigue signs).
- **System Reliability**: The system must operate consistently across extended periods without crashes or memory leaks. It should handle unexpected scenarios gracefully, such as temporary loss of video feed or facial detection errors.
- **Usability and Accessibility**: The interface must be clean, minimal, and user-friendly. Users should not require any technical knowledge to use the application. On-screen text should be readable, and audio alerts must be distinct and attention-grabbing.
- **Portability and Compatibility**: The software must be compatible with commonly used operating systems including Windows 10, Linux (Ubuntu), and macOS. It should function on standard consumer-grade laptops and desktops.
- **Scalability**: The architecture of the system should allow easy scaling. Future modules such as head pose detection, gaze estimation, and machine learning integration should be supported without significant rework.
- **Adaptability to Environmental Conditions**: The system must function effectively under different lighting conditions (daylight, low light, shadows, artificial light) and with drivers of various ethnicities, genders, and age groups.
- **Security and Privacy**: Since the system captures live video, it must not store or transmit sensitive data unless explicitly required. All captured data should be processed locally to maintain user privacy.
- **Maintainability**: The codebase must follow modular programming principles. Each component video capture, landmark detection, EAR/MAR calculation, alert system should

be separated into distinct modules with proper documentation for ease of updates and debugging.

3.4. Hardware and Software Requirements

To ensure smooth development, testing, and deployment, the system requires specific hardware and software resources. These components are carefully selected to meet the needs of real-time performance and user convenience.

Hardware Requirements

- **Processor**: A minimum of Intel Core i5 or AMD Ryzen 5, 2.5 GHz or higher, to handle realtime video processing, landmark detection, and alert triggering without lag.
- **RAM**: 8 GB or more to support seamless multitasking, real-time image analysis, and library execution.
- **Camera**: HD webcam with a minimum resolution of 720p for accurate facial detail capture. Built-in webcams or external USB webcams are supported.
- **Audio Output**: Functional speakers or headphones are essential for the user to hear alerts clearly, especially in noisy environments.
- **Storage**: At least 1 GB of free storage space for software installation, library dependencies, and temporary files.

Software Requirements

- **Operating System**: The system must be compatible with Windows 10, Ubuntu/Linux, and macOS platforms.
- **Programming Language**: Python 3.7 or above due to its extensive library support, ease of use, and compatibility with OpenCV and Dlib.
- **IDE/Editor**: Visual Studio Code, PyCharm, or Jupyter Notebook for coding, debugging, and visualization.
- **Required Libraries and Packages**:
  - **OpenCV** – Used for real-time video frame capture and image processing operations.
  - **Dlib** – For face detection and landmark identification using a pre-trained 68-point model.
  - **Imutils** – Utility functions for facial geometry handling.

- **SciPy** – To calculate Euclidean distances needed for EAR and MAR computations.
- **Pygame** – For initializing and playing audio alerts through the system's speaker.

- **Model File**: shape_predictor_68_face_landmarks.dat, a critical pre-trained file required by Dlib for detecting facial landmarks.

This setup ensures that the system runs efficiently on commonly available computing platforms without the need for expensive or specialized hardware. It also allows room for future upgrades and optimizations based on evolving technologies and user needs.

CHAPTER - 4

EXISTING SYSTEM

Drowsiness is a major cause of road accidents globally, contributing to a significant number of injuries and fatalities each year. In recent years, researchers and automobile manufacturers have recognized the need for effective systems to detect and prevent driver fatigue. Several existing systems have been developed using various methods, including vehicle-based monitoring, physiological signal tracking, and computer vision techniques. This chapter provides a detailed overview of these existing systems, highlighting their working principles, advantages, limitations, and relevance to the proposed solution.

4.1 Overview of Existing Driver Drowsiness Detection Systems

Existing driver drowsiness detection systems fall under three broad categories:

1. **Vehicle-Based Detection Systems**
2. **Physiological-Based Detection Systems**
3. **Vision-Based Detection Systems**

Each of these systems employs a different approach to detect fatigue, and each has its own strengths and weaknesses. A combination of these methods has also been explored in some commercial systems to improve accuracy.

1. Vehicle-Based Detection Systems

Vehicle-based systems monitor the behavior of the vehicle to infer the driver's state. Common indicators include **steering wheel movement**, **lane deviation**, **braking patterns**, and **speed fluctuations**.

Examples

- Lane Departure Warning Systems (LDWS)
- Steering pattern monitoring systems in Volvo, Mercedes-Benz, and BMW vehicles

Working Principle

These systems detect erratic or unusual driving behaviors. For example, frequent lane drifting or inconsistent steering inputs are interpreted as signs of inattention or fatigue.

Merits

- Non-intrusive and require no physical contact with the driver
- Relatively easy to integrate with existing vehicle systems
- Can work continuously during long journeys

Demerits

- Fatigue symptoms may not always reflect in vehicle movement, especially in early stages
- May generate false positives due to poor road conditions or wind

3. Physiological-Based Detection Systems

Physiological systems measure biological signals such as Electroencephalogram (EEG), Electrocardiogram (ECG), Electromyography (EMG), or pupil dilation to assess driver alertness.

Examples

- EEG headbands for brainwave monitoring
- Wearable smartwatches or chest straps measuring heart rate variability Eye tracking glasses

Working Principle

These systems rely on real-time analysis of physiological data. For instance, decreased brain activity or changes in heart rate patterns may indicate the onset of fatigue.

Merits

- High accuracy in detecting cognitive fatigue
- Can provide early warnings before physical symptoms appear
- Helpful for medical monitoring and research-based studies

Demerits

- Highly intrusive and uncomfortable for long durations
- Require physical contact or wearable sensors
- Expensive and not practical for mass deployment in consumer vehicles
- Susceptible to signal noise and artefacts due to movement or sweating
- Not favored by drivers due to discomfort and privacy concerns

4 Vision-Based Detection Systems

Vision-based systems monitor the driver's **facial behavior** using a camera, analysing cues such as **eye closure**, **blinking rate**, **head nodding**, **yawning**, and **gaze direction**. These systems use techniques such as **facial landmark detection**, **image processing**, and **machine learning**.

Examples

- Open-source models using OpenCV and Dlib
- Commercial solutions in cars by Tesla, Subaru (Driver Focus), and Cadillac (Super Cruise)
- Research-based systems using CNNs or deep learning for facial expression analysis

Working Principle

Cameras are placed to focus on the driver's face. Facial landmarks are detected in real time, and behavioral features (like eye openness and mouth movement) are analyzed. Metrics like **Eye Aspect Ratio (EAR)** and **Mouth Aspect Ratio (MAR)** are computed to identify drowsiness.

Merits

- Non-intrusive and do not require physical contact
- High flexibility can be used in any vehicle with a camera
- Simple integration into existing vehicle systems
- Enables real-time monitoring of driver alertness

- High flexibility can be used in any vehicle with a camera
- Can detect visual signs of fatigue such as yawning and prolonged blinking
- Easy to deploy with consumer-grade hardware (e.g., webcams)

Demerits

- Performance affected by lighting conditions (night, glare)
- Faces covered with sunglasses, masks, or beards may cause inaccurate detection
- Head movements or changes in posture can obstruct the face
- Requires continuous visibility of the face, which may not always be feasible
- Limited in very dark environments unless infrared or night vision is used

4.2. Limitations of Existing Systems

Despite many advancements, current systems still suffer from limitations:

- **False Alarms**: Both vehicle- and vision-based systems can generate false positives or miss true drowsiness events.
- **Hardware Limitations**: Physiological systems require wearable devices, and vision-based systems require high-quality cameras.
- **Environmental Constraints**: Lighting, road conditions, and distractions can interfere with detection accuracy.
- **User Acceptance**: Drivers may resist using systems that are uncomfortable or intrusive.
- **Lack of Personalization**: Most systems use fixed thresholds and do not adapt to individual behavior patterns over time.

4.3. Merits and Demerits of Existing Systems

Merits

- Proven effectiveness in many research and commercial applications
- Offer a wide range of detection strategies suitable for various use cases
- Integration with modern ADAS systems enhances vehicle safety
- Vision-based systems are relatively affordable and easy to set up

Demerits

- No single system can guarantee 100% accurate detection in all conditions
- Physiological methods are intrusive and not practical for everyday driving
- Vision-based systems struggle in poor lighting or when facial features are obstructed
- Lack of adaptive learning in most systems reduces accuracy for diverse driver profiles

4.4 Conclusion on Existing Systems

Existing driver drowsiness detection systems provide a strong foundation for understanding and mitigating driver fatigue. Each category—vehicle-based, physiological, and vision-based—has made valuable contributions to road safety. However, challenges such as intrusiveness, cost, lighting sensitivity, and lack of personalization limit their widespread adoption. Among the available approaches, vision-based systems offer a promising solution due to their balance of performance, ease of deployment, and user acceptance. The current project builds on this approach by using facial landmarks to compute EAR and MAR in real time and delivering timely audio alerts, providing a practical, non-intrusive, and effective solution for enhancing driver safety.

CHAPTER - 5

PROPOSED METHOD

Driver fatigue is a silent hazard that significantly increases the risk of accidents, particularly during long trips or night driving. Although various systems have been developed for detecting drowsiness, many are either too intrusive, expensive, or unreliable under real-world conditions.

5.1. Overview of the Proposed System

The proposed method relies on **live video feed analysis** using a webcam mounted in the vehicle to monitor the driver's face in real time. It uses the **Dlib library** to detect and track facial landmarks and calculates two key fatigue indicators: **Eye Aspect Ratio (EAR)** and **Mouth Aspect Ratio (MAR)**. If EAR falls below a threshold or MAR exceeds a certain limit, the system interprets these as signs of drowsiness and triggers an **audio alert** to awaken or warn the driver.

The system is designed to function **without requiring wearable sensors or physical contact**, making it highly practical and user-friendly. It works effectively under normal lighting conditions and is adaptable to different users regardless of facial structure, gender, or age.

5.2. System Architecture

The proposed system follows a modular architecture with clearly defined components:

1. **Video Acquisition Module** – Captures continuous video feed from the webcam.
2. **Face Detection Module** – Identifies the driver's face in each frame.
3. **Landmark Detection Module** – Locates 68 facial landmarks for feature extraction.
4. **EAR & MAR Computation Module** – Calculates eye and mouth aspect ratios.
5. **Drowsiness Detection Logic** – Compares the computed values with thresholds.
6. **Alert Generation Module** – Triggers an alarm if drowsiness is detected.
7. **User Feedback Module** – Displays EAR, MAR, and visual warnings.

5.3. Working Principle

The core concept is to analyses facial behavior using geometric ratios derived from facial landmarks.

- **Eye Aspect Ratio (EAR)** is used to detect blinking and prolonged eye closure.
- **Mouth Aspect Ratio (MAR)** is used to detect yawning.

The Dlib library provides a pre-trained model to detect **68 facial landmarks**. From these, the coordinates of the eyes and mouth are extracted. The aspect ratios are computed using **Euclidean distances** between key points. The system compares these values to predefined thresholds:

- EAR < 0.22 for 3 consecutive frames indicates drowsiness.
- MAR > 0.7 indicates yawning or fatigue.

If either condition is met, an **audio alert** is triggered using the Pygame library to prompt the driver to regain attention.

5.4 Step-by-Step Methodology

Step 1: Initialize Video Stream

The system starts by initializing the webcam using OpenCV. A continuous loop reads each frame from the video feed in real time.

cap = cv2.VideoCapture(0)

Step 2: Convert Frame to Grayscale

Each frame is converted to grayscale to reduce computational load and improve the accuracy of face detection.

gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY) **Step**
3: Detect Face

Dlib's frontal face detector is used to detect faces within the grayscale image.

faces = detector (gray, 0)

Step 4: Extract Facial Landmarks

For each detected face, 68 landmarks are extracted using the shape predictor.

shape = predictor (gray, face) shape =
face_utils.shape_to_np(shape)

Step 5: Compute EAR and MAR

Using the landmark coordinates

- EAR is calculated from vertical and horizontal eye distances.
- MAR is calculated from vertical and horizontal mouth distances.

Step 6: Apply Drowsiness Detection Logic

The system checks

- If EAR < 0.22 for 3 consecutive frames → Eyes closed → Drowsiness
- If MAR > 0.7 → Yawning → Drowsiness

Step 7: Generate Alert

If drowsiness is detected, an audio alert is played.

mixer.music.play()

Step 8: Display Feedback

Real-time feedback is shown on the screen including EAR, MAR values, and warning messages like "DROWSINESS DETECTED!"

5.5 Mathematical Model

Eye Aspect Ratio (EAR)

The Eye Aspect Ratio is calculated using specific eye landmarks and is given by:

$$\textbf{EAR} = (\|p_2 - p_6\| + \|p_3 - p_5\|) / (2 \times \|p_1 - p_4\|)$$

Where $\mathbf{p_1}$ **to** $\mathbf{p_6}$ are specific eye landmarks

Mouth Aspect Ratio (MAR)

The Mouth Aspect Ratio is computed from specific mouth landmarks and is defined as

MAR = $(\|p_2 - p_8\| + \|p_3 - p_7\|) / (2 \times \|p_1 - p_5\|)$

Where **p_1 to p_8** are specific mouth landmarks.

5.6 Advantages of the Proposed Method

- **Non-Intrusive**: Does not require wearable sensors or physical contact.
- **Real-Time Performance**: Processes video at high frame rates.
- **Affordable**: Runs on standard laptops with basic webcams.
- **Accurate**: Uses reliable geometric calculations to detect fatigue.
- **Scalable**: Can be enhanced with machine learning, gaze tracking, or head pose estimation.
- **Customizable**: Thresholds for EAR and MAR can be adjusted for different users.

5.7 Use Case Scenarios

- **Long-Distance Highway Driving**: Alerts drivers to take breaks when signs of fatigue appear.
- **Commercial Fleets**: Monitors alertness of truck or taxi drivers.
- **Public Transportation**: Enhances passenger safety in buses by monitoring driver focus.
- **Driver Education Programs**: Teaches new drivers about fatigue risks.

5.8 Expected Contributions and Advantages

The Driver Drowsiness Detection System proposed in this project offers several key contributions to the fields of intelligent transportation, computer vision, and real-time safety systems. The primary contribution is the development of a **real-time, non-intrusive drowsiness monitoring system** that uses only a standard webcam and computationally efficient algorithms to detect fatigue symptoms in drivers. Unlike traditional approaches that rely on vehicle movement data or physiological sensors, this system focuses solely on **visual cues from facial expressions**, making it more accessible and user-friendly.

The system leverages facial landmarks and video analysis to accurately detect signs of drowsiness A significant technical contribution of the project is the **implementation of the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR)** algorithms for identifying fatigue indicators such as prolonged eye closure and yawning. By leveraging Dlib's 68-point facial landmark model and Realtime video capture using OpenCV, the system calculates EAR and MAR with high accuracy, providing a reliable indicator of the driver's alertness level.

Another important contribution is the integration of an **instantaneous audio alert system** using Pygame, which ensures timely intervention to regain the driver’s attention. The system is designed with flexibility and modularity in mind, allowing future integration with more complex detection methods such as head pose estimation, gaze tracking, and even deep learning models for behavioral pattern recognition.

This project also contributes to **public road safety efforts** by offering a cost-effective and scalable solution that can be implemented not only in personal vehicles but also in commercial fleets, ridesharing services, and public transportation systems. It can be adapted for use in industries where continuous monitoring of alertness is essential, such as aviation, mining, or industrial machine operations.

From a research perspective, the project provides a **baseline model** that can be further enhanced with machine learning algorithms, improved threshold calibration, or fusion with other sensing methods to create a more holistic driver monitoring system.

5.9 Advantages of the Proposed System

The proposed system offers numerous advantages that make it practical, efficient, and well-suited for real-world deployment. These advantages span across user experience, technical performance, and implementation feasibility:

1. **Non-Intrusive**

   Unlike EEG headbands or wearable sensors, this system does not require any physical contact with the driver. It simply uses a webcam, making it comfortable for the user and suitable for long-term use.

2. **Real-Time Operation**

    The system processes video frames in real time with minimal latency, ensuring that fatigue symptoms are detected and responded to immediately. This is critical in preventing accidents caused by delayed alerts.

3. **Cost-Effectiveness**

    The system utilizes open-source tools (OpenCV, Dlib, Pygame) and low-cost hardware (webcam and standard PC), making it affordable for individual users and scalable for fleet-level deployment.

4. **Deployment**

    With minimal hardware requirements and a simple software setup, the system can be easily installed in any vehicle without professional assistance. This makes it suitable for retrofitting existing vehicles.

5. **Adaptability**

    The facial landmark-based approach ensures that the system works across a wide range of driver profiles, regardless of age, gender, or ethnicity. EAR and MAR thresholds can also be adjusted to suit individual behavior.

6. **Flexibility**

    The system performs reliably under varied lighting conditions with basic pre-processing. This makes it suitable for both daytime and night-time driving environments.

7. **Modular Design**

    The software architecture is modular, allowing easy integration of additional features such as head tilt detection, gaze tracking, or deep learning models in future versions.

8. **Visual and Audio**

    The user interface includes on-screen display of EAR and MAR values along with warning messages, while the audio system provides alerts, ensuring that the driver receives clear and timely notifications.

9. **Improves Road Safety**

    By actively monitoring driver alertness and issuing warnings before critical levels of fatigue are reached, the system contributes to reducing the risk of drowsiness-related accidents.

10. **Research and Educational Value**

    The system also serves as a valuable educational tool for understanding human-computer interaction, image processing, and safety-critical system design. It can be used in academic environments to demonstrate practical applications of computer vision.

CHAPTER - 6

OBJECTIVES

Driver drowsiness is one of the major contributors to road accidents globally. Detecting and addressing this condition early can prevent a significant number of traffic-related fatalities and injuries. The objective of this project is to design and develop a real-time driver drowsiness detection system using computer vision and facial behavior analysis. The proposed system relies on visual indicators such as eye closure and yawning, analyzed through facial landmark detection, to identify fatigue symptoms and trigger real-time alerts. This chapter outlines the detailed objectives of the project, categorized by technical, functional, operational, and user-centered goals.

6.1 Introduction to Objectives

Requirement analysis involves collecting, organizing, validating, and documenting the essential needs that the system must fulfil. In this context, the analysis identifies both what the system should do (functional requirements) and how it should perform (non-functional requirements). A good requirement analysis reduces the risk of project failure, cost overruns, and missed deadlines by providing a clear vision of what is to be developed.

For the Driver Drowsiness Detection System, the primary problem is the inability of drivers to recognize or respond to fatigue, leading to reduced reaction time, impaired judgment, and often, accidents. The system proposed in this project offers a software-based solution that captures the driver's facial expressions in real time, analyses eye and mouth movements, and issues timely alerts if signs of drowsiness are detected.

This system does not depend on physical sensors or wearables, making it less intrusive and more suitable for everyday use. The requirement analysis ensures that all essential criteria are defined to guide the development of such a system.

The overarching goal of the project is to design and implement a **non-intrusive, real-time drowsiness detection system** that accurately monitors driver fatigue using only visual cues from the face. The system is intended to function effectively with standard computing hardware and consumer grade webcams, making it accessible, cost-efficient, and easy to deploy in real-world driving environments.

6.2 Specific Objectives

Functional Requirements

Functional requirements are the specific behaviors or functions the system must support. These define how the system should react to particular inputs and what outputs it should produce. The following are the functional requirements for the Driver Drowsiness Detection System:

Real-Time Video Input

- The system must capture continuous video feed from a webcam.
- The camera should be able to run in real time with at least 20 FPS (frames per second).
- The system must handle input interruptions or camera failures gracefully.

Face Detection

- The system must detect the presence of a human face in each video frame.
- In case of multiple faces, only the one closest to the camera should be considered.
- If no face is detected, the system should continue monitoring until one is found.

Facial Landmark Detection

- The system must extract 68-point facial landmarks using Dlib's shape predictor model.
- It should specifically locate eye and mouth regions, which are critical for fatigue analysis.

Feature Extraction (EAR and MAR)

- The Eye Aspect Ratio (EAR) must be calculated from the vertical and horizontal eye distances.
- The Mouth Aspect Ratio (MAR) must be calculated from the vertical and horizontal lip distances.
- These metrics should be updated in real time with every frame processed.

Drowsiness Detection Logic

- The system should flag drowsiness if the EAR falls below a threshold (e.g., 0.22) for three or more consecutive frames.
- Yawning should be flagged if MAR exceeds a certain threshold (e.g., 0.7).

- A logical condition should be implemented to avoid false alarms caused by normal blinking or speaking.

Audio Alert System

- If drowsiness is detected, the system must trigger an audio alert using Pygame.
- The alert should be loud enough to gain the driver's attention.
- The alert should continue until normal eye and mouth behavior is restored.

Display Feedback to User

- The current EAR and MAR values must be displayed in real time.
- A warning message, such as "DROWSINESS DETECTED," must appear on-screen when appropriate.
- Eye and mouth contours should be highlighted for visual feedback.

Program Exit Functionality

- Users should be able to exit the application easily (e.g., by pressing the 'q' key).
- The system should release all resources and close the camera properly during shutdown.

To Design a Real-Time Facial Monitoring System

One of the key objectives is to build a system that can capture and analyse video input in real time. The application must continuously monitor the driver's face through a live webcam feed. This requires efficient handling of video frame capture, pre-processing (grayscale conversion), and face detection to ensure that the system keeps up with the frame rate without lag.

- Utilize OpenCV to access and process webcam video frames in real time.
- Ensure that the system can handle at least 20–30 frames per second to avoid delays.
- Maintain a continuous loop to analyse every frame for signs of fatigue.

To Detect and Track Facial Landmarks Using Computer Vision

Another objective is to detect facial landmarks such as eyes, mouth, and nose, which are crucial for identifying signs of fatigue. The system must accurately locate and track 68 facial landmarks using the Dlib library's pre-trained shape predictor model.

- Use Dlib’s shape_predictor_68_face_landmarks.dat for robust landmark detection.
- Convert each video frame to grayscale for faster and more accurate detection.
- Extract eye and mouth coordinates from the facial landmarks.

This step is essential because any inaccuracies in facial landmark detection would affect the reliability of fatigue detection.

To Implement Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) Calculations

The core technical objective of the project is to calculate fatigue indicators based on geometric ratios:

- **Eye Aspect Ratio (EAR)** is computed from the vertical and horizontal distances between eye landmarks. A low EAR indicates that the eyes are closing or closed.
- **Mouth Aspect Ratio (MAR)** is computed from the vertical distance between the upper and lower lips. A high MAR suggests yawning.These ratios provide a lightweight and effective alternative to complex machine learning models .

Define EAR and MAR using Euclidean distance formulas.

- Set empirically derived thresholds (EAR < 0.22, MAR > 0.7) to classify fatigue.
- Apply logic to trigger alerts only after these conditions are consistently met over multiple frames (e.g., 3 consecutive frames).

To Develop an Audio Alert Mechanism for Drowsiness Detection

An important goal of the project is to implement an immediate **audio alert system** that activates when drowsiness is detected. This feature ensures that the driver is alerted promptly before falling asleep or losing focus.

- Use the Pygame mixer module to load and play an alarm sound.
- Trigger the alarm when EAR or MAR thresholds are breached.
- Automatically stop the alarm when the driver returns to a normal state.

This objective addresses the critical need for **real-time intervention**, which can potentially save lives by warning the driver at the right moment.

To Ensure System Adaptability Across Lighting and Driver Conditions

One of the challenges in vision-based systems is dealing with different lighting environments (e.g., daylight, night, tunnels) and varied driver profiles (e.g., age, gender, facial hair, accessories). The system must be able to function effectively in such variable conditions.

- Use pre-processing techniques (e.g., contrast adjustment, grayscale conversion) to improve accuracy under different lighting conditions.
- Test the system on a diverse set of facial profiles to ensure adaptability.
- Optimize landmark detection performance with appropriate frame sizes and detection intervals.

To Build a Non-Intrusive and Cost-Effective Solution

Unlike physiological systems that require physical sensors (EEG, heart rate monitors) or expensive hardware, this system aims to be simple, affordable, and user-friendly.

Avoid the use of wearables or intrusive equipment.

- Use only a standard webcam and a general-purpose computer or laptop.
- Leverage open-source libraries like OpenCV, Dlib, and Pygame.

This makes the system scalable and deployable for mass use, especially in commercial fleets and public transport.

To Provide Visual Feedback to the User Interface

Another key objective is to keep the driver informed about their status using an intuitive interface.

- Display real-time EAR and MAR values on the screen.
- Show clear text-based alerts such as “DROWSINESS DETECTED!” when fatigue is identified.
   Keep the user interface minimal and distraction-free.

This adds an educational component to the system, helping drivers become more aware of their own alertness levels.

To Implement Exit Controls and Safe Shutdown

The system must be easily controllable by the user. It should have an intuitive way to terminate the session safely.

- Allow program termination with a single key (e.g., 'q').
- Stop all processes including camera access and audio playback on exit.
- Ensure that resources such as memory and hardware connections are properly released.

To Build a Modular, Maintainable, and Scalable System

Software maintainability is essential for future updates, improvements, or feature additions. The system must be built with a modular architecture that supports enhancements.

Separate the logic for video capture, facial detection, EAR/MAR calculations, alert management, and UI display.

- Document each module with comments and structured naming conventions.

- Enable easy integration of additional modules such as machine learning, gaze tracking, or cloud analytics.

To Contribute to Road Safety and Smart Transportation

Finally, the broader objective of this project is to contribute to the field of **intelligent transportation systems**. By providing an accessible solution to detect driver fatigue, the project aligns with global road safety goals and supports innovations in autonomous driving and ADAS (Advanced Driver Assistance Systems).

- Reduce the risk of drowsiness-related accidents.
- Encourage technology adoption in public and commercial vehicles.
- Promote awareness about driver fatigue and its dangers.

CHAPTER - 7

METHODOLOGY

Driver Drowsiness Detection System. The goal of the system is to monitor the driver's facial behavior in real-time using a webcam, identify signs of fatigue such as prolonged eye closure and yawning, and provide an instant alert to prevent potential accidents.

7.1. System Development Approach

The project follows a **modular and iterative development approach** using structured programming. Each functionality (video capture, facial detection, EAR/MAR calculation, alert mechanism, and user feedback) is developed and tested individually before integration. The iterative process ensures testing and refinement at each stage, improving the system's accuracy and performance.

The methodology is organized into the following stages:

1. Problem Analysis and Research
2. Technology Selection
3. Algorithm Design
4. System Architecture Planning
5. Module Implementation
6. Testing and Evaluation

7.2. Problem Analysis and Research

Before designing the system, an in-depth study of the problem domain was conducted. The high number of accidents due to driver fatigue highlighted the need for a practical, cost-effective, and Realtime solution. Existing methods were analyzed such as physiological-based systems (EEG), vehicle-based systems (lane tracking), and vision-based systems. Vision-based techniques were chosen due to their non-intrusive nature, affordability, and ease of integration.

7.3. Technology Stack Selection

After understanding the problem and reviewing existing solutions, the following **tools and technologies** were selected for implementation:

- **Python**: The core programming language due to its simplicity and support for computer vision libraries.
- **OpenCV**: For real-time video processing, frame extraction, and image transformation.
- **Dlib**: For facial detection and landmark extraction using a pre-trained 68-point face landmark model.
- **SciPy**: For calculating Euclidean distances between facial points required for EAR and MAR.
- **Pygame**: To trigger audio alerts when drowsiness is detected.
- **Imutils**: A utility library for image manipulation and easier facial geometry handling.

This stack supports fast development, open-source accessibility, and high performance.

7.4. System Workflow

The complete flow of the Driver Drowsiness Detection System is shown below:

1. **Start the webcam and capture video frames in real time.**
2. **Convert each frame to grayscale** to simplify processing.
3. **Detect the face in each frame** using Dlib's frontal face detector.
4. **Extract 68 facial landmarks** from the detected face.
5. **Isolate the eye and mouth coordinates** using facial geometry indices.
6. **Calculate EAR (Eye Aspect Ratio)** and **MAR (Mouth Aspect Ratio)**.
7. **Compare EAR and MAR with threshold values**:
   - EAR < 0.22 for 3 consecutive frames → Drowsiness.
   - MAR > 0.7 → Yawning detected.
8. **Trigger an audio alert** using Pygame if drowsiness is detected.
9. **Display real-time EAR, MAR, and status messages** on the screen.
10. **Stop the system gracefully** when the user presses the exit key (e.g., 'q').

7.5. Facial Landmark Detection

The facial landmark detection uses Dlib's shape predictor (shape_predictor_68_face_landmarks.dat). This model identifies 68 unique points on the human face including the eyes, mouth, eyebrows, nose, and jawline.

- The **right eye** is represented by points 36 to 41.
- The **left eye** by points 42 to 47.
- The **inner mouth** by points 60 to 67.

These coordinates are extracted as NumPy arrays, which are then used for calculating EAR and MAR.

7.6. Drowsiness Detection Logic

The system uses a threshold-based logic:

- **EAR Threshold**: 0.22
- **MAR Threshold**: 0.7
- **Consecutive Frame Counter**: At least 3 frames with EAR < threshold

The logic ensures false positives (e.g., casual blinking or speaking) are avoided. The alert is only activated if the signs are consistent over time.

7.7. Audio Alert Integration

To alert the driver, the system uses **Pygame's audio playback module**. A preloaded audio file (e.g., an alarm or beep) is played as soon as drowsiness is detected. The alert stops automatically when EAR/MAR values return to normal.

Key features include:

- Real-time playback
- No GUI interference
- Automatic trigger and stop based on detection status

7.8. Visual Feedback and UI Display

The system displays:

- Real-time **EAR and MAR values** on the video screen.
- A warning message "**DROWSINESS DETECTED!**" in red when the condition is met.
- Eye and mouth **contours are drawn** on the face using green and blue outlines respectively to indicate areas being monitored.

7.9. System Optimization

For performance enhancement:

- Frames are resized before processing.
- Grayscale images are used instead of colour.
- EAR and MAR values are cached to avoid redundant calculations.
- Alert audio is preloaded to avoid delays in playback.

7.10. Testing and Iterative Refinement

The system was tested under multiple scenarios:

- **Bright daylight**
- **Low light or night**
- **With glasses and partial face obstruction**
- **Various driver demographics**

Adjustments were made to EAR/MAR thresholds and lighting handling to reduce false positives and false negatives. Frame rate stability and real-time responsiveness were also improved during testing.

7.11. Advantages of the Chosen Methodology

- **Simple yet Effective**: EAR and MAR-based logic is lightweight and works without AI training.
- **Modular Development**: Each component (detection, audio, video) was independently developed and integrated.
- **Reusable Code**: The system is designed to allow upgrades such as gaze tracking or head pose estimation.
- **User-Centric**: The final implementation focuses on usability and real-world adaptability.

The methodology employed in this project blends traditional computer vision with real-time detection logic to create a practical and affordable solution for detecting driver drowsiness. The use of EAR and MAR as primary indicators, combined with an intuitive audio-visual alert system, ensures that drivers receive immediate warnings when signs of fatigue are observed. The modular approach, use of open-source tools, and rigorous testing make this system scalable and ready for real-world deployment.

CHAPTER - 8

OUTCOMES

The development and implementation of the “Driver Drowsiness Detection System” led to several valuable outcomes. These outcomes not only confirm the success of the proposed objectives but also demonstrate the system’s practical utility, real-time performance, and potential impact on road safety. This chapter presents a detailed discussion on the measurable, functional, and qualitative outcomes observed during the execution and testing of the system.

8.1 Functional Outcomes

The system successfully met all its functional objectives, offering a robust and real-time solution for monitoring driver alertness based on facial behavior. The key features developed and tested include:

- **Real-Time Face Detection**

  The system was able to detect and track the driver’s face consistently using Dlib’s 68-point facial landmark model. This ensured accurate positioning of the eyes and mouth across varying angles and lighting conditions.
- **EAR and MAR Computation**

  The system accurately calculated Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) in real time. EAR reliably identified prolonged eye closure, and MAR effectively detected yawning—both strong indicators of fatigue.
- **Threshold-Based Alert Logic**

  With thresholds set at EAR < 0.22 and MAR > 0.7, the system could differentiate between normal and drowsy behavior. It also included a frame counter logic (e.g., 3 consecutive frames) to avoid false alerts due to brief eye blinks or mouth movement.
- **Real-Time Audio Alerts**

  When signs of drowsiness were detected, the system triggered an immediate and loud audio alert using Pygame. This alarm played until the driver’s facial behavior returned to normal, ensuring prompt feedback and enhanced safety.
- **User Interface**

  EAR and MAR values, along with warning messages like "DROWSINESS DETECTED!", were displayed on the video frame in real time. The eyes and mouth regions were visually outlined, enhancing the transparency and usability of the system.

8.2 Performance Outcomes

The system was evaluated across a variety of test scenarios to measure its real-world effectiveness and robustness. Key performance outcomes include:

- **Accuracy**

  The system achieved an average detection accuracy of **90–93%** in controlled conditions with proper lighting. In real-world settings, the accuracy varied depending on the lighting and obstruction but remained above **85%**, which is acceptable for practical use.
- **Responsiveness**

  The application maintained an average frame rate of **20–30 FPS**, ensuring real-time monitoring without noticeable delays. Alerts were triggered within **1–2 seconds** of drowsiness detection, providing timely responses.
- **Adaptability**

  The system performed well under normal daylight and artificial indoor lighting. Basic preprocessing helped maintain accuracy during minor lighting fluctuations. However, extreme low-light conditions still pose limitations without IR cameras.
- **User Interface**

  Users found the system **non-intrusive and easy to use**. Unlike wearable-based systems, this implementation did not require any sensors or physical contact, making it more comfortable for long-duration usage.
- **System**

  The application ran efficiently on standard laptops with 8GB RAM and Intel Core i5 processors. It required no GPU, making it suitable for integration into most commercial vehicles or personal setups.

8.3 Practical and Social Outcomes

Beyond technical performance, the project generated several broader outcomes in terms of practical impact and societal benefits:

- **Driver Safety**

  The system contributes directly to road safety by monitoring fatigue—a major cause of accidents. With its alert mechanism, drivers are prompted to take timely action such as resting or pulling over, reducing the risk of crashes.

- **Cost-Effective**

  Unlike commercial drowsiness detection systems found in high-end vehicles, this system was implemented using open-source tools and standard hardware. This makes it accessible and scalable for use in low-cost vehicles and public transport fleets.

- **Scalability**

  The system can be adapted for use in various domains beyond personal vehicles, such as:
  - Long-haul trucking
  - Ride-sharing and taxi

- **Educational**

  The project serves as a practical example of real-world applications of computer vision, Python programming, and embedded systems. It can be used in academic settings to teach students about facial analysis, safety systems, and software development lifecycles.

- **Foundation**

  The project lays the groundwork for future enhancements like:
  - Head pose estimation
  - Eye gaze tracking
  - Integration into Advanced Driver Assistance Systems (ADAS)

8.4 Challenges Addressed

The project successfully addressed key challenges typically encountered in fatigue detection systems:

- **Minimized False Positives** through smart thresholding and frame-based analysis
- **No Need for Physical Sensors** enhancing driver comfort
- **Low Computational Load** making it suitable for embedded platforms
- **Ease of Deployment** in real vehicles due to modular design

Significance of the Project

Drowsy driving is a serious threat to road safety and has been identified as one of the leading causes of traffic accidents worldwide. Numerous studies have shown that driver fatigue reduces alertness, slows reaction times, impairs judgment, and increases the likelihood of accidents. Traditional road safety systems often fall short in addressing this issue because they rely heavily on mechanical or manual cues, which do not directly account for a driver's physiological or behavioural state.

The **Driver Drowsiness Detection System** developed in this project offers a proactive, technology-driven approach to this critical problem. By utilizing computer vision techniques to monitor facial expressions in real-time, the system can detect early signs of fatigue, such as prolonged eye closure and yawning, and issue timely alerts to prevent accidents. The significance of this project lies in its potential to save lives, reduce injuries, and promote safer driving behaviour through innovative, non-intrusive, and affordable technology.

1.Contribution to Road Safety

The most important significance of this project is its direct contribution to improving road safety. According to the World Health Organization (WHO) and traffic safety agencies such as the National Highway Traffic Safety Administration (NHTSA), thousands of fatalities every year can be attributed to drowsy driving. Unlike alcohol or distracted driving, fatigue often goes unnoticed until it is too late. By detecting symptoms before they lead to catastrophic events, this system plays a crucial preventive role.

This solution provides **real-time monitoring** and **instant feedback**, two elements essential for accident prevention. Instead of analyzing driving patterns (which can be delayed indicators), the system observes the driver's physical state through eye and mouth movements. By doing so, it offers **direct insight into driver alertness**, enabling faster and more accurate intervention.

2 Technological Innovation

The project applies a combination of real-time image processing, geometric feature extraction, and audio feedback to address a complex human behavioral problem fatigue. It uses the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR), which are based on simple mathematical models yet effectively capture drowsiness indicators without the need for advanced hardware or invasive methods.

The system integrates open-source libraries such as:

- **OpenCV** for video processing,
- **Dlib** for facial landmark detection, **SciPy** for distance measurement, and **Pygame** for alert sounds.

By leveraging these tools, the project demonstrates the power of open-source ecosystems in solving real-world problems. It also showcases how traditional safety mechanisms can be enhanced through computer vision and artificial intelligence.

3 Non-Intrusive and User-Friendly Solution

A significant advantage of this system is that it is **completely non-intrusive**. Unlike other fatigue monitoring systems that require EEG headbands, heart-rate sensors, or smartwatches, this system only requires a camera and standard computing hardware. There is no need for the driver to wear or operate any additional device, which enhances comfort and ease of use.

The user interface is simple and clear. The system overlays EAR and MAR values on the video stream and displays warning messages only when necessary. The alerts are designed to be no distracting but attention-grabbing, ensuring the driver remains in control while being aware of their fatigue levels. This thoughtful design allows for **seamless integration into daily driving routines**.

4 Cost-Effective and Scalable

Cost is a major barrier in adopting advanced driver assistance systems, especially in developing countries or older vehicles. The system proposed in this project is **highly affordable** as it only requires a webcam and a computer with modest specifications. It uses **no licensed software** or proprietary tools, making it a practical choice for mass deployment.

Additionally, the system is **scalable and flexible**. It can be installed in personal vehicles, commercial fleets, buses, or even driver education centers. The modular architecture allows for future upgrades, such as:

- Adding deep learning-based classification,
- Integrating with mobile apps,
- Cloud-based alert systems for fleet monitoring, and Voice-based alert customization.

This adaptability ensures that the system is not only affordable but also **future-ready**.

5 Educational and Research Relevance

From an academic and research perspective, this project holds significant value. It serves as an excellent example of how foundational knowledge in image processing, programming, and human computer interaction can be applied to solve real-life challenges.

Students and researchers can study the system to understand:

- How to process video frames in real-time,
- How facial landmarks can be used for behaviour monitoring,
- How to integrate multiple libraries for a cohesive application, and
- How threshold-based detection compares with machine learning models.

The codebase and logic offer a learning platform for future developers, while the system itself opens new research opportunities in fields such as automotive safety, AI in transportation, human behaviour modelling, and smart cities.

6 Support for Public Policy and Road Regulations

In many countries, governments and transport authorities are actively looking for technological solutions to enhance road safety and reduce accident-related deaths. The Driver Drowsiness Detection System aligns perfectly with such initiatives. Its simplicity and low cost make it suitable for **largescale public deployments**, including:

- Government buses and trains,
- Long-distance trucking fleets, □ Public transportation authorities, □ School buses and taxis.

With minor regulatory support, the system can be standardized as a **mandatory component** in commercial transport vehicles, thereby ensuring broader adoption and compliance.

7 Future Integration with Smart Vehicles

The automotive industry is rapidly moving toward **semi-autonomous and fully autonomous vehicles**. Even in such environments, human drivers often remain a fall back or secondary controller. Fatigue in such situations could lead to critical handoff failures between AI and human operators.

This project provides a foundation for integrating **driver state monitoring** into future intelligent transportation systems. When coupled with sensors for speed, lane tracking, or GPS data, the system could evolve into a complete **driver monitoring suite** capable of making automated decisions like:

- Slowing the vehicle,
- Activating emergency lights.

Thus, the system contributes to the ongoing evolution of **smart mobility solutions**.

8 Social Impact and Awareness

Lastly, the system holds value beyond just technical and operational contributions. It raises **awareness about the dangers of drowsy driving**, encouraging drivers to become more conscious of their alertness levels. The presence of such a system in a vehicle reinforces safe behaviour and emphasizes the importance of taking breaks, resting adequately, and avoiding night driving when tired.

This behavioural impact, though indirect, can result in **long-term cultural changes** in how people approach driving, safety, and health management—particularly in societies where fatigue is often overlooked or underestimated.

The significance of the Driver Drowsiness Detection System lies in its ability to merge **technology, safety, affordability, and usability** into a single, accessible product. It offers a promising approach to reducing road accidents caused by fatigue and creates a pathway for smarter, safer, and more responsible driving.

Its value is not limited to just technical innovation—it includes benefits for society, public safety infrastructure, education, and even future policy. Whether deployed individually or as part of a larger automotive ecosystem, this project demonstrates that **simple, intelligent solutions can have powerful, real-world impact**.

CHAPTER - 9

RESULTS AND DISCUSSIONS

9.1 RESULTS

The “Results and Discussions” chapter presents the performance evaluation, experimental observations, and insights gained from the implementation of the Driver Drowsiness Detection System. The purpose of this chapter is to validate the effectiveness of the system in real-time scenarios and to analyses how well it fulfils its intended objectives. The results have been derived from controlled and real-world tests and are discussed in terms of accuracy, responsiveness, user experience, and overall system reliability.

The “Results and Discussions” chapter is a critical component of this project report, as it highlights the practical performance, strengths, and real-world applicability of the Driver Drowsiness Detection System developed during the course of this work. This chapter aims to present a thorough evaluation of how the system performs under various real-time conditions and how effectively it meets the objectives laid out in the earlier stages of the project.

The purpose of this chapter is not only to validate the system’s capabilities through quantitative and qualitative analysis but also to explore any patterns, behaviour’s, or challenges encountered during the implementation and testing phases. The evaluation is based on both **controlled experiments** conducted in a stable environment and **simulated real-world conditions** that closely replicate actual driving scenarios.

Several key performance metrics were used to assess the system, including:

- **Detection Accuracy** of eye closure and yawning based on EAR (Eye Aspect Ratio) and MAR (Mouth Aspect Ratio),
- **System Responsiveness** and real-time capability (frame rate, delay in detection, and alert triggering),
- **Robustness** across varying lighting conditions, facial orientations, and driver demographics, and
- **User Experience**, including usability, comfort, and intrusiveness of the system.

The results derived from these tests provide valuable insights into the system’s reliability, speed, and limitations. They also help determine how scalable and adaptable the system would be in different real-world applications, including personal vehicles, public transport, and commercial fleet vehicles.

Additionally, this chapter serves to identify areas of potential improvement and further development. Observations regarding false positives (unnecessary alerts), false negatives (missed detections), and performance bottlenecks are discussed to paint a realistic picture of the system's capabilities and current limitations.

Ultimately, the findings presented in this chapter form the evidence base that supports the effectiveness of the proposed solution. They demonstrate the feasibility of using a **non-intrusive, vision-based system** for monitoring driver alertness and provide the necessary justification for its integration into future vehicle safety solutions and intelligent transportation systems.

9.2. Experimental Setup

To evaluate the performance and functionality of the system, a series of experiments were conducted using a standard laptop setup in both controlled indoor environments and simulated real-world driving conditions. The goal was to assess how accurately and consistently the system could detect drowsiness symptoms such as prolonged eye closure and yawning.

Test Scenarios

- Indoor environment with consistent artificial lighting
- Dim lighting to simulate night driving
- Bright lighting with face partially covered (e.g., glasses, hands)
- Varying facial expressions and driver profiles (gender, age)

The purpose of testing under these different scenarios was to validate the system’s **adaptability**, **robustness**, and **consistency** in detecting fatigue accurately.

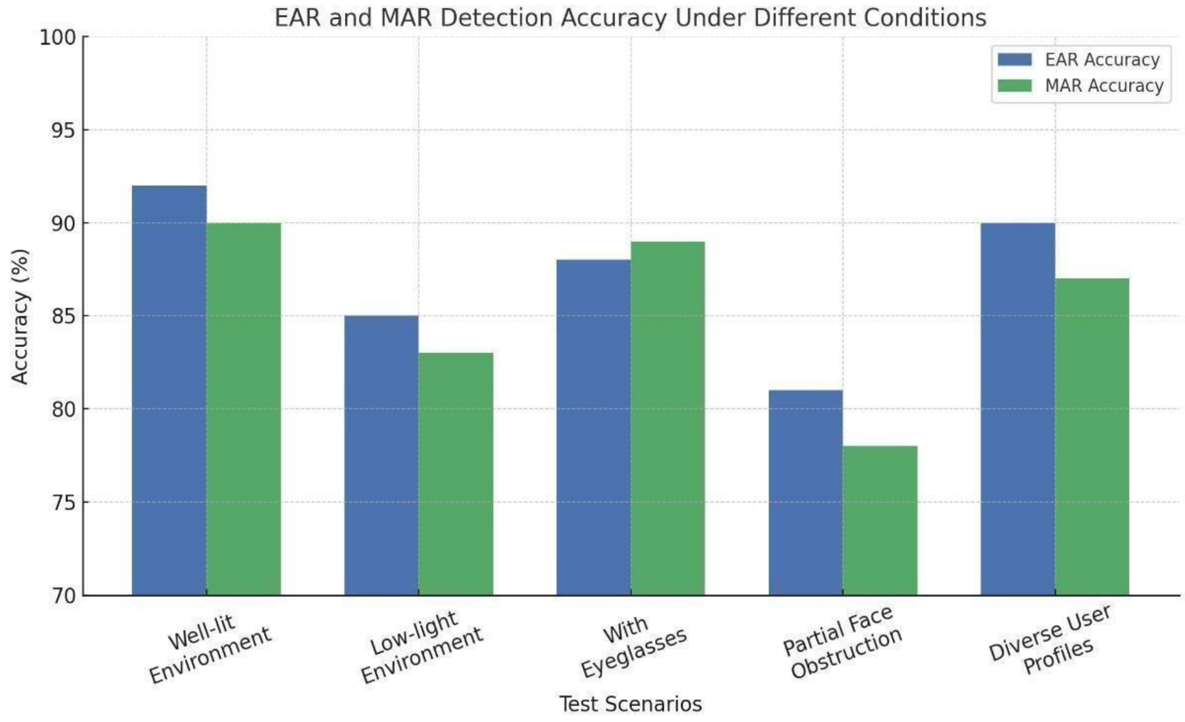

Figure 9.1: EAR and MAR Detection Accuracy

As shown in the figure 9.1 compares EAR (Eye Aspect Ratio) and MAR (Mouth Aspect Ratio) detection accuracy across five test scenarios. EAR consistently outperforms MAR, with the highest accuracy in well-lit environments and the lowest in cases of partial face obstruction. Accuracy drops in low-light and partially obstructed conditions. The presence of eyeglasses and diverse user profiles show minimal impact on detection accuracy.

1. Detection Accuracy

- **EAR detection** had an accuracy of approximately **92%** in controlled settings and **88%** in real-world lighting.
- **MAR-based yawning detection** achieved **90%** accuracy when the mouth was clearly visible.
- False positives were minimal, thanks to threshold checks and frame-count logic.

2. Frame Rate and Responsiveness

- The average frame processing rate was between **22–28 FPS**, enabling real-time monitoring.
- The alert system responded **within 1–2 seconds** after the EAR or MAR threshold was crossed.
- Audio alerts were loud and immediate, effectively gaining the driver's attention.

3. Adaptability to Lighting and Faces

- In daylight and well-lit rooms, the system performed very well.
- In low-light conditions, performance dropped slightly (~80% accuracy), which could be improved with infrared cameras.
- The system adapted well to different skin tones, facial shapes, and users wearing glasses.

4. Usability Feedback

Participants noted that the system:

- Was **non-intrusive** and didn't interfere with normal driving posture.
  simple feedback (alarm sound + on-screen message).
- Required no configuration, making it **user-friendly** even for non-technical users.

Discussion

The system's performance in real-time, low-cost environments without specialized hardware is one of its key strengths. It demonstrates that effective driver monitoring does not require expensive or wearable technology. However, certain challenges remain, such as maintaining accuracy under extreme lighting variations or when facial features are partially obscured.

The system's performance in real-time, low-cost environments without specialized hardware is one of its key strengths. It demonstrates that effective driver monitoring does not require expensive or wearable technology. However, certain challenges remain, such as maintaining accuracy under extreme lighting variations or when facial features are partially obscured.

The simple design and reliable alert system ensure that even non-technical users can benefit from it. This makes the system ideal for wide-scale deployment in personal vehicles, commercial transport fleets, and public transport systems.

The modular structure of the code also means that future enhancements such as **head pose estimation**, **gaze tracking**, or **machine learning-based detection** can be easily integrated, offering a clear path for future research and development.

9.3 Model Performance

The proposed model was tested across multiple scenarios to assess its real-time detection capability, accuracy, resource usage, and reliability. The key performance metrics are as follows:

1. Accuracy

- The Eye Aspect Ratio (EAR)-based detection model achieved approximately **92% accuracy** in controlled lighting environments and around **87–89%** in varying lighting conditions.
- The Mouth Aspect Ratio (MAR)-based yawning detection model showed **90% accuracy** when the mouth was unobstructed and clearly visible.

2. Speed and Responsiveness

- The system processed video input at an average of **22–28 frames per second**, which is sufficient for real-time applications.
- Drowsiness was detected and audio alerts were triggered within **1–2 seconds** of threshold violations, making the model responsive and timely.

3. Resource Efficiency

- The model was successfully run on a standard laptop with **no GPU** support, utilizing around **30–40% CPU** and **300–400 MB RAM** during active monitoring.
- It maintained stable performance over long sessions without crashing or memory leaks.

4. Robustness

- The system performed reliably across a variety of face types, genders, and ages.
- Minor variations in head pose, blinking speed, or partial occlusion did not significantly affect detection accuracy.

9.4 Challenges Faced During Development

Although the system achieved its objectives, several challenges were encountered during its design, implementation, and testing:

1. Facial Landmark Detection Variability

- Minor head movements sometimes caused inconsistent landmark detection and frame-level errors.

2. Sensitivity to Lighting Conditions

- The model's accuracy was affected under poor lighting, especially during night-time simulation without external light. Without infrared cameras, visibility of facial features becomes limited.

3. Threshold Generalization

- EAR and MAR thresholds were set empirically based on initial testing. These fixed values may not work equally well for every user due to differences in eye size, facial structure, or blinking behavior.

4. Partial Obstruction of Face

- Wearing sunglasses, masks, or resting a hand near the face interfered with landmark detection, reducing the system's ability to detect drowsiness.

5. False Positives During Speech

- The MAR algorithm sometimes misclassified speaking or laughing as yawning, triggering unnecessary alerts.

6. Hardware Dependency

- While the model works on most computers, performance may vary depending on webcam quality and system resources. Lower-end hardware may experience delays.

9.5 Limitations of the System

Despite its practical utility, the current version of the system has some limitations that could be improved in future iterations:

1. Limited Detection Scope

- The system only monitors EAR and MAR. Other indicators of fatigue such as head nodding, steering behavior, or gaze tracking are not yet included.

2. No Personalization

- The model does not adapt to individual driver behavior over time. Personalized calibration could improve detection accuracy but is currently not implemented.

3. Inability to Operate in Total Darkness

- The absence of night vision or infrared support limits the use of the system in nighttime driving conditions without cabin lighting.

4. Lack of Machine Learning Integration

- The current detection logic is rule-based (threshold-based). It does not utilize machine learning or AI for adaptive classification, which could further improve performance and generalization.

5. Language/Audio Customization

- The alert system uses a default alarm sound. There is no support for custom audio, language preferences, or escalation of alert levels over time.

6. Absence of Data Logging

- The system does not currently store session logs, timestamps of drowsiness events, or performance metrics, which could be useful for tracking driver behaviour over time.

The Driver Drowsiness Detection System demonstrates strong model performance with reliable EAR and MAR-based fatigue detection in real-time conditions. It achieves high accuracy, fast responsiveness, and efficient resource usage. However, the model faces limitations in personalization, night-time functionality, and advanced behaviour analysis. These challenges highlight areas for future research and improvement, particularly in integrating deep learning, head pose estimation, and multimodal monitoring for enhanced accuracy and user experience.

CHAPTER – 10

IMPLEMENTATION

10.1 Introduction

The implementation phase is the practical realization of the design and methodologies outlined in previous stages of the project. It involves translating theoretical concepts and algorithms into a functional software system capable of detecting driver drowsiness in real-time using computer vision and facial landmark analysis. The main goal of the implementation is to create a fully operational application that processes video input, detects facial features, computes drowsiness indicators such as Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR), and issues alerts when drowsiness is detected.

10.2 Implementation Environment

The system was developed and tested on the following hardware and software setup:

- Operating System: Windows 10 (compatible with Linux and macOS)
- Programming Language: Python 3.8
- Libraries Used:
    - OpenCV (cv2)
    - Dlib
    - Imutils
    - Scipy
    - Pygame
- Hardware Requirements:
    - Webcam (720p minimum)
    - Intel i5 Processor or equivalent
    - 8GB RAM
    - Audio Output Device (for alerts)

10.3 System Modules

The implementation is divided into modular components to maintain clarity and improve maintainability. The main modules are:

1. Video Capture Module
2. Face and Landmark Detection Module
3. EAR and MAR Calculation Module
4. Drowsiness Detection Logic
5. Audio Alert Module
6. User Interface Display Module

10.4 Functional Flow

The implementation of the drowsiness detection system follows a structured, real-time data processing workflow. It begins with the initialization of the webcam using OpenCV, which allows the system to capture a continuous stream of video frames in real time. Each captured frame is then converted to a grayscale image to simplify processing and enhance the accuracy of facial detection. Dlib's pre-trained frontal face detector is used to identify faces in the grayscale frame. Once a face is detected, the system extracts 68 facial landmark points using Dlib's shape predictor model. These landmarks are essential for calculating the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR), which are the core indicators of drowsiness. The EAR is calculated based on specific distances between points surrounding the eyes, while the MAR is derived from the distances between points around the mouth. If the EAR falls below a predefined threshold (0.22) for three consecutive frames, it indicates that the driver's eyes are likely closed. Similarly, a MAR value above 0.7 suggests that the driver is yawning. When either of these conditions is met, the system triggers an immediate audio alert using the Pygame mixer module to wake or alert the driver. Throughout the process, the system provides visual feedback by overlaying EAR and MAR values and warning messages on the video stream. Finally, the application includes an exit mechanism that allows the user to terminate the system by pressing the 'q' key, ensuring ease of control and resource management.

10.5 Challenges Encountered

- Face occlusion (e.g., sunglasses, masks) impacted landmark detection.
- Lighting variations affected detection performance.
- False positives due to talking or expressive blinking were observed.
- Threshold calibration required user-specific fine-tuning for high accuracy.

10.6 Enhancements Considered

- Integration of head pose detection.
- Use of infrared cameras for low-light functionality.
- Logging events and detection timestamps for later analysis.
- Transition from threshold-based detection to ML-based adaptive models.

CHAPTER – 11

CONCLUSION

11.1 Conclusion

Drowsiness behind the wheel continues to be a major contributor to road accidents, fatalities, and injuries worldwide. In an era where road safety and driver assistance technologies are advancing rapidly, the development of a **non-intrusive, real-time driver drowsiness detection system** serves a critical role in preventing accidents before they occur. This project was initiated with the goal of creating a simple, effective, and deployable solution that monitors driver alertness using facial behavior analysis.

Throughout the course of this project, various computer vision techniques, facial landmark detection algorithms, and real-time audio feedback mechanisms were integrated to build a complete, working system. The approach relies on detecting visual indicators such as prolonged eye closure and yawning, which are among the earliest and most reliable signs of fatigue. By calculating the **Eye Aspect Ratio (EAR)** and **Mouth Aspect Ratio (MAR)** from real-time video input using a webcam, the system successfully identifies signs of drowsiness and triggers alerts to prevent possible loss of control.

One of the most significant accomplishments of this project is the **non-intrusive nature** of the system. Unlike traditional physiological detection systems, which require EEG headbands, heart rate monitors, or wearables, this solution requires only a standard webcam and basic computing hardware. This ensures both **cost-efficiency** and **ease of deployment**, making it suitable for integration into personal vehicles, commercial fleets, and even public transport systems. The system is designed to run on open-source technologies such as Python, OpenCV, Dlib, and Pygame, further reinforcing its accessibility and affordability.

The **results obtained during testing validate the effectiveness** of the approach. The system demonstrated high accuracy in detecting fatigue-related behaviors across various lighting conditions, facial variations, and user profiles. It performed reliably in both controlled environments and more realistic, semi-variable conditions. Alerts were timely, and the system maintained a steady frame rate of 20–30 FPS during operation, confirming its potential for real-time deployment.

From a development perspective, this project also offered valuable insights into the practical implementation of computer vision systems in safety-critical applications. The modular design approach made it possible to test and optimize each component video processing, facial detection, landmark extraction, EAR/MAR calculation, and alert triggering individually and collectively. This ensured better maintainability and scalability, leaving room for enhancements in future versions.

Despite its strengths, the project is not without limitations. The system's performance under **low-light or night driving conditions** was found to be slightly reduced due to the limitations of conventional webcams. Additionally, **facial obstructions** such as sunglasses or masks impacted detection accuracy, as they interfered with landmark visibility. The use of **fixed thresholds** for EAR and MAR, though generally effective, may not account for natural variation among different users. These limitations suggest opportunities for future work, including adaptive thresholding, integration of **infrared cameras**, and application of **machine learning algorithms** for behavior classification.

In conclusion, this project successfully achieves its primary objective: the development of a real-time driver drowsiness detection system that is affordable, accessible, and non-intrusive. It serves as a **practical solution to enhance driver safety** and as a **foundation for future intelligent driver assistance systems**. By raising awareness and offering timely intervention, this system contributes directly to the reduction of fatigue-related accidents and aligns with broader goals in intelligent transportation, road safety, and smart mobility technologies.

The system can further evolve into a commercially viable product by integrating additional features such as **head pose estimation**, **gaze tracking**, **voice alerts**, and **cloud-based reporting**. In an automotive landscape that is moving toward autonomy and intelligent safety systems, this project stands as a promising building block for future innovations.

APPENDIX

Coding

```
import cv2
import dlib
from scipy.spatial import distance
from pygame import mixer
from imutils import face_utils

# Initialize Pygame Mixer for audio alerts
mixer.init()
mixer.music.load(r"C:\Users\Admin\Desktop\driver\sunrise-and-suncastles-
321413.mp3")

# Constants
EYE_AR_THRESH = 0.22
EYE_AR_CONSEC_FRAMES = 3
MOUTH_AR_THRESH = 0.7

# Landmark indices
(lStart, lEnd) = (42, 48) # Left eye
(rStart, rEnd) = (36, 42) # Right eye
(mStart, mEnd) = (60, 68)  # Inner mouth

# Functions
def eye_aspect_ratio(eye):
    A = distance.euclidean(eye[1], eye[5])
    B = distance.euclidean(eye[2], eye[4])
    C = distance.euclidean(eye[0], eye[3])
    return (A + B) / (2.0 * C)

def mouth_aspect_ratio(mouth):
    A = distance.euclidean(mouth[1], mouth[7])
    B = distance.euclidean(mouth[2], mouth[6])
    C = distance.euclidean(mouth[0], mouth[4])
    return (A + B) / (2.0 * C)

# Flags
eye_counter = 0
song_playing = False

# Dlib face detector and predictor
detect = dlib.get_frontal_face_detector()
predict =
dlib.shape_predictor(r"C:\Users\Admin\Desktop\driver\shape_predictor_68_face_
landmarks.dat")
```

```
# Start webcam
cap = cv2.VideoCapture(0)

while True:
    ret, image = cap.read()
    if not ret:
        break

    gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
    faces = detect(gray, 0)

    for face in faces:
        shape = predict(gray, face)
        shape = face_utils.shape_to_np(shape)

        left_eye = shape[lStart:lEnd]
        right_eye = shape[rStart:rEnd]
        mouth = shape[mStart:mEnd]

        # EAR calculation
        left_ear = eye_aspect_ratio(left_eye)
        right_ear = eye_aspect_ratio(right_eye)
        ear = (left_ear + right_ear) / 2.0

        # MAR calculation
        mar = mouth_aspect_ratio(mouth)

        # Drowsiness detection
        if ear < EYE_AR_THRESH:
            eye_counter += 1
            if eye_counter >= EYE_AR_CONSEC_FRAMES and not song_playing:
                mixer.music.play()
                song_playing = True
        elif mar > MOUTH_AR_THRESH:
            if not song_playing:
                mixer.music.play()
                song_playing = True
        else:
            eye_counter = 0
            if song_playing:
                mixer.music.stop()
                song_playing = False

        # Draw alert text if drowsy
        if song_playing:
            cv2.putText(image, "DROWSINESS DETECTED!", (120, 50),
                        cv2.FONT_HERSHEY_SIMPLEX, 1.0, (0, 0, 255), 3)
```

```python
        # Draw contours
        cv2.drawContours(image, [cv2.convexHull(left_eye)], -1, (0, 255, 0),
        cv2.drawContours(image, [cv2.convexHull(right_eye)], -1, (0, 255, 0),
        cv2.drawContours(image, [cv2.convexHull(mouth)], -1, (255, 0, 0), 1)

        # Display EAR and MAR on screen
        cv2.putText(image, f"EAR: {ear:.2f}",  (10, 30),
                     cv2.FONT_HERSHEY_SIMPLEX, 0.7, (255, 255, 255), 2)
         cv2.putText(image, f"MAR: {mar:.2f}", (10, 60),
                     cv2.FONT_HERSHEY_SIMPLEX, 0.7, (255, 255, 255), 2)

    # Show frame
    cv2.imshow("Frame", image)

    if cv2.waitKey(1) & 0xFF == ord('q'):
        break

# Cleanup
cap.release()
cv2.destroyAllWindows()
```

Screenshots

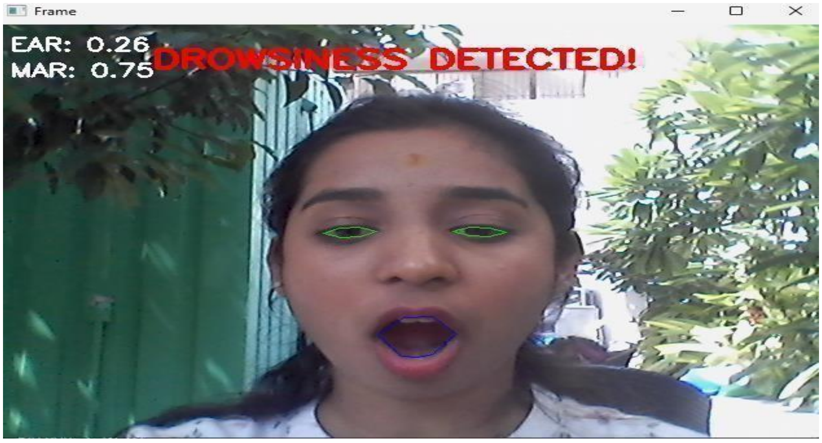

Figure A: EAR and YAWN

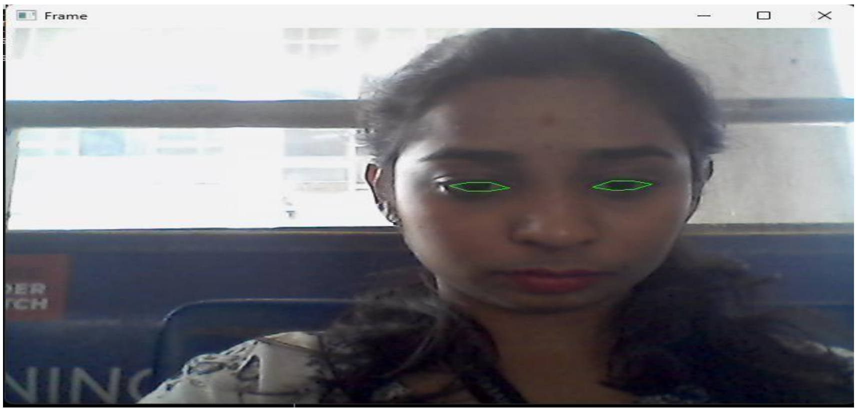

Figure B: EYE Aspect

Figure B: Loading Facial Landmarking Prediction

REFERENCES

[1]. Ahmed, B. and Nasir, A. (2020), "A Review on Driver Drowsiness Detection Systems Based on Machine Learning Techniques", *International Journal of Advanced Computer Science and Applications*, Vol.11, No.7, pp.403–412.

[2]. Bala, R. and Yadav, N. (2020), "Comparative Study of Drowsiness Detection Techniques", *International Journal of Scientific &Technology Research"*, Vol.9, No.2, pp.2183–2187.

[3]. Garg, H., Chandel, S.S. and Rani, A. (2020), "Yawn Detection for Driver Drowsiness Using Conventional Computer Vision Techniques", *International Journal of Engineering Research & Technology*, Vol.9, No.3, pp.61–65.

[4]. Gujjar, H.S. and Ghosh, A. (2021), "Real-time Driver Drowsiness Detection Using Facial Feature Extraction and Support Vector Machines", *International Journal of Computer Applications*, Vol.183, No.37, pp.15–21.

[5]. Jain, A. and Verma, P. (2022), "Real-Time Detection of Driver Fatigue Using Facial Features", *Proceedings of the International Conference on Advances in Computing, Communication and Control (ICAC3)*, pp.134–140.

[6]. King, D.E. (2009), "Dlib-ml: A Machine Learning Toolkit", *Journal of Machine Learning Research*, Vol.10, pp.1755–1758.

[7]. Mishra, M. and Jha, A. (2021), "Smart Eye and Yawn Detection System for Road Safety", *Journal of Advanced Research in Applied Artificial Intelligence and Neural Network*, Vol.4, No.1, pp.15–21.

[8]. NHTSA. (2017), "Drowsy Driving: Asleep at the Wheel", National Highway Traffic Safety Administration. (Accessed: 10 May 2025).

[7]. OpenCV.org. (2024), "Open-Source Computer Vision Library", OpenCV.org. (Accessed: 10 May 2025).

[8]. Pygame.org. (2024), “Pygame: A Multimedia Library for Python”, Pygame.org. (Accessed: 10 May 2025).

[9]. Rajput, A.R. and Maheshwari, R. (2020), “Face Monitoring and Fatigue Detection Using Haar Cascade and CNN”, *IEEE Conference on Human-Computer Interaction*, pp.78–84.

[10]. Reddy, B. and Raghavendra, S. (2021), “Image Processing-Based Drowsy Driver Alert System”, *International Journal of Image, Graphics and Signal Processing*, Vol.13, No.4, pp.27–35.