Driver Drowsiness Detection System

A PROJECT REPORT
Submitted towards the partial fulfillment of the requirements for the
Degree of B. Tech
in Computer Science and Engineering
By

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have submitted the B. Tech project report entitled **“Driver Drowsiness Detection System”** in partial fulfillment of the requirement for the degree of B. Tech in Computer Science and Engineering of Maulana Abul Kalam Azad University (formerly W.B.U.T) in the year 2025. It is hereby approved and certified as creditable study of technological subject carried out and presented in a manner satisfactory to warrant its acceptance as a prerequisite to the Degree of B. Tech in Computer Science and Engineering for which it has been submitted. It is understood that by the approval the undersigned does not necessarily endorse or approve any statement made. Opinion expressed or conclusion drawn therein but approve the report only for the purpose for which has been submitted.

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ABSTRACT

Drowsy driving is a leading cause of traffic accidents worldwide, resulting in numerous fatalities and injuries. To mitigate this risk, a robust Driver Drowsiness Detection System is developed using Machine Learning and Computer Vision techniques. The proposed system continuously monitors the driver's face, eye, and mouth movements to identify early signs of fatigue and prevent potential accidents.

The method utilizes state-of-the-art facial landmark detection algorithms by employing OpenCV and MediaPipe to extract critical facial features such as eyes and mouth. Specifically, the system computes two important metrics: the **Eye Aspect Ratio (EAR)**, to detect prolonged eye closure, and the **Mouth Aspect Ratio (MAR)**, to detect yawning — both of which are reliable indicators of driver fatigue. If the EAR falls below or the MAR rises above predefined threshold values for a sustained number of frames, the system classifies the driver as drowsy or fatigued.

Operating in real-time, the system processes video frames captured from a camera mounted inside the vehicle. Leveraging machine learning models trained on datasets of facial features ensures the detection mechanism remains precise and responsive. Upon detecting drowsiness or yawning, an audible alert is immediately triggered to prompt the driver to regain attention.

The proposed system offers an advanced, non-intrusive solution that can be seamlessly integrated into modern vehicles, thereby reducing the risk of accidents through timely and life-saving intervention.

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Chapter-1

Introduction

1.1 **Introduction**

Currently, transport systems are an essential part of human activities. We all can be victim of drowsiness while driving, drowsy driving has been reported to be one of the major contributors to accidents on the roads worldwide, causing numerous casualties in the form of serious injuries and death. With the growing use of personal and commercial vehicles, the risks of accidents due to driver drowsiness are increasingly emerging.

Research studies have shown that a driver who is drowsy has decreased reaction speed, lower levels of observation, and poor judgment capabilities, which results in extremely catastrophic outcomes for drivers on the roads. Various studies have suggested that around 20% of all road accident are fatigue related. drowsy driving caused 29,834 traffic fatalities between 2017-2021, with 6,726 occurring in 2021 alone According to data from AAA's [1].Addressing this issue is important not only for the safety of individuals but also for the economy which is battered by accidents.

The Driver Drowsiness Detection System tackles this challenge with more advanced technologies such as Python, Machine Learning (ML), and Computer Vision. It focuses on monitoring the driver's eye movements in real-time to detect early signs of fatigue and alert them before an accident happens. The system, designed on state-of-the-art algorithms Like MediaPipe's facial landmark detection, is highly accurate and efficient and non-intrusive, making it ideal for seamless integration into modern vehicles.

This project focuses on mitigating road accidents caused by drowsy driving through a detection system using Machine Learning and Computer Vision. By monitoring eye movements in real-time, the system identifies early signs of fatigue, aiming to reduce fatalities and injuries on the road.

1.2 **Motivation**

Drivers who operate vehicles at night, whether they are truck drivers transporting goods, cab drivers ensuring passengers reach their destinations, or emergency service drivers working tirelessly to save lives, face unique challenges. Night driving increases the risk of accidents due to reduced visibility and heightened fatigue, with truck drivers being especially vulnerable due to the extended hours they spend on the road. Statistics consistently show that truck-to- truck collisions are among the most frequent and devastating types of nighttime accidents.

Our **Driver Drowsiness Detection System** is designed with these realities in mind. While prioritizing **Heavy Vehicles drivers** due to their critical role and higher risk, the system is versatile enough to benefit all night-time drivers. It uses advanced technologies like Python, machine learning, and computer vision to continuously monitor signs of fatigue and inattentiveness, such as prolonged eye closure. By providing timely alerts, it acts as a life-saving intervention before an accident occurs. The motivation behind this project is to make advanced safety accessible to everyone, whether they are transporting. whether they are transporting goods or carrying passengers. This inclusivity ensures safer roads for everyone.

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Chapter-2

Related Work

2.1 **Related Work**

In this section, we discuss various methodologies that have been proposed by researchers for drowsiness detection during the recent years. Strengths and weaknesses have been identified for each technique and suggestions are given for their improvement in future.

Flores et al. [2] (2009) contributed to the field with a component of an Advanced Driver Assistance System (ADAS) that used artificial intelligence and visual data. This system monitored multiple driver behaviors, such as yawning, and eye blinks, offering a more comprehensive detection approach. While it performed well under changing light conditions, it occasionally generated false alarms, highlighting the need for further refinement. Similarly, Vitiable et al. [3] (2011) introduced a system that employs infrared light to create a bright-pupil effect, an 850nm infrared light source is fixed on the car dashboard causing a bright pupil effect. This makes eye detection easier as the eye’s retina has a property of reflecting 90% of the light incident on it. Drowsiness state is identified when the eyes are more than 80% closed for a certain period of time making eye detection straightforward. Their approach, implemented with Field Programmable Gate Array (FPGA) technology, enabled rapid image processing for real-time drowsiness detection. However, the method encountered difficulties when dealing with reflective glasses or other objects that interfered with the infrared signal. Mandeep and Gagandeep [4] (2012) proposed a method that uses the mean sift algorithm to detect eye blinks in real-time with a standard webcam resolution of 640x480. This system triggers an alarm if the eyes remain closed for a specific duration by comparing real-time eye- opening data against a predefined threshold. While the system achieved an impressive accuracy of 99%, it required retaining past frame data and struggled under poor lighting or when drivers wore glasses. Chuang-Wen et al. [5] (2013) presented an innovative smartphone application called “Car Safe”, which used dual cameras one for monitoring the driver’s face and another for assessing the vehicle's surroundings. The app evaluated eye blinks, and the proximity to other vehicles to detect drowsiness. Although portable and practical, the system achieved only 83% precision and faced challenges with varying face orientations. Sahayadhas et al. [6] (2013) explored physiological signal-based measures like EOG (Electroculogramsignal that measures cornea-retina potential difference) to detect eye movements to determine driver drowsiness. This approach provided accurate results by analyzing internal physiological states but was intrusive and less practical for non-invasive real-time use.

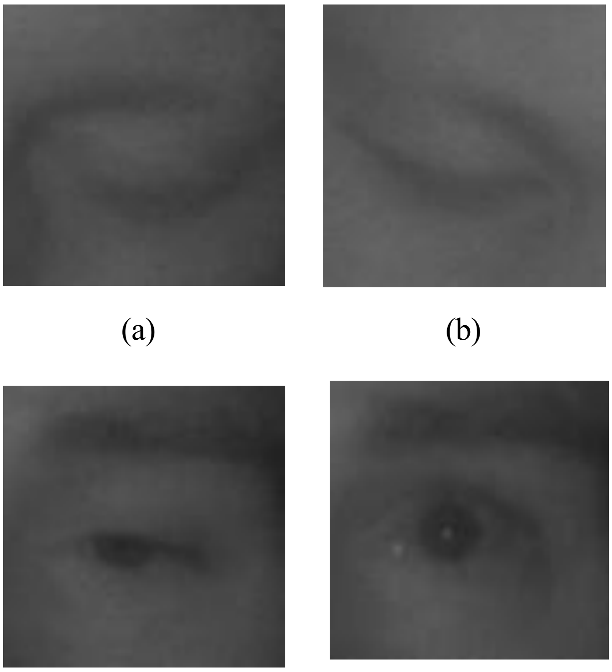
The related work includes various methodologies for drowsiness detection that have been proposed, including AI-based systems, infrared light technology, real-time eye blink detection, smartphone apps, and physiological signal analysis, each with strengths, limitations, and areas for improvement.

Chapter-3

Proposed Work

3.1 Dataset

The dataset utilized in this project is specifically curated for the development of a drowsiness detection system. It consists of two categories of labelled images:



(a) (b) (c) (d)

Fig 1: Show the input for training the model (a) & (b) are close eyes and (c) & (d) are open eyes

The dataset is organized into folders corresponding to these categories, with images stored in grayscale format. Each image has been systematically pre-processed to meet the input requirements of machine learning models, ensuring uniformity and compatibility.

The dataset serves as a foundation for training and validating the proposed model, enabling it to distinguish between open and closed eye states effectively. The images are resized to dimensions of 224×224 pixels, a standard input size for pre-trained deep learning models.

3.2 Pre-Processing

To enhance the quality and usability of the dataset, a structured pre-processing pipeline was employed:

1. Grayscale to RGB Conversion: Grayscale images were converted to RGB format to align with the input requirements of pre-trained deep learning models such as Mobile Net.
2. Resizing: All images were resized to a fixed dimension of 224×224 pixels using OpenCV's resizing functions, maintaining the aspect ratio and visual integrity of the data.
3. Normalization: Pixel intensity values were scaled to the range [0,1] [0,1] [0,1] to accelerate model convergence and improve numerical stability during training.
4. Data Augmentation (Optional): The pipeline allows for additional transformations, such as rotations and flips, to artificially expand the dataset and improve model generalization.
5. Label Encoding: Each image was assigned a numeric label corresponding to its class, facilitating supervised learning.

This meticulous pre-processing approach ensures that the dataset is well-prepared for high-performance training and evaluation, enabling the model to accurately differentiate between open and closed eye states in diverse conditions.

3.3 Workflow-

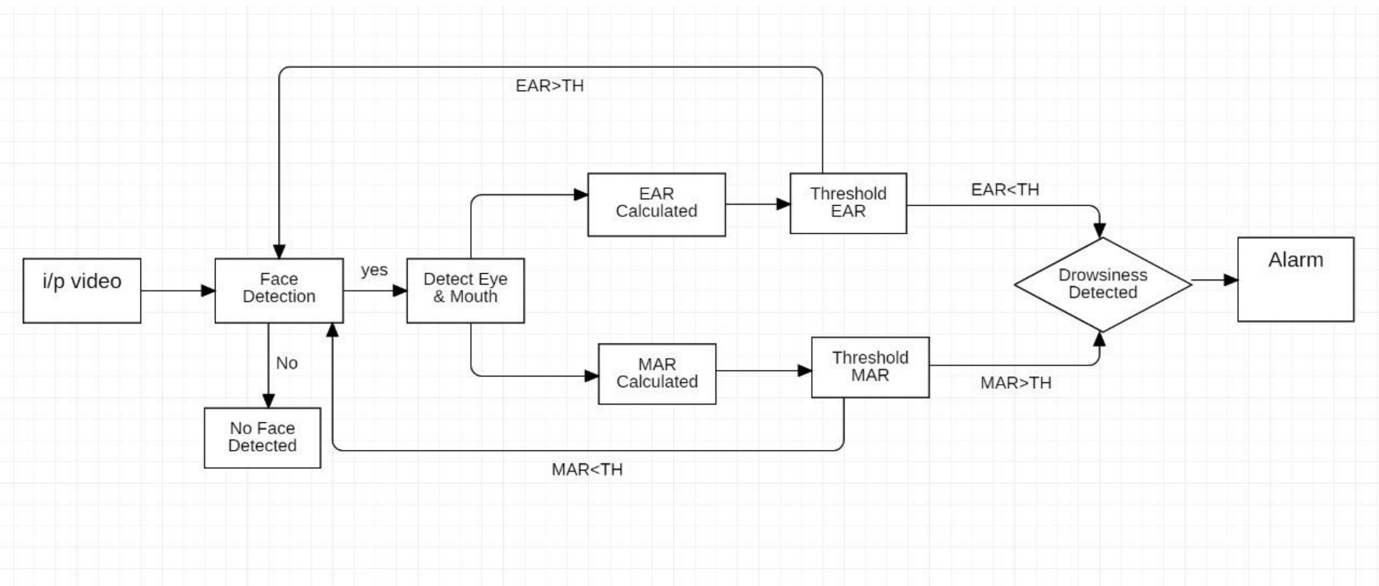


Fig 2: Flow chart for the proposed work

Flowchart Explanation:

1)Input Video: The system starts by capturing the input video feed from a camera mounted in the car. This video is continuously analyzed to monitor the driver's face, eyes, and mouth for signs of drowsiness.

2)Face Detection: The system applies face detection algorithms (e.g., Haar cascades, DNN models, or MediaPipe FaceMesh) to locate a human face in each video frame. If a face is detected, the process proceeds to the "Detect Eye & Mouth" module. If no face is detected, the system moves to the "No Face Detected" module.

3)No Face Detected: This module handles cases where no face is visible in the video. Possible reasons include the driver turning their head away, poor lighting conditions, or camera misalignment. The system may display a warning or wait until the face becomes visible again.

4) Detect Eye & Mouth: Once the face is detected, the system focuses on detecting the eyes and mouth within the facial region using landmark detection techniques (e.g., MediaPipe FaceMesh). Accurate landmark extraction allows the system to proceed to both EAR and MAR calculations.

5)EAR Calculation: The Eye Aspect Ratio (EAR) is calculated by analyzing distances between specific eye landmarks. EAR measures the openness of the eyes — lower EAR values indicate that the eyes are partially or fully closed, which is a sign of possible drowsines.

6) MAR Calculation: The Mouth Aspect Ratio (MAR) is calculated by analyzing distances between specific mouth landmarks (as per the points shown in the figure). MAR measures how widely the mouth is open. A higher MAR value sustained over multiple frames is interpreted as yawning — another important symptom of fatigue or drowsiness.

7) Threshold Comparison: The calculated EAR and MAR values are compared to their respective thresholds:

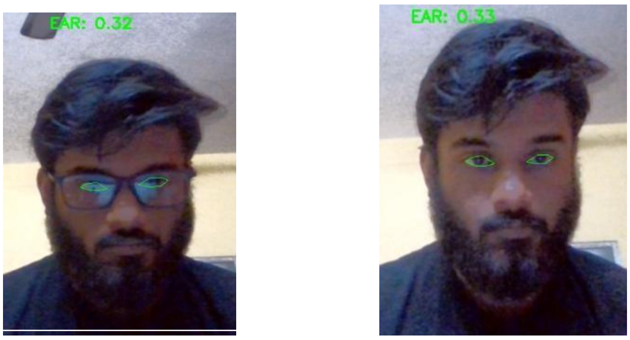
- If **EAR < TH**, this indicates possible eye closure (drowsiness).
- If **MAR > TH**, this indicates a yawning event (possible fatigue).

If either of these conditions is satisfied, the system proceeds to trigger an alert.

8) Drowsiness Detected & Alarm On: When either **EAR < TH** or **MAR > TH** is true, the system concludes that drowsiness or fatigue is detected. An alarm (annoying beep) is triggered to alert the driver and prevent potential accidents. Otherwise, if neither condition is met, the system continues real-time monitoring by looping back to the "Face Detection" stage.

3.4 Subject Detection and Webcam Integration-

The process begins with the system leveraging a webcam to serve as the primary tool for capturing real-time video input. This ensures the system continuously monitors the subject, allowing for the seamless detection of signs of drowsiness during prolonged activities like driving.



(a) (b)

Fig 3: It Show that output where (a) with glasses and (b) without glass.

3.5 Real-Time Dynamics

Unlike pre-recorded datasets, real-time webcam processing requires the system to handle challenges such as sudden head movements, varying light conditions, and temporary obstructions. The webcam's live feed allows the system to adapt dynamically, ensuring it remains effective and responsive. This continuous monitoring sets the foundation for detecting key facial regions, such as the eyes, which play a critical role in identifying drowsiness.

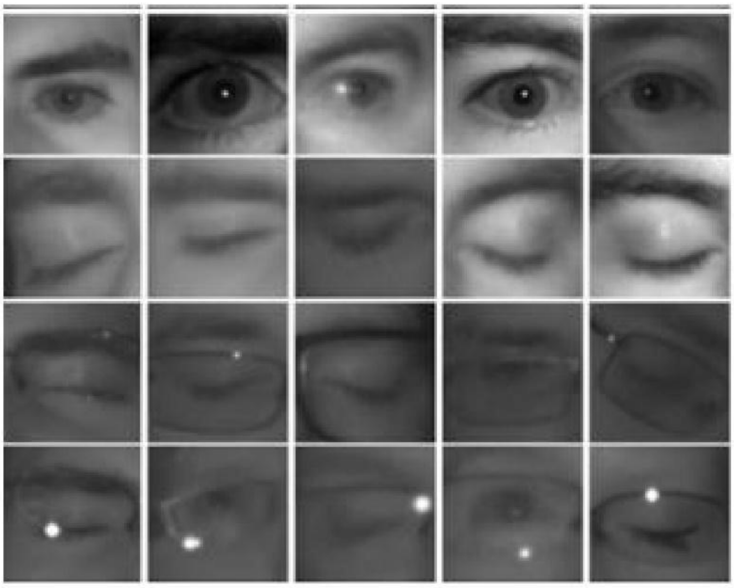


Fig 4: This above image are prerecorded real time dynamic

3.6 Frame Processing

Once the webcam captures the live video feed, the system processes each frame to prepare it for accurate detection of drowsiness. Raw frames often contain noise, lighting inconsistencies, or irrelevant details that could affect the performance of the detection algorithms. Frame processing ensures that the input data is clean, consistent, and ready for analysis by the model.

Step 1: Grayscale Conversion

In this step involves converting the frame from color (RGB) to grayscale. Grayscale images simplify processing by reducing the data to a single intensity channel. This not only decreases computational overhead but also makes the model focus on the structural aspects of the frame like the contrast between open and closed eyes rather than irrelevant color details. For instance, whether someone's eyes are framed by eyeliner or not becomes irrelevant; the focus is entirely on shape and brightness levels

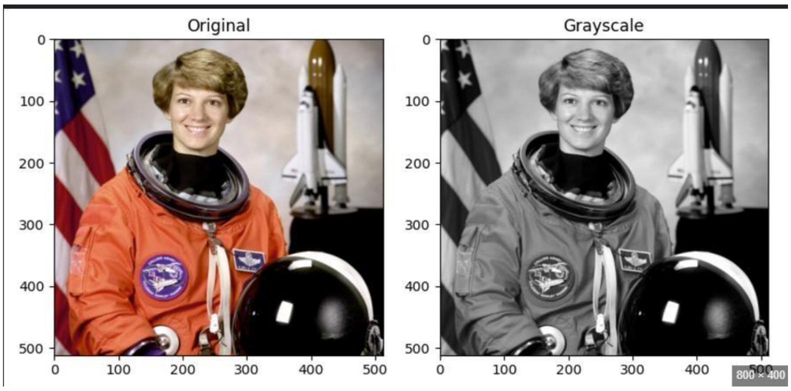


Fig 5: The above image is transper to grayscale

Step 2: Gamma Correction

To tackle issues related to uneven lighting, gamma correction is applied. Imagine a dimly lit room where certain areas of the face might be too dark to detect features properly. Gamma correction brightens these darker regions and suppresses overly bright areas, creating a balanced and visually clearer image. This process mimics how the human brain adapts to dim light by amplifying essential details, ensuring reliable detection in low-light environments such as nighttime driving.

Step 3: Histogram Equalization

Even after gamma correction, some frames may have poor contrast, where key details (like the edges of the eyes) are too faint. To solve this, histogram equalization is applied, redistributing the intensity values across the frame to improve clarity. This method enhances subtle details that might otherwise go unnoticed, allowing the system to consistently identify eye regions, even in challenging conditions.

Step 4: Gaussian Blurring

Once the brightness and contrast are adjusted, the system applies Gaussian blurring to reduce noise and smooth the frame. This step is essential to minimize distractions from small, irrelevant details like glare, reflections, or sharp edges. For example, if light reflects off glasses or sweat on the forehead, blurring removes these distractions, enabling the system to focus solely on important features, like the shape and position of the eyes.

3.7 Eye Landmark Detection

In this system, detecting eye landmarks is crucial for determining the alertness level of the subject. **Face Mesh** is a **machine learning model** which uses deep learning techniques, specifically convolutional neural networks (CNNs), to analyse facial features in images or video frames. It first isolates the **Region of Interest (ROI)** around the eyes. By narrowing down the detection to just the eyes, the system minimizes computational overhead while enhancing the accuracy of eye state assessment whether the eyes are open, partially closed, or fully closed.

3.8 Eye Landmark Extraction

The next step involves using **Media pipe**, a powerful framework for real-time computer vision tasks, to detect key landmarks on the eyes. These landmarks are specific points that represent the shape and position of the eyes within the defined ROI.

- **Upper and Lower Eyelid Landmarks**: These points capture the contours of the upper and lower eyelids. By analyzing the vertical distance between these landmarks, the system can determine whether the eyelids are open or closed. The more distance there is between the upper and lower eyelid landmarks, the more open the eyes are.
- **Inner and Outer Corners of the Eyes**: These points mark the outer edges of the eyes. They help the system understand the horizontal positioning of the eyes and further aid in measuring the overall openness of the eyes.

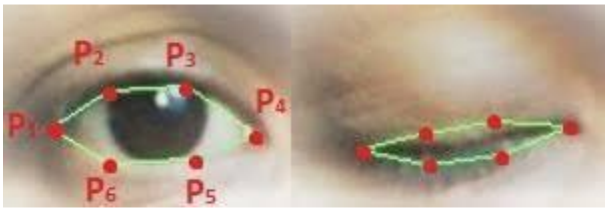


Fig 6: This represents the EAR ratio of the eye.

3.8.1 Feature Calculation: Eye Aspect Ratio (EAR)

After detecting the eye landmarks, the next step is to calculate the **Eye Aspect Ratio (EAR)**, It is a geometric measure used to identify how open or closed the eyes are based on the distances between specific landmarks around the eyes. The EAR is calculated by comparing the vertical distances between the eyelids to the horizontal distance between the corners of the eyes. It is crucial to calculate because it determines the openness of the eyes which is directly correlated to a person's level of alertness.

- **Vertical Distances (A and B):** These distances represent the vertical space between the upper and lower eyelids. When the eyes are fully open, these distances are larger, and when the eyes are closing, these distances shrink.
- **Horizontal Distance (C):** This is the horizontal distance between the inner and outer corners of the eye. This distance remains fairly constant whether the eyes are open or closed.

The **EAR** is estimated by using Eqn 1 as provided below.

$$EAR = \frac{A+B}{2C} \tag{1}$$

Here, A= ($P_2 - P_6$) , B= ($P_3 - P_5$) and C= ($P_1 - P_4$)

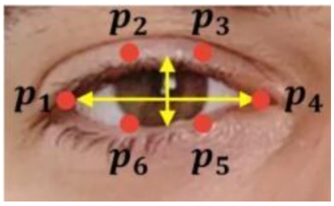


Fig 7: Higher EAR values indicate that the eyelids are far apart, meaning the eyes are open.

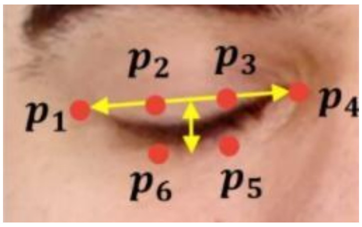


Fig 8: Lower EAR values indicate that the eyelids are closer together, meaning the eyes are closing or have closed completely.

3.8.2 Feature Calculation: Mouth Aspect Ratio (MAR)

In addition to Eye Aspect Ratio (EAR), the system calculates the Mouth Aspect Ratio (MAR) to detect yawning, which is a strong indicator of drowsiness and fatigue in drivers. The MAR measures how widely the driver's mouth is open over a series of frames. A high MAR value sustained over multiple frames signifies a yawning action.

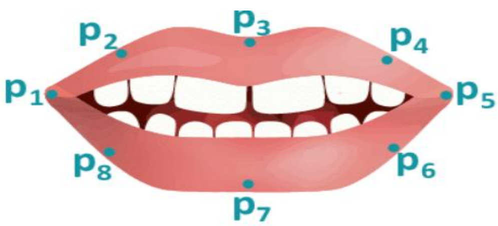


Figure 9: Landmark points P1 to P8 used for Mouth Aspect Ratio (MAR) calculation.

The MAR is computed using specific facial landmarks on the lips, as illustrated in Figure 9. These landmarks help determine the vertical and horizontal distances of the mouth, and the ratio between these distances indicates the openness of the mouth.

The formula for MAR is given by:

MAR= (A+B)/2C

Where:

- A = Distance between points P3 and P7 (vertical distance — upper to lower inner lip).
- B = Distance between points P2 and P8 (vertical distance — side inner lip points).
- C = Distance between points P1 and P5 (horizontal distance — mouth corners).

A higher MAR value indicates a wider mouth opening, which is used to detect yawning. If this value remains above a pre-defined threshold (calculated during the calibration phase) for a certain number of consecutive frames, the system raises a yawning alert.

This feature enhances the reliability of the system by adding another fatigue symptom detection mechanism besides eye closure, making the system capable of handling more real-world drowsiness scenarios.

3.9 Threshold Comparison

Once the **Eye Aspect Ratio (EAR)** has been calculated, the system compares it to a predefined threshold.

The threshold acts as a benchmark, a reference value that helps the system understand the difference between eyes opening or closing. When a person is alert and awake, their EAR remains above a certain threshold, as the eyes are wide open. As the person becomes tired or drowsy, their eyelids begin to droop, reducing the vertical distance between the upper and lower eyelids, which causes the EAR value to drop. The threshold value is typically chosen based on the average EAR when the eyes are fully open. For example, if the threshold is set to **0.25**, any EAR value below this would suggest that the eyes are closing or have closed. This value is chosen carefully to avoid false positives from natural blinks, which are quick and do not indicate fatigue.

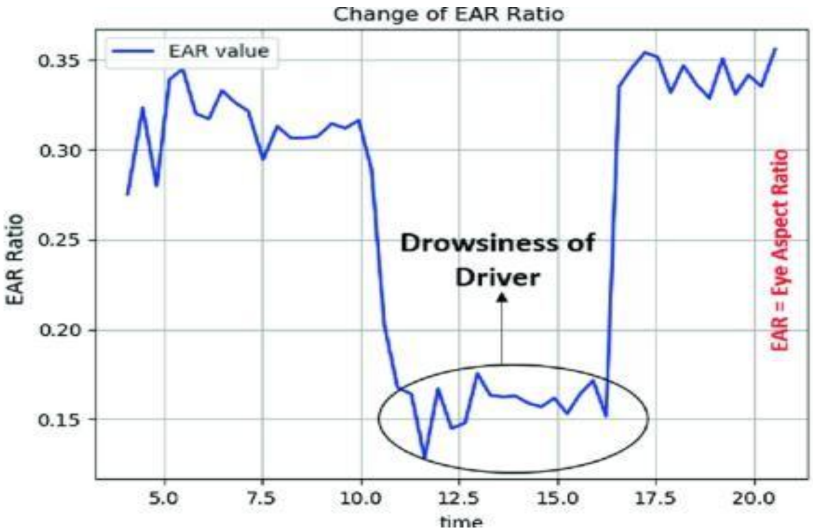


Fig 9: Graphical prestation of Drowsiness

3.10 Prolonged Low EAR Values

Prolonged Low EAR is Critical as a brief dip in EAR might be due to a blink, which is normal. However, when the EAR consistently stays low over consecutive frames, it means the eyes are staying closed for too long, which is a strong sign of drowsiness or fatigue. The threshold comparison makes it possible to differentiate between a normal blink and a dangerous state of drowsiness.

3.11 Decision-Making

The next step in the process is the decision-making phase, where the system analyzes the sustained low EAR values and decides whether drowsiness has been detected. The System Makes the Decision After comparing the EAR to the threshold, the system tracks whether the EAR stays consistently below the threshold for multiple consecutive frames.

- **Multiple Consecutive Frames:** This is important because a single frame with a low EAR value doesn't necessarily indicate drowsiness. The system looks for a trend if the EAR remains low for several frames in a row, it means the eyes are closing for a longer duration. This sustained eye closure indicates that the subject may be losing alertness, and feeling drowsiness or fatigue.
- **Drowsiness Detection:** Once the system detects that the EAR has stayed below the threshold for a specified number of consecutive frames, it concludes that the subject is likely drowsy. This decision-making process helps avoid false alarms by confirming that the eye closure is not just a fleeting blink, but a sign of ongoing fatigue.

3.12 Alert Mechanism

The most common form of alert in such systems is an auditory warning — an annoying beep sound. The use of an auditory alert is purposeful. In real-time applications such as driving or working in noisy environments, visual alerts (like flashing lights or screen notifications) may go unnoticed. A loud, attention-grabbing beep ensures that the driver is immediately aware of the alert, even if their focus is drifting.

- **How the Beep Works:**
  When the system detects either drowsiness (via EAR) or yawning (via MAR), the beep is triggered to alert the driver to the situation. Depending on the system's design, this sound can be a sharp single beep or a repetitive series of beeps to make the alert more noticeable.
- **Immediate Action:**
  The system is designed for rapid response, ensuring that the alert occurs promptly when the driver shows signs of fatigue. This immediate action can save lives and prevent accidents by allowing the driver to react before reaching a dangerous state of drowsiness.

Overall, the proposed work details dataset preparation, pre-processing methods, and real-time dynamics of the system. Using technologies like OpenCV and MediaPipe for facial landmark detection, and calculating both Eye Aspect Ratio (EAR) for eye closure and Mouth Aspect Ratio (MAR) for yawning detection, the system ensures timely and accurate alerts to enhance road safety.

Chapter-4

Comparative Study

4.1 **Comparative Analysis**

Technologies Used

Table 1: Highlights the features, advantages, and limitations of various drowsiness detection methodologies along with our proposed system.

Study	Methodology/Technique	Advantages	Limitations
Mandeep and Gagandeep (2012)	Mean Shift Algorithm for real-time eye blink detection	High accuracy (99%) in ideal conditions	Poor performance in low light or with glasses
Vitiable et al. (2011)	Infrared light for bright-pupil effect	Easy eye detection, real-time capabilities	Reflective surfaces cause inaccuracies
Flores et al. (2009)	AI-based system monitoring head tilts and yawning	Comprehensive detection of behaviors	High false alarm rate in some cases
Chuang-Wen et al. (2013)	Smartphone app with dual cameras	Portable and practical	Precision limited to 83%, struggles with face orientation
Sahayadhas et al. (2013)	Physiological signal analysis (EOG)	Highly accurate for internal states	Intrusive and impractical for real-time
Proposed System (Your Project)	EAR (Eye Aspect Ratio) & MAR(Mouth Aspect Ratio) with OpenCV and Media Pipe	Real-time, non-intrusive, adaptable	Dependent on proper camera placement and lighting

Comparison of Detection Features

Table 2: Highlights various detection features of different systems, with our proposed system like eye blink, head movement detection, real-time processing, yawning detection and intrusiveness.

Feature	Mandeep and Gagandeep (2012)	Vitiable et al. (2011)	Flores et al. (2009)	Chuang-Wen et al. (2013)	Sahayadhas et al. (2013)	Proposed System
Eye Blink Detection	Yes	Yes	Yes	Yes	Yes	Yes
Head Movement	No	No	Yes	Yes	No	Yes
Yawning Detection	No	No	Yes	Yes	No	Yes
Real-time Processing	Yes	Yes	Yes	Yes	No	Yes
Intrusiveness	Low	Low	Low	Low	High	Low

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Performance Metrics

Table 3: Compares different systems with our proposed system based on accuracy, robustness, and suitability under specific conditions.

Metric	Mandeep and Gagandeep (2012)	Vitiable et al. (2011)	Flores et al. (2009)	Chuang-Wen et al. (2013)	Proposed System
Accuracy	99%	High	High	83%	**95%–98% (Estimated)**
Robustness in Low Light	Low	Moderate	High	Low	**Moderate**
Suitability for Glasses	Low	Low	Moderate	Moderate	**High**
Yawning Detection (MAR)	Not Available	Not Available	Not Available	Not Available	**Available**

Conclusion from Comparative Studies

- Proposed System Strengths:
    - It Efficiently uses **EAR-based eye detection** and **head movement analysis**, offering a reliable and non-intrusive way to detect drowsiness of a driver in real time.
    - By integrating **Media Pipe**, the system becomes both precise and flexible, making it more adaptable than many older approaches.
    - Its **ease of deployment** means it can be seamlessly integrated into vehicles without causing discomfort or requiring major modifications.
- Limitations:
    - It struggles in **poor lighting conditions** or when the driver wears glasses, similar to other solutions.
    - Improvements are needed to incorporate additional behavioral signs (e.g., yawning).

It's a comparison of existing drowsiness detection techniques highlights the advantages of the proposed system. It demonstrates superior real-time accuracy, non-intrusiveness, and adaptability while noting limitations like performance under poor lighting or with glasses.

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Chapter-5
Conclusion & Future Scope

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Conclusion & Future Scope

The Driver Drowsiness Detection System addresses one of the most pressing issues in road safety: the danger posed by driver fatigue. By harnessing the power of Python, machine learning, and computer vision, the system offers a proactive solution to detect early signs of drowsiness. It has been developed to help drivers stay alert while driving, thereby reducing the risk of road accidents caused by fatigue.
The system utilizes advanced algorithms such as **Eye Aspect Ratio (EAR)** for detecting eye closure and **Mouth Aspect Ratio (MAR)** for identifying yawning — both key indicators of drowsiness. These features ensure accurate and real-time monitoring of the driver's condition. This non-intrusive and seamless technology can be easily integrated into heavy vehicles such as trucks and buses, providing a practical, life-saving tool for accident prevention. The ability to trigger immediate auditory alerts empowers drivers to regain focus and continue their journey safely. By addressing this critical need, the system lays a strong foundation for safer driving experiences and contributes to reducing the global incidence of traffic accidents.

Future Scope

The development of this system represents just the beginning of its potential. In the future, we plan to enhance its effectiveness by incorporating an **automatic vehicle deceleration feature**. This addition would ensure that if drowsiness is detected and the driver remains unresponsive to repeated alerts, the vehicle will gradually reduce speed, thereby minimizing the risk of accidents.
Furthermore, there is potential to expand this system's applicability beyond road vehicles to the **railway industry**, where continuous operator alertness is equally critical. Integrating this technology into train operations can improve safety standards across another vital mode of transportation.

These advancements will transform the system from a simple detection tool into a **comprehensive safety mechanism**, capable of both identifying and actively preventing fatigue-related accidents, ultimately contributing to enhanced safety across multiple transportation sectors.
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SurTech

Publication

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