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Driver drowsiness detection system

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Abstract

Driver fatigue is a major cause of road accidents, especially in long-distance and night driving scenarios. Continuous monitoring of driver alertness is essential to prevent such incidents. This paper presents a real-time Driver Drowsiness Detection System using computer vision techniques. The system captures live video input, processes facial features such as eye closure, and determines fatigue levels based on temporal analysis. A fatigue percentage model is introduced to provide a more intuitive understanding of driver condition. When fatigue exceeds a predefined threshold, an alert is generated. The proposed system is cost-effective, non-intrusive, and suitable for real-world deployment in intelligent transportation systems.

Keywords: Driver Drowsiness; Computer Vision; Fatigue Detection; OpenCV; Haar Cascade

1. Introduction

Road safety has become a critical concern due to the increasing number of vehicles and long driving durations. One of the major causes of road accidents is driver drowsiness, which reduces reaction time and decision-making ability. Studies indicate that fatigue-related accidents often occur without prior warning, making early detection extremely important [1].

Traditional vehicle safety systems focus on mechanical and environmental factors but fail to monitor the driver's physical state. This limitation has led to the development of intelligent driver monitoring systems that can detect fatigue in real time. Advances in Artificial Intelligence and Computer Vision have enabled the creation of non-intrusive solutions that analyze driver behavior through visual data. [2] [3]. Recent approaches use facial feature analysis such as eye closure, blinking rate, and head movement to determine drowsiness levels. These techniques are more practical compared to sensor-based systems, which require physical contact and increase system complexity. Vision-based systems are cost-effective and suitable for real-time applications.

- Driver drowsiness is one of the leading causes of road accidents, as it significantly reduces a driver's reaction time, alertness, and decision-making ability during critical situations.
- Traditional vehicle safety systems mainly focus on mechanical and environmental factors and do not effectively monitor the driver's physical or mental condition, creating a major gap in road safety.
- This project utilizes computer vision techniques to continuously monitor driver behavior, detect signs of fatigue in real time, and provide immediate alerts to help prevent accidents and improve overall driving safety.

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2. Literature study

Various techniques have been proposed for detecting driver fatigue, ranging from physiological signal monitoring to image-based analysis. Early methods used EEG and heart-rate sensors to detect drowsiness. Although accurate, these methods are intrusive and difficult to implement in real-world scenarios.

With advancements in computer vision, researchers shifted towards non-intrusive approaches using image processing. Techniques such as Haar Cascade [4] classifiers and Support Vector Machines (SVM) have been widely used for face and eye detection. These methods provide real-time performance and are suitable for practical applications. Recent studies have focused on deep learning approaches such as Convolutional Neural Networks (CNN) for fatigue detection. These models can learn complex patterns from large datasets and improve detection accuracy. However, they require high computational power and large training datasets [5] Several systems also analyze behavioral patterns such as yawning and head movement to improve detection accuracy. However, challenges such as lighting conditions, occlusion, and camera positioning still affect system performance. Therefore, there is a need for a balanced approach that combines accuracy, efficiency, and practicality. [7]Some research studies focus on behavior-based methods such as steering wheel movement, lane deviation, and driving patterns to detect driver drowsiness; however, these methods often identify fatigue at a later stage when the driver's condition has already become critical.

Advanced systems using infrared cameras [9] are capable of detecting driver fatigue even in low-light or night conditions, but these systems are expensive, complex to implement, and not easily affordable for common users or standard vehicles [10] . The literature survey reveals that various approaches have been proposed for driver drowsiness detection, including physiological methods, behavioral analysis, and computer vision techniques.

Overall, existing research highlights the need for a balanced system that is accurate, efficient, and suitable for real-time applications, which motivates the development of the proposed approach.

Table 1 Advantages and challenges of driver drowsiness detection techniques

Source	Technique	Advantages	Limitation
[1]	Haarcascade (face and eye detection)	Fast and suitable for real-time applications with low computational cost.	Accuracy may decrease under poor lighting and condition efficiency
[2]	Eye Aspect Ratio Method (EAR)	Provided maximal accurate detection of eye closure and blinking pattern	Requires precise facial landmark detection and may fail with glasses
[3]	CNN-based Deep Learning	High accuracy and ability to detect complex fatigue pattern	Requires large datasets and high computational power
[4]	Infrared camera based Detection	Works effectively in low-light and night conditions	Expensive and not suitable for low-cost systems
[7]	Steering Behavior Analysis	Non-intrusive and does not require camera setup	Detects drowsiness at a later stage, less reliable
[8]	Proposed System (OpenCV + Haarcascade)	Real time cost efficient, easy to implement, and suitable for practical use	Increased system complexity and processing time

3. Methodology

The proposed Driver Drowsiness Detection System follows a real-time computer vision-based approach to monitor driver alertness continuously. The system processes live video input and analyzes facial features, particularly eye closure behavior, to determine fatigue levels. The methodology is divided into multiple stages

The proposed system is designed to operate continuously in real-time without requiring any manual intervention. The camera captures frames at a constant rate, and each frame is processed independently while maintaining temporal continuity for fatigue analysis. This ensures that the system can respond instantly to any change in driver behavior and detect drowsiness at an early stage before it becomes critical.

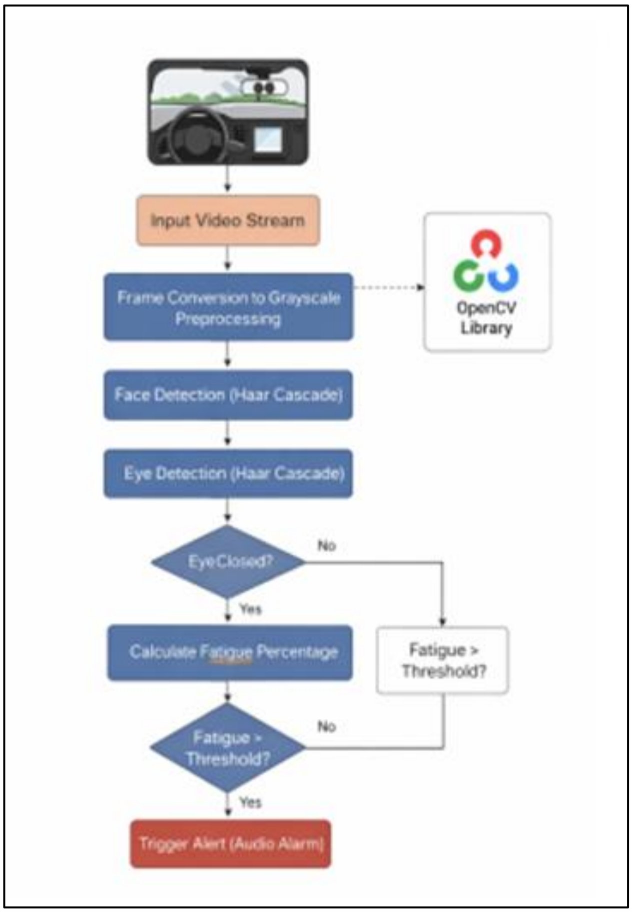

Figure 1 The general layout of the proposed Driver Drowsiness Detection technique

The system captures video frames, converts them into grayscale, and detects the face and eye regions using Haar Cascade classifiers. It continuously analyzes eye closure duration across consecutive frames to identify signs of fatigue. When the detected fatigue exceeds a predefined s

To enhance detection accuracy, the system focuses on the most relevant region of the face, specifically the eye area. By restricting processing to this region of interest (ROI), the computational load is reduced significantly, allowing faster execution. This approach also minimizes the influence of irrelevant facial features and background noise, thereby improving the reliability of detection.

3.1. Improved Preprocessing via camera detection and visual Alerts

The system incorporates temporal filtering to avoid false positives caused by natural blinking. Human blinking typically lasts for a very short duration; therefore, the system only considers prolonged eye closure across multiple consecutive frames as an indicator to fatigue. This filtering mechanism ensures that normal eye movements do not trigger unnecessary alerts, making the system more robust and practical. A detailed explanation is provided in the following section.

3.2. Image Acquisitions And Processing:

The system captures real-time video frames using a camera. Each frame is converted into grayscale to reduce computational complexity and improve processing speed. Let the input frame be represented as:

$$I(x,y)I(x,y)I(x,y)$$

The system begins by capturing real-time video frames using a webcam or in-vehicle camera. Each frame is processed continuously to monitor the driver's facial features.

To reduce computational complexity and improve processing speed, the captured color frames are converted into grayscale images, which retain essential information while simplifying further analysis [14].

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where x and y denote pixel coordinates.

The grayscale conversion is performed as:

$$Ig(x,y)=0.299R+0.587G+0.114B \text{ -----------(1)}$$

To enhance image quality under different lighting conditions, histogram equalization is applied:

$$Ie= H(Ig) \text{ -----------(2)}$$

where H represents the histogram equalization function. This step improves contrast and ensures better feature detection.

3.3. Face Detection

Face detection is performed using the Haar Cascade classifier. The classifier scans the image using sliding windows and identifies facial regions based on trained features.

Let the detected face region be:

$$F=\{(x,y,w,h)\} \text{ ----------(3)}$$

where x,y represent coordinates and w,h represent width and height of the face bounding box.

Among multiple detected faces, the system selects the largest face region:

$$Fdriver = max(area(F)) \text{ ------------------------(4)}$$

Face detection is performed using the Haar Cascade classifier, which identifies facial features by scanning the image with predefined patterns. The algorithm detects regions in the frame that match the characteristics of a human face, enabling accurate localization of the driver's face in real time.

When multiple faces are detected in a frame, the system selects the largest face region, assuming it belongs to the driver. This helps in focusing only [17] on the relevant subject and avoids interference from other faces or background objects, thereby improving detection accuracy and system efficiency.

3.4. Eye Detection

Eye detection is carried out using the Haar Cascade classifier applied to the upper region of the detected face, as the eyes are located in this area. By restricting detection to this region of interest (ROI), the system improves accuracy and reduces computational time while focusing only on relevant facial features.

The eye region is extracted from the upper half of the detected face:

$$ROI(eye) = (Fdriver) /2 \text{ ---------------------- (5)}$$

Eye detection is again performed using Haar Cascade. Let the number of detected eyes be:

$$E=\{e1,e2,...,en\} \text{------------------------}(6)$$

If no eyes are detected:

$$E = 0 \Rightarrow \text{Eyes Closed ------------------------}(7)$$

Otherwise;

$$E \geq 0 \Rightarrow \text{Eyes Open ------------------------}(8)$$

3.5. Eye Closure Time Calculation

The system continuously monitors the presence or absence of detected eyes in consecutive frames. If the eyes are not detected for a certain number of frames, it is considered as eye closure, which serves as a key indicator of driver fatigue. This real-time tracking helps distinguish between normal blinking and prolonged eye closure.

To distinguish between blinking and drowsiness, the system tracks consecutive frames where eyes remain closed.

Let:

- Nc = number of consecutive closed frames
- Tf = time per frame

Then, eye closure time is:

$$Tc = Nc \times Tf \text{ ------------------------}(9)$$

This temporal analysis helps detect prolonged eye closure.

3.6. Fatigue Percentage Estimation :

A fatigue percentage model is used to quantify drowsiness level.

$$Fatigue\% = (Tmax/Tc) \times 100 \text{ -----------------}(10)$$

where:

- Tc = eye closure duration
- Tmax = maximum threshold time

The fatigue level is categorized as:

0%–30% → Alert

30%–70% → Moderate fatigue

70%–100% → High fatigue

3.7. Threshold - Based

The system compares eye closure time with a predefined threshold:

$Tc > Threshold \Rightarrow Drowsy$

$Tc \leq Threshold \Rightarrow Normal$

To reduce false detection, smoothing is applied:

$$N_c > N_{min} \Rightarrow \text{Confirm Drowsiness}$$

The system compares the calculated eye closure time with a predefined threshold to determine whether the driver is drowsy, ensuring reliable detection while minimizing false alarms.

3.8. Alert Generation System

When fatigue exceeds the threshold, the system triggers an alert

Alert=If 1, if $T_c \geq T_{threshold}$

If 0 , otherwise

When the fatigue level exceeds the threshold, the system activates an audio and visual alert to immediately warn the driver and help restore attention.

The fatigue percentage model provides a continuous measure of driver alertness instead of a simple binary classification. This allows the system to indicate gradual changes in driver condition and warn the driver before reaching a critical state. The use of color-coded feedback further enhances user understanding by providing intuitive visual cues regarding fatigue levels.

To enhance detection accuracy, the system focuses on the most relevant region of the face, specifically the eye area. By restricting processing to this region of interest (ROI), the computational load is reduced significantly, allowing faster execution. This approach also minimizes the influence of irrelevant facial features and background noise, thereby improving the reliability of detection.

4. Results and discussion

The proposed Driver Drowsiness Detection System was implemented and tested using a standard webcam under different driving scenarios to evaluate its performance and reliability. The system was able to successfully detect the driver's face and eye regions in real time using the Haar Cascade classifier. During normal conditions, when the driver's eyes remained open, the system consistently displayed an "Eyes Open" status and maintained a low fatigue percentage, indicating stable and accurate monitoring.

In simulated drowsiness conditions, where the driver intentionally kept their eyes closed for a longer duration, the system effectively detected prolonged eye closure and began calculating the fatigue percentage. It was observed that the fatigue percentage increased gradually with the duration of eye closure, providing a continuous measure of driver alertness. Once the predefined threshold (3.5 seconds) was exceeded, the system triggered an audio alarm and displayed a visual warning, confirming correct functionality of the alert mechanism.

The system was also tested under different environmental conditions such as varying lighting intensity, slight head movements, and the presence of spectacles. It was found that detection accuracy was higher in well-lit environments and when the driver's face was clearly visible to the camera. Minor inaccuracies were observed in low-light conditions or when the driver wore reflective glasses, as these factors sometimes affected eye detection performance. However, the system remained stable and responsive in most practical scenarios.

A key advantage of the proposed system is the use of fatigue percentage instead of binary detection. This allows gradual monitoring of driver fatigue and provides early warnings before reaching a critical state. Compared to traditional systems that only detect drowsiness after it occurs, this approach improves safety by enabling proactive alerts.

Overall, the experimental results demonstrate that the proposed system is effective, reliable, and suitable for real-time applications. The combination of temporal eye closure analysis and fatigue percentage estimation provides meaningful insights into driver behavior. Although some limitations exist, the system offers a strong foundation for future enhancements using advanced machine learning techniques and improved detection algorithms.

Sample frame representation for the proposed Driver Drowsiness Detection system showing (a) original frame, (b) grayscale image, (c) face detected frame, (d) eye detection, and (e) fatigue analysis output.

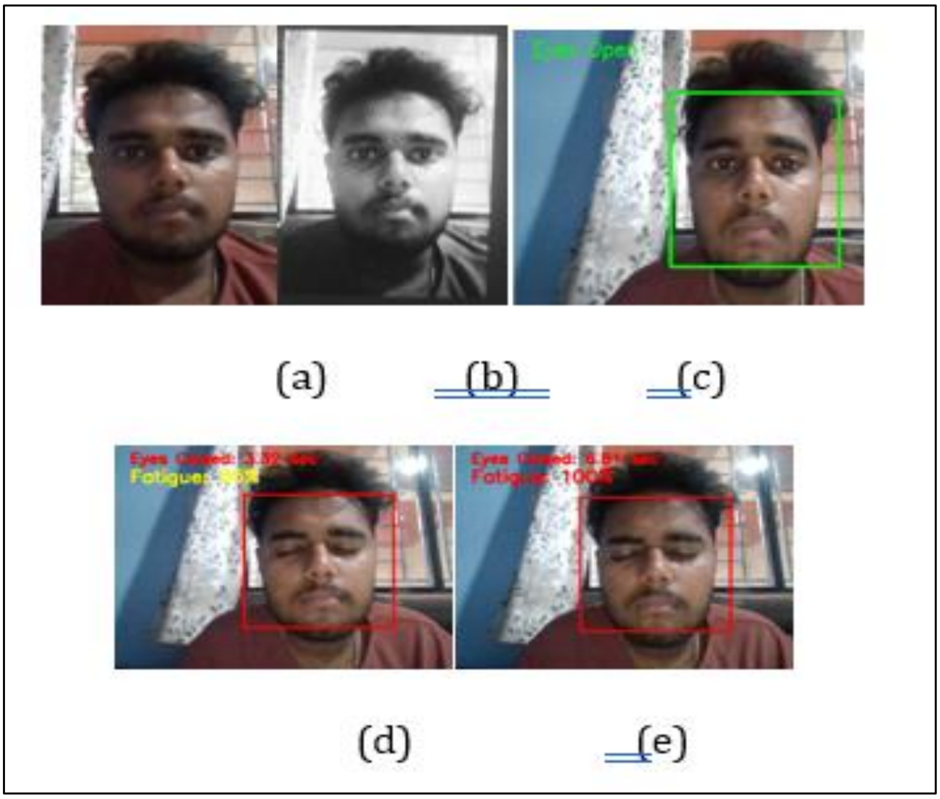

Figure 2 Sample frame representation for proposed driver drowsiness detection system shows (a) original frame, (b)grayscale image, (c) face detected frame, (d) eye detection, (e) fatigue analysis output

The dataset consists of real-time video frames captured using a webcam under different driving conditions. The frames are processed through multiple stages including pre processing, face detection, and eye detection. The original input frame is first converted into grayscale to reduce computational complexity and enhance feature extraction. This step simplifies the image while preserving important structural details required for detection.

Further, face detection is performed using the Haar Cascade classifier, which accurately identifies the driver's face region. Once the face is detected, the upper portion of the face is extracted as the region of interest for eye detection. The eye detection stage determines whether the eyes are open or closed in each frame. This information is then used to calculate the duration of eye closure over consecutive frames.

The final stage represents the fatigue analysis output, where the system calculates fatigue percentage based on eye closure duration. The system gradually increases the fatigue level as the eyes remain closed for longer periods. When the fatigue exceeds the predefined threshold, the system triggers an alert indicating drowsiness.

The analysis demonstrates that the proposed approach effectively processes real-time video frames and provides accurate detection of driver fatigue. The combination of grayscale preprocessing, Haar Cascade-based detection, and temporal fatigue analysis ensures reliable performance. The system performs efficiently under normal lighting conditions, although slight variations may occur under low-light or occlusion scenarios.

Table 2 Performance evalution of driver drowsiness detection system

Test Scenario	**precision**	**Recall**	**Accuracy**
Normal Condition	0.95	0.95	0.95
Low Light	0.91	0.88	0.90
HeadMovement	0.89	0.87	0.89
Wearing Glasses	0.87	0.84	0.86

The results indicate that the proposed Driver Drowsiness Detection System achieves high accuracy under normal conditions, with precision, recall, and accuracy values reaching up to 0.95, demonstrating the system's effectiveness in controlled environments.

However, performance slightly decreases under challenging conditions such as low light, head movement, and wearing glasses, due to factors like poor visibility and reflection, which affect eye detection accuracy but still maintain acceptable reliability for real-time applications.

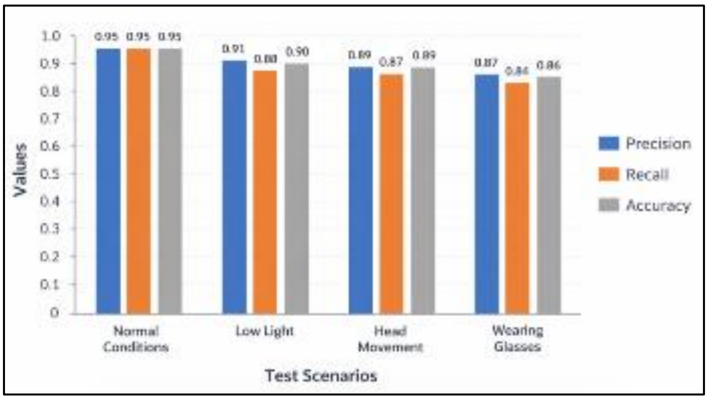

Figure 3 Proposed Driver Detection System

The graphical representation clearly shows the comparative performance of the system across different test scenarios using precision, recall, and accuracy metrics, providing a visual understanding of system effectiveness.

It can be observed that the system performs best under normal conditions, with all three metrics showing high values, while slight variations occur under challenging conditions such as low light and head movement.

The graph highlights that although there is a minor drop in performance in difficult scenarios, the overall accuracy remains consistently high, demonstrating the robustness and reliability of the proposed driver drowsiness detection system.

5. Conclusion

The proposed Driver Drowsiness Detection System effectively detects fatigue in real time using computer vision techniques and provides timely alerts to prevent accidents.

The system achieves high accuracy under normal conditions and maintains reliable performance even under challenging scenarios like low light and head movement.

Overall, the solution is cost-effective, non-intrusive, and suitable for real-world applications, with potential for further improvements using advanced technologies.

The proposed Driver Drowsiness Detection System successfully detects driver fatigue in real time using computer vision techniques, continuously monitoring eye behavior and generating timely alerts to help prevent accidents and improve overall road safety.

The system demonstrates high accuracy and performance under normal driving conditions, while still maintaining acceptable reliability under challenging scenarios such as low lighting, head movement, and the presence of glasses, proving its robustness in practical situations.

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