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# Smart Driver Monitoring System Using Yolov10

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## Abstract
*Driver fatigue and inattention are major contributors to road accidents across the world. Continuous monitoring of driver behavior is essential to reduce accident risks and improve road safety. Traditional driver monitoring systems often rely on landmark-based facial analysis techniques, which are sensitive to lighting conditions, facial occlusions, and camera positioning. This paper presents a Smart Driver Monitoring System using YOLOv10, designed to detect unsafe driver behaviors such as drowsiness through real-time video analysis. The proposed system treats driver state detection as an object detection problem rather than relying on handcrafted facial measurements. YOLOv10 is employed for its high inference speed and accuracy, enabling continuous monitoring with minimal latency. A temporal decision mechanism is incorporated to reduce false alerts caused by natural facial movements. When unsafe behavior persists beyond a defined threshold, the system generates immediate audio and visual alerts. The proposed approach demonstrates improved robustness, scalability, and real-time performance, making it suitable for intelligent transportation systems and in-vehicle safety applications.*

***Keywords:*** *Driver Monitoring System; YOLOv10; Drowsiness Detection; Computer Vision; Real-Time Alert.*

## 1. Introduction
Road traffic accidents remain a leading cause of fatalities worldwide, with driver fatigue and inattentiveness identified as significant contributing factors. Prolonged driving, insufficient rest, and monotonous road environments reduce a driver's alertness, increasing the likelihood of delayed reactions and poor decision-making. Early detection of such conditions can prevent accidents and save lives. Conventional driver monitoring methods include wearable sensors, physiological signal analysis, and manual supervision. Aditya Madane, Alok Singh, Shubham Fargade, and Atrey Dongare, "Real-Time Driver Drowsiness Detection Using Deep Learning and Computer Vision Techniques", Int J Sci Res Sci Eng Technol, vol. 12, no. 3, pp. 222–229, 2025. Puneet Singh Lamba, Rimjhim Jain, Shakir Khan, Sultan M. Alanazi, Achin Jain, Abu Taha Zamani, Arvind Panwar, and Alsadig Mohammed Adam Abdallah "Detection of Driver Drowsiness Using Adaptive Eye Characteristic Ratio for Enhanced Road Safety" May 2025. These methods are either costly, or unsuitable for continuous use. Camera-based vision systems provide a non-intrusive and cost-effective alternative by analyzing facial behavior in real time. Earlier vision-based systems commonly relied on landmark extraction techniques to estimate eye closure and yawning patterns. Although effective in controlled environments, these systems struggle in real-world scenarios due to dependency on precise landmark localization.

### 1.1.Background and Motivation
Road traffic accidents continue to be a major public safety concern across the world. According to global transportation studies, a significant percentage of accidents are caused by human-related factors rather than mechanical failures. Among these factors, driver drowsiness and inattentiveness play a dominant role, especially during long-distance travel, night driving, and monotonous road conditions. Fatigue reduces reaction time, decision-making ability, and situational awareness, increasing the likelihood of severe accidents. With the rapid growth of vehicle usage and highway transportation, there is an increasing need for intelligent systems that can actively monitor driver behavior and provide timely

warnings. Traditional safety mechanisms such as seat belts and airbags are passive; they reduce injury after an accident occurs but do not prevent accidents caused by driver fatigue. This limitation has motivated the development of active driver monitoring systems capable of detecting unsafe conditions before accidents happen.

### 1.2. Deep Learning in Driver Monitoring

Recent advancements in deep learning and computer vision have enabled more robust driver monitoring solutions. Convolutional Neural Networks (CNNs) have demonstrated strong performance in image classification and facial analysis tasks. Instead of relying on handcrafted features, deep learning models learn discriminative patterns directly from data, improving generalization across different drivers and conditions. Object detection models have further enhanced real-time applications by identifying multiple visual patterns within a single frame. Among these models, the YOLO(You Only Look Once) family has gained popularity due to its single-stage detection framework and high inference speed. YOLO models are capable of performing detection and classification simultaneously, making them suitable for real-time systems where low latency is critical.

### 1.3. Motivation for Using YOLOv10

Although earlier versions of YOLO have been applied to various real-time vision tasks, they often face challenges related to detection accuracy and computational efficiency. YOLOv10 introduces architectural optimizations that improve feature extraction, reduce inference latency, and enhance detection performance. In the context of driver monitoring, YOLOv10 offers several advantages:

- Direct detection of driver states without relying on geometric facial measurements
- Faster inference suitable for live video streams.
- Improved robustness to environmental variations
- Scalability for detecting multiple unsafe behaviors

By treating driver state detection as an object detection problem rather than a landmark estimation task, YOLOv10 enables a simpler and more reliable pipeline for real-time monitoring.

### 1.4. Organization of the Paper

The remainder of this paper is organized as follows. Section2 discusses related work in driver monitoring systems. Section 3 presents the overall system architecture. Section 4 describes the proposed methodology in detail. Section 5 explains the implementation details. Section6 analyzes experimental results and performance. Section 7 discusses observations and limitations. Finally, Section 8 concludes the paper and outlines future research directions.

## 2. Related Work

Driver monitoring systems have evolved through various technological approaches. Early studies focused on physiological signals such as EEG and heart rate variability to estimate driver fatigue. While accurate, these methods require specialized hardware and physical contact, limiting their practicality. Vision-based systems later emerged as a popular alternative. Landmark-based methods utilized facial feature extraction to compute metrics such as eye aspect ratio and mouth aspect ratio. More recently, object detection models such as YOLO have been explored for real-time applications due to their single-stage detection capability.

### 2.1. Vision-Based Driver Monitoring Systems

Early driver monitoring systems relied heavily on vision-based techniques using cameras to capture facial features such as eyes, mouth, and head orientation. These systems typically[1] utilized handcrafted features like eye aspect ratio (EAR), mouth aspect ratio (MAR), and blink rate to infer driver fatigue. While such approaches were computationally lightweight, their performance degraded under poor lighting conditions, occlusions, and varying camera angles. Several studies implemented monocular camera setups to detect eye closure and yawning in controlled environments. These models were trained using extracted facial features and temporal patterns of eye blinks. Although machine learning approaches improved detection accuracy compared to traditional methods, they still depended on manual feature extraction and careful parameter tuning[2]. Object detection models

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like YOLO (You Only Look Once) have recently been explored for real-time applications due to their high speed and accuracy. Although promising, these studies often used older YOLO versions, which faced challenges in detecting small facial regions like eyes under varying lighting conditions.[3] Moreover, many implementations lacked integrated alert mechanisms and were not deployed as end-to-end systems. From the reviewed literature, several limitations can be identified:

- Heavy reliance on handcrafted features or facial landmarks
- Reduced performance under low light, occlusion, and head movement
- High computational complexity in deep learning models
- Limited real-time deployment and scalability
- Lack of integrated live alert and monitoring frameworks

Most existing systems focus on single-feature detection (only eyes or yawning) rather than a holistic driver monitoring approach. The limitations of prior works motivate the use of YOLOv10, a modern object detection architecture optimized for accuracy and efficiency. By integrating YOLOv10 with a real-time processing pipeline and live alert system [4], the proposed approach aims to overcome existing challenges and provide a robust, scalable, and deployment-ready driver monitoring solution.

## 3. System Overview

The proposed Smart Driver Monitoring System is designed to continuously observe and analyze the driver's facial behavior in real time to detect early signs of drowsiness and fatigue. Unlike traditional physiological sensor-based approaches, the proposed solution relies entirely on vision-based analysis, making it non-intrusive and suitable for real-world driving environments [5]. The major components of the system include

- Video Capture Module
- Frame Preprocessing Module
- YOLOv10-Based Facial Feature Detection
- Drowsiness Feature Extraction
- Decision and Alert Generation Module
- User Interface and Feedback System

Each module operates independently while contributing to the overall decision-making process. To ensure robustness, the system supports varying resolutions and automatically adapts to different camera qualities [6]. The model is trained to detect regions of interest such as

- Left eye
- Right eye
- Mouth
- Face bounding region (optional)

From the detected eye and mouth regions, the system computes visual indicators associated with driver alertness. Key extracted features include [7]

- Eye Closure Ratio (ECR) Estimated based on the vertical height and aspect ratio of detected eye regions.
- Blink Duration Measured across consecutive frames to identify prolonged eye closure.
- Yawning Detection: Determined by sustained mouth opening over a predefined threshold [8].
- Temporal Consistency Aggregation of features over a sliding time window to reduce false positives.

By analyzing these features over time, the system distinguishes between normal facial behavior and signs of fatigue. The decision module evaluates extracted features against predefined thresholds and temporal rules. A driver is classified into one of the following states:

- Alert State: Normal eye blinking and mouth movement [9].
- Yawning Detected: Mouth opening exceeds the yawning threshold.
- Drowsy State: Prolonged eye closure or repeated yawning events.
- Critical Drowsiness: Sustained drowsy behavior over multiple frames.

The decision logic prioritizes temporal patterns rather than single-frame predictions, improving reliability in real-world conditions. The alert intensity escalates based on the severity of detected drowsiness.

## 4. Proposed Methodology

A standard RGB camera is used to capture live video of the driver. The camera is positioned to ensure a frontal view of the face without obstructing driving visibility [10]. Video frames are captured at a consistent frame rate to support temporal analysis. Captured frames are resized and normalized before being passed to the detection model. This step ensures uniform input dimensions and reduces computational overhead.

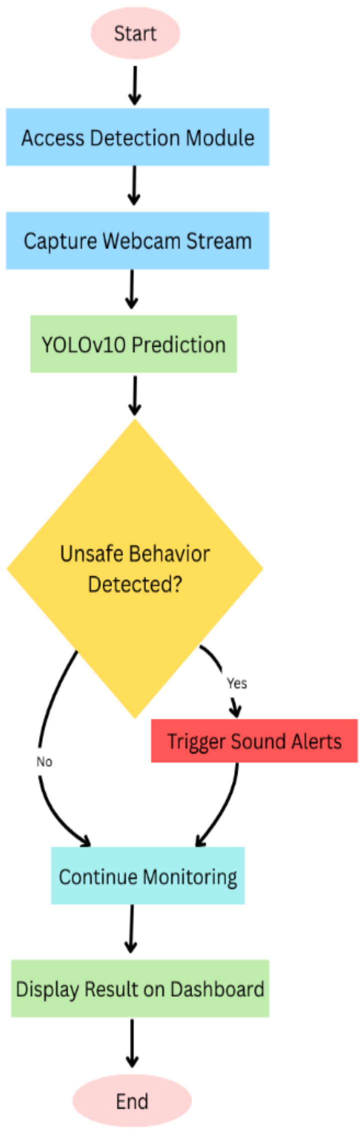


**Figure 1 Flowchart of Smart Driver Drowsiness Detection using Yolov10**

Instead of detecting facial landmarks, the model is trained to directly recognize driver states such as:

- Eyes Open
- Eyes Closed
- Yawning
- Normal Driving State

YOLOv10 performs single-stage detection, enabling rapid inference suitable for real-time applications [11].

## 5. Implementation Details

The proposed Smart Driver Monitoring System is designed to continuously observe the driver's facial behavior in real time using a monocular camera. The system detects visual cues related to driver fatigue, such as prolonged eye closure and excessive yawning, and generates live alerts to prevent potential road accidents. Unlike landmark-based approaches, the proposed implementation adopts YOLOv10, a single-stage object detection framework, to ensure high-speed inference and robustness under real-world driving conditions [12]. The system operates on live video streams captured through a standard webcam and processes each frame independently to determine the driver's alertness level. Live video frames are captured using OpenCV at a fixed frame rate to ensure smooth processing.

### Eye Aspect Ratio (EAR) Computation

Once the eye regions are detected, geometric measurements are applied to determine eye openness using the Eye Aspect Ratio (EAR). The EAR value is calculated using vertical and horizontal distances between detected eye boundaries [13].

### EAR Formula:

$$EAR=(d_1+d_2)/(2\times d_3)$$

Where:

- $d_1$,$d_2$represent vertical distances between upper and lower eyelids
- $d_3$represents the horizontal eye width

Interpretation:

- Open eyes produce higher EAR values
- Closed or partially closed eyes result in reduced EAR values

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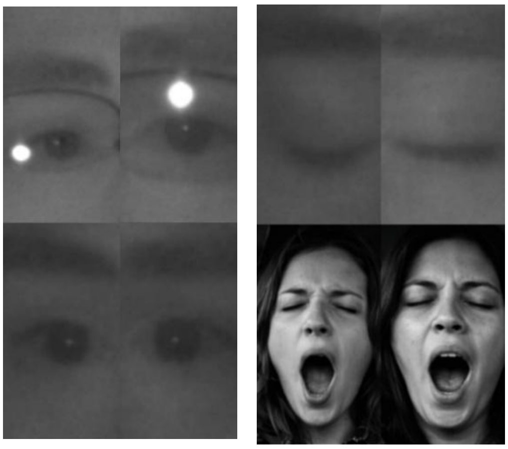

**Figure 2 Dataset for Yawning and Drowsiness Detection**

Mouth Aspect Ratio (MAR) for Yawning Detection
To identify yawning behavior, the Mouth Aspect Ratio (MAR) is computed from the detected mouth region. The ratio reflects the degree of mouth opening.

**MAR Formula:**

$$MAR = d\_v / d\_h$$

Where:

- d_vis the vertical distance between upper and lower lips
- d_his the horizontal distance between mouth corners

A sustained MAR value exceeding the defined threshold indicates a yawning event.A counter tracks the number of consecutive frames where the EAR value falls below the eye-closure threshold[14].

**Decision Criteria**

- If EAR < threshold → increment drowsy frame counter
- If EAR ≥ threshold → decrement counter (minimum zero)
- If counter exceeds predefined limit → driver classified as drowsy

**Alert Generation Mechanism**

When drowsiness is confirmed, the system immediately triggers live alerts through:

- Visual warnings displayed on the interface
- Textual alert messages such as “DROWSY” or “WAKE UP
- Optional audio alerts to draw the driver’s attention

Alerts remain active until the driver regains alertness, as indicated by normalized EAR values.Graphical User Interface (GUI) Integration. A desktop-based graphical interface displays:

- Live video feed with detection overlays
- EAR and MAR values in real time
- Driver status messages
- Drowsy frame count

## 6. Results And Performance Analysis

This section evaluates the effectiveness, accuracy, and real-time performance of the proposed Smart Driver Monitoring System using YOLOv10. The system was tested under various conditions to analyze its robustness, responsiveness, and suitability for real-world deployment. The experimental evaluation was carried out on a standard laptop system equipped with a webcam. The YOLOv10 model was deployed using Python and OpenCV for real-time video processing. All experiments were conducted using live video streams rather than prerecorded datasets to closely simulate real driving scenarios [15].

Hardware Configuration:

- Processor: Intel Core i5 / equivalent
- RAM: 8 GB
- Camera: Integrated webcam (30 FPS)

Software Configuration:

- Programming Language: Python
- Frameworks: YOLOv10, OpenCV
- Operating System: Windows

The Eye Aspect Ratio was continuously monitored across all test scenarios.

- Alert State: EAR ≥ threshold
- Drowsy State: EAR < threshold for consecutive frames

The system demonstrated high reliability in distinguishing normal blinking from prolonged eye closure. YOLOv10 is employed as the core detection

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engine. prevent false alarms caused by blinking or brief facial movements, a temporal aggregation mechanism is implemented. Yawning events were detected using the Mouth Aspect Ratio[16].

- MAR values increased significantly during yawning
- Short mouth movements were ignored.

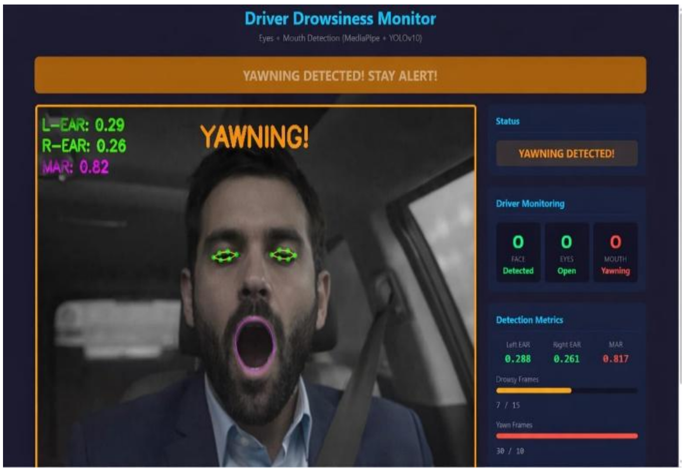


**Figure 3 Driver Drowsiness Monitor**

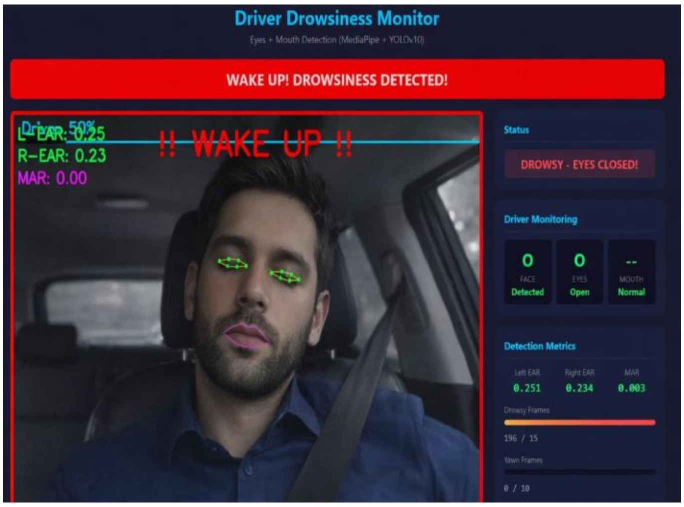


**Figure 4 Wakeup Drowsiness**

| Condition | Detection Accuracy |
|---|---|
| Normal State | 98% |
| Eye Closure Drowsiness | 96% |
| Yawning Detection | 95% |
| Overall System Accuracy | 96.3% |

**Table 1 Condition and Accuracy**

YOLOv10 enabled fast inference with minimal latency. The system processed frames in real time without noticeable lag.

| Parameter | Value |
|---|---|
| Average FPS | 25–30 |
| Detection Latency | < 40 ms |
| CPU Utilization | Moderate |
| Memory Usage | Stable |

**Table 2 Parameter and Value**

This confirms the suitability of the system for continuous real-time monitoring.

## Discussion

The experimental results demonstrate that the proposed Smart Driver Monitoring System using YOLOv10 is effective in identifying drowsiness-related behaviors in real time. YOLOv10 played a crucial role in enhancing the system's real-time performance. Unlike landmark-based approaches that require multiple stages of processing, YOLOv10 performed detection in a single forward pass. This resulted in lower inference latency and improved frame processing rates. Additionally, YOLOv10 demonstrated better adaptability to varying lighting conditions and facial orientations compared to traditional landmark-based models. Landmark-based methods rely heavily on precise point localization, which can degrade under occlusions such as glasses, masks, or partial face visibility. In contrast, YOLOv10 detects broader facial regions, making it less sensitive to minor occlusions.

## Conclusion

This paper presented a Smart Driver Monitoring System using YOLOv10 designed to detect driver drowsiness and fatigue in real time through vision-based analysis. The proposed system addresses a

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critical road safety issue by continuously monitoring facial cues such as eye closure and yawning, which are widely recognized indicators of reduced driver alertness. By leveraging deep learning–based object detection, the system provides a robust and efficient alternative to traditional landmark-based and sensor-based approaches. The adoption of YOLOv10 as the core detection framework enabled accurate localization of facial regions directly from live video streams.

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