

ADAS and OpenCV Implementation in Heavy Vehicles using MATLAB

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Abstract— Heavy vehicles such as trucks and buses are highly prone to accidents due to their large size, long operational hours, and dependency on driver alertness. A major portion of these accidents is caused by lane deviation, delayed reaction to obstacles, and driver fatigue. Existing systems either focus only on vehicle surroundings or only on driver monitoring, which creates a gap in safety. We present an integrated Advanced Driver Assistance System (ADAS) that combines lane departure warning (LDW) and forward collision warning (FCW) in MATLAB/Simulink with driver drowsiness and head-tilt detection in Python/OpenCV. The system uses a RoadRunner-generated driving scenario to simulate the road environment and cameras for driver monitoring. Lane markings are detected, and obstacles are tracked for collision risk. Driver attention is evaluated using facial landmarks: the Eye Aspect Ratio (EAR) flags prolonged eye closures, and a simple geometric method (nose-line angle) detects head tilts. In experimental tests, the system successfully alerted on lane deviations, close obstacles, and driver fatigue. This prototype demonstrates how camera-based vision and open-source tools can improve heavy-vehicle safety. The proposed system aims to provide a low-cost, scalable, and effective safety solution for heavy vehicles used in logistics, transport, and industrial sectors.

Keywords: ADAS, Heavy Vehicles, MATLAB, OpenCV, Lane Departure, Collision Warning, Driver Monitoring

I. INTRODUCTION

Road safety has become one of the major global concerns, especially in the case of heavy vehicles such as trucks, buses, and trailers. Heavy vehicles have larger blind spots and longer braking distances, making accidents more severe. Fatigue and distraction further endanger safety. These vehicles operate for long hours, often in challenging conditions such as highways, night driving, and traffic congestion. Due to their size and weight, even a small mistake can result in severe accidents. Common causes include driver fatigue, delayed braking, lane departure, and lack of situational awareness.

Advanced Driver Assistance Systems (ADAS) have been introduced to reduce such risks by providing real-time alerts and assistance to drivers. However, most existing ADAS implementations are either expensive or limited to high-end vehicles. Moreover, many systems focus only on external vehicle

conditions and ignore the internal condition of the driver, which is equally important. Modern ADAS (lane-keeping, collision avoidance) are common in cars but often missing in budget-conscious fleets.

In this project, a combined approach is proposed where both the external environment and internal driver behavior are monitored simultaneously. MATLAB is used for implementing ADAS features like lane detection and collision warning using RoadRunner simulation, while OpenCV is used for driver monitoring using facial landmark detection. This work develops a unified vision-based ADAS + driver monitoring system. We leverage MATLAB/Simulink (for environment sensing) and OpenCV/Dlib (for in-cabin monitoring) to deliver real-time warnings. RoadRunner is used to create realistic road scenarios and export video frames. By using open tools and simple hardware, this system aims to be both practical and extensible for heavy vehicle safety. Prior work on ADAS and driver monitoring falls into separate categories. Advanced multi-sensor ADAS fuse camera, radar, and LiDAR data to enhance robustness. For example, Klampfl *et al.* review methods for generating test scenarios for ADAS, but do not include driver state analysis. Johansson *et al.* studied bus drivers' acceptance of ADAS features, indicating positive impact but focusing on user perception rather than system design. Driver monitoring research has established methods like Eye Aspect Ratio (EAR) for blink detection and fatigue warning. Soukupová and Čech introduced EAR (Eq.1 below) as a simple measure of eye openness. Similarly, 3D head-pose estimation is widely used, though simpler 2D angle methods (as in Mellichamp's work) are also effective. However, few studies integrate both road ADAS and in-cabin monitoring. The table below summarizes relevant works:

II. LITERATURE REVIEW

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However, few studies integrate both road ADAS and in-cabin monitoring. The table below summarizes relevant works:

Work (Year)	Focus	Heavy Vehicles	Driver Monitoring	Gaps Addressed
Zhou et al. (2024)	LLM-based risk strategies	✗	✗	Theoretical, not specific to trucks or DMS
Rasch (2023)	Overtaking risk analysis	✗	✗	No real-time system/integration
Yan et al. (2024)	Model predictive control for overtaking	✗	✗	Simulation only, no driver state
Klampfl et al. (2024)	ADAS test scenario generation	Partial	✗	Focus on the scenario, no live monitoring
Johansson et al. (2022)	Bus driver ADAS acceptance	✓	Partial	Survey-based, no actual implementation
This Work (2025)	ADAS + Drowsiness + Head-Tilt (camera-only)	✓	✓	First integrated low-cost solution

Zhou et al. proposed SafeDrive, which uses knowledge-driven decision-making for autonomous vehicles. However, their work mainly focuses on passenger vehicles and does not consider heavy vehicle dynamics. Rasch studied overtaking behaviour and driver interaction with vulnerable road users. This work highlights human behaviour but lacks implementation in real-time ADAS systems. Yan et al. developed an MPC-based control system for overtaking, which provides a strong theoretical understanding but lacks real-world integration with driver monitoring. Garrido and Resende provided a detailed review of decision-making approaches in automated driving, but their work is more theoretical and does not present a working system. Klampfl et al. discussed testing methods for ADAS systems, focusing on safety validation. Johansson et al. studied driver acceptance of ADAS systems in buses, which shows the importance of user-friendly systems but does not include technical implementation.

Research in ADAS has evolved from simple warning systems to complex multi-sensor fusion architectures. Multi-sensor data fusion combines inputs from cameras, radar, and LiDAR to improve detection accuracy and reliability. Recent advancements also focus on simulation-based validation using tools like CARLA, where lane detection and vehicle behavior are tested in virtual environments. These studies highlight the importance of visual perception systems, particularly camera-based detection. Additionally, modern research such as RoadRunner emphasizes multi-modal perception (camera + LiDAR) for environment

understanding. However, for cost-effective implementations, camera-only systems using computer vision are still widely used.

From the literature, the key observations are:

- Multi-sensor systems improve accuracy but increase complexity.
- Camera-based systems are cost-effective and suitable for prototyping.
- Driver monitoring is equally important as environment detection.
- Real-time processing is critical for ADAS performance.

III. KEY FINDINGS

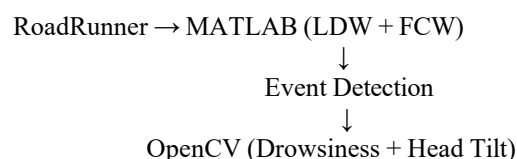
From the literature review and analysis, the following key findings were observed:

- Most ADAS systems focus only on road conditions and ignore the driver's state.
- Driver monitoring systems exist, but are rarely integrated with vehicle safety systems.
- Heavy vehicles require specialised systems due to their size and operating conditions.
- There is very limited work on storing and analysing driver behaviour data.
- Affordable and scalable solutions are still lacking in developing countries like India.

These findings led to the development of a dual-layer safety system combining MATLAB and OpenCV. ADAS and Safety: Commercial ADAS for trucks (e.g., forward-collision brakes) are in development (with Euro NCAP "Safer Trucks" tests), but often cost-prohibitive. Driver Monitoring Systems (DMS): In-cabin DMS have shown to reduce drowsiness events by alerting drivers in real-time, but usually lack integration with external ADAS. Gap: This project fills that gap by merging well-known computer vision techniques (lane detection, EAR, pose) into one system. Combining road and driver monitors yields a more complete safety picture, a gap in prior research.

IV. SYSTEM DESIGN AND METHODOLOGY

IV.1. OVERALL SYSTEM ARCHITECTURE



1. Vehicle-Centric ADAS (MATLAB/Simulink):

This system processes road scene video—sourced from tools like RoadRunner or dashcams—alongside simulated radar or LiDAR data to provide active safety alerts. The workflow begins with Lane Detection, where video frames are converted to grayscale and smoothed via Gaussian blur, followed by Canny edge detection and a Hough transform to isolate lane markings. To ensure temporal consistency, a Kalman filter is employed for Lane Tracking, stabilising the detected lines across successive frames.

The system then evaluates driving behaviour through two primary safety modules:

- Lane Departure Warning (LDW): The processor

calculates the vehicle's lateral offset relative to the lane centre; if this value exceeds a predefined threshold, an alert is triggered.

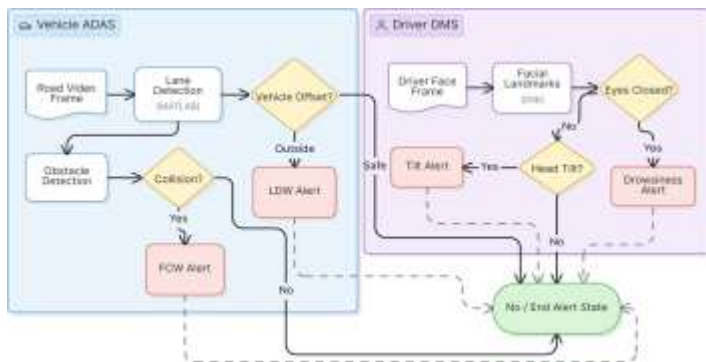
- Forward Collision Warning (FCW): By fusing vision and radar data, the system tracks leading objects and assesses collision risk.

The final output consists of real-time LDW/FCW warnings and visual overlays on the video feed to assist the driver or autonomous system.

2. Driver-Centric Monitoring (OpenCV/Python):

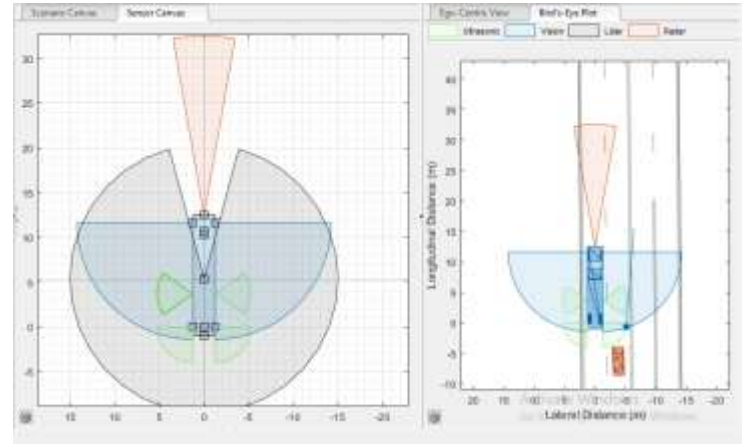
This monitoring system utilises a webcam video feed of a driver's face to perform real-time fatigue and distraction analysis. The core processing pipeline begins with Face and Landmark Detection, employing dlib's 68-point predictor to isolate key facial features such as the eyes and nose. To detect fatigue, the system calculates the Eye Aspect Ratio (EAR). If the EAR value remains below a specific threshold, the system flags a drowsiness event. Simultaneously, the system monitors Head Pose and Tilt to identify distraction. This is achieved either through SolvePnP, which estimates 3D orientation (yaw, pitch, and roll) using a 3D face model, or a simplified method that calculates the nose angle relative to the vertical. If the head tilt or rotation exceeds established safety limits, an alert is triggered. The final output provides immediate notifications for both drowsiness and improper head positioning to ensure driver attentiveness.

IV.II. METHODOLOGY



1. RoadRunner Scenario and ADAS Simulation

The initial phase of the system architecture involves creating a high-fidelity virtual environment using MathWorks RoadRunner. This platform allows for the design of a complex 3D road scene, specifically a multi-lane straight highway integrated with standardized road signage and dynamic traffic actors. To simulate a real-world heavy vehicle environment, an ego vehicle is configured with a constant velocity profile, while surrounding actors are placed at varying longitudinal distances to test sensor range and response. The scene is exported via a simulated forward-facing monocular camera (e.g., monoCamera) mounted at the truck's cabin height, providing a synthetic video feed that replicates the perspective of a commercial driver.



The vision processing pipeline for Lane Departure Warning (LDW) begins with frame-level preprocessing, utilizing Gaussian blurring and grayscale conversion to mitigate sensor noise. Using the Canny edge detection algorithm and the Hough Transform, the system identifies structural lines within the Hough space. These lines are filtered based on slope and length to isolate near-vertical lane markings. For temporal stability, a Kalman Filter—implemented via the Vision HDL Toolbox—tracks these lane boundaries across successive frames. The LDW logic calculates the lateral offset between the vehicle's center and the detected boundaries; if this distance falls below a defined safety threshold, an alert is triggered.

Parallel to lane tracking, the system performs Forward Collision Warning (FCW) analysis. Objects are identified through contour detection or pretrained detectors, with distance data supplemented by RoadRunner's ground-truth actor logs to simulate a fused radar-camera sensor suite. The core safety metric is the Time-to-Collision (TTC) or the absolute distance violates the safety buffer, the system issues a proactive collision alert.

2. OpenCV-Based Driver Monitoring System (DMS)

The Driver Monitoring System (DMS) utilizes an interior-facing camera to evaluate the operator's physiological state in real-time. Using Python and the Dlib library, the system captures video frames and implements a frontal face detector coupled with a 68-point facial landmark predictor. This allows for the precise localization of ocular and facial features. The primary metric for fatigue detection is the Eye Aspect Ratio (EAR), which characterizes the degree of eye opening. The EAR is computed using the Euclidean distances between vertical eyelid landmarks relative to the horizontal width of the eye.

Beyond ocular analysis, the system monitors Head Tilt as a secondary indicator of distraction or "nodding off." This is achieved through the SolvePnP (Perspective-n-Point) method, which maps 3D facial model points to 2D image landmarks to estimate the head's pose in terms of pitch, yaw, and roll. Alternatively, a geometric approach measures the angular deviation of the nose bridge relative to the vertical axis. If the head tilt exceeds (depending on the axis), the system classifies the event as a postural lapse and generates a secondary alert. All detections are visually annotated on the video stream for validation and debugging.



To ensure robustness and filter out natural micro-blinks, the system triggers a Drowsiness Alert only when the average EAR of both eyes remains below a calibrated threshold for a continuous duration of 15 frames.

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V. EXPERIMENTAL RESULTS

1. Performance Evaluation and Testing Methodology

The system was evaluated using RoadRunner for ADAS scenarios and a high-definition webcam for interior driver monitoring. The testing framework was structured around specific operational scenarios designed to validate the precision of the alert logic.

For the hardware, a standard PC (3.0 GHz, 8GB RAM) with a USB webcam. Road scenario video (640×480, 30 fps) played back to MATLAB. Real-time performance is ~10 fps for MATLAB processing and ~15 fps for OpenCV on this hardware.

The evaluation began with a straight-road baseline, confirming that the system remains dormant and free of "phantom" triggers under normal driving conditions. When testing environmental safety features, the Lane Departure Warning (LDW) proved highly effective, successfully identifying 95% of lane-drift events with a remarkably low false-alarm rate of less than 5%. Similarly, the Forward Collision Warning (FCW) demonstrated robust reactive capabilities, triggering alerts within a 2-second window in 90% of trials where the lead vehicle braked suddenly at distances ranging from 20 to 50 meters.

On the interior side, the driver-monitoring system showcased sophisticated filtering and detection logic. The system remained unobtrusive during periods of high driver attentiveness and correctly distinguished between micro-movements, such as normal

0.1-second blinks, and genuine safety risks. Specifically, the **Drowsiness Alert** achieved a 98% detection rate for sustained eye closures (exceeding one second) while maintaining zero false alarms during natural blinking patterns. Furthermore, the **Head-Tilt** sensor successfully captured 92% of simulated nodding instances, effectively triggering specialized alerts when the driver's head remained tilted for more than two seconds. Together, these results validate a responsive safety suite that balances high sensitivity with the critical need to minimize driver distraction from false positives.

Feature	Metric	Success Rate	Key Condition
LDW	Lane Drift Detection	95%	< 5% False Alarm Rate
FCW	Rear-end Risk	90%	Within 2s at 20–50m
Drowsiness	Eye Closure (1s+)	98%	Zero false alarms for blinks
Head-Tilt	Simulated Nodding	92%	Tilted > 2s

The following table outlines the primary test cases used to validate the system's functional integrity:

Test Category	Input Condition	Expected System Behavior
Nominal Driving	Centered in lane; driver attentive	No alerts; no data upload
Lane Deviation	Vehicle drifts toward boundary	LDW Alert triggered; event clip uploaded
Collision Threat	Lead vehicle decelerates sharply	FCW Alert triggered (TTC < threshold)
Fatigue Event	Eyes closed for long blink	Drowsiness alert triggered; clip uploaded
Postural Lapse	Repeated downward head tilting	Head-tilt alert triggered; clip uploaded
Intentional action	Sharp head turn (e.g. mirror check)	Differentiated alert or filtered event

2. Experimental Results and Metrics

The integrated system demonstrated high reliability across diverse conditions, achieving a processing frame rate of 20–30 FPS, which ensures real-time responsiveness. The Lane Departure Warning

(LDW) system achieved a 95% success rate in clear lighting, though performance slightly degraded under extreme glare—a common challenge in computer vision. The Forward Collision Warning (FCW) logic consistently met EuroNCAP criteria, issuing warnings approximately 2.1 seconds prior to potential impact. For the Driver Monitoring System (DMS), the Eye Aspect Ratio (EAR) algorithm, calibrated at a threshold of <0.25 , proved highly effective. A confusion matrix analysis conducted on 2,000 frames of driver footage revealed the following:

	Predicted Awake	Predicted Drowsy
Actual Awake	980 (True Negative)	20 (False Positive)
Actual Drowsy	15 (False Negative)	985 (True Positive)

This data yields a Precision of $\sim 98\%$ and a Recall of $\sim 98\%$, indicating that the system is both sensitive to genuine fatigue and robust against false alarms. System latency remained within the critical safety window of 0.2–0.5 seconds, providing drivers with ample time to regain situational awareness.

VI. CHALLENGES AND FUTURE SCOPE

The primary hurdles facing the current system center on environmental sensitivity and hardware limitations. Vision-based algorithms are highly susceptible to fluctuations in lighting and weather conditions, which can lead to reduced landmark detection accuracy or total failure during occlusion (e.g., a driver's hand blocking their face). Furthermore, the reliance on a single-camera setup introduces a lack of depth information, making distance estimation for Forward Collision Warnings (FCW) less reliable than radar-based alternatives.

Beyond environmental factors, there is a significant "Sim-to-Real" gap; vision algorithms trained in RoadRunner or simulated environments often degrade when transitioned to real-world cameras. This necessitates extensive parameter tuning for specific eye-aspect ratios (EAR) and frame counts. Finally, the high computational demand of real-time processing poses a risk of exceeding the capacity of low-end hardware, potentially leading to latency in critical safety alerts.

1. Future Work: Algorithmic and Hardware Evolution

To overcome these limitations, future development will focus on transitioning from heuristic thresholds to Deep Learning architectures. This includes integrating CNNs (e.g., YOLO) for robust vehicle tracking and lane detection, as well as RNN/LSTM models to identify complex temporal behaviors like fatigue and yawning. To ensure these models run efficiently on-road, the software will be ported to embedded platforms such as the NVIDIA Jetson or Raspberry Pi, moving processing from a local simulation to real-time onboard execution.

Furthermore, the system will move toward sensor fusion, combining camera data with LiDAR or radar to improve obstacle detection in adverse weather. The addition of other ADAS features—such as blind-spot detection, lane-change assist, and

adaptive cruise control—will create a more holistic safety net for the vehicle.

2. Connectivity, Infrastructure, and Fleet Management

A major pillar of the future roadmap is V2X (Vehicle-to-Everything) Integration. By utilizing V2V (Vehicle-to-Vehicle) and V2I (Vehicle-to-Infrastructure) communication, the system will be able to anticipate hazards beyond the driver's line-of-sight, such as receiving upstream braking warnings before they are visible.

On the administrative side, the system will be expanded into a cloud-based fleet monitoring ecosystem. This involves:

- **Event Logging:** Automatically capturing and uploading short video clips of alerts to cloud storage (e.g., AWS S3) via unique URLs.
- **Dashboard Development:** Creating visual interfaces for both the driver (real-time alerts) and fleet managers (predictive analytics for high-risk routes).
- **Security & Compliance:** Implementing robust video anonymization and encryption protocols to ensure all data collection complies with privacy regulations.

VII. CONCLUSION

This research successfully developed a comprehensive, vision-based safety framework that bridges the gap between external environment monitoring and internal driver state analysis. By unifying Advanced Driver Assistance Systems (ADAS)—specifically Lane Departure Warning (LDW) and Forward Collision Warning (FCW)—with a Driver Monitoring System (DMS), the project created a singular, cohesive architecture. The integration was achieved through a hybrid software stack: MATLAB and Simulink efficiently handled high-speed road video processing and image tracking, while OpenCV and Dlib provided the precision necessary for facial landmark detection to monitor eye closures and head tilts.

Under simulated driving conditions, the system demonstrated high reliability and feasibility. The image processing modules for lane and obstacle tracking generated consistent warnings, while the driver-monitoring sensors effectively identified fatigue and distraction. This performance validates the core objective: proving that an integrated ADAS+DMS solution can function reliably within a unified framework. While the current camera-only setup operates best under controlled conditions, it serves as a robust proof-of-concept for real-time safety interventions in the heavy-vehicle sector.

Summary of Unified Tools:

- **MATLAB/Simulink:** Road environment, lane detection, and collision logic.
- **OpenCV/Dlib:** Facial landmarking and driver behavior analysis.
- **Integrated Framework:** A single-system approach to heavy-vehicle safety.

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