STM JOURNALS

Journal of
Automobile Engineering
and Applications

ISSN: 2455-3360
Volume 13, Issue 1, 2026
January—April
DOI Journal: 10.37591/JoAEA

https://journals.stmjournals.com/joaea

Review JoAEA

A Review Paper of Automated Driving & ADAS Technologies

Paresh m Sangadiya[1,*], Sagar M Bechara[1], Rishabh Makwana[1], Mihir D Gajjar[2]

Abstract

Automated driving and Advanced Driver Assistance Systems (ADAS) are transforming road mobility, promising enhanced safety, improved traffic efficiency, and greater accessibility. This review presents a comprehensive synthesis of core technologies, system architectures, sensor modalities, perception, and decision-making algorithms, and evaluation methodologies underpinning contemporary ADAS and automated driving. We provide a detailed discussion of the functional components – sensors (camera, radar, LiDAR, ultrasonic), localization, perception, prediction, planning, control, and human–machine interfaces – and how these integrate within modular and end-to-end architectures. A two-page literature survey distills seminal and recent contributions across academic research and industrial deployments, highlighting breakthroughs in deep learning-based perception, sensor fusion strategies, robust localization, and simulation-based validation. Methodological approaches for developing and validating ADAS systems are summarized, including data-driven model training, closed-loop simulation, hardware-in-the-loop testing, and on-road trials. Key challenges are examined – safety assurance, handling edge-cases, sensing limitations in adverse weather, regulatory, and ethical considerations, cyber security, and human factors. Finally, we outline future directions such as scalable validation frameworks, V2X integration, AI interpretability, and shared autonomy paradigms. The review aims to serve researchers, engineers, and policymakers with a structured overview and practical recommendations for advancing safe, reliable automated driving systems. Automated Driving and Advanced Driver Assistance Systems (ADAS) represent a significant evolution in intelligent transportation, aiming to improve road safety, traffic efficiency, and driving comfort. This review paper provides a structured overview of key ADAS and automated driving technologies, including system architectures, sensor technologies, perception, decision-making, and control algorithms. It surveys major advancements in camera, radar, LiDAR-based sensing, sensor fusion, and deep learning techniques for environment understanding. Additionally, the paper discusses validation methodologies, safety challenges, human–machine interaction, and regulatory aspects. Future research directions such as V2X integration, scalable testing, and explainable AI are also highlighted.

Keywords: ADAS, automated driving, localization, perception, planning, safety assurance, sensor fusion, V2X

***Author for Correspondence**
Paresh m Sangadiya
E-mail: cpmanikandan07@gmail.com

[1]Assistant Professor, Department of Automobile Engineering, Atmiya University, Rajkot, Gujarat, India.
[2]Lecturer, Department of Automobile Engineering, Atmiya University, Rajkot, Gujarat, India.

Received Date: December 18, 2025
Accepted Date: January 03, 2026
Published Date: January 20, 2026

Citation: Paresh m Sangadiya, Mihir D Gajjar, Sagar M Bechara, Rishabh Makwana. A Review Paper of Automated Driving & ADAS Technologies. Journal of Automobile Engineering and Applications. 2026; 13(1): 1–7p.

INTRODUCTION

Today, automated driving and Advanced Driver Assistance Systems (ADAS) encompass a broad set of functionalities designed to assist or replace human driving tasks. From basic lane-keeping assistance and adaptive cruise control to fully autonomous vehicles capable of performing all driving tasks under defined conditions, these technologies rely on sensing, perception, decision-making, and control systems. The automotive industry, academia, and regulatory bodies have made significant progress in recent years; however, achieving robust, deployable autonomy across varied real-world scenarios remains a complex multidisciplinary challenge. This review organizes the field into component layers, summarizes influential literature, discusses common methodologies for development and validation, and identifies open problems and future research avenues [1–5].

Road transportation is a critical component of modern society, enabling economic growth, social connectivity, and mobility of people and goods. However, rapid motorization has also led to serious challenges such as traffic congestion, road accidents, environmental pollution, and increased energy consumption. According to global road safety reports, human error contributes to the majority of traffic accidents, including errors in perception, decision-making, fatigue, distraction, and improper vehicle control [6–9]. These challenges have driven significant research and industrial interest in Advanced Driver Assistance Systems (ADAS) and Automated Driving technologies, which aim to enhance vehicle safety, efficiency, and driving comfort by reducing reliance on human judgment alone (Figure 1).

Advanced Driver Assistance Systems represent the first major step toward vehicle automation. ADAS technologies assist the driver by providing warnings, partial control, or automated responses in critical situations. Common ADAS features include Anti-lock Braking Systems (ABS), Electronic Stability Control (ESC), Adaptive Cruise Control (ACC), Lane Departure Warning (LDW), Lane Keeping Assist (LKA), Automatic Emergency Braking (AEB), Blind Spot Detection (BSD), and Parking Assistance systems. These systems use a combination of sensors, electronic control units (ECUs), and control algorithms to monitor the vehicle’s surroundings and support safer driving decisions. Over time, ADAS has evolved from simple warning systems to more complex functions capable of actively intervening in vehicle control [10–13].

Automated driving technologies extend the capabilities of ADAS by enabling vehicles to perform driving tasks with reduced or no human intervention. The Society of Automotive Engineers (SAE) has classified driving automation into six levels, ranging from Level 0 (no automation) to Level 5 (full automation). While most production vehicles today operate at Levels 1 and 2, research prototypes and limited commercial deployments have demonstrated Level 3 and Level 4 automation in controlled environments. Fully autonomous vehicles (Level 5) remain a long-term goal, requiring breakthroughs in perception, decision-making, validation, and regulatory frameworks [14–17].

Figure 1. Exploring the future of safe driving.

The core of automated driving systems lies in their ability to perceive, understand, and interact with complex and dynamic driving environments. Unlike controlled industrial automation, road environments are highly uncertain and involve diverse actors such as pedestrians, cyclists, animals, and human-driven vehicles. Automated vehicles must operate reliably under varying lighting conditions, weather scenarios, traffic densities, and road infrastructures. To address these challenges, modern ADAS and automated driving systems rely heavily on multi-sensor architectures that integrate cameras, radar, LiDAR, ultrasonic sensors, Global Navigation Satellite Systems (GNSS), and Inertial Measurement Units (IMUs). These sensors provide complementary information that enhances robustness and redundancy (Figure 2).

Recent advances in artificial intelligence (AI), particularly machine learning and deep learning, have significantly accelerated progress in automated driving. Deep neural networks have achieved remarkable performance in tasks such as object detection, lane recognition, traffic sign classification, and semantic scene understanding. Sensor fusion techniques combine data from multiple sensors to overcome individual limitations and improve reliability. Additionally, high-definition (HD) maps and localization algorithms enable precise vehicle positioning, which is essential for accurate planning and control. Together, these technologies form a layered system architecture consisting of sensing, perception, localization, prediction, planning, and control modules [18].

Despite substantial technological progress, the widespread deployment of automated driving systems faces several unresolved challenges. Safety assurance remains the most critical concern, as automated vehicles must demonstrate performance that is equal to or superior to human drivers across a vast range of scenarios, including rare and hazardous edge cases. Validation and verification of these systems are difficult due to the enormous number of driving situations encountered in real-world operation. Furthermore, ethical considerations, legal liability, cyber security threats, and public acceptance play a crucial role in determining the pace of adoption. Human-machine interaction is another important factor, particularly in partially automated systems where safe and timely transfer of control between the vehicle and the driver is essential.

This review article aims to provide a comprehensive overview of Automated Driving and ADAS technologies, focusing on system components, key research developments, and evaluation methodologies. A detailed literature survey highlights foundational and recent contributions from academia and industry.

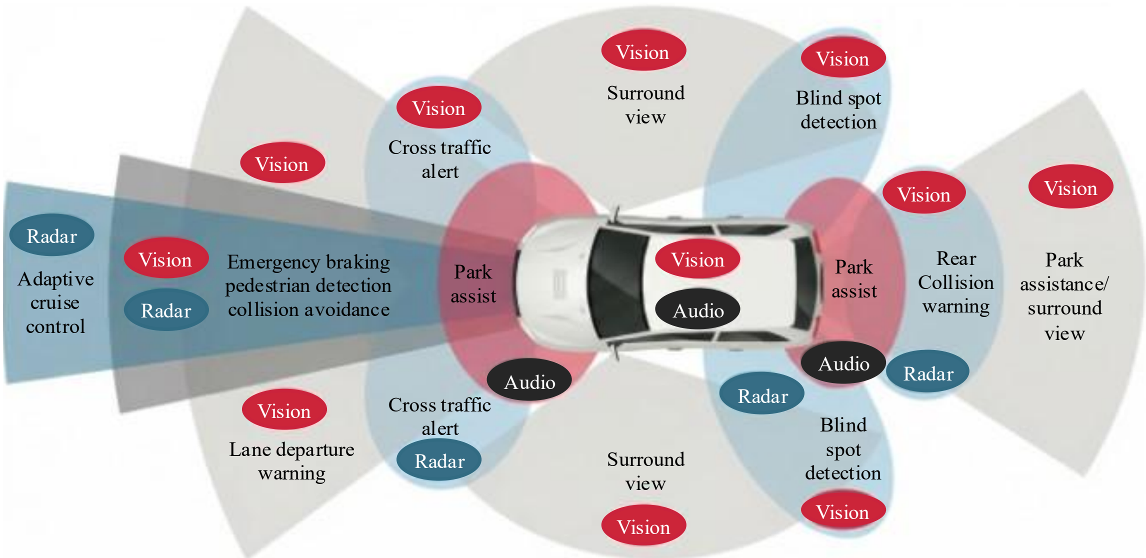

Figure 2. Vision and image processing in automotive ADAS/AD development.

The paper also discusses common development methodologies, major technical and non-technical challenges, and emerging research directions. By synthesizing existing knowledge and identifying future opportunities, this review seeks to serve as a useful reference for students, researchers, engineers, and policymakers involved in the field of intelligent transportation and automotive automation.

COMPONENTS OF AUTOMATED DRIVING & ADAS SYSTEMS

Automated Driving and Advanced Driver Assistance Systems (ADAS) are designed using a layered architecture. Each component performs a distinct function, enabling perception, decision-making, and control of the vehicle. Figure 3 presents a functional overview of major system components.

Sensing Systems

Sensing systems provide real-time information about the vehicle's surroundings. Cameras, radar, LiDAR, ultrasonic sensors, GPS, and inertial sensors are commonly used. Cameras capture visual cues such as lanes, signs, and obstacles. Radar offers accurate distance and speed measurement even in poor weather, while LiDAR generates high-resolution 3D point clouds for environment mapping. Ultrasonic sensors are effective for short-range detection.

Perception and Sensor Fusion

Perception systems interpret sensor data to identify objects, lanes, and free space. Sensor fusion combines multiple sensor inputs to improve reliability and reduce uncertainty. Modern perception systems extensively use deep learning algorithms.

Localization and Mapping

Localization estimates the vehicle's position within the environment. GNSS provides global positioning, while SLAM and HD maps ensure lane-level accuracy. Accurate localization is essential for path planning and navigation.

Prediction

Prediction modules estimate the future motion of surrounding road users. These estimates consider uncertainty and interaction between multiple agents, enabling safe maneuver planning.

Planning and Decision Making

Planning algorithms generate collision-free trajectories that satisfy traffic rules and vehicle constraints. Decision-making determines maneuvers such as lane changes, overtaking, or stopping at intersections.

Vehicle Control System

The control system converts planned trajectories into actuator commands for steering, braking, and acceleration. Control algorithms such as PID and Model Predictive Control ensure stability and comfort.

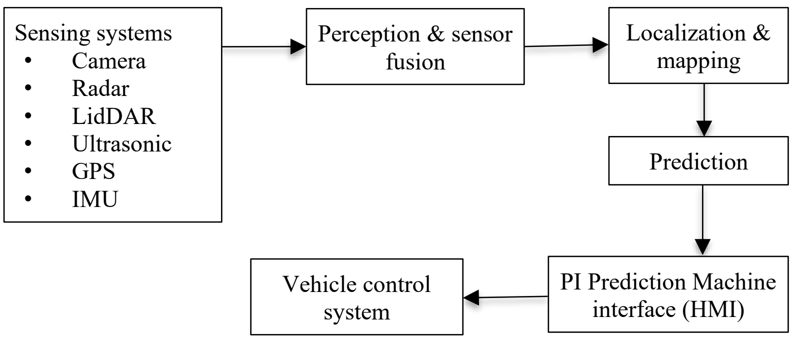

Figure 3. Architecture of Automated Driving and ADAS Systems.

Human–Machine Interface (HMI)

HMI enables communication between the driver and the automation system. Visual, auditory, and haptic feedback inform the driver about system status and takeover requests.

V2X Communication

Vehicle-to-Everything communication enhances situational awareness by sharing data with other vehicles and infrastructure.

LITERATURE SURVEY

The following literature survey highlights influential academic and industry contributions that have shaped the current state of ADAS and automated driving. The selection emphasizes widely-cited studies, foundational standards, and recent trends in perception, planning, validation, and safety assurance.

SAE International – Levels of Driving Automation (J3016)

The SAE J3016 taxonomy standardized automation levels (0–5) and provided a common language for researchers and regulators. It remains fundamental for defining system capabilities and regulatory requirements.

Kalra and Paddock (2016) – Driving to Safety

This work analyzed the safety paradox of autonomous vehicles, discussing probabilistic approaches to safety validation and the challenges of deriving acceptable risk levels compared to human drivers [2].

Bojarski et al. (2016) – End-to-end learning for self-driving cars

This paper demonstrated end-to-end deep learning from raw pixels to steering commands. While promising, end-to-end approaches raise questions about interpretability and safety guarantees compared with modular pipelines [3].

Geiger et al. (KITTI dataset, 2012–2013)

The KITTI benchmark accelerated research in vision-based perception by providing high-quality datasets for stereo, optical flow, object detection, and tracking. Benchmarks like KITTI spurred rapid progress in algorithms [4].

Chen et al. (2017) – Multi-view 3D object detection (MV3D)

MV3D and subsequent multi-sensor fusion methods combined LiDAR and camera data to improve 3D detection accuracy, establishing fusion as a standard practice for robust perception [5].

Waymo/Google and Waymo Open Dataset (2019)

Waymo's dataset and industry-scale efforts provided large-scale, labeled sensor data capturing complex urban driving scenarios, enabling data-hungry deep learning models and evaluation at scale [6].

Ziegler et al. (Berkley/Uber/others) – Motion planning frameworks

Classical motion planning techniques (graph search, sampling-based planners) combined with optimization approaches provided robust solutions for trajectory generation under constraints; modern systems often hybridize these with learned components [7].

Ulbrich et al. (2015) – Pedestrian intention prediction

Prediction research focused on modeling uncertainty and multi-modal futures. Bayesian approaches, Gaussian processes, and deep-learning planners contributed methods for anticipating other agents' behaviors [8].

Shalev-Shwartz et al. (2016) – On formal safety frameworks.

This paper argued for formal, provable safety frameworks and decompositions that enable system-level safety arguments, influencing how industry approaches verification [9].

NVIDIA DRIVE, Mobileye, and industrial perception stacks (2015–2021).

Commercial platforms integrated high-performance compute, optimized perception stacks, and mapping solutions. These efforts highlighted the engineering challenges of moving from research prototypes to production systems [10].

Simulation and Validation – CARLA, LGSVL.

Open-source simulators provided reproducible environments for training and testing perception and planning algorithms; simulation became essential for covering rare edge cases and scaling validation.

Sensor failure and robustness studies

Research into adverse weather sensing, sensor degradation, and redundancy strategies emphasized the need for robust fusion and fallback behaviors.

Human factors and takeover studies

Empirical studies examined driver behavior under partial automation, attention, trust, and the dynamics of safe handover between vehicle and driver.

METHODOLOGY

Now, developing, and validating ADAS and automated driving systems typically follows an iterative, multi-stage methodology:

1. *Data Collection:* Multi-sensor logging (camera, LiDAR, radar, IMU, GNSS) across diverse environments and edge cases.
2. *Algorithm Development:* Use supervised, self-supervised, and reinforcement learning for perception and decision modules. Classical model-based methods remain vital for control and verification.
3. *Simulation and Synthetic Data:* Leverage simulators for scenario generation, corner-case exploration, and training data augmentation.
4. *HIL and SIL Testing:* Hardware-in-the-loop and software-in-the-loop frameworks to validate real-time performance and integration.
5. *Field Trials:* Controlled track tests followed by instrumented on-road trials with safety drivers and phased deployment.
6. *Safety Assurance:* Fault-injection testing, formal verification where applicable, and safety cases aligned with standards (ISO 26262, ISO/PAS 21448).

Evaluation metrics include detection and tracking accuracy, localization error, trajectory tracking error, collision rates in simulation, and reliability metrics under different environmental conditions.

CHALLENGES

- Safety assurance and validation across the long-tail of edge cases.
- Perception limitations in adverse weather or occlusion.
- Explainability and interpretability of deep learning models.
- Regulatory harmonization and legal liability for automated actions.
- Cybersecurity risks and secure over-the-air updates.
- *Human factors:* handover, driver monitoring, and trust calibration.
- High-definition mapping dependence vs. map-less approaches.
- Cost, scalability, and energy consumption of sensors and compute platforms.

FUTURE SCOPE

Research and industry trends indicate several promising directions:

- *Scalable validation:* statistical validation methods, scenario-based testing, and distributed real-world data sharing.
- V2X and infrastructure augmentation to reduce sensing ambiguity in complex environments.
- Lightweight, efficient perception models for edge compute and energy-constrained platforms.
- Explainable AI methods to support safety cases and regulatory acceptance.
- Shared autonomy paradigms enabling flexible handover and cooperative driving among connected agents.
- Standardized datasets and benchmarks for safety-critical evaluation and cross-vendor interoperability.

CONCLUSION

Automated driving and ADAS technologies have advanced significantly, driven by breakthroughs in sensing, AI, and compute. Yet, robust deployment at scale requires continued progress in safety assurance, validation, and human-centered design. A balanced approach that combines data-driven learning with provable system-level guarantees, extensive simulation, and careful real-world validation will be crucial for achieving the societal benefits of automation while managing risks.

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