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Artificial Intelligence In Autonomous Vehicles: A Review Of The Perception, Localization, Planning And Control Stack

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Abstract—Autonomous vehicles use artificial intelligence to understand their surroundings, decide how to move and control steering, acceleration and braking with minimal or no human intervention. This paper reviews the AI technologies across the full autonomous driving stack. It traces the field from the DARPA challenge vehicles to modern systems and explains the levels of driving automation. Perception with cameras, radar and LiDAR, including deep object detection and point-cloud networks, is examined, followed by localization and mapping through LiDAR odometry and simultaneous localization and mapping, motion planning and control, and learning-based approaches including direct perception, conditional imitation learning, deep reinforcement learning and end-to-end planning-oriented networks. Large-scale datasets and simulation for training and validation are discussed. A five-layer modular architecture for an autonomous vehicle is proposed, together with research gaps, objectives, a comparison of modular and end-to-end approaches and an analysis of challenges including safety validation, rare scenarios, adverse weather, mixed traffic, cybersecurity, ethics and regulation. The review concludes that AI has made autonomous driving technically feasible in defined conditions, but that broad deployment depends on demonstrable safety and robust handling of the unexpected.

Index Terms—Autonomous vehicles, self-driving cars, perception, localization, motion planning, deep learning, reinforcement learning, sensor fusion

I. INTRODUCTION

Driving requires continuous perception, prediction and decision making. Human drivers do this well most of the time but are prone to distraction, fatigue and error. Autonomous vehicles aim to perform these tasks with AI, potentially improving safety, mobility for people who cannot drive and traffic efficiency.

The modern field began with the DARPA challenges. Stanley [1] won the 2005 desert race using machine learning for terrain classification, and Boss [2] won the 2007 Urban Challenge by navigating city-like traffic. Since then, deep learning and large datasets have transformed each part of the driving system. Yurtsever *et al.* [3] review common practices and emerging technologies.

This paper reviews AI across the autonomous driving stack and proposes a modular architecture.

II. BACKGROUND AND FUNDAMENTAL CONCEPTS

2.1 Levels Of Automation

SAE J3016 [4] defines levels from 0 (no automation) to 5 (full automation). At Level 4, the vehicle drives itself within a defined operational design domain, such as a mapped city area in good weather.

2.2 The Driving Stack

Fig. 1 shows the main components: perception, localization and mapping, prediction, planning and control, and how AI contributes to each.

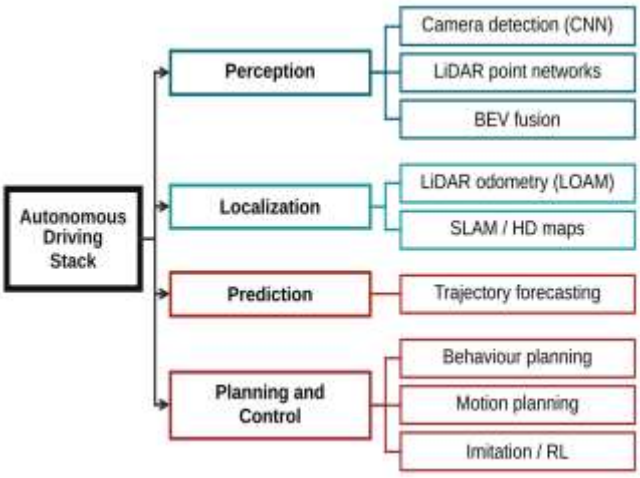


Fig. 1. Components of the autonomous driving stack and AI techniques used.

III. LITERATURE SURVEY

Perception. Object detectors such as YOLO [5] identify vehicles and pedestrians in camera images, PointNet [6] and PointPillars [7] detect objects in LiDAR point clouds, and BEVFormer [8] builds a bird's-eye-view representation from

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multiple cameras. Large datasets including KITTI [9], nuScenes [10] and the Waymo Open Dataset [11] support training and evaluation.

Localization. Zhang and Singh [12] proposed LOAM for real-time LiDAR odometry and mapping, and Cadena *et al.* [13] reviewed SLAM, which lets a vehicle build a map and locate itself simultaneously.

Planning and control. Paden *et al.* [14] surveyed motion planning and control techniques for urban self-driving vehicles, covering graph search, sampling-based and optimization-based planners and feedback controllers.

Learning-based driving. Chen *et al.* [15] proposed direct perception, learning affordance indicators such as distance to lane markings. Bojarski *et al.* [16] trained a CNN to map images directly to steering, and Codevilla *et al.* [17] conditioned imitation learning on navigation commands. Kiran *et al.* [18] surveyed deep reinforcement learning for driving. Hu *et al.* [19] proposed UniAD, integrating perception, prediction and planning into one network optimized for planning. Table I summarizes these works.

TABLE I Summary of Literature Survey

Sr. No.	Ref.	Year	Methodology	Findings	Research Gap
1	[1]	2006	Stanley DARPA vehicle	ML-based off-road autonomy	Desert environment only
2	[2]	2008	Boss urban vehicle	Navigated urban traffic	Hand-engineered rules
3	[12]	2014	LOAM LiDAR odometry	Real-time accurate mapping	Drift without loop closure
4	[15]	2015	Direct perception affordances	Compact driving representation	Highway simulation
5	[14]	2016	Survey of planning and control	Taxonomy of planners	Pre-deep-learning planners
6	[17]	2018	Conditional imitation learning	Command-following end-to-end driving	Simulation-heavy
7	[18]	2022	Survey of deep RL for driving	Mapped RL applications	Safety of RL exploration
8	[19]	2023	UniAD planning-oriented network	Unified perception–planning	Heavy computation

IV. RESEARCH GAP

- Demonstrating safety statistically would require enormous driving distances [20].
- Rare and unusual scenarios are under-represented in training data.
- Performance degrades in heavy rain, fog, dust and poor road markings.
- Mixed traffic with two-wheelers, pedestrians and animals, common in India, is rarely studied.
- End-to-end models are difficult to interpret and certify.

V. OBJECTIVES

- To review AI techniques across perception, localization, planning and control.
- To compare modular and end-to-end autonomous driving approaches.
- To propose a five-layer modular autonomous vehicle architecture.
- To examine datasets, simulation and validation methods.
- To discuss safety, ethical and regulatory challenges.

VI. PROPOSED SYSTEM ARCHITECTURE

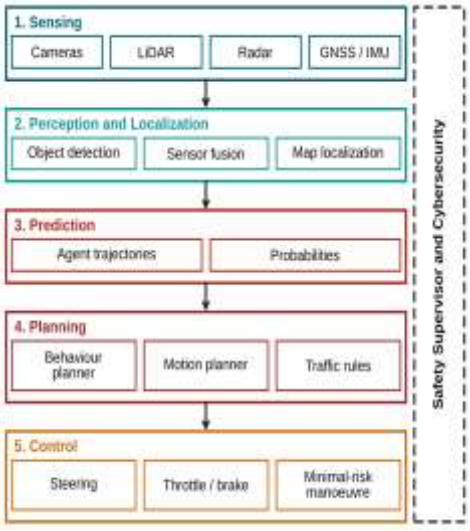


Fig. 2 presents the proposed architecture.

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Fig. 2. Proposed five-layer modular autonomous vehicle architecture.

6.1 Sensing Layer

Cameras, LiDAR, radar, ultrasonic sensors, GNSS and IMU provide redundant views of the environment and vehicle motion.

6.2 Perception And Localization Layer

Deep detectors identify objects and drivable space, a fusion module combines sensor outputs, and LiDAR odometry with an HD map provides centimetre-level localization.

6.3 Prediction Layer

Learned models forecast trajectories of surrounding road users with probabilities.

6.4 Planning Layer

A behaviour planner chooses manoeuvres such as following, overtaking or yielding, and a motion planner computes a smooth, collision-free trajectory respecting traffic rules.

6.5 Control Layer

Controllers track the planned trajectory through steering, throttle and braking, while a safety supervisor can trigger a minimal-risk manoeuvre.

VII. METHODOLOGY AND WORKING

Fig. 3 describes the driving loop. A common lateral control law, the pure-pursuit controller, computes the steering angle δ from wheelbase L, look-ahead distance l_d and the angle α to the look-ahead point:

$$\delta = \arctan(2L \cdot \sin \alpha / l_d) \quad (1)$$

Motion planners often minimize a cost combining progress, comfort and safety:

$$J = w_p \cdot J_{progress} + w_c \cdot J_{jerk} + w_s \cdot J_{collision} \quad (2)$$

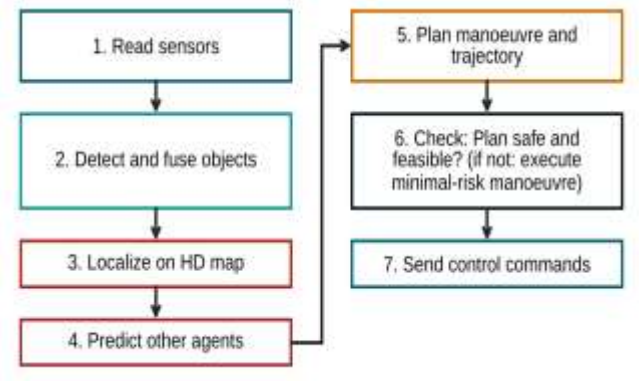


Fig. 3. Autonomous driving control loop.

Systems are validated in simulation such as CARLA [21], on closed tracks and in supervised road testing.

VIII. COMPARATIVE ANALYSIS

Table II compares modular and end-to-end approaches. Modular stacks are interpretable and easier to validate; end-to-end models reduce hand-designed components and can optimize the final driving objective, but are harder to verify

TABLE II Comparison of Modular and End-to-End Approaches.

Aspect	Modular Stack	End-to-End
Interpretability	High	Low
Validation	Per-module testing	Hard to verify
Error propagation	Between modules	Reduced
Data need	Moderate per module	Very high
Engineering effort	High	Lower design effort

IX. CHALLENGES AND FUTURE SCOPE

Table III summarizes challenges. Future directions include formal safety models such as Responsibility-Sensitive Safety [22], scenario-based validation, vehicle-to-everything communication, foundation models for driving, and datasets that reflect Indian road conditions.

TABLE III Challenges and Mitigation

Challenge	Mitigation
Safety validation	Simulation and scenario-based testing
Rare scenarios	Data mining; synthetic data
Adverse weather	Radar fusion; robust training
Mixed Indian traffic	Local datasets; behaviour models
Cybersecurity	Secure architecture; ISO/SAE 21434

X. CONCLUSION

AI underpins every layer of autonomous driving, from deep perception and LiDAR localization to learned prediction and planning. The reviewed literature shows rapid progress driven by large datasets and simulation, with modular and end-to-end approaches each offering advantages. Widespread deployment will depend on proving safety,

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handling rare events and adverse conditions, securing vehicles against attacks and establishing clear regulation.

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