

Review Article

Autonomous Vehicles and Intelligent Automation: Applications, Challenges, and Opportunities

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Intelligent Automation (IA) in automobiles combines robotic process automation and artificial intelligence, allowing digital transformation in autonomous vehicles. IA can completely replace humans with automation with better safety and intelligent movement of vehicles. This work surveys those recent methodologies and their comparative analysis, which use artificial intelligence, machine learning, and IoT in autonomous vehicles. With the shift from manual to automation, there is a need to understand risk mitigation technologies. Thus, this work surveys the safety standards and challenges associated with autonomous vehicles in context of object detection, cybersecurity, and V2X privacy. Additionally, the conceptual autonomous technology risks and benefits are listed to study the consideration of artificial intelligence as an essential factor in handling futuristic vehicles. Researchers and organizations are innovating efficient tools and frameworks for autonomous vehicles. In this survey, in-depth analysis of design techniques of intelligent tools and frameworks for AI and IoT-based autonomous vehicles was conducted. Furthermore, autonomous electric vehicle functionality is also covered with its applications. The real-life applications of autonomous truck, bus, car, shuttle, helicopter, rover, and underground vehicles in various countries and organizations are elaborated. Furthermore, the applications of autonomous vehicles in the supply chain management and manufacturing industry are included in this survey. The advancements in autonomous vehicles technology using machine learning, deep learning, reinforcement learning, statistical techniques, and IoT are presented with comparative analysis. The important future directions are offered in order to indicate areas of potential study that may be carried out in order to enhance autonomous cars in the future.

1. Introduction

Autonomous vehicles (AVs) and associated technologies have rapidly gained the attention of the research community. AV utilizes sensorial technologies such as computer vision, odometry, GPS, laser lights, sensors, and a mapping system to navigate. These technologies can be used to determine

environments and locations and recognize the suitable routes amid obstacles and signage [1, 2]. AVs are supposed to minimize vehicle accidents, enhance the flow of traffic and movability, reduce the utilization of fuel, be free from driving, and facilitate business operation and transportation [3–6]. Despite the massive potential advantages, there are many unsolved safety, security, legal and regulatory, social,

ethical, and technology issues [7–10]. In the AV system, it is expected to solve all the problems to avoid failure. In this survey, design, hardware, AI-based, and safety issues and current solutions of autonomous vehicles are discussed. Furthermore, scope of improvement in these solutions is provided as directions for AV research community.

Intelligent software and tools are required for efficient design and development of AVs. These tools are used during path planning, object detection, perception, act, operational testing, and risk assessment phases. In this survey, comprehensive analysis of tools is provided. Various tools and frameworks such as SysWeaver, SysAnalyzer, AutoSim, Flow, OpenCV, JESS, FuzzyJ, AuRa, and PaddleCV are analyzed based on functionality and applications. The latest releases and versions such as AutoSim 200, OpenCV 4.5.5, and FuzzyJ 1.2.2 are discussed so that researchers can contribute in various open-source tools and frameworks.

Since the middle of the 1980s, several car companies, research institutes, universities, and industries worldwide have studied and developed AV. To promote AV technology, there are well-known competitions. For example, 2007 Urban Challenge and 2005 DARPA Grand Challenge are organized by Defense Advanced Research Projects Agency (DARPA). In the USA, the first competition of DARPA Grand Challenge was organized in which AV was required to navigate 142 miles long desert track within 10 hours. In the first few miles, all the AV failed to navigate. The second competition DARPA Grand Challenge was organized in 2005 in which AV was required to navigate 132 miles long track that contains mountain passes, approximately 100 right and left turns, three narrow tunnels, and flat and dry lake beds [11]. In this competition, 4 AVs among 23 finalists completed the track in time. Stanley of Stanford University secured first place the AV, and second and third place was secured by AV of Carnegie Mellon University Sandstorm and Highlander, respectively. The third competition DARPA Urban Challenge was organized in 2007 in California, USA. AV was required to navigate 60 miles' long track containing human-driven cars and virtual urban atmosphere, and 6-hour time limits [12]. In this competition, 6 AVs among 11 finalists completed the track in time. In this competition, first place was secured by Boss AV of Carnegie Mellon University, Junior AV of Stanford University claimed second place, and Odin AV of Virginia Tech finished in third place. However, these competitions did not include tough challenges as presented in everyday traffic life. After the DARPA competition, there are several trials and competitions performed by different organizations. Some examples of these competitions are as follows: ELROB from 2006 to till now [13], (SparkFun), the AV Competition from 2009 to 2017, and Intelligent Vehicle Future Challenge from 2009 to 2013 [14]. In recent time, both industry and academic community accelerate the research work in the field of AV. Some notable companies which are performing cutting-edge research in AV are Google, Argo AI, Nvidia, Mercedes Benz, Ford, Volvo, Lyft, and Aptiv. Some universities such as Virginia Tech, MIT, Carnegie Mellon University, Stanford University, and University of Ulm have also conducted research in AV.

According to SAE J3016 standard, there are six levels in vehicle automation from 0 to 5 [15, 16]. Each level has its

own functionalities such as (i) Level 0: the individual operator is in-charge of all operating activities (No Automation), (ii) Level 1: the vehicle is controlled by a human driver, but the automation system assists in operating (Assistance to Drivers such as Tesla AutoPilot) [17], (iii) Level 2: the vehicle used automated features but the control and environment of the driving process require human intervention (Partially Automated Driving such as Tesla AutoPilot) [17], (iv) Level 3: the human driver should be ready to take control of the vehicle at any moment (Automated Conditional Driving), (v) Level 4: under some conditions, the automation system can drive the car automatically, but the human operator will still be able to control it (high-level automation of driving such as Waymo driverless cars [18]), and (vi) Level 5: under all the conditions, the automation system can drive the car automatically, but the human operator will be able to control it (fully automation Waymo driverless cars [18]). The driving choices of the vehicle consist of three different levels: tactical level (comprising lane-keeping and lane-changing), operational level (consisting of break and pedal control), and strategic level (containing routing) [19]. The tactical and operating controls are further divided into lateral and longitudinal control categories [19]. Several researchers and organizations are trying to achieve Level 5 automation. These challenges are covered in this work comprehensively.

AI is a critical technology for efficient autonomous vehicles functionality. AV utilizes AI and sensory technologies and minimizes the risk. In the field of object detection, computer vision, and semantic segmentation, deep learning has been very effective. On several common object detection datasets, deep learning techniques have raised the standard [20, 21] and have been commonly used in AV especially detection of people [22, 23], vehicle [24, 25], road signal [26, 27], and traffic lights [28, 29]. AI techniques play an important role (perception, decision-making, localization, and mapping) in a given area to improve the performance of AV [30]. Perception is described as an AV's repeatedly scanning and monitoring the environment with sensors, like human vision [31]. Several deep learning approaches have been utilized for perception and are considered one of AV's challenging areas [32]. AI also plays an important role in AV decision-making, such as automatic parking [33] and path planning [34]. The computational problem of creating or updating a map of an uncertain area is known as simultaneous localization and mapping (SLAM) [35].

The significant contributions of this work are as follows:

- (i) A comprehensive survey of AI and IoT-based autonomous vehicles research works is carried out.
- (ii) Safety standards and challenges for autonomous vehicles are discussed with currently available solutions.
- (iii) Research and development challenges for AI and IoT-enabled autonomous vehicles are presented.
- (iv) Tools and frameworks for autonomous vehicles used by researchers and organizations are highlighted.
- (v) Recent advancements in autonomous vehicles using cloud computing, machine learning, and deep

learning are discussed as future directions for researchers and organizations.

This work is organized as follows: the research methodology, data collection, and analysis methods are discussed in Section 2. Section 3 presents the theoretical background and recent artificial intelligence trends for autonomous vehicles. Section 4 presents the recent studies and developments over autonomous driving decision systems. Section 5 offers the current observations in safety standards and ethical challenges in autonomous vehicles. Section 6 presents the importance of artificial intelligence in IoT-enabled autonomous vehicles in recent studies. Section 7 shows the research challenges in integrating artificial intelligence-enabled autonomous vehicles. The intelligent system software and tools used for autonomous vehicles are elaborated in Section 8. Section 9 presents the artificial intelligence-enabled testing techniques for autonomous vehicles. Section 10 presents the importance of artificial intelligence in autonomous electric vehicles and associated applications. Section 11 shows the role of artificial intelligence in power train energy management and electric vehicles. Section 12 presents the autonomous driving subsystems in electric vehicles. Section 13 presents the advanced technologies and their roles in autonomous vehicles. Here, importance is drawn towards integrating artificial intelligence and other advanced technologies with autonomous vehicles. Finally, Section 14 concludes the paper with future directions.

2. Survey Materials and Methods

This section explains the survey method and data collection and analysis followed during the survey. Details are presented as follows.

2.1. Survey Research Method. The following survey methodology is followed in this work to survey artificial intelligence and its importance to autonomous vehicles.

This work has focused on those contributions that integrate artificial intelligence with autonomous vehicles. Furthermore, those systems and proposed approaches that apply artificial intelligence or its variant to improve the autonomous vehicle's experiences are taken up for study, in-depth, and feature-based analysis.

This work has studied and presented the analysis of how artificial intelligence is helpful in smartly operating the different types of autonomous vehicles, integrating IoT with autonomous vehicles, and handling the operation, coordination, communication, decisional systems, and data handling processes.

Furthermore, the use of advanced technologies and artificial intelligence in autonomous vehicles is explored in this work.

2.2. Survey Data Collection and Analysis. This section discusses the process of article collection, analysis, filtering, and survey preparation. Figure 1 shows the complete process in

detail. The essential phases of this process are briefly explained as follows:

Step 1: in the first step, articles are collected using Google Scholar and reputed publisher's search engines. This mainly includes Elsevier, IEEE, Springer, ACM, Wiley, Taylor and Francis, IET, Hindawi SAGE, and MDPI. To search an article, keyword-based search is applied that mainly include "artificial intelligence for autonomous vehicles," "artificial intelligence for unmanned vehicles," "artificial intelligence and advanced technologies for autonomous vehicles," "surveys on artificial intelligence and autonomous vehicle," "IoT and artificial intelligence for autonomous vehicles," "artificial intelligence in autonomous driving," "autonomous vehicles," "autonomous underwater vehicles," "machine learning and autonomous vehicles," "autonomous vehicles applications," and "autonomous electric vehicles."

Step 2: after selecting the articles, the key findings, advantages, disadvantages, and significant challenges that still need to be addressed are observed. The key findings include (i) autonomous vehicles and their classification, (ii) artificial intelligence role in autonomous vehicles or autonomous electric vehicles, (iii) role of artificial intelligence in autonomous driving or decision systems, (iv) ways to integrate artificial intelligence with autonomous systems, (v) intelligent tools and frameworks, (vi) training and testing autonomous levels and systems using artificial intelligence, (vii) artificial intelligence in on-road object detection and vehicle control system, and (viii) artificial intelligence and green energy solution for autonomous systems.

Step 3: after studying the key findings, the articles were classified into four categories, implementation, survey, discussion, and tutorial. An implementation-based article contains the integration of artificial intelligence in simulating or implementing autonomous experiences. The survey articles' category includes the significant studies of artificial intelligence in autonomous systems. Discussion and tutorial articles provide a detailed explanation and classifications of autonomous vehicles and the importance of artificial intelligence and autonomous vehicles.

3. Theoretical Background

This section introduces the recent studies on artificial intelligence and its application in autonomous vehicles. Details of similar approaches are briefly discussed in subsequent sections. Furthermore, this section discusses the comparative analysis of studies, surveys, and developments to observe the advantages, disadvantages, and future directions.

3.1. Recent Artificial Intelligence Trends for Autonomous Vehicles and Driving Systems. This section explores current advancements, surveys, and practices in artificial intelligence

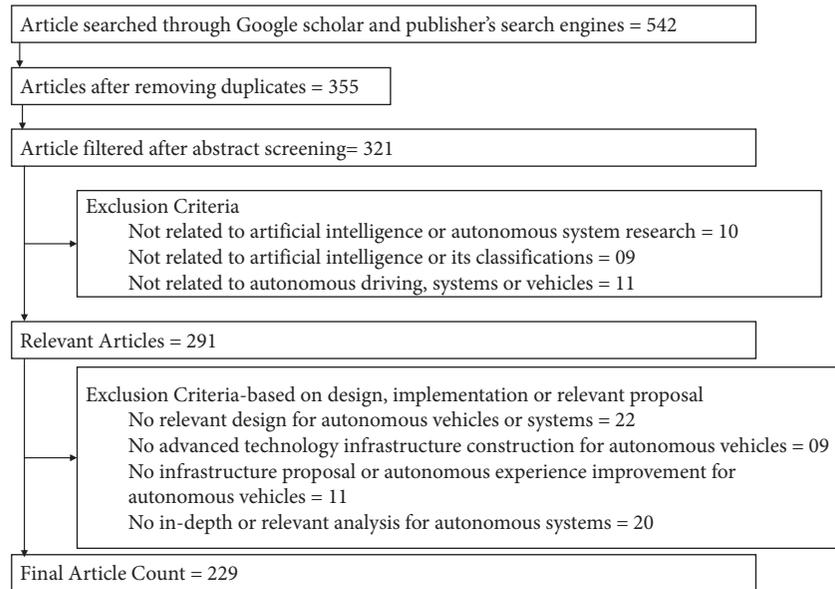


FIGURE 1: Autonomous vehicles' safety and security.

technology for AVs. This highlights the importance of AI for AVs. The details are as follows.

Khayyam et al. [36] discussed to integrate artificial intelligence with autonomous systems. Here, various types of artificial intelligence, their importance, and details of autonomous driving are explained. Furthermore, the development of the industrial revolution with the integration of artificial intelligence and IoT are discussed to address the high-performance embedded system in the autonomous industry. Additionally, the importance of cloud and edge computing in independent infrastructure is concerned, keeping the center's technical challenges such as delay, bandwidth, and security. Ma et al. [30] conducted an in-depth analysis of artificial intelligence in autonomous vehicles. In observations, it has been found that the current practices of using artificial intelligence in autonomous vehicles are limited to object detection and tracking. The object includes the traffic signs, on-road vehicles, on-road moveable or stationary items, and pedestrians. Here, the critical challenges to artificial intelligence for autonomous applications such as (i) sensor integration and performance issues to artificial intelligence and autonomous systems, (ii) complexities and uncertainties to autonomous and associated complex systems and recent developments, (iii) fine-tuning and optimization approaches, (iv) hardware concerns, and (v) artificial intelligence-integrated opportunities and future research directions are discussed. Cunneen et al. [37] surveyed to elaborate the use of artificial intelligence in various systems of autonomous vehicles. Here, the primary focus is drawn towards using artificial intelligence-integrated conceptual framing that supports governance and regulation. So far, little attention is drawn towards the conceptual frame. This work has discussed the role of conceptual structure in anticipatory governance. This role increases the accuracy and impact of safety concepts and directions in autonomous systems. This work is more of

theoretical development and can be extended to discuss the conceptual framing in various applications and use-cases.

Table 1 shows the comparative analysis of artificial intelligence-integrated autonomous systems surveys. This comparative analysis is performed mainly over fake intelligence-related domains relevant to autonomous systems or vehicles. These surveys discuss various challenges, solutions, and application scenarios. For example, attack and defense analysis is examined to identify the significant cyberattack scenarios to autonomous vehicles and systems.

3.2. Literature-Based Research Challenges to Autonomous Vehicles and Related Studies. This section explores the recent research challenges to autonomous vehicles. Details are presented as follows [21–25, 37–41].

Autonomous vehicles offer better driving decisional spectrum that avoids intoxication, distraction, fatigue, and inability to make timely decisions. All of these factors are associated with the ability of the technologies to outperform the human driving decisions abilities [37]. Thus, advancements in technology to avoid errors and give real-time responses are significant challenges for AI-integrated autonomous vehicles. Various research works have discussed the importance of the safety and performance metrics of autonomous vehicles. These metrics should include sensor error, programming bugs, unanticipated events and entities, cyberattack and threat probabilities, and hardware failures. Development of these metrics and analyzing these metrics in a real-time environment are essential to address in the future. Table 2 highlights the comparative analysis of autonomous driving systems.

There are various categories of cyberattacks, including attacks over control systems, driving system components, vehicle-to-everything network communications, and risk assessment and survey systems. The primary attack

TABLE 1: Comparative analysis of artificial intelligence-integrated autonomous vehicle system surveys.

Author	Year	A	B	C	D	E	F	G	H	I	J	Key findings	Challenges and future directions
Khayyam et al. [36]	2020	✓	×	✓	✓	✓	✓	×	×	×	✓	In this research work, various artificial intelligence and autonomous vehicle experiences are discussed. The autonomous vehicles and their developments are associated with industrial revolution, cloud and edge computing environments, IoT networks, and sensors. Furthermore, the research directions in integrating artificial intelligence with autonomous vehicles are explored.	This survey is a short discussion over artificial intelligence field and autonomous vehicles. This work can be extended to address the use of advanced technologies (such as blockchain, serverless computing, and unmanned aerial vehicle control) with autonomous vehicles. Furthermore, the computational complexities, security, and advanced technology integration can be studied in detail.
Ma et al. [30]	2020	×	✓	✓	✓	×	✓	✓	✓	×	✓	This is an in-depth survey covering the importance of artificial intelligence-integration with autonomous vehicles. Here, attentions are drawn to discuss the properties of autonomous vehicles, challenges, and comparative analysis of existing systems in this direction. Furthermore, the solution or architectures are proposed or discussed to address the existing challenges in similar systems.	This work can be extended to propose solutions or conducted in-depth studies over challenges such as complexities and uncertainties. The complexities and uncertainties can be resolved with advanced systems such as artificial intelligence-integrated decisional support system. Likewise, other issues can be addressed.
Cunneen et al. [37]	2019	×	✓	✓	✓	×	✓	✓	×	×	×	This is a detailed survey addressing the artificial intelligence and autonomous vehicle concerns. The role of artificial intelligence in decisional making and decisions limitations for autonomous vehicles is discussed. Furthermore, the shortcomings and safety discussions in artificial intelligence-intergrated autonomous vehicles are discussed.	This is a theoretical development and discussion over role of artificial intelligence for autonomous vehicles. This work can be extended to include the discussions over complexities and amplifications of emerging technologies in autonomous systems. Furthermore, risks associated with conceptual frameworks for deployment of autonomous vehicles are another important aspect to explore in detail.
Osório and Pinto [38]	2019	×	✓	✓	✓	×	×	✓	×	×	×	This work has discussed the uncertainty handling, unpredictability control and decision-making power of artificial intelligence for autonomous vehicles. Here, risks associated with successful manipulation of high levels of uncertainty are discussed.	This is theoretical development and discussion over role of artificial intelligence in information uncertainty and manipulability. The importance is drawn towards how the quality of decision processing artificial intelligence in improving the efficiency and welfare is important. However, this work can be extended to discuss the system complexities and manipulation proof of artificial intelligence for protecting the lives and welfare of society.
Li et al. [39]	2018	×	✓	✓	✓	✓	×	✓	✓	✓	×	This work has surveyed the issues of traffic in various countries and discussed the role of connected and autonomous vehicles to tackle these issues. The key benefits and need of artificial intelligence are discussed. In artificial intelligence, special focus is drawn towards the role of deep and reinforcement learning for autonomous vehicles.	This work can be extended to include more use cases that integrate advanced technologies such as blockchain, IoT, edge, fog, cloud, and serverless computing. Furthermore, more algorithmic approaches in artificial intelligence can be explored.

TABLE 1: Continued.

Author	Year	A	B	C	D	E	F	G	H	I	J	Key findings	Challenges and future directions
Kunze et al. [40]	2018	✓	×	✓	✓	✓	×	✓	×	×	×	This work has surveyed artificial intelligence-enabled long-term autonomy systems and features. The major areas where artificial intelligence plays an important role include navigation and mapping, knowledge representation and reasoning, perception, planning, learning, and interaction.	This work has discussed the different domains and brief about related work in these domains. The work can be extended to have in-depth discussions, identifying challenges in existing proposals, and develop discussions over possible solutions to challenges.
Kim et al. [41]	2021	×	✓	✓	✓	×	×	×	×	✓	✓	This work has identified the attack and defense strategies from 151 articles and conducted a comprehensive survey. The comprehensive survey investigates the autonomous vehicles in three major categories including autonomous control system, autonomous driver system and associated components, vehicle-to-everything network and communications.	Cyberattacks and defense strategies are explored which have grave impact over human life and safety. This work can be extended to discuss the complexities of proposed systems and related cyberattacks and defense strategies. Furthermore, attack and defense scenarios can be explored for in-depth analysis.

A: short survey, B: long and in-depth survey, C: autonomous driving or assistance, D: artificial intelligence, E: machine, deep, or reinforcement learning, F: artificial intelligence and IoT network for autonomous systems/driving/vehicles, G: artificial intelligence applications for autonomous, H: artificial intelligence and sensors for autonomous vehicles, I: artificial intelligence-based data analysis in autonomous systems, and J: other advanced technologies (such as cloud/edge/fog computing, blockchain, and serverless).

categories that need to be explored and researched include sensor attacks, mobile application-based vehicle information system attacks, IoT infrastructure-based attacks, physical attacks, and side-channel attacks. Furthermore, artificial intelligence is used in cybersecurity in attack identification. Autonomy architecture is another interesting aspect. In architecture, autonomous systems integrating sensors and actuators, control functions, vehicular monitoring environment, external control factors, speed, visibility, and object detection are critical subsystems to observe and explore.

With the increase in autonomous vehicles, the communication overheads will also increase. This causes delay or loss of packets which indirectly decreases the performance or increases the error in communication. Autonomous vehicles and their implementation are critical to human life.

The limitations of existing works are that extensive analysis of recent developments such as use of deep learning and IoT are not covered. Furthermore, discussion on intelligent tools and software are essential that is not included in existing works. Furthermore, developments of efficient simulation are required. Object detection, path planning, sensors, and use of cloud computing should be improved to develop autonomous vehicles.

4. Autonomous Driving Decision Systems

In the past, substantial progress in the development of control theory and the implementation of its findings are observed for an extended period. Increasingly, products come with built-in computers that make decisions. Recent years have seen a significant increase in the use of walking robots. Robots that look like humans are perceived as friendlier and more accepted in society. This strategy can

also be employed in self-driving automobiles. The idea of giving the illusion of human traits to robots is gaining traction. The types of robots that can be developed based on the drive type include [45] (i) wheeled robots, which are employed primarily for light work (for example, following a particular line or path), (ii) manned or unmanned tracked or crawling robots, which can maneuver in either man-made or natural settings, (iii) programmable robots that are capable of performing a specified sophisticated task in a natural and industrial setting, and (iv) combination of robots for different tasks. Autonomous driving is both a bold idea and a very feasible technological accomplishment. Many technical companies (including Audi, Ford, Tesla, Renault, Waymo, and ride-sharing firms Lyft and Uber) are battling to overcome technological hurdles and allow an altogether new style of driving that will surprise and thrill consumers. This section explores the importance of various technologies that are associated with autonomous driving systems. Details are presented as follows.

4.1. Advanced Technologies and Autonomous Driving Systems. Autonomous vehicles are becoming more intelligent thanks to recent advances in artificial intelligence and deep learning. Current AI techniques are used in most contemporary self-driving car components [43]. Driverless vehicles are complex systems for moving people or cargo. Like introducing AI-powered autonomous automobiles on public highways, introducing AI-powered autonomous vehicles on public roadways presents many challenges. Using the current framework and explainability of neural networks, it is tough to demonstrate the functional safety of these vehicles. To make use of deep learning methods, you will need enormous training datasets and plenty of

TABLE 2: Comparative analysis of autonomous driving systems or experiences.

Author	Year	A	B	C	D	E	F	G	H	I	J	Key findings	Challenges and future directions
Grigorescu et al. [42]	2020	×	✓	✓	✓	×	✓	✓	✓	×	×	This work has discussed the importance of deep learning in autonomous driving. Here, a set of challenges in autonomous driving systems are discussed that can be overcome with deep learning and artificial intelligence approaches.	This work can be extended to discuss the role of deep learning while integrating it with other autonomous driving assisting infrastructure. This includes advanced infrastructure aspects including IoT, cloud, and blockchain technologies.
Ning et al. [43]	2021	×	✓	✓	×	×	✓	✓	×	×	✓	This work has researched and categorised the present state of automated driving, and devised a taxonomy for self-driving vehicles. Furthermore, this work has proposed an hybrid human and artificial intelligence architectural concept. Autonomous driving was also summarized by the design of the vehicle itself. As with self-driving car technology, this work developed a taxonomy of autonomous driving technologies. We valued human information integrity and machine-human interaction above simple driver replacement.	This work can be extended to include safety standards and discussions. The proposed hybrid architecture includes the safety monitoring system which can be extended with other advanced technologies including drones and cloud computing environments. Furthermore, data security and privacy can be handled with blockchain technology as well. Further performance issues can be explored with advanced network such as 5G networks.
Kumar et al. [44]	2021	×	×	✓	×	×	✓	✓	×	✓	×	This work mainly discusses the use of drones in autonomous systems. Furthermore, the anticollision strategies for drone movement and traffic monitoring are discussed. Results are analyzed by varying the drones and on-road vehicles.	This work is relevant to real-time deployment and observations of autonomous systems. However, connection between drones and autonomous vehicles need to be explored in detail.
Kim et al. [45]	2020	✓	×	✓	×	×	✓	✓	×	✓	×	This research looked at system settings, components, operations, and real scenarios for autonomous vehicles, smart UAVs, and drones. The main research issues and security concerns for AI-based attacks are addressed.	This work is a short survey discussing the important technological aspects and their role in autonomous vehicles, driving and systems. This work can be extended to have in-depth discussions over technological aspects.
Wang et al. [46]	2020	×	✓	✓	×	×	×	×	×	✓	✓	This blockchain-based architecture supporting safety and security to autonomous vehicles and its networks.	Work can be extended to include smart-contract for different systems and subsystems for better credibility.

A: short survey, B: long and in-depth survey, C: artificial intelligence-based proposal/discussion, D: deep learning, reinforcement learning, F: AI-enabled motion control systems for autonomous vehicles, G: safety systems for AI-integrated autonomous driving, H: computational, hardware, and deployment challenges supporting AI technology, I: advanced technological solutions (drone, blockchain, and IoT), and J: AI-integrated safety or cyberattack protection systems/proposal or discussion.

processing capacity. This article presents an overview of deep learning for autonomous vehicle use. When designing AI-based self-driving vehicles, understanding the requirements and capabilities of the system serves as a blueprint. Grigorescu et al. [42] thoroughly discuss the deep learning models utilized in autonomous vehicle driving. Recurrent and convolutional neural networks and deep reinforcement learning are included in AI-based self-driving architectures and it is further elaborated in Section 13.9. The sampled driving approach starts with these tactics, which serve as the foundation for how individuals perceive, plan, and behave in the situation. Modular perception-planning-action pipeline end-to-end systems are used for deep learning techniques. The research described here unveils deep learning and AI

techniques for autonomous driving. Ning et al. [43] provide a taxonomy of current independent driving designs. After that, a proposal is made to integrate hybrid human-artificial intelligence into a semiautonomous driving system. This work has proposed a theoretical architecture based on hybrid human-artificial intelligence for improved usage. With this architecture, it is easy to categorize and overview potential technologies while illustrating benefits. In the proposal, research challenges associated with autonomous driving are also discussed.

Artificial intelligence and drone-based system to monitor on-road driving; Kumar et al. [44] discussed the importance of drones and Internet of Vehicles (IoV) for traffic monitoring. It has been observed that traffic cameras are

among the drawbacks of incomplete data collection, restricted medical assistance, and inability to follow vehicles after an accident. Artificial intelligence-integrated object detection and the drone-based system collects and transmits data about commuters, traffic patterns, and vehicle activity to various agencies for traffic planning. The authors have proposed software-defined networking (SDN) controlled drone networks to reduce control overhead and effectively handle on-road vehicle observation scenarios. Kim et al. [45] have investigated system settings, components, operations, and actual circumstances for significant application types, including autonomous vehicles, intelligent UAVs, and drones. This study has also provided instances and scenarios where autonomous vehicles can be used in public and private places with different viewpoints and circumstances. The primary research problems and security concerns about future AI-based attacks have been thoroughly discussed.

Artificial intelligence, machine learning, and cloud computing and autonomous driving: Yaqoob et al. [47] present a cross-domain solution for the Cognitive Internet of Vehicles (C-IoV) based on global AI fog computing and IoT AI service architecture. Furthermore, it explores the C-IoV for autonomous driving from the viewpoints of what, where, and how to compute. This work has used the Internet of Vehicles real-time task deployment to illustrate how the proposed approach works better than the existing alternatives. This work has presented a multilayered architecture for infrastructure assistance to autonomous vehicles and systems. Machine learning, cloud computing, fog computing, and IoT layer processing are proposed for autonomous vehicles.

Data security and autonomous driving systems: Ren et al. [48] reiterated that AVs will simplify driving, reducing driver fatigue and traffic accidents. The major credit goes to advances in artificial intelligence and Internet of Things; autonomous driving has come long. Despite its numerous benefits, it also brings new challenges, chief among them security. The authors analyze the security concerns of autonomous driving from many angles, focusing on how they are experienced, navigated, and managed. We describe the dangers and the associated defensive measures. Define emerging security risks, including deep learning-based self-driving cars. Ren et al. identified three kinds of possible assaults against current AVs and provided defensive strategies for each. Ren et al. investigated AVs' future, self-driving cars based on deep learning algorithms, and the new security risks. Ren et al. examined deep learning model security risks such as system faults, adversarial examples, model privacy, and hardware security. Singandhupe and La [49] present that robotics, augmented and virtual reality, and self-driving cars are interested in SLAM. SLAM collects information about the environment and then estimates the robot's location. While SLAM has been existed for over 30 years, it is responsible for the decade's self-driving cars. Singandhupe and La, in a concise manner, describe how SLAM techniques have contributed to the automotive industry. Singandhupe and La first sought to examine the various localization techniques available and to evaluate the state-of-the-art methodology. Finally, Singandhupe and La

addressed the concerns about autonomous vehicle security and how this matters. Singandhupe and La discussed several SLAM techniques for autonomous driving using the KITTI dataset. Singandhupe and La tried to categorize SLAM techniques utilizing Lidar-based or Stereo-based odometry. Singandhupe and La aim to highlight the security flaws in autonomous driving systems. Many academics have created and studied attacks, making it a highly intriguing topic for future research. Singandhupe and La have developed an approach that uses graph-based SLAM algorithms and focuses on the KITTI dataset to close the current research loop better. Singandhupe and La also wish to focus on integrating and validating state-of-the-art deep learning methods to SLAM since they may be helpful for data analysis. Kun et al. [50] discussed that automation, in and of itself, requires connected vehicles, but this comes with its own set of problems. When car-to-car communication is implemented, the system may keep people from running into each other and enable unauthorized access to personal data. There is a possibility that the collector will reuse every activity in the vehicle. The function of vehicle user interfaces in this legal framework varies widely between countries. As our technological solutions and legal frameworks influence consumer acceptance and user experience, these solutions and frameworks will have a significant impact. Interoperability issues, however, are not often discussed by the company or in the literature. To meet rising customer expectations, there is a need to build better user experiences on safer hardware and software infrastructures. In recent times, it has been observed that both in-car applications and sophisticated user interfaces have improved. Transportation is transforming. They are connected to the outside world and depend on computer power to conduct autonomous driving. Decades of precise, explicit management are giving way to frequent, intervention-based control. With these new developments, the community now faces new challenges and looks forward to new opportunities. We anticipate that vehicle designers and researchers will increase safe and affordable transportation that allows passengers to work and play while traveling. Wang et al. [46] discussed that autonomous driving could revolutionize transportation networks by making roads safer, making people more comfortable, and giving cars more intelligence. In autonomous driving, AVSNs may disseminate data in essential applications such as safety and entertainment. Autonomous driving, however, changes based on time, place, and queue constraints. Thus it is challenging to direct CAVs to disseminate significant amounts of information inside autonomous vehicle networks. On the other hand, attackers could share inaccurate information to mislead the network, putting CAVs at risk for security and privacy issues. Sophisticated blockchain-based autonomous systems provide secure content transmission and also offer an economic incentive approach. The blockchain-enabled autonomous system architecture will serve to safeguard content distribution. Wang et al. evaluated CAV and RSU trustworthiness using task-based and credit-based reputation models. To inspire CAVs to give credible information, the researcher examines the influence of reputation and task rewards. While encouraging roadside

units, to be honest, furthermore, authors have also designed a novel proof of reputation consensus method for blockchain-enabled autonomous vehicle networks. The architecture proposed does better in terms of dependability and security than existing approaches.

Artificial intelligence, IoT, and Autonomous Driving Systems: according to Khayyam et al. [36], many intelligent methods and technologies are being used to improve decision-making abilities with the advent of autonomous vehicles. Connecting AI and IoT for AV enables more dynamic and resilient control systems in environments. In addition to cloud hosting, new edge computing paradigms such as latency, network bandwidth, and security are difficulties for AVs. As a basis for future AI-based AV development, Khayyam et al. explore the architecture of an AI-based AV using edge computing. Du et al. [51] stated that anonymity in federation learning enables a community to gather, share, and analyze large quantities of data from numerous sources without revealing the original data. With computing capacity, multiple learning agents may be used to improve learning efficiency while also preserving the privacy of data owners. One of the reasons the federated learning business is on the rise is because privacy is a big issue. Future IoT systems will include numerous devices and privacy-sensitive data needing rapid connectivity, processing, and storage. It is possible that federated learning could serve as a solution to these problems. Du et al. started with the latest scientific study on federated learning and how it may be used for wireless IoT. Then, it is discussed that how important federated learning is in building a vehicle-based IoT and other possible associated avenues.

5. Safety Standards and Challenges in Autonomous Vehicles

Autonomous vehicles (AVs) is an active research area from last two decades. The rapid growth of vehicles on the road has increased the chance of traffic accidents that is considered a severe problem to the public and society. Human error factors such as inappropriate judgments, interruption, and exhaustion can be the reason for fatalities and accidents [52]. Hence, AV can be a solution to enhance vehicle safety and minimize traffic accidents and human driving errors. AV utilizes advanced technologies such as Electronic Controlled Units, path planning, Global Positioning System, 3D mapping, and light detection and ranging to reduce human driving mistakes, enhance safety, and optimize traffic flow [53]. Safety and security are the challenging tasks in AV to where significant research contributions are required.

Figure 2 demonstrates the safety and security of AV. Electrical and Electronics safety systems and mechanical safety systems are considered safety issues in AV's safety system. In contrast, cyber and physical security systems are identified as security issues in AV's security system.

Security of AV concentrates on defending the vehicle from deliberate attacks, and the safety of AV focuses on guarding the vehicle against incidental collapse [54]. A multisensor AV can pre-sense the attack conditions and handle accordingly. Here, AV can avoid the attack or

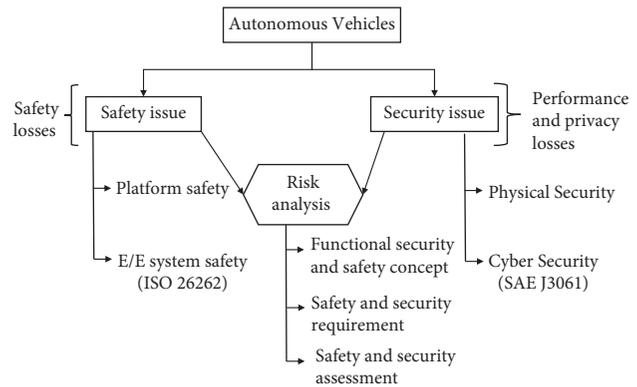


FIGURE 2: Autonomous vehicles' safety and security.

accident by changing its directions as well. These features are possible with integration of advanced technologies such as AI/ML, IoT, and Big Data analysis. The international standard ISO 26262 defined the operational security of Electrical and Electronics systems in AV [55]. ISO 26262 set of standards adapts to the International Electrotechnical Commission 61508 series of measures to deal with sector-specific electrical and electronic systems requirements in road vehicles. The international standard SAE J3061 defines the operational security in conventional vehicles [56]. SAE J3061 describes a process architecture of a cyber-physical vehicle system's security lifecycle. Standard SAE J3061 introduced a framework in which a communication bridge is established between cybersecurity and safety phases to integrate vehicle security and safety. However, how to combine security and safety analysis is missing in this standard. In the literature [57–59], the issues related to alignment for the cyber-physical system have been addressed.

Six levels of driving automation are described in SAE J3061 [15]. It delivers a classification with complete descriptions of all six groups (0 to 5), from without automation to fully functional automation, against the backdrop of vehicles and their function on roads. Every level of driving automation has additional safety and operational requirements. Moreover, various levels will face a more significant number of possible challenges, hazards, and risks. To ensure functional safety and evaluate failures, HARA is considered as a standardized process and found in ISO 26262 [60]. In addition to this work, the authors [61] introduced a HARA technique by utilizing ASIL at level 4 for AV. ASILs are recursively improved to obtain specific safety objectives for vehicles. To assess the hazards or threats in AV, ASIL is utilized and considered as a critical point. In [62], the authors used a fault tree in HARA, similar to an attack tree, where three nodes represent failure events. STRIDE is a threat model that can identify and classify possible threats to a system [63].

To conduct a systematic analysis of system architectures, the authors combine two techniques, STRIDE [63] and HARA [60], and proposed a new approach named SAHARA [64]. The STRIDE technique performs the security analysis, while the HARA approach of ISO 26262 conducts safety analysis. The co-analysis of security and safety is also served

by US2 [65], similar to SAHARA. For an attack, the security level is quantified first after that analyzes the safety hazards by US2. If an attack is introduced in safety hazards, then countermeasure of safety and security is required. Otherwise, countermeasure of protection is necessary.

The co-analysis of security and safety is also considered in [66] and introduced a technique that employed the standing methods, such as GORE. The results from security and safety analysis are considered by this approach to make the goal tree for addressing the necessities with correlated vulnerabilities. A new system theory-based hazard analysis approach is introduced in [67] to analyze the risk. It considers safety to be a control issue instead of a failure issue. This work is extended in [68] and introduced STPA-Sec. As a result, the authors outline a novel system thinking technique for safety to protect the complicated system against cyberattacks. In [69], the authors utilized STPA [67] and STPA-Sec [68] approaches and introduced a new methodology named as STPA-SafeSec to assure system security and safety by using highly effective mitigation approaches. Before selecting the appropriate mitigation approaches, the STPA-SafeSec method unified all the security and safety considerations and prioritized the system's most crucial component. Due to this analysis, the system can identify the potential loss due to particular security or safety exposure.

Several researchers have employed deep learning to enhance safety. In [42], the author explained application of deep learning in autonomous driving and reasoning about the safety such as (i) recognizing the consequences of potential errors and (ii) recognizing the more extensive system's meaning. In [70], the author utilized the convolutional neural network technique to determine the pedestrian. The task of this system is to detect the object with sufficient distance. After that, the system will manage the speed and braking system. The author describes safety as epistemic uncertainty, risk, and harm caused by unintended consequences [71]. After that, analysis is performed on the convenience of optimizing the empiric mean training cost and choice of the cost function. In [72], the authors described the accident issues due to machine learning approaches and specified inadequate artificial intelligence systems' harmful and unintended behavior. For accidental risk, the authors described five research problems and further categorised them into a specific area. Several significant areas of AV have been described as open problems such as data are considered as oil in the AV; the amount of data collected by an AV regularly is approximately petabytes; and it presents difficulties on the training procedure's parallelization along with storage resources:

- (i) In safety-critical systems, the usage of the deep learning approach is still an open problem. Few efforts are there to bring functional safety and computational intelligence communities closer. For example, time-series analysis of AV and its movement need deep learning for in-depth and accurate prediction of its feasibility. Deep learning is helpful in predicting the futuristic trends of AVs as a close system to operate efficiently. Deep

learning, one of the most important technologies, has made the realisation of self-driving cars a reality. For example, it may be used to provide answers to physics questions or to recognize photos in Google Lens, predict the behavior of vehicle movements, identify the roadside objects with more accuracy, among other things. It is a very adaptable tool that may be used to practically any situation without restriction.

- (ii) It will be difficult to accurately localize, categorize, and detect objects in the external world to mitigate perception errors. Perception error is one of the challenging tasks of AV safety.
- (iii) An accurate, stable, and effective decision-making system should be designed to respond to the surrounding environment promptly and adequately. To reduce the decision error, comprehensive and rigorous software and hardware system testing should be performed.
- (iv) To avoid failure, observe the behavior of the system in different-different scenarios and situations.
- (v) Cybersecurity for AV is the biggest concern for researchers. How securely wireless communication can be performed. Security and safety are significant concerns that can considerably influence the public's attitude towards the rising AV technology.
- (vi) The performance of AI techniques mainly depends on the correctness of the sensor data as input signals. The input of AI techniques is affected by sensor issues.
- (vii) Vehicle-to-everything (V2X) technology enables cars to connect with roadside units, vehicles, etc. Protection in privacy and secure communication among parties are still significant concerns for academia and industry people in AV.
- (viii) Software updates are taking too much time because the line of code is increasing day by day. An over-the-air mechanism has been introduced to overcome this problem, but many attacks are reported during the software updates.

6. Artificial Intelligence in IoT-Enabled Autonomous Vehicles

The role of Internet of Things (IoT) is significant in Industry 4.0 revolution [36]. This is due to the fact that intelligent autonomous devices communicate for better value chain. Industry 4.0 is focused on improving the business process. IoT is very essential for business process in Industry 4.0. The combination of AI and IoT will enable the researchers and organizations to achieve fully autonomous Level 5. IoT collects data, and AI analyzes the collected data to convert this into relevant information for decisions. IoT becomes smarter using AI synergy [73]. In AV, data generation, processing, and communication are required. Furthermore, traffic congestion and path planning information is sent

frequently. IoT provides the capability to vehicles to send and receive data as objects without human intervention.

Speech recognition and NLP are applications of artificial intelligence. Here, AI-based algorithms can be used to train the speech recognition system and read the messages written alongside the roadside units. Thus, speech and NLP are considered as well-known explanation of AI-based systems. Autonomous vehicles are developed these days which can follow the instructions by recognizing speech and text from base stations. These instructions are forwarded to Autonomous vehicles using IoT sensors. Furthermore, AI can be applied in IoT-enabled Autonomous vehicle to reduce traffic congestion [74]. Traffic signals and various devices collect information about traffic using IoT and information is sent to the AI-based predictive model for decision-making. Furthermore, updated path information can be sent to autonomous vehicle. Artificial intelligence and IoT can handle complex data which are generated from a large number of devices [75].

Various sensors and devices are connected to the IoT ecosystem, as depicted in Figure 3. There is requirement of connected and shared architecture that can communicate information in real time. For example, device information should be sent in real time and fast processing so that decision can be made. The advantage is that communication between devices and AV is efficient. Furthermore, various parts of AV are connected to a central point that sends and receives data. This will allow functioning AV effectively. There are four components in IoT-based autonomous vehicle platforms [36]:

- (i) Sensors and hardware components send and receive data from the vehicle to the vehicle or the base station.
- (ii) Communication network where data will be sent and received.
- (iii) Big Data is a collection of Volume, Velocity, and Variety data. There is a need for Big Data technologies to process large-scale data.
- (iv) Cloud where data will be saved so that it can be distributed to various objects.

There are various layers of data transfer between IoT devices. These data communication can be between vehicle to vehicle, vehicles to other devices. The decision-making by autonomous vehicles is based on inputs from various channels [76]. IoT devices that are connected send and receive essential data that can be analyzed by autonomous vehicles only if decision-making is based on AI such as neural networks or rule-based. The predictive model decides the output about line keeping, path planning, and object detection based on data from various sources. AI-based sensors are essential in AV, but in addition, IoT provides information about road conditions, weather, and specific area from connected devices in real-time. In smart cities, AI-based AV can be connected to the ecosystem for better path planning.

In Figure 4, communication of various sensors and devices with AV is depicted. Autonomous vehicle Cameras,

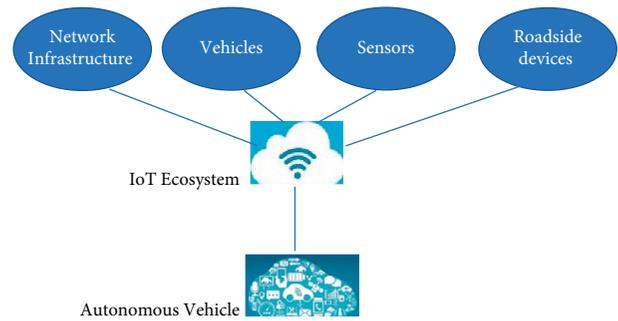


FIGURE 3: IoT ecosystem for AI-enabled autonomous vehicles.

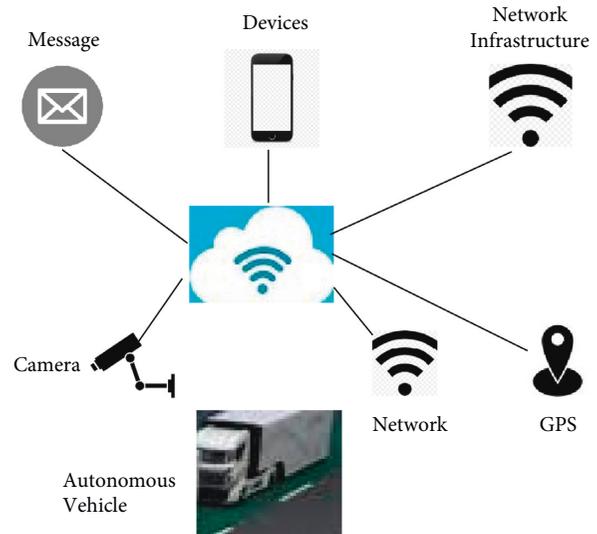


FIGURE 4: AI-enabled autonomous vehicles.

LiDAR, GPS, and network information are sent to the IoT cloud. Information is sent to various devices, base stations, and network infrastructure. Real-time data are possible by the use of the IoT cloud for better decision-making. IoT can be essential for AI-based AVs in the following phases:

Data collection: artificial intelligence-based AVs require a large amount of data for training. Data should be relevant and in real-time. IoT devices can provide this in the ecosystem.

Path planning: path planning is based on Monoeuvre planning used for high-level decisions, and Trajectory planning used for path from one state to another. In these planning strategies, IoT is essential to provide real-time data for efficient path planning.

Act: in this phase, object detection and weather information-related response is achieved. If data collection from IoT devices is more and path planning is efficient, this phase will be processed effectively.

In [77], the significance of intelligent transportation for IoT-based AVs is highlighted. If maximum tasks can be implemented in vehicles, it will save computational and data transfer time.

7. Research Challenges in Artificial Intelligence-Enabled Autonomous Vehicles

Autonomous vehicles can decide path planning and motion control based on a predictive model. There is a need for an improved AI-based model for AVs. In real-time architecture, each component needs to be addressed. For instance, recognizing a scene requires object detection and object tracking [78]. There is a lack of start-to-end depiction in current AV architectures [79]. The architecture of AVs should be able to handle system faults and manage scalability. Real-time architecture is required as AVs have to perceive surroundings with communicating with other vehicles in real-time. AI-based techniques can achieve this. The main agents in AVs are infrastructure and devices which should coordinate to perform accurately [80].

Automation levels are classified by the SAE on a scale from 0 to 5, where 0 signifies no automation and 5 signifies full performance. Companies and researchers are putting a lot of effort to achieve Level 5 [81]. SAEJ 3016 defines component classes required in architecture as follows:

- (i) Operational: in this class, the focus is on vehicle control.
- (ii) Tactical: in this class, path planning and object detection, and tracking is planned.
- (iii) Strategic: destination planning.

AI has improved AV design, development, validation, and real-time monitoring significantly. Perception, path planning, and decision-making can be achieved effectively by using AI. AI is used in AVs as follows:

- (i) Autonomous vehicles decide paths based on a predictive model.
- (ii) Autonomous vehicles learn from history to decide speed and path.
- (iii) The efficiency of the transportation system is improved.
- (iv) Intelligent use of real-time data provided by various sensors.

The issues in AI-enabled autonomous vehicles are elaborated as follows.

7.1. AI-Based Model Issues. There are three steps in the AI model for autonomous vehicles-data collection, path planning, and act [36]. In data collection, road, vehicles, and nearby object information is collected by various sensors. In path planning, the safe path from point A to point B is selected by AI techniques. In the act phase, decisions are finalized based on previous stages. If more data are analyzed, more accuracy will be obtained. The main issues faced by AI-based autonomous vehicles are checking road conditions and large-scale object detection. Highly scalable and fault-tolerant technologies are required for autonomous vehicles [47].

A limited amount of labeled training data is a real issue for AI in autonomous vehicles [82]. Training data validation is an open issue that can be addressed by data characterization and data collection [83]. Classification is also tricky on large distances. Data are not reliable in conditions where the sensor was not working fine. Inconsistent and complex data training is improper, which may provide incorrect output during validation and monitoring time.

The autonomous vehicle system was based on a rule-based controller [84]. Traditional machine learning models cannot be directly applied due to spatial and temporal data [85]. Deep learning-based models are suitable for a complex and nonlinear dataset. Deep learning can be deployed on new scenarios based on decision rules by knowledge. Deep learning provides better accuracy in less time. Furthermore, self-optimization based on complex data can be achieved by using deep learning. However, deep neural network architecture requires large-scale data to reduce variance [76]. In deep learning and machine learning architectures, parameter tuning for autonomous vehicles is computationally expensive. The reason is that there is a lack of information about how hidden layers and parameters are set up for autonomous vehicles. The number of layers selected in deep learning is a significant issue. If the number of layers is less, training is inadequate, and overfitting may occur if the number of layers is large. The solutions to problems can be coordinate descent, random search, and grid search.

7.2. Hardware Issues. The processing of sensor devices requires high processing speed and capacity. High computing devices rely on GPUs, CPUs, and FPGA [30]. Traditional CPUs cannot perform the processing required for AI. Thus, several researchers use GPUs for AVs development. The limitation of GPUs is that GPUs consume ten times more power as compared to FPGA. Google developed TPU, which serves 15–20 times better than GPUs [86].

Price and performance issues are associated with hardware. This is the reason that embedded systems are integrated into autonomous vehicles due to portability and energy efficiency. Several autonomous vehicles companies use LiDAR or high-resolution cameras for detecting and recognizing objects. LiDAR provides 3D images, whereas the camera provides 2D photos. LiDAR is used in Audi's Research vehicle, Google: Toyota Prius, Volvo: (Stoklosa, Cars), Apple's Lexus SUVs, and IR camera is used in BMW750i xDrive, Apple: Lexus SUVs [30]. LiDAR offers high-resolution 360-degree images but is vulnerable to weather conditions. The main issue with the use of LiDAR is its cost. Researchers have found a solution for this, LiDAR is used for training images, and image data are used for validation purposes [42]. Perception is problematic in complex areas. Various sensors are used, which results in the heterogeneous dataset, which is challenging to analyze.

7.3. Other Issues. Lack of good intelligent software is also an issue in AI-based autonomous vehicles [42]. Software that can predict with accuracy based on the unlabeled dataset is essential. Furthermore, more roads that are covered by

maps are needed. In developing countries, roads are not covered on maps which is not easy for path planning in autonomous vehicles [43]. In AI-enabled AVs, machines have complete control, so the issue is to design a system in the ASIL [44, 45].

8. Intelligent System Software and Tools for Autonomous Vehicles

Autonomous vehicles contain a lot of sensors that feed input in computing systems [87]. Intelligent and reliable software is required to process information from various sensors and decision-making. There are software and tools available specifically for the design and development phase where the model is trained on large numbers of 2D and 3D images and simulators. Furthermore, validation, runtime monitoring, and analysis of the trained model are necessary for a controlled manner. Specific software is available for this phase.

Software systems for autonomous vehicles should work like biological systems [88]. Multilayer architecture should be incorporated into this software. Traditional AI-based system capability is limited as compared to fuzzy logic and neural network-based systems. In [88], several types of system software such as Java Expert System Shell, Fuzzy Logic in Integrated Learning, Subsumption Architecture, and Autonomous Robotic Architecture are described. It is observed by researchers that several types of intelligent software are based on rule-based and computational intelligence.

In Figure 5, it is depicted that SysWeaver and SysAnalyzer are used to design and develop various modules and layers. TROCS and AutoSim are used for analysis and validation. Tools used in autonomous vehicles are as follows:

- (i) SysWeaver: it is a model-based design for integrating hardware and software components. Traditional programming language-based software cannot quickly achieve fault tolerance and reliability. These can be captured by model-based design [87]. It is designed by [89]. The system generates code when the model is configured for interfaces. Application agents, protocol agents, and state managers are software components. The timing model is based on rate monotonic scheduling.
- (ii) Autism: it is used for various scenarios such as lane change, etc. It is an emulator that can interact with the vehicle and allows the vehicle to sense virtual surroundings.
- (iii) SysAnalyzer: this tool is used to schedule various module timelines synchronously. It can also provide backup.

In [90], Eclipse IDE is used to implement an autonomous car. MATLAB and C++ were used for software development. In [91], Dynacar software is used for vehicle modeling. Various software/languages for autonomous vehicles are as follows:

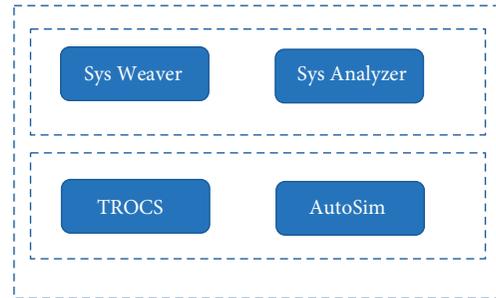


FIGURE 5: Tools for autonomous vehicle.

- (i) OpenPilot is open-source software to improve existing driving assistance. It is developed by comma.ai. Various applications such as lane centring and drive monitoring of OpenPilot are used in autonomous vehicles. Several companies are using OpenPilot for improving autonomous vehicles.
- (ii) Carla (<https://carla.org/>) is open-source software for research in autonomous driving. Various functionalities such as flexible API and baselines are available. CARLA 0.9.11 is a recent version.
- (iii) Flow (<https://flow-project.github.io/>): this open-source framework is developed by Mobile sensing lab members at UC Berkeley. Deep reinforcement learning is used for custom traffic scenarios.
- (iv) Point-Cloud library (<http://pointclouds.org/>): this library is used for managing point-cloud data. Furthermore, the Euclidean distance-based algorithm can be implemented by the use of this library.
- (v) OpenCV: this library is used for image processing. Several APIs are available to process images. Feature selection and object detection can be implemented by this library which is essential for autonomous vehicles. Lane detection, edge detection on images, region of interest, and road sign recognition are the applications of OpenCV in autonomous vehicles.
- (vi) Java Expert System Shell (JESS) (<http://www.jesruls.com/>): JESS is the rule-based engine that supports forward-chaining and backward chaining. PKD android is developed using JESS. The inputs are sent using JESS and NLG functions. JessDE platform is used, which is similar to Eclipse IDE. JESS is service based on network that is implemented as hardware. It is also used for implementing Autonomous Car Assistance.
- (vii) FuzzyClips and FuzzyJ: FuzzyCLIPS is developed in Isaac language, which is rule-based for geometric values. FuzzyJ is a Java-based API that is used for fuzzy logic systems.
- (viii) AuRA: Autonomous Robotic Architecture is a hybrid-based framework. In the deliberative

TABLE 3: Summary of various software/tools for autonomous vehicles.

Software/tool	Design techniques	Language/development
SysWeaver	Model-based	Models/Couplers
SysAnalyzer	Scheduling	Models
AutoSim	3D graphics, simulator	Simulator
Flow	Deep reinforcement learning	Python
OpenCV	Image processing, machine learning, object detection	C++
JESS	Symbolic AI	Java
FuzzyJ	Fuzzy logic	Isaac
AuRA	Neural network, genetic algorithm	LISPs

component, a plan sequence is included. In the reactive part, the run-time controller is included.

In [92], various virtual environments are highlighted. AirSim [93], ASM, CarMaker, OpenDS, PreScan, Racer, and VDrift are summarized based on the latest release, accessibility, platform, use-case, and programming languages. In Table 3, software and tools used for autonomous vehicles are outlined based on design techniques and language used.

9. Artificial Intelligence-Enabled Testing Techniques for Autonomous Vehicles

AVs have taken the transportation by a storm. The promises which it entails surely outweigh the challenges faced in bringing this technology to the masses and making it commercially viable. AVs are designed and developed using integration and interoperability of multiple intelligent systems driven by machine learning and deep learning algorithms. Almost all of the major car manufacturers such as Daimler with their MBUX, Hyundai with their Smart Sense, Audi's MMI Virtual Cockpit, and many more, in addition to the involvement of the tech companies such as Watson by IBM, Google, and Nvidia, are realizing AI's impact on the services offered and are transitioning towards the development and nurturing of AI [94].

The testing techniques that are most used today, e.g., miles driven and frequency of human intervention, are insufficient to fully advocate the safety of an autonomous vehicle [95]. Such techniques are misleading and cannot fully satisfy the safety requirements of an autonomous vehicle. The faulted assumptions can lead to failure of the autonomous vehicle system [96]. Since the autonomous vehicle itself uses a lot of AI technologies for different decisions, the quality of those decisions cannot be left to manual testing because of two reasons:

- (i) Systems with AI-enabled components can have a high density of errors due to the algorithmic bias and faulty predictive algorithms. The prediction of failure is so nondeterministic that makes the entire AI-enabled system so hard to test and verify [97].
- (ii) Non-AI-enabled testing might leave a lot of people induced errors which itself might break the whole concepts of automation [98].

To solve these issues, we explored different ways of testing autonomous vehicles. This section first reviews the

operational testing of autonomous vehicle consisting of full functional testing and validation. After that, it assesses the AI-enabled testing techniques because autonomous vehicle is a master amalgamation of AI-based technologies. AI-enabled techniques can shorten the testing and verification time for vehicle manufacturers and how it can be boon for making these more secure.

Autonomous vehicles seem to be coming from the sci-fi world into the real world suddenly. In the past 15 years, scientists and engineers have been working hard to make it a reality. However, Auto manufacturers are struggling to fine-tune AI algorithms that form the brain of the AV through metallic arms of obstacles and environments. The use of multidisciplinary sensors such as LiDAR enforces significantly different testing requirements not related with Vehicle movement but with respect to accuracy of measurement of these devices [99]. As 5G is being rolled out, it opens a new world of possibilities for autonomous vehicle industry [100]. To take care of these different testing requirements, the testing of autonomous vehicles will need to move from functional testing of components to a fully autonomous testing.

We need to be cognizant not only before the production and development of these vehicles but also during the whole lifecycle of the component involved. For example, for the demand of high level of parallel, time-critical, and fault-tolerant computing, FPGAs are suitable as they are programmable and customizable and can process high volumes of data in parallel on a single chip [101]. These chips need to be in working for at least 10 years. Nobody has tested the lifespan of these chips over a decade in outside road conditions. Hence, we need a comprehensive testing approach and techniques to take care of operational as well as software scenarios to ensure the quality of these autonomous vehicles.

In Figure 6, the components of autonomous vehicle are depicted. The testing of GPS, Radar, Sensors, and computing unit components are required for better functioning of AV.

9.1. Operational Testing Approaches. Autonomous vehicles are believed to be safe with the researchers' belief that the number of car accidents will be reduced. However, some of the autonomous vehicles crashes have attracted attention all over the autonomous vehicle industry [102]. The autonomous vehicles will spread across the world, so as the testing of autonomous vehicles on public roads. This will require a regulatory approach to the autonomous technology [103].



FIGURE 6: Components of autonomous vehicle.

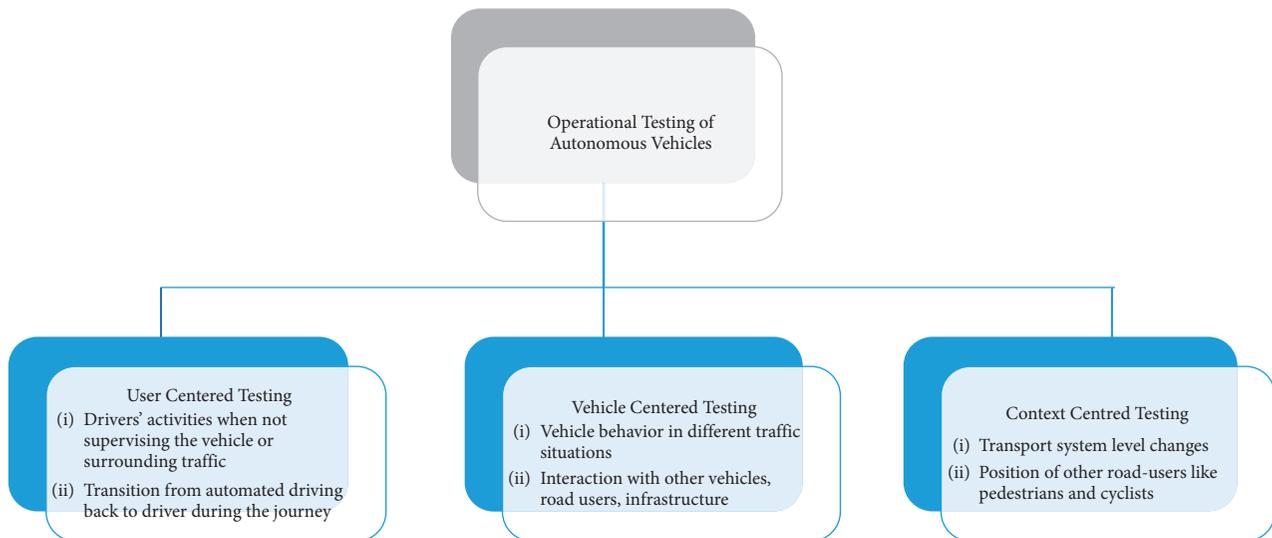


FIGURE 7: Autonomous vehicle operational testing.

To keep quality checks on an autonomous vehicle production, it needs to undergo a high-fidelity operational testing.

Few governments such as Taiwan have introduced regulatory frameworks for the testing of autonomous vehicles [104]. US and Chinese AV manufacturers have been testing the autonomous vehicles since long. Only Waymo has driven more than 20 million miles of autonomous driving at the time of writing. A Chinese company, WeRide has driven a total running distance of 2.6 million km using autonomous vehicle since its inception in 2019 (https://www.am.miraeasset.com.hk/insight/race_china_autonomous_vehicle/).

The operational testing of these vehicles can be divided broadly into vehicle centered testing, user centered testing, and context centered testing.

The various techniques of operational testing of AV are presented in Figure 7. An increased dependence on simulated and operational testing seems unavoidable to measure safety and reliability. Several standards such as IEC61508 and EN50129 include several parts of statistical evaluation from operational testing [105]. However, the autonomous vehicle core system relies heavily on machine learning and artificial intelligence algorithms. Despite intense research, there is no established operational testing process or tool

TABLE 4: Tools for testing of AV.

Tool	Underlying technique	Impact area	Languages
Facebook Infer	AI/ML	Automatically identify code quality issues, regressions, security vulnerabilities in AI/ML algorithms	Java or C/C++
Testim.io	Deep learning	Fast authoring with code flexibility boosts coverage	JavaScript
PaddleCV	Deep learning	Rich official model library, covering various visual tasks	Python
mltest	Deep learning	Machine learning testing framework for TensorFlow	Python
Torch-test-case	DL	Machine learning testing framework for PyTorch	Python
Functionize	NLP	Low code testing solution	NLP-based testing

which can satisfactorily validate the correct design. We need a different approach to testing to deal with this VUCA world which is going to change the face of humanity forever.

9.2. AI-Enabled Testing. There are thousands of algorithms with millions of lines of code are written in a single autonomous vehicle which will be deciding the next move of the vehicle in real time. This requires a complete suit of automation functional tests on source code. The testing practices used today will require another level of automation in terms of automatically created test cases and the mapping of test cases to requirements.

Telemetry usage data, especially errors in real time, are sent back to the manufacturers. Manufacturers use this real-time telemetry data to improve their software and send the system updates over the air. There is no need for every mobile owner to go back to the manufacturer or a dealer to fix it until there is anything serious. The car manufacturers will need a continuous testing facility throughout the life-cycle of an autonomous vehicle. The simulator- and algorithm-based automated testing can also be integrated. For example, the Udacity simulator testing which creates different randomly, manually modified scenes to identify the failures across the system.

Since the core AI- and ML-based systems have millions of hyperparameters to adjust which makes the normal testing out of question. We need to use AI-based testing tools which can adjust these parameters automatically based on the telemetry data collected from the vehicles over a span of time. In fact, real-time testing scenarios will be driving the next upgrade of firmwares which needs to be put in the autonomous systems. For example, the object detection systems will need to be continuously improved based on the real-time telemetry data for which the ML algorithms were not being trained for. As the real-time telemetry data will increase, so would be the ability of embedded ML algorithms for decision-making. According to our research, currently there is not a single fully compliant testing system which can make these adjustments in real time and can make the autonomous vehicle more secure [106].

9.3. AI Tools and Techniques Used. The fault detection in machine learning applications is like finding a needle in hay stack because there are no standard practices of creating a

test oracle to verify the correctness of the algorithms used [107]. Among the vehicle simulators, we can use a variety of tools. The most known is probably a Driving Simulator product from IPG makes use of AR and the vehicle-in-the-loop testing methodology (<https://ipg-automotive.com/products-services/test-systems/driving-simulators/#augmented-reality-with-vil>). It allows the tester to visualize the different objects in real time with the help of AR glasses.

Another test methodology called the “Hybrid Testing,” was developed in the scope of the EU-H2020 project INFRAMIX. This testing enables the evaluation of a real vehicle in a virtual scenario in an enclosed proving ground. The testing is usually performed with simulated traffic components and sensor signals, to make the environment simulating to real-life [105].

Sometimes because of the issues in the camera devices, result in a false induction and hence an empty photo. This might end up in generating an abundance of data in form of images [108]. Hence the machine learning algorithms used in autonomous vehicles might process a lot of unwanted data. A tool such as Zilong software (freely available at under BSD License) might help too. Vehicle identification is a crucial technique in autonomous vehicle operations while running on road. The testing goal should be to generate a test data of all the vehicle images captured by different cameras under various viewing angles. This will allow the testing of different vehicle identification algorithms in an efficient manner with different test input images. Vehicle companies should use vehicle re-identification (re-ID) techniques which can help in reducing the object identification load [109]. In Table 4, tools for AV testing are elaborated.

10. Autonomous Electric Vehicle and Its Applications

With rapid industrialization and recent development in the automobile sector, the need for fossil fuel drastically increased. Due to most gasoline-based vehicles used in routine transportation operations, GHE is grown and exploited in the natural environment. Hence, there is a need to save natural environmental conditions for saving the life of human beings. Therefore, the transformation of gasoline-based vehicles to electric vehicles and autonomous vehicles is essential. The electric vehicle has used the sources of electrical energy for driving it. Hence, it will save nature

against GHE and protect human beings against the exploited environmental conditions.

AV and AEV are driverless vehicles that are simple to drive, safe, and comfortable in operation. Most of the driver functions in ordinary vehicles are performed automatically in AV and AEV with the help of intelligent sensors, intelligent controllers, onboard computers, recent hardware and software applications, novel algorithms, etc. AV is proper for physically disabled and elderly people to live their life independently. Hence, the quality of life of the ordinary person will be enhanced due to decreasing the GHE and its independent operation. Imagine that one of the directors of the movie has gone to shoot. Still, he forgets the movie's script and other correlated important things or any person gone to do the shopping. He forgets his debit and credit cards, money, etc. The AV could be capable enough of bringing the missing items quickly by considering the abovementioned generalized uses of AEV.

10.1. Specialized Applications of AV/AEV

(i) Public Transportation

AV was introduced initially in the public transportation system in the driverless mode of operation. Nowadays, modern trends in public transportation are helpful in the cosmopolitan region for the tourists, own citizens, etc. Transportation is a big challenge in crowded, cramped, and cluttered areas in various cities. Still, due to the introduction of autonomous electric vehicles (AEVs), it is possible to manage the issues in crowded places.

(ii) Autonomous Underground Vehicle

One of the examples is a fully automated underground vehicle developed in Denmark. Its performance is encouraged to a resident of Denmark for its further utilization in a transportation system.

(iii) Autonomous Electric Tram

The first automated electric tram was designed and developed by Siemens in Germany. In 2018, the first test drive of the tram was conducted in Germany for a distance of seven kilometers. The use of smart devices, such as smart cameras, intelligent sensors, and intelligent software-based LiDAR systems, is helpful to the tram to drive in crowded areas of various cities without any obstacles. Due to the intelligent algorithm, pram in front of the tram, and intelligent monitoring and controlling system, a tram will operate very safely even in crowded areas. At the occurrence of any obstacle, the pram will be taking care of it with the help of other auxiliaries' apparatus, and the journey begins immediately after removing the barrier. During the long and short distance journey, the trams maintained safety throughout the trip, automatically stopped the tram at the desired destination, and immediately began for a different

destination. Tram responds immediately to crossing animals, human beings, other moving vehicles, different types of objects, and any other obstacles.

(iv) Autonomous Microbus

The testing of an autonomous microbus was completed in Finland in 2018. The primary objective of microbus is to reduce public transportation's load and utilize the available resources to minimize the GHE. The microbus operated for approximately seven months from 8.30 a.m. to 4.30 p.m. and completed about 4 to 7 journeys during working each hour. It is handy for the shorter distance, transporting the employees of nearby industries, citizens, etc. The main aim of this microbus is to motivate people to avail themselves of this bus to control pollution by 2022 and save the environment.

(v) Automated Robotics Bus

Again in Finland, another invention of an autonomous vehicle was introduced, called Automated Robotics Bus. It was also called GACHA. It is an automated shuttle operating in any weather conditions. It was the coordination of Japan-Finland efforts. This bus is capable enough of a driverless mode of operation with accurate obstacle detection, accurate navigation, and positioning. It is 2.5 meters wide, 5 meters long, and its height is about 3 m. It is a four-wheeled vehicle that operates at 45 km/hour speed and can cover a distance of 110 km, and the option of wireless and wired charging is possible to it. It carries 18 people in it, such as 11 people in seating mode and seven standing ways. It is clean, safe, and amicable to bring the remote peoples together in Finland during the winter season. It is suitable for all weather conditions and easily navigates in cloudy lousy weather conditions such as rains, storms, and fogs.

(vi) Fully Automated SEDRIC

The Volkswagen group initially launched SEDIRC Car under an autonomous level of 5. It is simple, well electrified, well digitally networked, safer, and sustainable. Due to being digitally interfaced, it is available at any interval, such as hiring a taxi. In 2017, voice commands and control button-based operating cars were launched in the motor show of Geneva. Due to the absence of a steering wheel, paddles, etc., it provides sufficient space and sufficient comfort during the journey. The journey information is mentioned in its display such as the length of distance in km, speed, time required to reach, safety, and traffic congestion.

(vii) Automated Electric Volvo Bus

A fully automated Volvo electric bus was designed and developed in 2019 in association with Singapore

University. It has a carrying capacity of 75 seats with a driverless mode of operation. Obstacles detection and control are obtained by using LIDAR 5 intelligent sensors. Automated Electric Volvo bus offers high flexibility, safety, compactness, reliability, sustainability, and high efficiency. Hence shortly, this bus will be reflected in public transportation.

(viii) Autonomous Electric Helicopter

VSR700 is one of innovated prototype Autonomous Electric Helicopters invented in 2020 by Airbus under the heavy test drive in France. It is designed and developed for operating alongside various naval assets. The objective is to empower the ships, enhance their scope by using intelligent sensors in association with helicopters, and enhance the information collection scenario from ship perspectives. Autonomous Helicopters are doing the job of surveillance of their targets' information and confirm the destination of reaching the ships at desired locations. Sustainability is enhanced in modern ships and autonomous helicopters by using faster intelligent sensors.

(ix) Autonomous Smart Truck

A fully automated electric truck was designed and developed in 2016 by the name Otto. Without a human driver, it operates with the help of the LIDAR system. These modern trucks are minimizing accidents and utilized for delivering heavy goods and services. In addition to this, Vera as Volvo autonomous electric truck is designed and developed for carrying goods from various destinations such as industries, dockyards, mines, ports, storage yards, and warehouses and has very efficient, safer, clean, and sustainable ways than ordinary trucks. Using intelligent cameras and other sensing devices, these Vera trucks are smartly operating, positioning, detecting, and controlling in more innovative ways and decreasing waiting periods and pollution. Hence, their performance increases technically and economically.

(x) Google Self-Driving Waymo

The testing of Waymo vehicles such as trucks and cars was completed in various weather conditions and road conditions in California. Driverless mode of operations is considered using computer-integrated cockpit and various sensing and controlling devices. It provides security and safety during the journey with information about other vehicles nearby.

(xi) Fully Autonomous Shuttle

In England, a fully autonomous Shuttle was designed and developed in 2017 by Harry's name and tested in London. In the UK, places where the lack of public transportation or no buses, no trains nearby the various locations for public transportation, decided to enhance the public transportation

more smartly. Hence, these shuttles are used in such areas to improve the efficiency of transport. It is acquired near about 5 to 6 people and covers the distance of 12 kms. It is operated using intelligent sensors, intelligent cameras, LiDAR, and other smart monitoring and control systems.

(xii) Autonomous Metro Train

It is a fully automated train design and developed by China in 2020 for the country Turkey. It is operating at a speed of 130 km/hr. It can carry about 1200 passengers with 4 to 5 carriages.

(xiii) Nuro's Fully Automated Vehicle

It is helpful for elders, the physically disabled, etc. It is also beneficial for transporting goods from one place to another place. It was developed in 2018 for delivering goods in a driverless manner [110].

(xiv) Autonomous Underwater Vehicle

It is used in marine earth science and is popular in the technical and defense sector also. The primary function of this vehicle is to obtain an improved image of the seafloor with a very high resolution from the vessel's surface. The different types of underwater vehicles are marine robots, hybrid automated underwater vehicles (AUV), bluefin Hovering AUV, AUV Urashima, hyper dolphin, and solar-powered autonomous vehicles II (SAUV) [111].

(xv) Autonomous Vehicles for Agriculture and Mining

Autonomous vehicles are used in the agriculture sector for various farming processes and used in mining operational tasks. Different types of agriculture and mining autonomous vehicles are autonomous agriculture tractors, unmanned ground vehicles used for smart farms, mining vehicles such as mining trucks, mining automated machines, etc.

(xvi) Automated Rover

It is an autonomous vehicle utilized for indoor and outdoor applications. It is an unmanned vehicle used where human intervention is not easily possible in various conditions. In those applications, self-detection and diagnosis of faults are the leading features of Rover [112].

11. Power Train Energy Management and Machine Learning Applications in AEV

The power train is defined as the generation of electric power with the help of different sets of components and subsystems in the EV to drive the wheels of the EV and move the vehicle from one place to another. The power train of an IC Engine vehicle is complex rather than an EV. Ordinary IC Engine vehicles have more than 100 moving components are present and out of which engine is the main component of a power train. Similarly, the various subcomponents and subsystems are axles, more comprehensive cooling systems,

differential transmission systems, drive shaft control systems for emission, etc. are used in EV. In the EV/AEV power train, 65% fewer subcomponents are used than the IC Engine vehicle power train.

The power train of EV/AEV consists of the following features: battery bank, DC to AC converter, controller for motor, electric drive motor, smart onboard charger, battery management system, DC to DC converter, intelligent temperature monitoring system, intelligent body control module, etc. These components are elaborated in the next section.

11.1. Essential Components of the Power Train of AEV/EV.

Battery Bank: its function is to store the energy in chemical form during the charging mode of operation and release electrical energy during its discharging mode of operation. It consists of different types of lithium ion cells used in series or parallel or combines hybrid ways.

Converter (DC to AC): DC output power obtained from the battery bank is converted into AC, and this AC power is utilized for driving the electric motor.

Motor Controller: it is also called a power train controller. It controls the desired rated speed and frequency of power feed to the motor. So that maintains the acceleration and related speed according to information of driver communication through acceleration and brakes.

Electric drive motor: it is utilized for the movement of vehicles. It converts battery-based electrical energy into shaft power movement of wheels of vehicles through its transmission system. Similarly, regenerative braking can be used under this mode of operation.

Charger on board: charging point of AC supply is converted into DC supply. Using a control system controls the technical parameters of the battery banks, such as current through the battery bank.

In addition to the above primary components, various hardware and software systems are present in EV/AEV power train systems such as electronic control unit, battery management system, thermal control, body control unit, and DC to DC converter, which are used in AEV. Data exchange and data processing are conducted under various software programs integrated with the EV power train system. Many electronics control units are used in AEV for performing a particular function.

Uniformity of equal voltage levels in all lithium ion battery cells is maintained using a battery management system (BMS). It is routine monitoring and controlling a cell's voltage to avoid malfunction and protect the system. The stable balancing of cells is obtained by using BMS and enhanced efficiency of the battery bank. It is also communicated very properly with EVSE, different electronic control units to maintain the rated parameters at the charging points. Various subsections of AEV/EV are getting the power by using the battery. Still, each subsection, such as mirror control, Horne, parking light, wipers, and lights, required a different voltage.

Hence, the DC to DC converter issued herewith fulfills their voltage needs besides the standard voltage levels.

A temperature control system monitors and controls the rated or optimum temperature of the power train system in AEV. So that avoids if any inconvenience during the normal running conditions of AEV. A body control unit also monitors and controls routine operations of AEV such as vehicle access control, mirror control, and power windows controls.

11.2. Power Train Efficiency in AEVs/EV and ICEVs. Power train efficiency of AEV is a ratio of power required to a vehicle to complete the drive cycle to its consumption of fuel energy. The comparative analysis of AEVs and ICEVs is mentioned in Figure 8. The energy input of ICEV is 100%. Out of which adequate energy is 15%, the rest of the percentages are consumed by various losses such as Idling loss 17%, energy loss 62%, and driveline losses 6%. In AEV, by considering the energy input of 100%, the adequate energy is about 80%, and the rest of the losses are only 20%, i.e., electrical losses are 145, and driveline losses are 6%.

11.3. Significance of Machine Learning and Deep Learning in the Operation of Autonomous Electric Vehicles. As per the global scenario, 1.40 billion road accidents are occurring each year, and a leading cause of accidents is the crashing of vehicles due to human mistakes and error. Hence, due to autonomous vehicles, the percentage of accidents decreases and saves human beings' lives. The cost of delivery is reducing due to the driverless mode of operation, and the vehicle's performance drastically rises. Machine learning (ML) can be used in the autonomous vehicle for the Advanced Driver Assistance System (ADAS) function to enhance a vehicle's entire performance. ML performs the various roles in the routine operation of autonomous electric vehicles are as follows.

Classification of obstacles, objects, and their intelligent detection: in existing vehicles, smart sensors, high definition cameras, LiDAR, Radar, etc., technology-based intelligent devices are used for the detection, classification of various obstacles, and objects. The results obtained from this system are satisfactory, but there are chances to get the wrong category of things due to the slight difference in pixel of images. There is the chance of accidents being created due to the wrong interpretation of images, and evil actions may happen. Due to the proper involvement of the intelligent, trained ML model in existing autonomous vehicles, the system's perception can be enhanced, precisely identifying the obstacles or objects. So, the accuracy of detection of objects is improved with safety and security using the ML model in AEV. Also usage of deep learning (DL) intelligent software developed the intelligent algorithms for training the neural network (NN) system in AEV. Using an image processor of different objects accurately classifies and detects, and accordingly, the vehicles react for further actions such as lane detection, stay in highway lanes, and path prediction very accurately. Distinguishing between human beings on highways, animals, other vehicles, lamp posts, etc. can be efficiently and accurately possible using ML and NN.

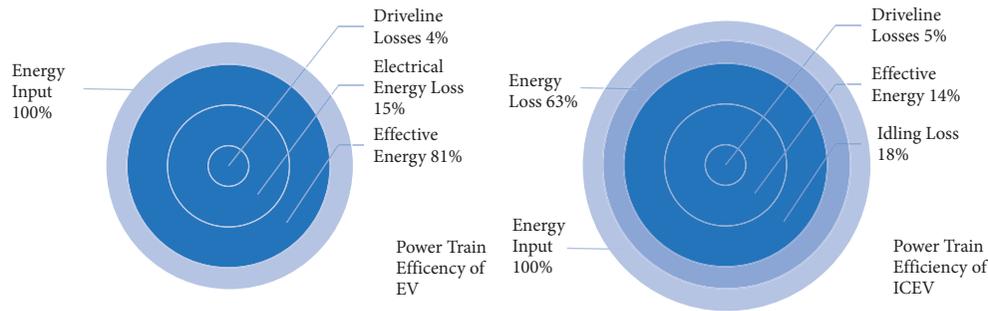


FIGURE 8: Efficiency of ICEV and AEV/EV [113].

The speed of moving objects, directions, free spaces, etc. quickly understands by ML.

Power Train in AEV using ML and DL: the various real-time data points are produced in the power train. By applying ML to these data points, the function of battery management, controlling of motors, etc. are improving. According to available power train data changes, ML offers the flexibility of boundary conditions as per the ages of the vehicle's system. Even changing operating conditions, the ML-based system has sufficient computing capability and is helpful even in real-time surrounding environmental conditions. The system is capable enough to identify the irregularities and provides regular information about warnings, maintenance, failure of motor controls, etc.

Security, safety, and reliability of AEV using ML: ML ensures the accurate operation of vehicles and avoids various accidents. ML also prevents accidents due to failures of different smart devices such as sensors, Radar, Cameras, and LiDAR. The data of multiple subsystems, such as state of charge, temperature control, speed, range, and battery level, are recorded. Furthermore, it is analyzed to conclude the performance of the AEV subsystem, such as motor performance and health index of AEV. The indicating system quickly concludes whether the AEV/EV operating is the average or abnormal mode of operations.

Identification of hacking, cyberattacks, and privacy in AEV-related data: using networking and intelligent computerized protected system with ML to ensure the security and confirm the detection of cyberattacks, hacking, etc. and overcome these problems quickly. Data privacy is easily maintained by using ML. Optimization of energy consumption in power train-based AEV/EV is obtained by combining Big Data from various sensors used in AEV/EV and ML.

12. Autonomous Driving Subsystems in AEV

Electric vehicles require multidisciplinary technologies such as electrical engineering, chemical engineering, and automobile/mechanical engineering. Furthermore, the Electrical Engineering system requires electric machines, power electronics, control systems, energy, battery management, and charging. Mechanical/Automobile Engineering involves gearing differential, chassis, suspension braking, steering, etc. The knowledge of IC Engines is also required in HEV. Chemical Engineering involves knowledge of batteries and

different kinds of chemical features and knowledge of fuel cells. Battery and fuel cells are energy sources, and it also requires the knowledge of fuels such as liquid and gases, which is helpful for EV development.

12.1. *Electric Vehicle Subsystems and Configurations.* It is classified into two types: (i) converted electric vehicle (retrofitting) and (ii) purpose-built.

(i) Converted Electric Vehicle/Retrofitting

Converting an existing diesel engine or petrol engine based vehicle to electric vehicle in place of IC Engine similar rated electrical motor is fitted and the rest of components are kept the same without any change. This type of EV design is simple, and it can use IC engine-based used vehicles of 15 to 20 years. This kind of EV is popular only when the cost to a customer per kilometer of driving is less in the converted EV than diesel engine/petrol engine EV. This is not a high-performance EV

(ii) Purpose-Built

All modern EVs are purpose-built. Purpose-built EV means the body and frame of the vehicle are nearly designed such that it takes into the set ration the structural requirements of the EV, and it also uses all the flexibility that the EV system offers. In IC Engine-based vehicles, the power flow or the energy flow is done mechanically. It uses bolted frames and rigid systems to transfer energy from one system to another. However, in EV, the power flow is done using electric wires, which are very flexible. It allows the distinction of different components of an EV throughout the vehicle, and energy transfer can be done using flexible wires. Hence, distinction flexibilities are very high in purpose-built EV. Type of the propulsion system used in EV is also a deciding factor. There may be gears or gearless; some may use a differential, others may not, some may use the single motor, and others may use multiple or dual motors. So, depending on the type of EV, the design of EV has to be done. It cannot be the same for all kinds of configurations. The type of energy sources used in an EV decides the design of EV a lot, so if a single battery-based vehicle is designed, it has to be



FIGURE 9: Propulsion system of EV.

suitable. If a multibattery system, it has to be done in another way. So, batteries can be used in the chassis of the vehicle, on the top side of the vehicle, or in the vehicle’s luggage space. Hence, all these possibilities are there, and they can be connected using a wiring arrangement. The design must be different when using a fuel cell in a fuel electric vehicle because the fuel to be stored is hydrogen. It requires a lot of auxiliary systems. Charging system is essential. The charging system for different types of energy uses may be different. It can be a board charger; it can be an IPT kind of system where secondary coils are to be installed in the vehicle. All these requirements have to be taken into considerations while designing a purpose-based EV.

12.2. Components of EV System. The essential component of the EV system is an electrical propulsion system. Under this system power converter, controller, power electronics, motor transmission, gears, and differential gears are used. The performance of EVs is increased by optimizing these subcomponents. EV will get higher performance operation with minimum energy. The motor is designed to have high power density; it has high torque density and efficiency in wide speed and torque ranges. Power electronics are generally created at a high switching frequency. Loss-making components such as gears and the differential can be avoided, but employing complicated control is the job of a complex control system or the controller.

12.3. The Propulsion System of EV. The movement of EV is obtained by using a propulsion system. Figure 9 shows the electric vehicle propulsion system [114]. Initially, energy is extracted from the energy sources such as conventional and nonconventional renewable energy sources. The raw power is processed and converted from one level to another by using different intelligent converters.

The stable energy supply is feeding to the electric drive motor, and the rotation of the engine is utilized for driving the wheels of EV with the help of a transmission system; finally, EV is starting to rotate. The propulsion system of EV is depicted in Figure 9.

12.4. Autonomous Electric Vehicle (AEV) Driving Subsystem. It is a complex system consisting of various driving subsystems such as object sensing, perception, and decision-making. Also, it consists of a robotics operating system, various hardware, the platform for cloud computing, devices for data storage, modeling and simulation, ML- and DL-based different training models, high definition mapping, and novel algorithms.

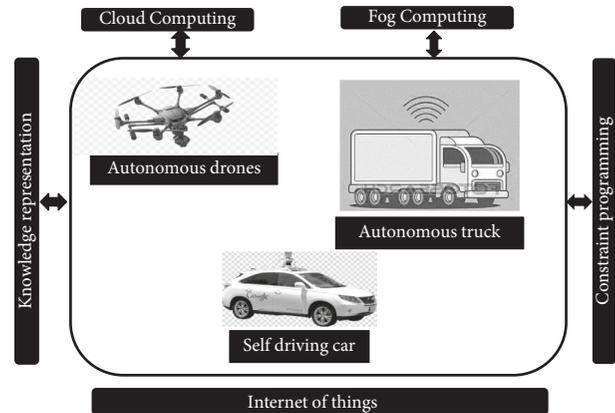


FIGURE 10: Advanced technologies for autonomous vehicles.

It collects the raw data from various sensors and extracts essential information from sensors using algorithms sub-systems. This algorithm information further gets the need for reliability and real-time data. The cloud platforms offer the offline computation of data and store the data in a different storage system of AEV using the medium of clouds. It is possible to test various types of novel algorithms and update mapping at a high definition range and offer intelligent recognition, following tracing with a particular decision of model.

AEVs are considered the future of vehicles, whereas the intelligent grid appears to be the grid of the future. Vehicle to Grid (V to G) is the link between these two technologies, and both get benefitted from it. Much research is going on to make electronics sensors in EVs more compact, rugged, and cheaper. Development of charging infrastructure with required EVSE should be significantly considered for safe and controlled energy transfer to EVs. Customer acceptance can be enhanced by increasing desired safety standards, reliability, durability, and efficiency of battery chargers with reduced charger cost. The modernization of the power system accelerates the utilization of EVs in terms of V to G technology. In an innovative grid environment, EVs become a possible solution to balance the power fluctuations due to the intermittent nature of RES [115–119].

13. Advanced Technologies and Autonomous Vehicles

This section discusses advanced technologies that play a vital role in the enhancement of autonomous vehicles. The technologies such as Internet of Things (IoT), cloud computing, autonomous drones, constraint programming, and knowledge representation, along with artificial intelligence, are explored in this section. Figure 10 illustrates the key technologies for autonomous vehicles.

13.1. Artificial Intelligence, IoT, and Autonomous Vehicles.

The convergence of AI and IoT have emerged as an essential domain towards enhancing human QoL. The automotive industry has begun to adopt digital systems and applications from product services to customers. In recent decades, artificial intelligence and IoT have perpetuated the development of connected autonomous vehicles independent of human interventions as drivers. Significant enhancements in servicing technologies, control systems, and high computing capability have empowered the development and performance of autonomous vehicles. The service values such as safety, cost, fuel efficiency, user comfort, and in-vehicle quality of experience are more focused.

The primary objective of IoT is to digitally sense, measure, analyze, and decision-making in a real-world scenario. These digital devices are interconnected globally through Internet as a backbone network to achieve extensive scalability. El-Hassan et al. [120] discussed the low-cost sensor-based intelligent systems for detecting road obstacles, collision avoidance strategy, traffic signal identification, lane identification, lane monitoring, and halt responses. The authors discussed the challenges between innovative prototype systems and real-world road systems for automotive vehicles. Wang et al. [121] addressed the control theory analysis for automotive vehicles over the brilliant system performance such as control, stabilization, and reachable components of the automotive system. The comparative study was conducted between autonomous vehicles and human drivers under a simulated environment for a mixed traffic scenario. Safavi et al. [122] addressed autonomous vehicle health forecasting using the Internet of Things and artificial intelligence. The sensors are the critical part of the intelligent system of autonomous vehicles; however, these sensors may fail to function properly due to various dynamic factors. To the multiple sensor failures, the authors proposed a neural network-based framework that involves sensor fault detection, faulty sensor isolation, faulty sensor identification, and forecasting of sensor health. Furthermore, the authors elaborate on the forecasting categories, including monotonic system life prediction and nonmonotonic behavior prediction. In Table 5, advanced technologies are summarized based on Cloud, Fog, and Edge computing.

13.2. Artificial Intelligence, Cloud Computing, and Autonomous Vehicles.

Fog computing is a paradigm shift in a computing platform that brings cloud computing facilities nearer to the edge system. Delay sensitive applications such as vehicular communication, data analytics, and data processing are carried at the proximity of the edge devices. Fog computing eliminates the delay and unnecessary network hopping. Sookhak et al. [123] discussed the need for fog vehicular computing to augment computational power and offloading data for storage. The authors proposed a fog vehicular computing framework consisting of four layers: edge network layer, service layer, core network layer, and cloud layer. The edge network layer consists of an embedded system and intelligent things. The service layer performed field area network service and multiedge services through fog computing servers. The

core layer performs IP protocol, security, QoS, and broadcasting. The cloud layer consists of data centers and cloud computing systems. Kong et al. [126] proposed the offloading of LiDAR sensor measurements from autonomous vehicles to the edge cloud servers for processing and analysis. The sensors generated environment data were transmitted to a lamp post for sharing with other passing autonomous vehicles.

13.3. Artificial Intelligence, Drones, and Autonomous Vehicles.

IoT-enabled drone-based application has widely perpetuated into the parcel delivery system. The integrated truck delivery approach and support from the drone systems have overcome the limitation in both delivery systems. The drones have computational resource limitations such as battery power and low payload. At the same time, the truck delivery system has the demerits of long hauling duration and lack of interior area coverage for parcel delivery. Wang et al. [138] discussed the combination of drone and truck-based parcel delivery systems. The authors proposed a framework for a simultaneous truck drone parcel delivery system. Three independent parcel delivery systems, namely, truck parcel delivery system, hybrid truck drone, and standalone drone parcel delivery system, have been explored in detail. The authors proposed scheduling and routing algorithms for the hybridized truck drone parcel delivery system. Sa et al. [139] presented an efficient framework for hybridized truck drone-based LMD. The collaborative routing strategy for truck routing along with a fleet of drones was discussed.

The estimation of efficient truck parking from where the drone can fly to deliver the parcel to customers was proposed. The collaborative routing is framed as an optimization problem using mixed linear integer mathematical model formulation [140]. The objective of this optimization problem is to minimize the delivery makespan to the last-mile customers. A greedy randomized metaheuristic-based feasible solution for a large-size problem was proposed. Fotouhi et al. [141] proposed a cost-effective visual-inertial (VI) odometry-based autonomous drone (VTOL) system. These VTOL-based autonomous drones are widely utilized for building infrastructure inspection, aerial surveillance, precision agriculture, and aerial cinematography [142]. These tasks require high performance in controller mechanism, low latency, obstacle avoidance, precise decision in landing and take-off, object tracking and picking and maneuver, and path planning.

Authors contributed to develop open-source software for system identification, calibrating parameters, and state estimation in different dynamic environments. Moon et al. [143] presented the various challenges towards autonomous drone racing technology. The authors analyzed the possibility of waypoint sequence estimation for the autonomous drone. Further high- and low-level navigations in the indoor and outdoor environment were studied. Patrik et al. [144] addressed autonomous drone systems for parcel delivery using the GNS. The medical aid delivery for patients in a remote natural calamitic scenario was considered for the study. The autonomous drone was assigned with the task

TABLE 5: Summary of key reference on advanced technologies for autonomous vehicles.

Research work	Year	Objective	Advanced technology				Method
			A	B	C	D	
El-Hassan [120]	2020	IoT low-cost sensor-based AV monitoring prototype	Y				Developed method based on LiDAR sensor for sensing environment AVs. Results show that the performance of sensor is better on roads.
Wang et al. [121]	2020	On-road traffic monitoring and control mechanism for AVs	Y				Proposed real-time road traffic monitoring for AVs. Experiment results validate that CAVs can be used for smooth traffic flow
Safavi et al. [122]	2021	Multi IoT sensor-based health and fault forecasting in AVs	Y				Proposed architecture for health and fault forecasting based on multiple sensors on IoT platform
Sookhak et al. [123]	2017	IoT data augmentation for vehicular services on the cloud computing	Y	Y			Developed mechanism for sensor data offloading on the cloud for AVs
Kong [124]	2020	AV sensor data offloading and computation on cloud computing	Y				Developed resource allocation for AV sensor data computation on cloud platform
Khayyam et al. [36]	2020	Integrated approach of AI & IoT for AVs	Y				Reviewed on various approaches towards combined AI and IoT for AVs
Nanda et al. [125]	2020	Internet-based AVs	Y				Surveyed on communication protocols, security, and privacy issues
Kong et al. [126]	2017	Millimetre wave IoT wireless device communication for cloud computing support	Y	Y			Designed mmWave-based IoT system for object recognition in real time
Garg et al. [127]	2017	Hybrid approach of mobile computing, software-defined network, and cloud computing for AVs	Y	Y			Hybrid method of distributed network-based vehicle management along with software-defined networks
Coutinho and Boukerche [128]	2019	Methodology for vehicular data offloading on to the cloud infrastructure for AVs	Y	Y			Reviewed on content delivery on cloud for AVs and discuss on limitation in exiting methodologies of connected AVs
Moustafa et al. [129]	2017	Fog computing for handling AV video data	Y	Y			Developed reverse mechanism for video content deliver on fog network for AVs
Wang et al. [114]	2019	Distributed fog network for connected AVs	Y	Y			Designed a cruise control based on connected fog network based for AVs
Thakur and Malekian [130]	2017	Internet of vehicles and fog computing-based vehicle congestion monitoring	Y	Y			Reviewed and developed vehicle congestion detection mechanism as part of intelligent transport system for AVs
Du et al. [131]	2020	Distributed cooperative fog network for data handling of AVs	Y	Y			Simulation of trajectory detection based on light gated recurrent unit (Li-GRU) neural network algorithm
Hou et al. [132]	2016	Vehicle infrastructure monitoring using fog computing approach	Y				Reviewed on vehicle communication, connectivity and mobility management.
Feng et al. [133]	2018	Edge computing and ACO framework for AVs	Y	Y			Developed edge computing and ACO-based communication services
Guo et al. [134]	2017	Mobile edge network for AV data offloading.	Y	Y			Designed and studied offloading on mobile edge network for AV sensor data
Sun et al. [135]	2019	User experience enhancement through adaptive allocation of resources on edge computing for AVs	Y	Y			Developed algorithm for dynamic resource allocation on edge for AVs
Baidya et al. [136]	2020	AV applications and services based on vehicular edge computing	Y	Y			Developed applications and services using edge network for AV
Yang et al. [137]	2020	AV accident data analysis based on edge computing framework	Y	Y			Designed ML model for AV accident data analysis and forecasting the health of AVs

A: IoT, B: cloud computing, C: fog computing, and D: edge computing.

TABLE 6: Research on autonomous vehicles by different companies.

Year	Manufacturing company	Contribution by the companies
1920	Houdina Radio control, Chandler Motor car	Houdina introduced Radio-controlled cars in 1925. In 1926, Chandler Motor car introduced an antenna that operated small electric motors which directed every movement of the vehicle.
1930	General Motors	Radio-controlled cars driven by electromagnetic fields accompanied by circuits inserted in roadways.
1950	General Motors Firebird, Radio Corporation of America	Electronic guide systems using wires were introduced by the General Motors Firebird.
1960	Citroen DS, Bendix Corporation, Stanford University, etc.	Citroen DS introduced magnetic cables embedded in the road in 1960. In 1970, Bendix Corporation introduced AV's powered and controlled by buried cables with roadside communicators depending on computer messages. Stanford developed a small wheeled robot.
1980	Defense Advanced Research Projects Agency, Mercedes Benz, etc.	Mercedes Benz in the year 1980 developed a vision-guided robotic van. In the same decade, DARPA-introduced an Autonomous Land driven Vehicle for the first time which used Lidars, computer vision, and robotic control.
1990	VaMP,Vita-2, Mercedes Benz, Jaguar Cars, Park Shuttle, People Mover, etc.	In 1994, twin robots of VaMP and Vita-2 of Daimler Benz introduced AV's passing in lane system and lane changes with autonomous passing cars. Jaguar cars funded Lucas Industries for making parts for semiautonomous cars. Park Shuttle was the first promoted driver less people mover that used artificial reference points inserted into the road surface to cross check its position.
2000	National Institute of Standards and Technology, DARPA, Radio-frequency identification, Royal Academy of Engineering, Toyota, aluminium division of Rio Tinto, Google	In 1998, Toyoto was the first to introduce Advance Cruise Control (ACC) on a production vehicle disclosing a laser-based system for its luxury sedan version.
2003	Tesla	Various models are developed by Tesla such as Model S, Model 3, Model Y, and Model X. Tesla Semi, Cybertruck, and Roadster are also in development phase.
2017-18	Apple	Apple's self-driving car effort, Project Titan, lost around 200 employees in January 2019. Apple bought Drive.ai five months later. Apple is purportedly buying the company to hire its people rather than buy its technology. With its self-driving vehicle fleet, Apple spent 2018. The California Department of Motor Automobiles registered 70 vehicles in September 2018. Apple's fleet logged 80,739 km of autonomous driving between April 2017 and November 2018.
2020	Audi	Ford makes its debut with hands-free technology in a car. The European Union has authorized the deployment of the A8's self-driving capability on public roads. The former Tesla Autopilot manager now serves as the CTO of Audi's Autonomous Intelligent Driving (AID) business.
2020	Autoliv	An airbag in the form of a cocoon is being developed in conjunction with Autoliv and will be integrated into the seat frame. In the case of an accident, it would protect drivers from flying debris or unbuckled passengers in the backseat. A prototype of the car was shown off at the AutoMobili-D exhibition in Detroit, Michigan, in January 2019.

such as object deductions and destination position reachability using GPS. The authors also proposed an auto drone navigation algorithm based on the positional deviation between the actual and desired landing positions.

13.4. Artificial Intelligence, Knowledge Representation, and Autonomous Vehicles. Gregor et al. [140] addressed

situational awareness by ontology framework for an autonomous vehicle in the manufacturing industry. The semantic representation is essential for reasoning systems and internal state machines to achieve the goal of the desired tasks. Pellkofer and Dickmanns [145] proposed an ontology to perceive the autonomous vehicle environment and robot telemetry. The work also discussed the knowledge graph for IoT robotic domine in the intelligent automotive production

intralogistics environment. Asmar et al. [146] examined the multifocal dynamic visual system for an autonomous vehicle. The advanced vision system consisted of the camera on a high bandwidth pan-tilt holder that performed the active gazing for the independent system. The authors addressed both static and dynamic knowledge representation. The static knowledge included a digital map of the real-world knowledge repository about the apriority performance parameters. In Table 6, advanced research on AV by various companies is presented.

The dynamic knowledge included computers, processes, scene trees, and sequence of tasks representing the mission objects [147]. The proposed system consists of decision-making units that performed three tasks, namely, behavior decision for vehicle gazing, behavior decision for maneuver, and centrally coordinated behavior for decision-making. Zhao et al. [148] addressed the knowledge representation for autonomous vehicle driving environment in a machine-readable format. Ontologies were proposed for safe driving based on road maps, driving lanes, and surrounding driving. The authors proposed core ontologies for the enhanced driver assistance control system. The proposed ontology included map ontology, control ontology, and car ontology. The map ontology describes the road network with the roads, lanes, markings, road intersections, and traffic signal status. The control ontology described the driving action, driving state, and maneuver path of the autonomous vehicle based on the GPS. The car ontology contained the details about sensors, vehicle engine status, the vehicle's exact location, and the vehicle's speed.

13.5. Artificial Intelligence, Machine Learning, and Internet of Things for Autonomous Heavy Vehicles. The concept of autonomous vehicles, where manual driving is not required, has gained many in this busy life. It has made many automotive manufacturers exploit every opportunity in developing autonomous vehicles. The technologies such as artificial intelligence, machine learning, and IoT have raised hopes for autonomous vehicles. This evolution leads to the enhancement of data analysis and prediction processes and procedures. Artificial intelligence has gained a wide range of scope in various autonomous sectors [149]. Till now, driving assistance systems such as proximity sensors and ADAS are experienced. Now, a step ahead with machine learning and IoT concepts, the future is driving towards autonomous vehicles. Competition in the current vehicle industry forced companies to adapt to the rapidly changing environments with technologies, improved features, safety, automation, and data transfer. The AI and IoT in combination will enhance the change for self-driving autonomous vehicles (AVs). This article lets us know how the latest developments of AI and IoT will assist in the quest for automated vehicles [149].

AI, ML, and IoT are the fields of computer science used to develop intelligent devices and intelligent machines. These Intelligent machines such as AVs respond and react like human brains through ML and AI. In the goal for evolving at full automation (i.e., self-driving), it is prominent

to know how AI works in hand with AV. Automated vehicles use significant amounts of input data from sensors and intelligent devices. These sensors of AV provide inputs such as time frame, movement detection, navigation directions, image recognition, voice, and word recognition, multiple touch recognition, virtual assistance, vehicle speed, vehicle acceleration and decelerations, mileage information, fuel status, vehicle location, and position [114, 150].

In October 2010, Segway Incorporated and General Motors jointly advanced a two-seat electric car with new features such as self-vehicle parking, crash avoidance, and vehicle patrol. In 2011, Volkswagen group commenced HAVeIt, having features such as Radar systems, cruise control, side observation for safer lane-changing, and TAP mode to maintain a particular distance from other vehicles. In 2014, Nissan's Infiniti Q50 introduced a virtual steering column. In 2018, Google planned to release self-driving cars with all the features such as lane-changing and hassle-free parking, with all the Adaptive Cruise control options [151].

13.6. AI in Autonomous Vehicles. AI in autonomous vehicles is applied in the following phases:

(i) Information Collection

AVs are built with multiple sensors and intelligent devices such as Radar sensors, cameras to capture images, and brilliant communication cables to produce a considerable amount of data from vehicle and vehicle surroundings. This information has the lane information, road signals, road signs, surrounding vehicles movement tracking and vulnerable road user's data, parking location details, and traffic status. This information is then sent and further processed.

(ii) Path Planning

This bulk data from AV systems will be stored and clubbed with past data from earlier rides in a database known as Big Data. AI agents act on this Big Data to produce sorted and meaningful algorithms by strategy control.

(iii) Act

The decisions made by AI agents are used to detect objects, traffic, parking areas, and bicycles; pedestrians make the AV reach the destination safely. AVs are also equipped with function controls such as steering control, gestures, and speech recognition. AI agents are responsible for making final decisions in demanding driving situations.

13.7. Challenges in AI-Driven Automated Vehicles

(i) Sensor issues

Sensors of the AV play a significant role in the automation process. Sensors can be classified mainly in 3 ways. Firstly, by using the already existing sensors, i.e., speed sensor, acceleration sensor, fuel sensor, steering angle sensor, etc.

Secondly, positioning sensors of the vehicle, i.e., GPS. Thirdly, surrounding sensors such as markings on the road, inclination, signboards, weather updates, surrounding vehicles detection, and vulnerable user's detections.

(ii) Complexity and uncertainty

Complexity involves dealing with vast amounts of information gathered from sensors and training the data model. Uncertainty occurs during sensor data collection; there may be noise that makes the input errors given to the sensors.

(iii) Complex model tuning issues

Deep learning, machine learning, and reinforcement learning methods are used in AVs. As a result, complex data models are generated, and then the parameter calibration for these models becomes complex. End-user has to develop a suitable tuning model by costly trial and error method. For example, we use supervised learning algorithms in automated vehicles and suppose if the trained data set and the input dataset are entirely different in some situations such as the traffic on the lanes, which is unpredictable, here comes a problem of complex model tuning issues. Training the datasets of metropolitan, cities, semi-urban and rural areas also involves complex model tuning issues. The passing of information from trained datasets to test datasets also becomes a great challenge for the artificial intelligence technical approach in automated vehicles.

(iv) Solving the hardware problem

Multiple computing systems are interconnected in AVs. Different computing models were proposed, such as multicore systems including CPUs, heterogeneous systems, and distributed computing systems are used in AV. The significant issues with GPU, CPU, and programmable gate arrays are programmed to change image processing and computer graphics. All these are used in real-time testing applications, and the cost becomes high for commercial deployment. Hence, there is a need for advanced hardware implementation.

13.8. Statistical Learning Methods in Autonomous Vehicles.

Considering different types of accidents such as rear crashes that occur frequently, driving style plays an essential role in designing ADAS Systems and Vehicle control systems. In ADAS systems, inputs for different driving styles are considered statistical methods such as acceleration, relative distance, and relative velocity [152]. Some statistical techniques used to find additional driving assistance are collision risk surrogates, trajectory feature extraction, discrete wavelet transform, and discrete Fourier transform [150]. In Cooperative Adaptive Cruise Control vehicles, we use statistical models to calculate real-time inconsistency in-vehicle communication, and kinematics laws are considered. According to an article by [149] Wang and Li, the safety of an

autonomous vehicle depends on the driver's performance and road crash tests performed in a suitable environment. By utilizing the data of automated vehicle crash details, statistical methods, logistic regression, and data classification are achieved.

In recent years, the emergence of connected autonomous vehicles are noticed. According to Yan [153], carrying sensors and connected vehicles can increase energy adaptability, better routing, and less traffic on roads. To calculate the usage fuel and discharge of fuel used unsupervised learning methods are applied on the real-world datasets of autonomous vehicles. Using unsupervised learning techniques, a new way for segregating driving conditions concerning velocity and acceleration has been applied on real-time AV datasets that work effectively [154]. As a reference from an article by Wanchfeld, unsupervised methods and statistical methods are to be applied to achieve autonomous vehicles' safety on-road testing. A linear dynamic system and a mixture of a linear dynamic system for context-aware robot system and expectation minimization were used to learn the model [155]. An optimal unsupervised algorithm was introduced to increase the fastness of the response, and hierarchical, K -means, and Gaussian matrix models were used to optimize the path for vehicles [156]. Vishnukumar et al. proposed a novel method using AI core-based machine and deep learning algorithms for real-time applications such as T&V and Advanced Driver Assistance System (ADAS) to improve their efficiency [157]. Mishra et al. proposed an AI-based camera to monitor the occupants in cabins and their behavior and also discussed wave power-based autonomous vehicles to enhance the facilities in various fields [158, 159]. In 2021, Malik et al. [160] introduced a new concept vehicle as a service to reduce the CO₂ effect on the environment.

Regression algorithms are used in the cases of prediction. These algorithms are used in automated vehicles to predict and maintain a relationship between the image and its position [161]. The output of usage of this algorithm is an image, its place, and its presence. Some of the regression algorithms used in self-driving vehicles are neural network regression, decision forest regression, etc. In ADAS, the data collected from all the sensors consists of different datasets that require filtering data from raw or irrelevant data. Hence, it forms a necessity for the classification of data that uses pattern recognition. Category of data helps in reducing the dataset. The SVM and HOG are widely used for component analysis. A supervised model was designed to avoid unwanted intervention while driving [162]. Trasnea et al. used the GrisSim to learn deep learning, reinforcement learning, and genetic algorithms to maximize the speed [163].

This concept includes creating and automating mathematical models and algorithms that can optimize the ability to perform particular tasks. Machine learning proceeds from examining survey models, operations and research, and statistics and explores the data. The primary task of a machine learning algorithm in the autonomous vehicle is frequently capturing and analyzing changes in the surrounding environment. Major tasks are as follows:

(i) Object Detection

Takumi [164] proposed multispectral images as input information for object detection in traffic. These are composed of RGB images, middle infrared photos, and multilateral information. Multispectral datasets are used for object detection in traffic. Liu et al. [165] discussed that multispectral detection pedestrian is required for the safety and existence of certain autonomous driving features using ConvNet fusion architectures, which combine two ConvNets on different DNNs stages, which attain better performance. Kuznetsova described a method for real-time object detection using hybrid viola-jones cascade with the conventional neural network [166]. Object detection is the most important technique for autonomous vehicles. The nearby vehicles, traffic lights, and signals should be detected and recognized. Localization and classification is achieved by object detection.

(ii) Object Identification/Recognition

Furqan et al. proposed a method for object identification naming decision tree and decision fusion based recognition system which combines two feature sets of RGB pixel values and nonlinear points from each pixel from the dataset [167]. Lidar-based viewpoints can detect the objects of any transition, and tracking can be achieved more effectively [168]. This technique involves dividing, partition making, clustering, and monitoring.

(iii) Object Classification

Yoshioka et al. presented object classification in the real world based on ReadAda Algorithm [169]. LiDAR 3D point object clouds improve object classification accuracy to 90%, distinguishing objects, persons, and electric poles on the path [170].

(iv) Object Localization

Localization is a crucial phenomenon for developing autonomous vehicles, especially in metropolitan areas [171]. A stereo camera is used to distinguish a long-standing object from an electric pole in an environment. The particle filter approach is used for localization for vigor and sensor fusion. Vision-based localization would work more effectively in an object localization process when the data are unable to retrieve from any hardware component in its failure, and the data can be retrieved by a single camera [172].

(v) Prediction of Moment

An unexpected change in the surroundings, signboards, traffic, shape of the lanes, and vehicle condition can drastically impact the behavior system of an autonomous vehicle [173]. The movement prediction has a statistical behavior that is resolved by various machine learning and deep learning techniques. With the study of multiple autonomous vehicles behavior concerning time and distance, the position can be predicted [174].

13.9. Deep Learning and Deep Reinforcement Learning Methods for Autonomous Vehicles. Deep learning comes under machine learning. In deep learning, inputs are taken from images, text, and sound and segregated. These models have more accuracy (sometimes more than humans) [175]. Models are trained by using multiple layers of input data. Deep learning enables them to notice a stop sign or differentiate a user from an electric pole. Conventional neural network is a deep learning technique used for image classification and feature extraction from training models. This technique can be used for automating the feature extraction process and image recognition. Reinforcement learning is a promising key in diving strategies, movement and action of automated vehicles, and perception planning. The deep learning neural network is more beneficial over the conventional machine learning technique [175]. According to Lee et al., deep learning techniques are used for autonomous vehicles in following a lane without taking many lane departures. These deep learning techniques are also used to set specific angle positions for steering [176]. Reinforcement learning methods are used for maintenance and controlling various aspects of connected autonomous vehicles. In [177], the authors proposed a hybrid approach of QEN and a TSK-FIS to control the tuning parameters for fuzzy control. Gu et al. have proposed a hybrid method deep reinforcement algorithm combined with the feedback control technique to improve the performance [156].

(i) Deep Reinforcement learning

Reinforcement learning is a technique in machine learning that enables the generation of a series of decisions. Deep Reinforcement learning further enhances reinforcement learning by using deep learning and multilayered neural networks. Deep reinforcement learning techniques are used in pipelined structures to train the models of deep neural networks associated with autonomous vehicles [178]. These deep reinforcement techniques are used for acquiring sensor amalgamation and spatial characteristics.

Diplomatic decision-making is a critical aspect of advanced driving systems that involves several challenges, such as uncertainty in other drivers' behaviors and the trade-off between safety and smartness. To avoid this type of situation, we use deep reinforcement learning techniques. An ultrasonic sensor calculates the distance from a target object by discharging ultrasonic sound waves and then converts them to electronic signals. A vehicle with ultrasonic sensors can detect conditions in its area; autonomous vehicles need to work on Big Data. An ultrasonic sensor needs to get data from thousands of connected vehicles, which is required for building better algorithms [36].

Accessory, which is crucial for the Advanced Driving Support System (ADAS), is a camera. It is used for vehicle parking, lane departure warning, and detecting real-time obstacles. This image has an array of pixels. Computer vision

algorithms convert images by converting low-level to high-level information images [36]. Unlike other sensors, Radar has a remarkable ability to transmit signals irrespective of poor weather conditions such as fog, rain, and snow and will not hinder even during poor light. These have overall signal perception from a vehicle. Radar has a better backup performance added to lidar and camera. Radar's output includes an object list containing speed, location, acceleration, motion type, and boundary information.

Similar to WiFi, dedicated DSRC is wireless communication. DSRC has a high data transfer rate among vehicles. DSRC is highly secured as well. These are used for both vehicles to vehicle and vehicle-to-infrastructure communications. The scope of DSRC is seen very high because of its low latency and high and secure transmission. This type of communication can be used to pay at parking slots and tolls, identify the curve approach on lanes, alert the driver, and alert construction sites.

Challenges in DSRC and AV:

- (i) DSRC spectrum or band should not affect the vehicle to infrastructure performance.
- (ii) Make sure that the driver responds accurately to the vehicle to infrastructure warnings.
- (iii) Maintaining and managing data security.
- (iv) Labeling the variables related to potential responsibility issues posed by vehicles to infrastructure communication systems.

Precise estimation of accurate position in automated vehicles becomes crucial in terms of driver safety and comfort. It is more critical at junctions and intersections to avoid accidents. Initially, GPS is used for this position tracking, but it may have some issues such as signal loss and 3 to 4 meters of accuracy. To avoid this, the use of pose sensors came into existence. Generally, in autonomous vehicles, these sensors are embedded into the road infrastructure system where the vehicle's external orientation (translation) is the output to be obtained. These sensors are placed at intersections and junctions at some heights such as surveillance cameras. According to Khayyam, an autonomous vehicle can have a right of 6 degrees of pose such as position (x, y, z) and angles while rolling (β, γ) . These AV pose sensors are used to calculate GPS in the movement of position receiver, acceleration parameters, and dynamic vehicle movements.

13.10. IoT in Autonomous Vehicles. IoT can connect devices to the Internet for sharing data. All the autonomous vehicles are interconnected to send and receive data from applied sensors and intelligent devices of surrounding pedestrians and cyclists around, nearby traffic sensors, parking locations, etc.

Following components are associated with IoT in autonomous vehicles:

- (1) Intelligent devices and sensors are the essential components and collect multiple pieces of information.

- (2) Mobile networks (3 G/4 G/5 G) and WiFi technologies.
- (3) All the data which are collected should be interchanged, stored, and processed.
- (4) Cloud services in AVs: here, the software as a service is provided by the cloud.
- (5) An advantage of IoT is intelligent control over vehicles, GPS, information services, etc.

IoT will support autonomous vehicles and transform the automobile industry, and in turn, the automobile industry will give a considerable boost to IoT. IoT will create an edge between auto manufacturers and software developers. IoT not only will transform the automobile industry but will also trigger a power struggle between automakers as the incumbent players on one side and software developers on the other side.

13.11. Recent Autonomous Vehicles Development Using Artificial Intelligence and Machine Learning.

- (i) AV sensor technology 2020

LiDAR systems will become crucial for autonomous vehicles. It works with visual sensors, ultrasonic sensors, and Radar systems to communicate with other vehicles. LiDAR sensors can continuously watch 360 degrees, and it also provides accurate depth information. One of the essential LiDAR sensors is Velodyne-64HDL 64E. A LiDAR sensor works by emitting the laser light, and it measures how long it takes to reach the sensor. Sensors and Radars were used before, but now the LiDARs came into the picture in making the most efficient Automated Vehicles.

- (ii) Vehicle-to-Infrastructure (V2I) Communication

In Vehicle-to-Infrastructure communication, data are exchanged between the vehicles and road infrastructure by using wireless transfer. Road infrastructure such as lane markings and traffic signals provide information to vehicles wirelessly and vice versa. Road infrastructure will have a significant impact on successful self-driving vehicles. V2I communication becomes brighter by adopting smart sensors in road signs, intelligent traffic signaling systems, and intelligent speed control units to endeavor smoother autonomous vehicle flow. New, creative, and intelligent infrastructure is required to stay in a digital ecosystem.

Few emerging technologies can be used to improve road safety, and mobility is like

- (1) Advanced road markings can be visible to both humans and machines in any road condition.
- (2) Smart signs also provide directional signage that both humans and machines can see in any road condition. Retro-reflective symbols offer more accuracy in navigation and faster decision-making for drivers as well as machines.

(3) Wireless communication is also required for driver safety, automation, and improved mobility.

(iii) Advanced driver assistance systems (ADASs)

Driving assistance systems are evolving more and more as per the need of the day. ADAS or advanced driver assistance systems will enhance the driver effectively and confidently in terms of safety. Standard ADAS systems include front collision warning, lane departure warning, adaptive cruise control, parking assistance systems, and many more. Blindspot detection systems, night vision systems, and other features enable the drivers to commute in a safer and better way for the future. Likewise, Mercedes are very keen to adopt these features to promote and to enhance safety for their customers.

14. Conclusion and Future Directions

The scientific community now accepts autonomous vehicles and autonomous driving as feasible solution due to advancement in AI. With artificial intelligence, autonomous vehicles and driving systems may make a choice that propels the industry into a new era of rapid development. Despite this, artificial intelligence has significant limitations, limiting the growth of autonomous driving. This work has conducted a comprehensive survey over artificial intelligence in autonomous vehicles, systems, and driving experiences. In observations, it is found that there is a lack of safety standards for autonomous systems, and AI is an important concept while designing the safety standards for futuristic autonomous systems. Furthermore, a comparative analysis of various studies on autonomous systems shows that integrating two or more advanced technologies (blockchain, IoT, cloud computing, fog computing, edge computing, and artificial intelligence) is required to make autonomous systems a reality. Here, the focus is drawn on how artificial intelligence monitors the vehicle's activities and movements. Intelligent tools are necessary for autonomous vehicle design and development. In this work, various latest release of tools and frameworks are analyzed in context of design techniques and programming languages used. The operational testing is essential for effective functionality of AVs. Thus, various testing techniques employed by organizations and researchers are highlighted in this work. The limitations of existing testing techniques are also discussed.

14.1. Future Directions. Various important future research directions in this field are briefly explained as follows [179–184]:

(i) An intentional attack on the AI system that interferes with its operation may put autonomous vehicles in danger of being destroyed. Attacks against stop signs, such as placing stickers on them to make them more challenging to identify, are two examples of such attacks. As a result of these

modifications, artificial intelligence may erroneously detect objects, resulting in the autonomous vehicle behaving in a way that puts humans in danger. Thus, there is a need to explore the RFID or IoT-based solutions that use artificial intelligence to solve these challenges.

- (ii) It is observed that self-driving cars will revolutionize our lives. There is a need that legislators must create legislation that benefits the country's economy and socially. Studies examine AVs' potential to become a "killer app" with dramatic consequences. AVs will have substantial impacts over time, even if they are still in development. Thus, there is a need to study the safety precautions before accepting them in real environments.
- (iii) Deep neural networks (DNNs) enable self-driving cars to learn how to move around their surroundings independently. Human brains are similar to DNNs because of this: both learn via trial and error. There is no hard and fast rule regarding autonomous driving and how many DNNs are required. Thus, there is a need to conduct an in-depth study in the future.
- (iv) A real-autonomous driving on-road environment requires millions of interactions between vehicles, people, and devices. To handle such an extensive infrastructure, there is a need for a high-end infrastructure which may be costly. Thus, there is a need to study how artificial intelligence can efficiently utilize the infrastructure for smooth autonomous experiences.
- (v) In future, more intelligent tools and software should be developed to implement better path planning and object detection in autonomous vehicles. Data communication should be of more velocity as real-time decisions are to be made.
- (vi) In autonomous systems, the machine learning system monitors machine activity to predict problems. The solution reduces unplanned downtime costs, extends asset life, and increases operational efficiency. There is a need to identify the best machine learning algorithms and approaches that monitor a machine or its activities. This task can be explored in the future.
- (vii) Early diagnosis of vasculature via fundus imaging may be able to prevent retinopathies such as glaucoma, hypertension, and diabetes, among others, from developing [185–187]. The overall purpose of this study is to create a new way for combining the benefits of old template-matching techniques with those of more current deep learning methods in order to achieve greater efficiency. A U-shaped fully connected convolutional neural network is used to train the segmentation of vessels and backgrounds in pixels of images (U-net). Likewise, other advanced technologies such as blockchain and quantum can be explored for AVs

[188, 189]. The wireless sensor network is used in autonomous vehicles for information communication [190–193].

Abbreviations

AI:	Artificial intelligence
AUV:	Automated underwater vehicles
ASIL:	Automotive safety integrity levels
AEV:	Autonomous electric vehicle
AV:	Autonomous vehicle
AVSN:	Autonomous vehicle social networks
CAV:	Connected autonomous vehicle
DSRC:	Dedicated short-range communications
DL:	Deep learning
DNN:	Deep neural network
DARPA:	Defense advanced research projects agency
EV:	Electric vehicle
EVSE:	Electric vehicle supply equipment
ELROB:	European land-robot
FPGA:	Field programmable gate array
GNS:	Global navigation satellite system
GPS:	Global positioning system
GORE:	Goal-oriented requirements engineering
GPU:	Graphics processing unit
GHE:	Greenhouse gas emissions
HARA:	Hazard analysis and risk assessment
HAVEit:	Heavily automated vehicles for intelligent transport
HOG:	Histogram of gradient descents
IEEE:	Institute of electrical and electronics engineers
IC:	Integrated circuit
IDE:	Integrated development environment
IA:	Intelligent Automation
ISO:	International organization for standardization
IoT:	Internet of things
IoV:	Internet of vehicle
JESS:	Java expert system shell
LMD:	Last-mile delivery system
LiDAR:	Light detection and ranging
ML:	Machine learning
MMI:	Man machine interface
MBUX:	Mercedes benz user experience
NLP:	Natural language processing
QEN:	Q estimator network
QoL:	Quality of life
QoS:	Quality of services
SAE:	Society of automotive engineers
SDN:	Software-defined network
SLAM:	Spatiotemporal localization and mapping
SVM:	Support vector machines
STPA-sec:	Systems theoretic process analysis
TSK-FIS:	Takagi-sugeno-type fuzzy inference system
TPU:	Tensor processing unit
V2X:	Vehicle-to-everything
V2I:	Vehicle-to-infrastructure
VTOL:	Vertical take-off and landing
VOUCA:	Volatile, uncertain, complex, ambiguous.

Data Availability

No data were used to support the findings of this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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