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Review Article

Artificial Intelligence in Self-Driving: Study of Advanced Current Applications

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Abstract - *In this paper, we investigate the advances of Artificial Intelligence (AI) in the field of self-driving technology. We provide an overview of the key processes involved in autonomous navigation, including perception, mapping, localization, path planning, and motion control. We highlight the crucial role of AI in the development of self-driving technologies, in particular Machine Learning (ML), Deep Learning Networks (DLN), and Computer Vision Techniques (CVT). Special attention is also given to various existing navigation approaches and the role of ADAS in assisting the driver in various tasks. We discuss how AI is used to solve the various environmental challenges faced by automotive sensors and the contribution of v2x communication and the SLAM system to safe and efficient navigation. Finally, We conclude with potential future research segments and opportunities for AI in the self-driving industry. Overall, this study emphasizes the growing importance of AI in the development of self-driving technology and its potential to revolutionize the transportation industry.*

Keywords - *Artificial Intelligence, Self driving, Navigation, Perception, Path planning, Vehicle control, ADAS, V2X, SLAM, Sensor fusion.*

1. Introduction

Autonomous Vehicles (AV) are vehicles that can navigate and drive without human intervention. They use a combination of sensors and advanced AI algorithms to detect their environment and make navigation decisions. AV can potentially increase safety, improve efficiency and reduce the need for human drivers [1].

AI has helped transform various aspects of the transportation industry, including perception, localization, mapping, path planning, and motion control. Different AI models, such as ML and DLN, have been used to improve these automatic processes and make them more efficient and accurate [5], [7], [11]. AI has been applied to perception to enhance perceptual and data analytic skills. Processing and analyzing collected data from various relevant sources (cameras, radar, and lidar devices) using real-time ML algorithms allow AVs to make judgments based on their environment. As a result, safety has improved, and the number of incidents brought on by human mistakes has decreased. Localization and mapping have also been improved by AI, which is able to pinpoint the vehicle's location and create maps of its surroundings. This information is used to assist with path planning and navigation. AI has revolutionized cognition and path planning, capable of processing large volumes of data in real-time and making informed decisions about the best way forward. DLN algorithms have been used to develop cognitive systems that can respond to changing conditions and make decisions based on their understanding of the environment. AI has also been utilized to enhance motion control, which results in higher safety and fewer human errors due to its ability to control vehicle movement precisely. This has been particularly important in developing advanced driver-assistance (ADAS) and vehicle-to-everything (V2X) communication systems. AI has been applied to sensor fusion to increase the precision of data from various sensors so that cars can make better judgments about their surroundings. This has been crucial in developing ADAS systems since they depend on accurate and full data from various sensors for proper operation.

The history of AVs can be traced back to the early 1900s when pioneering engineers and inventors first experimented with self-driving vehicles. However, it was not until the second half of the 20th century that technology advanced to the point where AVs could be used in real-world applications. In the 1980s, researchers at Carnegie Mellon College developed the first AV, a modified Chevrolet van called "Navlab" This vehicle used basic CVTs and sensor technology to navigate roads and avoid obstacles [2]. In the following years, several other universities and research institutions developed similar prototypes that laid the foundation for the development of AVs. The early 2000s saw significant advances in the field of AVs with the creation of the DARPA Grand Challenge, a competition to promote the development of self-driving vehicles.

In 2005, a team from Stanford College won the competition, proving the feasibility of AVs for the first time [3]. In the years that followed, the automotive industry began to invest heavily in AV technology, with major companies such as Tesla, Google, and Uber leading the way. The integration of AI, particularly ML and CVT, has been instrumental in enabling vehicles to make real-time decisions and navigate complex environments. Although AV technology is still in its development, it has the potential to transform mobility and transportation completely.

The use of AVs is anticipated to increase dramatically in the upcoming years as businesses attempt to overcome the technical and regulatory barriers preventing their commercialization. In general, the development of AVs has been a long and continuous process, with significant technological and governmental advancements. The incorporation of AI has significantly accelerated the development of these vehicles, and AI is expected to play a significant role in AVs in the future.

The Society of Automotive Engineers (SAE) defines five levels of driving automation. According to the standard [4], level zero represents no automation. Crude driver assistance systems such as adaptive cruise control, antilock brakes, and stability control start at level one. Level two is partial automation, where advanced assistance systems such as emergency braking or collision avoidance systems are integrated. With the accumulated knowledge of vehicle control and industry experience, Level Two automation is a feasible technology. Beyond this stage, the real challenge begins. The third level is conditional automation, where the driver can focus on tasks other than driving during normal operation.

However, the driver must respond quickly to vehicle warnings in an emergency and be ready to take control. In addition, Level 3 autonomous driving (AD) systems can only be used in limited areas of operational design, such as on highways. Levels 4 and 5 do not require human attention at all. However, level 4 can only be used operationally in a limited area where dedicated infrastructure or detailed maps are available. When the vehicle leaves these areas, it must end its journey by stopping automatically. The fully automated five-stage system can be used on any road network and in any weather. Currently, no production vehicles achieve levels 4 or 5 of driving automation. Table 1 shows the human intervention in driving and the vehicle features in each stage.

The application of AI in AD has been a growing area of research and development in recent years. Several studies have looked into how AI can be used in AVs for perception, control, and decision-making. We examine current research in the field and recent publications as follows.

Table 1. SAE Levels of Driving Automation [4]

<table>
<tr><th></th><th>SAE L0</th><th>SAE L1</th><th>SAE L2</th><th>SAE L3</th><th>SAE L4</th><th>SAE L5</th></tr>
<tr><td rowspan="2">What is required from the driver of the vehicle?</td><td colspan="3">When these driver assistance functions are activated, you are driving even if your feet are off the pedals and you are not steering.</td><td colspan="3">Even if you are in "the driver's seat," you are not driving whenever these AD features are activated.</td></tr>
<tr><td colspan="3">In order to ensure safety, you must constantly monitor these assistance systems and steer, brake, or accelerate as necessary.</td><td>You must drive if the feature demands it.</td><td colspan="2">There is no need for you to take over driving thanks to these automatic driving capabilities.</td></tr>
<tr><td></td><td colspan="3">These are driving assistance functions</td><td colspan="3">These are AD features</td></tr>
<tr><td>What do these features?</td><td>Their functions are restricted to issuing alerts and short-term assistance.e</td><td>These features assist the driver with acceleration, braking, or steering.</td><td>These features assist the driver with steering, braking, and acceleration.</td><td colspan="2">These features have limited driving capabilities and will not work until all necessary requirements are completed.</td><td>This function enables the car to be self-driven in any situation.</td></tr>
<tr><td>Feature examples</td><td>Automatic emergency braking.
Blind spot warning
Lane departure warning.</td><td>Lane centering
Or
Adaptive cruise control</td><td>Lane centering
And
Adaptive cruise control at the same time</td><td>Traffic jam chauffeur</td><td>Local driverless taxi
Pedals/steering wheel may or may not be installed</td><td>The same as level 4, but with the added ability to drive anywhere and in any circumstance</td></tr>
</table>

In regard to scene understanding, motion planning, decision-making, vehicle control, social behavior, and communication, Ben Elallid et al. They concentrated on techniques based on DLN and Reinforcement Learning (RL). Additionally, they outlined the outstanding issues and suggested potential future study trajectories [5]. A general survey of current advancements in AV software systems was presented by Pendleton et al. They highlighted recent advancements in each field and gave an outline of the fundamental elements of AV software [6]. An overview of the state of the art for DLN technologies for AD was presented by Grigorescu et al. They started by introducing recurrent neural networks (NN), the deep RL paradigm, and AI-based architectures for AD. They researched both the End2End systems, which immediately translate sensory data into steering commands, and the modular perception, planning, and action pipeline, each module of which is developed using DLN techniques. Also, they examined current issues with AI architectures for AD development, such as their security, training data sources, and computing hardware [7]. Ma et al. investigated how AI may support three key AV functions: vision, localization and mapping, and decision-making. In order to comprehend the potential applications of AI as well as the difficulties and problems involved in its implementation, They provided insights into potential opportunities for using AI in conjunction with other emerging technologies:

- High-resolution maps, Big Data, and high-performance computing.
- Augmented reality/virtual reality as an advanced simulation platform.
- 5G communications for networked AVs.

An overview of the most recent planning and control algorithms, with a focus on the urban environment, has been provided by Paden et al. They examined a variety of strategies and their efficacy. The models of vehicle motion used, the presumptions made about the structure of the environment, and computational requirements [8]. The challenges of vision, localization, path planning, and motion control were examined by Naz et al. in an overview of numerous contemporary AI algorithms employed by AVs [9]. DSAGAR and TS NANJUNDESWARASWAMY presented a comprehensive overview of an artificially intelligent vehicle, including its various components, several approaches such as NN and fuzzy logic (FL), and their benefits and drawbacks. They highlighted how various sensors and map generation make an AV more robust. Finally, they have described the incorporation of ML, and fuzzy neural vehicle systems control [10].

Several ML and DLN algorithms utilized in AD architectures for tasks like motion planning, vehicle localisation, pedestrian detection, traffic sign recognition, road marking identification, automated parking, vehicle cybersecurity, and fault diagnostics were described by R. Bachute et al. The technical features of the ML and DLN algorithms utilized in AD systems were also investigated. These algorithms were examined using parameters such as the mean union overlap rate, average precision, missed detection rate, false positive rate per image, and average number of erroneous image detections [11].

To the best of our knowledge, no review article comprehensively presents the application of AI to self-driving cars. Including:

- Perception, data analysis, and addressing environmental issues.
- The Navigation and path planning approaches and algorithms.
- The effect of using v2x communication and the SLAM system to safe and efficient navigation.
- The role of ADAS and vehicle motion control is to assist drivers with various tasks and control the vehicle's movement.

This motivated us to fill this gap in the literature and present the summary of our work.

We begin by examining the perception process constraints, sensor combination and fusion, and data collecting and processing. Later, we discuss the advantages of V2X communication on AVs for better traffic control and road optimization. Following that, we study several navigation approaches and road simultaneous localization and mapping. Finally, we look into AVs motion control and advanced vehicle driving assistance. Figure 1 summarizes our research process.

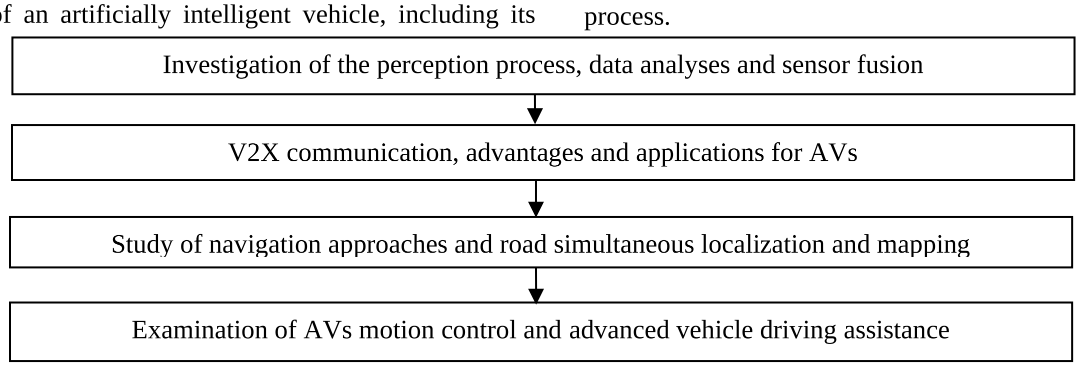

Fig. 1 Research process

2. Perception and Data Fusion

AI has revolutionized perception and data fusion in several areas. In perception, AI techniques such as CV machines enable the interpretation and understanding of visual information. By enabling data analysis and prediction, AI-powered ML algorithms improve perception systems far more. In order to provide a more thorough and accurate picture of a particular situation, data fusion employs AI to combine and evaluate data from several sources, including sensors, databases, and other data streams. Improvements in speed, accuracy, and dependability in various applications, such as transportation, military, and environmental monitoring, are among the main advantages of AI-powered perception and data fusion. Figure 2 shows how AVs perceive their environment based on 5 senses (camera LiDAR, long-range detection radar, medium and short detection radar and ultrasound) to have full coverage of the surrounding area.

2.1. Perception and Data Processing

AD sensors face various environmental conditions that can affect their performance, such as weather conditions, lighting, and road conditions Zhang et al. [12] and Vergas et al. [13]. AI plays a critical role in addressing these challenges and improving the accuracy and reliability of systems from AD. The following are some environmental concerns and how AI might help to resolve them:

2.1.1. Weather Conditions

Cameras, LIDAR, and radar sensors can all be affected by unfavorable weather conditions like snow, rain, and fog. Under these circumstances, object detection and classification accuracy can be improved by AI algorithms using methods like semantic segmentation and deep learning. To test how fog and snow affect the performance of different LiDARs, Jokela et al. conducted both indoor and outdoor tests [14]. They found that the more dense the fog and the farther away the target, the more performance degrades, but they also found that a darker target is more challenging for the sensors to detect than a brighter one. By converting map images to edge profiles to depict road markings in a series of LiDAR signal reflection peaks, Aldibaja et al. were able to identify the general causes of lateral drift in localization. While moist materials from the snow-rain weather leave a path of low reflectivity lines on the road, accumulated snow on the roadside produces abrupt intensity peaks with erratic distribution for LiDARs [15].

Sheeny et al. explored sensory data perception for autonomous and assisted driving using a large-scale RAdar dataset in bad weather. They provided instructions for setting up, calibrating, and labeling sensors as well as examples of data that had been gathered in various road and weather conditions [16]. DLN-based self-supervised ego-motion estimation was proposed by Almalioglu et al. as a reliable and additional method for localization in inclement weather. The recommended approach is a geometry-aware approach that combines the strong representational capabilities of visual sensors and the weather-independent data provided by radars utilizing an attention-based learning mechanism [17].

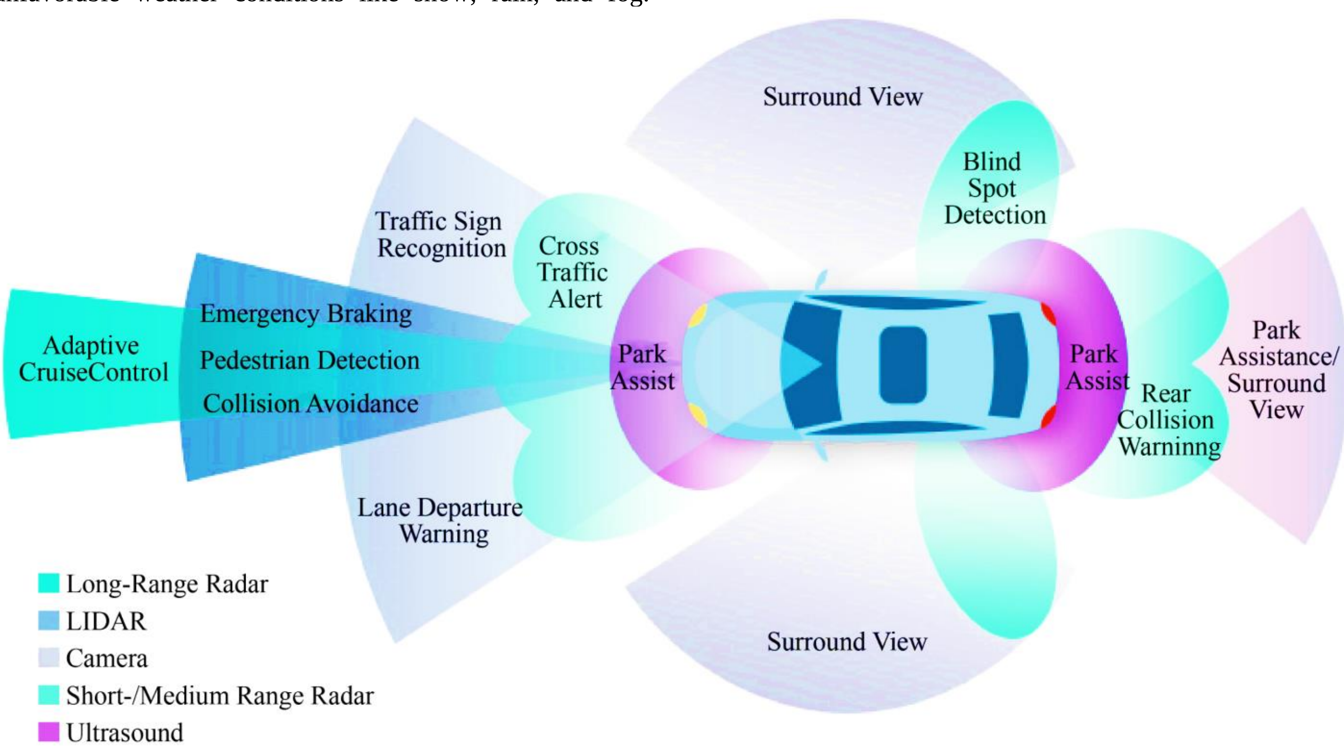

Fig. 2 How AVs perceive the environment [58]

2.1.2. Lighting

The effectiveness of sensors can be impacted by various lighting conditions, including shadows and reflections. These impacts can be taken into account by AI algorithms utilizing methods like adaptive thresholding and histogram equalization. A DLN-based picture-enhancing method for AD at night was introduced by Li et al. They created a convolutional NN-based light enhancement network. Before using it to produce image pairs for model development, they first developed a generation pipeline to transform images taken in bright light into images taken in low light. Eventually, based on the findings, they came to the conclusion that the LE network, which offers more detail and less noise with less computational effort, can better enhance low-light photos [18]. Rashed et al. suggested using motion data from both camera and LiDAR sensors to create a reliable and real-time convolutional NN architecture for moving object detection in low light. They created a dataset called "Dark-KITTI" to show the effects of their technique on the KITTI dataset by simulating a low-light situation. Compared to their starting points, they achieve a 10.1% relative improvement on Dark-KITTI and a 4.25% relative improvement on Standard-KITTI [19].

2.1.3. Road Conditions

Potholes, gravel, and uneven road surfaces can all influence sensor accuracy and make it challenging to determine the position and orientation of a vehicle. By merging data from several sensors and utilizing methods like particle filters and Kalman filters, AI algorithms can increase the precision of vehicle localization. A method for detecting roads that consider surface type variation, identifies paved and unpaved surfaces, and detects damage and other information on other road surfaces that may be relevant to driving safety was presented by Rateke and Wangenheim [20]. Chen et al. suggested a brand-new semi-supervised approach based on adversarial learning to extract road networks from remote sensing photos. A small number of poorly annotated data and a sizable amount of weakly annotated data are used for training in this method [21]. The You Look Only Once Version 3 CVT model library was used by Bucko et al. to achieve automatic pothole detection. This study aimed to investigate the effects of unfavorable circumstances on pothole identification [22].

2.1.4. Dynamic Objects

Dynamic objects such as other vehicles, pedestrians, and bicycles can pose a challenge to AD systems because they are constantly changing and can suddenly appear or disappear. AI algorithms can improve the accuracy of object detection and classification by using techniques such as DLN and Convolutional NN. E. Gomez Hernandez et al. proposed a technique for detecting moving objects in the environment of an AV by considering a DLN detector model and dynamic Bayesian occupancy. The goal of their work is to detect moving objects in traffic scenes by fusing semantic information with occupancy grid estimates. Furthermore, they use a Bayesian occupancy approach with a highly parallelized design to obtain the estimates for the occupancy grid [23]. Dangle et al. introduced an improved translation approach to convert thermal infrared to a visual color image using a unique Convolutional NN architecture. They created a pedestrian detection system for image enhancement, object recognition, and colorization.

The recognition model is given the colored and improved images using a pre-trained You Only Look Once version 5 architecture. Based on the coordinates of the edge surrounding the pedestrians, bounding boxes are generated on the resulting photos [24]. Using a monocular camera and LIDAR to track the dynamic object in three dimensions, Zhao et al. introduced a complete system for dynamic object tracking in three dimensions [25]. The system also includes a re-tracking mechanism that resumes tracking when the target reappears in the camera's field of view.

AI is essential for enhancing the accuracy and dependability of AD systems, particularly in difficult environmental circumstances. AD systems can better comprehend their surroundings, make decisions based on current information, and protect the safety of passengers and other road users by utilizing real-time AI approaches.

2.2. Sensors Fusion

Refers to the process of integrating multiple sensor inputs to provide a more accurate, comprehensive, and reliable representation of the environment. The following are some ways AI is used in sensor fusion:

2.2.1. Data Fusion

Involves integrating information from multiple sensors to obtain a comprehensive and accurate understanding of the environment. AI techniques, such as ML, DLN, FL and Bayesian networks, are used to process and analyze the massive amounts of data generated by AV sensors. ML and DLN algorithms can be trained on large datasets to recognize patterns, localize objects, and make decisions based on sensor data. FL is useful for modeling imprecise or uncertain information, while Bayesian networks provide a probabilistic framework for reasoning about data. Rubaital et al. proposed a multi-sensor data fusion for vehicle detection in AV applications. They explored the problem of data fusion of camera and LIDAR sensors and suggested a novel 6D data representation (RGB+XYZ) to facilitate visual inference [26].

A real-time data fusion network with fault tolerance and fault diagnosis features was created by Pan et al. The features of the input data are extracted in real time by introducing early features to create a lightweight network. By estimating the global and local reliability of sensors, they provided a novel approach to evaluating sensor dependability [27]. A multi-sensor data fusion technique was created by Liu et al. to process the sensor measurements from three different common sensor types and generate better navigational data for autonomous surface vehicle operation in a practical environment [28].

2.2.2. Sensor Selection

Refers to the process of choosing the most appropriate sensors for a given task or environment. AI techniques such as ML, DLN, and RL can be used to optimize this process. ML algorithms can analyze large volumes of sensor data to find patterns and correlations that can be utilized to enhance sensor choice. In order to train algorithms for sensor selection, DLN can be used to extract features from sensor data. By learning from experience, RL can be utilized to improve the performance of the sensor selection system gradually. To enhance robustness without sacrificing efficiency, Malawad et al. introduced a HydraFusion-based strategy for selective sensor fusion [29]. This method learns to identify the current driving environment and fuses the optimum sensor combinations accordingly.

2.2.3. Sensor Calibration

Is the process of modifying sensors to assure their accuracy and dependability. The calibration of sensors for AV can be optimized using AI techniques like ML and DLN. Large volumes of sensor data can be analyzed by ML algorithms to find patterns or anomalies that might point to calibration problems. Moreover, DLN techniques can be used to create more precise sensor activity models, increasing calibration accuracy. In order to ensure that the sensors deliver correct and trustworthy data for AV systems, AI approaches can also be employed to modify the sensors in real-time based on altering environmental conditions. OpenCalib is a toolkit Yan et al. have presented, including numerous sensor calibration techniques for AD vehicles. The most popular sensors are covered by OpenCalib, including LiDAR, cameras, IMUs, radar, and IMUs. It also includes a variety of application scenarios, including manual and automatic road scene calibration, assembly line calibration, and online calibration [30]. Ponton et al. have suggested employing static object data for an effective extrinsic calibration of multi-sensor 3D LiDAR systems for AV. They demonstrated an effective calibration approach for sensors fixedly installed in an AV, utilizing both time- and space-related information and proprioceptive/perceptual information [31].

A data-driven miscalibration detection system for a camera placed on a vehicle was presented by Jiang et al. They suggested a data-driven RGB camera miscalibration detection approach to identify the internally calibrated camera parameters. The specific procedure entails calibrating the raw picture with the erroneous internal parameter to obtain inaccurately calibrated image data, which is then added to the correctly calibrated internal camera parameters to create an improper internal camera parameter. This incorrectly calibrated image data is used as input data to the NN to train the network model and generate a network model to detect the incorrectly calibrated parameters [32].

In general, the application of AI in sensor fusion results in a more precise and trustworthy representation of the environment, which is crucial for applications like AVs, robots, and Internet of Things devices.

3. Vehicle-To-Everything Communication

V2X communication is a critical aspect of AVs, as it allows vehicles to communicate with other vehicles, road infrastructure, and other environmental devices. AI has the potential to play an important role in improving the functionality of V2X communications and making AVs safer and more efficient. Here are some applications of AI in V2X communications for AVs:

3.1. Traffic Management

AI systems can monitor traffic trends, forecast congestion, and make real-time adjustments to enhance traffic flow using V2X communication data. Large volumes of V2X data can be analyzed using ML techniques to find patterns and correlations that can be used to enhance traffic management. For instance, In order to facilitate quick and precise decision-making, AI may also be utilized to evaluate the enormous amounts of data created by V2X interactions in real-time. In this application, ML, a type of AI that can learn from past data and generate predictions using it, is frequently employed. Another kind is rule-based systems, which base choices on a set of predetermined rules. Wagner et al. suggest using a digital twin to implement the SPaT/MAP V2X connection between vehicles and traffic lights. The primary outcome of the suggested remedy is a comprehensive and adaptable traffic control system that makes use of an industrial PLC and ensures a standardized V2X protocol [33]. Kim et al. studied the path rerouting method based on V2X communication to enhance traffic flow and showed that V2X communication may enhance traffic flow in the case of a traffic jam. [34]. A DLN technique based on the unidirectional long short-term memory model was proposed by R. Abdellah et al. to estimate traffic in V2X networks. They explored the prediction challenges under various scenarios based on the quantity of packets sent each second. Processing time, mean square error and mean absolute error percentage are used to gauge the accuracy of predictions [98].

3.2. Real-time Decision-Making

AI algorithms can use V2X communication data to make real-time decisions in complex and unpredictable driving situations, such as entering a highway or avoiding an obstacle. AI can also be used to process the vast amounts of data generated by V2X communications in real-time to enable fast and accurate decision-making. One type of AI commonly used in this application is ML, which can learn from previous data and make predictions based on it. Another type is rule-based systems, which use a set of predefined rules to make decisions. Xu et al. proposed real-time AI perception of complex roads based on 5G-V2X for smart city safety. They combined AI algorithms and the 5G-V2X framework to propose a real-time street perception method [36]. A real-time regional route planning model for connected vehicles based on V2X communication was presented by Wang et al. They suggested a technique for route planning that accounts for the timing and phase of traffic lights on metropolitan road networks. They used real-time driving data from vehicles to dynamically calculate the resistance values of road segments based on the timing and phase information about traffic signals that V2X gathered. Then, all anticipated routes based on Dijkstra's algorithm are listed in accordance with the topology structure of the current road network. The best route is then determined by calculating the projected travel times of each alternative route and choosing the one with the shortest predicted travel times [37].

3.3. Route Optimization

Considering traffic patterns, road conditions, and other aspects, AI systems can use V2X communication data to optimize routing for AVs. ML, DLN, and RL can be applied to route planning. While DLN can be used to find patterns in data and enhance route planning, ML can be used to forecast traffic patterns and optimize routes based on past data. RL can be used to improve route design over time by taking into account feedback from drivers. Rasheed et al. suggested an adaptive 3D beam alignment intelligent vehicular network routing for mmWave 5G-based V2X communications. They initially suggested a 3D-based beam alignment and selection technique for location detection. A safe path for trusted data transmissions was then chosen using a group-based routing method [38].

Intersection-Based V2X Routing through RL in Vehicular AD Hoc Networks was presented by Luo et al. They suggested an intersection-based V2X routing protocol that includes real-time network state monitoring and a learning routing strategy based on past traffic flows via Q-learning. A multi-dimensional Q-table is set up to choose the best road segments for packet forwarding at junctions, and an improved greedy technique is used to choose the best relays on the pathways. Together, these two elements form the hierarchical routing protocol. The monitoring models can identify network congestion and make timely routing adjustments to avoid network congestion. This technique reduces communication delay and overhead while ensuring dependable packet transfer [39].

The functionality of V2X communications for AVs could be considerably enhanced by AI, making them safer, more effective, and more efficient.

4. Navigation and Path Planning

The ability of a vehicle to navigate its environment without human input or supervision is referred to as autonomous navigation. It includes perception to gather data about the environment and identify obstacles, localization and mapping to comprehend the position of the vehicle in the environment, path planning where algorithms are used to analyze the environment, motion control and decision-making to control the movement of the vehicle through the environment based on the generated path and make decisions to avoid obstacles and re-plan the path as needed to ensure that the vehicle is traveling. Figure 3 displays the fundamental navigational procedures for a vehicle. The autonomous driver's decisions are implemented into the powertrain and vehicle dynamics to provide acceleration and braking, regulate steering, and other functions.

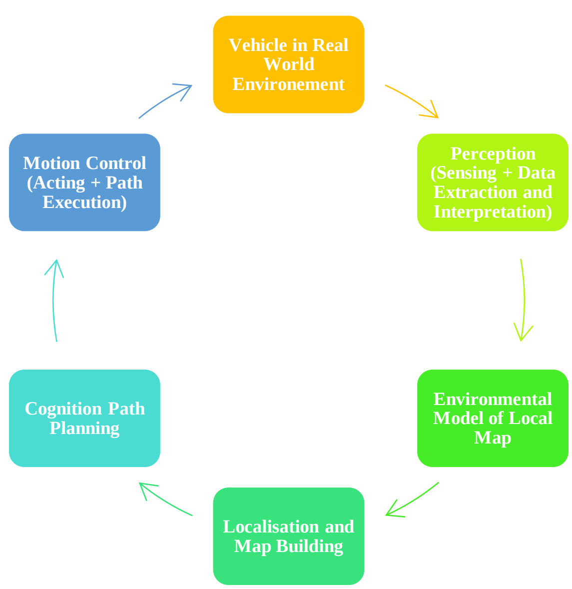

Fig. 3 Flow diagram for vehicle navigation

AI has several applications in path planning, which involves finding the optimal path for an AV to follow. Some of the most common applications of AI in path planning include autonomous navigation, real-time path planning, obstacle detection and avoidance, traffic management, and route optimization. Digital maps are created and updated using AI algorithms, which are also used to evaluate traffic patterns, produce motion plans, and optimize driving routes. These algorithms determine the most effective way by considering variables, including the current environmental circumstances, vehicle restrictions, and task objectives.

The prior knowledge of the surroundings needed for path planning can be used to categorize navigation strategies. The terms "local navigation" and "global navigation" are broadly distinguished. While the vehicle does not need prior information about the surroundings as in local navigation, global navigation requires the vehicle to have knowledge of the environment, the location of the obstacle, and the desired position. Global navigation techniques function in a known environment. Local navigation techniques deal with uncharted or hazy terrain.

4.1. Artificial Potential Filed

The target and obstacles act as charged surfaces, and the total potential creates an imaginary force on the vehicle. This imaginary force pulls the vehicle toward the target and keeps it away from the obstacles. A method for motion planning using harmonic functions, which uses the analytical description of the solution of Laplace's equation, was presented by Szulczyński et al. They consider an elliptical obstacle in a two-dimensional environment with static and dynamic targets. This method ensures collision avoidance and approach to the target [40]. On the basis of an enhanced artificial potential field algorithm, Wang et al. suggested obstacle avoidance path planning for AD vehicles. Using an enhanced artificial potential field. Duan et al. proposed an algorithm for active obstacle avoidance trajectory planning and tracking for AVs using an improved artificial potential field [100]. In order to complete trajectory planning for automatic driving, Li et al. suggested an enhanced artificial potential field approach that added the distance adjustment factor, dynamic road repulsion field, speed repulsion field, and acceleration repulsion field. To overcome the issues with the conventional artificial potential field technique, they developed an intrusive weeding algorithm [42].

4.2. Cell Decomposition

In this approach, the area is divided into a grid of smaller cells, each of which is assigned a unique identifier. Each cell is then analyzed and characterized based on its features, such as road type, traffic volume, and obstacles. This information is then stored in a database and used to create a map of the area. Mark et al. presented a greedy depth-first search algorithm and a cell decomposition approach based on GA for the path planning of a manipulator that can perform multiple activities simultaneously in a 3D environment [43]. A homotopy class algorithm and CD for path planning for robot motion planning was described by Wahdan et al. In this method, the motion planning problem of a rigid-body vehicle is divided into two subproblems. First, a given free space is decomposed into a finite number of simply shaped regions to make the second subproblem natural and simple. Then a detailed motion is planned from the start position to the goal using the global path mentioned above [44].

4.3. Roadmap Approach

This method is frequently applied to GPS navigation systems, which give vehicle instructions and real-time traffic updates. The method typically entails entering a starting point and a destination, after which the algorithm will determine the most effective path to get there. Alternative routes, traffic updates, and an anticipated arrival time might all be included. A vehicle navigation roadmap approach's main objective is to give drivers a precise and detailed strategy for getting to their destination quickly and securely. Niu et al. introduced a novel Voronoi visibility path planning method that combines the benefits of a visibility graph with a Voronoi diagram to overcome the path planning issue for unmanned ground vehicles. To compare roads, they employed the procedure known as "The Voronoi shortest path refined by minimizing the number of waypoints." [45]. A modified probabilistic RA algorithm-based intelligent vehicle path planning was described by Li et al. To improve the quality of the sample points generated, they created a pseudo-random sampling method based on uniform sampling. Next, they added random incrementation to change the sample points' fluctuation range and successfully avoid the obstacle space. Finally, they used a two-way incremental collision detection strategy to set the connection threshold between road points and lower the number of collision detection calls [46]. To eliminate uncertain path calculations associated with high time and space complexity of roadmap path planning methods in complex environments for mobile robots, Ayawli et al. introduced a roadmap algorithm with morphological dilatation of the Voronoi diagram [44].

4.4. Neural Network

The NN approach to vehicle navigation involves using a NN to process data from sensors on the vehicle to make decisions about the path and movement of the vehicle. This can include tasks such as path planning, obstacle avoidance, and lane keeping. A dataset of sensor data gathered from the vehicle travelling in various settings and situations is used to train the NN. After being trained, the network can forecast in real-time what the optimum move is for the vehicle. Ren et al. proposed a hybrid intelligent approach for real-time optimal control based on deep NNs to improve the autonomy and intelligence of navigation control of automatically controlled vehicles [48]. An NN-based prediction model for mission planning was put forward by Biswas et al. A group of AVs must work together to go to a set of destinations in an environment with static and moving impediments. They offered a three-layer solution for mission routing [49]. Motion planning for highly automated road vehicles was reported by Hegedüs et al. utilizing a hybrid strategy combining nonlinear optimization and synthetic NNs. They suggested a trajectory planning system based on nonlinear optimization to dynamically construct viable, comfortable, and adjustable movements for highly automated or autonomous road vehicles using model-based vehicle motion prediction [50].

4.5. Particle Swarm Optimization

A population-based optimization system called particle swarm optimization (PSO) is inspired by the social behavior of fish or birds. It can be utilized to solve issues in many different areas, including vehicle navigation. The particles in this method stand in for several paths or path plans that could be used to solve the navigational issue. A fitness function that computes the quality of the solution based on variables like distance, fuel consumption, and obstructions is used to evaluate the position of each particle. Particles then move and update their positions based on the best solutions found by themselves and other particles. The process is repeated until a satisfactory solution is found. For the purpose of optimizing the reentry trajectory of hypersonic vehicles with a navigation information model, Wu et al. presented a hybrid Gaussian pseudo technique [51]. Based on a modified particle swarm optimization technique, Guo et al. developed a global trajectory planning and multi-objective trajectory control for autonomous surface vehicles [52]. While Mao et al. proposed a full-width deviation correction method for trajectory planning of horizontal axis road headers based on an improved particle swarm optimization algorithm [53]. A motion planning algorithm that can be viewed as a component of a hierarchical framework addressing the challenging problem of driving was suggested by Arrigoni et al. The suggested approach involves numerically solving an optimization problem with an MPC formulation utilizing accelerated particle swarm optimization. The algorithm can operate in an urban setting while taking into account moving impediments and restrictions, including vehicle dynamics and road boundaries [54].

4.6. Fuzzy Logic

The FL approach is a mathematical method that allows one to deal with uncertain, imprecise, or vague information in a way that resembles human reasoning. Unlike traditional Boolean logic, which uses only binary true or false values, FL uses degrees of truth represented by real numbers between 0 and 1. The vehicle navigation system would process sensor data and make decisions using fuzzy rules and membership functions in an FL method. The system may, for instance, employ a fuzzy rule that says, "The vehicle should slow down if it is near an obstacle and the obstacle is moving." The degree to which the vehicle is "near" to an obstacle and the speed at which the impediment is "moving" would be determined by the membership function; because FL can accommodate the uncertainty and imprecision of sensor data and simulate human decision-making processes, it can be employed in-vehicle navigation. This is especially helpful in unexpected and dynamic circumstances, like traffic and changing weather conditions. Song et al. suggested a dynamic path planning approach based on FL and enhanced ant colony optimization (ACO). To discover the best path in a road network using the idea of virtual path length, the FL ant colony optimization, the classical ACO, and the enhanced ACO were each applied independently first [55]. Chen et al. suggested a conditional deep Q-network for directional planning and used it for end-to-end AD, where the global path directs the vehicle from the starting point to the destination. They utilize the concept of fuzzy control to address the dependence of various motion commands in Q-nets and create a defuzzification method to increase the stability of predicting the values of various motion commands [56]. A real-time traffic circle identification and navigation system for smart cities and automobiles was presented by A.H. Ali et al. employing laser simulator FL algorithms and sensor fusion in a road environment [57].

5. Simultaneous Localization and Mapping

Simultaneous Localization and Mapping (SLAM) is a critical technology for AVs. It allows the vehicle to create a map of its surroundings in real-time and determine its location within that map. Various types of AI are employed in SLAM, including:

5.1. Machine Learning

To analyze sensor data and produce predictions about the environment, ML techniques like NNs and decision trees can be utilized. These predictions can then be used to increase the SLAM system's accuracy. Semantic monocular visual localization and mapping in dynamic contexts was proposed by Xiao et al. They developed a comprehensive SLAM framework called Dynamic SLAM, which is a semantic monocular visual simultaneous localization and mapping system that makes use of DLN to enhance performance in dynamic situations [59]. A method for RGB-D SLAM that is reliable and stable in situations with high levels of dynamic activity was proposed by AI et al. By combining semantic segmentation and multiview geometry, they can recognize moving objects [60]. A method for unsupervised multichannel visual-LiDAR SLAM that can combine visual and LiDAR data was proposed by An et al. Their SLAM system consists of a 3D mapping component, a DLN-based loop closure detection component, and an unsupervised multichannel visual LiDAR odometry component. A multichannel recurrent convolutional NN is used in the visual LiDAR odometry component. RGB pictures and 360-degree 3D LiDAR data create depth images of the front, left and right viewpoints. The properties of a deep convolutional NN were employed to detect loop closures. The 3D mapping component of this method may immediately build 3D environment maps without the need for ground truth data for training [61].

5.2. Computer Vision

CVTs such as object recognition and feature extraction can be used to detect and identify landmarks in the roads that can be utilized as reference points for the SLAM system. Sualeh and Kim suggested a 3D MODT-based semantics-aware dynamic SLAM. To address the challenges of the dynamic world, they combined SLAM with visual LiDAR-based 3D MODT. By considering the finite processing resources and real-time needs, the suggested system conducts temporal classification of tracked objects. An efficient tracker based on IMM-UKF-JPDAF keeps track of the objects geographically while preserving the class association history to address the real-time limitations and defects of object identification. They created a dynamic object mask that, when applied to a classified LiDAR point cloud, may imitate cutting-edge semantic segmentation approaches. SLAM intelligently chooses the visual elements for tracking and mapping tasks using the dynamic mask provided by MODT [62].

5.3. Reinforcement Learning

Based on the rewards and penalties it receives for its activities, RL techniques can be used to optimize the behavior of the AV. This could enhance both the effectiveness and security of vehicle mobility. Botteghi et al. investigated using RL as an effective and robust solution to explore unknown indoor environments and reconstruct their maps. They used the algorithm SLAM for real-time robot localization and mapping [63]. A. Castellanos and A. Placed presented an Active SLAM Deep RL method. By incorporating the conventional utility functions based on optimal trial design theory into rewards, they were able to simplify the costly computations of the previous techniques and describe the Active SLAM paradigm in terms of model-free Deep RL [101]. Path planning for active SLAM based on Deep RL in uncharted areas is suggested by Wen et al. They use fully convolutional residual networks to find the obstacles and get a depth image. They use the Dueling DQN algorithm for robot navigation to plan the obstacle avoidance path, and they simultaneously use FastSLAM to produce a 2D map of the surrounding area [65]. Each of these AI methods improves the SLAM system differently and adds to the overall accuracy and dependability of the AV.

6. Motion Control and Advanced Driver Assistance

Motion control and ADAS are two different systems that serve different purposes in AVs and also use AI in different ways. Motion control is in charge of regulating the vehicle's movement, including steering, accelerating, and braking. Motion control systems use a number of sensors to gather information about the surrounding area and the position, speed, and orientation of the vehicle. AI systems then process the data to decide how to best control the vehicle's movements. On the other hand, ADAS systems are intended to help drivers with various activities, including monitoring the environment, operating the vehicle, and preventing collisions. Using sensors, cameras, and other technologies, ADAS systems may identify objects and potential collision hazards in the environment and alert the driver or take preventative action to avoid a collision. AI algorithms process this sensor data to identify things and potential dangers and make decisions about what action to take.

Motion control employs various AI methods, including rule-based systems, FL, ML, and DLN. Rule-based systems make judgments on vehicle movements, such as steering, stopping, and accelerating, using a set of predetermined rules. FL, which can be helpful in directing the vehicle in challenging driving situations, uses linguistic variables to express ambiguous and inaccurate information. Techniques for each ML that can learn from data include decision trees, support vector machines, and random forests. Artificial NNs are used to handle enormous amounts of data in a process known as DLN, which can be used to identify objects, detect obstacles, and forecast movements.

Moreover, ADAS employs AI in a number of different ways. One sort of AI that enables ADAS systems to learn from data and enhance their effectiveness over time is ML. Another form of AI called CVT enables ADAS systems to detect and recognize items like other vehicles, pedestrians, and traffic signals using cameras and sensors. ADAS systems also use natural language processing to facilitate speech recognition and communication between drivers and vehicles. RL is a sort of AI used in AD to provide the vehicle with the ability to learn from its actions and improve its behavior to accomplish a particular objective, such as navigating through traffic or avoiding hazards. Figure 2 shows how vehicles perceive their surroundings to bring off driver assistance.

6.1. Lane-Keeping

In order to locate a car within a lane and track lane markers on the road, AI algorithms are utilized. These algorithms build a 3D representation of the surrounding area and forecast the vehicle's future trajectory using sensor data from cameras and other sensors. The AI algorithms modify the car's steering based on this data to keep it in the center of the lane and at a safe distance from other moving vehicles. In response to shifting road circumstances like curves or shifting lane markers, the AI algorithms can also modify the vehicle's speed and direction in real-time. Lane departure prevention mode and lane-keeping co-pilot mode are two switchable assistance modes that Bian et al. introduced in their enhanced lane-keeping assistance system [67]. At the same time, a lane-keeping assistance system for an AV employing a support vector ML method was proposed by Karthikeyan et al. [66]. Zhou et al. presented a lane departure assistance system based on model predictive control using the linear programming method. The linear programming alternative is less computationally intensive than other models, such as the quadratic programming-based model, making this a preferred model for electronic control units in commercial vehicles [68].

6.2. Traffic Sign Recognition

Several types of AI can be used in traffic sign recognition, depending on specific application requirements and available resources. Using ML methods, such as convolutional NNs, to categorize traffic signs according to their visual characteristics is a typical strategy. Convolutional NNs are DLN models demonstrated to achieve high accuracy rating traffic sign recognition applications. They are particularly well adapted to picture recognition challenges. An alternative strategy is using rule-based expert systems that encode knowledge about traffic signs and their attributes, such as shape, color, and symbols. These systems, which recognize traffic signs using predetermined rules and heuristics, can be helpful when there is not enough data to train ML models.

Additionally, before using ML or rule-based algorithms, certain traffic sign identification systems preprocess the images using CVTs, including edge detection, image segmentation, and feature extraction. Using an effective convolutional NN, Bangquan et al. proposed an embedded real-time traffic sign recognition system [69]. Alghamgham et al. developed an autonomous traffic and road sign recognition system that recognizes real-time traffic sign images based on a deep convolutional NN [70]. While an enhanced traffic sign recognition method for intelligent vehicles was put forward by Cao et al. [102].

6.3. Adaptive Cruise Control

The ability for a vehicle to automatically change its speed in response to traffic circumstances is known as adaptive cruise control. This technology relies heavily on AI, and there are various types of AI that can be applied to increase the effectiveness of adaptive cruise control. ML algorithms can analyze vehicle sensor data and adjust speed accordingly. CVT algorithms can detect other vehicles on the road and predict their movements so the system can maintain a safe distance. Deep-learning algorithms can be used to detect different types of vehicles and adjust speed according to the risk they pose.

Li et al. studied the car-following behavior of vehicles with adaptive cruise control (ACC) using field experiments with a three-vehicle platoon. Their experiments investigated the response of ACC under different conditions in relation to three categories of influencing factors: ACC, distance setting, traffic speed level, and stimulation by the preceding vehicle. Lin et al. made a comparison of Deep RL and Model Predictive Control for ACC [72]. Nie and Farzaneh created an ACC system based on eco-driving for two common traffic scenarios with automobiles following. To accomplish the objectives of eco-driving, driving safety, comfort, and followability [73]. The Eco-CACC system, a cruise control system that automatically reduces a vehicle's speed close to a signalized intersection to conserve energy, was reviewed by Bas et al. for possible market penetration [74].

6.4. Obstacle Avoidance

AI algorithms are employed to recognize and distinguish between pedestrians, other cars, and fixed objects like buildings and street furniture in the vehicle's route. These algorithms build a 3D model of the surrounding area and forecast where obstacles will be in the future using sensor data from cameras, lidar, radar, and other sensors. Based on this knowledge, the AI algorithms design a safe trajectory for the car, taking into account things like the vehicle's speed, the amount of space on the road, and other drivers' and pedestrians' behavior. In order to avoid or reposition unexpected impediments, the AI algorithms can also change the vehicle's speed and direction in real-time. Behzadan and Munir proposed a framework based on Deep RL to evaluate the behavior of collision avoidance mechanisms operating with an optimal adversarial agent trained to place the system in unsafe states [75].

An unexpected collision avoidance method was put forth by Kim et al. Using Deep RL, they created an intelligent self-driving approach that reduces the severity of injuries in unforeseen situations involving traffic light violations at an intersection [76]. He et al. suggested a hierarchical control architecture with decision-making and motion control levels as the building blocks for an emergency steering control method. When making decisions, a path planner based on the kinematics and dynamics of the vehicle system selects a collision-free route after a dynamic threat assessment model continuously evaluates the danger of collisions and destabilization. The nonlinearity of the tire's cornering behavior and unknown external disturbances are considered by constructing a lateral motion controller at the motion control level. To follow a collision-free trajectory and ensure the closed loop is robust and stable, a backstepping sliding mode control based on an assessment of tire side force is used [77].

6.5. Emergency Braking

AI is essential to efficiently operating emergency braking, a crucial safety component in contemporary vehicles. Emergency braking systems can use various AI techniques like DLN, CVT, and ML. ML algorithms can analyze vehicle sensor data to determine whether emergency braking is required. A vehicle's path may contain pedestrians or other moving objects, which CVT algorithms can identify and assess for danger. The system may be trained to recognize various threats and react accordingly using DLN algorithms. Socha et al. presented an ML-based automatic emergency braking system for pedestrians with complete safety proof [78]. A sliding mode slip ratio controller and a mechanism for allocating braking torque based on rules were used by Chen et al. to design an emergency brake control strategy [79]. While a nonlinear model predictive deceleration control was used by

Mu et al. to build an automated emergency braking approach [80].

6.6. Parking Assistance

Parking assistance systems use aria to help drivers park their vehicles safely and efficiently. These systems employ a variety of AI techniques, such as sensor fusion, ML, and CVT. Machine vision algorithms are used to discern patterns and identify things in the car's environment, such as other vehicles, curbs, and barriers. Large data sets of parking scenarios are used to train ML algorithms that forecast the vehicle's most effective path and give drivers instructions. Sensor fusion combines data from many sensors, like cameras and ultrasonic sensors, to build a complete picture of the surrounding area and determine the exact distances to nearby objects.

Parking assistance systems can reduce stress for drivers and make parking simpler, safer, and more efficient by integrating these many forms of AI. Wijaya et al. presented a method for real-time semi-AV parking in which a visual parking assistance system provides maneuvering recommendations to the driver for reverse parking. To generate recommendations for the driver, the proposed system includes wide-angle lens correction, a global bird's-eye view, and user-guided vision-based parking line recognition [81]. A laser-based SLAM system for automatic parallel parking and tracking control was reported by Song et al. [82]. It incorporates path tracking, parking path planning, and environment perception and reconstruction.

6.7. Blind Spot Detection

Modern cars have a critical safety feature called blind spot recognition that aids drivers in avoiding crashes with other vehicles that might be in their blind areas. To make this technology effective, AI is essential. Blind spot detection systems frequently employ various AI techniques, including CVT, ML, and NNs. In the vehicle's environment, CVT is employed to recognize things, and ML algorithms are trained on vast data sets to discover patterns and foresee potential dangers. Real-time processing and sensor data analysis using NNs enable the system to provide precise predictions and alert drivers when a car is spotted in its blind zone. Blind spot detection systems are able to increase driver safety and reduce traffic accidents by combining these many forms of AI. A camera-based blind spot identification system was created by Kwon et al. The established research framework consisted of five stages: Data preprocessing, feature extraction, fully connected network model learning, vehicle blind spot adjustment, and false alarm reduction [83]. In replacement of the conventional radar-based approach, Zhao et al. proposed a camera-based DLN technique that accurately detects other cars in the blind spot [103]. To enhance blind spot detection, Lee et al. suggested employing generative adversarial networks to augment nighttime data [85].

Although both motion control and ADAS systems use AI, they perform different functions in AVs. Motion control systems are responsible for physical vehicle control, while ADAS systems monitor the environment and assist the driver.

7. Discussion

The use of AI in self-driving cars brings numerous benefits, including improved safety, increased efficiency, greater convenience, and better accessibility. AI technology enables self-driving cars to monitor and interpret complex traffic situations in real-time and make decisions faster and more accurately than human drivers, reducing the number of accidents caused by human error. Driving has become more practical and economical thanks to AI's ability to optimize routes and driving techniques to save on fuel and travel time. Self-driving cars with AI capabilities may also autonomously park, drive through traffic, and adjust to changing road conditions, improving accessibility for elderly and disabled individuals. According to recent studies, using AI-powered self-driving cars might cut road fatalities by up to 90%, enhance traffic flow, and expand mobility for millions of people [86].

Achieving fully AD cars is challenging, with several technical and societal challenges to overcome. Creating algorithms that can effectively perceive and comprehend the environment, including recognizing and responding to various objects and circumstances, is one of the largest problems. This requires addressing challenges in CVT, natural language processing, and decision-making under uncertainty [47] [88]. Furthermore, it is crucial to guarantee the dependability and robustness of AI systems because even little biases or errors in the algorithms can have major negative effects in the actual world. Other challenges include clarifying ethical and legal issues related to using AI in AVs and establishing standards for testing and validating AI-based systems [89]. Current research has concentrated on enhancing the interpretability and transparency of AI algorithms, creating AI systems that can learn from human demonstrations, and addressing moral questions surrounding the use of AI in autonomous cars.

There are several research segments for AD with AI, including:

7.1. Perception

Developing algorithms that can accurately perceive the environment, including object detection and recognition, scene understanding, and localization.

7.2. Planning and Decision Making

Developing algorithms capable of making safe and efficient decisions based on the perceived environment, including path planning, trajectory optimization, and motion control.

7.3. Human-Machine Interaction

Creating user interfaces using natural language processing, gesture recognition, and facial expression recognition to enable secure and effective communication between people and autonomous cars.

7.4. Reinforcement Learning

Developing algorithms that enable AVs to learn from their own experiences and improve their performance over time.

7.5. Explainable AI

Developing algorithms that can provide interpretable and transparent explanations for decisions made by AVs to enable greater trust and understanding of the technology.

7.6. Multi-agent Systems

Creating algorithms that let autonomous cars communicate with each other and work together to accomplish shared objectives like enhancing traffic flow or preventing crashes.

7.7. Cybersecurity

Creating methods to safeguard the privacy and security of autonomous cars, including defense against cyberattacks and secure data transfer.

7.8. Testing and Validation

Creating procedures for evaluating the dependability and safety of AD systems, such as certification, field testing, and simulation.

These are only a few research topics being investigated in the AD area.

As of early 2023, no fully autonomous self-driving cars are available for purchase on the market. However, several companies produce vehicles with advanced driver assistance features, such as lane departure warnings, adaptive cruise control, and automatic emergency braking. The most cutting-edge driving assistance technology, known as "Autopilot," is installed in Tesla vehicles and presently runs at autonomy level 2. Using its Super Cruise system, which functions at level 2 autonomy right now, General Motors further creates automobiles with cutting-edge driver-aid features. Although these technologies normally function at autonomy level 2 or 3, other automakers like Audi, BMW, and Mercedes-Benz also build vehicles with advanced driver assistance features. Despite the fact that these systems are not entirely autonomous, they show substantial advancements toward the creation of AVs that can operate without human interference.[90][91][92][93][94].

Several businesses are attempting to obtain increasing levels of autonomy in the AV industry, which is quickly developing. Autonomy levels 4 and 5 would let vehicles operate in all conditions without requiring human involvement, and companies like Tesla, Waymo, and General Motors strive toward this goal. Advanced sensing and mapping technologies and more sophisticated AI and ML algorithms must be created to reach this level of autonomy. Companies are also seeking to integrate self-driving vehicles into already-existing transportation networks, like ride-sharing services and public transportation systems [95][96]. The global market for self-driving cars is predicted to increase from 20.3 million units in 2021 to 62.4 million units by 2030, according to the Global Forecast Study [97]. With sales projected to reach nearly $326 billion by the end of 2030, the automotive industry is focused on developing driver assistance systems that will pave the way for self-driving cars.

8. Conclusion

In conclusion, the use of AI in self-driving technologies has the potential to completely transform the transportation sector. AI algorithms, ML, DLN, and CVT techniques are being developed, and they will eventually result in advanced AVs that can navigate challenging road settings and instantly adapt to changing conditions.

The advantages are obvious, even though there are still certain obstacles to be solved, such as guaranteeing the security and reliability of self-driving technology. In addition to improving transportation alternatives for those with disabilities or limited mobility, self-driving cars offer the potential to reduce traffic congestion and accidents caused by human error.

Moreover, AI can be used in self-driving technologies for purposes other than just personal transportation. Drones and self-driving trucks could revolutionize the transport sector, making it quicker, safer, and more effective.

Overall, new opportunities for the future of transportation have been made possible by incorporating AI into self-driving technologies. In the upcoming years, we may anticipate seeing increasingly sophisticated and trustworthy AVs on the road, thanks to ongoing research and development.

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