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TOPICAL REVIEW

State-of-the-Art Review on Recent Advancements on Lateral Control of Autonomous Vehicles

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ABSTRACT The most well-known research on driverless vehicles at the moment is connected autonomous vehicles (CAVs), which reflects the future path for the self driving field. The development of connected autonomous vehicles (CAVs) is not only increasing logistics operations, but it is also opening up new possibilities for the industry's sustainable growth. In this review, we will explore the cloud-controlled wireless network-based model of cyber physical aspect of the autonomous vehicle, which is coupled with unmanned aerial vehicles (UAVs). Additionally, this model is Internet of Things (IoT) managed and AI-based, with a blockchain-based security mechanism. Additionally, we'll focus on lateral control in autonomous driving, particularly the lane change maneuver, taking social behavior into account. Here, we briefly reviewed Vehicle-to-Everything (V2X) communication, which is carried out by on-board sensors and connected wireless medium that enhance the lane departure processes while retaining human driver behavior relying on obstacle avoidance.

INDEX TERMS AV, CPS, CAV, DCPS, IoV, DSRC, V2X, CAV-UAV, decision-making, blockchain, on-board units.

I. INTRODUCTION

Vehicle is a machine with a 100-year history that has altered the globe [1]. The use of a car as a form of transportation offers consumers considerable convenience and helps them save a lot of time. A significant number of traffic accidents caused by the rise in automobile ownership result in catastrophic injuries and significant monetary losses. Driving is dangerous and tiresome even though it is a necessary component of using a car. In fact, the great majority of collisions are caused by drivers' poor judgment, and around half of these collisions are brought on by the drivers' delayed reactions.

The automotive sector is experiencing significant upheaval due to the quick development of slashing technology like artificial intelligence and pattern recognition. The modern car is more than just a mechanical device [1]. It makes use of a variety of scientific studies to enhance the vehicle's current capabilities and safety. Vehicles are becoming more and more intelligent owing to these technologies. As the foundation of smart cars, autonomous driving has emerged as the technology that needs the most attention. Because some capabilities, such autonomous road recognition, route planning, and vehicle body state modification, relieve drivers of tiresome driving procedures and make driving safer and simpler.

Lane changes are often performed by driverless vehicles, and obstacle avoidance is a key component of autonomous driving. The autonomous car can gather information about obstacles and other vehicles in its path, choose the best routes and methods for avoiding them, and then nimbly adjust its

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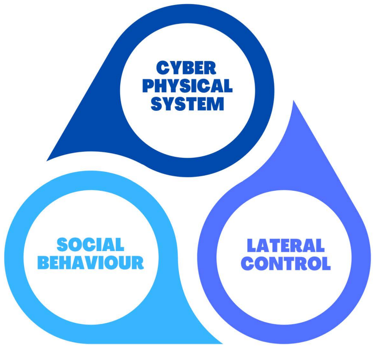

FIGURE 1. Integration of three aspects of futuristic autonomous vehicle.

speed and steering to ensure smooth and secure driving. As a result, simultaneous realization of lateral and longitudinal control is required for obstacle avoidance. The speed, safety, and efficiency of the obstacle avoidance procedure must also be taken into account. According to estimates, 1.2 million people die in traffic-related incidents that are the result of human error or weariness each year [1]. Research on the obstacle avoidance technique, particularly for the lane change scenario, has theoretical and practical relevance for the development of the rapidly expanding electric car and autonomous driving industries. For autonomous cars to reach the appropriate level of autonomy, many technologies are combined. The level of automation for autonomous vehicles has increased from zero to six, where level zero is no automation and level one is the starting level of automation [2]. Level 1- The majority of today's new cars include technologies like adaptive cruise control and lane-keeping assistance that fall under level 1 driver assistance. Level 2- The other self-control mechanisms, such as steering and acceleration/deceleration control, still call on a human driver to handle all other tasks and keep an eye on the road leads to the vehicle's partial Level 2 automation. Level 3- The conditional automation will allow the car to navigate difficult traffic circumstances and follow traffic signs without driver's intervention but would immediately need a person driver to assume control when a feature is activated. Level 4- It is considered to be a high automation level when a car is supposed to fully evaluate its surroundings and operate on its own even if a human driver doesn't react adequately to a request to take over. Level 5- This level is fully automated where the vehicle will solely transport people, and human interaction will be gone [3].

The focal focus of our literature evaluation in this case is level five automation. A fully autonomous vehicle (FAV) is the executive component of connected and autonomous vehicle (CAV) technology. In a futuristic, driverless car, CAV technology is the most promising. In this case, an interconnected environment is required, which will allow cars to interact with both other vehicles and the local infrastructure. Utilizing bidirectional connection hardware and sensors, the networked car may record and report traffic conditions from nearby vehicles. Through the use of connected vehicle technologies, vehicles will cooperate with one another and will be given access to a wealth of real-time data. The CAV technology is connected to the Intelligent Internet of Vehicular Things (IIoVT), internet of drones (IoD), artificial intelligence (AI), vehicular networks, and unmanned aerial vehicle (UAV), which all work together to create a cyber-physical system [4]. Unmanned aerial vehicles (UAVs) are robotic vehicles that can fly independently and are piloted by humans for a variety of tasks, including business, security, and strategic ones [5]. Sensors, cameras, GPS, and embedded systems are some of the key operating parts of UAVs [6].

Other enabling technologies, including the Internet of Things (IoT) and the Flying Ad hoc Network (FANET), can be connected with the AV eco-system in order for autonomous cars to reap their benefits. FANET is made up of UAVs (drones) that improve the functionality of AVs in a variety of ways, including boosting AV visibility, serving as aerial base stations, and acting as base stations for information offloading [7]. This is done through effective data sharing between the two technologies, and it significantly improves the service quality, scalability, and dependability of AVs. The operational security and data dependability of UAVs and AVs may be jeopardized by various security risks such as eavesdropping, DoS attacks, blackhole attacks, and other assaults that target communication links between these vehicles [8]. For UAV-UAV, AV-AV, and UAV-AV communications, coordinated and secure communication lines must be set up to guarantee dependable data sharing. In order to do this, several established communication technologies, including WiFi, Dedicated Short Range Communication (DSRC), LTE, and Zigbee, as well as developing such communications utilize technology like 5G based on the application's specifics paradism [4]. Furthermore, the sensing capabilities of autonomous cars are constrained since they only have on-board sensors that are based on cyber-physical sensing technology. In light of this, connected autonomous cars (CAVs) have the potential to be among the most revolutionary new transportation technologies in recent memory, opening up new possibilities for both vehicle technology and transportation business models. Determining the impact on traffic flow of modeling car-following and lane-changing behavior for CAVs has therefore become a central concern for the traffic theory community. However, current research in this area mostly focuses on car-following behavior and ignores lane-changing behavior in general, especially when it comes to decision-making concerns.

We need autonomous cars that are not just dependable and safe, but also enjoyable for users if we want to win over their approval. However, different vehicle users may perceive comfort differently than one another. For instance, some people could favor a mellow style of driving, while others would prefer a sporty style with fast accelerations. A human driver's style is often defined by a vast number of factors that reflect acceleration profiles, distances from other cars, speed while changing lanes, etc [9]. By integrating a cyber-physical system, we can enhance inter-vehicle communication, make lane-changing maneuvers much more effective,

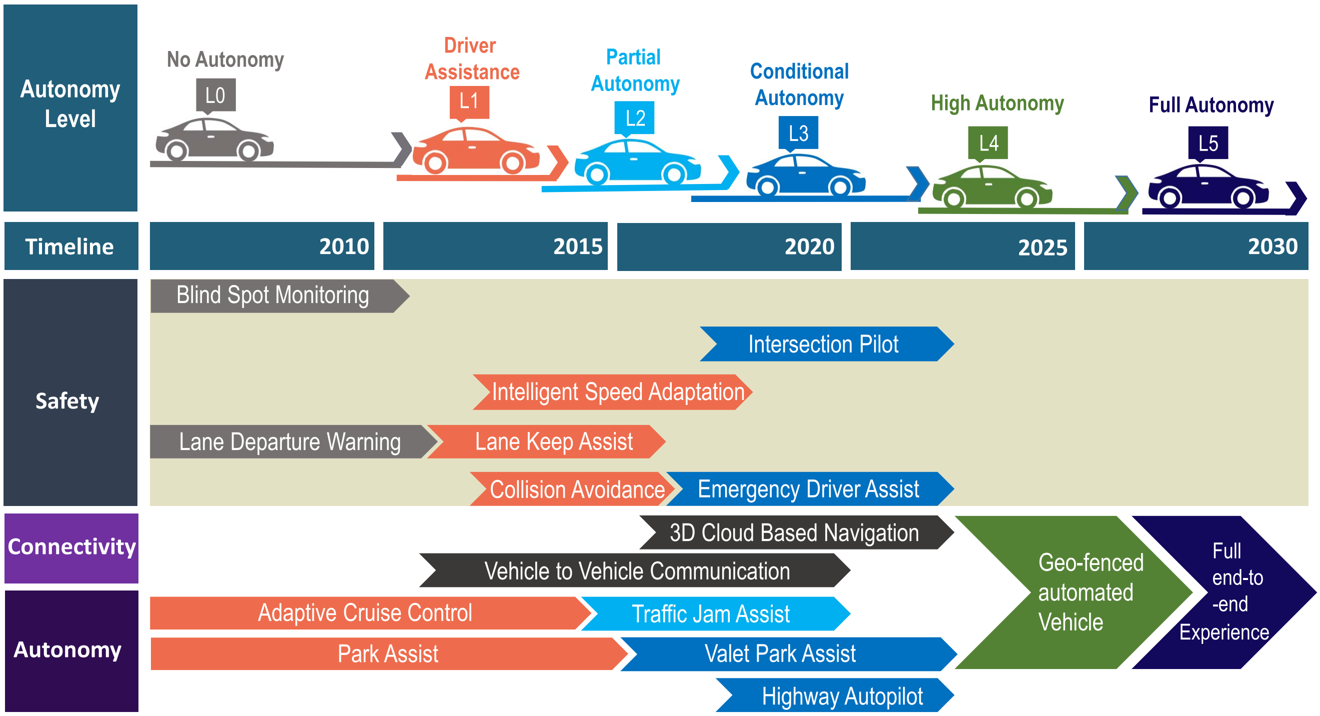

FIGURE 2. **5 levels of autonomous vehicle.**

and allow different driving styles that take into account social behavior. To provide a recommendation for future modern automobile technology, we will evaluate three components of this literature: cyber physical systems, lane-changing, and driving styles taking social behavior into account.

A. VEHICLES AND AUTONOMY

Driverless technology has been amply shown to function more safely and accurately than traditional vehicles, and it is widely acknowledged that this technology will continue to advance. Some advanced nations, like the United States, Britain, Japan, and Germany, have been doing research on autonomous cars since the 1970s. There is widespread agreement that autonomous cars will shape the future of the whole automotive sector among IT firms, automakers, governments, and other institutions. Research in this area has received a lot of funding and effort, and both technological and practical advancements have been accomplished. The primary unmanned vehicle technologies have been researched to a high level in the United States. The most well-known is the Google-developed autonomous automobile. In addition to using precise maps to navigate the road ahead, these cars incorporate cameras, radar sensors, and laser range trackers to see other traffic patterns. Simply enter the desired location, and the car will choose the best route on its own. The British business RDM Group was eager to deploy the prototype Lutz Pathfinder, the nation's first unmanned vehicle, as soon as the British government revealed the new regulation Google implying that UAVs would be legally available. Ten years were spent constructing the autonomous ''Cycab'' vehicle by the French INRIA business, which resembles a golf cart of the future. There are also a number of businesses in China that need our attention. Baidu, which has been creating driverless technology since 2013, is the most well-known. In 2016, Google unveiled its driverless car under the name Waymo, which runs a for-profit self-driving taxi service in the Phoenix, Arizona, area called ''Waymo One'' and has a detailed map of Chandler, Arizona. The company made the service available to the general public in October 2020, making it the only commercial self-driving service at the time. Waymo has been testing its vehicles on the streets of Phoenix-area cities, including Tempe, Mesa, and Gilbert. Since 2017, Cruise has operated their AVs Anywhere in San Francisco, the business's internal car-sharing service that enables any of its almost thousand workers to travel in a driverless cab. For the past few years, Zoox and Aurora have both been experimenting their AVs on the roadways of San Francisco.

Apple has been less forthcoming about its self-driving car initiatives than other AV businesses. Late in 2019, Cupertino, California, observed Apple vehicles on the road. Arlington, Texas, a city that is ahead of the AV curve, has worked with a number of businesses, including Drive.ai and Milo. Instead of focusing on single vehicles, Arlington has adopted a minibus-centric strategy.

In considering Europe, Stockholm, Sweden, which is renowned for its intentness of sophisticated IT companies. The city tested driverless buses in the beginning of 2018 as part of a collaboration between many governmental and commercial institutions.

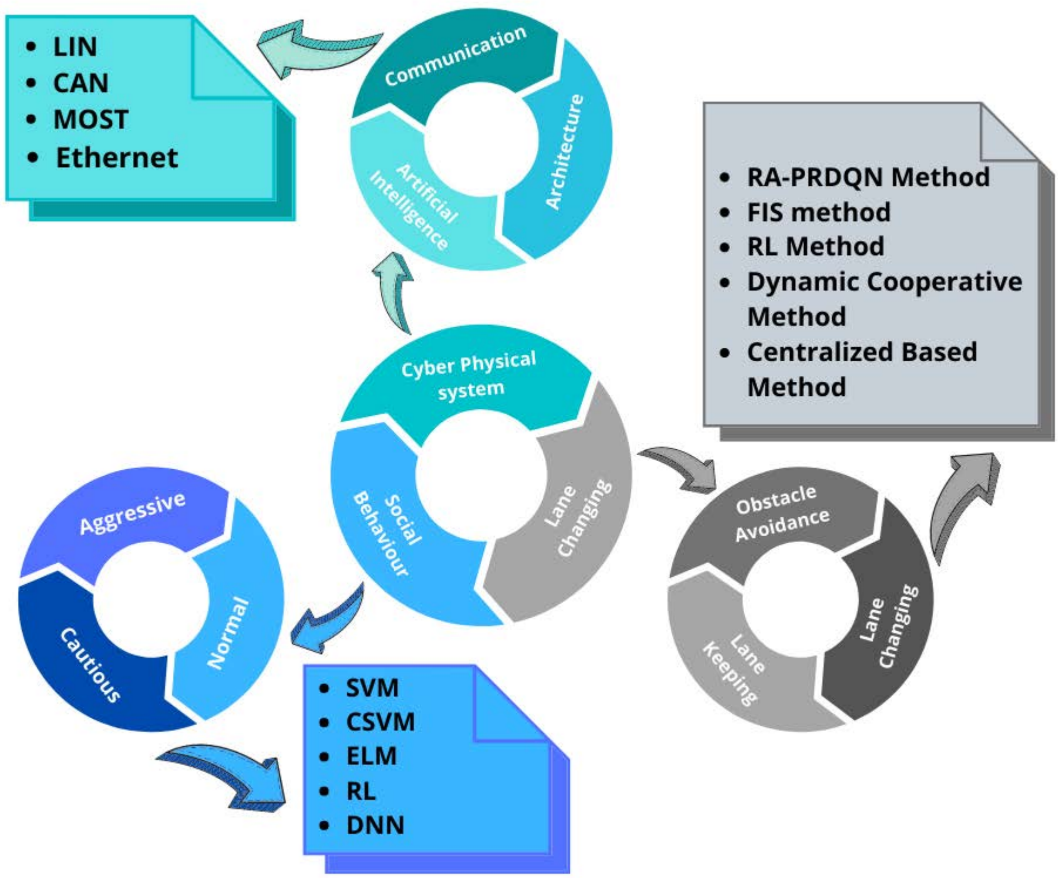

FIGURE 3. Overview of review.

FIGURE 4. Basic requirements of futuristic autonomous vehicle.

In terms of Asia, Woven City is a brand-new community situated at the foot of Mount Fuji in Japan. The city will be 175 acre in size, home to 2,000 permanent inhabitants, and be constructed from the bottom up to offer the appropriate venue for researchers, architects, scientists, and engineers to test the most advanced in autonomous car and smart city technologies.

Additionally, Singapore has developed a city-like research center, replete with junctions, traffic lights, and crosswalks, all built to the same standards as the rest of the island. Companies are encouraged to test their cars there, providing the downtown area a chance to acquire important information on how the AVs will function in real life scenarios.The South Korean city of Hwaseong is using a similar strategy with its K-City, the largest dedicated AV testing facility in the world. K-City is a replica city built only for testing AVs in realistic scenarios.

Without the required infrastructure, we will not be able to adopt fully autopilot vehicles overnight. New sorts of supply chain network will also be needed to accommodate the shift in production techniques. Future cities will become real-world digital centers. Cities will become better places to live because, as everyone know, modern technology is fundamentally sentient. Even in the most densely populated locations, the use of networked autonomous vehicles will improve road capacity and relieve traffic.

The infrastructure of cities is anticipated to undergo a major transformation in the unmanned future. For instance, since traffic signals were created with a focus on individuals, they might not be required anymore. Instead, robots may decide which vehicles should drive first, and therefore be more effective. Even for connected cars that are currently in existence, poor road markings include a challenge. For the adoption of AVs to be successful, it has to be upgraded. The road markers have to be both machine-readable and luminous. On sidewalks, curbs, and lanes, there should be sensors installed along the road. They will enable moving objects to monitor their environment and anticipate potentially hazardous circumstances. Road signs are now scanned by autonomous cars using computer vision. Machine-readable indicators, however, would be a far more dependable strategy. They'll have a transmittable embedded code in them. They'll communicate directly that algorithms can detect.

Hopefully, smart cities won't require any kind of parking due to the increasing number of autonomous vehicles. The predicted trend of shared mobility will force garages to relocate outside of downtown regions. Parking spots will be adjusted to fit more since self-driving cars can navigate better and fit into smaller driving lanes than conventional vehicles. In smart cities, all the area presently devoted to parking may be put to other purposes.

The development of effective autonomous cars may necessitate the implementation of 5G technology. The network claims that it is 100 times faster than existing 4G. By 2024, it's anticipated to service forty percent of the global population. Large-scale infrastructure would be needed for 5G wireless technologies. It will be necessary to construct new fiber-optic connections across this new infrastructure for driverless vehicles. This will be useful for upcoming infrastructure modifications for autonomous vehicles.

Driverless vehicles won't simply alter the way we move; they will also significantly alter the appearance of the existing infrastructure, both on highways and in cities. The AV revolution might usher in a time of smooth, predictable traffic as well as more effective public transportation. More open area will be available for usage by city dwellers. Additionally, there would be less dangers for bicycles and pedestrians, who frequently worry about large urban environments. Furthermore the persons who are physically handicapped or linguistically impaired, autonomous vehicles will build a number of amenities. They are capable of employing a variety of sign languages and gestures, and AVs can recognize these by using a variety of image processing techniques [10], [11]. With all of the advantages that autonomous cars and smart cities may provide, millions of people's quality of life will be enhanced while the environment is treated with the utmost respect. The level of interest in autonomous vehicles is rising dynamically all around the world since they provide enhanced safety and comfort for passengers. The market for autonomous vehicles is expanding quickly because of this. Future automotive sector supremacy will rest with the demand for fully self-driving vehicles.

II. CYBER-PHYSICAL SYSTEMS APPROACH

A cyber-physical system (CPS) is a tool that provides IT technologies to link the physical world (real world components) and computers (cyberspace) in order to produce real world values. It is a distributed, networked system that integrates computer operations (the cyber world) with physical processes (the physical world). A classic example of CPS

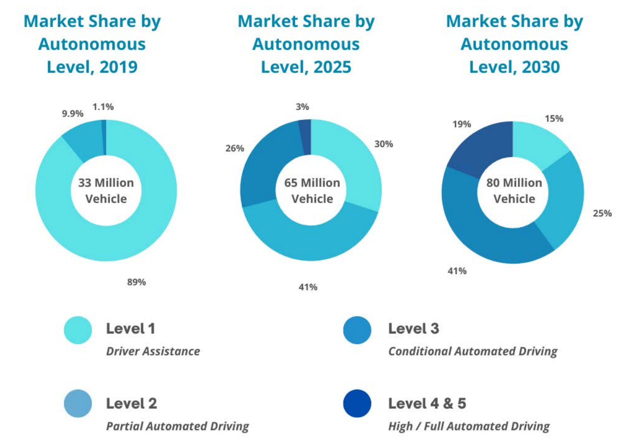

FIGURE 5. Increasing market size over the years.

is an autonomous vehicle. The controller, which represents the "Cyber" world, the physical plant, and the surroundings are the subsystems that make up an autonomous vehicle. The behavior and overall performance of the vehicle are determined by these several factors, which are strongly linked. The absence of global optimality in the selection of system architecture, physical characteristics, and control variables is the major weakness in present approaches to vehicle design and control. In this context, the proposed technology offers the possibility to broaden the system design domain and enhance CPS performance. As shown in Fig. 5 Autonomy in vehicles will increase rapidly in the near future, This will allow for an increase in the number of autonomous vehicles on the road. As a consequence of this, a greater number of cars will have the capacity to engage in sophisticated communication with one another, which will be critical to the achievement of global optimization on the roads.

A platform-based design (PBD) technique was presented, which uses contracts to perform high-level abstraction of the components of a CPS and can help with the entire design process. To reduce automotive energy usage and assure inter-vehicle safety, a CPS-based control framework for vehicle systems was created. Aside from the cyber and physical worlds, we must also consider the "Human" aspect of an autonomous vehicle. As a result, the interplay between the vehicle plant, control variables, multi-performance, and driving types must be thoroughly understood [12].

A. CPS CHALLENGES

The CPS's capacity to process and transfer data in real time between a network of broad and sophisticated systems while ensuring security is critical to its effectiveness. Table provides a list of the four main challenges for the development of CPS [13].

B. CPS AND IoT

There is considerable interest in the continuous integration of Embedded systems to computer networks, notably the

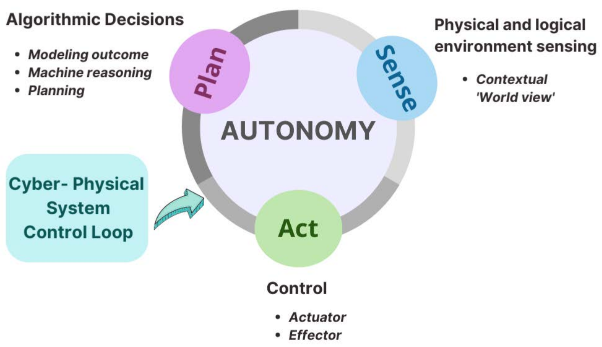

FIGURE 6. Architecture of autonomy employing a cyber-physical control loop.

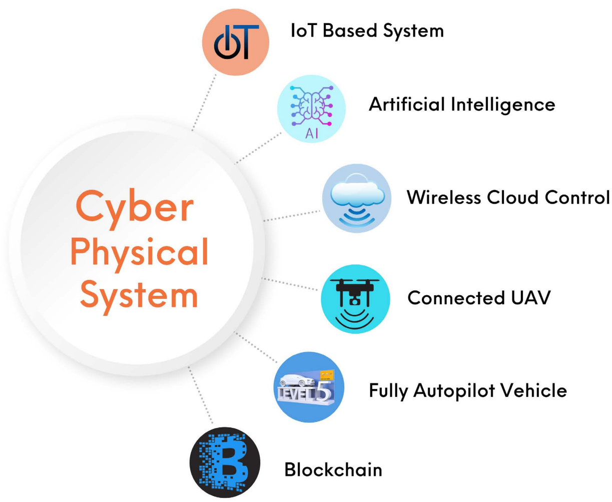

FIGURE 7. Elements of cyber physical system.

Internet enabling technologies including low-power wireless networks, communication protocols, and cloud computing make it possible to create new applications based on the interaction of Internet-connected objects [16], [17]. The Internet of Things (IoT) is the design paradigm that enables these applications. Autonomous Vehicles, Smart homes and workplaces, wireless sensor networks (WSN) in urban and rural infrastructures, industrial automation, and smart healthcare are only a few examples of important deployment domains.

Automated control systems can coordinate tasks and communicate information thanks to dispersed configurations of networked control systems [18], [19]. Due to their capacity for cooperative control, these distributed dynamic surroundingss (DNCSs) function as a particular kind of system of systems (SoS) [20]. We claim that a SoS, from a system-theoretic perspective, merges previously separate feedback control loops into a network of interdependent control loops, enabling the execution of cooperative tasks to accomplish a more important shared goal. For instance, a car's steering and braking systems may work together automatically to prevent a collision. These interactive feedback control loops could also have human supervision. Artificial intelligence (AI) will eventually be used to manage these systems, replacing the pre-programmed algorithms with neural networks and self-improving ones [21].

According to the context of complete autonomy more and more vehicle sensors will involve interaction with one another. In order to perform cognitive actions indynamic surroundingss, connected communications such as vehicle-to-vehicle (V2V), vehicle-to-cloud (V2C), vehicle-to-infrastructure (V2I), and vehicle-to-everything (V2X) are being used. This incorporates the availability of wireless communication and the synchronization of many modalities, including GNSS, cellular 5G/4G/LTE, WiFi, Bluetooth, and ultra-wideband (UWB).

Antennas are essential for establishing and sustaining robust wireless communication inside and between the relevant networks. While most automotive vehicle use scenarios may be satisfied with an industrial-grade antenna, there are situations when enhanced functional and mechanical dependability necessitates the use of an automotive grade antenna. Antennas that might be included in a car's dashboard, steering wheel, side mirrors, front or back windows, seats, and doors. There are several exterior combinational antennas available in the shark fin, puck, and dome types which are ideal installation shapes for the vehicle's roof. Typically these antennas are monopoles antenna, patch antenna, on-glass antenna, glued foil antenna, fractal antenna etc.

C. KEY FEATURES OF CPS

- **Embedded systems (ESs):** The field of CPSs extends beyond Embedded systems to encompass systems made up of OT, industrial devices, and general-purpose computers.
- **Wireless networks:** Systems connected through wired local area networks are included (LANs).
- **Internet access:** Unlike the IoT paradigm, CPSs may function without the use of Internet protocols.
- **Fully automated control and AI:** CPSs might run on optimization algorithm and in semi-autonomous settings

We view fully automatic control capabilities and potential advancements in AI-based control in CPSs to be an accessory (ie, not key) characteristics. Although computers play an important role in eliminating feedback loops in CPSs, human monitoring and intervention are still necessary and should be considered [22]. Therefore, we define as key features of CPSs the combination of the Following-

- Sensors and actuators provide real-time feedback control of physical processes.
- Controlling networked subsystems cooperatively.
- Computers complete the feedback control loops in semi-automated jobs at this level of automation, potentially permitting human control in some circumstances.

D. LEVELS OF AUTOMATION FOR CPS

The amount of automation necessary to qualify a system as a CPS is yet unknown [23]. As a result, we suggest the level where the desired system architecture assigns the computer the responsibility of closing the feedback control loops as a conceptual threshold. To put it another way, computers can acquire data from sensors and deliver orders to actuators without the need for a human intermediary. Attributing this level of automation is a difficult undertaking since it raises questions about the role of people in CPSs. This clear link between an automation threshold and CPSs as a class of systems serves two important reasons.

As first purpose, we define CPSs by referring to these systems as being controlled by a computational core, which is a commonly accepted domain in the CPSs community [24], [25] [26]. To integrate the discrete logic of cyber processes with the continuous dynamics of physical processes, real-time feedback control of physical processes necessitates hybrid system modeling. As a result, while some research groups use the term ''CPSs'' to refer to applications in a larger area, we stress this distinction to clarify the core characteristics of CPSs and avoid ambiguity in the idea.

As second purpose, we use a systems engineering viewpoint to examine CPSs outside the automated subsystem. As Leveson said:' ''automation usually does not eliminate humans, but instead raises their tasks to new levels of complexity'' [27]. This emphasis is important in CPSs in order to avoid limiting the system to its technological components and automated operations, and to examine the human roles and their consequences in the CPS. So the levels are,

1) The computer provides no aid; all choices and actions must be made by humans.
2) The computer provides a comprehensive set of decision/action options.
3) Narrows the selection down to a few.
4) Suggests options.
5) Executes that suggestion if the human approves.
6) Allows the human to exercise a limited right of disapproval before the execution is carried out automatically.
7) Executes automatically, and then must notify a person.
8) Informs the human only if asked.
9) Informs the human only if the computer decides.
10) The computer decides everything, acts autonomously, ignoring the human.

E. SECURITY CHALLENGES

Only when an AV is completely aware of its surroundings and has all of the necessary information can it operate efficiently and effectively. In order to accomplish this, AVs must maintain constant communication with their surroundings. However, because most of the communication channels employed in AVs are conventional and have been proven to be vulnerable to well-known cyber-attacks, the cyber-threats landscape for potential attackers in this context is vast. Information shared among many entities is likewise vulnerable to cyber-attacks.

TABLE 1. Cyber-physical system challenges [14], [15].

Challenge	Description
Heterogeneity	Unification of the data format from all sources.
Integrability	Ability to integrate all the sub-systems into one.
Interoperability	Systems must communicate using mutual platforms.
Security	Protection of sensitive data and systems against malicious attacks.

F. ARTIFICIAL COGNITION IN CPS

Most autonomous vehicle services (e.g., environmental perception and route planning) use AI. As the automobile industry transitions to serial manufacturing, the key difficulty is applying machine learning algorithms to mass-produced AVs.

The integration of intricate and connected internet of things (IoT), paired with cyber-physical systems (CPS), drives the unavoidable and autonomous growth of artificial cognition, however, there is a substantial void in current research on this topic [28].

Technologies that drive artificial cognition in CPS [28],

- CPS cognitive communities
    1) Cyber physical systems
    2) Internet of everything
    3) 5 level CPS architecture
    4) Agent-oriented architecture
    5) Object-oriented architecture
    6) Cloud optimized virtual object architecture
    7) Virtual engineering objects (VEO)
    8) Virtual engineering processes (VEP)
    9) Model-driven manufacturing systems (MDMS)
    10) Service oriented architecture (SoA)
    11) Dynamic intelligent swamps (DIS)
- CPS cognitive processes
    1) Connected devices and networks (CDN)
    2) Compiling for advanced analytics (CfAA)
    3) Business processes and services (BPS)
    4) Cloud distributed process planning (DPP)
    5) Physical and human networks (PHN)
- CPS cognitive societies
    1) Internet of things (IoT)
    2) Web of things (WoT)
    3) Social manufacturing (SM)
    4) Internet of people (IoP)
    5) Internet of services (IoS)
    6) Systems of systems (SoS)
- CPS cognitive platforms
    1) Internet protocol version 6 (IPv6)
    2) Internet-based system and service platforms (ISP)
    3) Model-based development platforms (MBDP)
    4) Knowledge development and applications (KDoA)

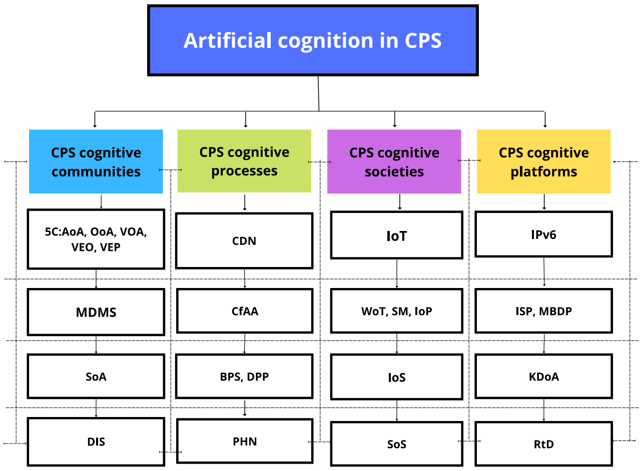

FIGURE 8. Design of a hierarchical cascading structure illustrating the development of artificial intelligence in CPS.

5) Real-time distribution (RtD)

The significance of these many notions and the connections between what at first view seem to be unconnected concepts are what give the hierarchical cascading method in Fig. 8 its coherence.

G. TECHNOLOGY FOUNDATIONS FOR SELF-ADAPTING SYSTEMS

The following important feedback management technologies predominated when theoretical framework was used to categorize the literature reviewed.

- Physical, informational, and financial movements are all integrated.
- Managing operational processes that are different.
- Gaining competitiveness by utilizing industrial digitalization
- Big Data is being used to increase production and service efficiency.

From the extensive literature reviewed on this topic, the requirements for cognitive feedback were categorized in Artificial cognition in CPS follows domain communities, processes, societies, and platforms. These domains represent how the changing roles of innovation, production, logistics, and the service processes require CPS advancements in the following

- Domain communities.
- Internet-based system and service platforms.
- Business processes and services.
- Dynamic real-time data from physical and human networks (perceived as data from intelligent swamps).

H. IMPORTANT CAVS COMMUNICATIONS AND PROCESSING FACTORS

The main components of in-vehicle and V2X communication technologies, as well as the computing difficulties of autonomous driving, are briefly discussed in this subsection. Modern communication protocols have chances to enhance CAV performance, but they also place high computational demands on the system. Additionally, autonomous driving increases the computational load on CAVs. It is crucial to comprehend the contemporary communications and computational components of CAVs and how they affect the design of OBCUs.

1) STANDARDS FOR CONNECTED VEHICLE COMMUNICATIONS

Local interconnection network (LIN), controller area network (CAN), FlexRay, media-oriented systems transport (MOST), and Ethernet are the in-vehicle networks that are most frequently utilized. Although LIN networks are the cheapest and quickest to set up, they are frequently employed in less urgent low-speed communication, including battery monitoring and temperature sensors. The most extensively used automotive network, CAN, is a low-cost, medium fault tolerance network found in a variety of engine controllers, transmission units, climate controllers, and other devices. FlexRay delivers far quicker speeds and more fault tolerance, which are typically necessary in applications like chassis control, safety radar, and supplemental restraint system, but at a significantly higher price. High-speed data transfer for in-vehicle entertainment, navigation systems, and infotainment systems is specially optimized for the MOST network. Although relatively new to production automobiles, wired Ethernet delivers high speed and has only been used in a small number of ECUs, cameras, and entertainment systems. The Ethernet network is a promising contender to rule the future generation of in-vehicle networks due to the deployment of numerous advanced features on many modern vehicles that demand high bandwidth, such as advanced driver assistance system (ADAS) and multimedia services [2].

To enhance traffic efficiency, promote road safety, and offer more traveler information services, V2X communication facilitates the transmission of information between cars as well as any other entity inside the vehicle network architecture. The Third Generation Partnership Project (3GPP) has designated a number of use case categories for V2X, including cooperative maneuvering, such as lane merging, lane changing, intersection management, cooperative perception, such as see-through, lifted seat, or bird's eye vision, cooperative safety, such as real-time situational awareness, warnings for traffic jams, traffic light violations, vulnerable pedestrian protection, autonomous navigation, such as real-time high definition map updates with real-time traffic information. Due to certain operational conditions, such as data transmission between high-speed cars, vehicles crossing from different directions, and between vehicles and roadside equipment, V2X communications confront a number of difficulties. More significantly, compared to basic safety applications, the sophisticated V2X use cases have highly strict latency and reliability requirements.

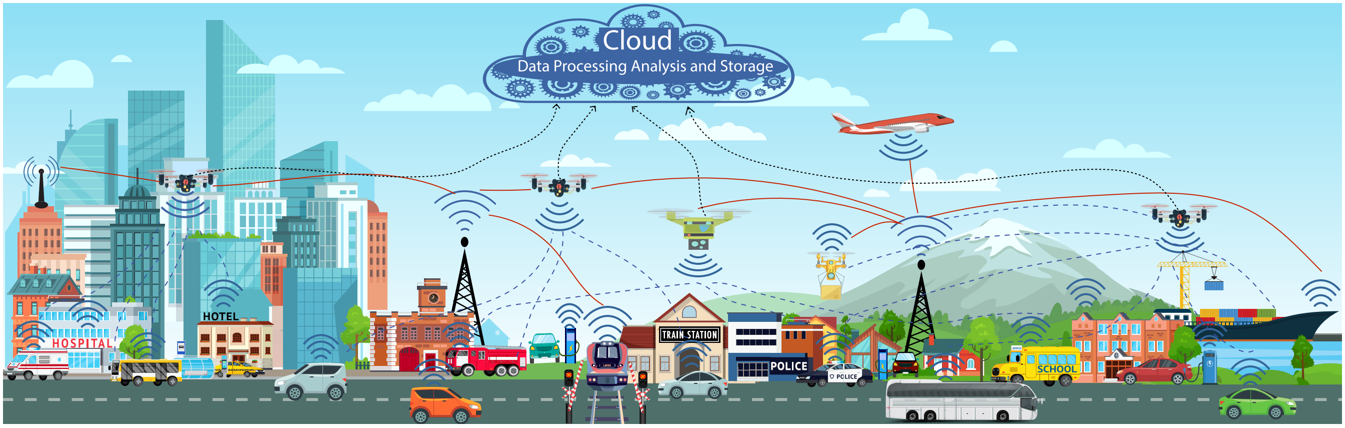

FIGURE 9. An overview of UAV-CAV environment using DSRC and C-V2X: CAV-UAV-cellular BS, CAV-UAV-pedestrian, smart building-UAV-CAV, CAV-UAV-traffic light, and CAV-UAV-cellular BS-smart building.

2) V2X COMMUNICATION PROTOCOL

The development of ground vehicle-based intelligent transportation systems and applications has been expedited thanks to the increased connectivity between vehicles. Vehicle-to-Infrastructure (V2I) communication allows connected and autonomous cars (CAVs) to interact with the highway infrastructure around them, allowing for traffic light signal and timing (SPaT) based vehicle speed planning to conserve energy and increase mobility. Vehicle-to-Vehicle (V2V) communication allows CAVs to communicate with one another. CAVs may exchange their position, speed, and acceleration information with other CAVs in their vicinity using V2V communication. CAVs can use neighboring vehicle information to organize coordinated maneuvers such as platoon formation and convoy formation to conserve fuel. Vehicle-to-Everything (V2X) communication allows CAVs to communicate with other traffic agents such as pedestrians. CAVs can reduce potential collisions and mishaps involving pedestrians and bikers, as well as significantly improve safety for other road transport agents, through using V2X [29].

3) C-V2X AND DSRC

There are currently two primary radio access technologies (RATs) that enable V2X communication: cellular V2X (C-V2X), which is based on 3GPP LTE/5G new radio, and dedicated short-range communications (DSRC), which is based on IEEE 802.11p (NR) [30]. When the communication devices are within a specific range of one another, DSRC technology, which is intended to operate in the 5.9 GHz ITS band, permits data transfer between automobiles, roadside infrastructure, and pedestrians. It has been fully tested, standardized, and implemented for V2X applications over the years, and a number of automakers, including Cadillac, Audi, and Volkswagen, have already installed DSRC devices to enable V2V and V2I communications [31]. Research has proven that DSRC's range, performance, and reliability are sufficient for applications involving fundamental safety [32], [33]. In order to compete with IEEE 802.11p-based vehicular communication technologies like DSRC and its European equivalent ITS-G5, the 3GPP standardized C-V2X as an alternative RAT technology in 2016. C-V2X uses the current cellular infrastructure to facilitate vehicle-to-vehicle communication [34]. For C-V2X to offer both Wi-Fi and cellular connection, 3GPP Release 14 established two complementing communication modes. For infotainment, telematics, and latency-tolerant informational safety use cases, automobiles talk to the cloud via the commercial cellular spectrum, whereas 5.9 GHz ITS uses the direct communication or sidelink channel over the PC5 interface to offer latency-sensitive communications. In smart cities, typical DSRC and C-V2X deployments with a range of connection choices are shown in Fig. 9. According to research, C-V2X can offer more coverage (as shown in the picture), improved dependability, better support for quality of service (QoS), 360° non-line-of-sight (NLOS) awareness, and higher capacity than DSRC [35]. Both RATs are capable of supporting basic safety use cases, such as traffic light information and emergency vehicle notifications, road work, and emergency brake warnings, with end-to-end latency needs of about 100 milliseconds under conditions of moderate vehicular congestion. The more sophisticated use case groupings, such as vehicle platooning, high throughput sensor sharing, intent sharing, autonomous and remote driving, and other safety-critical applications, have stricter QoS requirements that neither RATs can provide [2], [30].

4) FUTURE OF RADIO ACCESS TECHNOLOGIES(RATS)

A great deal of progress is being made to the next generation of these technologies, IEEE 802.11bd and NR V2X, with the goal of supporting better densities, throughput and reliability, longer ranges, submeter positioning, and ultra-low latency. Newly specified standards for NR V2X, which is intended to augment C-V2X for addressing advanced use cases, were recently established by 3GPP Release 16. According to preliminary investigations, NR V2X outperforms C-V2X in highway situations and is on the verge of meeting the QoS criteria for advanced V2X use cases [2].

5) COMPUTATIONAL ASPECTS OF AUTONOMOUS VEHICLE

Autonomous driving is primarily made possible by smart city efforts and contemporary vehicle connectivity capabilities. The combination of smart "things" and smart cars in a smart city environment provides a wide range of applications, such as intelligent transportation and safe autonomous driving [36]. In order to ensure safe driving, for instance, a contemporary autonomous car can perceive and interact with its surroundings. Additionally, wearable technology may identify passenger health emergencies and, in response, send an alarm to adjacent cars, communicate with an emergency caregiver, and enable smooth navigation through intelligent traffic light signals. An intelligent vehicle has the ability to stop and take protective measures on its own while communicating its position [3], [37]. The enabling infrastructure has to continuously increase processing power to efficiently run a variety of applications in order to fully exploit the benefits of autonomous driving. Traffic control, route optimization, and shareability of service are among the ongoing traditional studies on computational elements of autonomous driving. Due to the intensive computations required for dynamic path planning, cooperative driving support, and multimedia processing, autonomous driving places extra stress on information processing. Aspects of modern computing include the need for precise and prompt perception in order to fully comprehend the immediate environment. Autonomous Vehicles (AVs) have made extensive use of computer vision to recognize lanes and people, carry out tracking, etc. To carry out complicated tasks, common computer vision technologies like machine learning are used. Deep Neural Networks are frequently used in AVs for computer vision tasks such as processing datasets for geometrical reconstruction, cityscape analysis, and road vision. Many initiatives, such as Waymo, Tesla Autopilot, and Intel Mobil-eye autonomous driving systems, are increasingly adopting cutting-edge intelligent driving capabilities. As a desirable component of a contemporary lifestyle, automobile manufacturers like Toyota and Lexus are now working to integrate intelligent personal assistance, specifically Amazon Alexa, into their vehicles. The findings of previous research that examined more general CAV system development elements are summarized in Table 2. The main characteristics of the examined CAV systems and the factors relating to the technologies used for their implementation are underlined. The table helps in discovering similarities and differences in deployment choices, architectural considerations, analytical metrics, and performance indicators, and complementing improvement possibilities across the surveyed systems in addition to defining the scope of various systems.

6) ON-BOARD COMPUTATIONAL UNITS IN CONNECTED AND AUTONOMOUS VEHICLES

The creation of OBCUs with intriguing designs is made possible by the expanding effort being made to create CAVs [38], [39], [40], [41], [42], [43], [44]. It is a difficult hardware design effort to adapt the OBCUs architecture to suit into CAVs. The ultimate objective is to develop OBCUs that can execute tasks ranging from straightforward to computationally demanding autonomous driving algorithms. In order to accomplish the appropriate amount of connections, the CAV OBCU architecture may necessitate the adoption of several cutting-edge communication protocols and interfaces.

In ITS, conventional OBUs use one or more processors, such as MCUs or other general-purpose units with simple or intricate designs. Electrically erasable programmable read-only memory (EEPROM), random-access memory (RAM), SD cards, and flash memory are still included in standard OBU memory units. Common OBU communication interfaces mostly rely on the usage of GPS for positioning and ZigBee, Bluetooth, Wi-Fi, and LTE for wireless communication. In addition to these, general-purpose input/output (GPIO) and controller area network bus (CANBUS) as well as Ethernet and USB are frequently supported. Temperature, accelerometer, proximity, light, gyroscope, elevation, and fuel consumption sensors are already supported by several OBUs. The majority of current power sources rely on charged batteries, however creating sustainable alternatives is said to encourage energy collection.

A vehicle's many electronic subsystems and sensors may be monitored and controlled in real time by an on-board diagnostics (OBD) computer system. For current ITS, autonomous driving, and infotainment systems to function well, high-end computing processors are essential. Typical applications include object identification, traffic monitoring, recognition, complicated optimization, navigation, video processing, sensor fusion, and intelligent decision making, all of which can be computationally demanding and need the utilization of powerful hardware resources. GPUs are an example of high-end computing hardware that has been used for ITS and autonomous driving applications. High-speed interfaces, automotive peripherals, networking, display, scalable memory, and storage components all support the system. Additionally, it has an inbuilt security module to support it [44].

7) THE FUTURE OF CAV COMMUNICATIONS AND PROCESSING UNITS

Future CAVs will have immensely challenging communication and processing needs. Exploring expectations, difficulties, and technology developments can expose contemporary patterns, emphasize contemporary transitions, and pinpoint requirements for the future. The development of software-defined networks, the advancement of network function virtualization, and the implementation of cost-effective network infrastructure are among the future trends in linked cars and networks. The development of V2X communication and research into the anticipated value of establishing 5G networks for boosting system performance and the driving and safety experience of automobiles are the obvious directions in vehicular connectivity. Future cars will have to cope with interoperability concerns since certain technologies can't work together and there isn't smooth real-time end-to-end communication. Hybridizing communication technologies and promoting social IoT are a few examples of solutions. With social IoT, automobiles adopt a service-oriented design where diverse gadgets may cooperate on behalf of their owners and give or seek services. Autonomous cars must precisely see their surroundings, negotiate, and respond in unison in order to be completely functional and safe. Future objectives include enhancing high degrees of intervention and actuation capabilities with intelligent context awareness. Artificial intelligence, data science methods, and decision assistance hold great promise in this regard. Future emergency features in autonomous vehicles will reduce the possibility of human mistakes by applying brakes intelligently, changing lanes and routes, and avoiding delicate driving circumstances. In order to increase safety, the supporting computing system may need to incorporate various other sensing devices in addition to a camera, Lidar, sonar, and radar. However, the produced system's simplicity, including that of its hardware, application software, and operating systems, must not be compromised by architectural alteration. The following are some additional considerations for CAV communication and processing technologies:

- Architectural simplifications are used to provide implementations with better prices, sizes, and performances.
- Integrating cross-domain knowledge in information and communication technology.
- Involving a variety of academic and industrial stakeholders in research and development activities.

Future CAV technology intends to link passengers to their places of employment, residence, the police, caretakers, insurance providers, governmental networked services, and other geographically dispersed stakeholders. With the most current advancement in mobile technology, architectural simplifications, mobility, and effective V2X communications will all be held together by 5G capabilities. Fig. 9 presents a two-dimensional depiction of upcoming CAV deployments to show patterns [2].

I. V2X COMMUNICATION BETWEEN CAVs AND UAVs

For coordinated activities, ground vehicle connectivity can be used and expanded to include aerial vehicles. A communication link may be formed between Connected and Autonomous Vehicles (CAVs) and Unmanned Aerial Vehicles (UAVs) using Vehicle-to-Everything (V2X) communication technology (UAVs). For real-world applications, hardware construction and testing of a ground-to-air communication connection are critical. Dedicated Short Range Communication (DSRC) and 4G internet-based WebSocket communication were created as two separate communication channels. Both links were put through their paces in both fixed and dynamic scenarios. Both connections were then combined into a real-world use case scenario dubbed Quick Clear presentation. The goal was to use DSRC communication to convey ground vehicle position information from the CAV to the UAV. On the UAV side, a User Datagram Protocol (UDP) connection was created between the DSRC modem and the Raspberry Pi companion computer in order to provide the CAV position information to the companion computer. The Raspberry Pi makes two connections: first, it connects to a traffic contingency management system (CMP) through Transmission Control Protocol (TCP) to send CAV and UAV position data to the CMP. Second, the Raspberry Pi connects to a web server through a WebSocket connection to deliver photographs taken by the UAV's on-board camera. The Quick Clear demo was used for both static and dynamic flight tests. The findings indicate that this communication framework may be used in real-world situations.

J. SECURITY ISSUES IN UAV-AV INTEGRATION

- Data-related issues.
- Communication Security Issues.
- Authentication and Access Control.
- Physical Security Issues.
- Traditional Security Solutions.

1) IMPLEMENTATION OF BLOCKCHAIN IN V2V/V2X COMMUNICATIONS

For V2V/V2X communications, basic safety messages are trusted but not encrypted because they are broadcast to all the neighboring vehicles, while certificate messages are both trusted and encrypted. Blockchain technology can be implemented in vehicle-to-vehicle (V2V) and vehicle-to-cloud (V2X) communication systems to enable the secure transmission of basic safety messages or cooperative awareness messages between cars and RSUs and/or the cloud platform [57]. Blockchain is a new technology that has the potential to assist VA-NETs solve their security issues and prevent cyberattacks. Using an Intelligent Transport Systems (ITS) infrastructure with a wireless module that adheres to the IEEE 802.11p or Wireless Access in Vehicular Environments (WAVE) standard, the authors of [58] presented a blockchain architecture. When it comes to hardware, the OBUs (Onboard Units) are set up to handle two-way communication, which is made possible between infrastructure and vehicle and/or vehicle and vehicle. Periodically, the network receives safety notifications from the linked cars, such as their speed (s), location (p), and direction (d). Security Managers (SMs), which provide message broadcast between cars and related units in a blockchain network, are part of the ITS architecture. When a vehicle crosses a cross-domain boundary, these SMs, which are normally located on the upper layer of the system, are in charge of timely transferring data to the bordering SMs. This stage may be where the value of blockchain in VANETs is most clear, since nodes (such as cars and RSUs) may safely exchange information without the need for a centralized authority. On the other hand, in a conventional communication topology, all the encrypted data supplied by the participating nodes is managed by a reliable third-party authority. This calls for a complicated handshake that may be exchanged via different handover techniques. Due to the

TABLE 2. Future directions identified in the explored articles with a focus on communications and processing technologies.

Ref	**[36]**	**[45]**	**[46]**	**[47]**	**[48]**	**[49]**	**[50]**	**[51]**	**[52]**	**[53]**	**[21]**	**[54]**	**[31]**	**[55]**	**[56]**	**[38]**	**[29]**	**[4]**
Markers to future direction	**2017**	**2017**	**2017**	**2018**	**2018**	**2018**	**2018**	**2018**	**2019**	**2019**	**2020**	**2020**	**2020**	**2020**	**2020**	**2021**	**2021**	**2022**
Implementing V2X communication			✓	✓	✓				✓				✓				✓	✓
Hybridizing communication technologies					✓	✓						✓	✓					
Multiple AV under cooperative control							✓	✓		✓					✓		✓	✓
Adopting LTE/LTE+ Vehicular features				✓			✓		✓				✓		✓		✓	✓
Communication between CAV and UAV										✓							✓	✓
Enhancing QoS	✓		✓	✓	✓	✓						✓	✓			✓		
Using cost-effective networks		✓	✓			✓												
Embedding security features	✓	✓	✓	✓	✓	✓					✓					✓		✓
Integrating AI, data science techniques and decision support			✓	✓				✓			✓	✓		✓	✓	✓		
Adding social Iot		✓					✓											✓
Developing context awareness		✓	✓	✓														
Integrating ICT cross-domain knowledge			✓	✓														
Improving power harnessing aspects	✓																	

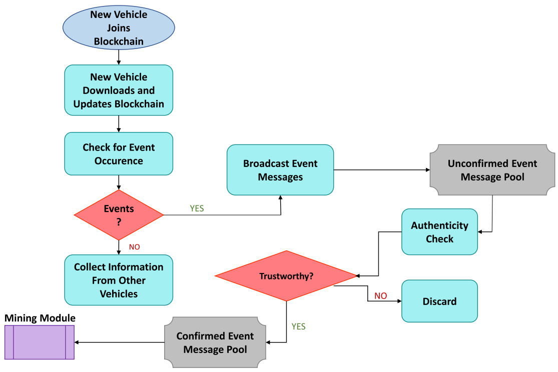

FIGURE 10. Broadcast module for blockchain.

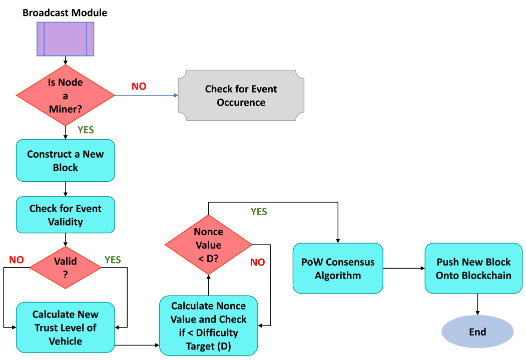

FIGURE 11. Mining module for blockchain.

enormous delay it causes, this is deemed ineffective for real-time applications. Since every SM in the network is connected to every other SM, a delay of this magnitude may be readily avoided in blockchains using "transport keys".

As seen in Figs. 10, the authors of [57] present a blockchain architecture for secure V2V communication. Every vehicle in this situation broadcasts its location via beacon messages, and a location certificate (LC) is created as digital evidence. Two parts make up this blockchain system: a broadcasting module and a mining module. During an event, a vehicle transmits event messages to its nearby cars using the broadcasting module. Event message data elements include event kind, fictitious ID, location proof, and level of trust. By verifying the event message in the mining module as shown in Figs. 11, the peer cars assess the sender vehicle's degree of trust. To verify the communication's credibility, these vehicles employ message verification policies. Therefore, it is clear that the usage of blockchain in VANET meets conditional anonymity while also guaranteeing the validity of the broadcasted messages. Compared to the central cloud servers, its dispersed data structure provides quicker access to information.

For distant areas where the Internet of Things devices confront network shortages and potential cyber threats, a federated learning-based data-accumulation system combining drones and blockchain can be deployed. The method includes a two-phase authentication process in which requests are evaluated first with a cuckoo filter, then with a timestamp nonce. Validating models with a Hampel filter and loss checks ensures secure accumulation. Every dorne has a zone attached to it, and zones are split up depending on the world's geographical regions. By using geographic data, the zone borders create rectangular areas (i.e., latitude and longitude). The data from each zone is used to create a dataset.

K. OPEN ISSUES AND FUTURE DIRECTIONS

The combination of UAVs and AVs will broaden the range of applications and services available. However, in order to reap the full benefits of such integration, the remaining issues must be resolved. We will examine the outstanding difficulties and potential research directions in this part, which will stimulate more debate and ideas within the scientific community.

- Resource Constraints Management
- Interpretability and Explainability of AI
- Reliability of Communication Channel
- Operational and Management Complexity

III. LONGITUDINAL AND LATERAL CONTROL OF AUTONOMOUS VEHICLES

The study of autonomous cars has recently made tremendous strides. As an illustration, autonomous cars enable features like Cooperative Adaptive Cruise Management (CACC) for safe vehicle following, lane maintaining, the control of lane change, and the adjustment of vehicle distances, which are the execution of longitudinal and lateral control of autonomous vehicles [59]. The basic functions of automated longitudinal vehicle control are keeping the vehicle a safe distance behind other vehicles and controlling vehicle's throttle and brake to maintain a relatively constant speed. On the other hand lateral vehicle control involves the steering of the vehicle. This control keeps the vehicle in the center of the lane and steers the vehicle into an adjacent lane while maintaining good passenger comfort. Lateral control is mainly concerned with lane keeping, turning, lane changing, and collision avoidance [60]. In this paper, we will give a short discussion about car following which is closely related to longitudinal vehicle control and then we will discuss about lane keeping precisely which is a mixed outcome of longitudinal and lateral control of autonomous vehicle. After that we will briefly focus on lane changing which is directly connected to lateral control. After reviewing this topic we will give our recommendations on the advancement of lateral control of autonomous vehicle.

A. CAR FOLLOWING

The method by which the autopilot keeps a safe distance from the car in front of it and follows it is referred to as car following. This process is related to longitudinal control with maintaining collision avoidance [61]. This modifies the vehicle's speed and acceleration in reaction to the state of the road by using the brake and throttle pedals as necessary. The longitudinal control includes Adaptive Cruise Control (ACC), inter-vehicle spacing, and nonlinear vehicle dynamics [62], [63]. Here, a smart autonomous controller is used in conjunction with a sensing tool like a radar to detect and maintain safe headway between vehicles at specific speeds and vehicle parameters like brake, throttle, vehicle wind drag, tire traction, and weight distribution, among others. These controls must choose the use of throttle or break when to ''go slow'' for a comfortable and fuel-efficient ride

B. LANE KEEPING

The fundamental goal of lane keeping is to keep the car in the middle of the road regardless of alterations in the surface of the road or other disturbances. It combines a longitudinal and lateral control outline. The processing on board sensors is often designed to detect any variation between the host vehicle and the reference line on the road. Utilizing vision technology, lane maintaining systems produce particular controller outputs based on yaw rate, gyroscopic measurement, and lateral offset. The method is also reliant on lateral wind and road curvature. There is already a video-based lane recognition algorithm for lane departure. In order to put the driver in a comfortable zone, lane maintaining assistant systems are primarily created to compensate for minor disturbances such road curvature, road bank angle, and wind gusts. Blind spot detection stimulates the driver's actions [64]. Surroundings (including vehicle speed, inter-vehicle space, lane lines) essential for longitudinal and lateral vehicle monitoring.

C. LANE CHANGING

To pass a slow-moving vehicle and continue on a rapid, smooth route, there must be need to change lanes. However, due to the driver's incorrect evaluation and prediction of adjacent vehicles and inadequate driving competence, this lane shifting move is the primary cause of several road accidents. As a result, driverless vehicles are a fantastic answer from this standpoint. A basic requirement of an autonomous car is lane changing. However, changing lanes and overtaking one or more vehicles is not an easy feat. The decision-making process for autonomous vehicles when changing lanes is difficult and complex. In cases where there is no driver present, drivers frequently avoid obstacles by changing lanes.

Based on observed impediments and the vehicle's position, the autonomous vehicle may choose the best obstacle avoidance strategy, and it can also adjust the speed and steering flexibly to provide a safe and stable driving situation. If the lane change approach is scientific, it will affect how successfully it can change lanes. The focus of many studies right now is path planning, and this has produced a wealth of findings [65]. On actual automobiles, several hypotheses have been proven. However, the current lane change planning optimization technique is cumbersome and not conducive to real-time computation during the actual driving process. So it makes more sense to develop a flexible and effective lane change trajectory planning system. Researchers are currently working to improve the efficiency of high-speed overtaking. Two crucial components of trajectory planning must be maintained in order to do this. One is the correct knowledge of the environment and surrounding barriers, and the other is the inclusion of vehicle dynamics and environmental limits. The proper execution of three sub-movements is referred to as the overtaking maneuver. (1) Change lanes to overtaking lane (2) pass the leading vehicle (3) return to original lane [66].

Lane change behavior may be classified into two situations: required lane changes and discretionary lane changes, depending on the various lane changing environments. The standard driving procedure, which requires the car to change lanes, is required. The crucial aspect of such behavior is that there is a final lane change point that the autonomous vehicle must pass through before arriving there, which often happens at junctions, lane merging, diversion, and barriers. The goal of an unmanned vehicle's discretionary lane change is to go to the driving destination and pass the car in front of it. This behavior frequently takes place when the car in front is moving more slowly than the one in back and the road conditions in the next lane are better. The basic goal of driving is to minimize travel time. There are three possible outcomes when cars decide to change lanes: stop, follow, or lane change. The car slows down gradually until it comes to a stop thanks to the braking system. When an unmanned vehicle must change lanes, but the circumstances do not allow for this to happen, stopping is a safe and efficient solution. Following the lead vehicle entails keeping the rear vehicle in its original lane by doing the same. When autonomous cars must make a discretionary lane change, the reality often falls short of following the vehicle is a workable strategy when the conditions are right for a lane shift.The Control system will preserve the initial condition while driving and watch for a chance to switch lanes. The autonomous vehicle can change lanes if there is adequate lane change space on the target lane and enough space between it and the front vehicle.

The primary challenge with autopilot mode is guaranteeing safety, flexibility, and a smooth driving.12 shows the decision making and execution process of lane changing. The Overtaking Expectation Parameter (OEP) is used to quantify the utility of the following vehicle when overtaking [67]. The OEP is then estimated using a non-lane-based complete velocity difference model that takes lateral movement and aggression into account. The path planning begins by concentrating on the geometric trajectory design for lane changing while assuming a collision-free environment. On the basis of route planning, trajectory planning optimizes the safe lane-shifting trajectory while taking into account real-time dynamics and obstacle limits and generates a desired yaw angle and yaw rate for lane change maneuvers.

In a mixed environment of autonomous vehicles and human-driven vehicles, reinforcement learning and optimal control techniques are employed for lane changing in addition to establishing the ideal trajectory. In addition, a fuzzy lateral trajectory tracking control is used to simulate human driving behavior.

A potential fix for these lane change problems is provided by the new Connected Autonomous Vehicle (CAV) technologies. A CAV can make a good lane change decision with the aid of real-time information on the vehicles in the area.

In the decentralized lane-changing techniques, every CAV makes its own lane-changing decisions and generates its

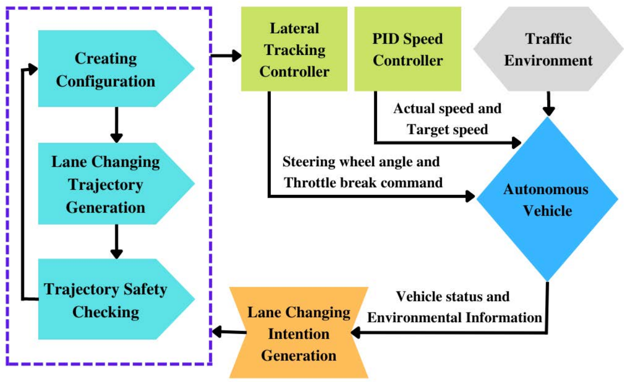

FIGURE 12. Flow chart of lane changing of autonomous vehicles.

trajectories autonomously, which typically leads in a smaller computational overhead. Decentralized lane-changing controls, on the other hand, take longer to negotiate with other CAVs because of the time delay in vehicle-to-vehicle (V2V) communication, and they are more likely to become stuck in a deadlock.

The centralized lane-changing control, on the other hand, is significantly more efficient, doesn't result in a communication stalemate, and can produce the best system. Only safe lane change has been the subject of previous studies on lane changing. Because under that situation, wireless communication between the nearby vehicles is not possible. But in this case, we're talking about connected autopilot vehicles, which can interact with one another since all of the cars in a certain location are linked by a wireless communication system. Here, the target vehicle plans a combined trajectory while taking into account the trajectory of other vehicles for lane changes. In that instance, when the subject car changes lanes, the vehicle in front of it automatically slows down and, if possible, accelerates to make a turn for the subject vehicle. And thus safe and high speed lane changing takes place maintaining collision avoidance.

D. TRAJECTORY TRACKING PID CONTROLLER

In many real-world applications, PID controllers are commonly used. [68] The control parameter may be found using the trial-and-error technique, and it is independent of the existing system model.The idea of feedback serves as the foundation for closed-loop automation systems used today. Measurement, comparison, and implementation make up the three components of the feedback theory. The difference between the actual and predicted values of the control variable, which is utilized to adjust the system response and carry out regulatory control, is the measurement's important component [1]. In engineering, the proportional, integral, and comparative frameworks are the most commonly utilized PID regulation is a term for differential control. Industrial control systems frequently use PID controllers as feedback loop components. There are three components: differential unit D, the integral unit I, and the proportional unit P. On proportional control, PID control is founded. Integral control removes steady-state errors, but it could also lead to more overshoot. Large inertial systems' responses are accelerated via differential control, and overshoot patterns are lessened. Numerous academic studies demonstrate the effectiveness of PID control in vehicle longitudinal control. PID controllers can be used to improve the performance of adaptive cruise control (ACC) and lane-keeping control (LKC). To provide comfort and safety, the vehicle lateral control problem, albeit somewhat complicated, requires increased robustness.

E. TRAJECTORY TRACKING MPC CONTROLLER

Due to the great precision required for managing systems with complex nonlinearities, determining the PID controller's settings is exceedingly challenging. The MPC approach has been demonstrated as a potential method to obtain good control performance in autonomous driving technology [69]. By integrating the present sampling states and the target states produced by the route planner, the MPC approach makes use of the vehicle model to forecast the future motion states of the vehicle [70]. Each time a period begins, the MPC controller creates regulates the course of events by lowering the goal function taking into account the control limitations. The input parameter for the vehicle low-level controller is determined by the first control action in the sequence. The goal states and the vehicle's present motion states are evolving over time. As a result, the next actions in the sequence do not fully fulfill the optimization criteria. Subsequent time steps will therefore replicate the same progress. The least inaccuracy and the best performance will finally be reached through these iteration phases. The MPC controller's primary job is to keep track of the anticipated states so that the vehicle can arrive at its destination while being safe and comfortable [71]. It is preferable to increase energy efficiency concurrently. A MPC-based autonomous car with the ability to avoid obstacles [72], [73], [74]. It can also be fitted with more sophisticated features, such as planning and control techniques that take into account the behavior of the driver. With other words, in autonomous cars, different trajectories and control tactics may be tailored for different drivers. A MPC controller may exhibit several aspects of the driver. By taking into account the randomized aspects of drivers' steering features, the MPC-based driver model might depict various driving skills maintaining safety by smoothly avoiding collision [75].

F. COLLISION AVOIDANCE

Path planning and tracking control algorithms have been extensively studied. Examples include inverse kinetic compensation feedback control, optimization algorithm based on sampling fusion and quadratic programming model, linear combination method using weighted cost function, integrated local path planning, and tracking control, using non-linear programming model, and others. It is difficult to apply these techniques directly to the collision scene of the vehicle because it has its own mechanical structure, stability, driver handling capacity, and other limitations. Consequently, in order to solve path planning issues, the movement states of other vehicles suggested to address the issue of traffic collisions [76]. Research and development of high-performance vehicle collision avoidance systems have become urgently necessary in order to enhance the active safety performance of the vehicle and lower the frequency of rear-end collision accidents. A variety of data about vehicles and traffic are taken into consideration by auto active collision avoidance systems, which use contemporary information and sensor technologies to acquire outside information, to evaluate the accident risk. The goal of the vehicle obstacle avoidance system's path planning is to create a trajectory free of collisions for proper safety [77]. The geometric properties of the barrier and the mobility limits of the autonomous vehicle are regarded to predict collision. Any collision avoidance system's main objective is to create a control algorithm that will prevent an impending accident. Collisions may be avoided using longitudinal control (emergency braking) and lateral control (active steering). The longitudinal distance between the vehicles limits the longitudinal control approach, in which case active lateral movement is preferable to avoid impediments. The autonomous vehicle must get obstacle information from detectors like radar detectors in order to perform the obstacle avoidance function. Prior to changing lanes, it is important to increase the distance from the obstruction in order to prevent a collision. When implementing an obstruction Several mechanisms exist for controlling the front wheel angle and the speed of the selected car.Cars can communicate information about drivers, other vehicles, and the road as vehicle-to-vehicle (V2V) communication technology develops [78]. The driver's intent, as well as details on the vehicle's condition, including its sideslip angle, intersection lights, and road conditions, are all available. In order to assure the safety of the vehicle, additional information is used. For safe driving, additional vehicle states and road information are needed in addition to the vehicle's condition.V2V communication-based obstacle avoidance algorithms have received a lot of attention recently [79]. In literature, the lane change vehicle states are obtained by the establishment of a vehicle information network. Calculate the anticipated acceleration value to manage the car's throttle and brake pedals in order to accomplish the road on the road while the vehicle is attempting to avoid a collision.

G. OBSTACLE DETECTION THROUGH ON BOARD SENSORS

Sensors are technologies that interpret environmental occurrences or changes into quantitative measurements for subsequent analysis. The whole AD system relies heavily on the detecting skills of an AV using a variety of sensors; the performance and cooperation of these sensors directly affects an AV's viability and safety [80].

One of the most important factors in any AD system is the selection of a suitable array of sensors and their ideal configurations, which will essentially be used to simulate human perception and the capacity to construct a trustworthy image of the environment. In order to overcome the limitations of specific sensor types and increase the effectiveness and dependability of the entire AD system, multi sensor fusion is effectively now a necessary process in all AD systems. Fig. 13 shows increasing demand for mapping and software in future vehicles. Recent reviews on the subject of multi-sensor fusion have included descriptions of the architectural framework and sensor technologies used in AVs [81], [82], [83], as well as processing stages like sensor calibration, state estimation, object and tracking [84], [85] and deep learning-based approaches [86], [87], [88].

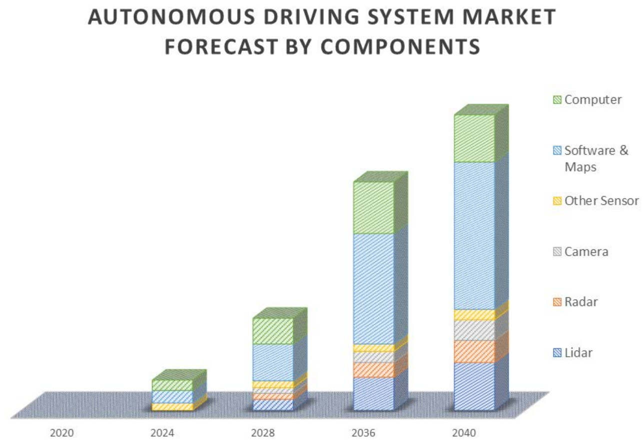

FIGURE 13. Market forecast for autonomous driving systems by components.

According to their basic operating principle, sensors are often divided into two distinct categories. Proprioceptive sensors, also known as internal state sensors, record the dynamical state and monitor the internal values of a dynamic system, such as force, rotational rate, tire load, power level, etc. Proprioceptive sensors include Inertia Measurement Units (IMU), encoders, inertial sensors (gyroscopes and magnetometers), and location sensors (Global Navigation Satellite System (GNSS) receivers). The exteroceptive sensors, also known as external state sensors, perceive and gather data from the environment of the system, such as distance measurements or light intensity. Exteroceptive sensors include things like cameras, radar, lidar, and ultrasonic sensors. Furthermore, sensors might be either passive or active. In order to provide outputs, such as vision cameras, passive sensors collect energy from their environment. Active sensors, such as LiDAR and radar sensors, on the other hand, release energy into the environment and then detect the ambient "response" to that energy to provide outputs [89]. The common onboard sensors and their placements on autonomous vehicles are shown in Fig. 14.

1) VISION CAMERAS

One of the most often used technologies for observing the environment is the camera. A camera captures crisp images of its surroundings by using the technique of detecting lights produced from the environment on a photosensitive surface (image plane) through a camera lens that is positioned in front of the sensor [82], [90]. With the right software, cameras can identify both moving and stationary obstructions within their range of vision and produce high-resolution photos of their surroundings. The cameras are very cheap. These features enable the vehicle's perception system to recognize road signs, traffic signals, lane markings, and barriers in the case of cars used for road traffic, and a variety of other objects in the case of off-road vehicles.

2) SOFTWARE AND MAPS

Software enables usability as well as programmability, which allows for more effective system development and improvement. Publish/subscriber, remote procedure call (RPC) or service, time synchronization, and multi-sensor cooperation are some of the features that are often supported by the software. The Robot Operating System is a good illustration of a middleware system in its conventional form (ROS). Several applications, such as object and lane detection, simultaneous localization and mapping (SLAM), prediction, planning, and vehicle control, are implemented on top of the operating system and the middleware system to generate control commands and send them to the drive-by-wire system in the vehicle. Controller Area Network (CAN bus) or Automotive Ethernet is used to link the many Electronic Manage Units (ECUs) found within the car. These ECUs are used to control the brakes, steering, and other components of the vehicle. In addition to analyzing the data from the sensors that are already mounted on the car, an autonomous driving vehicle is also expected to be able to interact with other vehicles, traffic infrastructure, pedestrians, and so on [91].

In addition to sensing and understanding the environment around the car, localization is also a very important task that runs on top of the self-driving system. GPS, GNSS, and IMU are all used a lot in an autonomous vehicle's system for figuring out where it is. GNSS is the name for all of the satellite navigation systems, like the US-made GPS, the European-made Galileo, and the Chinese-made BeiDou Navigation Satellite System (BDS) [91]. When different observation values and processing algorithms are used, the accuracy of GPS can change from a few centimeters to a few meters. GPS's strengths are its low cost and the fact that it doesn't get worse over time. The problem with GPS is that the GPS on vehicles today is only accurate to within one meter, and it needs a clear view of the sky, so it doesn't work in places like tunnels. Also, the GPS sensor data is updated every 100 milliseconds, which is not enough for the vehicle to be located in real time. The creation of autonomous cars necessitates the construction of high-resolution maps, which demand for more accurate and complete information regarding vehicle coordinates (lane markings, traffic lights, potholes, road signs, and elevation of curb, etc.), and real-time path planning updates. The use of autonomous mobile robots makes it possible to map challenging areas [92]. HD visualizations serve a number of purposes, including providing priori data for a level of downsizing, reducing sensor loads so that sensors can focus solely on processing moving objects, providing assistance in emergency situations when road markings are worn down or covered by snow, pinpoint localization, identifying other dynamic entities like other vehicles and pedestrians, and incorporating human psychology into visual displays [93].

The majority of the HD map collection comes from crowdsourcing and fleet surveys. Some technological and cartography behemoths use the first approach, sending a fleet of probe vehicles to explore certain areas. Its benefits include high efficiency and complete road information collecting, but the process of data acquisition is difficult, mapping is expensive, and regular updates are challenging. Most businesses use inexpensive i.e., crowdsourcing to install a sensor system on an OEM vehicles to communicate accurate position and picture data of the highways they are going on, and to combine recorded data into a single, enormous digital map for almost real-time updating [94].

3) LIDAR

In the 1960s, Light Detection and Ranging, or LiDAR, became widely employed in the mapping of aeronautical and aerospace terrain. The first commercial LiDARs with 2000 to 25,000 pulses per second (PPS) were created and provided by laser scanner manufacturers in the middle of the 1990s for topographic mapping applications [95]. One of the primary perception technologies for Advanced Driver Assistance System (ADAS) and AD cars, LiDAR technology has developed steadily at a substantial rate over the past few decades. LiDAR is a type of remote sensing that works by firing pulses of laser or infrared light that bounce off objects in the field of view.The equipment picks up on these reflections, and by measuring the time between the light pulse's emission and reception, it can estimate distance. The LiDAR creates a point cloud, which is a 3D representation of the scene, as it scans its surrounds.

4) RADAR

Prior to World War II, radio detection and ranging (also known as radar) was first developed. It worked on the premise that by emitting electromagnetic (EM) waves into the area of interest, targets would scatter their waves (or reflect them), allowing for further signal processing and target range determination. The relative speed and relative position of the identified obstacles are calculated using the Doppler feature of EM waves [90]. Currently, 24 GHz (Gigahertz), 60 GHz, 77 GHz, and 79 GHz frequencies are used by commercial radars that are on the market. The precision of range, velocity, and angle of 24 GHz radar sensors is less than that of 79 GHz radar sensors, which makes it difficult to detect and respond to various risks and will likely cause them to be phased out in the future [90]. Radar can operate day or night in gloomy, snowy, or overcast situations because the EM waves' propagation is unaffected by bad weather and their operation

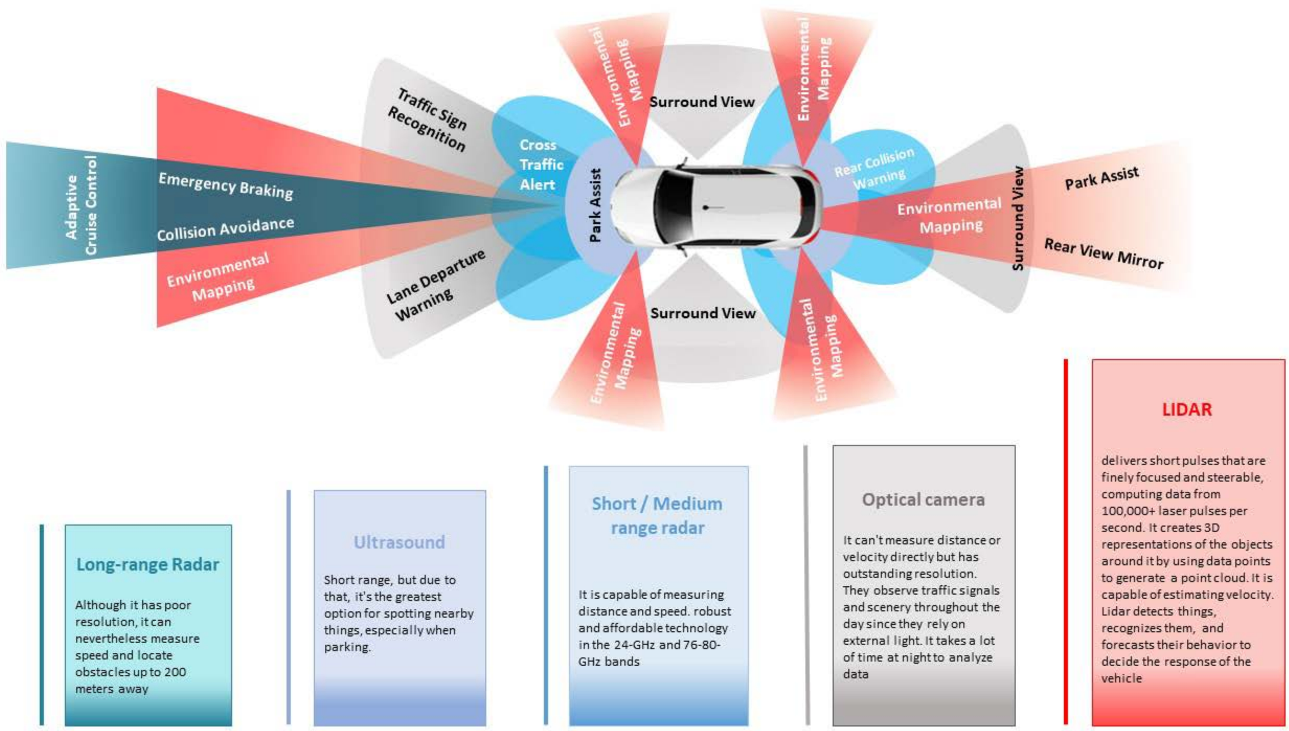

FIGURE 14. Sensors loaded in CAV to perceive it's environment.

is unaffected by the level of ambient lighting. Radar sensors have a number of disadvantages, including the inability to discriminate between static, immovable objects and metal items that are thought to be in the immediate vicinity, such as road signs or guardrails.In AD automobiles, radar sensors are frequently hidden in a number of positions, including the roof near the top of the windshield, behind the car bumpers, or on brand logos. As any angular misalignment might result in deadly implications for the operation of the vehicle, such mistakes include incorrect or delayed detections of obstructions nearby, it is crucial to assure the accuracy of mounting locations and orientations of radars during manufacture [96], [97]. The three main types of automotive radar systems are medium-range radar (MRR), long-range radar (LRR), and short-range radar (SRR). SRR and collision proximity warning are used by AV manufacturers for packing assistance, MRR and blind-spot detection are used for side/rear collision avoidance systems, and LRR is used for early detection and adaptive cruise control [90].

5) SONAR/ULTRASONIC SENSOR

Sound Navigation And Ranging (SONAR) sensing is an alternative to laser sensing in certain applications; its operation is similar to that of RADAR. Due to the slow sound wave propagation and narrow detection range, ultrasonic sensors are equally effective in frost, haze, rain, and dirt. They also have a closed detection sensitivity of 0.15–6 m, outstanding very near-range 3D modeling, consistent linear response, high accuracy, and sharpness. They are small, affordable, and vulnerable to EMI, wind, temperature changes, and humidity. However, due to their narrow range, they are useless for measuring speed. In order to function properly, sensors must have temperature and humidity compensations. Some of its most common uses are for speed detection, parallel parking, reverse parking, blind-spot sensing, and kick-to-open lift-gates [98].

6) SENSOR FUSION

LIDAR technologies outperform cameras in terms of accuracy and field of view (FOV), serving as a 3D system for environment mapping and a 2D system for people detection. When identifying a person, both geometric and motion-based algorithms are used to handle both static and moving pedestrians [99]. However, there are instances when the laser beams stop working because the walker is either too near or too far away, something that is very important for vehicles that drive themselves. In addition, motion-based detection via the use of cameras is very sensitive to noise. Interference between different kinds of laser-based sensors might affect their effectiveness when vehicles travel at the same speed and in the same direction. If the receiver picks up two signals in close proximity and it's hard to tell which one is the host vehicle's, the wavelength adjuster might automatically create a multi-shot wavelength laser to remedy the problem. Then, the vehicle's LIDAR laser pulses could determine the actual distance.

Integration with other wave/pulse-based sensors, such as radar, LIDAR, and ultrasonic, looks to have the potential to increase the final result's accuracy and guarantee a high degree of correctness and precision. There seems to be a lot of harmony between AV advancements and commercial luxury cars when it comes to sensor choice. Although LIDAR and RADAR function well when attempting to measure distance, a vision camera may pick up on other details, such as the presence of targets and traffic lights [100]. The idea here is to have cameras act as a surrogate for human eyes since most traffic signals are created with drivers' visual perception in mind. The dividing function of traffic light colors—three concentric lenses (green, yellow, and red) and a horizontal or vertical structure [101]—is supported by a clustering method. Following traffic light detection, the distance between the oncoming vehicle and the lights is often assessed to be between 10 and 115 meters during daylight hours and between 20 and 30 meters during the night [101].

The efficiency of the result of obstacle detection might be greatly enhanced by the precise fusion of data obtained from many sources of sensors [102]. In [103], the authors offer a multi-sensor industrial detection system that combines camera and LiDAR detections to provide a more accurate and reliable beacon detection system.

7) COMPUTERS

As a key aspect of an autonomous vehicle, the computer system is crucial to driving independently. For safety, the "computer" must comprehend the road surroundings and deliver the car accurate control instructions. Sensors initiate everything. Like human eyes, these sensors provide real-time environment data to the computer. OS connects hardware (sensors, computation, communication) and applications. Within the OS, drivers connect software and hardware devices; the network module offers an abstraction communication interface; the scheduler regulates competition for all resources, and the file system abstracts all resources. Safety-critical circumstances necessitate a real-time OS.

IV. DRIVING STYLES ACCORDING TO SOCIAL BEHAVIOR

Autopilot driving is one of the worthy options for reducing road accidents. Autonomous vehicles are not only secure and dependable, but they are also pleasant to ride in. The majority of users prefer Autopilot mode, which replicates human driving characteristics. Some people favor quick accelerations and sporty driving, while others prefer a more slow and careful approach. The researchers investigated this topic by creating an Artificial Potential Field (APF) that incorporates driving habits and traffic circumstances, and the APF values are incorporated into the Model Predictive Control (MPC) design process. Many academics have been approached about adopting a feature-based inverse reinforcement learning (IRL) method to learn driving styles from demos. This method, however, is more expensive and requires a large amount of data. If money and time are constraints, we can use the APF mixed MPC, which considers both safety and human driving styles. The trajectory planning and tracking for automobile following and lane-changing operations is separated into two groups based on driving behaviors. Users can pick from two driving modes: cautious and aggressive. The optimization mechanism of the MPC controller is paired with optimized APF modeling of the driving environment and driving styles in this scenario.

In recent years, academics have studied AV decision-making and motion planning. Markov Decision Process (MDP) and Bayesian networks aid in threat assessment and decision making. To maneuver AVs safely and effectively among pedestrians, partly visible MDP is researched for robust decision making. MDP is complicated to compute. AVs use threat assessment, Bayesian networks, and temporal window filtering to make decisions. A maneuver decision-making algorithm is based on the Multiple Attribute Decision Making (MADM) approach. MCDM is also used to choose the best driving maneuver.

In addition to the decision-making mentioned methods above, the use of data-driven learning-based decision-making methods as depicted in Fig. 3, such as the Support Vector Machine (SVM) [115], the Clustered SVM (CSVM) [116], the Extreme Learning Machine (ELM), the Kernel-based Extreme Learning Machine (KELM) [117], reinforcement learning (RL) [109], and Deep Neural Networks (DNN) [118], is becoming increasingly common. References [115] and [116] the authors of build a decision-making system by merging MDP with RL due to the fact that RL may bring numerous advantages in the process of tackling complicated uncertain sequential choice issues. DNN is used to construct a decision-making system that mimics human behavior and has the ability to adjust to the actual circumstances of the road [119].

A. PROBLEM FORMULATION

The majority of recent studies focus on motion planning and decision-making independently. The fact that the decision-making module's design does not completely account for the efficiency of motion planning presents an evident disadvantage. As a result, sub-optimal routes may be selected that involve abrupt turning and braking often. The boundaries for the design of the motion planner are often used as the decision-making constraints throughout the modeling phase. Following the choice, motion planning will be carried out sequentially within the predetermined restrictions. The motion planner may have a difficult time locating workable solutions if the limitations are set too narrowly. The calculation required for motion planning would significantly rise if the limits were set too broadly. Finding the ideal solution for the motion planning within the anticipated time budget would therefore not be simple. In this effort, decision-making and path planning will be further examined in an integrated manner to address the identified limitations of the current method.

TABLE 3. Lane changing considering social behavior.

Author	Publishing year	Highlights	Research Gap
Goufa Li [104]	2022	Here proposed an RA-PRDQN method based on deep learning reinforcement is combined with risk assessment tools to discover the best possible course of action with the least amount of risk.	(1) Breaking behavior is not synchronized with the steering behavior in longitudinal control (2) Driving styles also conflict lane change decision
Weida Wang [105]	2021	A prediction method based on a long short-term memory (LSTM) neural network and a fuzzy inference system (FIS) is proposed by this literature. Due to actuating control limitations, even if the reference velocity of AV is occasionally less than zero, the real velocity is still greater than zero. When compared to the suggested technique using prediction, the recommended strategy was unable to anticipate and avoid lane-changing cars.	Due to actuating control limitations, even if the reference velocity of AV is occasionally less than zero, the real velocity is still greater than zero. When compared to the suggested technique using prediction, the recommended strategy was unable to anticipate and avoid lane-changing cars.
Kang Sun [106]	2021	This research proposes a centralized two stage optimization based cooperative lane change (CTO-CLC) solution for linked autonomous vehicles to reduce the adverse influence on the traffic flow.	It is challenging to meet the vehicle's exact control requirements without using MPC or another control approach.
Vishal Mahajan [107]	2020	Using a small number of characteristics, an end-to-end machine learning model for forecasting lane-change maneuvers from unlabeled data is constructed and reported in this study. The model is based on an innovative, extensive dataset collected from German motorways by drones with cameras. A support vector machine (SVM) model is trained to learn the boundaries of the clustered labels and automatically label the new raw data after density-based clustering is applied to identify lane-changing and lane-keeping operations.	The quantity and type of the recognized maneuvers are therefore limited because the data used to compile them were taken from a small section of the route. This study does not distinguish between labels for left or right lane changes; as a result, more research needs to be done on the use of velocity direction as a frame of reference.
Yuewen Yu [67]	2020	This article suggests a multi-player dynamic game theory-based lane-changing decision-making model for changing lanes in a mixed environment where the overtaking expectation parameter of the following vehicle is estimated in accordance with the lateral move and aggressiveness.	The proposed algorithm cannot execute properly when it faces more complex road geometries
Yonggang Liu [108]	2021	Through the use of cubic polynomial interpolation, a path planning model and a motion planning model are created based on the local trajectory produced by the global positioning system. A proposed optimal trajectory function is then based on these models.	Here the mounted sensors are ideal but some kind of noises create an adverse situation on sensing operation which create a negative impact on decision making and trajectory planning. Furthermore, regarding the lane change trajectory computation, the robustness and flexibility of the suggested methodology in complicated dynamic situations have to be improved.
Xin Xu [109]	2018	The decision-making process for intelligent vehicles was proposed in this work using an RL technique with value function approximation and feature learning. An MO-API approach was presented, and the driving decision-making problem was modelled as an MDP.	The proposed RL method cannot perform precisely in respect of more complex traffic conditions.
Zhen Wang [110]	2021	The dynamic cooperative lane change model for CAVs with potential vehicle accelerations is proposed in this research. This model uses three steps—lane-changing decision making, cooperative trajectory planning, and trajectory tracking.	This proposed lane changing method doesn't clarify multiple lane changing aspects which is more complicated case
Shaosong Li [73]	2019	This paper develops an obstacle avoidance controller for autonomous vehicle navigation based on nonlinear model predictive control. Lateral control is additionally taken into account for vehicle stability	The random movement of moving object is not considered in the predictive horizon.
Peng Hang [55]	2020	In order to deal with decision-making and motion planning for lane-change movements of au-	To further enhance the capability of decision making for linked autonomous cars, consid-

TABLE 3. ***(Continued.)*** **Lane changing considering social behavior.**

		tonomous vehicles (AV), this research introduces a unique integrated strategy that takes into account the social behaviors of other traffic users. The potential field is adopted in the motion planning model to describe surrounding vehicles with different behaviors and road constraints, and Model Predictive Control (MPC) is used to predict the state and trajectory of the autonomous vehicle in this situation. Stackelberg's Game theory is applied to solve decision-making.	eration of more complicated driving situations need to be taken into account.
Haoran Li [9]	2021	For the vehicle control in this research, a hybrid trajectory planning and tracking method is provided. First, the Artificial Potential Field (APF) technique is used to mimic driving behaviors and traffic situations. Second, the APF values are incorporated into the Model Predictive Control (MPC) design process, which may optimize the trajectories and control outputs, as well as the simulation experiments are carried out in two situations (car-following and lane-changing)	The algorithm falls short of the real-time computing efficiency criterion, which is a problem for many MPC controllers. As a result, the method suggested in this paper cannot be used in genuine autonomous systems.
Jiqian Dong [111]	2021	In this study, here providing a Deep Reinforcement Learning (DRL) based system that fuses input from other cars near the CAV and from those further downstream, and uses the fused data to direct lane changes, a particular context of CAV operations.	It may be important for research to take into account temporal data, such as past information on the vehicle's position, speed, and acceleration, allowing for the potential for longer periods of the CAV's decision-making process. By include such previous data in the research, it may be possible to address theories about how impending traffic circumstances downstream may need CAV rerouting or proactive evasive measures.
Yingji Xia [112]	2021	In order to comprehend the lane shifting intents of nearby cars, a Human-like Lane Changing Intention Understanding Model (HLCIUM) for autonomous driving is presented in this study. The suggested model mimics how human drivers focus on the nearby cars and detect their intents to change lanes by mimicking the selective attention process of human visual systems.	It should also be considered how dynamically spatially salient the traffic scenarios are. These additions would provide the framework for predicting lane-changing maneuvers in a manner that is human-like and set the groundwork for the creation of sophisticated human perception-based models that are better able to simulate driving behaviour in humans.
Ang Ji [113]	2020	This study compares two different optimization techniques to create a lane-changing model based on game theory. To meet its goals, here must first analyze the reward function that drivers experience while making discretionary lane changes and then quantify it in a cost equation that balances safety and time savings. The findings of the study of each potential strategy combination indicate that there is a societal divide in the game of discretionary lane-changing.	The genuine parameters of an efficient car-following model should be gathered from highways and will replace the values given here for a more accurate assessment. Additionally, this model is unable to demonstrate how it functions in challenging traffic conditions.
Hongtao Yua [114]	2018	This study provides a lane-changing model based on game theory that imitates human behaviour by engaging with other cars through lateral movements and turn signals. Based on their responses, nearby cars and drivers' hostility is inferred. With this paradigm, the controller has the ability to gather data and pick up new skills through interactions in real time.	Due to the quick lane changes, the predicted aggressiveness may not match the true number. Here, the lateral movement is virtually linear and is controlled by a PID controller. Later on, the lateral control may be included in the game as well. The size of the game will therefore grow. Additionally, the present model can only provide one-step predictions. The model might be expanded to anticipate many stages in the future.

Additionally, individual drivers have distinctive driving habits, which means that they may choose differently even in the same situation. For instance, aggressive drivers may decide to speed up in response to a neighboring vehicle's overtaking conduct in order to prevent the overtaking. However, nervous drivers may slow down and give other vehicles more room to pass. As a result, in an ideal world, AVs' integrated decision-making and path planning systems would

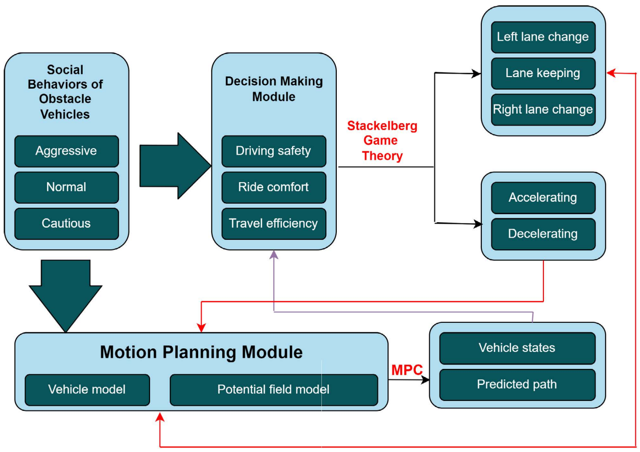

FIGURE 15. Schematic diagram of the integrated framework for decision making and planning considering social behaviors.

be flexible enough to accommodate different social interaction styles. Three alternative driving trajectories for obstacle vehicles—aggressive, cautious, and normal, will be taken into account in this research in the suggested methodology. The more efficient and dynamic performance of the vehicle is more important to aggressive drivers, thus they will use the steering wheel and/or pedals more frequently. Conversely, cautious drivers prioritize their comfort and safety when driving. They take meticulous operational steps as a result. The average drivers, who occupy the middle position, are more inclined to trade off driving safety, trip effectiveness, and vehicle comfort when making decisions. The rule-based method, the model-based approach, and the learning-based approach can be used to categorize the algorithms for recognizing driving styles. Fuzzy logic is a useful rule-based method for identifying driving styles. The decision tree, the Monte Carlo Markov model, and the Gaussian mixture model are a few of the model-based strategies. Learning-based methods, such as neural networks, Bayesian learning, k-Means, and support vector machines, have gained popularity recently. Since the primary goal of this paper is to explore how surrounding cars' driving behaviors affect the ego AV's decision-making, it is expected that it is possible to recognize nearby vehicles' driving behaviors. There are several driving scenarios for the development of AV algorithms. The objective scenario for system design and proof of concept in this study is lane-change because it is one of the most frequent actions in highway settings. Fig. 15 shows the schematic design of the integrated strategy for decision-making and path planning for an AV lane shift. In terms of lateral actions, there are three alternatives available: left lane change, lane keeping, and right lane change. In terms of longitudinal movements, there are only two possibilities: acceleration and deceleration. The decision-making algorithm seeks to select the best alternative while taking into account the driving habits of obstacle vehicles. Motion planner will choose the best velocity and course within restrictions for AV based on decision-making outcomes and the driving habits of obstacle vehicles.

B. INTEGRATED SOLUTION CONSIDERING SOCIAL BEHAVIORS

The decision-making and planning of AVs would be influenced by social behaviors, which may be represented by various driving styles of obstacle vehicles. Therefore, it would be beneficial to categorize driving behaviors and incorporate their distinctive characteristics into the algorithm for integrated decision-making and motion planning.

C. RESEARCH TOWARDS PREDICTING INDIVIDUAL DRIVING BEHAVIOR IN INTELLIGENT VEHICLES

The initial definition of an AV was a single intelligent vehicle that uses other nearby cars' behavior to forecast its own short-term trajectories and then uses algorithms, models, functions, and other techniques to make appropriate driving decisions, such staying in lane or changing lanes.

1) INDIVIDUAL INTELLIGENT VEHICLE MOTION-PLANNING MODEL

Recently, machine learning has been widely used in the field of driver behavior identification, especially by Tesla, which does behavior prediction and trajectory planning using artificial intelligence and data learning based on camera visual perception.

2) PREDICTION OF INDIVIDUAL INTELLIGENT VEHICLE BEHAVIOR RECOGNITION

- Prediction of Individual Intelligent Vehicle Driving Behavior on Roads: Driving styles on public roads can be categorized as straight or lane-changing. To guarantee smooth and safe driving in continuous traffic flow, AVs must effectively predict and evaluate both behaviors.
- Prediction of Individual Intelligent Vehicle Driving Behavior at Intersections: Road intersections are essential for directing traffic as well as for gathering, turning, and evacuating cars. A key topic of research for AVs is how to navigate through junctions safely and effectively. Individual intelligent cars cannot collaborate with other vehicles to navigate complicated junctions because they are unable to communicate with them.

D. IoV MODEL OPTIMIZATION

- **Prediction of IoV driving behavior on roads:** The use of car-following models and data-driven car-following models in IoV contexts for intelligent transportation systems can boost the sophistication of ACC systems. These models can adapt to China's complicated driving settings and aggressive driving behavior since they are based on nonparametric methodologies (artificial intelligence, machine learning, deep learning, etc.), but they need a lot of high-precision data as a sample dataset.
- **Prediction of IoV driving behavior at intersections:** The suggested multi-vehicle cooperative control model at junctions and the intersection behavior choice model

are used as examples for further discussion. The intersection traffic model, which is in line with the development trend of coordinated vehicle-road development, can assist AVs in assessing the traffic conditions of other vehicles at intersections using V2I and V2V technologies. It can also be used in conjunction with dedicated short-range communication (DSRC) technology to realize multi vehicle coordinated control at unsignalized intersections. The use of HMM, driver intention analysis, and other technologies can provide new areas for study, add to the body of knowledge about autonomous driving at junctions, and enhance the comfort and safety of predicting driving behavior in sporadic traffic flow. The data gathered is incomplete, and the judgment outcomes contain mistakes, as these models rely driver decisions on past vehicle trajectory, independent of the impact of other cars entering the junction.

V. RECOMMENDATION

We have already mentioned that the fully autonomous vehicle (FAV) on which our literature evaluation is based is still in the early stages of development. Because of this, the research's perspective is centred on futuristic phenomena. The IIoV, IoD, IoT, AI, UAV, and CAV are all included in the mentioned cyber-physical system, which is connected to a wireless communication network.One vehicle will wirelessly connect with another vehicle using unmanned aerial vehicles at level five automation. A number of moving unmanned aerial vehicles (UAVs) will cover a short area and provide the vehicles information about their surroundings. There is a master drone in a group of UAVs, and the rest are follower drones that operate and communicate using the information from the master drone. In accordance with this approach, several drone groups will cover a substantial region and a cloud server that serves as a central hub for information exchange and stores all of the data for this substantial area is accessible. Here, the master drones have direct access to the cloud server for communication and feed the data to the automated cars for a safe and efficient ride. This UAV-AV communication will not be impacted by adverse weather or environmental circumstances, and this technology will ease traffic congestion and play a significant part in reducing accident risk. Here if the distance from UAV plane and ground plane has become very high then it can cover a wide area but the data transmission speed will be lower so this distance must be an optimal distance for smooth and seamless communication. In this case, the wireless communication systems must have a high level of security when transmitting data over the network which blockchain can provide. The technology of autonomous vehicles will drastically alter if the system is built properly. The driverless vehicles will then regularly connect and exchange information in a comfortable manner. This will greatly lower the likelihood of a traffic collision and further improve the pleasure and safety of the journey. Additionally, the CAV technology analyses driving habits while taking social behaviour into account. Additionally, it will continue to prioritize passengers when it comes to driving habits. The vehicle will restrict its acceleration and speed for V2I communication in line with the infrastructure. Via V2V communication, lane maintaining and lane shifting maneuvers will also function flawlessly. The majority of collisions are caused by drivers making poor overtaking decisions. Therefore, this prospective technology will effectively handle these cases. Moreover, in case of a break failure of a vehicle, there will be a secondary fail-safe circuit and other connected vehicles will notify it by means of V2V communication. Thus this system will be able to escape a severe accident.

Here, we've covered three different facets of autonomous driving. Most literary works have included one or two of these issues. We thus anticipate that the combined study of our three main features of autonomous driving will lead the research to the next level in this context.

VI. CONCLUSION

Shortcomings: Recent years have seen the completion of a number of research and trials on vehicle automation, including those on individual intelligence AVs, IoV, UAVs, and mixed traffic flow driving behaviour prediction. These studies produced priceless information and expertise that helped advance the creation of AVs. The majority of conventional individual intelligent vehicle behaviour prediction models can only be used for certain traffic scenarios and cannot be adjusted to complicated scenarios, such as complex crossings, according to a systematic analysis of the literature that was conducted here. Although the combination of IoV and CAVs has several benefits, the training datasets that are currently available are not sufficiently robust and the existing data collecting, analysis, and organisation procedures are not methodical. Because of this, CAV technology is not yet ready for general use. Driving behaviour prediction application still presents a substantial issue despite being coupled with decision-making procedures. The study of mixed traffic flow has gained much importance over time. The comfort of autonomous driving in a mixed driving environment is currently subpar and theoretical and applied research is still limited.

Prospects: The implementation of V2X multi terminal interactive communications may be made possible by the use of IoV and CAV. AVs can use convolutional neural networks, machine learning, deep reinforcement learning, and other algorithms to perform intelligent learning, creating a positive feedback loop that will eventually lead to intelligent, highly autonomous, or even completely autonomous driving. The vehicular communication system will undergo a significant transformation if the cyber-physical system of connected autonomous vehicles can be implemented successfully. The vehicle's longitudinal and lateral control will be smoother and more effective, and it will modify its driving style based on an analysis of social behaviour.

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