Research and Analysis of Deep Learning for Distributed Autonomous Vehicles

Nanting Chen

School of Computer Science, Zhuhai College of Science and Technology, Zhuhai, 519000, China

C1810131371@outlook.com

Abstract. Autonomous driving technology is evolving from individual vehicle intelligence to collective intelligence, and the deep integration of vehicle networking, distributed computing, and deep learning has become the key path to overcoming the bottlenecks of perception and computing power. This paper systematically reviews the three-stage development process of distributed computing, from cloud centralization and edge collaboration to intelligent collaboration, and constructs a technical framework encompassing data coordination, computing power scheduling, task allocation, and consistency assurance. It summarizes typical applications in the fields of environmental perception, vehicle status monitoring, communication optimization, collaborative decision-making, and security protection, and provides an in-depth analysis of the core challenges currently faced, including heterogeneous data integration, real-time constraints, communication reliability, security and privacy, and model generalization. Looking ahead, breakthroughs in technologies such as lightweight collaborative learning, physical knowledge embedding, privacy computing, integrated communication-computation-control, and digital twin will further deepen the integration of the three, laying a foundation for fully autonomous intelligent transportation systems.

Keywords: Autonomous vehicles, Deep learning, Internet of Vehicles, Distributed computing, Multi-sensor fusion.

1. Introduction

With the breakthrough development of key technologies such as artificial intelligence, the Internet of Vehicles, and distributed computing, traditional transportation systems are undergoing a profound intelligent transformation. As a core component of intelligent transportation systems, autonomous vehicles have always developed following the core principles of safety, efficiency, and reliability. The traditional intelligent autonomous riding mode of bicycles heavily relies on the vehicle's own sensors and computing units, and in complex dynamic traffic environments, it gradually reveals inherent limitations such as limited perception range, onboard computing bottlenecks, and insufficient decision-making reliability in extreme scenarios, making it difficult to meet the stringent requirements of high-level autonomous driving (L4/L5) for full-domain perception and collaborative decision-making.

In this context, deep learning technology, with its powerful feature extraction and complex pattern recognition capabilities, has become a key driving force in enhancing the intelligence level of bicycles. Research shows that deep learning can effectively empower multiple core aspects of autonomous driving. For example, by building a new type of vehicle health monitoring system and deep learning decision model, real-time diagnosis of vehicle status and safety assurance can be achieved [1]; training deep learning models using roadside LiDAR data can significantly improve the accuracy of vehicle detection and tracking in complex scenarios [2]; based on multi-sensor and deep learning models, it can also effectively identify abnormal driving behavior and alert the driver [3]. In addition, deep learning has also shown great potential in specific scenarios such as bridge overloaded vehicle identification and high-precision estimation of road adhesion coefficients [4,5], continuously enriching and improving intelligent driving solutions.

In order to break through the bottleneck of bicycle intelligence in a fundamental way, the convergence with Internet of Vehicles and distributed computing technology is an inevitable road. Internet of Vehicles enables traffic participants to share a lot of information in real time by communicating with everything (V2X); And at the same time by computer's collective brain through power collaborations on task coordination it forms. The Internet of Vehicles can fully share information with other traffic participants in real time by Vehicle to Everything (V2X) communication; At the same time, it collaborates with different node "power" to realize the collective brain which is powerful and flexible. Combining the two is necessary if people are to have a leap from "individual smarts" (autonomous) to "all smart together" (collective smarts). And even i'm doing that right now and also integrating like the fuzzylógic and deep learning to make a smarts collaborative vehicle speed control model [6]; designing in-vehicle network (CAN bus) security protection strategies based on deep learning to ensure communication security [7]; optimizing V2X communication strategies using distributed deep learning [8]; alternatively, wide-area vehicle detection can be achieved through remote sensing imagery and deep learning technology, supporting large-scale distributed perception [9]. At the same time, research is carried out to improve the anti-interference performance of V2X Communication at High Speed with Deep Learning [10], and to explore the use of Lightweight Deep-Learning Models for Distributed Road Surface Condition Monitoring and so on[11]. In other words, point out another paradigm of autonomous driving which is decentralized and autonomous that including perception, communication, computation and decision.

The purpose of this paper is to review how people use distributed computing, deep learning and internet of vehicle in the autonomous vehicles today and what problem it has. It introduces the process of distributed computing technology in autonomous cars, tells people about some important technologies and typical applications related to it. Also points out the hottest topics and difficulties now. Combined with the future improvement on deep learning technology, study what is left of more profound integration. And summarize how people make a bit further to have safety and credibility as well for this sort of systemic intelligent autonomous drive. It will have certain references after the above-mentioned research was completed.

2. The Development of Distributed Systems

The application of distributed computing in autonomous driving has undergone an evolution from centralized to collaborative approaches, in line with the upgrading of technological requirements.

The first phase is the cloud-centralized model. In the early stages (corresponding to L2 and below levels), a centralized architecture was mainly used, in which all vehicle data was uploaded to the cloud for processing. Although this kind of model has strong computational capabilities and can use the advantages of the power in the cloud to do various complex calculation work, its problem is that it depends heavily on communication, network, single point failure problems are difficult for real-time control.

And the second one is Edge Collaboration Model. At which point people have the “cloud-edge-end” appearing because there is a need for real-time in Level 3 Autonomous Driving due to the creation Transfering part of the calculations to roadside edge nodes, so that it can make it shorter. The collaboration sense can become better and respond quickly after a short time. Focus on the whole task of clouds.

And the last stage is intelligent cooperation model. L4/L5 high-level autonomous driving, the system will breakdown hierarchy, and it's going to have a lot of different nodes like cars, roads, clouds all dynamically cooperating smartly: Deciding on learning power, strong distribution string of power calculating real-time dynamic distributing, real time best allocating computing capacity data sets workload and moreso. It gives a judge mint basis fully understand all autoignitions.

3. Core Technologies of Distributed Computing

So the paper should build an important technological system based on distributed computing as well as in-depth learning and cars networking so that people can have a real-time, trusty collaborative intelligent vehicle. It mainly revolves around these 4 main ones.

3.1. Data Collaboration Technology

This tech is about how to tackle the heterogeneity and spatiotemporal asynchronous problem between cars, roads and clouds and try to realize a good combination of different kinds of information. Data collaboration mainly means the integration of all kinds of different data which are very different both on mode and format [3,9]. People can understand that there’s a little more depth taken up in this learning, and if they chose to utilize a cross modality fusion model by all means, but just using those particular characteristic areas which would not be something seen when simply looking at the data [3]. Remote sensing images & Deeps Learnings large feature detections the groundwork to observe huge amount of teams [9].

3.2. Computing Power Scheduling Technology

As per the feature of different and dispersed computing resource in terms of distributed environment. Computing Power Scheduling Technology aims to allocate & scale up all existing Computational Resources on different nodes as per requirement for making decisions within few milliseconds. It's basic thought it cleverly distributes computational power among autos, outposts and clouds based upon node burdens, network circumstances and the significance of each job. Just like how adaptiveness in distribution deep learning approach, so that people could allocate the number of compute resource for v2x according to current time communication [8]. And also there’s methods like Model compression, Knowledge distillation to have a really small model that people can still run on their terminal device.

3.3. Task Allocation Techniques

This tech is about making autonomous cars simpler by breaking up complicated jobs like sensing what’s around and deciding together into many smaller ones. Then people give different parts that need help a chance at doing them all at once, which can make everything run smoother. Then the allocation method also needs to consider what task’s importance as well as different nodes’ performance, communication cost. Speaking of example cooperative speed control: Perceive, decide, etc can be processed at both roadside and car so response is fast [6] if there is a complex recognition scenario this type of heavy processing might as well use the cloud for a good balance on accuracy and efficiency [4].

3.4. Consistency Assurance Technology

In order for the system to run properly and safely, consistency assurance technologies break all those uncertainties regarding network delay/interrupting so all of them can have global data/state/decision. Communication uncertainty caused by very dynamic environments is the major one [10]. And then the securer’s mechanism is using consensus to make sure every state synced, then using DL doing a verifiable trust. As for example, the intrusion detection system based on deep learning is to make sure the integrity of internal network communication in car [7], meanwhile, with physical rules in model can improve logical correctness and predictability in making decision for every node [4,5].

4. Application of Distributed Computing in the Field of Autonomous Driving

With the combined development of Distributed computing and deep learning of Internetofthings, autonomous drive technology made a large number of progress in some big application scene like 5. Its main value is concentrated in these 5 point below.

4.1. Environmental Perception

Distributed Computing: It would be impossible for one car or road in this case to see something like if they all collaborated and distributed it across different cars, it would make more sense using Deep Learning as well. According to the roadside LiDAR, study the use of Deep Learning for Carboard detection and trailing this will help people to correctly blend it with what is perceived on a board in complex areas in the city. [2] Also, by means of the improved deep model to process remote sensing pictures can realize effective and extensive scale car detection and also could give important information help for area-wide traffic observation and collaborative judgement among different node [9].

4.2. Vehicle Status Monitoring

Deep-learning decisions and distributed nodes collaboratively analyzing their data have made great improvement in order to be as accurate as people can possibly be regarding the car state currently: There are some scholars who put forward an automobile health surveillance model which, through on-board, edge as well as cloud information, can accomplish faults anticipation and status evaluation, laying the groundwork for auto upkeep and secure travel [1]: And at that time because I'm working on Vehicle dynamics by using a physicalistic DL model, i also distributed to use datasets which are estimating Road Surface Adhesion Coefficient (RSAC),which is for vehicle stability [5]. It can also be applied for finding overloaded vehicles on bridge, indirectly making sure the traffic safety of vehicles [4].

4.3. Communication Optimization

Using distributed computational along with V2X, people will be able to distribute the work such that it becomes easy for people to transfer the vital data and achieve great collaboration driving by making AV 2x model via DL distribution where resource is allocated based upon actual car's situation and its present day’s network conditions thus improving link [8]. and in the meantime, other works adopt DL techniques that boost an anti-interference-able for V2X these can successfully transmit packets at even much higher speeds movement and cut inter-node interference so there is quicker info-sharing of important traffic information [10].

4.4. Collaborative Decision-Making

And in this application direction it’s like a lot of cars with each other, many nodes use that kind of distributed structure, also integrate deep learn to make those kinds of decisions higher or faster. Also, some articles' research studies using Fuzzy with DL to make a smart cars' speed adjuster. Speeding could also get distributed and collaborated as nodes share traffic info from different place so that would enhance whole traffic efficiency [6]. When is the case at which time edge node will quickly make decision locally, while the obstacle avoided. Meanwhile, the cloud carries out overall traffic flow adjustment work; Therefore researchers could reach a nice compromise between being accurate and real time on hard places.

4.5. Safety Protection

It's distributed compute and we’ll have a co-operative defensive Multi-Node setup understanding of what learning from an anomaly is for me, so that people get a bit safer. About those on inside can bus’s safety hazards: Deep learning has also been used for discovering such invasions, nodes monitor on their own buses and do so one by another as they watch over each other - in other words, if there is an attack or tampering then this would happen [7]. And how the thing itself is arranged permits for data encryption and trusted verification between multiple parties, plus all those detection functions so people can start trying to prevent data violations and cyber attacks.

5. Current Challenges

5.1. Challenges of Heterogeneous Data Fusion and Collaborative Perception

Distributed system data sources vary greatly on board sensor, roadside unit, remote sensing, cloud as well as different modality, different formats and spatiotemporal characteristic makes it really hard to achieve proper spatiotemporal synchronization and feature alignment [3,9]. Current approaches have a hard time getting to just-right mix of fusing stuff accurately and doing so super speedy in complicated ever-changing situations, holding back the full, super-duper-accurate view of things.

5.2. Strict Real-Time Requirements and Limited Computational Resources

When it comes to high-level autonomous driving people only need the decision latency of 1ms but even that would also be unachievable as there is a delay because of the distribution system itself along with tasks like schedule's tasks and collaborative inference. No Edge on Board Computation Capability exists of these types of Deep learning Model [8-10]. Lightweight technologies such as model compression, knowledge distillation are the hottest research topics [11]. In actual use, how can people achieve both real-time effect in extreme situation and good performance at same time is still great problem.

5.3. Communication Reliability Bottlenecks in High-Dynamic Environments

When the speed of moving vehicles is very fast, there will be big changes in topology. Network communication link is interfered, causing latency jitter, high packet loss rate and disconnection [8,10] It breaks down the data-sync base. Relies on, resulting in big syncing issues between Nodes and multi-Nodes decs. That is because bettering V2X comm proc. And throwing adding anti-Noise is necessary to guarantee a good team-up.

5.4. System Security and Data Privacy Risks

Distributive architectures, open v2x communication have more area of attack and there are dangers like bad entry and changing information (like can bus attacks [7]) At the same time, frequent data sharing at many points increases the danger of exposing private information like people's travels and habits. But developers should construct an effective defense for security and privacy, and cooperate with each other more about date.

5.5. Insufficient Model Generalization Capability and Decision Interpretability

Currently, most data driven deep leaning model rely a lot on the training data distribution and its generalizability is also very low when there is an extreme weather or rare long tail condition like specific road condition [4,5,11]. And deep neural network has a blackbox problem, its decisions are hard to explain. So people will not totally rely on it for safety critical tasks like autonomous driving [4,5,11]. In addition, the 'black box' characteristic of deep neural networks makes their decision-making process lack interpretability, which makes it difficult to fully trust them in the safety-critical field of autonomous driving.

5.6. The Dilemma of Ensuring Consistency in Dynamic Environments

In distributed systems where nodes dynamically join or leave and network conditions are uncertain, ensuring that all participating nodes achieve global consistency in data, state, and even final decisions is a tremendous technical challenge. Decision-making conflicts may lead to serious safety accidents; therefore, developers need to design highly robust distributed consensus protocols.

6. Future Development Trends

To deal with the above problems, Future Development can be developed in the direction of further deep integration.

6.1. Lightweight Collaboration and Adaptive Computing Power Scheduling

Research will continue on the latest lightweight methods like neural architecture search and adaptive model compression so people can create the best set of models for any situation and device. And also formed a kind of smart computing power scheduling system that could use things like the different model slices, calculation operations done with tasks and networks for clever allocation to take advantage of all available system computing power when given just some resources to work with, compute follows task [8,11].

6.2. Integration of Physical Mechanisms and Data-Driven Approaches

To meet the problems of generalization and interpretability, Deep Learning + Physical Knowledge will be common. Future distributed decision making model will have a deeper integration with the physical law and knowledge, like vehicle dynamics, traffic flow theory etc [4-5]. people can develop "physics neural network", "scientific machine learning". So that the model could be restricted by physical rules besides learning from data, thus it will improve the robustness and transparency of decision making in an unknown situation.

6.3. Trusted Collaborative Learning under Privacy Computing

And Federated Learning was closely related with some other private computing technologies such as differential privacy and secure multiparty calculation & homomorphic calculation making sure all the model training from different car manufacture or different regions go on safely. Data should be seen but not seen: [3, 7]. A Blockchain trusted data evidence/exchange, when that is there then people get the footings under which to say people had real ownership and were traceable.

6.4. Communication-Computing-Control(3C) Integrated Intelligent Collaboration

Beyond this mere stacking of communications with computing. It's heading towards a combination of communications, computing and controls. With DL approach for Joint Optimization of Wireless Resources, Computation offloading, and command gen (WRC-Gen), helps too novel from 6G integrated sense &compute comm, ai native tech so it will fit nicely and change quickly when moving rapidly between network, cpu / compute, & auto-driving app requirements that make things work together more smoothly at super speed [8,10].

6.5. Simulation and Continuous Evolution Based on Digital Twins

Building a high-fidelity distributed autonomous driving digital twin platform will become a key technology in this field. This platform can simulate complex traffic scenarios, vehicle interactions, and the collaboration of the full technology stack on a large scale and at low cost, providing abundant data (especially extreme and long-tail data) for algorithm training, testing, and validation, thereby accelerating technological iteration [2,9]. At the same time, the parallel operation and interactive evolution of digital twins with real systems are key infrastructures for achieving continuous system optimization and lifelong learning.

7. Conclusion

This paper systematically reviews the integration and application of distributed computing, deep learning, and the Internet of Vehicles in the field of autonomous vehicles, outlining the three-stage development process of distributed technology from cloud-centralized, to edge-collaborative, and finally to intelligent-collaborative. It constructs the main technical system of distributed computing based on data collaboration, computing power scheduling, task allocation, and consistency assurance. By combining relevant literature, the paper clarifies the practical application significance of distributed computing in autonomous driving environmental perception, vehicle status monitoring, communication optimization, collaborative decision-making, and security protection. It also analyzes current research hotspots and existing challenges and provides targeted directions for future development.

The deep integration of distributed computing with deep learning and the Internet of Vehicles is an important approach for autonomous driving to break the limitations of single-vehicle intelligence and advance towards higher levels of autonomous driving. Its core significance lies in enhancing the safety, efficiency, and reliability of autonomous driving systems based on multi-node collaborative perception, computing power sharing, and task allocation. Currently, relevant research has made significant progress in the fields of distributed collaborative perception, multi-source data fusion, V2X communication optimization, vehicle status monitoring, and security protection. The research results presented in the literature lay the foundation for the practical application of distributed autonomous driving.

At the same time, distributed autonomous driving still faces challenges such as heterogeneous data fusion difficulties, real-time and computing power limitations, communication obstacles, security and privacy risks, and a lack of model generalization capability. In the future, with the continuous advancement of technologies such as lightweight distributed deep learning, physics- and data-driven integration, federated learning, B5G/6G communications, and digital twins, the current limitations will gradually be broken. This will further deepen the integration of distributed computing with deep learning and the Internet of Vehicles, promoting autonomous vehicles towards full autonomy, intelligence, and connectivity, thereby providing strong support for the implementation of intelligent transportation systems.

References

[1] Hossain, N.M., Rahman, M.M., Tusher, H.E., et al. (2026) Optimised decision-making model for vehicle health monitoring system leveraging deep learning algorithm. Advanced Engineering Informatics,69(PA):103896-103896.

[2] Zhou, S., Yang, H., Lashkov, I., et al. (2025) Deep learning-based vehicle detection and tracking from roadside LiDAR data through robust affinity fusion. Expert Systems With Applications,279127338-127338.

[3] Onsu, A.M., Simsek, M., Fobert, M., et al. (2025) Intelligent multi-sensor fusion and anomaly detection in vehicles via deep learning. Internet of Things,31101561-101561.

[4] Liu, J., Li, Y., Dong, S., et al. (2025) Overloaded vehicle identification for long-span bridges based on physics-informed multi-task deep learning leveraging influence line. Engineering Structures,333120163-120163.

[5] Li, X., Ren, M. (2025) Road adhesion coefficient Estimation: Physics-informed deep learning method with vehicle dynamics model. Expert Systems With Applications,260125387-125387.

[6] Yadav, L. A., Goyal, K.S. (2024) An Efficient and Intelligent System for Controlling the Speed of Vehicle using Fuzzy Logic and Deep Learning. International Journal of Advanced Computer Science and Applications (IJACSA),15(3).

[7] Aswal, K., Pathak, H. (2024) Advancing Vehicle Security: Deep Learning based Solution for Defending CAN Networks in the Internet of Vehicles. EAI Endorsed Transactions on Internet of Things,10(1).

[8] Osman, A.R. (2023) Optimizing Autonomous Vehicle Communication through an Adaptive Vehicle-to-Everything (AV2X) Model: A Distributed Deep Learning Approach. Electronics,12(19).

[9] Ragab, M., Abdushkour, A.H., Khadidos, O.A., et al. (2023) Improved Deep Learning-Based Vehicle Detection for Urban Applications Using Remote Sensing Imagery. Remote Sensing,15(19).

[10] Ahmed, R.O., Nagy, S.S., et al. (2021) Enhancing the Reliability of Communication between Vehicle and Everything (V2X) Based on Deep Learning for Providing Efficient Road Traffic Information. Applied Sciences,11(23):11382-11382.

[11] Hassam, T., EunSung, J. (2023) Comparative Study on Distributed Lightweight Deep Learning Models for Road Pothole Detection. Sensors (Basel, Switzerland),23 (9).