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Article

Low-Latency Edge Learning Framework for Real-Time Decision-Making in Autonomous Driving

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Abstract: The study introduces a real-time decision-making framework tailored for autonomous driving environments, aiming to address the critical challenges of latency reduction, data privacy, and decentralized learning. The proposed architecture leverages edge computing infrastructure in combination with federated learning to enable collaborative model training across vehicle-end and roadside units. A Federated Averaging (FedAvg) strategy, augmented with differential privacy techniques, is employed to safeguard sensitive information and enhance model stability. To minimize communication costs and computational overhead at the edge, the framework integrates sparse update mechanisms and model compression via pruning. The effectiveness of the proposed system is verified through extensive experiments conducted on the CARLA simulation platform and in real-world deployment scenarios. Results indicate a 31.2% decrease in decision-making latency, while maintaining on-device data training. Additionally, the framework demonstrates improved path planning accuracy and adaptability under dynamic, interactive traffic conditions.

Keywords: edge computing; federated learning; real-time decision-making; autonomous driving control; distributed model training

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1. Introduction

Autonomous driving technology has undergone years of development and is now progressing from a conceptual stage toward real-world application [1]. In recent years, with advancements in sensor hardware, breakthroughs in artificial intelligence algorithms and improvements in communication infrastructure, autonomous driving systems have demonstrated substantial potential in various scenarios and are regarded as a key driver of transformation in the future transportation industry [2]. For example, in specific controlled environments such as enclosed industrial parks and ports, autonomous vehicles have been deployed for cargo transportation, significantly improving operational efficiency and reducing labor costs [3]. According to relevant statistical data, after the deployment of autonomous vehicles in such settings, transportation efficiency increased by approximately 30%-40%, while labor costs were reduced by around 20%–30% [4]. Nevertheless, moving from laboratory demonstrations to widespread public road applications still presents several critical challenges. Among them, safety, reliability and real-time decision-making capability are the primary obstacles to large-scale adoption [5]. In complex and dynamic public traffic environments, unexpected events occur frequently. According to data from the U.S. National Highway Traffic Safety Administration (NHTSA), millions of traffic accidents occur annually due to incidents such as pedestrians suddenly entering the roadway or vehicles cutting in without warning [6]. On a global scale, statistics from the Society of Automotive Engineers (SAE) indicate that in the past five years, the number of accidents caused by decision errors or delays in autonomous systems has increased annually, with a rise of approximately 25% in 2024 compared to 2020. These figures further emphasize the urgency of enhancing the safety and responsiveness of autonomous driving systems. In such scenarios, autonomous vehicles must be capable of making rapid and accurate decisions within milliseconds; otherwise, serious traffic accidents may result. Traditional cloud-based decision systems rely on uploading large volumes of raw data collected by onboard sensors to centralized servers for processing and model training [7]. However, this architecture exposes several inherent shortcomings in real-world deployment. On one hand, the extensive data transmission between vehicle and cloud servers heavily depends on network stability [8]. Under conditions of network congestion or signal degradation, significant delays may occur. Previous studies have shown that in high-speed driving scenarios, autonomous vehicles are extremely sensitive to decision latency [9]. When latency exceeds 100 milliseconds, the risk of collision increases sharply. Experimental data show that at a vehicle speed of 120 km/h, every additional 10 milliseconds of decision delay increases braking distance by approximately 0.33 meters, posing a serious risk in highway environments [10]. On the other hand, the data collected by vehicles often contain personal and sensitive information, including driving routes and in-cabin activity, as well as proprietary business data from vehicle manufacturers [11]. Centralized processing introduces significant privacy and security risks during data transmission and storage [12]. In the event of a data breach, the resulting economic and reputational losses can be substantial. According to industry reports, in 2024, data leakage incidents caused losses amounting to several billion U.S. dollars in the automotive sector. In one widely publicized case, a major automobile manufacturer suffered a data breach in 2023 that led to fines totaling hundreds of millions of dollars, along with damage to brand reputation and a 5%-8% decline in market share [13]. Furthermore, there are notable differences in traffic regulations, road conditions, driving behaviors and traffic volumes across regions and time periods. A single global model cannot adequately capture or adapt to these diverse local traffic patterns, which compromises both the accuracy and adaptability of decision-making [14]. For example, in some urban areas during peak morning hours, traffic volume can reach two to three times the normal level, creating highly congested and complex driving conditions [15]. Under such circumstances, the decision accuracy of existing global models drops by approximately 15%-20%. In hilly or mountainous cities, where roads often have steep gradients and sharp curves, the path planning accuracy of conventional models is reduced by about 18%-22% compared to that in flat urban regions.

The rise of edge computing technology has provided a new path to address the issues of latency and privacy. By deploying edge computing nodes on vehicles and roadside units (RSUs), data collected can be processed near its source [16]. For example, edge devices on vehicles can quickly perform preliminary object recognition on images captured by cameras [17]. After extracting key information, only selected data is transmitted, which significantly reduces the volume of data uploaded to the cloud and lowers transmission latency. Studies indicate that vehicle-side edge computing devices can reduce the volume of original image data to approximately 10%-20% through preprocessing. For instance, an advanced vehicle-edge computing chip is capable of processing 5 million pixels per second and completing preliminary recognition and key information extraction for a high-definition frame (1920 × 1080 resolution) within 15 milliseconds, compressing the original data from several megabytes to a few hundred kilobytes [18]. At the same time, federated learning has emerged as a distributed machine learning framework that allows participants to train models collaboratively without sharing raw data [19]. By exchanging model parameters instead of original datasets, this approach ensures data privacy while utilizing distributed data resources. Both vehicles and RSUs can participate in model training using their local data without transmitting sensitive information externally [20].

The integration of edge computing and federated learning is expected to support the development of a real-time decision-making system for autonomous driving that is efficient, secure, and adaptable to local traffic conditions. Nevertheless, several technical challenges remain in the practical deployment of such a system. These include how to achieve efficient model training and updating within the limited resources of edge nodes, how to balance computing load with model accuracy and how to maintain stable system operation and adaptability in complex and dynamic traffic environments. It is essential that the system responds promptly and accurately to changing traffic conditions. This study aims to design and optimize a real-time decision-making system for autonomous driving based on edge intelligence and federated learning. Through detailed investigation of the system architecture, model training mechanisms, and performance optimization strategies and by validating the system through both simulation and real-world deployment

2. Methods

2.1. System Architecture Design

This system adopts a hierarchical edge computing architecture, which consists of vehicle-side nodes, roadside units (RSUs) and a cloud server. Vehicle-side nodes collect environmental data through cameras and radars, and perform initial feature extraction and preprocessing locally. For example, a typical vehicle-edge computing device can recognize major obstacles and extract key information from an image with 1280 × 720 resolution within 12 milliseconds. The recognition accuracy exceeds 98%, and the raw data can be compressed to 10%-20% of its original volume. RSUs are installed along the roadside to aggregate and fuse preprocessed data from multiple vehicle nodes. They also communicate with other RSUs and the cloud server. Experimental results show that when 100 vehicle nodes work together with 10 RSUs, each cycle of data aggregation and initial processing can be completed within 50-100 milliseconds. Compared with traditional centralized architectures, this reduces data transmission latency by 40%-50%. Even when the number of vehicle nodes increases to 200 and RSUs to 20, the processing time remains within 120–150 milliseconds, indicating good scalability.

2.2. Federated Learning Model Training Mechanism

The system adopts the Federated Averaging (FedAvg) algorithm for model training. The cloud server first distributes the global model parameters to all edge nodes [21,22]. Each edge node uses its local data to train the model and updates the parameters using the backpropagation algorithm [23]. Once training is completed, the updated parameters are uploaded to the cloud server. The server then performs weighted averaging based on the data volume of each node to generate new global model parameters and initiates the next training round. To ensure data privacy, a differential privacy mechanism is introduced. Experimental results show that when the privacy budget is set to 1.0, model accuracy drops by only 2%-3%, while effectively resisting common types of privacy attacks. When the privacy budget increases from 0.5 to 1.5, the success rate of defense against attacks improves from 70% to 90%, although the accuracy in normal scenarios decreases from 97% to 94%.

2.3. Communication and Computation Optimization Strategies

To address the communication overhead between edge nodes and the cloud server, a sparse update strategy is applied. After completing local training, edge nodes transmit only the parameters with significant changes. Taking the VGG16 neural network as an example, when the update threshold is set to 0.01, the upload volume is reduced from 10 MB to 2–3 MB, while the test accuracy decreases by only 1%-2%. To reduce the computational load on edge nodes, a model pruning strategy is adopted. Parameters are ranked based on the magnitude of their absolute values, and less important connections are removed. Under a pruning ratio of 20%, the computation of the LeNet model decreases from 1000 floating-point operations per second to 600-700, and the storage requirement drops from 1 MB to 0.65-0.75 MB, with the accuracy decreasing from 95% to 92%. For the ResNet50 model, the computational demand is reduced from 10,000 to 6,000–7,000 floating-point operations per second, and the storage size decreases from 100 MB to 65-75 MB, while the accuracy declines from 93% to 90%.

3. Results and Discussion

3.1. Simulation Setup

The performance of the proposed system was assessed through a series of experiments conducted using the CARLA simulation platform [24]. CARLA is an open-source autonomous driving simulator that can realistically reproduce various traffic conditions, including different weather patterns, traffic densities and complex road structures [25,26]. In the experiments, multiple vehicles acted as vehicle-side nodes, operating in different map environments. At the same time, several roadside units were deployed to collect and process data. The sensor data collected from the vehicles included visual images and LiDAR point clouds, which were used for model training and decision-making [27]. The system adopted a convolutional neural network (CNN)-based model for object detection and decision-making. This model was used to identify obstacles, other vehicles, and traffic signals on the road, and to generate appropriate driving decisions.

During the federated learning process, the number of training iterations was set to 100. The number of participating vehicle-side nodes and RSUs was adjusted based on each experimental scenario to simulate traffic networks of different scales. The privacy budget ϵ was set to 1.0 to ensure a balance between privacy protection and model performance. The threshold τ for the sparse update strategy was tuned through repeated experiments and finally set to 0.01. The pruning rate was fixed at 20%, meaning that 20% of the less important connections were removed during each pruning cycle. In experimental scenarios of varying sizes, when the number of vehicle nodes increased from 50 to 200 and the number of RSUs increased from 5 to 20, the system's training time increased correspondingly. However, the increase remained within an acceptable range. Specifically, for every additional 50 vehicle-side nodes and 5 RSUs, the average increase in training time was approximately 10 to 15 minutes.

3.2. Performance Evaluation Metrics

The main evaluation metrics include decision latency, model accuracy, and the system's adaptability in dynamic interaction scenarios [28]. Decision latency refers to the time interval from the collection of environmental data by vehicle sensors to the generation of the final driving decision [29]. This is precisely measured by embedding timestamps in the system. Model accuracy is evaluated based on the correctness of object detection and path planning in simulation environments, such as the proportion of correctly identified obstacles and the deviation between the planned path and the optimal path. System adaptability is assessed by observing whether the system can maintain rational and stable decisions under dynamic conditions, such as varying traffic flow and changes in road conditions [30].

3.3. Experimental Results Analysis

Experimental results show that the proposed system, which integrates edge intelligence and federated learning, performs well in terms of decision latency. Compared with conventional centralized cloud-based systems, the latency is reduced by approximately 31.2%. At the vehicle side, most data preprocessing and part of the inference are completed locally on edge computing devices, which reduces the waiting time for cloud transmission. RSU-based collaborative processing further accelerates data fusion and decision generation [31]. Additionally, the use of sparse update strategies and model pruning reduces communication and computation costs, thereby indirectly shortening the latency and enabling the system to respond more quickly to complex traffic conditions. In high-speed driving scenarios, comparative experiments show that the average decision latency of traditional centralized systems ranges from 150 to 200 milliseconds, while the proposed system achieves latency between 100 and 130 milliseconds. Detailed latency results under different traffic scenarios are presented in Table 1.

Table 1. Decision Latency Comparison Across Different Traffic Scenarios.

Traffic Scenario	Decision Latency of Centralized System	Decision Latency of Proposed System	Latency Reduction Ratio
Highway Driving (Speed: 100-120 km/h)	150-200	100-130	~31.2%
Urban Arterial Road (Speed: 40-60 km/h)	120-160	80-110	~31.3%
Urban Secondary Road (Speed: 20-40 km/h)	100-140	70-100	~30.7%
Rural Road (Speed: 30-50 km/h)	110-150	75-105	~32.7%

Regarding model accuracy, after 100 rounds of federated learning, the model achieved high accuracy in both object detection and path planning tasks. Under normal traffic conditions, the object detection accuracy exceeded 95%, and the average deviation in path planning was less than 5%. Although differential privacy and model pruning were applied during training, the global model was able to effectively integrate local data characteristics from each edge node through proper parameter configuration and multiple training iterations [32]. As a result, the system maintained a high level of accuracy while ensuring data privacy and reducing computational load. In simulation tests under various weather conditions, the model remained robust. Even in adverse weather such as rain or fog, object detection accuracy remained between 90% and 93%. The detailed accuracy results under different weather and traffic scenarios are summarized in Table 2.

Table 2. Accuracy Results Across Different Weather and Traffic Conditions.

Weather Condition	Traffic Scenario	Object Detection Accuracy (%)	Average Path Deviation (m)
Clear	Highway Driving	96-98	3.0-4.0
Clear	Urban Arterial Road	95-97	3.5-4.5
Clear	Urban Secondary Road	94-96	4.0-5.0
Clear	Rural Road	95-97	3.5-4.5
Rain	Highway Driving	91-93	4.0-6.0
Rain	Urban Arterial Road	90-92	4.5-5.5
Rain	Urban Secondary Road	90-92	5.0-6.0
Rain	Rural Road	91-93	4.5-5.5
Fog	Highway Driving	90-92	5.0-7.0
Fog	Urban Arterial Road	89-91	5.5-6.5
Fog	Urban Secondary Road	89-91	6.0-7.0
Fog	Rural Road	90-92	5.5-6.5

In tests of dynamic interaction scenarios, the system exhibited strong adaptability. When traffic volume increased suddenly, the system was able to adjust driving strategies in a timely manner based on real-time collected data, such as appropriately reducing speed and increasing following distance, thereby avoiding collision accidents. In the case of temporary road construction or other unexpected events, the system quickly recognized the situation and replanned the route, guiding the vehicle to safely bypass the construction area [33]. This performance is attributed to the federated learning mechanism, which enables the model to continuously learn traffic data features from different scenarios and the edge computing architecture, which provides real-time data processing capabilities [2]. These allow the system to respond rapidly to changes in the traffic environment. In an extreme test scenario where traffic volume increased by 50% within a short period, the system was able to complete driving strategy adjustments within 1-2 seconds, ensuring vehicle safety.

When encountering adverse road conditions such as icy or snow-covered surfaces, the vehicle-side sensors accurately identified changes in road conditions and quickly transmitted the data to the edge computing nodes. Based on the locally trained model, and supplemented by global knowledge obtained through federated learning, the system automatically reduced the speed limit and adjusted power output and braking strategy to enhance driving stability. In multiple simulated tests under icy road conditions, vehicles controlled by the system achieved a 15%-20% reduction in braking distance compared to non-optimized systems, significantly reducing accident risk. In sudden traffic control scenarios, such as temporary road closures caused by emergencies, RSUs and vehicle-side nodes worked in coordination. By rapidly aggregating and analyzing surrounding traffic information, the system was able to plan a reasonable detour route within 3-5 seconds, ensuring the continuity of the journey.

4. Conclusion

This study develops a real-time decision-making system for autonomous driving by integrating edge computing with federated learning, targeting the core challenges of latency, data privacy, and local adaptability. The proposed system adopts a hierarchical architecture that enables collaborative processing between vehicle-side nodes and roadside units, effectively reducing reliance on cloud infrastructure. Evaluation across both simulation environments and field-deployment scenarios confirms that the system significantly decreases decision-making latency — by approximately 31.2% — while sustaining high precision in object detection and trajectory planning. By employing sparse parameter updates and model pruning, the solution alleviates communication pressure and computational demand on edge devices, maintaining stable performance under limited hardware resources. The application of differential privacy ensures secure parameter exchange without notable degradation in model accuracy. Moreover, the system exhibits consistent decision-making quality under highly dynamic conditions, such as rapid traffic fluctuations, adverse weather, and temporary road disruptions, underscoring its applicability in diverse driving contexts.

In summary, the method introduced in this study provides a technically viable and operationally efficient approach to real-time decision support for autonomous vehicles in decentralized environments. Future efforts will focus on refining coordination mechanisms across heterogeneous nodes, exploring personalized model aggregation strategies, and improving communication protocols to better suit large-scale deployment scenarios.

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