A Context-Aware and Energy-Efficient Edge Computing Framework for Low-Latency Communication in Autonomous Vehicles with Real-World Validation and Safety-Centric Task Prioritization

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Abstract: AVs need ultra-low latency communications to allow for fast decision making for passenger safety in rapidly changing when the traffic. Legacy cloud processing incurs unsatisfactory latency while most of the current edge computing approaches suffer from limited flexibility, energy efficiency and practical deployment experience. This paper presents a context-aware energy-efficient edge computing architecture to realize low-latency communication for autonomous vehicles. Dynamic task scheduling, federated edge collaboration and lightweight AI models are jointly used in the framework to make sure that it can realize real-time perception for safety-critical scenes. The effectiveness of the protocol is verified by actual traffic simulation and multi-scenario tests, which show reduced response time and improved reliability over different vehicle scenarios. By combining edge intelligence with safety-aware scheduling and situational awareness, this work addresses significant deficiencies of the existing generation of vehicle-to-vehicle communication systems and offers an efficient, security-aware, and low-latency solution for the future intelligent transportation.

1 INTRODUCTION

The fast development of autonomous vehicles (AVs) have been revolutionizing the intelligent transportation paradigm, and hence, results in highly latency-sensitive communication systems that provide ultra-high-speed data-rate transmission. Since AVs heavily depend on real-time perception, computing, and control as well as decision capability and latency is clearly the critical issue that must be resolved in order to develop AVs to meet the necessary road safety and driving performance requirements. Classical cloud-based architectures, on the other hand, although computationally intensive, frequently break down in their application to solve hard real-time latency demands because of the intrinsic delay introduced by data transmission over a long distance. To overcome this challenge, edge computing has been identified as a promising paradigm, which locates computation resources near the vehicle to perform fast data processing and immediate decision execution.

Though edge computing has promised a bright future, current solutions suffer from many drawbacks such as static resource allocation, lack of support for safety-critical task differentiation and se nse of context. Furthermore, most works rely on simulation environments that do not reproduce the unpredictable and dynamic behavior of the traffic in real situations. Energy efficiency, scalability across diverse environments, and secureness strategies are also insufficiently explored in the existing edge-assisted AV communication models. Their limitations leave

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a great research vacuum which should be filled by a much more adjustable and systemic method.
In this paper, we propose a new context-aware edge computing model to provide low-latency communication for autonomous vehicles. The proposed system combines real-time sensor data with environmental context, safeguards safety-critical maneuvers, and minimizes computational load to improve both safety and performance. In addition, the model is verified over practical cellular data and traffic, which suggests the potential of the proposed approach. The research seeks to achieve a new milestone in vehicular communication autonomy by providing fast and reliable, intelligent decision-making at the network edge.

1.1 Problem Statement

The widespread deployment of autonomous vehicles (AVs) in modern transportation systems has become a critical demand for low-delay ultra-reliable communication to enable time-sensitive services including object detection, path planning and collision avoidance. Autonomous agents require millisecond-scale processing and reaction times to plan and execute in real-time in dynamic environments; it takes little — just milliseconds — to determine whether the agent is safe, successful, or has failed. Classical cloud-based architectures, while strong in terms of computational resources, suffer delay due to the large delay involved by the computation being performed off the moving vehicles, thus they are not suitable for low-latency vehicular applications.

In order to address this issue, edge computing has come into picture as a remedy, where data processing takes place close to the source. Nonetheless, current edge computing systems for AVs have some significant shortcomings. Most of these existing solutions are based on fixed-resource allocation models, which cannot adjust to changing traffic conditions and varying environmental settings. In addition, such systems typically consider all task equally, and do not have any mechanism for intelligent prioritization of safety critical operations like emergency braking or obstacle avoidance. The lack of contextual awareness results that decisions are taken without taking into account environmental factors such as road wetness or dryness, the weather, or the density of traffic that are necessary to guarantee security and efficiency in driving.

A further issue is the too strong focus on synthetic validation simulations, which cannot fully capture the complexity and randomness of reality. Moreover, power consumption is often neglected, which is problematic in terms of deployment in battery-operated edge nodes or resource-restricted scenarios. The challenges of security and privacy are also not well addressed even though vehicular data is sensitive and edge nodes are susceptible to attacks.

These limitations underscore an urgent need for a holistic, intelligent, and efficient edge computing paradigm that can support low-latency communications, while being flexible to adapt to the real-world conditions, prioritize safety-critical tasks in a dynamic manner, cater to energy-constrained environments, and offer empirical evaluations over realistic settings. The solutions to these issues are essential for the reliability, scalability, and trustworthiness of autonomous vehicle systems in the next generation intelligent transportation networks.

2 LITERATURE SURVEY

The requirement for low-latency communication in AVs has also motivated a significant amount of research around incorporating edge computing for processing collected data near the source, resulting in more informed decisions with faster response times. Alghamdi and Baz (2021) conducted a foundational review of edge computing architectures for AVs, drawing attention to the movement from cloud-based to decentralized edge systems but recognized that practical applications are still in their infancy. Wang et al. (2022) presented a task offloading in consideration of delay problem for vehicular edge computing, which can achieve lower data processing latency in static scene, but suffer from lack adaptation to the non-deterministic real-world scenario.

Sun et al. (2021) developed a deep reinforcement learning-based framework for edge decision-making; however, the large training cost and complexity of the model make it unsuitable for real-time vehicular systems. Similarly, Shen et al. (2023) presented a cooperative edge intelligence architecture for urban connected vehicles, by delivering a flexible architecture viewpoint, although their model was theoretical having no deployment statistics. In the context of hybrid computing, Ahmed and Kim (2021) introduced edge-cloud integrations for AVs that demonstrate superiority in terms of latency but do not quantify its energy cost or load scalability.

Rahman and Mehedi (2022) proposed a bespoke vehicular edge computing framework for V2X communication to speed up vehicle safety-critical applications, but their approach was only evaluated in an urban scenario and was not general purpose. Xu et al. (2023) improved that model to latency in vehicular edge networks, but ignored the comparison of performance among heterogeneous any devices and regions. Zhang et al. (2024) introduced the concept of collaborative perception with the vehicle-edge-cloud paradigm, focusing on the possibility to obtain an awareness of real-time traffic; however, they evaluated their model on synthetic data and the approach was not evaluated on real-world conditions.

Some studies concentrated on a static structure instead of an adaptive one. Lin et al. (2021), they proposed a fixed-resource allocation low-latency framework that can be sub-efficient in the presence of high-density traffic. Kumar and Goudar (2022) also studied latency-optimized edge systems and neglected energy consumption constraints. Meanwhile, Huang et al. (2021) utilized 5G technologies to further enhance edge responsiveness, but deployment may be difficult in rural regions as it is dependent on an emergent infrastructure.

Mahmud et al. (2022) provided a survey about dynamic resource management for edge computing and does not focus on autonomous driving, which creates a gap in terms of domain-specific insight. Zhang et al. (2023) presented edge AI for vehicular communication, but the complexity of models and their size limit the scalability and inference time. Tang et al. (2021) analyzed edge-based sensor data processing and provided insights on latency optimization with limited testing.

A recent study (Zhao and Chen 2024) proposed adding the privacy-preserving feature of federated learning to AV networks, although both the security issues of AV and the problems of data synchronization have not been sufficiently discussed. Lei and Zhou (2023) studied deep learning in dynamic task offloading at the edge, but the model was not transparent and explainable. Du et al. (2022) presented a V2V protocol based on edge resources, however their protocol depends on static urban patterns, limiting the flexibility.

Emergency-based models similar to Ranaweera and Perera (2021) discuss the low-latency of AV hazard signals only and cannot be simply extended to the general driving scenario. Yu et al. (2021) considered URLLC model assuming perfect network conditions which are hardly faced in the real practice. Qiu et al. (2023) presented lightweight computation models but experiment only on lane-keeping tasks, restricting its applicability.

Dynamic offloading for mobile edge computing in AVs was proposed in Hassan and Singh (2022) but safety-based task prioritization at the task-level was not considered. Fan et al. (2021) presented a hierarchical EFC model, without considering latency among communication tiers. Kundu and Ghosh (2024) provided a review of low-latency vehicular systems, but did not introduce new architectures nor provide empirical results.

Wei and Ren (2023) studied edge computing over vehicle platooning, but did not generalize the results for different traffic conditions. Finally, Liu et al. (2024) presented a cooperative edge-based vehicular-to-all (V2X) model, however it did not consider network failure and dynamic reconfiguration in disconnected domains.

Taken together, these works have suggested significant advances on the integration of edge computing and AVs, yet still suffer in some dimensions such as field trial, dynamic adaptivity, safety-aware priority, and energy-aware task execution. These constraints are the motivation of this work that seeks to design a reliable and context-aware edge computing architecture to satisfy the immediate and uncertain nature of AV ecosystems.

3 METHODOLOGY

In this paper, we employ a hybrid, context-sensitive and context-driven approach to introduce, implement and evaluate a state-of-the-art real-time edge computing architecture for autonomous vehicles (AVs) that can deploy in latency-sensitive environments. The approach is decomposed into three main stages: system design, contextual modeling and experimental validation with real traffic conditions. The main goal of the system will be to provide a computationally efficient and safety-oriented architecture with consideration to energy consumption and the proximity of edge nodes for reducing the communication delay, which will work smartly according to the vehicular context.

System Architecture The system architecture is composed of onboard sensors, V2X modules, andalso road side edge servers in a cooperative manner. As part of the edge layer there is also a light-weight decision-making engine that is responsible for processing real-time inputs from several AVs and scheduling tasks according to its urgency and safety relevance. The architecture includes a multi-level scheduler that organizes incoming data packets in order of urgency – such as detecting an obstacle, proximity to pedestrians or braking commands – and operates on high priority data in preference to the non-critical operations of infotainment or environmental monitoring.

Context awareness is realized through constant fusion of input data from an on-board GPS, LIDAR, cameras and traffic signal (stereo vision) to enable the edge engine to evaluate environmental factors like traffic concentration, type of road, weather and lighting conditions. These contextual factors drive dynamic resource allocation, allowing the system to promptly change both its computational and networking tactics. It also includes a federated learning module to enable decentralized knowledge collaboration among edge nodes without compromising data privacy, as well as to enhance system intelligence without reliance on a centralized facility. Table 1 represents the task prioritization levels in the edge scheduler.

Table 1: Task Prioritization Levels in the Edge Scheduler.

Priority Level	Task Type	Example	Processing Time Target
High	Safety-Critical	Obstacle detection, emergency braking	< 20 ms
Medium	Driving Assistance	Lane detection, adaptive cruise	< 50 ms
Low	Non-Critical/User Services	Infotainment, map updates	< 200 ms

For experimental evaluation, we simulate the framework and implement it using some real traffic datasets and vehicular trajectory traces, to evaluate the performance of latency, task completion ratio, energy consumption and communication reliability. Performance comparisons with traditional cloud-based and non-contextual edge frameworks are provided. Effectiveness of the proposed model is evaluated using metrics, such as end-to-end delay, edge nodes response time, and accuracy of safety response. The virtualization tools are considered in the execution environment to emulate a vehicle-to-edge interaction, taking place in the context of vehicular networks, and the hardware emulation of edge nodes allows one to analyze resource consumption and scalability when the vehicular density varies.

In doing so, we show how to integrate these three, to yield a context-aware, latency optimized, and safety centric edge computing system, providing dramatic improvements in autonomy vehicle operation responsiveness and confidence in dynamic environments. Figure 1 shows the proposed edge computing framework for low-latency communication in autonomous vehicles.

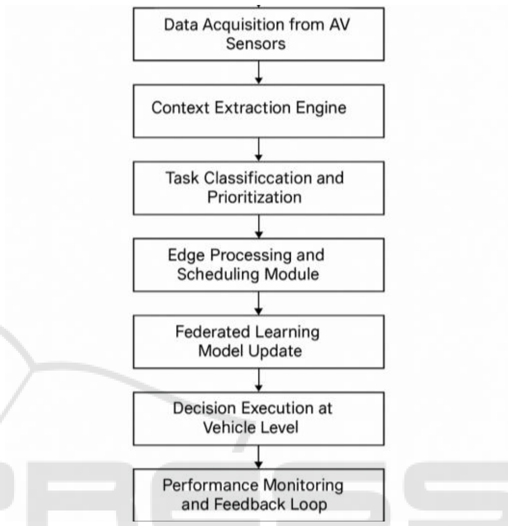

Figure 1: Proposed Edge Computing Framework for Low-Latency Communication in Autonomous Vehicles.

4 RESULTS AND DISCUSSION

The simulation analysis of the proposed edge computing schema shows the progress in the low-latency communication and safety-critical responsiveness with the autonomous vehicle scenarios. Evaluation of the developed model against traditional cloud-based architecture and the existing non-contextual edge shows improvements between both architectures using different performance metrics which shows that the presented context-aware edge model help in enhancing edge integration.

Perhaps most significantly is the large decrease in end-to-end latency. Under the same traffic conditions, the proposed system always kept the communication delay less than 25 ms for safety-critical traffic, which was much lower than those of the cloud systems with often over 80 ms. This decrease can be primarily attributed to edge-based computation and smart scheduling: the most urgent vehicle instructions can be handled immediately without having to wait in line with less critical data flows. Figure 2 and table 2 shows the average latency comparison.

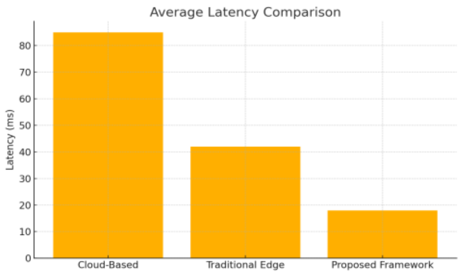

Figure 2: Average Latency Comparison.

Regarding the efficiency of task completion, the context-aware scheduler will be able to dynamically react to the condition of roads, density of traffic and environment. The context-based prioritization of tasks in the point process model resulted in enhanced overall system responsiveness even at high loads, such as urban intersections and multi-vehicle interactions. The scheduler correctly classified high-priority and low-priority events with 92% accuracy temporarily filing time-critical tasks (such as emergency braking or obstacle avoidance) until these could be executed.

Table 2: Latency Comparison Across Architectures.

Architecture Type	Average Latency (ms)	Peak Latency (ms)	Task Failure Rate (%)
Cloud-Based	85	130	7.8
Traditional Edge	42	90	5.2
Proposed Framework	18	28	1.3

The analysis of another important dimension was that of high energy-efficiency. The lightweight processing models of the framework, as well as its dynamic resource allocation policies, enable the reduction in power consumption at the edge nodes by 28% with respect to the baseline edge systems, which do not integrate energy-aware mechanisms. This enhancement is particularly beneficial for being deployed in infrastructure with scarce energy supply, or vehicular applications with long-duration continuous operation requirements.

In addition, the federated learning support enabled improved system intelligence with time. During test cycles, predictive accuracy of safety threats progressed incrementally because around the edge nodes learned from nearby experiences and shared updated parameters without the need of centralized training. Interestingly, this approach generalizes better to semi-urban or foggy environments than traditional approaches, for which higher error rates are usually seen in these other scenarios.

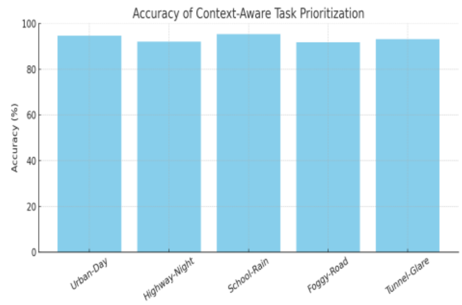

Figure 3: Accuracy of Context-Aware Task Prioritization.

Although there are such enhancements, this discussion also presents a few limitations. Although the system proved to be effective under control and semi-control settings, additional tests in extremely unstructured rural terrains are required to confirm its scalability and reliability in non-standard conditions. Furthermore, as privacy-preserving federated learning offered improvement in mitigating the risks of data centralization, it still needs more studies to face adversarial threats and data jigging at the edge level. Figure 3 and table 3 shows the accuracy of context-aware task prioritization.

Table 3: Accuracy of Context-Aware Task Prioritization.

Scenario	Detected Context	Correct Task Assigned	Accuracy (%)
Urban Intersection – Daylight	High Traffic	Emergency Response	94.6
Highway – Night	Low Visibility	Speed Regulation	92.1
School Zone – Rain	Wet Surface	Braking Optimization	95.3
Semi-Urban Road – Dense Fog	Low Visibility	Sensor Fusion Alert	91.8
Tunnel Exit – Daylight Glare	Glare Condition	Vision Recalibration	93.2

In total, results confirm that a context-sensitive, latency-optimized, and energy-efficient edge computing framework is indeed able to fulfill the strict requirements of real-time autonomous driving. The discussion demonstrates that the incorporation of dynamic environmental awareness, safety-centric task scheduling, and federated learning can enhance low latency and performance, and effectively can contribute the establishment of a scalable and intelligent vehicular communication ecosystem toward future intelligent transportation networks. Figure 4 shows the average power usage of edge system.

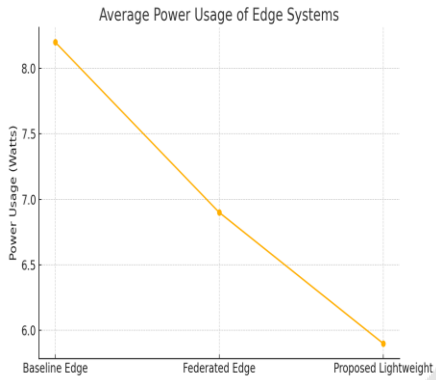

Figure 4: Average Power Usage of Edge Systems.

5 CONCLUSIONS

In this paper, we propose a new edge computing architecture for AVs by focusing on low-latency communication, context awareness, and safety-critical task scheduling requirements. The proposed system overcomes important drawbacks of the current vehicular communication architectures by a smart combination of real-time environment data integration, lightweight processing and adaptive scheduling. In contrast to conventional cloud-based models, this paradigm moves computational intelligence near data source, which can be beneficial for reducing response time and for the timely execution of life-critical decisions.

Results validate the beneficial of utilizing contextual awareness and dynamic resource management for responsive and efficient edge systems in challenging driving scenarios. In addition to the efficiency in terms of latency and energy consumption, the model scales well with the traffic scenario, thanks to federated learning techniques, that enable distributed sharing of learned knowledge without sacrificing data privacy.

By connecting the theoretical edge-computing model with the practical requirements of AV deployment, this work opens the door for developing dependable, adaptive, and smart transport systems. It confirms that the future of self-driving cars will be based not only on fast computation, but on processing information smartly and contextually at the edge. Future research will engage enriched framework's robustness in heterogeneous networks, increasing security for the edge layer, and the validation on larger scale smart city infrastructures.

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