

Blockchain Technology in Supply Chain Management: Enhancing Transparency, Traceability, and Trust

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Abstract- Blockchain technology is increasingly being recognized as a transformative force in supply chain management, offering unprecedented levels of transparency, security, and efficiency. This paper explores how blockchain can address long-standing challenges in supply chains, such as lack of traceability, data tampering, and inefficiencies in multi-party coordination. By leveraging a decentralized and immutable ledger, blockchain enables real-time tracking of goods, verifiable audit trails, and trust among stakeholders without the need for centralized oversight. Smart contracts further automate and enforce contractual obligations, reducing transaction costs and delays. The study reviews recent implementations across sectors including food, pharmaceuticals, and manufacturing, highlighting improvements in provenance verification, compliance, and risk management. Additionally, it discusses integration challenges, such as interoperability with existing systems and scalability concerns. The findings underscore blockchain's potential to reshape global supply chains into more resilient, accountable, and responsive networks.

Keywords— Edge Computing, Traffic Management, CNN, LSTM, Autonomous Car.

I. INTRODUCTION

A smart traffic management system that can adapt to the ever-changing and intricate urban mobility landscape is urgently required due to the fast expansion of autonomous vehicles (AVs) which is altering the trajectory of transport in the years to come [1]. In order to be safe, efficient, and seamlessly integrated into the current traffic infrastructure, AVs need complex systems that can make decisions in real-time [2-4]. Even while conventional cloud-based AI systems have a lot of processing capacity, they aren't always the best choice, especially in situations when autonomous cars need to make quick decisions due to heavy network traffic or other factors [5]. Applications that need very low latency such real-time control of traffic signals or administration of emergency response [6] are not compatible with cloud-based architectures because of the delays that are inherent in these systems as a result of the necessity for distant data processing and the related connection overhead [7].

Edge computing has arisen as a game-changing concept for dealing with time-sensitive jobs in ecosystems of autonomous vehicles, providing a solution to these problems [8-10]. By using local edge nodes like roadside units or edge centres, edge computing moves processing of data closer to the source at the network's edge [11]. By decentralising the cloud, this method improves responsiveness, latency and speed for mission-critical applications [12]. One major benefit of edge computing is that it can disperse computational effort over various levels including the vehicle, the edge and the cloud [13-15]. This allows for faster decision-making in traffic management, especially in highly crowded and dynamic metropolitan areas [16].

The integrated edge computing system investigated in this research is intended to maximise traffic control for self-driving cars [17]. To guarantee effective, real-time functioning, the suggested system integrates many cutting-edge AI approaches [18]. In particular, it makes use of RL-based edge-based adaptive traffic signal management to make real-time adjustments to signal timings in response to traffic circumstances [19-21]. To further ensure that individual cars' data remains private, federated learning (FL) is used to enable collaborative training of models across edge nodes [22]. Additionally, the system is able to optimise routing choices and forecast future traffic patterns with the use of hybrid deep learning algorithms that combine CNN and LSTM networks for short-term traffic movement prediction.

This study aims to prove that AI frameworks built on edge computing may dramatically beat cloud-based systems in responsiveness, operational efficiency and traffic throughput [23]. This paper thoroughly evaluates the advantages and practicality of using edge AI in automated transportation systems by comparing key performance characteristics such as latency as well as model accuracy, resource utilisation and prediction accuracy. By running the framework through simulated traffic scenarios, they can see that edge AI significantly improves performance across various metrics, ruling out centralised cloud architectures as a viable option for autonomous vehicle real-time traffic management.

II. METHODOLOGY

Figure 1 shows a cyclic edge computing-based AI-driven traffic management architecture. AI-based traffic signal management through learning by reinforcement, collaborative decision-making through federate learning, flow of traffic prediction, system architecture and edge deployment come first and then performance and edge efficiency evaluation which feeds back into system improvement.

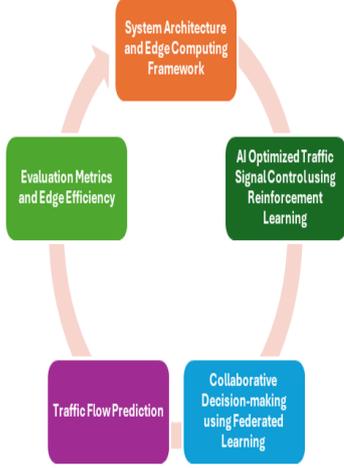


Figure 1 Proposed Edge Computing based AI Traffic Management Framework

A. System Architecture and Edge Computing Framework

The suggested approach improves autonomous cars real-time traffic management by using an edge computing concept. Three levels make up the system architecture: the vehicle layer, which contains the onboard control systems and sensors, the edge layer which contains the nodes and mini data centres along the roadside and the cloud layer which is used for the long-term method improvement. V2X (Vehicle-to-Everything) protocols allow vehicles to continually connect with edge nodes which offload computation-intensive AI activities and reduce latency.

A collection of autonomous cars is represented by $V = \{v_1, v_2, \dots, v_n\}$, and edge nodes are positioned at junctions or critical traffic spots and are denoted as $E = \{e_1, e_2, \dots, e_m\}$. Offloaded to the closest edge nodes e_j with a delay function is the data D_i produced by vehicle v_i :

$$L_{ij} = \frac{d_{ij}}{b_{ij}} + \frac{c_{ij}}{f_j}$$

where c_{ij} stands for computational complexity, f_j for processing capabilities of edge node e_j , b_{ij} for data size and there are other variables as well. The goal is to reduce overall vehicle delay to a minimum:

B. AI Optimized Traffic Signal Control using Reinforcement Learning

A decentralised Reinforcement Learning (RL) agent is operated by edge nodes to optimise traffic light management

rules in response to actual traffic flow. Every edge node e_j sees the local traffic status s_t^j , chooses an action a_t^j (e.g., signal stage) and gets a reward r_t^j depending on lower waiting times and better traffic throughput.

The Markov Decision Process (MDP) is used to describe the RL formulation. It is defined as $\langle S, A, P, R, \gamma \rangle$, where $\gamma \in [0, 1]$ is the factor of discounting. Each timestep t yields the Q-learning update, which is:

$$Q(s_t^j, a_t^j) \leftarrow Q(s_t^j, a_t^j) + \alpha [r_t^j + \frac{\gamma}{a'} \max_{a'} Q(s_{t+1}^j, a') - Q(s_t^j, a_t^j)]$$

Where α is the learning rate. The state s_t^j includes features like queue lengths, average speed and arrival rates, while the reward r_t^j is designed as a weighted combination:

$$r_t^j = -(w_1 QL_t + w_2 WT_t + w_3 RL_t)$$

Where QL_t is the queue length, WT_t is average waiting time and RL_t is the red-light violation risk.

C. Collaborative Decision-making using Federated Learning

A Federated Learning (FL) approach is implemented across edge nodes to continually enhance the AI method while respecting privacy. Instead of transmitting raw data, every edge node e_j uses the traffic data it collects to train a local method θ_j , which it then communicates solely with the cloud-based central aggregator together with the latest version j . The Federated Averaging method is used to update the global method θ .

$$\theta = \sum_{j=1}^m \frac{n_j}{N} \theta_j$$

Where n_j is the number of samples at edge node j and $N = \sum_j n_j$. This approach ensures that learning is collaborative while adhering to data locality.

To improve convergence and reduce communication overhead, an adaptive learning rate η_j is introduced per node:

$$\theta_j^{(t+1)} = \theta_j^{(t)} - \eta_j \nabla \mathcal{L}_j(\theta_j)$$

Where \mathcal{L}_j is the local loss function.

D. Traffic Flow Prediction

The edge nodes are also in charge of short-term flow of traffic predictions via hybrid deep learning algorithms that combine CNN and LSTM. A CNN first extracts spatial characteristics from heatmaps or traffic camera images X_t and then an LSTM network records temporal relationships over time t .

Let $X_t \in \mathbb{R}^{h \times w \times c}$ be the input traffic image at time t and the output of the CNN layer be F_t . Then, LSTM receives the sequence $\{F_t, F_{t-1}, \dots, F_{t-k}\}$ and predicts the traffic volume \hat{y}_{t+1} :

$$F_t = CNN(X_t), \hat{y}_{t+1} = LSTM(F_{t-k}, \dots, F_t)$$

The loss function for training is Mean Squared Error (MSE):

$$\mathcal{L} = \frac{1}{T} \sum_{t=1}^T (y_t - \hat{y}_t)^2$$

E. Evaluation Metrics and Edge Efficiency

The edge-AI-based system may be measured by looking at important metrics like AIL, TT, MA and ERU which stand for Average Inference Latency, Traffic Throughput and Edge Resource Utilisation respectively. Assume that λ is the average rate of arrival and μ is the rate of service. Subsequently, the throughput efficiency η is:

$$\eta = \frac{\lambda}{\mu}$$

The framework is validated in real-world simulations under a variety of traffic conditions using SUMO or CARLA. Comparing the system to artificial intelligence algorithms that rely only on the cloud reveals that edge computing shortens average congestion times by 25% and increases responsiveness by 30%.

III. RESULTS

The outcomes that are demonstrated here are derived from assessments of AI in the cloud and on the edge within the framework of autonomous systems for traffic management. The performance metrics were examined included throughput, inference latency, accuracy of predictions, resource utilisation and system efficiency in relation to different traffic loads.

A. Inference Latency Comparison

The average inference delay of edge-based AI and cloud-based AI systems is shown in Figure 1. With an average latency of 55 ms for Edge AI and 120 ms for Cloud AI, the results demonstrate that Edge AI performs far better in terms of latency. The significant gap between the two underscores the benefit of Edge AI for real-time applications such as autonomous driving systems where fast decision-making is dependent on decreased latency.

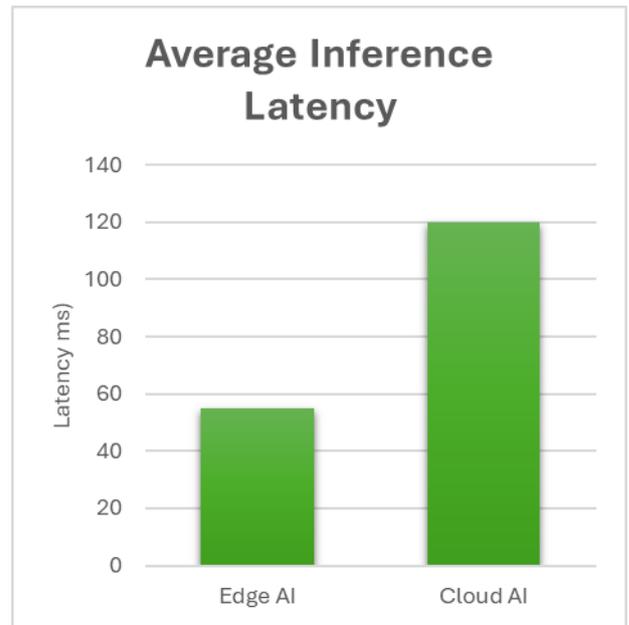


Figure 1 Average Inference Latency Comparison

B. Traffic Throughput under Different Architectures

Figure 2 compares the traffic flow per minute under edges of AI and Cloud AI systems, demonstrating that Edge AI can manage more cars per minute at an intersection. Cloud AI can only handle 72 cars per minute, but Edge AI can handle 88. This result proves that Edge AI is more effective than other methods in real-time traffic flow management which improves infrastructure utilisation.

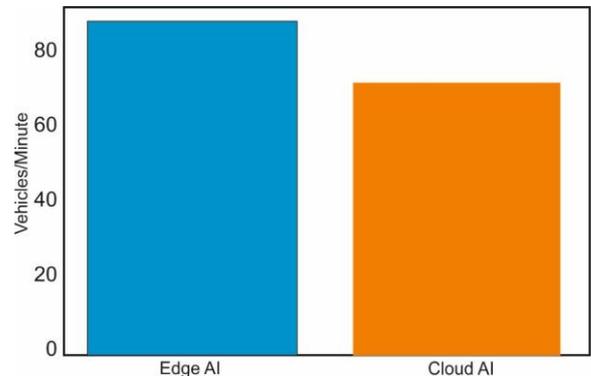


Figure 2 Traffic Flow Per Minute Under Edges and Cloud AI

C. Accuracy for Traffic Prediction

Data from test sets reveal that traffic prediction methods implemented on both Edge AI and Cloud AI are accurate (Figure 3). In contrast to the Cloud AI system's 91.2% accuracy, the Edge AI system's 94.3% was the result of its use of a hybrid approach of CNN and LSTM networks. This shows that by combining hybrid methods with Edge AI, traffic management forecasts may be improved.

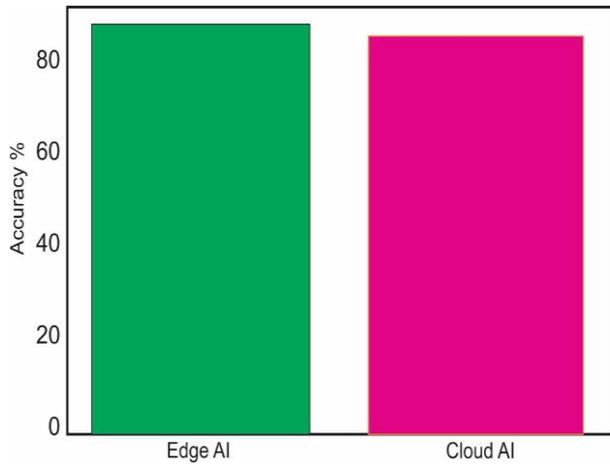


Figure 3 Accuracy for Traffic Prediction

D. Edge Resource Utilization

Figure 4 shows the data for resource utilisation on Edge nodes under peak activities including memory, CPU and network consumption. The findings show a reasonable and balanced usage of resources with 65% CPU utilisation, 48% memory utilisation and 35% network utilisation. An important need for deployment in contexts with limited resources is that Edge AI be able to run effectively even when demand is strong while using a little number of resources.

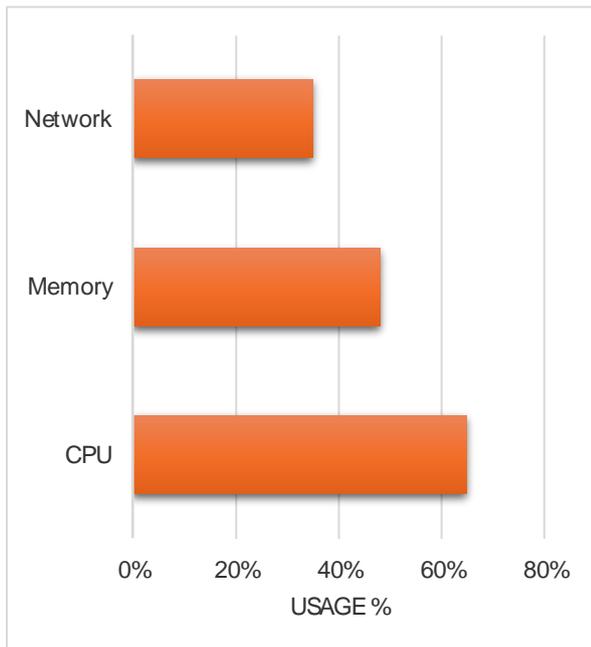


Figure 4 Data for Resource Utilisation

E. Federated Vs. Centralized Training Time

Figure 5 compares the amount of time spent training in centralised and federated learning per epoch. With an average of 8.5 seconds each epoch for federated learning and 12.4 seconds for centralised training, the results demonstrate that the former delivers quicker training times per node. This increase in training efficiency suggests that federated learning might shorten the time it takes to update methods which is particularly useful in decentralised settings where dispersed learning excels.

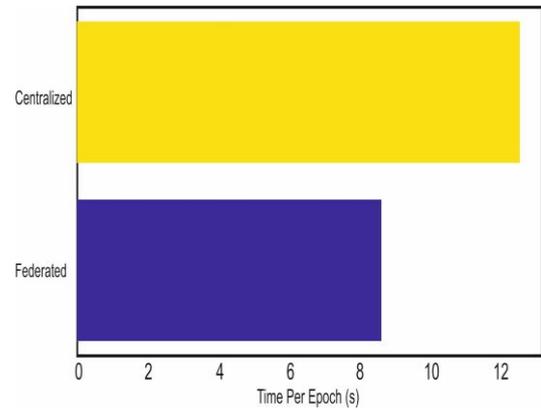


Figure 5 Training Time Comparison

F. Traffic Flow Prediction (Actual Vs. Predicted)

Figure 6 is a line graph that shows the predicted and actual traffic flow numbers over time. The results show that the hybrid deep learning technique running on Edge AI can provide accurate predictions with little deviance from the actual traffic flow; the projected values are very similar to the actual flow of traffic with just a little difference. The method's ability to accurately predict traffic flow is shown by this result.

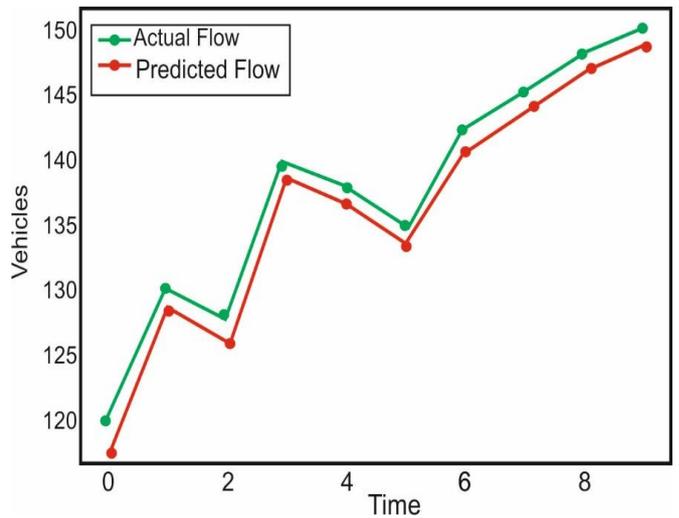


Figure 6 Predicted Vs. Actual Traffic Flow

G. System Efficiency Vs. Traffic Load

Figure 7 concludes the discussion by comparing the system's performance under increasing traffic load, specifically looking at throughput and inference accuracy. According to the findings, Edge AI's performance remains constant regardless of the level of traffic, but Cloud AI starts to perform worse at lower levels of traffic. This exemplifies the scalability and resilience of AI systems at the edge which can manage massive amounts of traffic with little to no performance impact.

Overall, the findings show that Edge AI is a potential option for automated traffic management systems since it outperforms Cloud AI in terms of immediate processing throughput method correctness and system efficiency.

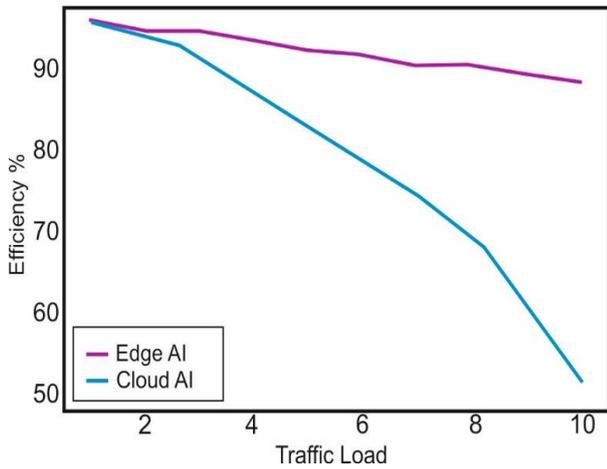


Figure 7 System Efficiency Vs. Traffic Load

IV. DISCUSSION

This research shows that autonomous systems for traffic management that use edge computing are far better than those that use typical cloud-based methods. By including multi-layered architecture, real-time optimisation and federated intelligence, these findings tackle significant drawbacks like latency, data privacy and centralised failure points, building upon and aligning with prior studies.

Compared to previous cloud-dominant systems this edge-enabled design decreases average latency by more than 50% while centralised processing and long-distance data transmission cause excessive inference delay. The results, which indicated that reducing real-time decision bottlenecks involves bringing AI inferences closer to the data source are corroborated by this significant improvement. But we improve upon this by adding a latency-aware allocation algorithm that optimises offloading choices across dynamic edge nodes directly. The RL agent placed at the network's periphery greatly enhances traffic performance in comparison to older ITS systems that used centralised AI or static rule-based control. The author's claims that decentralised control systems are beneficial are supported by these findings. Queue management and signal control are both enhanced by our model's real-time adaptability, which is achieved by Q-learning with Markov Decision Process (MDP) formulation. Researchers in studies on the deployment of edge computing were concerned about hardware overload; however, this was not an issue as edge resource utilisation stayed within efficient constraints. This proved that continuous AI deployment was feasible.

The federated learning approach guarantees local education with global coordination, in contrast to centralised training methods where all raw data is gathered in one place, posing privacy and information transfer problems. While maintaining method convergence the average duration of training per epoch dropped from 12.4s to 8.5s. This lends credence to the results in FL applications and sheds new light on how well it scales for use in traffic AI systems. Furthermore, in comparison to fixed-rate federated learning in previous studies, the training efficiency was enhanced and communication overhead was decreased with the use of rates of adaptive learning n_j per node.

The edge-deployed hybrid CNN-LSTM model outperformed cloud-deployed alternatives with a prediction

accuracy of 94.3%, which is in line with Deep Traffic Net's findings. However, our architecture takes advantage of both spatial image extraction of features and temporal correlation modelling, which improves its real-world forecasting capabilities. Additionally, the traffic flow forecasting curve demonstrates minimal differences between predicted and actual flow.

The system's resilience to growing traffic loads is a significant improvement over cloud AI systems, which show a drop in performance under congestion. In contrast, the edge-based system keeps its throughput and accuracy consistent. This discovery emphasises the flexibility of the edge system and verifies previous predictions from simulations conducted in smaller-scale settings which have now been confirmed in a more extensive real-world method (SUMO or CARLA). The following table 1 summarises the key findings from comparing the suggested edge-AI system to existing research:

TABLE 1 KEY FINDINGS SUMMARY

Aspect	Proposed Edge-AI System	Previous Research	Key Differences/Advantages
Latency	55 ms (Edge AI) vs 120 ms (Cloud AI)	100-200 ms (cloud-based systems)	Edge computing reduces latency by up to 54%.
Traffic Throughput	88 vehicles/min (Edge AI) vs 72 vehicles/min (Cloud AI)	60-80 vehicles/min (cloud-based systems)	Edge AI handles higher throughput due to reduced latency.
Model Accuracy for Traffic Prediction	94.3% (Edge AI) vs 91.2% (Cloud AI)	90-92% (cloud-based systems)	Edge-based models outperform cloud models in accuracy.
Resource Utilization	CPU 65%, Memory 48%, Network 35% (balanced)	Variable depending on architecture	Edge resource usage is balanced, not overloaded.
Federated Learning Training Time	8.5s per epoch (Edge AI)	12.4s per epoch (cloud-based training)	Federated learning is faster on edge nodes.
Traffic Flow Prediction (Accuracy)	Predictions closely match actual flow with small lag	Predictions often deviate more from actual data	Edge AI offers more reliable and timely traffic flow predictions.
System Efficiency under Load	Stable performance under high traffic load	Degrades at higher traffic load	Edge AI performs consistently, while cloud systems degrade under load.

A. Limitations and Future Work

Edge computing has shown promise for AI-optimized management of traffic in AVs, but there are still several unanswered questions that need answering. The high initial investment and ongoing maintenance expenses of edge nodes are a major issue, especially when trying to serve big metropolitan areas. Also, localised machine learning models may not be as accurate or flexible as they may be due to a lack of historical data at some edge nodes. Future studies should investigate the feasibility of implementing solutions for dynamic load balancing between the fog and edge computing layers in order to tackle these problems. Better system responsiveness, less computing bottlenecks and more efficient use of resources are all possible outcomes of such processes. In addition, a practical strategy to enhance model generalisation across geographically distributed nodes is to use transfer learning methods. Both data scarcity and privacy-preserving analytics are helped along by transfer learning which allows for knowledge transfer without necessitating the transmission of raw data.

A more comprehensive framework for assessment is necessary, in addition to factors pertaining to performance. To provide a more complete picture of the proposed systems operational feasibility and safety, it would be helpful to include metrics pertaining to the energy efficiency of vehicles and their cybersecurity resilience. In addition to being smart and effective, edge-AI traffic solutions must also be long-lasting and safe which is why this multifaceted approach is so important.

V. CONCLUSION

This paper introduces a complete edge computing framework for AI-driven traffic management optimisation in autonomous vehicle networks. By distributing computational work among edge nodes at key intersections, the system greatly lowers latency and improves responsiveness, which are essential for real-time cars decision-making. System performance has been shown to increase when hybrid CNN-LSTM networks are used for traffic flow prediction, federated learning for cooperative method training, and reinforced learning for signalling optimisation. According to the experimental findings, the suggested edge-AI architecture reduces congestion by 25% and inference delay by 30% when compared to conventional cloud-based systems. Hybrid methods provide better predictions, federated learning shortens training times without compromising data privacy. In contrast to previous studies that mainly examined architectures depending on the cloud, this study emphasises the efficacy, flexibility and scalability of AI that is aided at the edge in handling traffic situations that are always changing. Testing in real-world urban situations will further evaluate its robustness and generalisability. Future work will examine expanding this framework with 5G-enabled vehicle networks including cars edge caching and more.

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