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A Federated Multi-Task Meta-Learning Framework for Collaborative Perception and Adaptation in Connected and Automated Vehicles

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Abstract

Connected and Automated Vehicles (CAVs) operate in dynamic environments influenced by traffic patterns and pedestrian behaviour, which complicates the development of real-time navigation algorithms with voluminous data communicated by CAVs, raising privacy concerns. To address these challenges, we propose Federated Learning (FL) for concurrent and collaborative learning across fleets to generate privacy-preserving personalised models that adapt to diverse environments. Combining graph neural networks (GNNs) enables the real-time modelling of vehicle interactions and captures spatial and temporal dependencies. Utilising a message-passing paradigm, GNNs facilitate dynamic communication among vehicles. By aggregating information from neighbouring nodes, GNNs learn meaningful feature representations that enhance perception in CAVs, improving their responsiveness and enabling route optimisation and traffic flow enhancement. In this work, Model Predictive Control (MPC) influences GNNs to improve vehicle state prediction. It optimises control actions that minimise a cost function, such as travel time, fuel consumption, or collision risk, while adhering to constraints. GNNs enable the system to adapt its predictive model based on evolving vehicle relationships. At the same time, MPCs re-optimise control actions in response to these changes, allowing the CAVs to manage trajectories and make informed decisions adaptively in dynamic environments. The Federated Multi-Task Meta-Learning Framework for Collaborative Perception and Adaptation in Connected and Automated Vehicles (FedCAV) model is deployed across Edge, Fog, and Cloud layers to optimise performance, with a total estimated latency of 210 ms for 10 vehicles, influenced by local model training. Its low first-byte latency of 25 to 34 ms enhances communication efficiency, facilitating real-time decision-making and adaptive interactions.

Keywords
Connected and Automated Vehicles, Federated Learning, Graph Neural Networks, Model Predictive Control, Edge computing, Fog computing

1. Introduction

Connected and Automated Vehicles (CAVs) are equipped with technology that allows them to communicate with each other and their environment, enhancing road safety and operational efficiency. CAVs utilise many technologies, including sensors, cameras, and machine learning algorithms, to perceive their environment and make informed decisions (Gregurić et al., 2023). Applications of CAVs span autonomous driving, intelligent traffic management, and vehicle-to-everything (V2X) communication, all of which contribute to improved traffic flow and reduced vehicular accidents (Chellapandi et al., 2023). Despite their potential, CAVs face challenges like data privacy concerns, high communication overhead, and the need for robust machine learning models that can learn from diverse driving environments.

Federated Learning (FL) is increasingly recognised as an essential technology for enhancing the capabilities of CAVs within the Internet of Vehicles (IoV). It enables vehicles to collaboratively learn from data while preserving privacy, addressing significant concerns related to data sharing in cooperative perception and decision-making processes (Drissi, 2023).

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Integrating FL with IoT facilitates improved traffic management and routing optimisation, contributing to sustainable urban development (Zhang et al., 2023). However, data heterogeneity and the need for efficient client selection remain critical, as they can affect model accuracy and increase communication overhead (Liu et al., 2024). Additionally, the introduction of blockchain in FL frameworks can mitigate data silos and enhance privacy protection by ensuring high-quality data source selection (Acar and Sterling, 2023). Furthermore, robust defence mechanisms are essential to counteract emerging cyber threats in mobile environments, ensuring the integrity of federated learning systems (Pang et al., 2024).

Collaborative perception and adaptation in CAVs enhance situational awareness and operational efficiency. Research indicates that integrating vehicle-road systems, such as self-powered vehicle-road integrated electronics (SVRIE), significantly improves collaborative sensing capabilities, allowing vehicles to accurately monitor road conditions and tyre health (Qu et al., 2024). Additionally, unicast-based cooperative perception strategies enable CAVs to share information dynamically, optimising resource allocation and enhancing decision-making in mixed traffic scenarios (Shao et al., 2024). The evolution from single-agent to collaborative detection models, facilitated by Vehicle-to-Everything (V2X) communication, further underscores the importance of real-time data sharing to address occlusion and sensor failures (Jahn et al., 2024; Yang and Liu, 2023). Moreover, unified frameworks that integrate perception and mapping tasks can enhance the accuracy and consistency of situational awareness, demonstrating the potential for collaborative mapping among vehicles (Khoshkangini et al., 2022).

Research Query: How can federated learning enable privacy-preserving, real-time collaborative perception and adaptive decision-making in CAVs operating in dynamic environments?

The proposed FedCAV framework combines three core methodologies: (1) federated multi-task meta-learning to train shared models across CAV fleets, (2) GNNs with Model Predictive Control (MPC) to model spatial-temporal vehicle interactions and optimise real-time trajectory planning, and (3) a multi-layered edge-fog-cloud architecture that balances latency and computational efficiency.

The rest of the article is organised as follows. Section 2 elaborates on previous research relevant to our problem statement, while Section 3 provides the Federated Multi-Task Meta-Learning Framework for Collaborative Perception and Adaptation in Connected and Automated Vehicles (FedCAV) system overview. A novel architecture is pictographically illustrated in Section 4 with the key elements such as FedCAV: system architecture with federated learning-enabled DSRC algorithm for V2V communication, cooperative decision-making in CAVs with GNN and MPC, state-space representation of CAV dynamics, and model personalisation with cloud analytics. Section 5 is concerned with the observed effects of the performance analysis. Finally, the conclusion gives a summary and critique of the findings, paving the way for identifying areas for further research.

2. Literature review

Recent studies (Avianto et al., 2022; Priya et al., 2024) have highlighted the importance of federated multi-task learning (MTL) frameworks that accommodate diverse data distributions across vehicles. The work on applying FL in CAVs with MTL enhances model performance with the challenges associated with training models on non-IID (Independent and Identically Distributed) data, which is common in vehicular environments. The algorithms based on Expectation-Maximization (EM) can be computationally intensive, which holds back their practical implementation. This is especially true in resource-constrained environments typical of CAVs, where computational power and communication bandwidth are limited. Although the framework addresses non-IID data distributions, the inherent variability in data across different vehicles can still pose challenges. If the local data distributions are too diverse, the model may fail to generalise well across different tasks, leading to suboptimal performance for certain clients.

The need for rapid adaptation in CAVs has led to the exploration of federated meta-learning techniques focused on enhancing the efficiency of federated meta-learning (Chai et al., 2021). Their research demonstrates how meta-learning can facilitate quick adaptation to new driving conditions, thereby improving the overall performance of CAVs. This is particularly crucial in real-time scenarios, where vehicles must respond promptly to changing environments and traffic conditions (You et al., 2024). Validation on larger-scale and diverse datasets that capture the complexity of real-world traffic conditions is necessary to ensure the scalability and generalizability of the approach. The paper does not address potential security and privacy concerns associated with federated learning, such as model inversion or membership inference attacks.

The state-of-the-art studies present a model-agnostic approach to federated learning that supports multi-task optimisation with the significance of maintaining data privacy while enabling vehicles to learn collaboratively from diverse datasets. This approach is particularly relevant for CAVs, where sensitive data must be protected (Basnet and Ali, 2021). By

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employing clustered federated learning techniques, the authors demonstrate how vehicles can optimise their learning processes without compromising individual data security, thus addressing a critical challenge in the deployment of FL in CAVs (Bas et al., 2021). Although the framework focuses on fast convergence, the actual speed of adaptation to rapidly changing environments may still be limited. Factors such as network latency, communication delays, and the computational constraints of edge devices can hinder the responsiveness of CAVs in critical situations.

The adaptability of federated learning is further demonstrated through research that examines its applications for Lidar super-resolution in automotive contexts (Zheng et al., 2020). This work highlights the necessity of tailoring learning algorithms to meet the unique requirements of CAVs, particularly in enhancing their perception capabilities within intricate environments. Vehicles can improve their situational awareness by utilising federated learning while preserving privacy and adopting safer and more efficient navigation systems (Okegbile et al., 2023; Barrachina et al., 2019). However, the study by Zheng et al. (2020) does not specifically tackle the temporal aspects of vehicle movements or how federated learning might be employed to recognise and adjust to these dynamics over time.

The cross-silo heterogeneous model federated multi-task learning strategy enables vehicles from different silos to collaborate, promoting the exchange of knowledge and experiences across various driving environments (Han et al., 2022; Cao and Zoldy, 2021). This collaboration contributes to creating resilient and flexible CAV systems that perform effectively in diverse conditions. It can be concluded that cross-silo federated learning can greatly improve the adaptability and efficiency of CAVs, thus advancing the development of smarter transportation systems (Qu et al., 2020; Tollner et al., 2024). However, the effectiveness of this cross-silo federated learning approach is heavily dependent on a strong infrastructure, which includes high-speed internet and dependable communication networks. In areas where infrastructure is lacking, the effectiveness of this method may be considerably compromised.

3. FedCAV: Generic Overview

Figure 2 depicts a multi-layered architecture for CAVs, enabling collaborative perception and adaptation through the seamless integration of edge, fog, and cloud computing. The automotive layer encompasses individual CAVs engaging in Vehicle-to-Vehicle (V2V) communication using decentralised networking resources, while the edge layer facilitates local decision-making through real-time interaction modelling and processing complex vehicle interactions. The fog layer aggregates data from multiple CAVs, coordinates GNN-based vehicle interactions, performs predictive analytics, and manages traffic through Vehicle-to-Network (V2N) communication. Meanwhile, the cloud layer provides centralised data processing, extensive analytics on aggregated data, and model training and updates, ensuring dynamic communication and adaptation across all layers for optimised performance and decision-making in CAV systems.

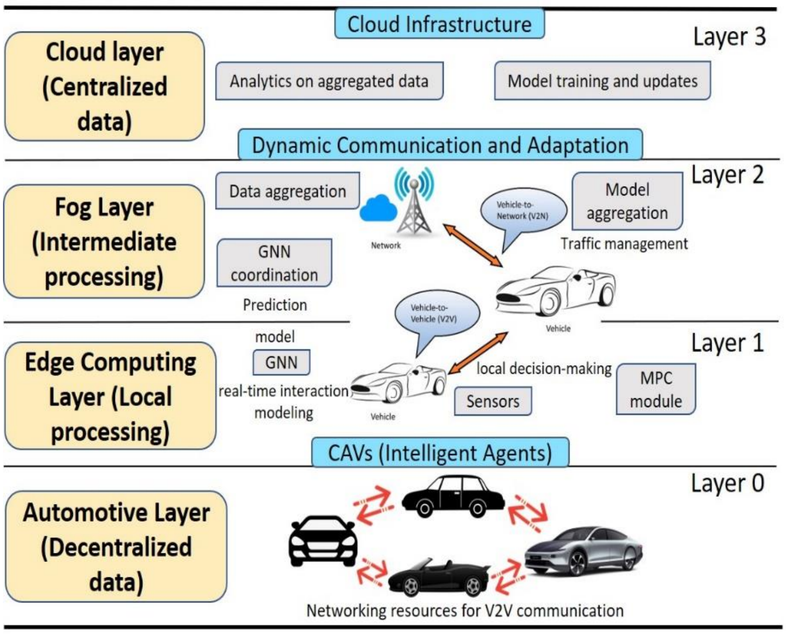

Fig.2. FedCAV: Multi-layered federated learning framework

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3.1. Layer 0: Automotive Layer (Decentralised Data)

The Automotive Layer, comprising intelligent agents, serves as the foundational tier of the architecture, featuring individual CAVs that actively engage in direct communication with one another. These vehicles utilise advanced V2V communication protocols to facilitate seamless data exchange in a decentralised manner, thereby enhancing situational awareness and collaborative decision-making while eliminating reliance on centralised infrastructure. This decentralised approach provides a more resilient network and empowers vehicles to operate autonomously and responsively in dynamic environments.

3.2. Layer 1: Edge Computing Layer (Local Processing)

The Edge Layer involves local decision-making by utilising onboard sensors and computational resources to process real-time data, allowing vehicles to respond immediately to their environment. Integrated within this layer is a Model Predictive Control (MPC) module, which empowers the vehicle to make informed decisions based on predictive models, optimising its actions for efficiency. Additionally, the layer facilitates real-time interaction modelling, enabling vehicles to dynamically assess and adapt to interactions with their surroundings and other vehicles, thereby enhancing overall adaptive behaviour. GNNs are used to analyse and interpret the complex web of vehicle interactions, significantly improving the decision-making processes and promoting a more intelligent and responsive autonomous driving experience. This layer is responsible for real-time data processing and decision-making by utilising GNNs to analyse data from the interface layer, capturing spatial and temporal dependencies essential for CAV operations. This layer focuses on real-time analysis and decision-making, where analysis enables immediate processing of data collected from CAVs, traffic signals, and pedestrian movements. Decision-making implements control actions based on the processed data, ensuring timely responses to dynamic traffic conditions.

3.3. Layer 2: Fog Layer (Intermediate Processing)

The Fog Layer serves as an intermediate processing hub, where data from multiple CAVs is aggregated to form a comprehensive dataset, enabling GNNs to coordinate vehicle interactions and optimise performance based on the aggregated information. This layer also conducts predictive analytics to predict traffic conditions while combining data from various vehicles to support extensive traffic management strategies, enhance overall decision-making capabilities, and facilitate cohesive operational frameworks through Vehicle-to-Network (V2N) communication between CAVs and centralised infrastructure. An intermediary between the edge and cloud layer facilitates intermediate processing to reduce latency by processing data closer to the source before sending it to the cloud—moreover, storage for temporarily holding data or model updates, optimising bandwidth and response times.

3.4. Layer 3: Cloud Layer (Centralized Data)

The Cloud Layer is dedicated to centralised data processing and storage, facilitating comprehensive analysis and decision-making. This layer exploits advanced analytics on aggregated data collected from diverse sources, yielding valuable insights that enhance operational efficiency. It enables model training and updates, managing the development of complex models, including those utilising GNNs from the lower layers, and ensuring that these models are continually refined and disseminated throughout the architecture to maintain optimal performance and adaptability. The cloud layer provides extensive computational resources for model training and updates. Its primary functions include model training that involves aggregating data from multiple edge devices to train a global model. This process ensures the model learns from diverse driving environments, enhancing its robustness. Model updates distribute updated models back to edge devices, allowing them to refine their local models based on the latest global insights.

4. FedCAV: System Architecture

The FedCAV architecture consists of multiple layers, such as Edge, Cloud, and a Fog layer, each serving distinct functions in data processing and model training. Layer 0 focuses on the V2V communication using a Federated Learning-Enabled Dedicated Short-Range Communications Algorithm. Layer 1 handles cooperative decision-making in CAVs with GNN and MPC. Layer 2 manages dynamic communication and adaptation with the state-space representation of CAV dynamics, while Layer 3 is dedicated to model personalisation, as depicted in Figure 3.

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4.1 Federated Learning-Enabled DSRC (FL-DSRC) for V2V Communication

Step 1: Network Initialization and Model Distribution

Each vehicle V_i initialises its communication and model training system by initialising the parameters,

- Max_Range ← Range of DSRC communication (e.g., 300 meters)
- Max_Slots ← Number of time slots available per frame (e.g., 100 slots)
- $Model_i^0$←Global model distributed to the vehicle V_i by a central server
- Current_Channel←Default DSRC channel

Step 2: Local Model Training

Each vehicle trains its local model using its data $Model_i^{t+1} \leftarrow Model_i^t - \eta \nabla L_i (Model_i^t)$ where η is the learning rate and ∇L_i is the gradient of the loss function L_i concerning the model parameters.

Step 3: Channel Sensing and Access for Model Update Sharing

To share model updates, each V_i senses the communication channel before transmitting,

$RSSI_i$ ← Received Signal Strength Indicator for each nearby V_i

$$SINR_i = \frac{Pi \cdot Gi,j}{\sum_{k \neq 1} Pk \cdot Gk,j + Nj}$$

If $SINR_i$ is below a threshold, V_i waits before transmitting its model update. $V_{i,}$ with a sufficiently high $SINR_i$ transmits their model updates.

Step 4: Time Slot Assignment Using TDMA

To prevent collisions during model update sharing, a Time Division Multiple Access (TDMA) scheme is used where slot selection is based on $Slot_i \leftarrow \min (Slot_{avail} (t))$, with which V_i chooses the earliest available slot for transmission. If a collision is detected, a backoff mechanism is applied, $\text{Backoff Time}_i = \text{random } (0, \text{Max\_Backoff\_Time})$, where random(a,b) generates a random number between a and b. Messages are prioritised based on their importance (e.g., emergency messages) with $P_{emergency} > P_{control} > P_{informational}$ where *P* represents priority with queue management Q_i←Sort messages in descending order of priority and transmit messages in order from the queue.

Step 5: Model Aggregation and Update

Once vehicles have transmitted their local model updates, they aggregate the models,

$$\text{Global Model}_j^{t+1} = \frac{1}{n} \sum_{i=1}^{n} wi.\, Model_i^{t+1}$$

where n is the number of vehicles participating in the update, and w_i is the weight assigned to each V_i update, which is proportional to the size of the local dataset or based on the quality of the update.

Step 6: Data Transmission and Update Sharing

Vehicles transmit their aggregated models during their assigned time slot

$TX_{model,j} \leftarrow \text{Global Model}_j^{t+1}$

Step 7: Adaptive Communication and Learning

After transmission, the communication channel is re-evaluated, and vehicles adapt their transmission strategies.

$$SINR_i(t+1) \leftarrow \frac{Pi \cdot Gi,j}{\sum_{k \neq 1} Pk \cdot Gk,j + Nj}$$

If SINR drops, vehicles adapt by selecting a better communication channel or adjusting transmission power. Vehicles adjust their learning rate or other training parameters based on the quality of communication, $\eta(t+1) = \eta(t) \cdot \text{Adaptation Factor}$, where the Adaptation Factor depends on factors like latency and SINR.

Step 8: Periodic Global Model Update and Synchronisation

Periodically, vehicles synchronise with the central server or other vehicles to update the global model. The central server aggregates models from all vehicles and distributes the updated global model.

$$\text{Global Model}_{server}^{t+2} \leftarrow \frac{1}{m} \sum_{j=1}^{m} wi.\, Model_j^{t+1}$$

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4.2 Cooperative Decision-Making in CAVs with GNN and MPC

CAVs are represented as a graph $G = (V, E)$, where V is the set of vertices representing the vehicles in the fleet, and E is the edges representing the communication links between vehicles. Each vehicle $V_i \in V$ is associated with a feature vector $x_i \in R^d$, where d is the dimension of the feature space that encodes information such as position p_i, speed s_i direction d_i, and status $stat_i$ as idle or active. Edges have features representing the nature of vehicle interactions, such as distance or communication quality $E = [e_{ij}$ for $(V_i, V_j) \in E]$. The message m_{ij} sent from node V_j to node V_i is defined as $m_{ij} = \mathrm{Msg}(x_j, x_i, e_{ij})$. The updated state of node V_i is computed by aggregating messages from its neighbours

$$x_i^{(t+1)} = \mathrm{Aggregate}\ (\{m_{ij} \mid j \in N(i)\}) + x_i^{(t)}$$

where $N(i)$ is the set of neighbours of node V_i, and t denotes the iteration step in the message-passing process. The vehicle updates its state based on the aggregated messages

$$x_i^{(t+1)} = \mathrm{Update}(x_i^{(t)}, m_i)$$

This iterative process allows vehicles to adapt their states based on the collective information from the fleet, leading to improved decision-making. The information sharing and effective action coordination among vehicles can be mathematically formulated as an optimisation problem aimed at minimising a collective loss function across all vehicles in a fleet. The primary goal of cooperative decision-making among CAVs is to optimise their collective behaviour while considering individual vehicle objectives. This optimisation can be framed mathematically as $\min_u \sum_{i=1}^{n} Li(xi, u)$ where u represents the control inputs for the vehicles (e.g., acceleration, steering angle), $L_i (x_i, u)$ is the loss function for vehicle V_i, which quantifies its performance based on its state x_i and the shared control inputs u and n is the total number of vehicles in the fleet.

4.1 State-Space Representation of CAV Dynamics

The dynamics of a CAV can be represented using a state-space model. Let the state of the vehicle at the time t be represented as $X(t) = [\, x(t), y(t), \phi(t), v(t)]^T$ where $x(t)$ and $y(t)$ are the V_i position coordinates, $\phi(t)$ is the heading angle, and $v(t)$ is the velocity. The control inputs are defined as $u(t)=[a(t), \delta(t)]^T$ where a(t) is the acceleration and δ(t) is the steering angle. The V_i dynamics can be described by the following kinematic equations $\dot{x}(t) = v(t) \cos(\phi(t))$, $\dot{y}(t) = v(t) \sin(\phi(t))$, $\dot{\phi}(t) = v(t)/L \tan(\delta(t))$ and $\dot{v}(t) = a(t)$ where L is the distance between the front and rear axles. MPC optimises the control inputs over a finite prediction horizon N to minimise a cost function J,

$$J = \sum_{k=0}^{N-1}(\alpha.\ \mathrm{cost}_{\,travel}(t+k) + \beta.\ \mathrm{cost}_{\,collision}(t+k))$$

where $\mathrm{cost}_{travel}(t) = \text{travel time}(t) + \text{fuel consumption}(t)$ and collision $\mathrm{cost}_{collision}(t) = \sum_{j=N} collision\ risk(t, j)$ where N represents neighbouring vehicles and pedestrians. The GNN predicts the future trajectories of surrounding vehicles based on historical data and is represented as $X_{pred}\ (t+k) = f(h_i^{(t)}, u(t), k)$ where f is a function learned by the GNN that outputs the predicted state. The predicted trajectories from the GNN are incorporated into the MPC optimisation problem. The MPC then updates its cost function to include collision avoidance constraints based on these predictions

$$J = J + \lambda\ .\ \sum_{k=1}^{N} collision\ risk\ (X_{pred}\ (t+k))$$

where λ is a weighting factor that adjusts the importance of collision avoidance. The MPC continuously re-optimises control actions based on the updated state predictions from the GNN, enabling adaptive trajectory management in dynamic environments.

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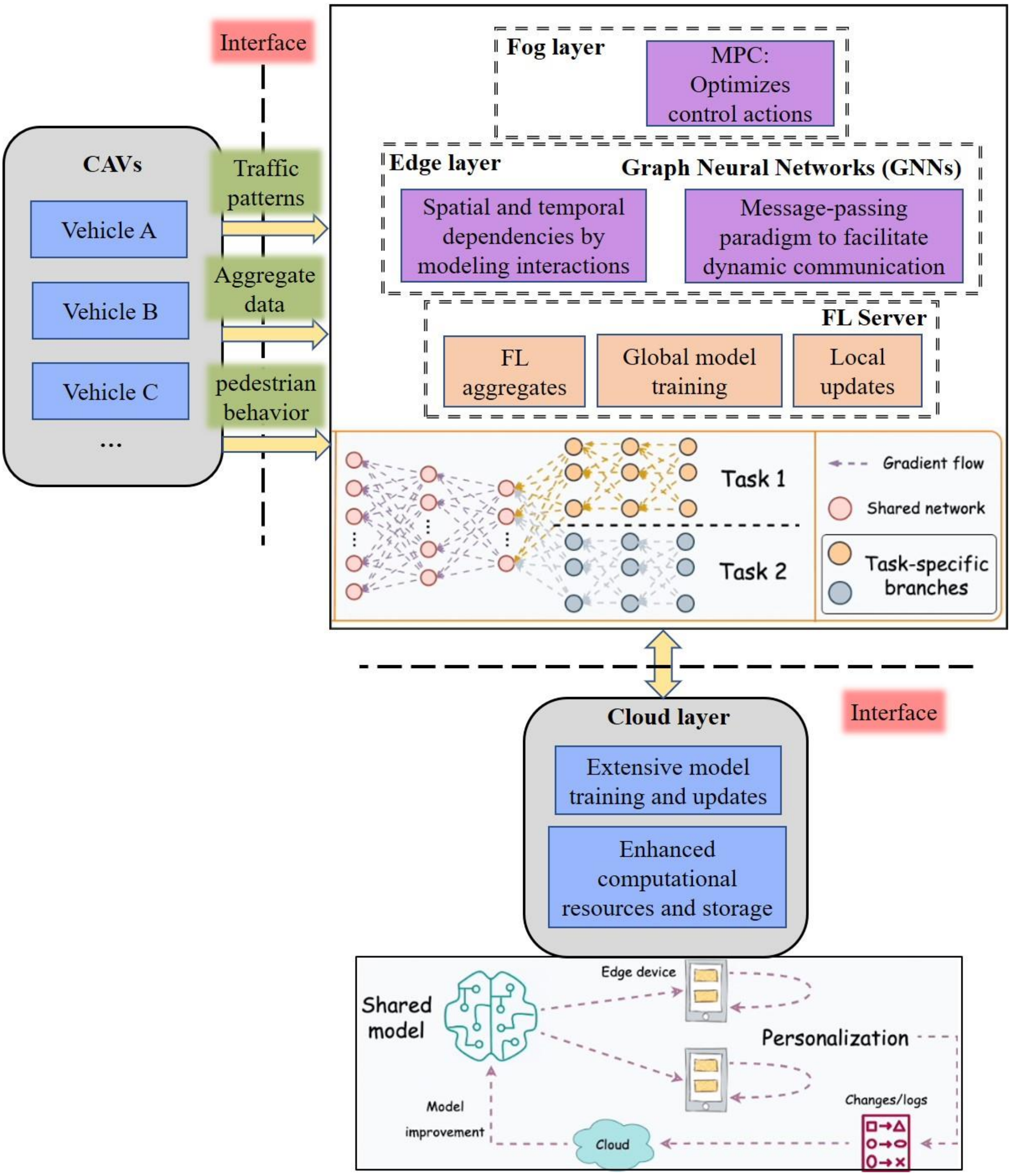

Fig.3: FedCAV for collaborative perception, dynamic communication, and model adaptation in CAVs

4.2 Model Personalisation with Cloud Analytics

The Cloud Layer functionality aggregates local models, performs extensive training with regularisation, personalises models for individual vehicles, and manages storage and retrieval of model data. After updating the global model, the Cloud Layer supports model personalisation by tailoring the global model to specific vehicles based on their unique environments or preferences. Each V_i receives a personalised model $Model_i^{personal}$ from the Cloud $Model_i^{personal} = Global\ Model^{t+2} + \Delta_i$ where Δ_i is the personalisation term that accounts for Vi's specific conditions or preferences. The personalisation term can be derived from V_i unique data or feedback and is typically small compared to the global model. The cloud receives periodic updates or feedback from edge and fog layers to continually improve the shared model, with each V_i sending feedback on the model performance, $feedback_i^{t+3}$, which can be used to refine the global model further

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$$\text{Model}_{\text{improved}}{}^{t+4} = \text{Global Model}^{t+2} + \frac{1}{N}\sum_{i=1}^{N} Feedback_i{}^{t+3}$$

The feedback may include error rates, performance metrics, or other indicators that help improve the model in future iterations. This setup ensures that the federated learning process is scalable, efficient, and adaptable to the dynamic needs of CAVs.

5. Performance Analysis

The inference from the key latency components in the V2V communication using an FL-DSRC algorithm highlights several critical aspects of the communication process and their impact on overall latency. Local model training introduces variability in latency, primarily influenced by the dataset size and model complexity. In a hypothetical scenario with 10 vehicles, the estimated latency is approximately 210 ms, with local model training contributing the most at 80 ms, followed by data transmission at 40 ms, and channel sensing and access at 10 ms. This sample (Table 1) demonstrates how various stages of optimisation contribute to the overall reduced latency in FedCAV:

Table 1. Estimated Latency of Federated Learning Components in a Vehicular Network

Component	Estimated Latency (ms)
Network Initialization	20
Local Model Training	80
Channel Sensing and Access	10
Time Slot Assignment	5
Model Aggregation	10
Data Transmission	40
Adaptive Communication	5
Periodic Global Model Update	30
Total Estimated Latency	**210 ms**

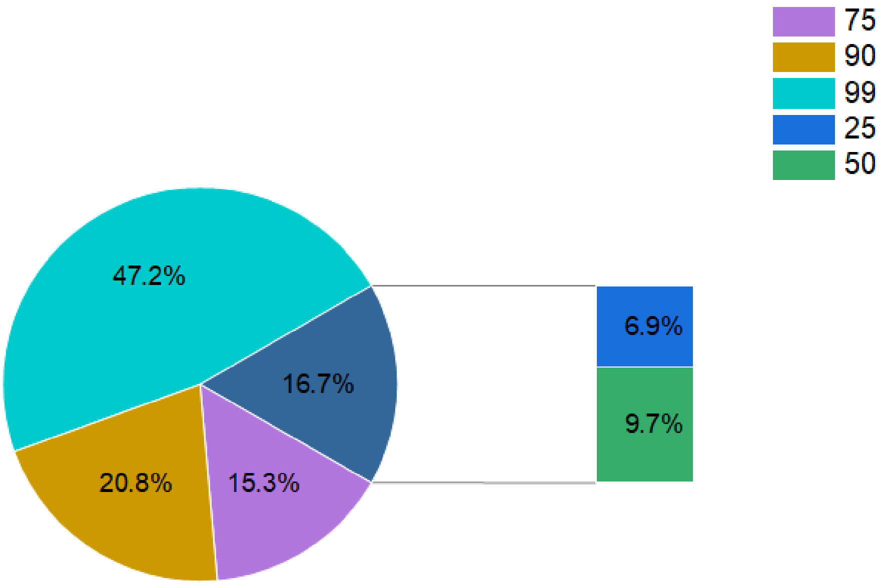

Fig.4: FedCAV latency measure

The relatively low first-byte latency observed in the FedCAV system significantly enhances communication efficiency. With initial latency values starting at 25 ms and only rising to 34 ms at the highest observed level, the system demonstrates a robust capability to maintain swift communication among vehicles. This efficiency is important for real-time decision-making and data sharing, enabling vehicles to respond promptly to dynamic road conditions and traffic scenarios. The gradual increase in communication time relative to latency indicates that the system can effectively manage higher loads without a drastic decline in performance, thereby supporting seamless interactions among connected vehicles. As a result, the FedCAV framework optimises operational efficiency and enforces a safer driving environment by ensuring that vehicles

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can communicate effectively and adaptively in real time. This positive relationship between low latency and enhanced communication efficiency underscores the potential of FedCAV systems to revolutionise the landscape of CAVs.

Table 2 First-byte latency and time

	Time (ms)
First-byte Latency	Proposed FedCAV
25	5
50	7
75	11
90	15
99	34

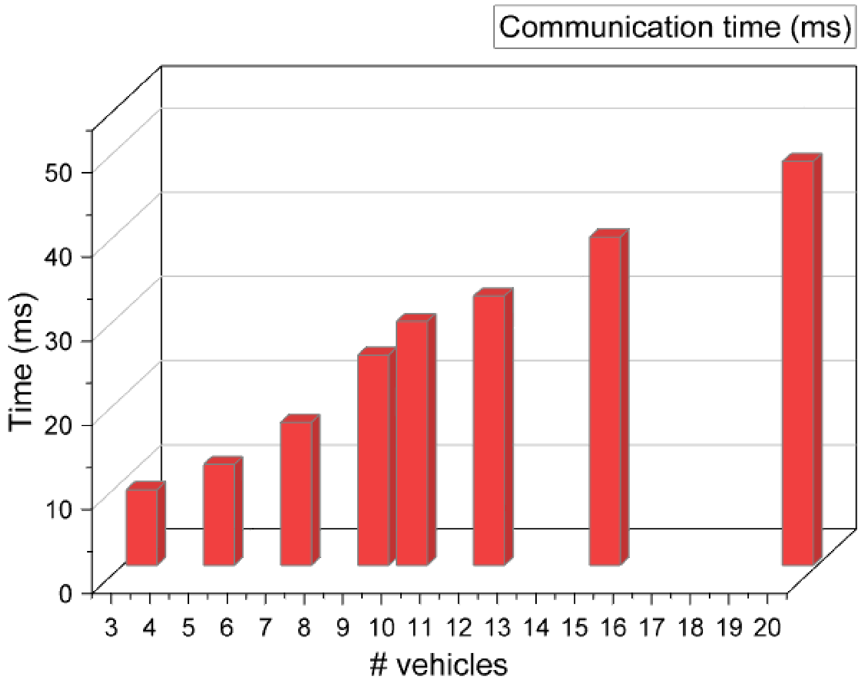

Fig.5: Communication times versus number of vehicles

The plot in Figure 5 shows a clear trend where communication time increases with the number of vehicles. There is a positive correlation between the two variables. The increase in communication time is not linear, with more evident escalation as the number of vehicles grows. For instance, the communication time increases by 3 ms from 3 to 5 vehicles (9 ms to 12 ms) and by 4 ms from 9 to 10 vehicles (25 ms to 29 ms). As the number of vehicles rises, the communication time escalates due to increased data-sharing demands among vehicles, greater complexity in managing communication, and possible interference and delays in data transmission.

6. Practical implications in real-world scenarios

- ✓ By utilising V2V communication, CAVs share real-time data about their ambiences, improving situational awareness and reducing the likelihood of accidents through collaborative decision-making.
- ✓ The integration of edge, fog, and cloud computing allows predictive analytics to predict traffic conditions, enabling better traffic flow management and reducing congestion through coordinated vehicle interactions.
- ✓ The multi-layered architecture supports local decision-making through onboard sensors, allowing vehicles to respond immediately to dynamic environments, thus enhancing responsiveness in driving behaviour.
- ✓ The decentralised approach prevents failures and enables vehicles to operate autonomously, even in challenging conditions.
- ✓ The Cloud analytics for model personalisation enables custom-configured driving models to individual vehicle conditions and preferences, enhancing user experience and operational efficiency.

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7. Conclusion

In this work, the FedCAV framework is presented as a robust multi-layered architecture that effectively integrates edge, fog, and cloud computing to enhance the performance of CAVs. The system optimises communication efficiency and reduces latency using federated learning, graph neural networks, and model predictive control. It also facilitates real-time decision-making and adaptive vehicle interactions, ultimately contributing to a safer and more responsive driving environment. The performance analysis indicates that while local model training significantly contributes to overall latency, the system maintains low first-byte latency and efficiently manages higher communication loads, promoting real-time responsiveness and safety in dynamic driving environments. Future research directions should prioritise enhancing the scalability of federated learning algorithms to support larger vehicle fleets while ensuring effective low latency. Advanced optimisation techniques can be explored for real-time decision-making and adaptive communication strategies in highly dynamic environments to maximise system performance and resilience in diverse traffic scenarios.

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