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A Survey of Federated Learning for Connected and Automated Vehicles

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Abstract— **Connected and Automated Vehicles (CAVs) represent a rapidly growing technology in the automotive domain sector, offering promising solutions to address challenges such as traffic accidents, congestion, and pollution. By leveraging CAVs, we have the opportunity to create a transportation system that is safe, efficient, and environmentally sustainable. Machine learning-based methods are widely used in CAVs for crucial tasks like perception, planning, and control, where machine learning models in CAVs are solely trained with the local vehicle data, and the performance is not certain when exposed to new environments or unseen conditions. Federated learning (FL) is a decentralized machine learning approach that enables multiple vehicles to develop a collaborative model in a distributed learning framework. FL enables CAVs to learn from a broad range of driving environments and improve their overall performances while ensuring the privacy and security of local vehicle data. In this paper, we review the progress accomplished by researchers in applying FL to CAVs. A broader view of various data modalities and algorithms that have been implemented on CAVs is provided. Specific applications of FL are reviewed in detail, and an analysis of research challenges is presented.**

I. Introduction

Connected and automated vehicles (CAVs) are the key to future intelligent transport systems. With the advent of big data, the Internet of things (IoT), edge computing, and intelligent systems, CAVs have the potential to improve the efficiency of the overall transportation system, and reduce traffic accidents, congestion, and pollution. Robust network communication and significantly increased internet speed are expected to be guaranteed with the onset of advanced communication infrastructures. Currently, CAVs are generating a tremendous amount of raw data, up to one to two terabytes per vehicle per day [1] from various sources like engine components, electronic control units (ECU), perception sensors, and vehicle-to-everything (V2X) communications. This large amount of data is sent to the cloud continuously or periodically for monitoring, prognostics, diagnostics, and connectivity features [2]. These data are also private and come under strict privacy protection regulations in various regions. One such example is the General Data Protection Regulation (GDPR) in the European Union [3]. Even with the development of advanced machine learning (ML) techniques and vehicle connectivity, it has not been feasible to have a centralized framework to collect data from every vehicle and train an ML model securely. These limitations led to the development of a new ML paradigm known as Federated Learning (FL) [4], [5].

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FL is a new technology breakthrough that has been actively implemented in several application domains. FL has been coined by Google [6] and was initially used for mobile keyboard prediction in Gboard [7] to allow multiple mobile phones to cooperatively and securely train a neural network (NN) model. In FL, the edge devices/clients only send the gradients or the learnable parameters to the cloud server rather than sending massive local datasets in a Centralized Learning (CL) framework. The cloud server performs a secure aggregation [8] of the received gradients/weights and updates the global model parameters that are transmitted back to the clients/edge devices. This procedure, known as a communication round, continues iteratively until the convergence criteria are met in the global model optimization. The key advantage of FL is reducing the strain on the network while also preserving the privacy of the local data. FL is a potential candidate that can utilize the data available from each CAV and develop a robust ML model.

In this survey, we provide a comprehensive survey of FL for CAV (FL4CAV), including diverse applications and key challenges. The FL4CAV concept is illustrated in Fig. 1.

Despite the mutual benefits of connectivity between vehicles, the issues of invasion of privacy, accuracy, effectiveness, and communication resources are essential problems to be addressed. FL frameworks have received attentions for their

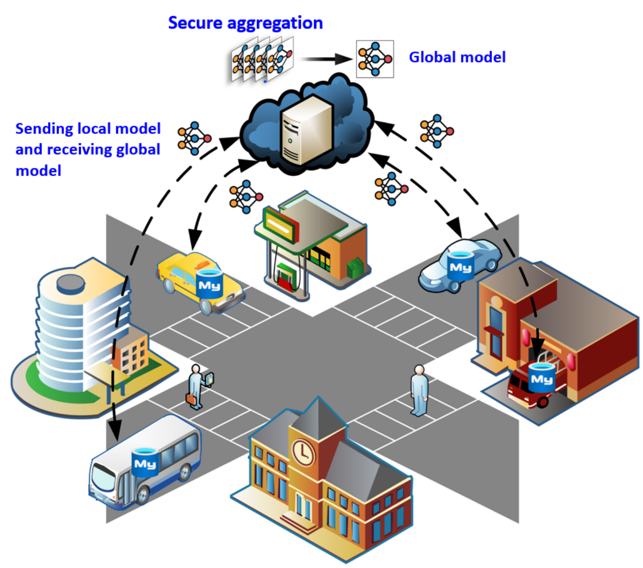

Fig. 1. Federated learning for CAV (FL4CAV).

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TABLE I
COMPARISON OF ML APPROACHES IN CONNECTED AND AUTOMATED VEHICLES

Features	**Edge Learning (On-Vehicle only)**	**Centralized Learning**	**Federated Learning**
Model training	Local vehicle	Central server	Local vehicle training and central server aggregation
Model applicability	Personalized model	Single global model	Single global model but can be personalized
Privacy protection	✓✓	✗✗	✓
Learning efficiency	✗	✓	✓✓
Performance on heterogeneous/anomaly data	✗	✓✓	✓
Communication (Data transmission) requirement	✓✓	✗✗	✗
Training data volume	✗✗	✓✓	✓
Current research progress	✓✓	✓✓	✗
Compatibility with CAVs	✓	✗✗	✓✓

✓✓ best, ✓ high, ✗ low, ✗✗ worst.

natural ability to preserve privacy by transmitting only model data between the server and its clients without including local vehicle data. In particular, the model data packets are smaller than the user data, thus saving the consumption of communication resources. Recently there have also been efforts on training decentralized FL that allows multiple vehicles to collaboratively train a model without needing a central server [9], [10].

After a review of data modality, data security and algorithms in CAV, this survey focus on most of the critical applications of FL4CAV, such as steering wheel angle prediction, vehicle trajectory prediction, object detection, motion control application, and driver monitoring. This survey also highlights the current challenges and future research directions of FL4CAV. A detailed comparison of the on-device vehicle training, CL, and FL approach is described in Table I.

The remainder of this paper is organized as follows: Section II highlights the diverse data modalities, data securities, and algorithms of FL in CAVs. Section III reviews the application of FL in CAVs with detailed examples. The multi-modal data, algorithms, and datasets used in the relevant literature are also summarized. Current challenges are discussed in Section IV and Section V presents the conclusion of this study and outlines future work.

II. OVERVIEW OF DATA MODALITIES, DATA SECURITIES AND ALGORITHMS

Each CAV as a client, undertakes sensing data acquisition, signal processing, storage, communication, perception, and decision-making. For sensing data acquisition, a variety of sensors are integrated into CAVs, including Global Navigation Satellite Systems (GNSS), multi-modal cameras, Radio Detection And Ranging (RADAR), Light Detection And Ranging (LiDAR), and Inertial Measurement Unit (IMU) to capture the vehicle, driver, passenger, and external information.

The tasks for CAVs are also diversified, including target speed tracking, behavior prediction, object detection, driver monitoring, and more. After training on an ML models with local data, clients send the trained model to the server. Then, the server shares a generalized model with clients for perception, prediction, and decision-making purposes. The FL4CAV framework shows a trend towards multi-modal sensing data, massively parallel clients, and multi-class tasks. Recent efforts have been conducted to understand the applicability and challenges of implementing FL to CAVs [11]–[15]. A detailed overview of the data modalities of CAVs, data security, and FL algorithm is presented below.

A. Data Modality

CAVs collect multi-modal data from various sensors to conduct tasks, such as navigation, perception, and etc. The FL training process involves vehicles that may have a different variety of sensors. The data collected by sensors depend on the sensor type, the sensor's range, the accuracy/precision of the sensor, sensor placement, and the operating environment. The operating environment, such as snow, heavy rain, or fog, can reduce the sensor visibility, thereby deteriorating the data quality. These factors lead to variations that can significantly affect the sensor performance. The performance of the FL model is directly dependent on the quality of the data collected by vehicles. The data resolution, size, sampling rate, etc., obtained from CAVs are generally heterogeneous, and processing the data is also a challenging task. Hence a detailed review is presented to understand the various data modalities in FL4CAV applications.

Images, especially visible RGB images, are one of the most important data modalities for CAVs. Vision-related tasks such as steering wheel angle prediction III-B, Traffic sign recognition [16], semantic segmentation [17], object detection III-D, and driver monitoring [18] use images captured by the camera as the data source. In most applications, a variant of the Convolutional Neural Network (CNN) model is trained to achieve the intended functionality. However, due to its intrusive design, privacy issues are always criticized for image-based systems, especially for in-cabin, and driver-related applications [18]–[21]. FL focuses on the model parameters and ignores the data, which addresses the drawback that visual image-based systems tend to compromise user privacy. Moreover, FL also solves the data transmission problem caused by the inflated data size of images and videos, leading to a more efficient learning framework.

LiDAR data provides a solid foundation for autonomous driving capabilities. LiDAR data have also been utilized for object detection tasks [22]–[24]. LiDAR generates 3D point clouds that can detect objects accurately even under adverse weather conditions, unlike cameras that are not robust. However, the dense point cloud of LiDAR data makes transmission a daunting task. Therefore, compared with the image-based FL systems, the system of FL for LiDAR data is more interested in improving learning efficiency and saving communication resources.

Vehicle status data such as vehicle position, velocity, acceleration, throttle/brake command and other vehicle parameters are also an important part of the CAV data modality, which reflects more about the vehicle rather than external information. These data can reveal sensitive information about the driver's location, habits, and behaviour that could potentially compromise their privacy and security. FL provides the best solution that could address these privacy concerns while utilizing these data for improving several applications such as collision avoidance [25], vehicle trajectory prediction III-C, and motion control application III-E. Techniques such as Recurrent Neural Networks (RNN), Transformer and Reinforcement Learning (RL) are generally used for training these time-series data.

B. Data Security

Robust and secure privacy-preserving techniques are essential for protecting sensitive data during the FL process for CAVs. It is demonstrated that the FL process can still be vulnerable to various malicious attacks, such as when one or more participants are compromised, and they could transmit false parameters to hinder the global model performance. The FL central server is also prone to attack and thereby causing the entire learning process to collapse [26].

Homomorphic Encryption, Secure Multi-Party Computation, Differential Privacy, and Blockchain-based techniques are few of the widely employed methods for preserving privacy in FL4CAVs. These approaches aim to maintain and minimize the trade-offs between model performance and data privacy thereby ensuring the data security while enabling effective model performance.

Differential Privacy (DP) is a widely used approach that safeguards data privacy by injecting random noise into the data before transmitting it to the server, preventing unauthorized extraction of sensitive information. Another disruptive technology gaining traction in CAV applications is blockchain-based methods, leveraging the decentralized and tamper-resistant nature of blockchain to enhance data integrity, transparency, and security [27]–[33]. Blockchain is a type of digital ledger technology that securely transfer data in a decentralized framework. Data from CAVs share their data with the vehicular network, and the information is stored on the blockchain. The system is designed to protect data privacy and data security as well as to provide higher security to the overall vehicular networks engaged in the learning process [34]. A detailed analysis of various privacy preservation approaches is presented in [35].

C. Federated Learning Algorithm

Most of the existing literature uses the FedAvg algorithm [6] for the FL aggregation process in the server—see Table II. FedAvg applies Stochastic Gradient Descent (SGD) optimization on local vehicles and does a weighted averaging of the weights from the vehicles in the central server. FedAvg performs multiple local gradient updates before sending the parameters to the server, reducing the number of communication rounds. For FL4CAV, data on each CAVs are dynamically updated at each communication round—see Algorithm 1.

Algorithm 1 FedAvg for Dynamic Data Updating CAVs

Input: Vehicle set $\mathbb{V}$, communication rounds T, isolated time-varying local dataset $\xi = \{\xi_v^{(t)} : v \in \mathbb{V}\}$, local epochs E, learning rate η, loss function f
Output: Aggregated global model w

```
Initialize w_0
for t = 0, ..., T − 1 do
    Perform local SGD for vehicle v ∈ 𝕍 in parallel do
        Sample ξ_v^(t), compute g_v^(t) := ∇̃ f_v(w_v^(t), ξ_v^(t))
        w_v^(t+1) ← w_v^(t) − η_t g_v^(t)        ⟹ SGD (E epochs)
    end for
    w^(t+1) ← Σ_{v∈𝕍} (|ξ_v^(t)| / |ξ^(t)|) (w_v^(t+1))   ⟹ FedAvg
end for
Output the aggregated global model w ← w^(T)
```

Data heterogeneity, client drift, and data imbalance from clients have proved to significantly impact the performance of FedAvg optimization resulting in unstable convergence. The data obtained from CAVs are typically non-independent and identically distributed (non-IID). There is a need to develop an FL framework that could perform well with the varying data distribution from CAVs. FedProx [36] algorithm combines FedAvg with a proximal term to improve convergence and reduce communication cost. Fed-ADAM [37] has shown improved convergence and optimization performance by incorporating ADAM optimization in FedAvg algorithm. Dynamic Federated Proximal (DFP) algorithm is an extension of the Federated Proximal Algorithm (FPA) that can effectively deal with non-iid data distribution by dynamically varying the learning rate and regularization coefficient during the learning process [38]. Federated Distillation (FD) [39] uses knowledge distillation to transfer knowledge in a decentralized manner leading to a significant reduction in the communication size compared to a traditional FL and also can have the ability to handle non-iid data samples [40]. There have been efforts to address the client heterogeneity, and it is an ongoing research area [41]–[44].

TABLE II

LITERATURE OVERVIEW OF FL APPLICATION TO CAVS

Literature	Time	Data Modality	Application	Base Model	FL Algorithm	Dataset
[45]	2020	Time series data of multiple features from sensors	Turn signal prediction	LSTM	FedAvg	Ford's Big Data Drive [45]
[46]	2020	Time series - Traffic flow	Traffic flow prediction	GRU	FedAvg	Caltrans Performance Measurement System (PeMS) dataset [47]
[48]	2021	RGB image	Steering angle prediction	Two-stream CNN	Async FL	Self-collected
[49]	2021	RGB image	Steering angle prediction	Self-defined CNN	FedAvg	Self-collected
[22]	2021	RGB image and LiDAR	Object detection	YOLO CNN	FedSGD	Canadian Adverse Driving Conditions Dataset [50]
[51]	2021	Trajectory data	Vehicle cooperative positioning	MLP	FedVCP	Didi Chuxing GAIA Initiative [52]
[53]	2021	RGB image	Traffic sign recognition	CNN	TFL-CNN	BelgiumTS [54]
[55]	2021	Traffic accident data	Traffic accident prediction	MLP	Dynamic FL Economic Framework	1.6 million UK traffic accidents [56]
[38]	2022	RGB image and trajectory data	Target speed tracking	Self-defined NN	DFP (FedAvg for aggregation)	Berkeley deep drive [57] and dataset of annotated car trajectories [58]
[16]	2022	RGB image	Traffic sign recognition	LeNet-5	FedAvg	German Traffic Sign Recognition Benchmark [59]
[17]	2022	Multi-modal image	Semantic Segmentation	BiSeNet V2	FedAvg + Variants	Cityscapes [60] and IDDA [61]
[23]	2022	RGB image and LiDAR	3D object detection	U-Net	HFCL (FedAvg for aggregation)	Lyft Level 5 dataset [62]
[63]	2022	Vehicle position, velocity and acceleration + Driver behavior	Trajectory prediction	LSTM	FedAvg+Variants	US-101 and I-80 data sets of NGSIM [64]
[25]	2022	Vehicle position, velocity and acceleration	Collision avoidance	Deep RL	SFRL (FedAvg for aggregation)	Self-generated
[20]	2022	RGB image	Driver activity recognition	ResNet-56	FedGKT	State Farm Distracted Driver Detection [65] and AI City Challenge 2022 [66]
[67]	2022	Time series - Vehicle speed	Traffic flow prediction	LSTM	FedNTP	CRAWDAD Vehicular dataset [68]
[69]	2022	RGB image	Driver activity recognition	ResNet18	Efficient hierarchical asynchronous FL (EHAFL)	State Farm Distracted Driver Detection [65] and YawDD [70]
[18]	2023	RGB image	Driver activity recognition	ResNet-34	FedProx + Variants	State Farm Distracted Driver Detection [65] and Drive&Act [71]
[21]	2023	RGB image	Driver fatigue detection	Bayesian CNN	FedSup	Blinking Video Database [72] and Eyeblink8 [73]

III. APPLICATIONS OF FL FOR CAV

This section reviews a few important applications in detail of FL in CAVs. The FL4CAV literature, including data modalities, underlying models, applications, and datasets, are highlighted in Table II. Different applications on CAV are highly dependent on different strengths of FL, such as protecting privacy, improving learning efficiency, enhancing generalization ability, reducing communication overhead, etc.

A. In-Vehicle Human Monitoring

FL has the potential to enhance the security of user data on board, while enabling knowledge transfer and ensuring the generalization ability of the model. However, in human-related applications where data is highly heterogeneous and personalized, it can be challenging to balance the generalization ability of the model with the need for personalization to specific users [74].

Driver monitoring applications, such as distraction detection, are critical safety features that monitor the driver's steadiness and alertness, and warn the distracted driver to apply safety-critical actions [20], [21]. Driver privacy may be a bigger concern than steering wheel angle prediction and object recognition, leading to FL's ability to be more highlighted in terms of privacy protection. However, the driver monitoring application is a highly personalized application where the driver's behavior is strongly associated with personal habits, emotions, cultural background, and even the interpretation of instructions. For human-related applications like driver monitoring, personalized FL is the dominant solution [18].

Passenger monitoring applications are an emerging research area that involves detecting passenger intents of boarding and alighting and warning of dangerous behavior in public transportation [75]. However, this field has not yet received much attention due to the lack of available datasets and the difficulty of monitoring multiple users simultaneously. Nevertheless, the ability of FL to integrate knowledge about public transportation and the growing demand for passenger monitoring makes it a promising application in this area.

B. Steering Wheel Angle Prediction

Steering wheel angle prediction needs to adapt for different driving and environment conditions and thus requires continuous model updates for high accuracy. FL provides these opportunities by combining several vehicles to collaboratively learn from new data and update the model in relatively short time. FL offers the benefit of continuous and collaborative learning, low communication overhead and data security that is needed to develop a robust prediction model. The steering wheel angle is predicted from the RGB images collected from the front-facing camera as input, which can be further trained by a CNN model. [76], [77]. Related literature has demonstrated that FL can collaboratively train the prediction model at a significantly lower communication cost while also preserving privacy and achieving similar performance as centralized learning [48], [49], [78].

C. Vehicle Trajectory Prediction

A robust vehicle trajectory prediction allows CAVs to perform proper motion planning as well anticipate potentially dangerous behaviors of other vehicles, such as sudden lane change, skidding, or hard braking, in order to react proactively and prevent accidents [79]. This is a challenging task and would requires substantial amounts of vehicle data for training a model. FL proves to be viable solution that provides a collaborative learning framework with multiple vehicles while keeping the sensitive local data private and secure. It has been reported that the FL approach achieves a similar performance over centralized learning [63], [80].

FL models are trained on diverse data from various vehicles operating in different scenarios. This enhances the model's generalization and enables autonomous vehicles to handle rare events like traffic accidents, adverse weather, and risky behaviors. Additionally, the FL framework supports continuous learning and model updating, allowing quick adaptation to dynamic traffic, road conditions, and unfamiliar scenarios.

D. Object Detection

Object detection is one of the main functions of the visual perception system intended to detect and localize objects using sensor data such as LiDAR and high resolution image/video. These data are large in size and sensitive in nature. As a result, there are limitations to deploying robust detection models on a traditional centralized learning approach due to privacy and communication overhead. These concerns can be mitigated through the use of a FL-based approach for CAVs. FL can effectively help CAVs detect diverse objects in different driving scenarios, road types, traffic conditions, and weather types. FL enables the CAV framework to learn efficiently with low communication overhead, which is particularly advantageous when the volume of data is much larger than the size of the model while also ensuring the privacy of the data.

FL has already been in practice much before for computer vision-related tasks such as developing safety hazard warning solutions in smart city applications [81]. Object detection accuracy generally struggles under adverse weather circumstances such as snow. It has demonstrated that the CNN-FL framework improves the detection accuracy and performs better than the centralized and gossip decentralized models [22]. Recently there have been numerous studies to improve the performance of FL on complex tasks like object detection [82]. A hybrid federated and centralized learning (HFCL) framework was proposed that allows vehicles with computational resources to be part of the FL training process while the others transmit their local data to the server like a centralized learning process. The trade-off between the computational and communication overhead of the vehicles is addressed. The performance of HFCL is not shown to be better than a centralized learning approach in this example [23] and is a subject for further research and improvement. It is demonstrated that with multi-stage resource allocation and robust device selection, the performance of FL significantly improved compared to traditional centralized learning and baseline FL approaches [83].

E. Motion Control Application

FL approach enables CAVs to train and optimize controller parameters collaboratively. A few potential benefits are enabling CAVs to adapt to unseen routes/traffic scenarios or operating conditions because of past data from other CAVs, on-ramp acceleration, driving in congested traffic scenarios, and so on. FL enables CAVs to quickly adapt to different driving scenarios, including unfamiliar and unvisited roads, cities, and countries. Additionally, FL may enable CAVs to adjust driving styles based on different driving habits, climates, scenarios, and cultural norms.

FL offers significant benefits in enabling CAVs to swiftly adapt to changing driving environments, thereby enhancing safety, comfort, energy efficiency, and overall driving experience. FL has been employed to dynamically update control parameters, resulting in improved target speed achievement with enhanced driver comfort and safety [38]. Additionally, FL finds application in optimizing control parameters collaboratively across CAVs at traffic intersections, leading to collision avoidance and improved driving comfort [84].

IV. Future Challenges

In this section, we review various challenges in the state-of-the-art technology and the future scope of research.

A. Resource Limitations

1) Massively parallel CAVs raise questions about collaboration capabilities, management, and resources: Huge CAVs participation in FL could increase the solve time, memory utilization, and therefore the computational power for the global model update. In particular, the vision-related perception tasks have concerns such as high communication costs and not being flexible towards heterogeneous datasets. Decentralized FL and Clustered FL [85] are also being explored to reduce the communication overhead.

2) Lack of sufficient real-world datasets, simulators, and pre-trained base models: There is a need for more real-world datasets (different weather conditions and traffic scenarios), realistic high-fidelity FL4CAV simulators for seamless FL integration [83], and good pre-training models. Federated transfer learning is a new approach that has been adopted to improve the model performance, and accuracy [18], [31].

B. Imperfect Methodology

1) Privacy and security issues: Massive data also leads to privacy and security concerns. This problem must be addressed to train the ML model efficiently without compromising on the model's accuracy and redundancy.

2) Lack of robust approach for vehicle selection and resource allocation: Currently, there is no popular mechanism that can select non-redundant data from CAVs to minimize the network strain. There are ongoing efforts to develop robust methods to select vehicles and resource allocation schemes [86]–[88]. In [89], the overall training process was demonstrated to be efficient due to incorporating a client selection model. The setup looks at the resource availability of the clients and then determines the clients eligible to be part of the FL global model learning process. In [80], it is demonstrated that the model performance was improved with CAVs that were selected by a trust-based deep reinforcement.

3) Catastrophic forgetting: CAVs cannot keep all user data due to storage capacity limitations, and new data will always be generated during iteration. Therefore, when the FL framework is updated on new data in iteration—see Algorithm 1, the global model forgets the previous knowledge and leads to catastrophic forgetting.

4) Lack of robust fairness and incentive mechanism: There is a need for a robust rewarding mechanism, since the amount of information shared by CAVs is different and highly inconsistent (Data imbalance). There needs to be a fair incentive mechanism to reward CAVs for their contributions.

C. Inadequate Evaluation Criteria

1) FL suitability evaluation for new users: It is often difficult for the newcomer vehicle to make any informed decisions. In [80], a trust-aware Deep RL model is proposed to assist new vehicles in making superior trajectory and motion planning decisions.

2) Need for high capability diagnostics: There are several noise factors that could influence the decision of the FL, such as faulty sensors in a visual perception case and incorrect imputation of missing data. The development of a robust diagnostic that can identify and eliminate the updates from these vehicles is needed.

V. Conclusion

In summary, FL is a new technology that has started to be applied in the CAV domain. This paper reviews various developments, data modalities, and algorithms of FL4CAV, and provides a broad list of applications of FL in CAVs.

We observe that FL4CAVs also presents unique challenges such as ensuring data integrity, addressing communication latency, managing heterogeneous data sources, and maintaining model synchronization across different vehicles. However, with proper design and implementation, FL can offer significant advantages in terms of privacy preservation, network efficiency, and collaborative intelligence for CAVs.

Further promising applications of FL in energy-efficient modeling, cooperative driving, anomaly detection, and predictive maintenance hold significant potential for enhancing the performance, safety, and efficiency of CAV systems. With the support of cloud infrastructure, 5G, and V2X technology, the adoption of FL models is expected to drive substantial advancements in the CAV domain, leading to an efficient, safe, and intelligent transportation system.

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