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Federated Learning for Vehicular Internet of Things: Recent Advances and Open Issues

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ABSTRACT Federated learning (FL) is a distributed machine learning approach that can achieve the purpose of collaborative learning from a large amount of data that belong to different parties without sharing the raw data among the data owners. FL can sufficiently utilize the computing capabilities of multiple learning agents to improve the learning efficiency while providing a better privacy solution for the data owners. FL attracts tremendous interests from a large number of industries due to growing privacy concerns. Future vehicular Internet of Things (IoT) systems, such as cooperative autonomous driving and intelligent transport systems (ITS), feature a large number of devices and privacy-sensitive data where the communication, computing, and storage resources must be efficiently utilized. FL could be a promising approach to solve these existing challenges. In this paper, we first conduct a brief survey of existing studies on FL and its use in wireless IoT. Then, we discuss the significance and technical challenges of applying FL in vehicular IoT, and point out future research directions.

INDEX TERMS Federated learning, IoT, vehicular networks, collaborative learning.

I. INTRODUCTION

With the advent of information and communications technology, it has become technically easier to collect a large amount of data, and therefore data-driven approaches are attracting great interests from both industry and academia. Traditional big data-based machine learning systems collect data to a certain location, such as the central servers. However, in recent years, privacy has been one of the most important concerns in the wide deployment of these big data platforms. Typically, data belongs to different parties, which may fail to exchange data among themselves due to privacy restrictions, such as General Data Protection Regulation (GDPR) [1].

In the Internet of Things (IoT) era, user devices generate a large amount of data that can be used to improve the user experience of a system. However, users are reluctant to provide their personal data due to the risk of data misuse and leakage. On the other hand, some IoT applications in vehicular environments, including cooperative driving, must make timely decisions based on different types of vehicle sensor data, including Global Positioning System (GPS), camera, radar, and so on. In addition, there are two main considerations. Firstly, while the cloud can process data and make decisions based on global information, collecting and transferring data from distributed agents to the cloud requires a high bandwidth and incurs a high delay. Secondly, while the distributed agents can process data based on local information and knowledge, the decisions made are normally influenced by local scenarios only, rather than reflecting the global scenarios.

In order to solve the aforementioned issues, FL has been proposed by Google [2] to allow multiple parties to jointly train a model, which consists of neural network parameters, while mitigating the privacy risks. In [2], multiple clients (or workers) cooperate with the central server to train a deep neural network model. The central server first disseminates an initial model of the training to the clients. Based on the model, each client calculates its local updates of the global model, such as stochastic gradient descent (SGD), based on its own local dataset. After a predefined training period, all clients send their own updates (SGD) to the central server, and the central server aggregates these updates to calculate a global model. Federated averaging (FedAvg) algorithm is introduced to aggregate local updates generated by the clients. These steps are repeated until the central server achieves a satisfactory global model. Since all local datasets gathered by the clients are not transferred and stored at the central server, data privacy is achieved.

Different from conventional decentralized learning approaches, FL is expected to achieve the following key advantages:

- *Better suitability for non-IID distributed and unbalanced data:* FL relaxes the assumption of independent and identically distributed (IID) data. While existing decentralized approaches basically assume an IID distribution of data among training agents, FL can achieve better performance in non-IID data by efficient client selection and using aggregation algorithms. FL is also capable of handling unbalanced data distribution. Different clients could have different sizes of data with different levels of importance. FL, which is based on a loose federation of clients and the leadership of the server, leads to an efficient handling of unbalanced data.
- *Low communication overhead:* FL reduces the size of communication data by only sharing the local updates of the global model between the central server and clients. It is also possible for FL to determine whether to choose a client for training or not depending on the available communication bandwidth, which ensure efficient communication and improved system performance.
- *Larger data for training:* Due to the low communication overhead and privacy-preserving feature, FL is able to involve a large number of participants, which is important for training a deep neural network model with high accuracy.

These advantages has facilitated the rapid expansion of interests in FL-based systems in various sectors, including smart phone applications, supply chain, healthcare, finance, and so on. Emerging vehicular IoT systems involve a larger amount of vehicle sensor data and various types of applications in complex vehicular environments where limited communication, computing and storage resources must be optimally utilized to support the quality-of-service (QoS) of each end user [3]. Meanwhile, novel services, such as cooperative autonomous driving and intelligent transport systems demanding unprecedented high reliability, high accuracy, and quick response, are emerging. Some services experience an extreme variance in their resource demands with respect to time, location, context, as well as individual users. Current vehicular IoT systems only consider the intelligence of a single vehicle agent or depend on the collection of vehicle data to the cloud, which is unable to satisfy the needs of emerging services. In addition, vehicles are equipped with different types of sensor devices that generate and handle privacy-sensitive data, and the environments vary with time and road types. In order to realize a more intelligent vehicular IoT system, a privacy-preserving collaboration among different vehicles and roadside units is needed urgently.

FL perfectly matches with these needs as it can efficiently utilize the computing capabilities of decentralized agents (vehicles) and preserve the privacy of the local data. However, due to the complex and dynamic feature of vehicular environments, the collaboration among a huge number of entities faces some challenges. Considering the limited communication resources in vehicular environments, mobile edge computing (MEC) [4]–[6] has been widely discussed in providing a short delay for end users by conducting data caching and computation offloading to end users nearby. MEC is expected to incorporate FL in order to achieve the level of true intelligence in complex vehicular environments. However, the deployment of FL in vehicular IoT encounters several key challenges. First, the selection of clients for FL should address the mobility, communication bandwidth, and the specific scenarios that the clients could represent. The consideration of mobility and communication bandwidth ensures a successful dissemination of the learning model and an accurate aggregation of local updates from the clients. The consideration of vehicle scenarios guarantees that selected data for training includes a wide range of samples, avoiding the overfitting for a non-representative scenario. Second, most vehicular IoT applications have stringent QoS constraints. This urges us to put more efforts on enhancing the FL architecture for a better fit for vehicular environments. Third, the dynamicity of vehicular environments makes the communication and computational resource allocation particularly difficult. Therefore, it becomes important to design efficient resource allocation algorithms that could satisfy the need of FL.

Due to the aforementioned issues, conducting an efficient learning in vehicular environments is a difficult scientific problem. It is important to design a FL scheme that could evaluate and improve one's own behaviors with a low communication overhead. In this paper, we give a survey on the technical challenges and existing solutions regarding the integration of FL with vehicular IoT, and discuss future research directions. The main contributions of this paper are as follows.

- This is the first survey paper discussing about the recent advances related to vehicular IoT and FL, as well as the application of FL in vehicular IoT-related scenarios.
- We not only discuss the technical challenges of applying FL in vehicular IoT, but also explain the necessary improvements that should be made for IoT technologies in order to support FL in vehicular environments.
- We describe possible future research directions related to the integration of FL and vehicular IoT, and provide

TABLE 1. List of Abbreviations

CIFG	Coupled Input and Forget Gate
CVS	Compressed video sensing
DRL	Deep reinforcement learning
DNN	Deep neural network
DGD	Deterministic gradient descent
DTN	Delay tolerant network
FAug	Federated augmentation
FD	Federated distillation
FedAvg	Federated averaging
FL	Federated learning
GAN	Generative adversarial network
GDPR	General data protection regulation
GPS	Global positioning system
IID	Independent and identically distributed
IoT	Internet of Things
IoV	Internet of Vehicles
ITS	Intelligent transport systems
LSTM	Long short-term memory
MEC	Mobile edge computing
MGD	Momentum gradient descent
ML	Machine learning
MPC	Multi-Party Computation
QoS	Quality of service
RSU	Road side unit
SGD	Stochastic gradient descent
SET	Sparse evolutionary training
STC	Sparse ternary compression
UAV	Unmanned aerial vehicle
URLLC	Ultra-reliable low-latency communications
V2X	Vehicle-to-everything
VANET	Vehicular ad hoc networks
VR	Virtual reality

some new concepts and ideas that could promote the related studies.

The remainder of the paper is organized as follows. We first introduce the fundamentals of FL covering definitions, classifications, basic algorithms, and procedures in Section II. Then, we give a literature review on the recent advances of FL in Section III. Section IV addresses the technical challenges and existing solutions for the use of FL in wireless IoT environments. By reviewing the open problems and recent efforts on the use of FL in vehicular environments, Section V discusses the potential advantages and technical issues of using FL in vehicular IoT. Section VI points out the future search directions from different perspectives, and finally Section VII draws our conclusions. Table 1 shows the list of abbreviations used in this paper.

II. FEDERATED LEARNING FUNDAMENTALS

A. MAIN CONCEPT

As shown in Fig. 1, FL is a distributed machine learning approach where multiple clients (workers) train a common model using own local data under the instruction of a central server. Instead of sending raw data to the central server, which is common in the traditional centralized learning approach, each client only sends an update of the common global model to the central server who initializes the model. By using distributed training at the clients, the central server can enrich the training result without sacrificing the privacy of the client data. The basic steps for FL are as follows.

1) *Client selection:* The central server must specify the client nodes that should be involved in the model training. The client selection should consider the data distribution, the features of client nodes, the model training requirements, and so on.
2) *Model dissemination:* Once the client nodes are selected, the central server sends the initial model to the selected client nodes for the purpose of distributed learning at these clients.
3) *Distributed learning:* Each client node trains the model using own local data, and calculates an update to the central model, such as SGD for the federated averaging model.
4) *Client feedback:* Each client sends its own updates to the central server.
5) *Aggregation:* The central server calculates a new version of the global model by aggregating the updates from the client nodes according to an algorithm (such as FedAvg) that is designed to optimize the performance of FL. Some clients (stragglers) should be neglected at this phase depending on the training results, update losses, or some other reasons.
6) *Model testing:* The central server test the aggregated global model using the data belonging to the rest of the world (i.e., the entities that did not participate in the training). According to the testing results, the central server could tune some hyper parameters to repeat the training process, or continue with the next step which is model update.
7) *Model update:* The server updates the shared model (i.e., the model that will be disseminated to all the devices) according to the aggregated result from the clients.

Table 2 shows the comparison of FL with other learning approaches including the centralized learning, data center distributed learning and peer-to-peer learning. FL can provide an acceptable learning accuracy with privacy preservation and a low communication overhead.

B. CLASSIFICATION

As shown in Fig. 2, FL approaches can be classified into three categories, namely, horizontal federated learning, vertical federated learning, and federated transfer learning. Horizontal FL is the learning in the scenarios where multiple datasets from different clients are the same in the feature space but different in the sample space. For example, the datasets from different hospitals represent the same feature space, i.e. the information of patients, but different in the sample space, i.e. the data from different patients. Vertical FL deals with the clients that have data with the same sample space but with different feature space, such as the bank statement and shopping history information of the same group of people. Federated transfer learning applies to multiple datasets that differ both in the sample space and feature space.

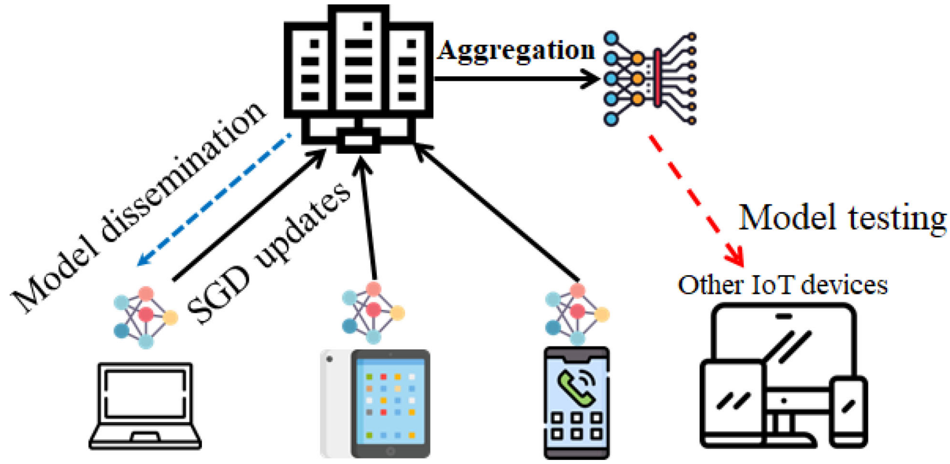

FIGURE 1. Federated learning.

TABLE 2. Comparison of FL With Other Learning Approaches

	Centralized learning	Data center distributed learning	Peer-to-peer distributed learning	Federated learning
Concept	Collecting all the data at the central server, and processing the data with a centralized manner.	Sharing all the data among multiple servers and processing the data in parallel.	Multiple client process own local data in a decentralized manner, and then share local updates of the training model among the clients. No central server exists.	Multiple clients analyze own local data collaboratively, and then send local updates the training model to the central server for aggregation.
Data distribution	Data are stored on the same server.	Data are distributed among multiple servers, but shared among all the servers.	Data are distributed on multiple clients, and there is no raw data exchanges among multiple clients.	
Accuracy	High.	Moderate.	Moderate.	Low.
Communication	All data should be collected, and thus the communication overhead is large.	Raw data exchanges are conducted among servers, and thus the communication overhead is large.	Communication overhead is larger than FL because more signaling overheads are needed to achieve a synchronization among multiple clients.	Communication overhead is smaller as compared with other learning approaches. Communications are only required between the central server and each client.
Privacy	All data are uploaded to the central server, and thus privacy risks exist.	All data are shared by all servers, and thus privacy risks exist.	Privacy is protected by avoiding the exchange of raw data.	

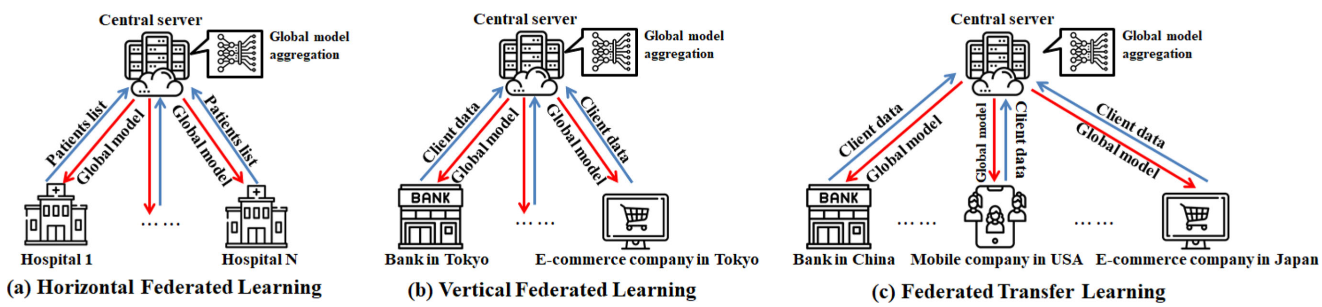

FIGURE 2. Classification of federated learning.

C. REPRESENTATIVE FEDERATED LEARNING APPLICATION AND ALGORITHM

Gboard [7], a virtual keyboard software for mobile touch screen, is the first application that shows the significance of FL. In Gboard, FL is used to train a Long Short-Term Memory (LSTM) model, namely Coupled Input and Forget Gate (CIFG), using mobile devices. The purpose of the FL in Gboard is to predict the next word input based on user data. The experimental results show that the FL-based CIFG model outperforms the central server-based model and n-gram model on the learning efficiency while preserving the user privacy. Gboard is one of the first implementations of FL for a commercial use.

Federated averaging (FedAvg) algorithm [2] is a widely used FL algorithm that combines local SGD on each client with the central server that performs model averaging. FedAvg

TABLE 3. Recent Studies on FL

Research focus	Publication	Research summary
Learning speed	Liu and Jin [10]	A proposal that uses MGD to accelerate the convergence speed of FL.
Communication	Liu and Jin [11]	A modified SET algorithm to reduce the size of model parameters for communications.
	Chen et al. [12]	A communication-efficient scheme for FL that employs a layerwise asynchronous update strategy.
	Sattler et al. [13]	An approach that considers downstream compression and complex learning environments including non-IID, small batch sizes, and unbalanced data.
	Wang et al. [14]	An approach that reduces communication overhead by eliminating some irrelevant updates from clients based on the global tendency suggested by the central server.
	Jeong et al. [15]	A scheme that combines FD and FAug to reduce communication overhead without losing too much on the accuracy.
	Yao et al. [16]	A feature fusion method for aggregating the features of both the local and global models.
Incentive	Bao et al. [17]	A blockchain for FL to provide trust and incentive.
	Toyoda and Zhang [18]	An incentive-aware blockchain-enabled FL based on mechanism design.
	Zou et al. [19]	A model for dynamic behaviors of mobile devices (clients) based on evolutionary game theory.
	Martinez et al. [20]	A blockchain-based workflow for recording and incentive purposes.
Non-IID data	Duan et al. [21]	An adaptive FL framework that alleviates the negative impact of imbalanced data based on the data augmentation and rescheduling of training.
Online scenario	Li et al. [22]	An online FL approach that derives model parameters for new devices based on the local data and existing model.
Client selection	Wang et al. [23]	Techniques to evaluate the contributions of clients in training process considering both horizontal FL and vertical FL.
	Song et al. [24]	Proposal of Contribution Index, a new metric based on Shapley value to evaluate the contribution of different clients in a horizontal FL.
Privacy & Security	Xu et al. [25]	VerifyNet, a FL framework that enhances the privacy of local gradients and provides verification to the aggregated results from the central server.
	Nasr et al. [26]	A white-box inference method to conduct a privacy analysis on FL models.
	Wang et al. [27]	An attack method that can target a specific client and compromise the client level privacy.
	Triastcyn and Faltings [28]	A relaxation of differential privacy that provides better privacy guarantees for clients.
	Zhang et al. [29]	A privacy-enhanced FL scheme based on the additively homomorphic cryptosystem.
	Sharm et al. [30]	A security solution for federated transfer learning models.
	Cao et al. [31]	A scheme that can detect poisoned local models during the training of global model.
	Gao et al. [32]	A privacy-preserving framework for heterogeneous federated transfer learning.

allows clients to perform multiple batch updates on local data and exchanges the updated weights rather than the gradients, which is more efficient in terms of communications.

In FL, a statistical model (e.g., linear regression, neural network, boosting) is chosen to be trained on the clients. Clients start training after receiving the initial model and calculation tasks from the central server. Although most existing FL systems use neural networks in the training of local updates, the neural network is not the only option. In this paper we use FL to denote the federated learning with neural networks unless specifically mentioned.

III. RECENT ADVANCES OF FL

There are some survey papers discussing the basic concept and technologies about FL [8], [9]. Different from existing works, this section puts a special focus on recent literature published in the last two years. Existing studies mainly discuss about two different broad topics, namely, the enhancement of learning efficiency, and privacy & security issues. Table 3 summarizes the recent studies on FL.

A. LEARNING EFFICIENCY OF FL

The convergence speed of learning is an important issue for FL. While most existing works use SGD or its integration with momentum, Liu *et al.* [10] employ momentum gradient descent (MGD), a deterministic gradient descent (DGD) approach with momentum, in the model training phase. The approach is called momentum federated learning (MFL). MFL utilizes the advantage of DGD over SGD in convergence speed under convex optimization, and therefore shows faster convergence performance on MNIST and CIFAR-10 datasets.

Although FL avoids transmitting the raw data by conducting distributed learning at clients, there are still some information should be shared between clients and the central server in order to update the global shared model. This communication overhead should be seriously controlled especially in a network bandwidth limited scenario. There are many studies discussing about the improvement of communication efficiency of FL. Recent study [11] formulates FL as biobjective optimization problem with two objectives of communication cost minimization and learning accuracy maximization. Then, the authors introduce a multi-objective evolutionary algorithm to reduce the communication costs while improving the learning accuracy. Sparse evolutionary training (SET) is enhanced to reduce the connections of deep networks without sacrificing the performance, and thus reduce the size of model parameters for communications.

Chen *et al.* [12] propose a communication-efficient scheme for FL that employs a layerwise asynchronous update strategy considering both the client side and server side operation. An asynchronous learning approach is used on the client side training, and a temporally weighted aggregation strategy is used on the server side to reduce the communication overhead and improve the learning efficiency. Two data sets with different deep neural networks (DNNs) are used in the experiments to show the advantage of the proposal over conventional FL approaches. Sattler *et al.* [13] introduce an approach that conducts compression on the downstream communications and considers complex learning environments including non-IID, small batch sizes, and unbalanced data. The approach is named sparse ternary compression (STC). The authors show that STC is communication-efficient by using four different learning tasks to demonstrate the performance advantage of STC over federated averaging.

Wang *et al.* [14] propose CMFL, a communication-mitigated federated learning approach that reduces communication overhead by eliminating some irrelevant updates from clients. This is achieved by the server sending the global tendency information to the clients, and a client avoiding the transmissions if its update does not match with the global tendency. The authors show that CMFL is able to reduce the size of data exchange between the clients and the central server while ensuring the convergence of learning. In [15], Jeong *et al.* introduce a scheme that can achieve significant reduction of communication overhead with a very small level of accuracy reduction. In the scheme, the communication payload size is determined based on the output dimension, which is called federated distillation (FD). Federated augmentation (FAug), a generative adversarial network (GAN) based data augmentation scheme is also introduced to solve the non-IID problem. In [16], the authors propose a feature fusion method to aggregate the features for both the local and global models. The aggregation is able to reduce the communication costs and stimulate the convergence.

Bao *et al.* [17] propose FLChain, a blockchain for FL to provide trust and incentive. FLChain maintains client information and training details for public auditability. Incentive mechanism is integrated to motivate the clients to behave honest and monitor other clients with misbehavior. Toyoda and Zhang [18] employ the theory of mechanism design, a field in economics and game theory, to design an incentive-aware blockchain-enabled FL. They introduce repeated competition for FL in order to enable rational behaviors of clients. A generic full-fledged protocol is designed on a public blockchain. In [19], Zou *et al.* consider a special FL system where each mobile device allocates own data and computation resources among different model owners (central servers with different learning objectives). They model dynamic behaviors of mobile devices (clients) using evolutionary game theory. Two metrics, specifically the accuracy and energy consumption, are defined for the benefits and costs, respectively. Martinez *et al.* [20] present a workflow for recording and incentive purpose based on blockchain technology. A smart contract-based scheme is integrated to conduct validation and verification of gradients in order to determine the reward for the corresponding client.

Non-IID data could cause a degradation of learning accuracy of FL. In [21], the authors propose adaptive FL framework that alleviates the negative impact of imbalanced data by using two approaches. First, for the global imbalance, data augmentation is conducted for minority classes. Second, the framework reschedules the training of clients to solve the local imbalance. In order to deal with a scenario where new devices keep joining the system, Li *et al.* [22] introduce an online FL approach that derives model parameters for new devices based on the local data and existing model without revisiting the data of existing devices. The approach shows a comparable accuracy to conventional algorithms with smaller computation, communication and storage costs.

Client evaluation and selection also could have a significant impact on the learning performance. Wang *et al.* [23] discuss the techniques to evaluate the contributions of clients in FL process. They propose two different approaches for horizontal FL and vertical FL, respectively. For the horizontal FL, the contribution is evaluated by comparing with and without the contribution of a client. In the vertical FL, Shapley values [23] are used to assess the contribution of each client. Considering some limitations of Shapley value-based approaches, Song *et al.* [24] define Contribution Index, a new metric that enhances Shapley value to evaluate the contribution of different clients in a horizontal FL. Two gradient-based methods are also proposed to speed up the calculation process of Contribution Index.

B. PRIVACY & SECURITY OF FL

The privacy and security concern of FL also receive great attentions in the relevant areas. Xu *et al.* [25] introduce VerifyNet, a FL framework that enhances the privacy of local gradients with a double-masking protocol. VerifyNet also provides an approach to verify the integrity of the aggregated results from the central server by using the homomorphic hash function and pseudorandom technologies. The experiments on real-world data are conducted to show the tractability of VerifyNet. Nasr *et al.* [26] design a white-box inference method to conduct a privacy analysis on FL models. The privacy vulnerabilities of SGD are discussed. In [27], the authors study the privacy risk of FL, and propose a GAN-based attack that allows servers to target a specific client and compromise the client level privacy. Triastcyn and Faltings [28] introduce Bayesian differential privacy, a natural relaxation of differential privacy that provides better privacy guarantees for clients. The main idea is based on a fact that FL tasks are often focused on a particular type of data.

In order to protect the privacy of the gradients from an untrusted server, Zhang *et al.* [29] propose a privacy-enhanced FL scheme based on the additively homomorphic cryptosystem which enables applying functions on encrypted data without revealing the values of the data. A distributed selective SGD method is employed to achieve distributed encryptions and reduce the communication costs. An authentication mechanism is also incorporated to verify the clients. Sharm *et al.* [30] enhance the security of existing federated transfer learning models under malicious setting where some players could arbitrarily deviate from the predefined protocol. They use a variant of Multi-Party Computation (MPC) to improve usability under existence of malicious clients. In [31], Cao *et al.* analyze the effect of poisoned data and the number of attackers on the performance of distributed poisoning attacks, and propose a scheme to drop poisoned local models during the training of global model. Gao *et al.* [32] introduce

TABLE 4. Recent Studies on FL and Wireless IoT

Research focus	Publication	Research summary
FL framework	Wang et al. [33]	A FL framework for MEC systems.
	Liu et al. [34]	A FL-based imitation learning framework for cloud robotic systems.
	Zhou, et al. [35]	A FL framework for social recommender systems.
	Yin et al. [36]	A FL framework for data collaboration for IoT.
	Lu et al. [37]	A blockchain based FL framework for privacy-preserving data exchange in industrial IoT.
	Ren et al. [38]	A FL-based framework for the joint allocation of communication and computing resources in large scale IoT environments.
	Fantacci and Picano [39]	A FL framework to solve the allocation of virtual machine replica copies in hybrid cloud-MEC networks.
	Lu et al. [40]	An asynchronous FL mechanism for MEC which checks client updates before uploading them to the central server.
	Yan et al. [41]	A FL framework for power allocation in decentralized wireless networks.
	Mowla et al. [42]	A FL-based jamming attack detection mechanism for flying ad hoc networks.
	Chen et al. [43]	A FL framework for minimizing “breaks in presence” in wireless VR networks.
	Nguyen et al. [44]	A FL-based intrusion detection system for IoT.
	Saputra et al. [45]	A FL-based energy demand prediction approach for electric vehicle networks.
	Verma et al. [46]	A web service-based implementation of FL for cross domain enterprise data sharing.
	Yu et al. [47]	A FL-based proactive content caching scheme for edge computing.
	Sozinov et al. [48]	A FL-based model for human activity recognition.
	Zhou et al. [49]	A FL-based realtime data processing architecture for multi-robot systems.
	Doku et al. [50]	A combination of FL with blockchain to determine data relevance.
Incentive	Pandey et al. [51]	A FL framework for MEC systems.
	Kang et al. [52]	A reputation-aware incentive mechanism for FL in mobile networks.
	Zhan et al. [53]	A DRL-based incentive mechanism for FL in edge computing environments.
	Yunus and Ercetin [54]	An incentive mechanism takes into account the capability difference of clients.
	Feng et al. [55]	A joint pricing and relay node selection approach for FL in wireless relay networks.
Commun. & comput.	Choi and Pokhrel [56]	A multichannel ALOHA scheme for FL in a cellular system.
	Yang et al. [57]	An over-the-air computation-based aggregation approach for FL in wireless environments.
	Ang et al. [58]	A robust design for FL under noisy communications.
	Zhu et al. [59]	A broadband analog aggregation framework for low latency FL in wireless networks.
	Yang et al. [60]	An analytical work regarding the effect of different scheduling policies on FL in wireless environments.
	Ahn et al. [61]	A discussion on implementation of FL over wireless channels.
	Amiri and Gunduz [62]	Three techniques to achieve efficient FL in a fading multiple access channel.
	Mills et al. [63]	An improvement of FedAvg algorithm with Adam optimization and a compression scheme.
	Wang et al. [64]	A control algorithm for FL in resource-constrained edge computing environments.
	Hua et al. [65]	A discussion on the FL approaches with second-order optimization methods.
	Tran et al. [66]	An analytical model for FL over wireless networks with special focus on the energy consumption, learning time, training accuracy, and heterogeneity of clients.
Decentralization	Savazzi et al. [67]	A server-less variant of FL for massive IoT networks.
	Qu et al. [68]	A blockchain-based approach to achieve decentralized privacy protection for FL.
	Kim, et al. [69]	A blockchain-based approach for enabling on-device FL without any central servers.
	Khan et al. [70]	A social-aware clustering-based self-organizing FL scheme.
Resource allocation	Anh et al. [71]	A deep Q-learning algorithm for resource allocation in mobile crowd FL.
	Chen et al. [72]	A joint wireless resource allocation and user selection for FL.
Privacy & security	Hao et al. [73]	A privacy-enhanced FL scheme for industrial IoT with differential privacy.
	Kang et al. [74]	A reputation-based approach for security protection of FL in mobile networks.
	Zhang et al. [75]	A poisoning attack against FL systems based on GAN.

a privacy-preserving framework for heterogeneous federated transfer learning, which uses an end-to-end secure multi-party learning approach.

IV. FL AND WIRELESS INTERNET OF THING

We give an overview of the recent studies on FL and wireless IoT by classifying these works into three different categories, namely, the studies on the application of FL for wireless IoT, the studies on technologies for enabling FL in wireless IoT, and the efforts on privacy & security improvement. The recent studies are summarized in Table 4.

A. APPLICATION OF FL FOR WIRELESS IOT

Wang *et al.* [33] propose a FL framework for MEC systems for optimizing computing, caching and communications. A collaboration among mobile devices and edge servers is discussed for a better training of FL models in optimizing the system performance. In [34], a FL-based imitation learning framework is proposed for cloud robotic systems with heterogeneous sensor data. The study shows that FL is able to improve the efficiency and accuracy of imitation learning at a robot by using the knowledge of other robots. Zhou *et al.* [35] propose a FL framework for social recommender systems. FL is used to learn a centralized model using the collaboration between a large number of clients with context-awareness and big data supports. Yin *et al.* [36] propose a FL-based secure data collaboration framework for IoT. Based on a blockchain-based mechanism, the framework enables the collaboration between multiple parties on learning with privacy preservation. A combination of blockchain and FL is introduced in [37] for a privacy-preserving data exchange in industrial IoT. FL is integrated into the consensus process of a permissioned blockchain to improve the efficiency of computation and data sharing.

Ren *et al.* [38] propose a FL-based framework for large-scale IoT environments with edge computing. They use FL for the purpose of joint allocation of communication and computing resources. Fantacci and Picano [39] uses FL to solve the allocation of virtual machine replica copies in hybrid cloud-MEC networks. They use FL to predict the user application demands in order to maximize the hit percentage. In [40], Lu *et al.* introduce a privacy-preserving asynchronous FL mechanism for MEC. An asynchronous test process is inserted after each round of training at a client, which determines whether the updates from the client will be sent to the central server or not. A FL framework for power allocation in decentralized wireless networks is investigated by Yan *et al.* [41]. The framework adopts an on-line Actor-Critic algorithm for the local training, and a collaboration among clients is achieved by sharing the gradients and weightages. Mowla *et al.* [42] propose a FL-based jamming attack detection mechanism for flying ad hoc networks. A client selection approach based on Dempster-Shafer theory is also used to improve the efficiency of FL. Chen *et al.* [43] propose a FL-based framework for minimizing "breaks in presence" in wireless virtual reality (VR) networks. They use FL to predict the location and orientation of users by enabling multiple clients to collaboratively train their deep echo state networks based on local data.

Nguyen *et al.* [44] propose a FL-based intrusion detection system for IoT. Based on FL, the system can aggregate behavior profiles efficiently based on device-type-specific communication profiles automatically, and no labeled data are required for detection. Saputra *et al.* [45] use FL to conduct accurate energy demand prediction with low communication overhead for electric vehicle networks. The charging stations work as clients in FL process, and only exchange trained model with the charging station provider without exchanging raw user data. Verma *et al.* [46] propose a web service-based implementation of FL for cross domain enterprise data sharing. Yu *et al.* [47] introduce a FL-based proactive content caching scheme for edge computing. In this FL model, the mobile devices work as clients, and the base station is the central server.

Sozinov *et al.* [48] apply FL for human activity recognition. They find that FL could achieve a comparable accuracy to the centralized learning. Zhou *et al.* [49] propose a FL-based real-time data processing architecture for multi-robot systems. Doku *et al.* [50] uses a combination of FL with blockchain to determine data relevance and store relevant data in a decentralized manner.

B. TECHNOLOGIES FOR ENABLING FL IN WIRELESS IOT

Pandey *et al.* [51] propose a crowdsourcing framework to support FL in wireless IoT environments with a communication-efficient way. They introduce an incentive mechanism based on Stackelberg game model to attract the participation of clients in FL. Kang *et al.* [52] introduce a reputation-based client selection mechanism for FL in mobile networks. The learning efficiency of FL is improved by providing more incentives to the clients with higher reputations. Zhan *et al.* [53] design a deep reinforcement learning (DRL) based incentive mechanism for FL in edge computing. DRL is used to determine the optimal strategies for the central server and clients. Yunus and Ercetin [54] consider the capability difference of clients in the incentive mechanism design. Feng *et al.* [55] propose a joint pricing and relay node selection approach for FL in wireless relay networks where a Stackelberg game is used to model the problem.

Choi and Pokhrel [56] propose a multichannel ALOHA scheme for improving the communication efficiency of FL in a cellular system. It is argued that an adaptation of access probability based on the significance of local updates at each user could improve the aggregation performance in FL. Yang *et al.* [57] propose an over-the-air computation-based aggregation approach for FL in wireless environments. A sparse and low-rank modeling approach is used to maximize the number of clients that could satisfy the mean-squared-error requirement. Ang *et al.* [58] propose a robust design for FL under noisy communications. They consider the noise in both aggregation and broadcast process, and provide a formulation for the training problem. In [59], Zhu *et al.* present a broadband analog aggregation framework for low latency FL in wireless networks. The waveform-superposition property of multi-access channels is utilized to achieve a communication-efficient aggregation of updates. Yang *et al.* [60] analyze the effect of different scheduling policies on FL in wireless environments. Three different well-used scheduling algorithms, namely, random scheduling, round robin, and proportional fair are discussed. The implementation issue of FL over wireless channels is discussed in [61].

Amiri and Gunduz [62] consider a bandwidth-limited fading multiple access channel between the clients and the central server, and propose three different techniques to improve the performance of FL. Mills *et al.* [63] improve the federated averaging algorithm by using Adam optimization and a compression scheme. Adam optimization speeds up the convergence speed, and the compression scheme reduces the communication overhead. Wang *et al.* [64] analyze the convergence bound for FL with non-IID data, and propose a control algorithm that achieves a tradeoff between local updates and global aggregation in order to improve the accuracy of FL for resource-constrained edge computing systems. Hua *et al.* [65] investigate the FL problem over wireless networks considering model aggregation errors, and propose an approach that updates local models by second-order optimization methods. Tran *et al.* [66] provide an analytical model for FL over wireless networks with special focus on the energy consumption, learning time, training accuracy, and heterogeneity of clients.

Savazzi *et al.* [67] propose a server-less variant of FL for massive IoT networks. An adaptation of the FedAvg algorithm for distributed consensus paradigms is proposed. Qu *et al.* [68] use a blockchain-based approach to achieve decentralized

TABLE 5. Research Efforts on Vehicular IoT

Layer	Research focus	Publication	Research summary
Perception	Positioning	Jo et al. [76]	An algorithm that integrates GPS and in-vehicle sensor information.
		Soatti et al. [77]	A positing scheme that improves the position accuracy by enabling information sharing among vehicles.
		Shieh et al. [78]	A vehicle positioning method that uses two one-dimensional signal-direction discriminators.
		Williams and Barth [79]	A qualitative analysis on positioning requirements.
	Key technologies	Guo et al. [80]	A CNN-based compressed video sensing technology with special focus on analyzing the temporal correlation of video frames.
		Guo et al. [81]	A survey on the applications of compressed sensing.
		Alasmary et al. [82]	A discussion on the problem of sensing vehicles with roadside cameras.
	Cooperative perception	Ding et al. [83]	A kinematic information aided user-centric access approach for cooperative perception.
		Huang et al. [84]	A study on the redundancy of collective perception for connected vehicles.
		Sridhar and Eskandarian [85]	A system that uses visual and inertial sensors to perform cooperative localizations.
Networking	Multi-hop routing	Wu et al. [86]	A multi-hop routing for VANETs with fuzzy constraint Q-Learning.
		Wu et al. [87]	A vehicle-to-Roadside communication scheme.
	DTN	Cao et al. [88]	A survey on DTN.
		Du et al. [81]	A vehicular DTN Scheme with enhanced buffer management.
	Broadcast	Wu et al. [91]	A sender-oriented broadcast protocol with packet size awareness.
		Wu et al. [92]	A fuzzy logic-based sender-oriented broadcast protocol.
		Abbasi et al. [93]	An analysis on the performance of multi-hop broadcasting.
		Shah et al. [94]	A receiver-oriented broadcast protocol with a time barrier mechanism.
		Jia et al. [95]	A receiver-oriented broadcast protocol with a resource reservation mechanism.
	Resource management	Zhang et al. [96]	A transmission scheduling mechanism for cognitive vehicular networks.
		Duo et al. [97]	A handover scheme for cellular/IEEE 802.11p hybrid vehicular networks.
		Chen et al. [98]	A game theoretical resource allocation for vehicular communications.
Application	Computing	Feng et al. [99]	An autonomous vehicular edge computing framework.
		Wang et al. [100]	A game theoretical approach for computation offloading in vehicular environments.
		Zhang et al. [101]	A task offloading method based on Markov decision process.
	Use case	He et al. [102]	A discussion on vehicular data cloud services.
		Wu et al. [103]	A decentralized data storage scheme for VANETs.
		Khattak et al. [104]	A discussion on smart city applications with LoRaWAN-based vehicular IoT.
		Siegel et al. [105]	A survey on connected vehicle applications and technical challenges.

privacy protection for FL. A similar block-chain based approach is also discussed in [69] for enabling on-device FL without any central servers. Khan *et al.* [70] propose a self-organizing FL scheme for wireless IoT. First, cluster heads are selected based on a decentralized approach among self-organizing nodes by considering social relationship and computational capability. Then, the cluster head nodes perform the same functions as the central servers in the conventional FL.

Anh *et al.* [71] propose a deep Q-learning algorithm for resource allocation in mobile crowd FL. The energy, computational resource, and wireless resource are considered in the algorithm. Chen *et al.* [72] discuss the performance optimization of FL over wireless networks. They consider joint wireless resource allocation and user selection problem in order to minimize the loss function.

C. PRIVACY & SECURITY

Hao *et al.* [73] propose a privacy-enhanced FL scheme for industrial IoT. This scheme is able to preserve the privacy of local gradients and shared parameters by achieving example-level differential privacy with a distributed Gaussian mechanism. In order to improve the security level of FL in mobile networks, Kang *et al.* [74] introduce the concept of reputation based on a consortium blockchain. Based on the reputation metric, the central server selects the clients with high reputation values. Zhang *et al.* [75] propose a poisoning attack against FL systems based on GAN.

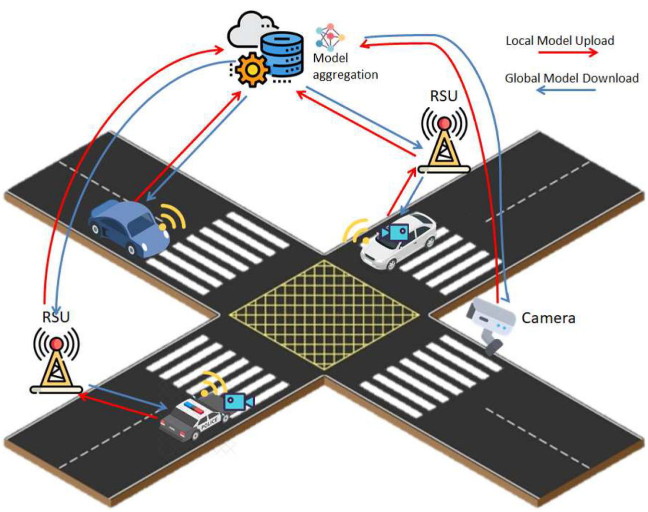

FIGURE 3. FL and vehicular IoT.

V. FEDERATED LEARNING AND VEHICULAR IOT

A. OVERVIEW OF VEHICULAR IOT

There are plenty of studies about vehicular IoT. As shown in Table 6, we give a brief review of these research efforts by classifying them into three different categories in terms of IoT layer architecture, namely, the perception layer, networking layer, and application layer studies.

1) PERCEPTION LAYER

A positioning approach with high accuracy and reliability is required in vehicular IoT systems in order to enable delay-sensitive and mission-critical applications. However, the conventional GPS receiver cannot satisfy the requirements. Some research efforts target for achieving a better positioning service. Jo *et al.* [76] propose an algorithm that integrates GPS with in-vehicle sensor information to achieve accurate positioning in various driving conditions. Soatti *et al.* [77] propose a positing scheme that improves the position accuracy by enabling information sharing among vehicles in cooperative ITS. The scheme uses an implicit cooperative positioning approach where vehicles share some physical features, such as traffic lights and inactive cars in the surrounding areas, to refine their location estimates. Being independent of explicit ranging information between vehicles, this approach is easy-to-implement. Shieh *et al.* [78] propose a vehicle positioning method that uses two one-dimensional signal-direction discriminators mounted on a vehicle to calculate the relative position of another vehicle by measuring the coming directions of the signal emitted from the vehicle. A recent analysis on vehicle positioning requirements for vehicular IoT applications is conducted by Williams and Barth [79].

Low-cost sampling technologies, such as compressed video sensing (CVS), are widely used in vehicular IoT for one of the perception approaches. Some studies discuss how to improve the accuracy of CVS. Guo *et al.* [80] propose a convolutional neural network (CNN) based compressed video sensing technology that uses CNN in analyzing the temporal correlation of video frames in the measurement domain. Guo *et al.* [81] conduct a survey on the applications of compressed sensing in vehicular IoT systems. Alasmary *et al.* [82] discuss the problem of sensing vehicles with roadside cameras. They study the effect of vehicle mobility and camera activation time in order to reduce the number of activated sensors.

Ding *et al.* [83] use a kinematic information aided user-centric access approach to satisfy the ultra-high reliability and low latency requirements of cooperative perception in autonomous driving. Huang *et al.* [84] conduct a study on the redundancy of collective perception for connected vehicles. A probabilistic data selection scheme is proposed to reduce the redundancy while ensuring the system reliability. In [85], Sridhar and Eskandarian propose a system that uses visual and inertial sensors to perform cooperative localization based on the relative information of two vehicles sharing a common field of view.

2) NETWORKING LAYER

There are many types of communication approaches available for vehicular networks including cellular communications, IEEE 802.11p, and mmWave. IEEE 802.11p is the default standard for vehicle-to-vehicle communications. The mobility of vehicle is one of the main reasons that makes the vehicle-to-everything (V2X) communication challenging, especially for IEEE 802.11p where multi-hop communications are required duo to the limited signal coverage. The mobility could incur a frequent change of network topology and also result in various node densities in different roads or hours. In a highly mobile or dense environment, it is particularly difficult to find the best communication path using a simple mathematical model especially when there are multiple types of communication approaches are available. There are some routing protocols addressing the issue of providing an efficient route in V2X communications [86], [87]. Due to limited coverage of IEEE 802.11p, when the network density is low, the issue of intermittent connectivity occurs. For the purpose of providing communications for devices with intermittent connectivity, delay tolerant network (DTN) protocols are also discussed in the literature [88], [89].

The communications in vehicular environment can be classified into two categories in terms of networking perspective, namely, unicast communications and broadcast communications. Aforementioned studies [86]–[89] consider unicast communications. The broadcast communications are used to disseminate some messages including control messages and safety-related messages. The multi-hop broadcasting of messages is challenging due to the lack of retransmissions for broadcast MAC frames. The multi-hop broadcast protocols can be further classified into two categories, namely, sender-oriented protocols [91]–[93] and receiver-oriented protocols [94], [95]. In the sender-oriented protocols, the forwarder nodes are specified by the upstream forwarder (or the sender) node. In the receiver-oriented protocols, the forwarder nodes are selected based on probabilistic approaches.

In addition to routing protocols, there are some research efforts on resource management in vehicular environments. These studies cover different aspects including the transmission scheduling in cognitive environment [96], handover efficiency in cellular/IEEE 802.11p hybrid vehicular networks [97], and resource allocation for vehicular communications [98].

3) APPLICATION LAYER

There are many studies on the computing or task offloading issues in vehicular IoT. The concept of autonomous vehicular edge computing is proposed in [99] to utilize the computational resources of vehicles in vicinity. An ant colony optimization-based scheduling algorithm is used for task offloading. In [100], a computation offloading approach is proposed based on a game theoretical approach by considering QoS constraints, communication overhead, and the distance between the vehicle and the access point. Liu *et al.* discuss multi-task scheduling problem by considering the dependency between tasks, and solve the problem by prioritizing the tasks. Zhang *et al.* [101] discuss task migration problem with a consideration of offloading delay, and formulates the problem as a finite horizon Markov decision process.

He *et al.* [102] design a multi-layer vehicular cloud platform based on vehicular IoT technologies targeting for intelligent parking applications and vehicular data mining services.

TABLE 6. Recent Studies on FL and Vehicular IoT

Research focus	Publication	Research summary
FL framework	Lu et al. [106]	An asynchronous FL scheme with a hybrid blockchain for IoV.
	Samarakoon et al. [107]	A FL-based estimation of network status for URLLC.
	Ye et al. [108]	A FL-based image classification in vehicular IoT.
	BRIK et al. [109]	A discussion on possible applications of FL for UAVs.
	Lu et al. [110]	An asynchronous federated learning scheme for resource sharing in vehicular IoT.

A decentralized data storage scheme for vehicular networks is proposed in [103] to enable decentralized storing of information with moving vehicles. Khattak *et al.* [104] discuss possible smart city applications with LoRaWAN-based vehicular networks. More interesting vehicular IoT applications are surveyed in [105] where technical challenges and opportunities are also discussed.

B. OVERVIEW ON FL FOR VEHICULAR IOT

There are several studies focusing on the use of FL in vehicular IoT. These research efforts are summarized in Table 6. Lu *et al.* [106] discuss secure data sharing problem in Internet of Vehicles (IoV), and propose an asynchronous FL scheme based on a hybrid blockchain. FL is used to relieve the communication load and privacy concerns. Samarakoon *et al.* [107] discuss the problem of joint power and resource allocation for ultra-reliable low-latency communications (URLLC) in vehicular environments. FL is used to estimate the tail distribution of the network-wide queue lengths that reflects the network status. Ye *et al.* [108] discuss the use of FL for image classification in vehicular IoT. A selective model aggregation approach is introduced to select local models calculated at vehicles by considering the local image quality and the computational capability of each vehicle. BRIK *et al.* [109] discuss possible applications of FL for unmanned aerial vehicles (UAVs). Lu *et al.* [110] propose an asynchronous federated learning scheme for resource sharing in vehicular IoT. They use a local differential privacy technique to protect the privacy of local updates. An asynchronous approach is employed in FL to enable distributed peer-to-peer model updates between vehicles, which is more suitable for a decentralized vehicular network.

As shown in Fig. 3, FL can be used in vehicular environments to train a global model by using the data collected at vehicles with privacy protections. The federated learning in vehicular IoT is expected to bring the following benefits.

- Better efficiency: Designing an efficient resource allocation in vehicular environments is particularly challenging due to the dynamic and decentralized features of vehicle networks. FL could enable better utilization of network resources, storage and computational resources by conducting a collaborative learning among heterogeneous agents including vehicles, roadside units (RSUs) or cellular base stations.
- Better privacy: Vehicles are attached with different types of sensor devices. However, the exchange of the sensor date with other vehicles or the cloud arises privacy concern, resulting in strict restrictions for the use of vehicular big data. FL provides a way to utilize vehicular big data while mitigating privacy risks.
- Shorter response time: In a FL system, a client can conduct actions based on the global knowledge and local data, which achieves a lower latency as compared with the conventional approaches that make decision at the central server side. The FL can be incorporated with edge computing to facilitate various real-time systems for vehicular IoT.
- Better utility: By utilizing the data from a large number of devices with a privacy-preserving approach, FL could enable some new applications that could not be possible for the conventional learning approach.

C. FL AND PERCEPTION IN VEHICULAR IOT

1) PERCEPTION TECHNOLOGIES FOR AUTONOMOUS VEHICLES

Since every single perception technology has its own limitations, it is important to employ a multi-modal evaluation approach, which draws a conclusion by aggregating the results and knowledge coming from different sensors. However, different sensing devices could draw different conclusions which could be contradictory with each other. It is even possible that each sensor only has very limited and imprecise information. We have to take into account all these contradictory, imprecise, and inaccurate features of the sensed data. It is also important to use collaborative computing to achieve multi-agent collaborative perception in order to improve contextual awareness of a vehicular IoT system. Here, FL based approaches can be used to find an efficient solution by using the knowledge from multiple vehicles with different scenarios, which is important to further improve the perception efficiency and accuracy at each single vehicle.

Considering an efficient utilization of wireless resource and short delay, it is important to conduct learning in the vicinity of vehicles. In order to apply FL for decentralized networks, the approach based on vehicle clustering can be incorporated as shown in Fig. 4. Some vehicle are selected as the central servers of FL based on a decentralized clustering approach proposed in [111], [112]. The dissemination of the global model of FL can be done by a broadcast protocol, such as [91], and the model updates from the clients to the central server could use unicast protocols [86].

2) VEHICLE BASED PERCEPTION

Vehicles are always equipped with multiple sensors. By analyzing data from multiple vehicles, we can achieve the purpose of improving ITS, surveillance systems, user behavior

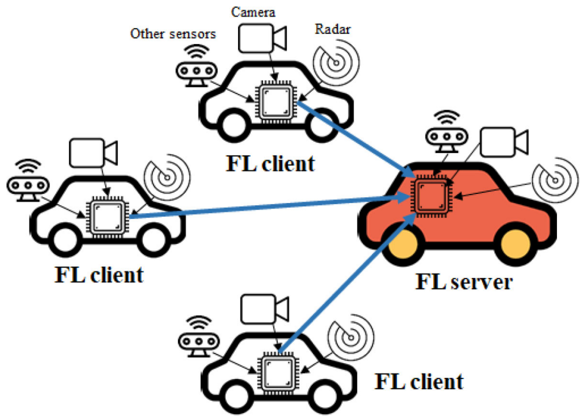

FIGURE 4. **FL based perception for vehicular IoT.**

analysis and so on [113]. For example, GPS, vehicle velocity, inter-vehicle distance data can be used to analyze the road condition, which enables a better navigation system and road system. The vehicle camera data can be used for the purpose of surveillance, accident alert, and car insurance. However, it is challenging to collect these data from multiple vehicles since these data are privacy-sensitive and the data size is too large. In order to solve this problem, FL could be a possible way to conduct distributed perception by processing the data at the end vehicles and then integrating the results to make the final decision.

D. FL AND VEHICULAR NETWORKING

Vehicles could have different types of communication interfaces, which forms a multi-access communication environment [114]. The networking resource allocation in vehicular environments is extremely challenging due to the frequent change of network topology and unstable wireless signals. Most vehicular IoT applications exhibit strict requirements on the response delay and reliability. In order to achieve an efficient communication in a highly mobile multi-access vehicular environment, we have to find the best network resource allocation policy in a complex and varying environment.

Since the best networking policy is dependent on the distribution of communication, computing, and storage resources, it is difficult to use a simple mathematical model to define the problem. Therefore, a data driven intelligent approach should be considered. However, each vehicle only has limited information about the environment, and the exchange of data with different parties arise privacy concerns. Considering the importance of including data from different road conditions in the learning with privacy protection, FL would be the best solution. FL can utilize vehicular big data generated from a large number of vehicles, and build a global model that could be used by any vehicles. FL can also be easily integrated with edge computing where the edge computing provides an underlying infrastructure for FL. The following problems are considered to be important for the era of vehicular networking and FL.

- FL-based networking with vehicular big data: FL can be employed to solve a joint optimization problem of communication interface selection and route selection problem based on collaborative learning among vehicles.
- FL-based intelligence for spatiotemporal changes: The spatial and temporal changes of vehicular environment require an intelligent approach that can evolve with the change of environment. Therefore, it is important to design a FL scheme that could work properly in vehicular environments with spatiotemporal changes.
- Efficient networking enabling FL in vehicular environments: Due to the dynamic topology of vehicular networks, the communication between clients and the central server of FL faces challenges. Communication and signaling protocols should be improved to support an efficient implementation of FL in vehicular environments. Different types of communication protocols including unicast and broadcast protocols should be designed to satisfy different QoS constraints of communications in FL.

E. FL AND VEHICULAR IOT APPLICATIONS

FL could facilitate the advance of various types of vehicular IoT applications. For example, in the existing autonomous driving systems, each vehicle is trained online based on the observation of single vehicle, resulting in a limited knowledge about the environment. FL can provide more information for each vehicle by using the collaboration among vehicles. Duo the ability of expanding the data size and types by involving more workers (clients) in training, FL is capable of supporting emerging applications such as intelligent traffic signal control, navigation systems, collaborative autonomous driving, EV charging decision, collision avoidance systems, vehicle platooning, automatic road enforcement based on decentralized vehicle cameras, and so on. However, in order to achieve a seamless integration of FL and vehicular IoT applications, the following topics need further investigations.

- FL framework for emerging applications: Different applications could have different level of requirements on the sensing, communication, computing, and storage resources. It is important to design a suitable FL framework for each application in order to optimize the performance. On the other hand, a common FL architecture for vehicular IoT should be designed to enable fast deployment of a FL system with easy parameter tuning according to the application requirements.
- Protocols for supporting FL in vehicular environments: Existing protocols for FL do not adequately consider the dynamic feature of vehicular environments. It is necessary to design mobility-aware protocols for FL including the client selection, model aggregation, and model disseminations.

VI. FUTURE RESEARCH DIRECTIONS

The dynamic and complex features of vehicular IoT scenarios, the limited resources, and the heterogeneity of network entities require an efficient FL learning scheme and relevant technologies, which opens up many interesting research topics as the following.

- **FL framework for emerging vehicular IoT applications:** FL framework design would continually be an important research topic due to the outstanding performance of collaborate learning in the relevant areas. More applications can be benefited from the use of FL. It is interesting to find new applications that could be possible with FL. The framework design should consider the underlying sensing and networking infrastructure in order to achieve the convergence of intelligent sensing, networking, and computing in vehicular IoT.
- **Resource allocation with FL:** The overall performance of the system depends on the allocation of limited resources including communication, computing, and storage resources, among the agents. Conventional mathematical optimization approaches face challenges in solving the resource allocation problem since the vehicular environment is complex, and the information observed at each vehicle is imprecise and contains errors. Neural network shows its advantages in solving complex problems by utilizing big data. The big data related to user data traffic, network status, resource allocation strategy and the corresponding QoS satisfaction rate can be utilized to find the optimal solution. A FL approach that uses neural networks in local training is expected to be a promising way to solve the resource allocation problem for vehicular IoT.
- **Big data empowered approaches with FL:** Data driven approaches are attracting increasing interests due to its capability of finding a good solution for a complex system. With FL, an efficient use of vehicular big data with privacy protection becomes possible. This would create new opportunities for a study on data driven approaches in learning the best policy in vehicular IoT. An efficient use of cross domain big data would also be an interesting topic. As a simple example, it is possible to use vehicle traffic big data to improve the communications in vehicular networks [115]. Thanks to the privacy-preserving feature of FL, the use of big data becomes possible, which creates a need on establishing new schemes for better big data utilization.
- **Communication, computing, and caching strategies for FL:** The application of FL in vehicular environments involves a large number of heterogeneous devices, which requires an efficient underlying infrastructure to support collaborative learning. Due to the special characteristics of vehicular environments, the design of more enhanced communication, computing, and caching strategies for FL needs special concerns.
- **Vehicular environment-aware FL:** FL protocols should be configured to support an efficient deployment of FL in vehicular environments. Therefore, the studies regarding vehicular environment-aware FL protocols and algorithms are expected to attract more attentions with the rapid development of FL systems. The related efforts should include different perspectives such as the client selection algorithms, data aggregation protocols, data dissemination protocols, and so on.
- **Privacy, security & incentive:** FL is proposed to achieve privacy protections to the local data. However, in a scenario where dishonest clients and servers exist, the conventional FL approach could also face privacy risks. Therefore, the problem of how to realize a more trusty FL by eliminating all the possible risks requires further discussions. In order to be resistant to potential attacks, the security issue is also important for a FL system because it determines the usability of the system. The incentive problem needs investigations as well for the purpose of involving more workers to improve the accuracy of a FL system.
- **Collaborative intelligence:** The vehicular IoT involves various types of devices including vehicles, sensors, RSUs, base stations, edge severs, cloud servers, and other devices. An efficient collaboration of these heterogeneous devices with FL could reach the level of collaborative intelligence that achieves intelligent perception of environment, intelligent networking, and intelligent processing of vehicular big data. The related areas of collaborative intelligence should be discussed from the perspectives of both efficient collaboration among heterogeneous devices and efficient learning approaches with collaborations.

VII. CONCLUSION

With the growing interest in federated learning from both industries and academics, a discussion on the use of FL in vehicular IoT environments becomes important. In this paper, we discussed the existing studies, technical challenges, possible solutions, and open problems regarding the application of FL in vehicular IoT. We first conducted a survey on the recent efforts of FL and then explained its applications and challenges in wireless IoT environments. Existing studies on the use of FL for vehicular IoT were also reviewed with detailed discussions on the technical issues. We then discussed the future research directions on the integration of FL with vehicular IoT taking into account both the application of FL for vehicular IoT, and the enhancement of vehicular IoT technologies for supporting FL. We believe this work could expedite the research process for both FL and vehicular IoT.

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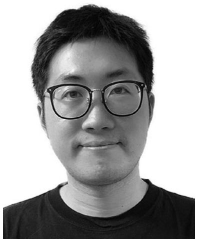

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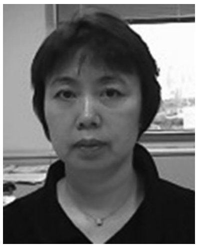

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