Federated Learning for Connected and Automated Vehicles: A Survey of Existing Approaches and Challenges

Vishnu Pandi Chellapandi, *Member, IEEE*, Liangqi Yuan, *Graduate Student Member, IEEE*, Christopher G. Brinton, *Senior Member, IEEE*, Stanislaw H. Żak, *Life Member, IEEE*, and Ziran Wang, *Member, IEEE*

***Abstract*—Machine learning (ML) is widely used for key tasks in Connected and Automated Vehicles (CAV), including perception, planning, and control. However, its reliance on vehicular data for model training presents significant challenges related to in-vehicle user privacy and communication overhead generated by massive data volumes. Federated learning (FL) is a decentralized ML approach that enables multiple vehicles to collaboratively develop models, broadening learning from various driving environments, enhancing overall performance, and simultaneously securing local vehicle data privacy and security. This survey paper presents a review of the advancements made in the application of FL for CAV (FL4CAV). First, centralized and decentralized frameworks of FL are analyzed, highlighting their key characteristics and methodologies. Second, diverse data sources, models, and data security techniques relevant to FL in CAVs are reviewed, emphasizing their significance in ensuring privacy and confidentiality. Third, specific applications of FL are explored, providing insight into the base models and datasets employed for each application. Finally, existing challenges for FL4CAV are listed and potential directions for future investigation to further enhance the effectiveness and efficiency of FL in the context of CAV are discussed.**

***Index Terms*—Federated learning, connected and automated vehicles, distributed computing, privacy protection, data security.**

I. Introduction

CONNECTED and automated vehicles (CAV) are the key to future intelligent transportation systems (ITS) that encompass both ground and air transportation [1], [2], [3], [4], [5], [6], [7], [8], [9]. With the advent of Big Data, the Internet of Things (IoT), edge computing, and intelligent systems, CAVs have the potential to improve the overall transportation system by reducing traffic accidents, congestion, and pollution [10], [11], [12], [13]. CAVs integrate both Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication capabilities, facilitating an enhanced perception of the environment beyond the direct line of sight [14], [15], [16]. This involves interaction with other vehicles, traffic signals, pedestrians, and other elements of the transportation ecosystem. Furthermore, CAVs are designed to assume control of driving tasks by the human operator under certain conditions, using a variety of sensors and sophisticated machine learning (ML) algorithms to achieve autonomous operation.

Currently, CAVs are generating a tremendous amount of raw data, between 20 and 40 TB per day, per vehicle . The various sources of these data include engine components, electronic control units (ECU), perception sensors, and vehicle-to-everything (V2X) communications. This large amount of data is sent to other vehicles, roadside infrastructures, or the cloud, continuously or periodically for monitoring, prognostics, diagnostics, and connectivity features [17]. This flow of data has driven the flourishing deployment and application of ML in CAVs, including areas such as Advanced Driver-Assistance Systems (ADAS) [18], automated driving [19], ITS [20], and sustainable development [21].

A. Motivation

Due to the large amount of data required to train ML models, concerns have been raised about data security in terms of the legitimacy of data collection, data misuse, and privacy breaches. Data collected by various sensors in CAVs, are also considered private and are subject to stringent privacy protection regulations in different regions. One such example is the General Data Protection Regulation (GDPR) in the European Union [22], which imposes strict requirements and guidelines on the handling and processing of personal data to ensure individuals' privacy rights are protected. Even with the development of advanced ML techniques and vehicle connectivity, it has not been feasible to have a secure framework to collect data from every vehicle and train an ML model. These limitations led to the development of a new ML paradigm known as Federated Learning (FL) [23], [24]. The term Federated Learning (FL) has been coined by Google [25]. FL was initially used for mobile keyboard prediction in Gboard [26] to allow multiple mobile phones to cooperatively and securely train an ML model. FL has been extensively applied in various fields such as industry [27], [28], [29], energy [30], [31], healthcare [32], [33], and more.

Manuscript received 3 October 2023; revised 31 October 2023; accepted 10 November 2023. Date of publication 14 November 2023; date of current version 23 February 2024. *(Corresponding author: Ziran Wang.)*

The authors are with the College of Engineering, Purdue University, West Lafayette, IN 47907 USA (e-mail: cvp@purdue.edu; liangqiy@purdue.edu; cgb@purdue.edu; zak@purdue.edu; ryanwang11@hotmail.com).

Color versions of one or more figures in this article are available at https://doi.org/10.1109/TIV.2023.3332675.

Digital Object Identifier 10.1109/TIV.2023.3332675

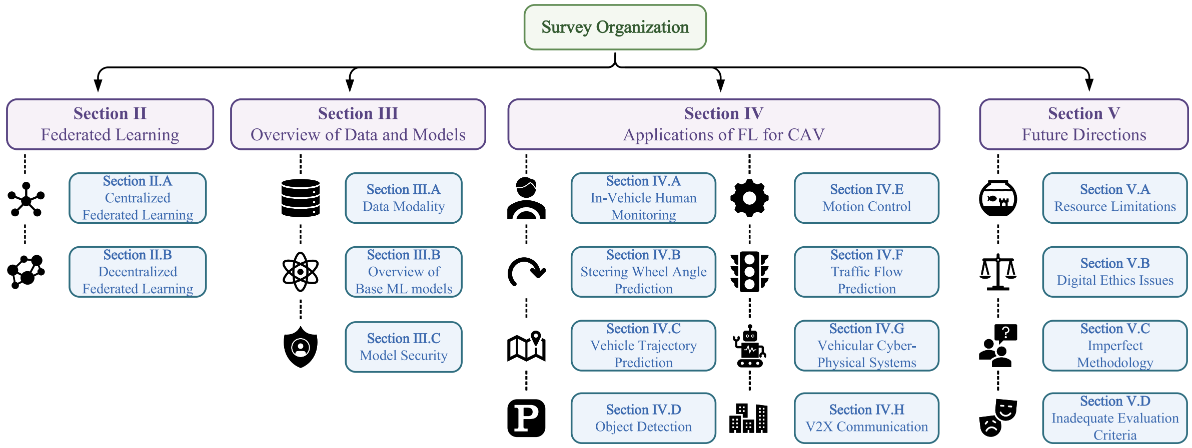


Fig. 1. Roadmap of this survey paper.

In FL, edge devices/clients only send the gradients or the learnable parameters to cloud servers rather than sending massive local datasets in a centralized learning framework. Cloud servers perform a secure aggregation of the received gradients/weights and update the global model parameters that are transmitted back to clients/edge devices [34]. 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.

Despite the benefits of V2X communications among CAVs, the invasion of privacy, accuracy, effectiveness, and communication resources is an essential concern to be addressed. FL frameworks have received attention for their 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. Similarly, FL frameworks distribute training tasks to each client, and the server does not perform training but only aggregates, which can reduce the computational demand on the server and improves training efficiency. Recently, there have also been efforts to train a decentralized FL that allows multiple vehicles to collaboratively train a model without needing a central server [35], [36]. In our first survey of FL for CAV (FL4CAV) presented in [37], we emphasized applications and explored foundational challenges in the subject. Building upon that conference version, this extended journal paper further delves into the underlying methodologies, provides a more comprehensive review of recent developments, and introduces novel insights and evaluations, thereby presenting a more exhaustive and nuanced understanding of the field.

B. Paper Organization

In this paper, we provide a survey of FL4CAV, including deployment of various FL frameworks on CAVs, data modalities and security, diverse applications, and key challenges. The organization of this survey is shown in Fig. 1. The following topics are covered in this survey:

- A systematic review of FL algorithms is conducted, specifically focusing on their deployment in CAVs. Additionally, we examine the integration of ML models within the FL framework for CAV applications.
- Data modalities and data security considerations in CAVs are summarized, highlighting the diverse range of multi-modal data generated by various sensors.
- Critical applications of FL4CAV are explored, such as driver monitoring, steering wheel angle prediction, vehicle trajectory prediction, object detection, motion control application, traffic flow prediction, and V2X communications.
- Current challenges and future research directions of FL4CAV are highlighted, such as performance, safety, fairness, applicability, and scalability. A comparison of our survey with other related surveys can be found in Table I.

The remainder of this survey is organized as follows. In Section II, we describe the two main FL frameworks along with their algorithms. In Section III, we discuss various data modalities, ML methods used in FL4CAV applications, and FL data security in CAVs. Section IV reviews various applications of FL in CAVs. The multi-modal data, algorithms, and datasets used in the relevant literature are also summarized. Challenges and potential research areas are discussed in Section V. In Section VI, we present conclusions of this survey.

II. Federated Learning Methods

In this section, we describe the FL frameworks in terms of two categories: centralized FL and decentralized FL. An illustration of the categories is shown in Fig. 2. In addition, we provide an overview of the ML techniques that are commonly used as base models on local devices during the FL process. The steps of this process can be described as:

1) *Global Model Distribution:* The edge server disseminates the global model parameters to K vehicles.
2) *Model Update Using Local Data:* Each vehicle independently trains the ML model using its own local data.

TABLE I
COMPARISON OF RELATED SURVEYS OF FEDERATED LEARNING FOR CONNECTED AND AUTOMATED VEHICLES

Survey	**Time**	**Focused topic in FL**	**CFL & DFL**	**Vehicle Data Modality**	**Vehicle Application**	**Highlights**
Du *et al.* [38]	2020	Vehicular IoT	✗	✗	✗	• First survey of FL in vehicular IoT
Jiang *et al.* [39]	2020	Smart city	✗	✗	✗	• Opportunities of FL in the context of smart cities, such as interactions between CAVs and an urban sensing system.
Savazzi *et al.* [40]	2021	Automated industrial	✓	✗	✗	• Opportunities of FL in next-generation connected industrial systems, including robotics, vehicles, and drones
Nguyen *et al.* [41]	2021	IoT	✓	✗	✗	• FL in IoT applications, such as intelligent healthcare, transportation, city, unmanned aerial vehicles (UAV), and industrial
Javed *et al.* [42]	2022	Vehicular IoT Network	✗	✗	✗	• Integrating blockchain and FL for vehicular IoT network.
Yuan *et al.* [43]	2023	Decentralized FL	✓	✗	✗	• Taxonomies and variants of DFL • Analysis and state-of-the-art developments in different network topologies for DFL
This paper	**2023**	**FL for CAV**	✓	✓	✓	• **Advantages and disadvantages of CFL and DFL in CAV and state-of-the-art deployments.** • **Diverse data modalities and security in CAV** • **Facilitating 8 vehicle applications through FL** • **Challenges and future research directions of FL for CAV across 4 major categories and 11 subcategories.**

✓ Yes, ✗ No.

TABLE II
COMPARISON OF MACHINE LEARNING APPROACHES IN CONNECTED AND AUTOMATED VEHICLES

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

✓✓ Very high, ✓ high, ▲ average, ✗ low.

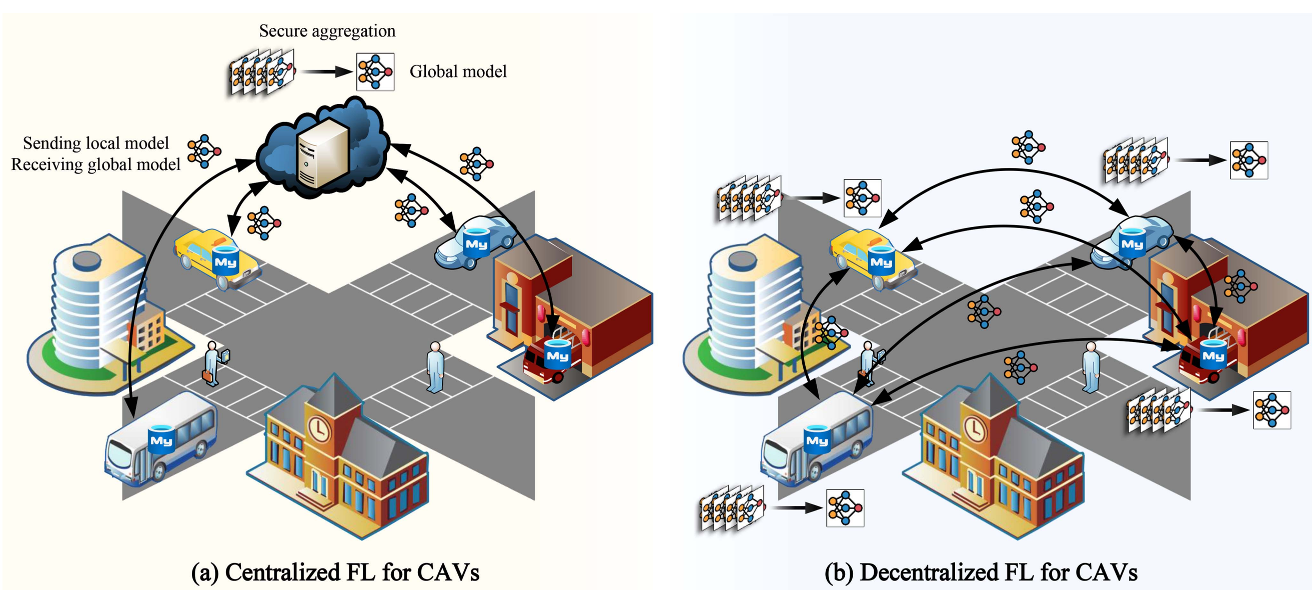


Fig. 2. Illustration of (a) centralized and (b) decentralized federated learning for connected and automated vehicles.

TABLE III
LITERATURE OVERVIEW OF FL FOR CAV ALGORITHMS

Literature	Time	CFL	DFL	Base Model	FL Algorithm
Doomra *et al.* [133]	2020	✓		LSTM	Averaging
Liu *et al.* [134]	2020	✓		GRU	Averaging (randomly client selection aggregation.)
Zhang *et al.* [135]	2021	✓		Two-stream CNN	Averaging
Aparna *et al.* [136]	2021	✓		CNN	Averaging
Rjoub *et al.* [137]	2021	✓		YOLO	Averaging
Kong *et al.* [138]	2021	✓		MLP	Averaging
Zhou *et al.* [139]	2021	✓		CNN	Averaging (hierarchical)
Saputra *et al.* [140]	2021	✓		MLP	Averaging (optimal economic client selection aggregation)
Barbieri *et al.* [141]	2021		✓	PointNet	Mesh topology
Zeng *et al.* [46]	2022	✓		MLP	Averaging
Stergiou *et al.* [66]	2022	✓		LeNet-5	Averaging
Fantauzzo *et al.* [67]	2022	✓		BiSeNet V2	Averaging
Elbir*et al.* [142]	2022	✓		U-Net	Averaging (hybrid federated and centralized learning architecture)
Han *et al.* [143]	2022	✓		LSTM	Averaging
Fu *et al.* [82]	2022	✓		RL	Averaging (reputation, quality, and overhead client selection aggregation)
Doshi *et al.* [70]	2022	✓		ResNet-8 & 56	Knowledge Distillation (FedGKT)
Sepasgozar *et al.* [144]	2022	✓		LSTM	Averaging
Yang *et al.* [145]	2022	✓		ResNet-18	Averaging (partial model weight update)
Zhou *et al.* [146]	2022	✓		Transformer	Averaging (spatial and temporal client selection aggregation)
Yuan *et al.* [71]	2023	✓		ResNet-34	Averaging (selective aggregation; meta-learning personalization)
Yuan *et al.* [147]	2023		✓	ResNet-34	Gossip protocol
Zhao *et al.* [72]	2023	✓		CNN	Averaging (hierarchical)
Du *et al.* [148]	2023	✓		LSTM	Averaging (hierarchical)
Parekh *et al.* [149]	2023	✓		CNN	Averaging
Wang *et al.* [150]	2023	✓		LSTM	Averaging

This training process typically adopts a simple Stochastic Gradient Descent (SGD) algorithm. The computational infrastructure is usually limited.

3) *Local Update Upload:* After training the model, each vehicle applies privacy-preserving techniques such as differential privacy (introduces artificial noise to the parameters) and then uploads/communicates the model parameters to the selected central server (Centralized Federated Learning, i.e., CFL) or other vehicles (Decentralized Federated Learning, i.e., DFL).

4) *Aggregation of Vehicle Updates:* The server securely aggregates the parameters uploaded from K vehicles to obtain the global model. Furthermore, it tests the model's performance.

A. Centralized Federated Learning

In this section, we review two major aggregation methods in the centralized framework, namely averaging and a more recent technique called knowledge distillation.

1) Averaging: Most of the existing literature uses the Federated Averaging (FedAvg) algorithm [25] for the FL aggregation process on the server—see Table III. FedAvg applies SGD optimization to local vehicles and performs a weighted averaging of the weights of the vehicles on 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 CAV are dynamically updated at each communication round.

A typical FL setup has K vehicles that have their own local data sets and the ability to perform simple local optimization. At the central server, the optimization problem can be represented as

$$\min_{x\in\mathbb{R}^d}\left[f(x)=\frac{1}{K}\sum_{i=1}^{K}f_i(x_i)\right], \tag{1}$$

where $f_i:\mathbb{R}^d\to\mathbb{R}$ for $i\in\{1,\ldots,K\}$ is the local objective function of the ith vehicle. The local objective function of the ith vehicle can have the form,

$$f_i(x_i)=\mathbb{E}_{\xi_i\sim\mathcal{D}_i}[\ell(x_i,\xi_i)], \tag{2}$$

where ξ_i represents the data that have been sampled from the local vehicle data $\mathcal{D}_i$ for the i^{th} vehicle. The expectation operator, $\mathbb{E}$, is acting on the local objective function, $\ell(x_i,\xi_i)$, with respect to a data sample, ξ_i, drawn from the vehicle data, $\mathcal{D}_i$. The function $\ell(x_i,\xi_i)$ is the loss function evaluated for each vehicle, x_i, and data sample, ξ_i. Here, $x_i\in\mathbb{R}^d$ represents the model parameters of vehicle i, and $X\in\mathbb{R}^{d\times K}$ is the matrix formed using these parameter vectors. The learning process is performed to find a minimizer of the objective function, $x_i=x^*=\arg\min_{x\in\mathbb{R}^d}f(x)$.

The data obtained from CAVs are typically non-independent and non-identically distributed (non-IID). FedAvg faces challenges in realistic heterogeneous data settings, as a single global model may not perform well for individual vehicles, and multiple local updates can cause the updates to deviate from the global objective [44]. Several variants of FedAvg have been proposed to address the challenges encountered by FL, such as data heterogeneity, client drift, local vehicle data imbalance, communication latency, and computation capabilities. FedProx algorithm, FedAvg with a proximal term, has been proposed to improve the convergence and reduce communication cost [45]. Dynamic Federated Proximal [46] algorithm (DFP) is an extension of FedProx that could effectively deal with non-IID data

Algorithm 1: CFL for Dynamic Data Updating CAV.

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 $\{\eta_t\}_{t=0}^{T-1}$, loss function f

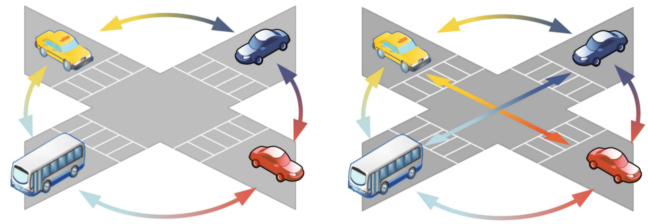
Output: Aggregated global model θ

For each vehicle $v \in \mathbb{V}$ initialize model: $\theta_v^{(0)} \in \mathbb{R}^d$
for $t = 0, \ldots, T-1$ **do**
  Perform local SGD **for** vehicle $v \in \mathbb{V}$ **in parallel do**
    Sample $\xi_v^{(t)}$, compute $g_v^{(t)} := \widetilde{\nabla} f_v(\theta_v^{(t)}, \xi_v^{(t)})$
    $\theta_v^{(t+1)} \leftarrow \theta_v^{(t)} - \eta_t g_v^{(t)}$ $\Rightarrow$ SGD (E epochs)
    Vehicle sent model θ_v to server
  end for
  $\theta^{(t+1)} \leftarrow \sum_{v\in\mathbb{V}} \frac{|\xi_v^{(t)}|}{|\xi^{(t)}|}(\theta_v^{t+1})$ $\Rightarrow$ Aggregation on server
  Server sent model $\theta^{(t+1)}$ to vehicles
end for
Output the aggregated global model $\theta \leftarrow \theta^{(T)}$

distribution by dynamically varying the learning rate and regularization coefficient during the learning process. FedAdam [47] has shown improved convergence and optimization performance by incorporating ADAM optimization in the FedAvg algorithm. Improving the performance of the FL model is an ongoing research activity [48], [49], [50], [51].

2) Knowledge Distillation: In this subsection, we discuss the integration of knowledge distillation with FL. Federated Distillation (FD) [52] uses knowledge distillation to transfer knowledge in a decentralized manner, leading to a significant reduction in the communication size compared to a traditional FL. It also has the ability to handle non-IID data samples [53]. Wang et al. [54] proposed a conceptual framework called FD for CAV (FDCAV), where CAVs share their outputs (e.g., bounding boxes) with a central server, which computes the average output from the global model and sends it back to vehicles. The vehicles then update their local models based on the output of the global model [54].

Another approach is to deploy a teacher model on the server and student models on the clients. In this process, client devices usually train and deploy a smaller, simpler model to mimic the behavior of a larger, more complex model residing on the server. It allows for the transfer of knowledge from the larger server model to the smaller client model, thereby reducing computational complexity and enhancing efficiency. For example, in Federated Group Knowledge Transfer (FedGKT) [55], a ResNet-55 or ResNet-109 is deployed on the server, while a ResNet-8 is utilized on the clients. Similarly, Federated Knowledge Distillation (FedKD) [56] employs a comparable approach, conducting experiments on natural language recognition tasks. Knowledge distillation with FL is particularly beneficial in scenarios where computational resources or storage capacities are constrained or where the deployment of larger models is infeasible. CAVs are prime examples of such application scenarios. The CFL is summarized in Algorithm 1.



(a) Ring (b) Fully-connected

Fig. 3. Ring (*left*) and fully-connected topology (*right*)—four vehicles.

B. Decentralized Federated Learning

In the CFL paradigm, model parameters (weights or gradients) are transmitted to a central server, often a Road-Side Unit (RSU), where the FL server-side aggregation process takes place. On the contrary, DFL relies on a consensus among the vehicles, fostering collaboration to collectively update global parameters without the need for a central server. The DFL algorithm is shown in Algorithm 2. The scalability of CFL is limited by the computational capacity of the server, which requires a dedicated infrastructure. The dependence on a single server introduces a potential point of failure in the learning process and can lead to communication congestion between the server and vehicles, especially when handling a substantial number of vehicles [57].

DFL offers scalability by accommodating a large number of vehicle clients without relying on a central server, and exhibits enhanced robustness since the collaborative training among vehicles can continue even if an individual vehicle becomes unavailable. DFL relies on the V2X communication module to send model data directly to other neighboring vehicles for updates [58], [59].

The primary concept behind the DFL process is to establish consensus among vehicles by enabling communication exclusively between adjacent neighbors. This communication process can be effectively represented by employing a consensus/gossip matrix within a network topology graph. More precisely, a vehicle i communicates with vehicle j based on a non-negative weight that represents the connectivity of vehicle i and vehicle j, that is, $w_{ij} > 0$. The case $w_{ij} = 0$ indicates that no communication takes place between i and j. Similarly, for self-loops, the associated weight is represented by $w_{ii} > 0$. Fig. 3 shows examples of two commonly employed network topologies, namely the ring and the fully connected for the $n = 4$ client/vehicle configuration. In the fully connected topology setting, all vehicles interact with each other, whereas in the ring topology, vehicles interact only with neighboring vehicles. These associated weights can be compiled into a matrix of dimension $n \times n$ and can be written as $W = [w_{ij}] \in [0, 1]^{n\times n}$. The most standard name for W used in the literature is *gossip* or *mixing matrix*.

The mixing matrix, $W = [w_{ij}] \in [0, 1]^{n\times n}$, is a non-negative, symmetric ($W = W^\top$) and doubly stochastic, that is, $W\mathbb{1} = \mathbb{1}, \mathbb{1}^\top W = \mathbb{1}^\top$ matrix, where $\mathbb{1}$ is the column of ones. Then, the consensus operation can be represented as,

$$\theta_i^{(t+1)} = \sum_{j\in[n]} w_{ij}^{(t)}\, \theta_j^{(t)}, \tag{3}$$

Algorithm 2: DFL for Dynamic Data Updating CAV.

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 $\{\eta_t\}_{t=0}^{T-1}$, loss function f, mixing matrix W

Output: Personalized model θ_v for each vehicle $v \in \mathbb{V}$

1: For each vehicle $v \in \mathbb{V}$ initialize model: $\theta_v^{(0)} \in \mathbb{R}^d$
2: **for** $t = 0, \ldots, T-1$ **do**
3: **Perform** local SGD **for** vehicle $v \in \mathbb{V}$ **in parallel do**
4: Sample $\xi_v^{(t)}$, compute $g_v^{(t)} \leftarrow \widetilde{\nabla} f_v(\theta_v^{(t)}, \xi_v^{(t)})$
5: $\theta_v^{(t+\frac{1}{2})} \leftarrow \theta_v^{(t)} - \eta_t g_v^{(t)} \Rightarrow$ SGD (E epochs)
6: Vehicle sent model $\theta_v^{(t+\frac{1}{2})}$ to other vehicles
7: **end for**
8: Aggregate models of other vehicles $u \in \mathbb{V}$: $\theta_v^{(t+1)} \leftarrow \sum_u W\, \theta_u^{(t+\frac{1}{2})} \Rightarrow$ Aggregation on clients
9: **end for**
10: Each client deploys a personalized model $\theta_v \leftarrow \theta_v^{(T)}$

where θ is the model parameter (weights/gradients).

However, DFL also encounters notable limitations, including hindered convergence (caused by the heterogeneity of data) and network latency, and the need to synchronize/arbitrate parameters and adapt to dynamic network topologies during vehicle communications. These challenges arise from the decentralized nature of the FL framework, which requires efficient mechanisms to address disparities in data distribution and network connectivity among the participating vehicles [60], [61], [62], [63], [64].

III. Overview of Data Modalities, Base Machine Learning Models, and Securities

The concept of FL4CAV is illustrated in Fig. 2. 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.

CAV tasks are diversified to include tracking the target speed, prediction of behavior, motion planning, motion control, object detection, and in-vehicle human monitoring. After training on 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.

An overview of the data modalities, the base ML models of CAVs, and data security is presented next.

A. Data Modality

CAVs collect multi-modal data from various sensors to perform tasks such as navigation and perception. The impact of different types of data modalities during the FL process on sensor fusion is dynamically diverse [65]. 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 sensor visibility, thereby deteriorating 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 the vehicles. The data resolution, size, and sampling rate obtained from CAVs are generally heterogeneous, and processing the data is also a challenging task. In the following, we review the various data modalities in FL4CAV applications that are illustrated in Fig. 4.

1) Image: Images, especially visible RGB images, are one of the most important data modalities for CAVs. Vision-related tasks, such as driver monitoring Section IV-A, steering wheel angle prediction Section Section IV-B, object detection Section IV-D, traffic sign recognition [66], and semantic segmentation [67] use images captured by the camera as the data source. In most applications, various ML models are trained to achieve the intended functionality. However, due to its intrusive design, privacy issues are always a concern for image-based systems, especially for in-cabin and driver-related applications [68], [69], [70], [71], [72]. Privacy concerns for visual image-based systems are addressed by FL since only the model parameters are transmitted while the user data are kept locally in the vehicle. Moreover, FL also solves the data transmission problem due to the large size of images and video data, thus leading to a more communication-efficient learning framework.

2) Lidar: LiDAR data is vital for automated driving capabilities, which has been used for object detection tasks [73], [74] and cooperative perception scenarios [75], [76]. LiDAR generates 3D point clouds that can detect objects accurately even under adverse weather conditions, unlike camera data that are unreliable under similar conditions. However, the dense point cloud of LiDAR data makes transmission a demanding task. FL system for LiDAR data can improve learning efficiency and save communication resources while being able to handle large data sets.

3) Radar: Radar sensors are used for object detection and collision avoidance in applications such as automatic emergency braking, traffic alerts, and adaptive cruise control [77], [78], [79], [80]. Radars have long operating ranges, good measurement accuracy, and are operational in varying weather conditions [81]. Radar data provides critical information about the vehicle's surroundings, including the position and the speed of other objects. Similarly to LiDAR, the FL system for Radar can also improve learning efficiency and save communication resources.

4) Vehicle Status and GNss: Vehicle status data such as velocity, acceleration, throttle/brake command, vehicle global position through GNss, and other vehicle parameters are also an important part of the CAV data modality. These parameters

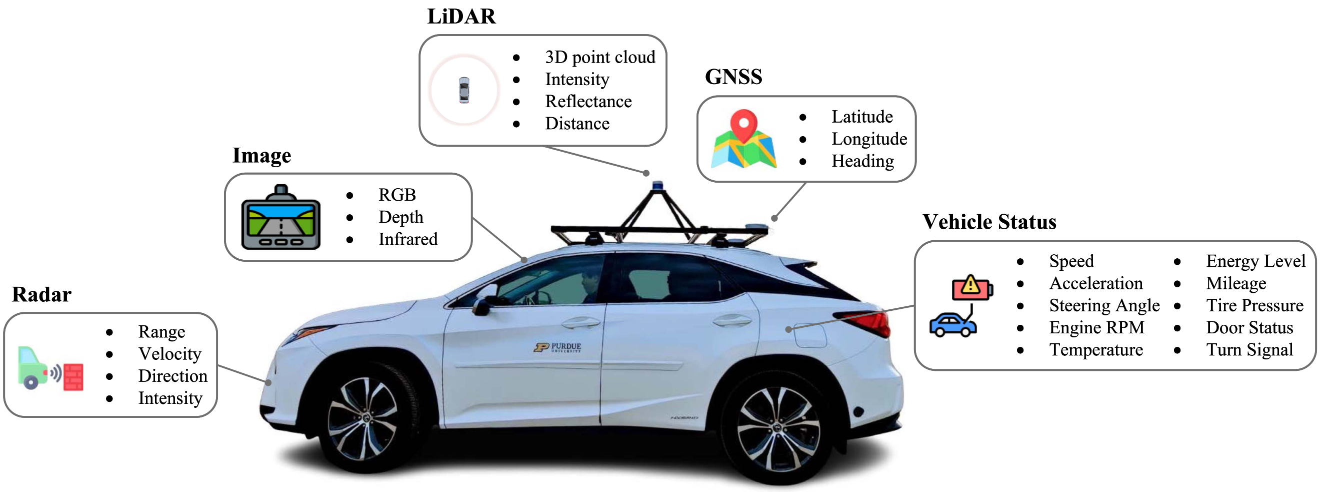


Fig. 4. Illustration of various data sources from a connected and automated vehicle.

are relevant primarily to the vehicle rather than to the external environment. These data typically reveal sensitive information about driver locations, habits, and behaviors that could potentially compromise their privacy and security. FL addresses these privacy concerns well while utilizing these data to improve several applications such as collision avoidance [82], vehicle trajectory prediction Section IV-C, and motion control application Section IV-E.

B. Base Models in FL4CAV Applications

ML has been widely used to achieve superior performance in various complex tasks, given the availability of multi-modal data from in-vehicle sensors. Furthermore, the ML in FL4CAV shows the feasibility of implementation in real time, which is required due to the limited computing and communication resources of vehicle equipment. We next discuss the various ML architectures that are used as base models in critical tasks of CAVs.

1) Multilayer Perceptron: A Multilayer Perceptron (MLP), as a classic ML architecture, consists of multiple layers of fully connected neurons. It can be applied to various vehicle-related tasks, including perception, decision-making, and control. MLP provides a flexible and versatile tool for modeling complex relationships in vehicle-related data. However, its performance in specific tasks may be limited due to the computational demand for large models. Due to their applicability, MLPs are widely employed in vehicle trajectory prediction (Section IV-C), motion control (Section IV-E), and traffic flow prediction (Section IV-F).

2) Convolutional Neural Network: Convolutional Neural Networks (CNNs) are presently one of the most popular architectures in ML. They are known for their excellent performance in handling image-related tasks. CNN uses convolutional layers to automatically extract features from images and learn to associate these features with corresponding labels. CNNs exhibit versatile performance in performing a wide range of tasks, including, but not limited to, classification (as exemplified by LeNet [83], ResNet [84]), object detection (such as the YOLO [85] framework), and mask generation for semantic segmentation (represented by models such as U-Net [86], BiSeNet [87]), among others. Due to its high efficiency in extracting features from image data, CNNs are widely applied in various vehicle-related applications, such as in-vehicle human monitoring (Section IV-A), steering wheel angle prediction (Section IV-B), object recognition (Section IV-D).

3) Recurrent Neural Network: Recurrent Neural Networks (RNNs) excel at extracting spatial relationships in features. They are specifically designed to capture temporal dependencies in sequences of data. Some popular RNN architectures include Long Short-Term Memory (LSTM) [88] and Gated Recurrent Unit (GRU) [89]. In the context of vehicles, RNNs have found extensive applications in modeling the motion and behavior of vehicles, their surroundings, and targets. Using their sensitivity to time series data, RNNs can effectively capture the dynamics and temporal patterns in various vehicle-related scenarios, for example vehicle trajectory prediction (Section IV-C) and traffic flow prediction (Section IV-F).

4) Transformer: Transformer [90] architecture and its variant, Vision Transformer (ViT) [91], have emerged as powerful alternatives to traditional CNNs and RNNs. The Transformer architecture, initially introduced for natural language processing tasks, has shown exceptional performance in various domains, including computer vision. Transformers take advantage of self-attention mechanisms to capture global dependencies across the input sequence or image. This allows them to effectively model long-range dependencies and contextual relationships, leading to improved performance in tasks such as image classification, object detection, and semantic segmentation. Transformers' ability to capture global context and long-range dependencies makes them well-suited for various tasks in the automotive domain [92]. Transformers and ViTs have attracted substantial attention in the fields of FL [93] and CAV [94] due to their ability to effectively capture global information. Transformers and ViTs have a potential for a wide range of vehicular applications (Section IV).

5) Generative Network: Generative networks form images based on input data, such as mask labels and super-resolution. These networks, also known as Generative Adversarial Networks (GANs) [95] or Variational Auto-Encoders (VAEs) [96], exhibit a distinctive ability to generate high-quality and realistic images. Generative networks have attracted attention in both the FL [97] and CAV [98] domains. However, there is still no unified framework that incorporates all three technologies. With the extensive application of generative networks in CAV, combined with FL's enhancement of privacy protection and learning efficiency, they have a potential for various applications. In vehicular applications, generative networks provide several use cases, such as vehicle trajectory prediction (Section IV-C). One application lies in super-resolution, where generative networks can enhance the resolution and details of low-resolution images, proving useful for tasks such as license plate recognition and surveillance systems. Furthermore, generative networks can also be utilized to augment and improve data sets in training data sets for vehicle-related tasks.

6) Reinforcement Learning: Reinforcement learning (RL) demonstrated superior capabilities in solving complex decision-making problems, surpassing human-level performance in various domains [99]. RL improves the abilities of the agent through interaction with the environment, enabling the agent to learn optimal policies through trial and error. RL has been extensively applied in CAV operations, such as motion control (Section IV-E), vehicle trajectory prediction (Section IV-C),vehicular CPS (Section IV-G), and resource allocation [100], [101], [102].

C. Model Security

Robust and secure privacy preservation techniques are essential to protect sensitive data during the FL training process for CAVs. It is demonstrated that the training 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 attacks that may cause the entire learning process to collapse [103]. The type of data considered in this section refers to the model parameters, such as gradients or weights, that are transmitted to the server/neighboring vehicles. These are not the raw data used for the training of the local model, as they are inherently preserved in the FL process.

Homomorphic encryption, differential privacy, and blockchain-based techniques are notable methods to preserve privacy in FL4CAV. These approaches aim to minimize the trade-offs between model performance and data privacy, ensuring data security while enabling effective model performance. A review of various cyber-security threats can be found in [104], [105], [106], [107], [108], [109]. We will next discuss some of the widely used privacy-preserving techniques.

1) Homomorphic Encryption: Homomorphic Encryption (HE) is a powerful technique that allows the server to perform training on encrypted vehicle data without the need for decryption, thus ensuring data privacy and security. In particular, it allows direct computation on encrypted data with decrypted results [110].

2) Differential Privacy: Differential Privacy (DP) is an approach that safeguards data privacy by injecting random noise into the data before transmitting them to the server, preventing unauthorized extraction of sensitive information while also preserving data ownership and alignment with regulatory compliance. However, there is a trade-off between privacy settings and accuracy that can impact the performance of the models. DP has been used in multiple applications of FL4CAV for incorporating data security [111], [112], [113], [114], [115]

3) Secure Multi-Party Computation: Secure Multi-Party Computation (SMPC) employs cryptographic techniques to encrypt and partition the data, enabling collaborative computation on these data with output results accessible to vehicles. While SMPC introduces considerable communication overheads, it excels in preserving data security and privacy. The SMPC integration framework with FL facilitates model training on data without exposing model parameters [116], [117]. In an FL setup, SMPC can substantially encrypt the communication of model updates. Furthermore, vehicles can apply SMPC for collaborative intermediate computations, ensuring that even if the central server is compromised, no meaningful information can be derived from these computations.

4) Physical Security: In model security enhancement, reinforcement at the physical layer emerges is a key approach. Beyond the security measures required for both the vehicle and the server, hardware-level security technologies, such as the Trusted Execution Environment (TEE), offer participants in FL an isolated, secure, and confidential execution environment [118]. With the support of TEE, vehicles can process and store data within a protected environment, iterating and refining their local models. Similarly, the server, using the support of TEE, can execute model aggregations in a secure context.

5) Blockchain: Another disruptive technology gaining traction in CAV applications is blockchain-based methods, leveraging the decentralized and tamper-resistant nature of blockchain to improve data integrity, transparency, and security [119], [120], [121], [122], [123], [124], [125], [126]. Blockchain is a type of digital ledger technology that securely transfers data in a decentralized framework. CAVs share their data with the vehicular network and the information is stored on the blockchain. Blockchain provides a secure, credible, and decentralized approach to FL, enabling collaborative model training while safeguarding data privacy [127]. The system is designed to protect data privacy and security, as well as to provide greater security to the general vehicular networks involved in the learning process [128]. An analysis of various privacy preservation approaches is given in [105], [129].

In FL4CAV, the model parameters of individual vehicles can be stored as transactions on the blockchain, ensuring transparency and accountability. This creates trust among the vehicles, as the model updates can be verified. Additionally, blockchain enables incentive mechanisms through smart contracts, which reward CAVs that contribute high-quality model updates or share their computational resources for training.

TABLE IV
LITERATURE OVERVIEW OF FL FOR CAV APPLICATIONS

Literature	Time	Data Modality	Application	Dataset
Doomra et al. [133]	2020	Time series data of multiple features from sensors	Turn signal prediction	Ford's Big Data Drive [134]
Liu et al. [134]	2020	Traffic flow	Traffic flow prediction	Caltrans Performance Measurement System (PeMS) dataset [152]
Zhang et al. [135]	2021	RGB image	Steering angle prediction	Self-collected
Aparna et al. [136]	2021	RGB image	Steering angle prediction	Self-collected
Rjoub et al. [137]	2021	RGB image and LiDAR	Object detection	Canadian Adverse Driving Conditions Dataset [153]
Kong et al. [138]	2021	Trajectory data	Cooperative positioning	Didi Chuxing GAIA Initiative [154]
Zhou et al. [139]	2021	RGB image	Traffic sign recognition	BelgiumTS [155]
Saputra et al. [140]	2021	Traffic accident data	Traffic accident prediction	1.6 million UK traffic accidents [156]
Barbieri et al. [141]	2021	RGB image and Sensor data	Object detection	nuScenes dataset [157]
Zeng et al. [46]	2022	RGB image and trajectory data	Target speed tracking	Berkeley deep drive [158] and dataset of annotated car trajectories [159]
Stergiou et al. [66]	2022	RGB image	Traffic sign recognition	German Traffic Sign Recognition Benchmark [160]
Fantauzzo et al. [67]	2022	Multi-modal image	Semantic segmentation	Cityscapes [161] and IDDA [162]
Elbir et al. [142]	2022	RGB image and LiDAR	3D object detection	Lyft Level 5 dataset [163]
Han et al. [143]	2022	Vehicle Status	Trajectory prediction	US-101 and I-80 data sets of NGSIM [164]
Fu et al. [82]	2022	Vehicle position, velocity and acceleration	Collision avoidance	Self-generated
Doshi et al. [70]	2022	RGB image	Driver activity recognition	State Farm Distracted Driver Detection [165] and AI City Challenge 2022 [166]
Sepasgozar et al. [144]	2022	Vehicle velocity	Traffic flow prediction	CRAWDAD Vehicular dataset [167]
Yang et al. [145]	2022	RGB image	Driver activity recognition	State Farm Distracted Driver Detection [165] and YawDD [168]
Zhou et al. [146]	2022	Trajectory data	Trajectory prediction	Didi Chuxing GAIA Initiative [154]
Yuan et al. [71]	2023	RGB image	Driver activity recognition	State Farm Distracted Driver Detection [165] and Drive&Act [169]
Yuan et al. [147]	2023	RGB image	Driver activity recognition	State Farm Distracted Driver Detection [165] and The 7th AI City Challenge [170]
Zhao et al. [72]	2023	RGB image	Driver fatigue detection	Blinking Video Database [171] and Eyeblink8 [172]
Du et al. [148]	2023	3D head position	Lane-change prediction	Self-collected
Parekh et al. [149]	2023	RGB image	Traffic sign recognition	German Traffic Sign Recognition Benchmark [160]
Wang et al. [150]	2023	Vehicle pose	Trajectory prediction	VeReMi [173]

These incentives encourage active participation and foster collaboration among vehicles [110], [130], [131], [132].

IV. APPLICATIONS OF FL FOR CAV

In this section, we review some applications of FL in CAV. The FL4CAV literature, including FL configuration, data modalities, underlying models, applications, FL algorithm, and datasets, can be found in Tables III and IV. The strengths of FL, such as protecting privacy, improving learning efficiency, improving generalization ability, and reducing communication overhead, resulted in several FL4CAV applications.

A. In-Vehicle Human Monitoring

In-vehicle human monitoring is a critical issue for CAV and ITS. The in-vehicle human monitoring serves not just the driver but also extends to the other passenger monitoring in vehicles [173]. Beyond the application in commercial taxis, human monitoring becomes particularly critical in large public transportation modes such as buses, subways, ferries, and more, where adequate human personnel for service may be lacking. Consequently, computer-aided monitoring programs can effectively offer superior service quality and protect passenger safety by handling tasks such as passenger counting, passenger traffic, detecting elderly falls, and emergency situations such as fires.

FL significantly enhances privacy protection, enriches and diversifies knowledge, and improves learning efficiency, which makes it crucial for the application of human monitoring in the vehicle in the deployment of CAVs. Given the sensitivity of personal privacy and the rarity of traffic accidents, FL serves as a valuable tool in these contexts. FL has the potential to enhance the security of user data onboard while enabling knowledge transfer and ensuring the generalizability of the model. However, in human-related applications where data are highly heterogeneous and personalized, it can be challenging to balance the generalization ability of the model with the need for personalization to specific users [174].

Driver monitoring applications, such as distraction detection, are critical safety features that monitor driver stability and alertness and warn distracted drivers to apply safety-critical actions [148], [175], [176], [177], [178]. The computational and communication efficiency issues in driver activity recognition are addressed in [70] and a novel framework (FedGKT) was proposed to reduce communication bandwidth and asynchronous training requirements. Driver privacy may be a greater 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. This user heterogeneity poses a challenge for FL systems. For human-related applications, such as driver monitoring, personalized FL is the dominant solution [71]. A DFL framework was proposed in [147] that incorporates a gossip protocol for knowledge dissemination. This framework not only achieves personalized models without requiring any additional processing, but also incorporates a knowledge dissemination technique that significantly accelerates the training process.

Passenger monitoring applications are an emerging research area that involves detecting passengers' intents to board and leave and warning of dangerous behavior in public transportation [179]. 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 FL a promising application in this area.

B. Steering Wheel Angle Prediction

The prediction of the angle of the steering wheel has become a crucial feature of self-driving. The performance of ADAS features, such as lane keep assist and lane departure warning, is based on the prediction of the steering angle [180], [181]. The steering wheel angle prediction is used to estimate the steering wheel rotation angle based on the input of road images. The prediction of the steering wheel angle manages the lateral positioning of the vehicle, even under challenging circumstances, such as on unpaved and unmarked roads. The steering wheel angle prediction needs to adapt to different driving and environmental conditions, and thus requires continuous model updates for high accuracy.

FL achieves the above objectives by enabling several vehicles to collaborate in learning from new data and updating the model in a 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.

It was demonstrated that FL can collectively train the prediction model while, at the same time, significantly reducing communication costs. The study presented in [135] demonstrated a significant improvement in edge model quality through the use of FL in CAV. Specifically, the study involved predicting steering wheel angles using two modalities of data: images and optical flow. In [136], the performance of FL and centralized learning in steering angle prediction was assessed under different levels of noise and the results were comparable. Furthermore, this study considered the implications of communication load and disruptions, providing a comprehensive evaluation of the systems. This makes FL suitable for applications involving an increasing number of CAVs, specifically for tasks such as steering wheel angle prediction.

C. Vehicle Trajectory Prediction

An accurate vehicle trajectory prediction allows CAVs to perform proper motion planning, as well as anticipate potentially dangerous behaviors of other vehicles, such as sudden lane change, skidding, or hard braking, react proactively and prevent accidents [182], [183], [184], [185], [186]. This is a challenging task and would require substantial amounts of sensitive vehicle data to train a model for trajectory prediction.

FL is a viable solution that provides a collaborative learning framework with multiple vehicles while keeping sensitive local data private and secure. FL models are trained on diverse data from various vehicles operating in different scenarios. This enhances the generalization of the model and enables vehicles to handle rare events such as traffic accidents, adverse weather, and risky behaviors. Additionally, the FL framework supports continuous learning and model updates, allowing quick adaptation to dynamic traffic, road conditions, and unfamiliar scenarios.

Trajectory prediction models commonly rely on time series data that encompass vehicle/passenger position, velocity, and acceleration. These models leverage the strength of deep neural networks, mainly RNNs, and Transformers, that have proven effective in predicting trajectories for various entities, including vehicles and pedestrians, while also capturing their behavioral patterns [187]. FL framework has been shown to be effective in learning spatio-temporal features with the Transformer model [146] (or the LSTM model [188]) while also protecting user privacy. FL coupled with One-Class Support Vector Machine (OC-SVM) has been used to detect anomalous trajectories at traffic intersections [189]. The reported findings indicate that the federated approach improves both the overall accuracy of anomaly detection and the benefit of individual data owners. FL has been reported to perform similarly to centralized learning [143], [190], [191]. Centralized learning requires that all data from the private vehicle be transferred to the central server for training, whereas the data are kept locally in the vehicle in the case of FL.

D. Object Recognition

Object recognition is one of the main functions of the visual perception system of CAVs 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 from a privacy point of view. As a result, there are limitations to deploying robust detection models in a traditional centralized learning approach due to privacy and communication overhead. These concerns can be mitigated by using an FL-based approach for CAVs. FL can effectively help CAVs detect various 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 ML model while also ensuring the privacy of the data.

FL has already been used in computer vision-related tasks, such as developing safety hazard warning solutions in smart city applications [192]. The accuracy of object detection models is generally poor under adverse weather conditions such as snow and rain. FL frameworks have been shown to improve detection accuracy [193] and perform better than the centralized and gossip-decentralized models [137]. Recently, studies have been carried out to improve the performance of FL on complex tasks such as object detection [194]. In [54], it has been shown that with multistage resource allocation and appropriate vehicle selection, FL performance improved significantly compared to traditional centralized learning and baseline FL approaches.

In [141], a decentralized FL method is used for object classification using LiDAR on CAVs. The parameters of the ML model (PointNet [195]) are communicated through V2V networks. It has been experimentally confirmed that FL is highly effective compared to self-learning approaches.

Another important application of FL is the recognition and detection of license plates. It is used in ITS for applications such as traffic safety and violations, traffic monitoring, illegal/overtime parking detection, and parking access authentication. ML techniques have been shown to be highly efficient in detecting objects and recognizing license plates [196], [197], [198], [199]. However, due to the large size of the data from all vehicles, it is not feasible to train on a real-time edge device. FL techniques offer numerous advantages to license plate detection and recognition systems, namely: privacy protection, enabling collaborative learning, and reduced network bandwidth requirements. These benefits of using FL contribute to increased effectiveness and adaptability of such systems in real-world scenarios [200], [201].

E. Motion Control

The motion controller of the vehicle executes the desired trajectory by determining the optimal control of the acceleration pedal position (longitudinal acceleration motion), the steering of the vehicle (lateral motion) and the brake position (longitudinal deceleration motion) [202], [203], [204]. FL enables CAVs to train and optimize controller parameters collaboratively. Some potential benefits of using FL are enabling CAVs to adapt to unseen routes/traffic scenarios or operating conditions due to previous data from other CAVs, acceleration on the ramp, driving in congested conditions, or challenges associated with higher vehicle speed [205]. FL enables CAVs to adapt to different driving scenarios, including unfamiliar roads, cities, and countries. Furthermore, FL may allow CAVs to adjust driving styles based on different driving habits, climates, scenarios, and cultural norms.

FL has been used to dynamically update the controller parameters, resulting in improved achievement of the target speed with enhanced driver comfort and safety [46]. Additionally, FL finds application in collaborative optimization of control parameters between multiple vehicles at traffic intersections, resulting in the avoidance of collisions and improved driving comfort [206], [207]. In [208], FL is utilized to improve brake performance under different driving conditions and environments by accurately determining road friction coefficients. This approach ensures the privacy of the driver while optimizing the braking action. In [46], an FL framework is proposed to optimize the controller design for CAVs with variable vehicle participation in the FL training process.

Reinforcement Learning (RL) approach has been widely applied for motion control in vehicles due to its ability to train in complex scenarios with dynamic environments. RL enables CAVs to learn control policies for the required objectives with user feedback and sensor measurements [100], [209], [210], [211], [212]. There are open research problems in motion control of CAVs that could be addressed by FL such as platooning, lane change maneuvers, merging on-ramps, signalized, and unsignalized intersections. A review of existing CAV control methods is provided in [213], [214], [215], while applications of ML to CAV control are reported in [216], [217], [218], [219], [220], [221].

F. Traffic Flow Prediction

Traffic flow prediction is one of the critical components of an ITS for efficient traffic control, safety, and management. Accurate predictions using historical data to forecast future traffic conditions can lead to reduced traffic congestion, such as optimal route recommendation and variable road signal timing. Predicting traffic flow can also allow timely notification to authorities of occurrences of events, such as accidents and congested road conditions. ML techniques, such as CNNs and RNNs, have shown promising results in predicting traffic flow [222], [223], [224].

FL has been used to predict traffic flow with improved accuracy while ensuring privacy and scalability. Sources for model training include data from CAV, RSUs, and traffic sensors. The predictions could be in real-time or for future time intervals, and the model can be trained to predict traffic patterns and improve the accuracy of traffic flow predictions. FL allows CAVs to collaboratively learn from their data while addressing privacy concerns.

In [134], a Gated Recurrent Unit (GRU) network is trained using FL to predict traffic flow. Experimental evaluations of a real-world data set show that the FL-based approach can achieve predictions comparable to those of traditional centralized approaches. In [225], an FL-based Spatial-Temporal Networks (FedSTN) algorithm was proposed to predict traffic flow. The algorithm employs various methods like Recurrent Longterm Capture Network, Attentive Mechanism Federated Network, and Semantic Capture Network (SCN) to learn spatial-temporal and semantic information. It is reported that the FedSTN algorithm outperforms in terms of higher prediction accuracy compared to existing baselines such as Auto-Regressive Integrated Moving Average (ARIMA), eXtreme Gradient Boosting (XGBoost), FedGRU, and ST-ResNet [226]. In [227], a Long-Short-Term Memory (LSTM) is trained in an FL framework for traffic flow prediction along with an RL that is used for resource optimization. In [144], an FL framework employing LSTM algorithm has been trained on a real Vehicular Ad hoc NETwork (VANET) data set based on V2V and V2R communication for the prediction of network traffic. The above developments show the benefits of using FL for complex tasks such as traffic flow prediction.

G. Vehicular Cyber-Physical Systems

Vehicular Cyber-Physical Systems (VCPS) encompass the integration of physical systems, cyber systems, and vehicular communication networks [228]. Physical systems comprise vehicles, roads, and telematics/edge devices, while cyber systems include data centers, central servers (i.e., cloud), and traffic management systems. Vehicular networks, namely Cellular Vehicle-to-Everything (C-V2X) and V2X communication networks, play a key role in facilitating information sharing to improve driving comfort, safety, and traffic management. VCPS utilizes various technologies to enhance the vehicular network and enable seamless and robust communication between vehicles and systems.

FL plays a critical role in VCPS by enhancing data privacy and addressing resource constraints. FL uses a collaborative and distributed learning framework that captures data heterogeneity while eliminating the need to transfer local data from vehicles. This enables VCPS to benefit from FL's ability to preserve data privacy and facilitate efficient learning without compromising resource limitations.

In [229], an FL framework is proposed to detect and mitigate data leakage in VCPS while enhancing data privacy. The proposed scheme achieves good accuracy, efficiency, and high security based on simulations of a real-world data set. In [230], an FL framework (OES-Fed) is proposed for outlier detection and noise filtering in vehicular networks. In [231], extreme value theory (EVT) and personalized FL are proposed to model anomalous events caused by the non-heterogeneous data distribution among vehicles in vehicular networks. In [232], an efficient and secure FL framework is combined with the Deep Q-Network (DQN) to ensure an efficient and secure scheme to reduce the latency of vehicular data sharing in vehicular networks.

FL has gained significant acceptance for enhancing the resilience and robustness of VCPS networks against adversarial attacks. This is achieved through the integration of FL with techniques such as differential privacy [233] and blockchain-based approaches [132], [234]. These combinations have shown promising results in improving the security and reliability of the VCPS network.

H. Vehicle-to-Everything Communication

An efficient and robust V2X communication such as V2V and V2I is a crucial step towards achieving an ITS. V2X communication plays a pivotal role in improving traffic management and enhancing driving comfort. As ITS development progresses further, we expect a substantial increase in data transmission due to a large number of vehicles. This surge in data poses challenges in terms of communication and energy consumption. Moreover, given the private and sensitive nature of the data, ensuring data security is essential. Therefore, it is crucial to address these issues by adopting energy-efficient approaches and establishing low-latency transmission in V2X communication [235].

FL offers a promising solution for learning parameters with minimal latency and data transmission due to its decentralized training framework. It ensures data security while enabling efficient client/server selection during the training process [236], [237], [238] and resource management [239], [240]. These approaches have demonstrated an effective reduction in communication overload, addressing a significant challenge in FL implementations.

In [241], [242], extreme value theory was used in conjunction with an FL framework to model anomalous events, specifically large queue lengths. Lyapunov optimization was also incorporated for power allocation, which contributed to improving system performance.

V. Challenges and Future Directions

In this section, we review various challenges in the use of FL4CAV as well as future research directions, as shown in Fig. 5.

A. Resource Limitations and Utilization

1) Collaboration Capabilities and Management in Massively Parallel CAVs: Significant participation of CAVs in FL could increase the solve time and memory utilization, and therefore calls for an increase in computational demand for a global model update. In particular, vision- and LiDAR-related perception tasks are characterized by large data sets that lead to high communication costs. Decentralized FL and clustered FL [243], [244], [245], [246] are being explored to reduce communication overhead.

The high communication demands and low reliability of 5G networks call for the development of 6G-V2X systems. Integrating 6G, V2X, and multi-access edge computing (MEC) powered by ML techniques creates the potential to achieve efficient and collaborative processing at the network edge. This approach aims to overcome the limitations of current 5G systems and pave the way for improved performance and reliability in future networks [247], [248].

2) Challenges Due to 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 [54], [249], [250], [251], and good pre-trained models.

3) Low Model Accuracy: FL often struggles with a trade-off between the accuracy achieved through model personalization and imposing high computational requirements on edge devices during learning. Split learning is one potential solution that enables efficient inference in resource-constrained edge clients while capturing both generalization and personalization capabilities [252].

4) Inefficient Resource Utilization: Some of the issues of FL related to resource optimization include idle of powerful edge devices, underutilized network infrastructure, neglected edge devices without proper network connectivity, and discouraged sharing of parameters from edge devices with diverse privacy requirements [253]. Therefore, there is a need for a robust FL framework that jointly utilizes and optimizes the resources of the device, server, and network infrastructure.

Cooperative FL is a promising solution that overcomes these shortcomings and has been shown to be feasible and beneficial for learning processes leading to improved ML performance and resource efficiency [254]. In another related study [255], a cooperative architecture and an FL combined with an RL-based algorithm are proposed for the allocation of resources in CAV networks.

B. Digital Ethics Issues

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 the model's accuracy and redundancy.

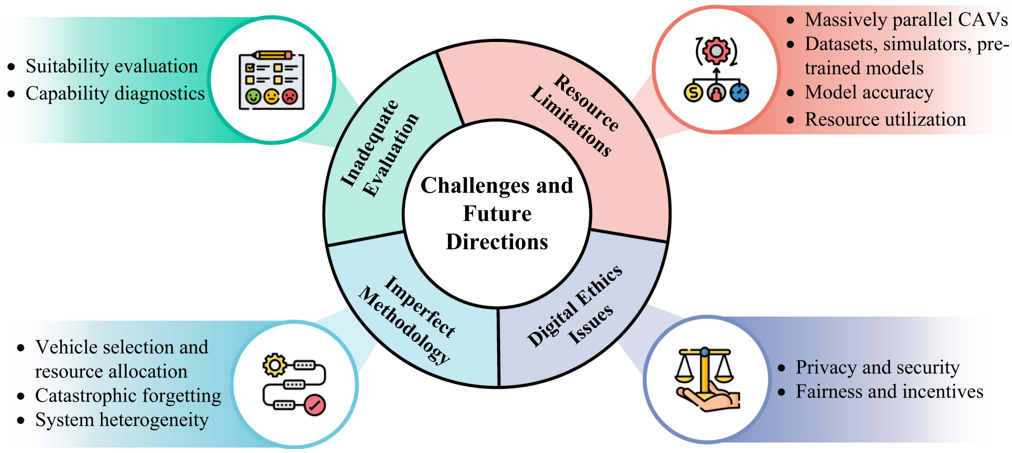


Fig. 5. Illustration of challenges and future directions of federated learning for connected and automated vehicles.

2) Fairness and Incentives: There is a need for appropriate rewarding policies and incentive mechanisms for CAVs to share the quality data needed for efficient model training performance [256].

C. Imperfect Methodology

1) Lack of Methods for Efficient Vehicle Selection and Resource Allocation: Currently, there are no efficient methods that can filter useful data from CAVs to minimize network loading. There are ongoing efforts to develop reliable methods to optimally select vehicles and resource allocation schemes for efficient model training and communication [257], [258], [259], [260]. In [261], the overall training process was demonstrated to be efficient when 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 [190], it is demonstrated that the model performance was improved with CAVs that were selected by trust-based deep RL.

2) Catastrophic Forgetting: CAVs cannot store all user data due to storage capacity limitations, and new data will always be generated during training iteration. Therefore, when the FL framework is updated on new data in iteration, the global model might forget the previous knowledge, which may lead to catastrophic forgetting. This is another open research problem in FL4CAV.

3) System Heterogeneity in FL4CAV: Poor performance of the FL model (longer training time and a larger number of communication rounds) is generally caused by poor connectivity and slower devices (straggler devices). In traditional FL, a communication round is not complete until the data from all the chosen devices are available. Hence, various adaptive strategies have been proposed to minimize the impact of stragglers and also eliminate them, if possible [262], [263].

D. Inadequate Evaluation Criteria

1) FL Suitability Evaluation for New Users: It is often difficult for the newcomer vehicle to make any informed decisions. In [190], a trust-aware Deep RL model is proposed to assist new vehicles in making better 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 robust diagnostics that can identify and eliminate the updates from these vehicles is needed.

VI. Conclusion

This survey paper reviews FL algorithms, data modalities, model security, and provides a list of critical applications and challenges of FL4CAV. Currently, FL4CAV 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 are in the areas, such as privacy-preserving driver behavior modeling, anomaly detection, and predictive maintenance. With the advent of cloud infrastructure, 6 G, V2X technology, and flying cars, the use of FL models is expected to provide significant breakthroughs.

References

[1] G. Pan and M.-S. Alouini, “Flying car transportation system: Advances, techniques, and challenges,” *IEEE Access*, vol. 9, pp. 24586–24603, 2021.
[2] X. Zhang et al., “Intelligent amphibious ground-aerial vehicles: State of the art technology for future transportation,” *IEEE Trans. Intell. Veh.*, vol. 8, no. 1, pp. 970–987, Jan. 2023.
[3] M. Biparva, D. Fernández-Llorca, R. I. Gonzalo, and J. K. Tsotsos, “Video action recognition for lane-change classification and prediction of surrounding vehicles,” *IEEE Trans. Intell. Veh.*, vol. 7, no. 3, pp. 569–578, Sep. 2022.
[4] D. Cao et al., “Future directions of intelligent vehicles: Potentials, possibilities, and perspectives,” *IEEE Trans. Intell. Veh.*, vol. 7, no. 1, pp. 7–10, Mar. 2022.
[5] A. Hadjigeorgiou and S. Timotheou, “Real-time optimization of fuel-consumption and travel-time of CAVs for cooperative intersection crossing,” *IEEE Trans. Intell. Veh.*, vol. 8, no. 1, pp. 313–329, Jan. 2023.

[6] H. Pei, J. Zhang, Y. Zhang, X. Pei, S. Feng, and L. Li, "Fault-tolerant cooperative driving at signal-free intersections," *IEEE Trans. Intell. Veh.*, vol. 8, no. 1, pp. 121–134, Jan. 2023.
[7] L. Guo, H. Chu, J. Ye, B. Gao, and H. Chen, "Hierarchical velocity control considering traffic signal timings for connected vehicles," *IEEE Trans. Intell. Veh.*, vol. 8, no. 2, pp. 1403–1414, Feb. 2023.
[8] Z. Wang, C. Lv, and F.-Y. Wang, "A new era of intelligent vehicles and intelligent transportation systems: Digital twins and parallel intelligence," *IEEE Trans. Intell. Veh.*, vol. 8, no. 4, pp. 2619–2627, Apr. 2023.
[9] H. Zhang, G. Luo, Y. Li, and F.-Y. Wang, "Parallel vision for intelligent transportation systems in metaverse: Challenges, solutions, and potential applications," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 53, no. 6, pp. 3400–3413, Jun. 2023.
[10] Y. Liu, Z. Wang, K. Han, Z. Shou, P. Tiwari, and J. H. Hansen, "Vision-cloud data fusion for ADAS: A lane change prediction case study," *IEEE Trans. Intell. Veh.*, vol. 7, no. 2, pp. 210–220, Jun. 2022.
[11] L. Chen et al., "Milestones in autonomous driving and intelligent vehicles: Survey of surveys," *IEEE Trans. Intell. Veh.*, vol. 8, no. 2, pp. 1046–1056, Sep. 2023.
[12] M. Hu, J. Li, Y. Bian, J. Wang, B. Xu, and Y. Zhu, "Distributed coordinated brake control for longitudinal collision avoidance of multiple connected automated vehicles," *IEEE Trans. Intell. Veh.*, vol. 8, no. 1, pp. 745–755, Jan. 2023.
[13] X. Tang et al., "Prediction-uncertainty-aware decision-making for autonomous vehicles," *IEEE Trans. Intell. Veh.*, vol. 7, no. 4, pp. 849–862, Dec. 2022.
[14] Z. Wang, G. Wu, P. Hao, and M. J. Barth, "Cluster-wise cooperative ECO-approach and departure application for connected and automated vehicles along signalized arterials," *IEEE Trans. Intell. Veh.*, vol. 3, no. 4, pp. 404–413, Dec. 2018.
[15] Z. Wang, K. Han, and P. Tiwari, "Digital twin-assisted cooperative driving at non-signalized intersections," *IEEE Trans. Intell. Veh.*, vol. 7, no. 2, pp. 198–209, Jun. 2022.
[16] H. M. Wang, S. S. Avedisov, T. G. Molnár, A. H. Sakr, O. Altintas, and G. Orosz, "Conflict analysis for cooperative maneuvering with status and intent sharing via V2X communication," *IEEE Trans. Intell. Veh.*, vol. 8, no. 2, pp. 1105–1118, Feb. 2023.
[17] Z. Wang et al., "Mobility digital twin: Concept, architecture, case study, and future challenges," *IEEE Internet Things J.*, vol. 9, no. 18, pp. 17452–17467, Sep. 2022.
[18] J. Nidamanuri, C. Nibhanupudi, R. Assfalg, and H. Venkataraman, "A progressive review: Emerging technologies for ADAS driven solutions," *IEEE Trans. Intell. Veh.*, vol. 7, no. 2, pp. 326–341, Jun. 2022.
[19] O. Natan and J. Miura, "End-to-end autonomous driving with semantic depth cloud mapping and multi-agent," *IEEE Trans. Intell. Veh.*, vol. 8, no. 1, pp. 557–571, Jun. 2023.
[20] C. Park, G. S. Kim, S. Park, S. Jung, and J. Kim, "Multi-agent reinforcement learning for cooperative air transportation services in city-wide autonomous urban air mobility," *IEEE Trans. Intell. Veh.*, vol. 8, no. 8, pp. 4016–4030, Aug. 2023.
[21] M. Singh and R. Dubey, "Deep learning model based CO2 emissions prediction using vehicle telematics sensors data," *IEEE Trans. Intell. Veh.*, vol. 8, no. 1, pp. 768–777, Jan. 2023.
[22] P. Voigt and A. Von dem Bussche, "The EU general data protection regulation (GDPR)," in *A Practical Guide*, 1st ed., Cham, Switzerland:Springer International Publishing, 2017, pp. 10–5555.
[23] Q. Yang, Y. Liu, T. Chen, and Y. Tong, "Federated machine learning: Concept and applications," *ACM Trans. Intell. Syst. Technol.*, vol. 10, no. 2, pp. 1–19, 2019.
[24] P. Kairouz et al., "Advances and open problems in federated learning," *Foundations Trends Mach. Learn.*, vol. 14, no. 1–2, pp. 1–210, 2021.
[25] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. Y. Arcas, "Communication-efficient learning of deep networks from decentralized data," in *Proc. 20th Int. Conf. Artif. Intell. Statist.*, 2017, pp. 1273–1282.
[26] A. Hard et al., "Federated learning for mobile keyboard prediction," 2018, *arXiv:1811.03604*.
[27] W. Zhang et al., "Blockchain-based federated learning for device failure detection in industrial IoT," *IEEE Internet Things J.*, vol. 8, no. 7, pp. 5926–5937, Apr. 2021.
[28] X. Zeng et al., "Homophily learning-based federated intelligence: A case study on industrial IoT equipment failure prediction," *IEEE Internet Things J.*, vol. 10, no. 8, pp. 7356–7365, Apr. 2023.
[29] W. Zhang et al., "R ^{2} Fed: Resilient reinforcement federated learning for industrial applications," *IEEE Trans. Ind. Inform.*, vol. 19, no. 8, pp. 8829–8840, Aug. 2023.
[30] W. Zhang et al., "Semi-asynchronous personalized federated learning for short-term photovoltaic power forecasting," *Digit. Commun. Netw.*, vol. 9, pp. 1221–1229, 2022.
[31] B. Chen, X. Zeng, W. Zhang, L. Fan, S. Cao, and J. Zhou, "Knowledge sharing-based multi-block federated learning for few-shot oil layer identification," *Energy*, vol. 283, 2023, Art. no. 128406.
[32] W. Zhang et al., "Dynamic-fusion-based federated learning for COVID-19 detection," *IEEE Internet Things J.*, vol. 8, no. 21, pp. 15884–15891, Nov. 2021.
[33] B. Chen et al., "DFML: Dynamic federated meta-learning for rare disease prediction," *IEEE/ACM Trans. Comput. Biol. Bioinf.*, early access, Jan. 26, 2023, doi: 10.1109/TCBB.2023.3239848.
[34] K. Bonawitz et al., "Practical secure aggregation for privacy-preserving machine learning," in *Proc. ACM SIGSAC Conf. Comput. Commun. Secur.*, 2017, pp. 1175–1191.
[35] A. Nedić, A. Olshevsky, and M. G. Rabbat, "Network topology and communication-computation tradeoffs in decentralized optimization," *Proc. IEEE Proc. IRE*, vol. 106, no. 5, pp. 953–976, May 2018.
[36] V. P. Chellapandi, A. Upadhyay, A. Hashemi, and S. H. Żak, "On the convergence of decentralized federated learning under imperfect information sharing," *IEEE Control Syst Lett.*, vol. 7, pp. 2982–2987, 2023, doi: 10.1109/LCSYS.2023.3290470.
[37] V. P. Chellapandi, L. Yuan, S. H. Zak, and Z. Wang, "A survey of federated learning for connected and automated vehicles," 2023, *arXiv:2303.10677*.
[38] Z. Du, C. Wu, T. Yoshinaga, K.-L. A. Yau, Y. Ji, and J. Li, "Federated learning for vehicular Internet of Things: Recent advances and open issues," *IEEE Open J. Comput. Soc.*, vol. 1, pp. 45–61, 2020.
[39] J. C. Jiang, B. Kantarci, S. Oktug, and T. Soyata, "Federated learning in smart city sensing: Challenges and opportunities," *Sensors*, vol. 20, Oct. 2020, Art. no. 6230.
[40] S. Savazzi, M. Nicoli, M. Bennis, S. Kianoush, and L. Barbieri, "Opportunities of federated learning in connected, cooperative, and automated industrial systems," *IEEE Commun. Mag.*, vol. 59, no. 2, pp. 16–21, Feb. 2021.
[41] D. C. Nguyen, M. Ding, P. N. Pathirana, A. Seneviratne, J. Li, and H. V. Poor, "Federated learning for Internet of Things: A comprehensive survey," *IEEE Commun. Surveys Tuts.*, vol. 23, no. 3, pp. 1622–1658, thirdquarter 2021.
[42] A. R. Javed et al., "Integration of blockchain technology and federated learning in vehicular (IoT) networks: A comprehensive survey," *Sensors*, vol. 22, Jun. 2022, Art. no. 4394.
[43] L. Yuan, L. Sun, P. S. Yu, and Z. Wang, "Decentralized federated learning: A survey and perspective," 2023. *arXiv:2306.01603*.
[44] L. Collins, H. Hassani, A. Mokhtari, and S. Shakkottai, "Fedavg with fine tuning: Local updates lead to representation learning," in *Proc. Adv. Neural Inf. Process. Syst.*, 2022, pp. 10572–10586.
[45] T. Li, A. K. Sahu, M. Zaheer, M. Sanjabi, A. Talwalkar, and V. Smith, "Federated optimization in heterogeneous networks," *Proc. Mach. Learn. Syst.*, vol. 2, pp. 429–450, Mar. 2020.
[46] T. Zeng, O. Semiari, M. Chen, W. Saad, and M. Bennis, "Federated learning on the road autonomous controller design for connected and autonomous vehicles," *IEEE Trans. Wireless Commun.*, vol. 21, no. 12, pp. 10407–10423, Dec. 2022.
[47] S. J. Reddi et al., "Adaptive federated optimization," in *Proc. Int. Conf. Learn. Representations*, 2022.
[48] D. A. E. Acar, Y. Zhao, R. Matas, M. Mattina, P. Whatmough, and V. Saligrama, "Federated learning based on dynamic regularization," in *Proc. Int. Conf. Learn. Representations*, 2022.
[49] X. Li, K. Huang, W. Yang, S. Wang, and Z. Zhang, "On the convergence of FedAvg on Non-IID data," in *Proc. Int. Conf. Learn. Representations*, 2020.
[50] J. Wang, Q. Liu, H. Liang, G. Joshi, and H. V. Poor, "Tackling the objective inconsistency problem in heterogeneous federated optimization," in *Proc. Adv. Neural Inf. Process. Syst.*, 2020, pp. 7611–7623.
[51] J. Wang et al., "A field guide to federated optimization," 2021, *arXiv:2107.06917*.
[52] E. Jeong, S. Oh, H. Kim, J. Park, M. Bennis, and S.-L. Kim, "Communication-efficient on-device machine learning: Federated distillation and augmentation under non-IID private data," 2018, *arXiv:1811.11479*.

[53] L. Liu, J. Zhang, S. H. Song, and K. B. Letaief, "Communication-efficient federated distillation with active data sampling," in *Proc. IEEE Int. Conf. Commun.*, 2022, pp. 201–206.

[54] S. Wang et al., "Federated deep learning meets autonomous vehicle perception: Design and verification," *IEEE Netw.*, vol. 37, no. 3, pp. 16–25, May/Jun. 2022.

[55] C. He, M. Annavaram, and S. Avestimehr, "Group knowledge transfer: Federated learning of large CNNs at the edge," in *Proc. Adv. Neural Inf. Process. Syst.*, 2020, pp. 14068–14080.

[56] C. Wu, F. Wu, L. Lyu, Y. Huang, and X. Xie, "Communication-efficient federated learning via knowledge distillation," *Nat. Commun.*, vol. 13, Apr. 2022, Art. no. 2032.

[57] A. Nguyen et al., "Deep federated learning for autonomous driving," in *Proc. IEEE Intell. Veh. Symp.*, 2022, pp. 1824–1830.

[58] S. Lu, Y. Yao, and W. Shi, "Collaborative learning on the edges: A case study on connected vehicles," in *Proc. Workshop Hot Topics Edge Comput.*, 2019.

[59] S. R. Pokhrel and J. Choi, "A decentralized federated learning approach for connected autonomous vehicles," in *Proc. IEEE Wireless Commun. Netw. Conf. Workshops*, 2020, pp. 1–6.

[60] Y. Li, Q. Xie, W. Wang, X. Zhou, and K. Li, "GCN-based topology design for decentralized federated learning in IoV," in *Proc. 23rd Asia-Pacific Netw. Operations Manage. Symp.*, 2022, pp. 1–6.

[61] L. Barbieri, S. Savazzi, M. Brambilla, and M. Nicoli, "Decentralized federated learning for extended sensing in 6G connected vehicles," *Veh. Commun.*, vol. 33, 2022, Art. no. 100396.

[62] X. Liu, Z. Dong, Z. Xu, S. Liu, and J. Tian, "Enhanced decentralized federated learning based on consensus in connected vehicles," 2022, *arXiv:2209.10722*.

[63] E. T. M. Beltrán et al., "Decentralized federated learning: Fundamentals, state-of-the-art, frameworks, trends, and challenges," *IEEE Commun. Surv. Tut.*, vol. 25, no. 4, pp. 2983–3013, Fourthquarter 2023, doi: 10.1109/COMST.2023.3315746.

[64] M. Wilbur, C. Samal, J. P. Talusan, K. Yasumoto, and A. Dubey, "Time-dependent decentralized routing using federated learning," in *Proc. IEEE 23rd Int. Symp. Real-Time Distrib. Comput.*, 2020, pp. 56–64.

[65] L. Yuan, D.-J. Han, V. P. Chellapandi, S. H. Żak, and C. G. Brinton, " FedMFS: Federated multimodal fusion learning with selective modality communication," 2023, *arXiv:2310.07048*.

[66] K. D. Stergiou, K. E. Psannis, V. Vitsas, and Y. Ishibashi, "A federated learning approach for enhancing autonomous vehicles image recognition," in *Proc. 4th Int. Conf. Comput. Commun. Internet*, 2022, pp. 87–90.

[67] L. Fantauzzo et al., "FedDrive: Generalizing federated learning to semantic segmentation in autonomous driving," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, 2022, pp. 11504–11511.

[68] L. Yuan and J. Li, "Smart cushion based on pressure sensor array for human sitting posture recognition," in *Proc. IEEE Sensors*, 2021, pp. 1–4.

[69] A. Mishra, S. Lee, D. Kim, and S. Kim, "In-cabin monitoring system for autonomous vehicles," *Sensors*, vol. 22, no. 12, 2022, Art. no. 4360.

[70] K. Doshi and Y. Yilmaz, "Federated learning-based driver activity recognition for edge devices," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, 2022, pp. 3338–3346.

[71] L. Yuan, L. Su, and Z. Wang, "Federated transfer-ordered-personalized learning for driver monitoring application," *IEEE Internet Things J.*, vol. 10, no. 20, pp. 18292–18301, Oct. 2023.

[72] C. Zhao, Z. Gao, Q. Wang, K. Xiao, Z. Mo, and M. J. Deen, "FedSup: A communication-efficient federated learning fatigue driving behaviors supervision approach," *Future Gener. Comput. Syst.*, vol. 138, pp. 52–60, Jan. 2023.

[73] A. M. Elbir, B. Soner, S. Çöleri, D. Gündüz, and M. Bennis, "Federated learning in vehicular networks," in *Proc. IEEE Int. Mediterranean Conf. Commun. Netw.*, 2022, pp. 72–77.

[74] Y. Liu, Y. Tian, B. Sun, Y. Wang, and F.-Y. Wang, "Parallel LiDARs meet the foggy weather," *IEEE J. Radio Freq. Identification*, vol. 6, pp. 867–870, 2022.

[75] R. Xu et al., "V2v4real: A real-world large-scale dataset for vehicle-to-vehicle cooperative perception," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, 2023, pp. 13712–13722.

[76] Y. Ma et al., "MACP: Efficient model adaptation for cooperative perception," 2023, *arXiv:2310.16870*.

[77] N. Pandey and S. S. Ram, "Classification of automotive targets using inverse synthetic aperture radar images," *IEEE Trans. Intell. Veh.*, vol. 7, no. 3, pp. 675–689, Sep. 2022.

[78] A. Venon, Y. Dupuis, P. Vasseur, and P. Merriaux, "Millimeter wave FMCW RADARs for perception, recognition and localization in automotive applications: A survey," *IEEE Trans. Intell. Veh.*, vol. 7, no. 3, pp. 533–555, Sep. 2022.

[79] Y. Liu et al., "Parallel radars: From digital twins to digital intelligence for smart radar systems," *Sensors*, vol. 22, no. 24, 2022, Art. no. 9930.

[80] C. Cui, Y. Ma, J. Lu, and Z. Wang, "REDFormer: Radar enlightens the darkness of camera perception with transformers," *IEEE Trans. Intell. Veh.*, early access, Nov. 06, 2023, doi: 10.1109/TIV.2023.3329708.

[81] I. Bilik, O. Longman, S. Villeval, and J. Tabrikian, "The rise of radar for autonomous vehicles: Signal processing solutions and future research directions," *IEEE signal Process. Mag.*, vol. 36, no. 5, pp. 20–31, Sep. 2019.

[82] Y. Fu, C. Li, F. R. Yu, T. H. Luan, and Y. Zhang, "A selective federated reinforcement learning strategy for autonomous driving," *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 2, pp. 1655–1668, Feb. 2023.

[83] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," *Proc. IEEE Proc. IRE*, vol. 86, no. 11, pp. 2278–2324, Nov. 1998.

[84] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2016, pp. 770–778.

[85] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2016, pp. 779–788.

[86] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in *Proc. Med. Image Comput. Comput.-Assist. Interv.: 18th Int. Conf.*, 2015, pp. 234–241.

[87] C. Yu, J. Wang, C. Peng, C. Gao, G. Yu, and N. Sang, "BiSeNet: Bilateral segmentation network for real-time semantic segmentation," in *Proc. Eur. Conf. Comput. Vis.*, 2018, pp. 325–341.

[88] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[89] K. Cho et al., "Learning phrase representations using RNN encoder-decoder for statistical machine translation," in *Proc. Conf. Empirical Methods Natural Lang. Process.*, 2014, pp. 1724–1734, doi: 10.3115/v1/D14-1179.

[90] A. Vaswani et al., "Attention is all you need," in *Proc. Adv. Neural Inf. Process. Syst.*, 2017.

[91] A. Dosovitskiy et al., "An image is worth 16x16 words: Transformers for image recognition at scale," in *Proc. Int. Conf. Learn. Representations*, 2020.

[92] Y. Tian, J. Wang, Y. Wang, C. Zhao, F. Yao, and X. Wang, "Federated vehicular transformers and their federations: Privacy-preserving computing and cooperation for autonomous driving," *IEEE Trans. Intell. Veh.*, vol. 7, no. 3, pp. 456–465, Sep. 2022.

[93] H. Li et al., "FedTP: Federated learning by transformer personalization," *IEEE Trans. Neural Netw. Learn. Syst.*, early access, May 23, 2023, doi: 10.1109/TNNLS.2023.3269062.

[94] R. Xu, H. Xiang, Z. Tu, X. Xia, M.-H. Yang, and J. Ma, "V2X-ViT: Vehicle-to-everything cooperative perception with vision transformer," in *Proc. Eur. Conf. Comput. Vis.*, 2022, pp. 107–124.

[95] I. Goodfellow et al., "Generative adversarial nets," in *Proc. Adv. Neural Inf. Process. Syst.*, 2014.

[96] D. P. Kingma and M. Welling, "Auto-encoding variational bayes," in *Proc. Int. Conf. Learn. Representations*, 2013.

[97] J. Zhang, L. Zhao, K. Yu, G. Min, A. Y. Al-Dubai, and A. Y. Zomaya, "A novel federated learning scheme for generative adversarial networks," *IEEE Trans. Mobile Comput.*, early access, May 22, 2023, doi: 10.1109/TMC.2023.3278668.

[98] D. Roy, T. Ishizaka, C. K. Mohan, and A. Fukuda, "Vehicle trajectory prediction at intersections using interaction based generative adversarial networks," in *Proc. IEEE Intell. Transp. Syst. Conf.*, 2019, pp. 2318–2323.

[99] R. S. Sutton and A. G. Barto, *Reinforcement Learning: An Introduction*. Cambridge, MA, USA: MIT Press, 2018.

[100] G. Li et al., "Lane change strategies for autonomous vehicles: A deep reinforcement learning approach based on transformer," *IEEE Trans. Intell. Veh.*, vol. 8, no. 3, pp. 2197–2211, Mar. 2023.

[101] D. C. Selvaraj, S. Hegde, N. Amati, F. Deflorio, and C. F. Chiasserini, "An ML-aided reinforcement learning approach for challenging vehicle maneuvers," *IEEE Trans. Intell. Veh.*, vol. 8, no. 2, pp. 1686–1698, Feb. 2022.

[102] J. Lu, L. Han, Q. Wei, X. Wang, X. Dai, and F.-Y. Wang, "Event-triggered deep reinforcement learning using parallel control: A case study in autonomous driving," *IEEE Trans. Intell. Veh.*, vol. 8, no. 4, pp. 2821–2831, Apr. 2023.

[103] R. A. Mallah, G. Badu-Marfo, and B. Farooq, "Cybersecurity threats in connected and automated vehicles based federated learning systems," in *Proc. IEEE Intell. Veh. Symp. Workshops*, 2021, pp. 13–18.

[104] Z. Ju, H. Zhang, X. Li, X. Chen, J. Han, and M. Yang, "A survey on attack detection and resilience for connected and automated vehicles: From vehicle dynamics and control perspective," *IEEE Trans. Intell. Veh.*, vol. 7, no. 4, pp. 815–837, Dec. 2022.

[105] N. Hussain, P. Rani, H. Chouhan, and U. S. Gaur, "Cyber security and privacy of connected and automated vehicles (CAVs)-based federated learning: Challenges, opportunities, and open issues," in *Federated Learning for IoT Applications*, Berlin, Germany: Springer, 2022, pp. 169–183.

[106] B. Ghimire and D. B. Rawat, "Recent advances on federated learning for cybersecurity and cybersecurity for federated learning for Internet of Things," *IEEE Internet Things J.*, vol. 9, no. 11, pp. 8229–8249, Jun. 2022.

[107] M. Alazab, S. P. RM, M. Parimala, P. K. R. Maddikunta, T. R. Gadekallu, and Q.-V. Pham, "Federated learning for cybersecurity: Concepts, challenges, and future directions," *IEEE Trans. Ind. Inform.*, vol. 18, no. 5, pp. 3501–3509, May 2022.

[108] M. A. Ferrag, O. Friha, L. Maglaras, H. Janicke, and L. Shu, "Federated deep learning for cyber security in the Internet of Things: Concepts, applications, and experimental analysis," *IEEE Access*, vol. 9, pp. 138509–138542, 2021.

[109] M. Pandey et al., "A review of factors impacting cybersecurity in connected and autonomous vehicles (CAVs)," in *Proc. 8th Int. Conf. Control, Dec. Inf. Technol.*, 2022, pp. 1218–1224.

[110] Y. Peng, Z. Chen, Z. Chen, W. Ou, W. Han, and J. Ma, "BFLP: An adaptive federated learning framework for internet of vehicles," *Mobile Inf. Syst.*, vol. 2021, pp. 1–18, 2021.

[111] J.-H. Chen, M.-R. Chen, G.-Q. Zeng, and J.-S. Weng, "BDFL: A Byzantine-fault-tolerance decentralized federated learning method for autonomous vehicle," *IEEE Trans. Veh. Technol.*, vol. 70, np. 9, pp. 8639–8652, Sep. 2021.

[112] M. Basnet and M. H. Ali, "A deep learning perspective on connected automated vehicle (CAV) cybersecurity and threat intelligence," in *Deep Learning and Its Applications for Vehicle Networks*, Boca Raton, FL, USA: CRC Press, 2023, pp. 39–56.

[113] A. A. Korba, A. Boualouache, B. Brik, R. Rahal, Y. Ghamri-Doudane, and S. M. Senouci, "Federated learning for zero-day attack detection in 5G and beyond V2X networks," in *Proc. AlgoTel èmes Rencontres Francophones sur les Aspects Algorithmiques des Télécommunications*, 2023.

[114] N. Hussain, P. Rani, H. Chouhan, and U. S. Gaur, *Cyber Security and Privacy of Connected and Automated Vehicles (CAVs)-Based Federated Learning: Challenges, Opportunities, and Open Issues*. Cham, Switzerland: Springer International Publishing, 2022, pp. 169–183.

[115] A. R. Sani, M. U. Hassan, and J. Chen, "Privacy preserving machine learning for electric vehicles: A survey," 2022, *arXiv:2205.08462*.

[116] D. Byrd and A. Polychroniadou, "Differentially private secure multiparty computation for federated learning in financial applications," in *Proc. 1st ACM Int. Conf. AI Finance*, 2020, pp. 1–9.

[117] K. Bonawitz et al., "Practical secure aggregation for federated learning on user-held data," in *Proc. ACM SIGSAC Conf. Comput. Commun. Secur.*, 2017, pp. 1175–1191.

[118] F. Mo, H. Haddadi, K. Katevas, E. Marin, D. Perino, and N. Kourtellis, "PPFL: Privacy-preserving federated learning with trusted execution environments," in *Proc. 19th Annu. Int. Conf. Mobile Syst., Appl., Serv.*, 2021, pp. 94–108.

[119] M. Singh and S. Kim, "Blockchain based intelligent vehicle data sharing framework," 2017, *arXiv:1708.09721*.

[120] G. Rathee, A. Sharma, R. Iqbal, M. Aloqaily, N. Jaglan, and R. Kumar, "A blockchain framework for securing connected and autonomous vehicles," *Sensors*, vol. 19, no. 14, 2019, Art. no. 3165.

[121] Y. Fu, F. R. Yu, C. Li, T. H. Luan, and Y. Zhang, "Vehicular blockchain-based collective learning for connected and autonomous vehicles," *IEEE Wireless Commun.*, vol. 27, no. 2, pp. 197–203, Apr. 2020.

[122] S. R. Pokhrel and J. Choi, "Federated learning with blockchain for autonomous vehicles: Analysis and design challenges," *IEEE Trans. Commun.*, vol. 68, no. 8, pp. 4734–4746, Aug. 2020.

[123] S. M. Basha, S. T. Ahmed, N. S. N. Iyengar, and R. D. Caytiles, "Interlocking dependency evaluation schema based on block-chain enabled federated transfer learning for autonomous vehicular systems," in *Proc. 2nd Int. Conf. Innov. Technol. Convergence*, 2021, pp. 46–51.

[124] Y. He, K. Huang, G. Zhang, F. R. Yu, J. Chen, and J. Li, "Bift: A blockchain-based federated learning system for connected and autonomous vehicles," *IEEE Internet Things J.*, vol. 9, no. 14, pp. 12311–12322, Jul. 2022.

[125] A. R. Javed et al., "Integration of blockchain technology and federated learning in vehicular (IoT) networks: A comprehensive survey," *Sensors*, vol. 22, no. 12, 2022, Art. no. 4394.

[126] Z. Zhu et al., "Crowdsensing intelligence by decentralized autonomous vehicles organizations and operations," *IEEE Trans. Intell. Veh.*, vol. 7, no. 4, pp. 804–808, Dec. 2022.

[127] W. Zhang et al., "CFSL: A credible federated self-learning framework," *IEEE Internet Things J.*, early access, Jun. 15, 2023, doi: 10.1109/JIOT.2023.3286398.

[128] A. Dorri, M. Steger, S. S. Kanhere, and R. Jurdak, "BlockChain: A distributed solution to automotive security and privacy," *IEEE Commun. Mag.*, vol. 55, no. 12, pp. 119–125, Dec. 2017.

[129] M. Billah, S. T. Mehedi, A. Anwar, Z. Rahman, and R. Islam, "A systematic literature review on blockchain enabled federated learning framework for internet of vehicles," 2022, *arXiv:2203.05192*.

[130] Y. Lu, X. Huang, K. Zhang, S. Maharjan, and Y. Zhang, "Blockchain empowered asynchronous federated learning for secure data sharing in internet of vehicles," *IEEE Trans. Veh. Technol.*, vol. 69, no. 4, pp. 4298–4311, Apr. 2020.

[131] H. Liu et al., "Blockchain and federated learning for collaborative intrusion detection in vehicular edge computing," *IEEE Trans. Veh. Technol.*, vol. 70, no. 6, pp. 6073–6084, Jun. 2021.

[132] Y. He, K. Huang, G. Zhang, J. Li, J. Chen, and V. C. Leung, "A blockchain-enabled federated learning system with edge computing for vehicular networks," in *Proc. IEEE Globecom Workshops*, 2021, pp. 1–6.

[133] S. Doomra, N. Kohli, and S. Athavale, "Turn signal prediction: A federated learning case study," 2020, *arXiv:2012.12401*.

[134] Y. Liu, J. James, J. Kang, D. Niyato, and S. Zhang, "Privacy-preserving traffic flow prediction: A federated learning approach," *IEEE Internet Things J.*, vol. 7, no. 8, pp. 7751–7763, Aug. 2020.

[135] H. Zhang, J. Bosch, and H. H. Olsson, "End-to-end federated learning for autonomous driving vehicles," in *Proc. Int. Joint Conf. Neural Netw.*, 2021, pp. 1–8.

[136] M. Aparna, R. Gandhiraj, and M. Panda, "Steering angle prediction for autonomous driving using federated learning: The impact of vehicle-to-everything communication," in *Proc. 12th Int. Conf. Comput. Commun. Netw. Technol.*, 2021, pp. 1–7.

[137] G. Rjoub, O. A. Wahab, J. Bentahar, and A. S. Bataineh, "Improving autonomous vehicles safety in snow weather using federated YOLO CNN learning," in *Proc. Mobile Web Intell. Inf. Syst.: 17th Int. Conf.*, 2021, pp. 121–134.

[138] X. Kong, H. Gao, G. Shen, G. Duan, and S.K. Das, "FedVCP: A federated-learning-based cooperative positioning scheme for social internet of vehicles," *IEEE Trans. Comput. Soc.*, vol. 9, no. 1, pp. 197–206, Feb. 2022.

[139] X. Zhou, W. Liang, J. She, Z. Yan, I. Kevin, and K. Wang, "Two-layer federated learning with heterogeneous model aggregation for 6G supported internet of vehicles," *IEEE Trans. Veh. Technol.*, vol. 70, no. 6, pp. 5308–5317, Jun. 2021.

[140] Y. M. Saputra, H. T. Dinh, D. Nguyen, L.-N. Tran, S. Gong, and E. Dutkiewicz, "Dynamic federated learning-based economic framework for internet-of-vehicles," *IEEE Trans. Mob. Comput.*, vol. 22, no. 4, pp. 2100–2115, Apr. 2023.

[141] L. Barbieri, S. Savazzi, and M. Nicoli, "Decentralized federated learning for road user classification in enhanced V2X networks," in *Proc. IEEE Int. Conf. Commun. Workshops*, 2021, pp. 1–6.

[142] A. M. Elbir, S. Coleri, A. K. Papazafeiropoulos, P. Kourtessis, and S. Chatzinotas, "A hybrid architecture for federated and centralized learning," *IEEE Trans. Cogn. Commun. Netw.*, vol. 8, no. 3, pp. 1529–1542, Sep. 2022.

[143] M. Han, K. Xu, S. Ma, A. Li, and H. Jiang, "Federated learning-based trajectory prediction model with privacy preserving for intelligent vehicle," *Int. J. Intell. Syst.*, vol. 37, no. 12, pp. 10861–10879, 2022.

[144] S. S. Sepasgozar and S. Pierre, "Fed-NTP: A federated learning algorithm for network traffic prediction in vanet," *IEEE Access*, vol. 10, pp. 119607–119616, 2022.

[145] Z. Yang, X. Zhang, D. Wu, R. Wang, P. Zhang, and Y. Wu, "Efficient asynchronous federated learning research in the internet of vehicles," *IEEE Internet Things J.*, vol. 10, no. 9, pp. 7737–7748, May 2022.

[146] X. Zhou, R. Ke, Z. Cui, Q. Liu, and W. Qian, "STFL: Spatio-temporal federated learning for vehicle trajectory prediction," in *Proc. IEEE 2nd Int. Conf. Digit. Twins Parallel Intell.*, 2022, pp. 1–6.

[147] L. Yuan, Y. Ma, L. Su, and Z. Wang, "Peer-to-peer federated continual learning for naturalistic driving action recognition," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, 2023, pp. 5249–5258.

[148] R. Du, K. Han, R. Gupta, S. Chen, S. Labi, and Z. Wang, "Driver monitoring-based lane-change prediction: A personalized federated learning framework," in *Proc. IEEE Intell. Veh. Symp.*, 2023, pp. 1–7.
[149] R. Parekh et al., "GeFL: Gradient encryption-aided privacy preserved federated learning for autonomous vehicles," *IEEE Access*, vol. 11, pp. 1825–1839, 2023.
[150] Z. Wang and T. Yan, "Federated learning-based vehicle trajectory prediction against cyberattacks," 2023, *arXiv:2306.08566*.
[151] C. Chen, *Freeway Performance Measurement System (PeMS)*. Berkeley, CA, USA: University of California, 2002.
[152] M. Pitropov et al., "Canadian adverse driving conditions dataset," *Int. J. Robot. Res.*, vol. 40, no. 4–5, pp. 681–690, 2021.
[153] GAIA, *Didi Chuxing Gaia Initiative*. Beijing, China: Didi Chuxing, Oct. 2016.
[154] R. Timofte, K. Zimmermann, and L. V. Gool, "Multi-view traffic sign detection, recognition, and 3D localisation," *Mach. Vis. Appl.*, vol. 25, pp. 633–647, Apr. 2014.
[155] D. Fisher-Hickey, "*1.6 Million U.K. Traffic Accidents*. San Francisco, United States: Kaggle, Sep. 2017.
[156] H. Caesar et al., "nuScenes: A multimodal dataset for autonomous driving," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, 2020, pp. 11621–11631.
[157] F. Yu et al., "BDD100k: A diverse driving dataset for heterogeneous multitask learning," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, 2020, pp. 2636–2645.
[158] S. Moosavi, B. Omidvar-Tehrani, and R. Ramnath, "Trajectory annotation by discovering driving patterns," in *Proc. 3rd ACM SIGSPATIAL Workshop Smart Cities Urban Analytics*, 2017, pp. 1–4.
[159] J. Stallkamp, M. Schlipsing, J. Salmen, and C. Igel, "The German traffic sign recognition benchmark: A multi-class classification competition," in *Proc. Int. Joint Conf. Neural Netw.*, 2011, pp. 1453–1460.
[160] M. Cordts et al., "The cityscapes dataset for semantic urban scene understanding," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2016, pp. 3213–3223.
[161] E. Alberti, A. Tavera, C. Masone, and B. Caputo, "IDDA: A large-scale multi-domain dataset for autonomous driving," *IEEE Robot. Automat. Lett.*, vol. 5, no. 4, pp. 5526–5533, Oct. 2020.
[162] R. Kesten et al., "Lyft level 5 AV dataset 2019," 2019. [Online]. Available: https://level5.lyft.com/dataset
[163] U.S. Department of Transportation Federal Highway Administration, "Next generation simulation (NGSIM) vehicle trajectories and supporting data," 2016. [Online]. Available: http://doi.org/10.21949/1504477
[164] State farm, *State Farm Distracted Driver Detection*. San Francisco, USA: Kaggle, 2016.
[165] M. Naphade et al., "The 6th AI city challenge," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops*, 2022, pp. 3346–3355.
[166] R. M. Fujimoto et al., "CRAWDAD gatech/vehicular (V. 2006-03-15)," *IEEE Dataport*, Dec. 13, 2022. [Online]. Available: https://dx.doi.org/10.15783/C74S3Z
[167] H. Yang, L. Liu, W. Min, X. Yang, and X. Xiong, "Driver yawning detection based on subtle facial action recognition," *IEEE Trans. Multimed.*, vol. 23, pp. 572–583, 2021.
[168] M. Martin et al., "Drive&act: A multi-modal dataset for fine-grained driver behavior recognition in autonomous vehicles," in *Proc. IEEE/CVF Int. Conf. Comput. Vis.*, 2019, pp. 2801–2810.
[169] M. Naphade et al., "The 7th AI city challenge," in *Proc. The IEEE Conf. Comput. Vis. Pattern Recognit.*, 2023, pp. 5537–5547.
[170] G. Pan, L. Sun, Z. Wu, and S. Lao, "Eyeblink-based anti-spoofing in face recognition from a generic webcamera," in *Proc. IEEE 11th Int. Conf. Comput. Vis.*, 2007, pp. 1–8.
[171] T. Drutarovsky and A. Fogelton, "Eye blink detection using variance of motion vectors.," in *Proc. Eur. Conf. Comput. Vis. Workshops*, 2014, pp. 436–448.
[172] R. W. Van Der Heijden, T. Lukaseder, and F. Kargl, "VeReMi: A dataset for comparable evaluation of misbehavior detection in vanets," in *Proc. Secur. Privacy Commun. Netw.: 14th Int. Conf.*, 2018, pp. 318–337.
[173] H. Mu, L. Yuan, and J. Li, "Human sensing via passive spectrum monitoring," *IEEE Open J. Instrum. Meas.*, vol. 2, pp. 1–13, 2023.
[174] A. Ferrari, D. Micucci, M. Mobilio, and P. Napoletano, "Deep learning and model personalization in sensor-based human activity recognition," *J. Reliable Intell. Environments*, vol. 9, no. 1, pp. 27–39, 2023.
[175] Z. Hu, S. Lou, Y. Xing, X. Wang, D. Cao, and C. Lv, "Review and perspectives on driver digital twin and its enabling technologies for intelligent vehicles," *IEEE Trans. Intell. Veh.*, vol. 7, no. 3, pp. 417–440, Sep. 2022.
[176] S. Ansari, F. Naghdy, and H. Du, "Human-machine shared driving: Challenges and future directions," *IEEE Trans. Intell. Veh.*, vol. 7, no. 3, pp. 499–519, Sep. 2022.
[177] Y. Lu et al., "A shared control design for steering assistance system considering driver behaviors," *IEEE Trans. Intell. Veh.*, vol. 8, no. 1, pp. 900–911, Jan. 2023.
[178] Y. Ma et al., "M2DAR: Multi-view multi-scale driver action recognition with vision transformer," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, 2023, pp. 5286–5293.
[179] Q. Liu, Q. Guo, W. Wang, Y. Zhang, and Q. Kang, "An automatic detection algorithm of metro passenger boarding and alighting based on deep learning and optical flow," *IEEE Trans. Instrum. Meas.*, vol. 70, pp. 1–13, 2021.
[180] U. M. Gidado, H. Chiroma, N. Aljojo, S. Abubakar, S. I. Popoola, and M. A. Al-Garadi, "A survey on deep learning for steering angle prediction in autonomous vehicles," *IEEE Access*, vol. 8, pp. 163797–163817, 2020.
[181] M. Bojarski et al., "End to end learning for self-driving cars," 2016, *arXiv:1604.07316*.
[182] B. I. Sighencea, R. I. Stanciu, and C. D. Căleanu, "A review of deep learning-based methods for pedestrian trajectory prediction," *Sensors*, vol. 21, no. 22, 2021, Art. no. 7543.
[183] J. Liu, X. Mao, Y. Fang, D. Zhu, and M.Q.-H. Meng, "A survey on deep-learning approaches for vehicle trajectory prediction in autonomous driving," in *Proc. IEEE Int. Conf. Robot. Biomimetics*, 2021, pp. 978–985.
[184] Y. Huang, J. Du, Z. Yang, Z. Zhou, L. Zhang, and H. Chen, "A survey on trajectory-prediction methods for autonomous driving," *IEEE Trans. Intell. Veh.*, vol. 7, no. 3, pp. 652–674, Sep. 2022.
[185] X. Liao et al., "Driver digital twin for online prediction of personalized lane change behavior," *IEEE Internet Things J.*, vol. 10, no. 15, pp. 13235–13246, Aug. 2023.
[186] S. Teng et al., "Motion planning for autonomous driving: The state of the art and future perspectives," *IEEE Trans. Intell. Veh.*, vol. 8, no. 6, pp. 3692–3711, Jun. 2023.
[187] C. Wang, L. Ma, R. Li, T. S. Durrani, and H. Zhang, "Exploring trajectory prediction through machine learning methods," *IEEE Access*, vol. 7, pp. 101441–101452, 2019.
[188] N. Majcherczyk, N. Srishankar, and C. Pinciroli, "Flow-FL: Data-driven federated learning for spatio-temporal predictions in multi-robot systems," in *Proc. IEEE Int. Conf. Robot. Automat.*, 2021, pp. 8836–8842.
[189] C. Koetsier, J. Fiosina, J. N. Gremmel, J. P. Müller, D. M. Woisetschläger, and M. Sester, "Detection of anomalous vehicle trajectories using federated learning," *ISPRS Open J. Photogrammetry Remote Sens.*, vol. 4, 2022, Art. no. 100013.
[190] G. Rjoub, J. Bentahar, and O. A. Wahab, "Explainable AI-based federated deep reinforcement learning for trusted autonomous driving," in *Proc. Int. Wireless Commun. Mobile Comput.*, 2022, pp. 318–323.
[191] C. Wang, X. Chen, J. Wang, and H. Wang, "ATPFL: Automatic trajectory prediction model design under federated learning framework," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, 2022, pp. 6563–6572.
[192] Y. Liu et al., "FedVision: An online visual object detection platform powered by federated learning," in *Proc. AAAI Conf. Artif. Intell.*, 2020, pp. 13172–13179.
[193] Z.-Q. Zhao, P. Zheng, S.-T. Xu, and X. Wu, "Object detection with deep learning: A review," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 30, no. 11, pp. 3212–3232, Nov. 2019.
[194] S. Wang, Y. Hong, R. Wang, Q. Hao, Y.-C. Wu, and D. W. K. Ng, "Edge federated learning via unit-modulus over-the-air computation," *IEEE Trans. Commun.*, vol. 70, no. 5, pp. 3141–3156, May 2022.
[195] C. R. Qi, H. Su, K. Mo, and L. J. Guibas, "PointNet: Deep learning on point sets for 3D classification and segmentation," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, pp. 652–660, 2017.
[196] W. Wang and J. Tu, "Research on license plate recognition algorithms based on deep learning in complex environment," *IEEE Access*, vol. 8, pp. 91661–91675, 2020.
[197] W. Puarungroj and N. Boonsirisumpun, "Thai license plate recognition based on deep learning," *Procedia Comput. Sci.*, vol. 135, pp. 214–221, 2018.
[198] D. Zang, Z. Chai, J. Zhang, D. Zhang, and J. Cheng, "Vehicle license plate recognition using visual attention model and deep learning," *J. Electron. Imag.*, vol. 24, no. 3, pp. 033001–033001, 2015.
[199] S. Zherzdev and A. Gruzdev, "LPRNet: License plate recognition via deep neural networks," 2018, *arXiv:1806.10447*.

[200] X. Kong et al., “A federated learning-based license plate recognition scheme for 5G-enabled internet of vehicles,” *IEEE Trans. Ind. Inform.*, vol. 17, no. 12, pp. 8523–8530, Mar. 2021.

[201] R. Xie, C. Li, X. Zhou, and Z. Dong, “Asynchronous federated learning for real-time multiple licence plate recognition through semantic communication,” in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process.*, 2023, pp. 1–5.

[202] S. Xiao, X. Ge, Q.-L. Han, and Y. Zhang, “Resource-efficient platooning control of connected automated vehicles over VANETs,” *IEEE Trans. Intell. Veh.*, vol. 7, no. 3, pp. 579–589, Sep. 2022.

[203] B. Paden, M. Čáp, S. Z. Yong, D. Yershov, and E. Frazzoli, “A survey of motion planning and control techniques for self-driving urban vehicles,” *IEEE Trans. Intell. Veh.*, vol. 1, no. 1, pp. 33–55, Mar. 2016.

[204] F. Tian, Z. Li, F.-Y. Wang, and L. Li, “Parallel learning-based steering control for autonomous driving,” *IEEE Trans. Intell. Veh.*, vol. 8, no. 1, pp. 379–389, Jan. 2023.

[205] R. K. Manna et al., “Control challenges for high-speed autonomous racing: Analysis and simulated experiments,” *SAE Int. J. Connected Automated Veh.*, vol. 5, no. 12-05-01-0009, pp. 101–114, 2022.

[206] T. Wu, M. Jiang, Y. Han, Z. Yuan, X. Li, and L. Zhang, “A traffic-aware federated imitation learning framework for motion control at unsignalized intersections with internet of vehicles,” *Electronics*, vol. 10, no. 24, 2021, Art. no. 3050.

[207] P. P. Kannan, Y. Al-zuhairi, and M. A. Igartua, “Hybrid autonomous connected vehicle platooning with federated learning: State of the art and simulation framework,” in *Proc. XV Jornadas de Ingeniería Telemática: Coruña, España*, 2021, pp. 277–280.

[208] S. Liu, Y. Fu, P. Zhao, F. Li, and C. Li, “Autonomous braking algorithm for rear-end collision via communication-efficient federated learning,” in *Proc. IEEE Glob. Commun. Conf.*, 2021, pp. 01–06.

[209] I.-M. Chen and C.-Y. Chan, “Deep reinforcement learning based path tracking controller for autonomous vehicle,” *Proc. Inst. Mech. Eng., Part D: J. Automobile Eng.*, vol. 235, no. 2–3, pp. 541–551, 2021.

[210] D. Chen, L. Jiang, Y. Wang, and Z. Li, “Autonomous driving using safe reinforcement learning by incorporating a regret-based human lane-changing decision model,” in *Proc. Amer. Control Conf.*, 2020, pp. 4355–4361.

[211] A. Folkers, M. Rick, and C. Büskens, “Controlling an autonomous vehicle with deep reinforcement learning,” in *Proc. IEEE Intell. Veh. Symp.*, 2019, pp. 2025–2031.

[212] P. Wang, C.-Y. Chan, and A. d. L. Fortelle, “A reinforcement learning based approach for automated lane change maneuvers,” in *Proc. IEEE Intell. Veh. Symp.*, 2018, pp. 1379–1384.

[213] Z. Wang, G. Wu, and M. J. Barth, “A review on cooperative adaptive cruise control (CACC) systems: Architectures, controls, and applications,” in *Proc. 21st Int. Conf. Intell. Transp. Syst.*, 2018, pp. 2884–2891.

[214] Z. Wang, Y. Bian, S. E. Shladover, G. Wu, S. E. Li, and M. J. Barth, “A survey on cooperative longitudinal motion control of multiple connected and automated vehicles,” *IEEE Intell. Transp. Syst. Mag.*, vol. 12, no. 1, pp. 4–24, Spring 2020.

[215] T. Liu, L. Cui, B. Pang, and Z.-P. Jiang, “A unified framework for data-driven optimal control of connected vehicles in mixed traffic,” *IEEE Trans. Intell. Veh.*, vol. 8, no. 8, pp. 4131–4145, Aug. 2023.

[216] S. Grigorescu, B. Trasnea, T. Cocias, and G. Macesanu, “A survey of deep learning techniques for autonomous driving,” *J. Field Robot.*, vol. 37, no. 3, pp. 362–386, 2020.

[217] S. Kuutti, R. Bowden, Y. Jin, P. Barber, and S. Fallah, “A survey of deep learning applications to autonomous vehicle control,” *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 2, pp. 712–733, Feb. 2021.

[218] D. Li, D. Zhao, Q. Zhang, and Y. Chen, “Reinforcement learning and deep learning based lateral control for autonomous driving [application notes],” *IEEE Comput. Intell. Mag.*, vol. 14, no. 2, pp. 83–98, May 2019.

[219] S. Sharma, G. Tewolde, and J. Kwon, “Lateral and longitudinal motion control of autonomous vehicles using deep learning,” in *Proc. IEEE Int. Conf. Electro Inf. Technol.*, 2019, pp. 1–5.

[220] S. N. Wadekar et al., “Towards end-to-end deep learning for autonomous racing: On data collection and a unified architecture for steering and throttle prediction,” 2021, *arXiv:2105.01799*.

[221] V. P. Chellapandi, Y. Nagaraj, J. Supplee, S. Hernandez-Gonzalez, H. Borhan, and S. H. Żak, “Predictive control of diesel oxidation catalysts with federated learning in connected vehicles,” in *Proc. IEEE Forum Innov. Sustain. Transp. Syst.*2024.

[222] N. A. M. Razali, N. Shamsaimon, K. K. Ishak, S. Ramli, M. F. M. Amran, and S. Sukardi, “Gap, techniques and evaluation: Traffic flow prediction using machine learning and deep learning,” *J. Big Data*, vol. 8, no. 1, pp. 1–25, 2021.

[223] P. Sun, N. Aljeri, and A. Boukerche, “Machine learning-based models for real-time traffic flow prediction in vehicular networks,” *IEEE Netw.*, vol. 34, no. 3, pp. 178–185, May/Jun. 2020.

[224] A. Miglani and N. Kumar, “Deep learning models for traffic flow prediction in autonomous vehicles: A review, solutions, and challenges,” *Veh. Commun.*, vol. 20, 2019, Art. no. 100184.

[225] X. Yuan et al., “FEDSTN: Graph representation driven federated learning for edge computing enabled urban traffic flow prediction,” *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 8, pp. 8738–8748, Aug. 2023.

[226] J. Zhang, Y. Zheng, and D. Qi, “Deep spatio-temporal residual networks for citywide crowd flows prediction,” in *Proc. AAAI Conf. Artif. Intell.*, 2017.

[227] X. Yuan, J. Chen, N. Zhang, C. Zhu, Q. Ye, and X. S. Shen, “FedTSE: Low-cost federated learning for privacy-preserved traffic state estimation in IoV,” in *Proc. IEEE Conf. Comput. Commun. Workshops*, 2022, pp. 1–6.

[228] D. B. Rawat and C. Bajracharya, *Vehicular Cyber Physical Systems*. Berlin, Germany: Springer, 2017.

[229] Y. Lu, X. Huang, Y. Dai, S. Maharjan, and Y. Zhang, “Federated learning for data privacy preservation in vehicular cyber-physical systems,” *IEEE Netw.*, vol. 34, no. 3, pp. 50–56, May/Jun. 2020.

[230] Y. Lei, S. L. Wang, C. Su, and T. F. Ng, “OES-Fed: A federated learning framework in vehicular network based on noise data filtering,” *PeerJ Comput. Sci.*, vol. 8, 2022, Art. no. e1101.

[231] P. Zheng, Y. Zhu, Y. Hu, and A. Schmeink, “Data-driven extreme events modeling for vehicle networks by personalized federated learning,” in *Proc. Int. Symp. Wireless Commun. Syst.*, 2022, pp. 1–6.

[232] X. Li, L. Cheng, C. Sun, K.-Y. Lam, X. Wang, and F. Li, “Federated-learning-empowered collaborative data sharing for vehicular edge networks,” *IEEE Netw.*, vol. 35, no. 3, pp. 116–124, May/Jun. 2021.

[233] F. O. Olowononi, D. B. Rawat, and C. Liu, “Federated learning with differential privacy for resilient vehicular cyber physical systems,” in *Proc. IEEE 18th Annu. Consum. Commun. Netw. Conf.*, 2021, pp. 1–5.

[234] F. Ayaz, Z. Sheng, D. Tian, and Y. L. Guan, “A blockchain based federated learning for message dissemination in vehicular networks,” *IEEE Trans. Veh. Technol.*, vol. 71, no. 2, pp. 1927–1940, Feb. 2022.

[235] Z. Zhou, F. Xiong, C. Xu, Y. He, and S. Mumtaz, “Energy-efficient vehicular heterogeneous networks for green cities,” *IEEE Trans. Ind. Informat.*, vol. 14, no. 4, pp. 1522–1531, Apr. 2018.

[236] J. Konečnỳ, H. B. McMahan, F. X. Yu, P. Richtárik, A. T. Suresh, and D. Bacon, “Federated learning: Strategies for improving communication efficiency,” 2016, *arXiv:1610.05492*.

[237] Y. Li, Z. Zhang, Z. Zhang, and Y.-C. Kao, “Secure federated learning with efficient communication in vehicle network,” *J. Internet Technol.*, vol. 21, no. 7, pp. 2075–2084, 2020.

[238] R. Song, L. Lyu, W. Jiang, A. Festag, and A. Knoll, “V2X-boosted federated learning for cooperative intelligent transportation systems with contextual client selection,” 2023, *arXiv:2305.11654*.

[239] S. B. Prathiba, G. Raja, S. Anbalagan, K. Dev, S. Gurumoorthy, and A. P. Sankaran, “Federated learning empowered computation offloading and resource management in 6G-V2X,” *IEEE Trans. Netw. Sci. Eng.*, vol. 9, no. 5, pp. 3234–3243, Sep./Oct. 2021.

[240] X. Li, L. Lu, W. Ni, A. Jamalipour, D. Zhang, and H. Du, “Federated multi-agent deep reinforcement learning for resource allocation of vehicle-to-vehicle communications,” *IEEE Trans. Veh. Technol.*, vol. 71, no. 8, pp. 8810–8824, Aug. 2022.

[241] S. Samarakoon, M. Bennis, W. Saad, and M. Debbah, “Federated learning for ultra-reliable low-latency V2V communications,” in *Proc. IEEE Glob. Commun. Conf.*, 2018, pp. 1–7.

[242] S. Samarakoon, M. Bennis, W. Saad, and M. Debbah, “Distributed federated learning for ultra-reliable low-latency vehicular communications,” *IEEE Trans. Commun.*, vol. 68, no. 2, pp. 1146–1159, Feb. 2020.

[243] A. Taïk, Z. Mlika, and S. Cherkaoui, “Clustered vehicular federated learning: Process and optimization,” *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 12, pp. 25371–25383, Dec. 2022.

[244] S. Hosseinalipour et al., “Parallel successive learning for dynamic distributed model training over heterogeneous wireless networks,” *IEEE/ACM Trans. Netw.*, early access, Jul. 10, 2023, doi: 10.1109/TNET.2023.3286987.

[245] R. Parasnis, S. Hosseinalipour, Y.-W. Chu, C. G. Brinton, and M. Chiang, “Connectivity-aware semi-decentralized federated learning over time-varying D2D networks,” in *Proc. 24th Int. Symp. Theory, Algorithmic Found., Protoc. Des. Mob. Netw. Mob. Comput.*, 2023, pp. 31–40.

[246] W. Fang, D.-J. Han, and C. G. Brinton, “Submodel partitioning in hierarchical federated learning: Algorithm design and convergence analysis,” 2023, *arXiv:2310.17890*.

[247] B. Yang et al., "Edge intelligence for autonomous driving in 6G wireless system: Design challenges and solutions," *IEEE Wireless Commun.*, vol. 28, no. 2, pp. 40–47, Apr. 2021.

[248] W. Fang, Y. Jiang, Y. Shi, Y. Zhou, W. Chen, and K. B. Letaief, "Over-the-air computation via reconfigurable intelligent surface," *IEEE Trans. Commun.*, vol. 69, no. 12, pp. 8612–8626, Dec. 2021.

[249] W. Lobato, J. B. D. Costa, A. M. d. Souza, D. Rosário, C. Sommer, and L. A. Villas, "FLEXE: Investigating federated learning in connected autonomous vehicle simulations," in *Proc. IEEE 96th Veh. Technol. Conf.*, 2022, pp. 1–5.

[250] S. Dai, S. I. Alam, R. Balakrishnan, K. Lee, S. Banerjee, and N. Himayat, "Online federated learning based object detection across autonomous vehicles in a virtual world," in *Proc. IEEE 20th Consum. Commun. Netw. Conf.*, 2023, pp. 919–920.

[251] J. Hu, S. Sun, J. Lai, S. Wang, Z. Chen, and T. Liu, "CACC simulation platform designed for urban scenes," *IEEE Trans. Intell. Veh.*, vol. 8, no. 4, pp. 2857–2874, Apr. 2023.

[252] D.-J. Han, D.-Y. Kim, M. Choi, C. G. Brinton, and J. Moon, "SplitGP: Achieving both generalization and personalization in federated learning," in *Proc. IEEE Conf. Comput. Commun.*, 2023, pp. 1–10.

[253] H. Wang, J. Xie, and M. M. A. Muslam, "FAIR: Towards impartial resource allocation for intelligent vehicles with automotive edge computing," *IEEE Trans. Intell. Veh.*, vol. 8, no. 2, pp. 1971–1982, Feb. 2023.

[254] S. Wang et al., "Towards cooperative federated learning over heterogeneous edge/fog networks," *IEEE Commun. Mag.*, early access, May 08, 2023, doi: 10.1109/MCOM.005.2200925.

[255] Q. Zhang, H. Wen, Y. Liu, S. Chang, and Z. Han, "Federated-reinforcement-learning-enabled joint communication, sensing, and computing resources allocation in connected automated vehicles networks," *IEEE Internet Things J.*, vol. 9, no. 22, pp. 23224–23240, Nov. 2022.

[256] L. Yuan, Z. Wang, and C. G. Brinton, "Digital ethics in federated learning," 2023, *arXiv:2310.03178*.

[257] S. Wang, F. Liu, and H. Xia, "Content-based vehicle selection and resource allocation for federated learning in IoV," in *Proc. IEEE Wireless Commun. Netw. Conf. Workshops*, 2021, pp. 1–7.

[258] Z. Tianqing, W. Zhou, D. Ye, Z. Cheng, and J. Li, "Resource allocation in IoT edge computing via concurrent federated reinforcement learning," *IEEE Internet Things J.*, vol. 9, no. 2, pp. 1414–1426, Jan. 2022.

[259] R. Albelaihi, L. Yu, W. D. Craft, X. Sun, C. Wang, and R. Gazda, "Green federated learning via energy-aware client selection," in *Proc. IEEE Glob. Commun. Conf.*, 2022, pp. 13–18.

[260] W. Fang, Z. Yu, Y. Jiang, Y. Shi, C. N. Jones, and Y. Zhou, "Communication-efficient stochastic zeroth-order optimization for federated learning," *IEEE Trans. Signal Process.*, vol. 70, pp. 5058–5073, 2022.

[261] T. Nishio and R. Yonetani, "Client selection for federated learning with heterogeneous resources in mobile edge," in *Proc. IEEE Int. Conf. Commun.*, 2019, pp. 1–7.

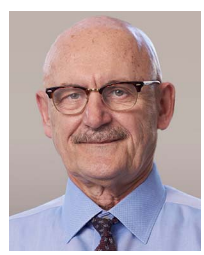
[262] S. Wang et al., "Adaptive federated learning in resource constrained edge computing systems," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 6, pp. 1205–1221, Jun. 2019.

[263] J. Liu et al., "Adaptive asynchronous federated learning in resource-constrained edge computing," *IEEE Trans. Mobile Comput.*, vol. 22, no. 2, pp. 674–690, Feb. 2023.

Vishnu Pandi Chellapandi (Member, IEEE) received the B.E. degree from the College of Engineering Guindy, Anna University, Chennai, India, and the M.S. degree from the University of Michigan, Ann Arbor, MI, USA, in 2018. He is currently working toward the Ph.D. degree with the School of Electrical and Computer Engineering, Purdue University, West Lafayette, IN, USA. He is also a Technical Specialist with the Connected and Intelligent Systems Group, Cummins Research and Technology, Columbus, IN, USA. His research interests include federated learning, distributed optimization, systems, and optimal controls.

Liangqi Yuan (Graduate Student Member, IEEE) received the B.E. degree from the Beijing Information Science and Technology University, Beijing, China, in 2020, and the M.S. degree from the Oakland University, Rochester, MI, USA, in 2022. He is currently working toward the Ph.D. degree with the School of Electrical and Computer Engineering, Purdue University, West Lafayette, IN, USA. His research interests include sensors, the Internet of Things, signal processing, and machine learning.

Christopher G. Brinton (Senior Member, IEEE) received the M.S. and Ph.D. (with Hons.) degrees in electrical engineering from Princeton University, Princeton, NJ, USA, in 2013 and 2016, respectively. He is a Elmore Assistant Professor with the School of Electrical and Computer Engineering, Purdue University, West Lafayette, IN, USA. Prior to joining Purdue University, he was the Associate Director of the EDGE Lab and a Lecturer of electrical engineering with Princeton University. His research interests include the intersection of networked systems and machine learning, specifically in distributed machine learning, fog/edge network intelligence, and data-driven network optimization. Dr. Brinton was the recipient of the NSF CAREER Award, the ONR Young Investigator Program Award, the DARPA Young Faculty Award, and the Intel Rising Star Faculty Award. He is currently an Associate Editor for IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, in the ML and AI for wireless area.



Stanislaw H. Żak (Life Member, IEEE) received the Ph.D. degree in electrical engineering from the Warsaw University of Technology, Warsaw, Poland, in 1977. From 1977 to 1980, he was an Assistant Professor with the Institute of Control and Industrial Electronics, Warsaw University of Technology. From 1980 to 1983, he was a Visiting Assistant Professor with the Department of Electrical Engineering, University of Minnesota, Minneapolis, MN, USA. In 1983, he joined the School of Electrical and Computer Engineering, Purdue University, West Lafayette, IN, USA, where he is currently a Professor. He has been involved in various areas of control, optimization, fuzzy systems, and neural networks. He has coauthored Topics in the Analysis of Linear Dynamical Systems (Polish Scientific Publishers, 1984) and *An Introduction to Optimization: With Applications to Machine Learning*, 5th edition (Wiley, 2024), and has authored *Systems and Control* (Oxford University Press, 2003). He was an Associate Editor for *Dynamics and Control* and IEEE TRANSACTIONS ON NEURAL NETWORKS.

Ziran Wang (Member, IEEE) received the Ph.D. degree in mechanical engineering from the University of California, Riverside, Riverside, CA, USA, in 2019. He is a tenure-track Assistant Professor with the College of Engineering, Purdue University, West Lafayette, IN, USA, where he directs the Purdue Digital Twin Lab. Prior to this, he was a Principal Researcher with Toyota Motor North America R&D in Mountain View, CA, USA. His research interests include automated driving, human-autonomy teaming, and digital twins. Dr. Wang is the Founding Chair of the IEEE Technical Committee on Internet of Things in Intelligent Transportation Systems, and an Associate Editor for four journals.