

A Survey on Federated Learning in Intelligent Transportation Systems

Rongqing Zhang, *Member, IEEE*, Hanqiu Wang, Bing Li, *Member, IEEE*, Xiang Cheng, *Fellow, IEEE*
and Liuqing Yang, *Fellow, IEEE*

Abstract—The development of Intelligent Transportation System (ITS) has brought about comprehensive urban traffic information that not only provides convenience to urban residents in their daily lives but also enhances the efficiency of urban road usage, leading to a more harmonious and sustainable urban life. Typical scenarios in ITS mainly include traffic flow prediction, traffic target recognition, and vehicular edge computing. However, most current ITS applications rely on a centralized training approach where users upload source data to a cloud server with high computing power for management and centralized training. This approach has limitations such as poor real-time performance, data silos, and difficulty in guaranteeing data privacy. To address these limitations, federated learning (FL) has been proposed as a promising solution. In this paper, we present a comprehensive review of the application of FL in ITS, with a particular focus on three key scenarios: traffic flow prediction, traffic target recognition, and vehicular edge computing. For each scenario, we provide an in-depth analysis of its key characteristics, current challenges, and specific manners in which FL is leveraged. Moreover, we discuss the benefits that FL can offer as a potential solution to the limitations of the centralized training approach currently used in ITS applications.

Index Terms—Federated learning, ITS, traffic flow prediction, target recognition, vehicular edge computing.

I. INTRODUCTION

In recent years, the accelerated urbanization process has led to a marked increase in vehicular traffic, necessitating the development of an efficient and effective traffic management system. The Intelligent Transportation System (ITS), initiated in the early 1970s, is a traffic management system aimed at enhancing transportation efficiency [1]. ITS capitalizes on a robust infrastructure and incorporates advanced technologies to improve transportation system performance. Its foremost goal is to integrate diverse road information comprehensively and to fully leverage the power of the internet, cloud computing, artificial intelligence, and other advanced technologies within the transportation field. This integration will enable the achievement of comprehensive information perception and the ability to make scientifically informed decisions [2]. A conceptual overview of the typical ITS framework is depicted in Fig. 1.

R. Zhang, H. Wang and, B. Li are with the School of Software Engineering, Tongji University, Shanghai 201804, China (e-mail: rongqingz@tongji.edu.cn; 2031562@tongji.edu.cn; lizi@tongji.edu.cn).

X. Cheng is with the School of Electronics, Peking University, Beijing 100871, China (e-mail: xiangcheng@pku.edu.cn).

L. Yang is with the Internet of Things Thrust and Intelligent Transportation Thrust, Hong Kong University of Science and Technology (Guangzhou), Guangzhou 511458, China, and also with the Department of Electronic and Computer Engineering, Hong Kong University of Science and Technology, Hong Kong SAR 999077, China (e-mail: lqyang@ust.hk).

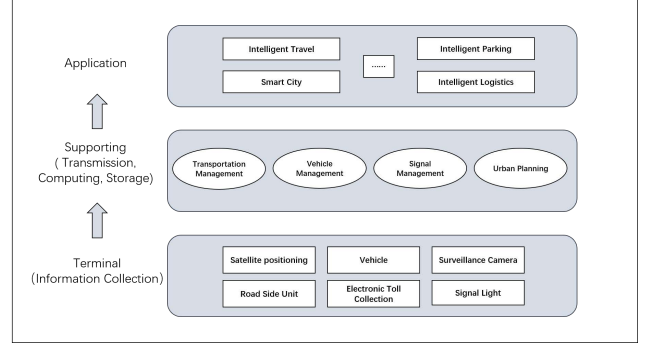


Fig. 1. Framework of a typical ITS.

Comprehensive urban traffic information is an essential component of modern urban transportation management, offering benefits to both urban residents and the environment. The deployment of ITS can enhance the utilization of transportation resources and improve traffic efficiency by leveraging advanced technologies such as artificial intelligence and machine learning. These technologies equip drivers with essential information, facilitating informed decision-making in urban road navigation. Moreover, the deployment of ITS has the potential to mitigate environmental pollution by reducing congestion and the associated carbon emissions. ITS provides real-time traffic information, which helps drivers avoid congestion and take alternative routes, thereby reducing the number of vehicles on roads and decreasing carbon emissions. The reduction in emissions contributes to the development of a sustainable and harmonious urban environment. As such, ITS has emerged as a representative application in the field of Internet of Things (IoT). The main scenarios in which ITS are commonly deployed include traffic flow prediction, traffic target recognition, and vehicular edge computing.

Traffic flow prediction is crucial in ITS for effective traffic management, control, and planning [3]. With the rapid growth of urbanization and vehicular technology in recent years, the number of vehicles in urban areas has increased significantly, leading to traffic congestion and related challenges. Traffic flow prediction estimates future traffic flow by analyzing historical traffic data patterns. Accurate traffic forecasting information can provide crucial guidance for urban road network planning and enable the rapid real-time prediction of complex traffic scenarios, thus alleviating traffic congestion. Furthermore, comprehensive traffic information can help residents make more informed travel plans, provide more efficient route navigation, and create a safe and comfortable public travel environment, thereby improving the safety and efficiency of

the transportation system.

Traffic target recognition is also a crucial application in ITS that encompasses the detection and identification of both road targets and in-vehicle targets through technologies such as image recognition. With the recent advancements in autonomous driving technology, target recognition in traffic scenes has gained increased attention. Target recognition involves identifying road targets such as traffic signs, obstacles, and pedestrians, as well as in-vehicle targets including drivers, passengers, and objects. Comprehensive traffic information provided by accurate target recognition can benefit both city management and residents by aiding in transportation planning and improving the efficiency and safety of the transportation system.

Vehicular edge computing is a promising strategy for the efficient execution of application tasks, facilitating the offloading of tasks from smart vehicles to the edge for processing. The offloading employs a wireless link between the smart vehicle and the Road Side Unit (RSU) to transfer task data and obtain processing results. With the increasing volume of urban traffic data and the demand for real-time information processing, traditional methods, which transfer all data back to the cloud computing center, often lead to bandwidth wastage and increased latency. Vehicular edge computing enhances computational efficiency and leverages edge devices to achieve efficient utilization of resources. By analyzing and processing data in real-time at the edge, it offers immediate guidance based on current road conditions and available resources. The utilization of edge computing provides several benefits, including reduced latency, increased bandwidth utilization, and lower energy consumption.

The centralized training mode is widely used in current ITS applications, as illustrated in Fig. 2. This approach involves uploading source data to a cloud server with high computing power for management and centralized training. However, it has several limitations:

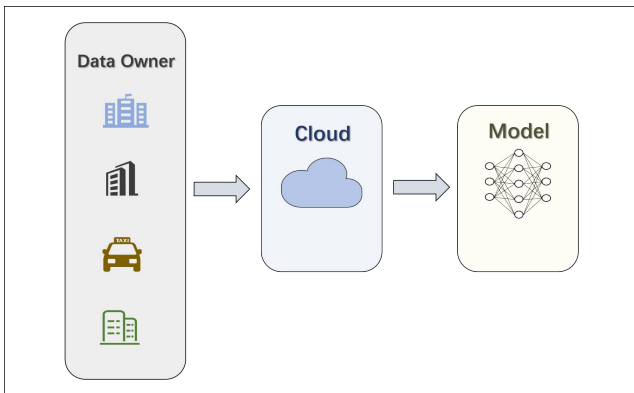


Fig. 2. Centralized training.

- **Data privacy.** The centralized training approach aggregates global data and collects all user data on a centralized server for unified management, without considering the privacy information contained in different organizational data sets. As a result, the centralized training approach can lead to uncontrolled data flows and sensitive data leakage. For instance, in traffic flow prediction scenarios,

different data owners may have access to different types of data, such as cab companies owning users' trajectory data and governments owning road data, which may contain users' private information. Uploading all the data to a central server may result in potential privacy leakage, leading to significant privacy and security concerns among users. Therefore, the centralized training approach is limited in terms of ensuring user security and protecting data privacy.

- **Poor real-time performance.** The massive data generated in ITS requires a large amount of computing resources, which poses a challenge for centralized servers to meet the real-time performance requirements of users. In addition, the delay caused by transmitting data to a remote server for processing and then returning the results to the user also reduces the speed of response. Such delay may have a significant impact on time-sensitive applications, such as real-time traffic flow prediction and autonomous driving.
- **Data silos.** Due to network security isolation and industry privacy concerns, data barriers exist between different organizations, departments, and systems, resulting in data silos that prevent secure data sharing. This leads to the fact that some of the valuable data cannot be used to train an effective model, resulting in a significant bottleneck for many applications, as illustrated in Fig. 3.

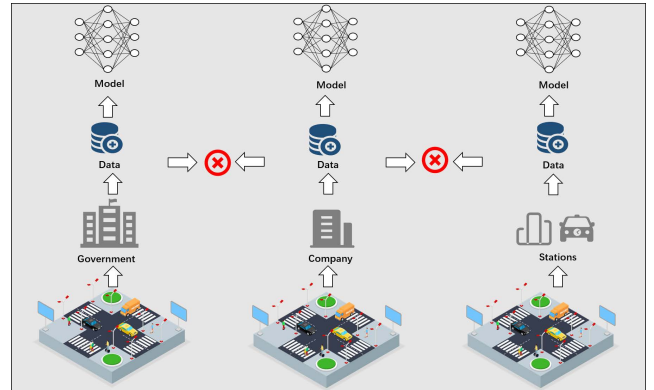


Fig. 3. Data silos.

The limitations have motivated the development of decentralized training approaches that can address the challenges and enable more efficient and secure data processing in ITS. Hence, in view of the aforementioned limitations of centralized training, federated learning (FL) is proposed as a potential solution. This paper provides a comprehensive review of the application of FL in ITS, concentrating on three principal scenarios: traffic flow prediction, traffic target recognition, and vehicular edge computing. For each scenario, we provide an overview of its key characteristics and current challenges, outline the specific ways in which FL is leveraged, and elaborate on the benefits that FL can bring as a potential solution.

II. FEDERATED LEARNING

As data privacy concerns intensify, sharing data between different organizations becomes more challenging. Given that

data frequently contains highly sensitive private information, owners stringently restrict its sharing. Additionally, with the explosion of data volume, the computation and communication costs of centralized data processing can be unaffordable. As a result, research has suggested FL as a method to protect machine learning privacy [4], [5].

FL is a novel training method within the distributed model training framework. As illustrated in Fig. 4, this method consists of multiple participating clients, each possessing a subset of local data for training, coupled with a central server responsible for aggregating the clients' model updates. FL enhances data isolation during model training, protects data privacy, and enables efficient collaborative learning among multiple participants. It allows both the storage of data and the model training phases to occur locally, thereby promoting collaborative training of globally optimal models. Through exclusive reliance on central server interactions for model updates, FL has shown great potential in improving the efficiency and security of machine learning within ITS applications, leading to extensive research and development in recent years[6].

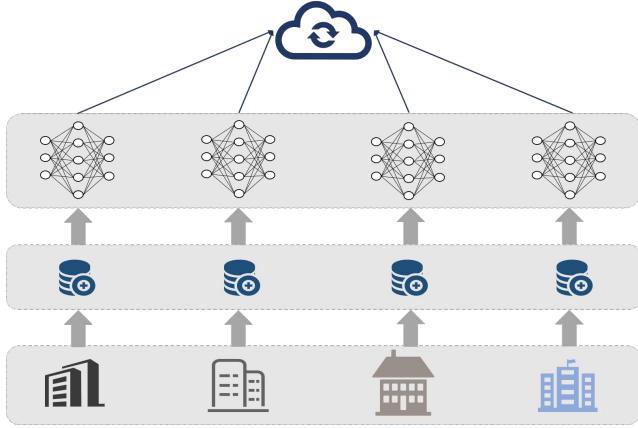


Fig. 4. FL framework.

In FL, model training is performed locally, and each organization uploads the encrypted model parameters to the cloud after the completion of local model training. The cloud then aggregates the parameters to obtain the updated model parameters, which are subsequently redistributed to each organization for model updating. Recent studies have shown that FL provides a trade-off between model performance and privacy protection [7]. This is because, in FL, data remains locally with the organizations, and only model parameters are shared with the cloud. This approach can reduce the risk of sensitive data exposure during model training. Moreover, the distributed structure of FL allows organizations to collaborate on model development without the need for a centralized data repository. The FL methodology entails four primary stages, which are illustrated in Fig. 5.

- 1) In FL, the initiation phase involves establishing a global model, which is randomly initialized by the cloud server in the first round of training. This model is then transmitted to each participating organization, along with its weights. In subsequent rounds, the cloud server sends the current global model weights to each organization.

- 2) During the FL process, participating organizations utilize their own local data to train the model and iteratively update the model's weights.
- 3) Each participating organization sends the updated model weights to the cloud server without sharing their local data, thus preserving data privacy and confidentiality.
- 4) Following the receipt of updated model weights from each participating organization, the cloud server aggregates the model weights and updates the global model. Subsequently, the cloud sends the updated model weights to the participating organizations, and this iterative process is repeated until the global model converges.

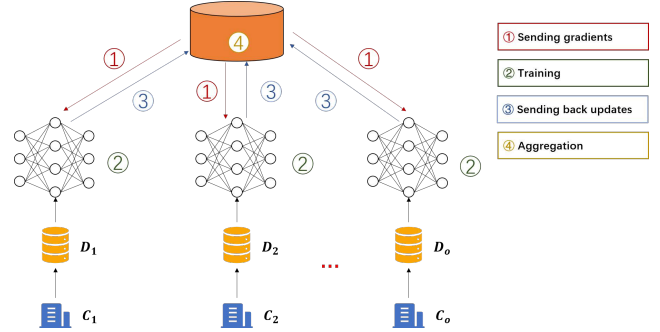


Fig. 5. FL steps.

The aforementioned steps highlight several notable advantages of FL. Firstly, FL enables data isolation by ensuring the confidentiality of local data throughout the training process, aligning with the requirements for user data privacy protection in modern data-driven applications. Secondly, FL supports multi-party collaboration, where each participant contributes their training data to build a shared global machine learning model, thereby promoting equality among all parties involved in the process. Finally, FL allows each organization to maintain independence while simultaneously exchanging model weights, which enhances the global model's efficiency. The combination of these advantages makes FL a promising approach for developing collaborative machine learning solutions within distributed environments.

Accordingly, we introduce FL into the within of ITS and provide an overview of current related research.

III. FEDERATED LEARNING IN TRAFFIC FLOW PREDICTION

A. Traffic Flow Prediction Scenario

Traffic flow prediction is a critical issue within the field of ITS. It involves the estimation of future traffic volume in a specific area by analyzing the patterns of traffic changes based on historical data. Fig. 6 illustrates a heatmap of traffic conditions in Beijing, China, serving as a visual representation of the city's current traffic flow. The provision of accurate traffic forecasting is essential for facilitating timely and reliable traffic condition predictions, enabling individuals to make travel plans that optimize travel time and enhance the safety and efficiency of the transport system [8]. In general, traffic flow prediction scenarios exhibit four key characteristics:

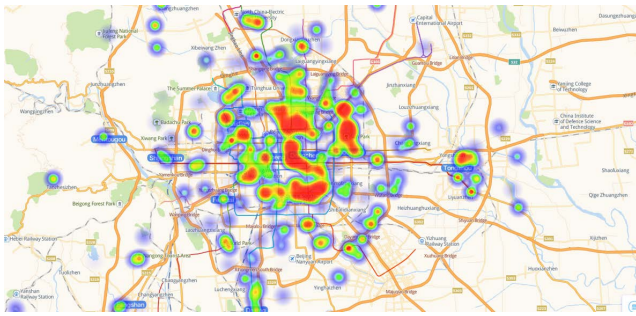


Fig. 6. A heatmap of Beijing, China

- 1) High privacy. The challenge of maintaining high privacy is paramount in the context of traffic flow prediction. This is because GPS track data used for this purpose often contains sensitive information regarding users' daily behaviors, which cannot be shared freely.
- 2) Rich types of data. The various scenarios associated with traffic flow prediction are characterized by diverse data types, including weather features, spatio-temporal features, POI (Point of Interest) semantic features, connection relationships, among others. Such rich data can enable a multifaceted portrayal of traffic flow changes.
- 3) High real-time requirements. Short-term traffic forecasting relies on real-time information, emphasizing the criticality of prompt feedback to the road and timely adjustments to vehicle decisions. Consequently, addressing this challenge forms a central focus in the traffic prediction problem.
- 4) Sensitive data structure features. The data used for traffic flow prediction is characterized by sensitive data structure features, containing not only intersection feature data but also topology information. This presents a potential privacy risk when data providers in the ITS domain, such as government agencies and companies, exchange data during cooperation and sharing activities. The topological information may contain sensitive data, thus requiring careful handling and management to prevent unauthorized data access and privacy breaches.

Numerous studies have been conducted to address the challenges posed by the characteristics of traffic flow prediction, as shown in Table I.

B. Federated Learning in Traffic Flow Prediction

The majority of current traffic prediction research is focused on exploiting the spatio-temporal correlation of urban traffic, and extracting the unique features and inter-region correlations within traffic data. Among the popular models for traffic flow prediction, the Graph Convolutional Neural Network (GCN) has emerged as a promising approach due to its ability to incorporate the natural graph structure properties of traffic data and integrate spatio-temporal features [9], [10], [11]. However, during the model training process, the GCN is associated with several issues, such as high data privacy risks, time-consuming training, and high communication costs, which pose significant challenges to the development of traffic flow prediction research.

In response to these challenges, recent studies have proposed the use of FL in the field of traffic flow prediction. Xia *et al.* [12] proposed a FL integrated GCN to address the challenges of balancing accuracy and time cost while preserving privacy. By utilizing horizontal local road network FL, the global graph convolutional road network model was replaced to reduce computing and communication costs while preventing data privacy exposure. However, existing GNN-based models employing FL in ITS tend to overlook the topological information of the traffic network, thereby risking privacy breaches. To address this challenge, Zhang *et al.* [13] proposed a differential adjacency matrix protection method. The method involved transforming the original adjacency matrix at the organization side by a Gaussian matrix to protect local topological information, and constructing the global adjacency matrix at the server side by processing the adjacency matrices from different organizations. Additionally, the FL approach in traffic flow prediction typically involves participants with the same sample space but different spatial characteristics on the traffic flow data set. To address the issue of different spatial characteristics of participants, the Vertical FL (VFL) is required. Yuan *et al.* [14] developed the federated graph attention layer to capture short-term temporal information without loss of spatial information among areas by sharing parameters based on VFL.

Moreover, some studies have focused on potential security issues associated with the integration of FL in traffic flow prediction. To address such security challenges, including single point of server failure and malicious vehicles, researchers have proposed a blockchain-based FL framework [15], [16]. In this framework, the central server is replaced by a set of trusted consensus nodes to mitigate the risk of single point of failure. Model updates are verified by miners and stored in the blockchain, which can detect malicious vehicles and defend against potential security attacks. Another potential security risk in FL is inference attacks, where an attacker may recover data from the gradient parameters to infer the original user data by inverting the shared gradients. To mitigate this risk, some researchers have added local differential privacy on local gradients to protect the privacy information [17]. Additionally, Deng *et al.* have proposed a solution by encrypting the model parameters and using homomorphic encryption to prevent attackers from performing inference attacks [18].

The efficiency of communication in introducing FL in traffic flow prediction is also a critical aspect that deserves further investigation. To address the scalability challenges of FL frameworks, an improved federated averaging algorithm with random subsampling of participants was designed in [19] to reduce communication overhead. A federated scheme employing integrated clustering was proposed to cluster organizations based on latitude and longitude, and the global model is eventually integrated at each clustering center. Similarly, a client clustering approach was introduced in [20], where clients with similar model parameters are grouped into the same cluster, reducing communication costs for the transmission of model updates in the FL system. To enhance the communication efficiency of FL, an asynchronous algorithm was designed in [21] to account for the impact of rounds on the aggregation

TABLE I
FEDERATED LEARNING IN TRAFFIC FLOW PREDICTION.

Applications	Reference	Main Ideas	Advantages
Traffic Flow Prediction	[12]	Replace the global road network model by horizontal local road network.	Reduce computing and communication costs while preventing data privacy exposure.
	[13]	Propose a differential adjacency matrix protection method.	Protect the topological information of the traffic network.
	[14]	Develop the Federated Graph Attention layer to share parameters based on VFL.	Address the problem of participants with different spatial characteristics.
	[15], [16]	Design a blockchain-based FL framework and replace the central server by a set of trusted consensus nodes.	Address single point failure of server and malicious vehicles.
	[17], [18]	Encrypt model parameters.	Mitigate the inference attacks.
	[19]	Improve the federated averaging algorithm with clustering organizations based on latitude and longitude.	Enhance the scalability of FL and reduce communication overhead.
	[20]	Propose a client clustering approach based on local model similarity.	Reduce communication costs on transmission of model updates.
	[21]	Design an asynchronous algorithm for model parameter uploading and downloading decisions.	Enhance the communication efficiency of FL.
Travel Time Estimation	[22]	Construct a global model as shared by all clients and a fine-tuned personalized model for each client to capture individual driving habits.	Address non-IID caused by personal driving habits and the inconsistency with data among clients.
	[23]	Train a customized neural network travel time estimator for each area using locally collected data.	Cross-area travel time estimation.
Crowd Flow Prediction	[24]	Learn spatio-temporal features from human trajectory and classify clients with similar spatio-temporal features into same cluster.	Improve the efficiency and accuracy of FL-based human mobility prediction.
	[25]	Propose a mobility vertical federated framework that allows the learning process to be conducted over vertically partitioned data.	Enable forecasting of mobility covering a joint location domain.
Route Planning	[26]	Implement a hierarchical clustering approach to partition the traffic data into groups, and utilized FL to train the models among all stations.	Protect the privacy and reduce the communication cost.
Destination Prediction	[27]	Use blockchain instead of centralized servers in FL.	Eliminate single points of failure.
Parking Management	[28]	Adopt FL and LSTM to promote the collaboration in parking space estimation.	Protect user privacy.

results.

The aforementioned studies have demonstrated improved experimental results by more effectively integrating traffic prediction with FL, thus addressing the limitations of traditional traffic prediction methods.

C. Federated Learning in Applications of Traffic Flow Prediction

In addition to the challenge of predicting traffic flow, there exist numerous specific applications in the domain of traffic flow prediction that incorporate FL techniques. In this context, we offer a comprehensive explication of these applications.

Travel time estimation has emerged as a key area of research within ITS in recent years, aiming to compute average travel time from the origin to the destination using historical data. Accurate travel time estimation is crucial for transportation agencies and individuals to plan and optimize travel routes, reduce congestion, and improve overall traffic flow. In view of the sensitivity of user travel information, which cannot be shared due to privacy concerns, a personalized FL strategy has been developed in [22]. This strategy leverages the FL principles to construct a global model, which is designed as an online generative model shared by all clients. This approach also incorporates a fine-tuned personalized model for each client to capture their individual driving habits and compensate for residual errors resulting from localized global model predictions. In addition, privacy and security concerns present challenges in cross-area travel time estimation, particularly with respect to data exchange among different areas. To address these challenges, Zhu *et al.* proposed a novel approach that trains a customized neural network travel time estimator for each area using locally collected data. The proposed approach incorporates FL for training the model, thereby enabling the exchange of information among different areas while preserving individual data privacy [23].

In recent times, crowd flow prediction has become an increasingly critical topic. With the rapid growth of urban areas and the increasing complexity of transportation systems, there is a growing need to develop advanced technologies and methodologies to better understand and manage human mobility. The authors of [24] proposed an enhanced FL framework by incorporating clustering algorithms. This approach involves leveraging human trajectory data to extract spatio-temporal features and grouping clients with similar features into clusters. By applying clustering algorithms, the proposed approach aims to improve the efficiency and accuracy of FL-based human mobility prediction. To address the challenge of achieving predictions for the entire location domain, which can vary significantly across different organizations, a mobility vertical FL prediction framework was developed for the mobility prediction problem, as described in [25]. This framework allows for joint learning to be performed over vertically partitioned data belonging to multiple organizations. Specifically, the mobility data is vertically partitioned by location, allowing for each organization to contribute their respective data while ensuring that sensitive information is kept private.

FL has demonstrated strong performance across various applications. For instance, in a recent study by Zeng *et al.* [26], a multi-task FL framework was proposed to optimize traffic prediction models for route planning. The authors implemented a hierarchical clustering approach to partition the traffic data into groups, and utilized FL to train the models among all stations without sharing data. FL has emerged as a powerful tool for accurate location services while preserving user privacy, particularly for destination prediction tasks [27]. In order to mitigate the risk of malicious users, blockchain technology can be leveraged in place of centralized servers, thereby eliminating single points of failure. FL continues to find practical applications in the domain of parking management, where privacy concerns remain a paramount consideration. Parking space information, which includes sensitive details such as the arrival and departure times of vehicles, is crucial to capturing a basic overview of daily parking requests. In a recent study by Huang *et al.* [28], an FL-based approach was proposed for real-time prediction of the number of available parking spaces in a car park.

In summary, FL has demonstrated efficacy in addressing privacy concerns in traffic data and enhancing the security of the training process, applicable to both broad traffic flow prediction and specific applications within this domain.

IV. FEDERATED LEARNING IN TRAFFIC TARGET RECOGNITION

A. Traffic Target Recognition Scenario

The traffic target recognition scenario refers to the use of image recognition techniques in ITS and encompasses two main subcategories: road target recognition and in-vehicle driving assistance. Road target recognition employs computer vision techniques in automotive assisted driving systems, whereby forward-facing cameras are used to identify common traffic signs, road targets, and other relevant objects as illustrated in Fig. 7. The ultimate objective is to leverage this information to make informed decisions and enhance driving safety. In-vehicle driving assistance involves employing advanced technologies to provide real-time support and assistance during the driving process, such as driver emotion recognition and steering wheel angle detection as demonstrated in Fig. 8. The objective is to enhance both the convenience and safety of driving for drivers.



Fig. 7. Road target recognition.

The traffic road recognition scenario exhibits several distinct challenges, including:

- 1) Lack of sufficient data. Most driving images contain private information, such as images of the driver's face, and as a result, this data cannot be shared, leading to an insufficient training data for collaborative model development.

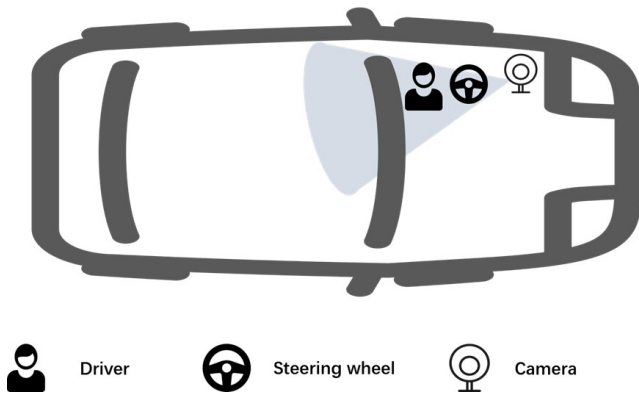


Fig. 8. In-vehicle driving assistance.

- 2) High resource consumption. The transmission of image data requires a significant amount of bandwidth and storage resources, which can be costly, especially in situations where large amounts of data need to be transmitted frequently.
- 3) High computational load. If all data is aggregated to the center for unified processing, the computational load at the center can become overwhelming, leading to significant delays in the recognition process.
- 4) High real-time requirements. Target recognition scenarios typically require quick recognition results to make the right decision, resulting in high computational latency requirements.

Overall, the traffic target recognition scenario presents several significant challenges, including the lack of sufficient data, high resource consumption, high computational load, and high real-time requirements. Researchers are actively developing new approaches, such as FL, to address these challenges and improve the accuracy and efficiency of traffic target recognition as shown in Table II. In the following part, we will specifically describe the application of FL in traffic target recognition scenarios.

B. Federated Learning in Road Target Recognition

In the context of generic road target recognition, concerns regarding sensitive image data leakage [42] and the high overhead of real-time data transmission [43] have prompted the use of FL for localized vehicle training. Road target recognition scenarios primarily involve target recognition and target detection, including pothole detection and traffic sign recognition.

Roads constitute a critical infrastructure for any country, and inadequate road conditions may result in vehicle damage and hazardous driving conditions. Therefore, the assessment and maintenance of road defects represent a fundamental component of ITS. Potholes, as shown in Fig. ??, commonly arise due to gradual road degradation induced by various factors such as harsh weather, heavy traffic loads, and natural wear and tear of road materials. Potholes present a significant safety hazard to both vehicles and their occupants, as well as adversely impacting vehicle performance, resulting in potential damage to tires, wheels, and suspension systems.

Automated road defect detection through the utilization of computer vision technology represents a promising approach to maintaining road safety and efficiency. In the context of pothole detection, Rahman *et al.* [29] applied a prototype of FL to address the limitations of previous methods that were both time-consuming and prone to errors. Specifically, when a vehicle encounters a pothole, a notification response is transmitted to the central server. The central server then collates and aggregates the data obtained from various vehicles and updates the road condition periodically. Alshammari *et al.* [30] also proposed an approach to facilitate pothole detection on portable devices. Specifically, they designed a 3D pothole detection system based on FL. The proposed approach employs the YOLO model for road defect detection via size estimation, identifying objects such as patched potholes and fake road bumps. For road damage detection, Yuan *et al.* [31] proposed an adaptive FL strategy for facilitate robust model learning from diverse edges.

As vehicles drive on roads, sensors and cameras play a critical role in detecting and recognizing traffic signs. Traffic signs are essential for ensuring an orderly and safe driving experience. For instance, warning signs remind drivers to be cautious and avoid obstacles, while indicator signs help ensure adherence to road directions. Additionally, traffic light signs aid in the controlled movement of vehicles at intersections. As such, the accurate identification and effective utilization of traffic signs have significant implications for driver assistance systems, as well as autonomous driving, enhancing the overall safety and efficiency of vehicular transportation. Xie *et al.* [32] addressed privacy in traffic sign data, which contains a substantial amount of location privacy information, by employing a prototype FL approach. The authors proposed a novel solution that integrates spike neural networks and FL to enhance traffic sign recognition privacy. This approach holds significant promise for protecting sensitive information and mitigating privacy risks associated with traffic sign data. In the context of remote sensing image-based vehicle target recognition, Xu *et al.* [33] also leveraged FL to address concerns regarding the privacy of remote sensing data. This approach offers a promising solution to mitigate the risk of data leakage while also addressing issues associated with inaccurate training results and slow training speeds when dealing with single-node remote sensing data. Image classification tasks may encounter challenges associated with the diversity of image quality and computational power across client vehicles, which can have an impact on the accuracy and efficiency of FL models. To address this issue, Ye *et al.* [34] proposed a selective model aggregation approach to identify and select the optimal local models for FL, thus improving overall model performance. This approach holds great potential for enhancing the accuracy and efficiency of FL in image classification tasks, particularly in situations where computational resources and image quality may vary widely among client devices. Similarly, to protect user data privacy and improve model training efficiency in the generic target recognition scenario, Zhang *et al.* [35] proposed an asynchronous federated aggregation protocol. The protocol selects the optimal local models based on the local quality of each classification tree.

TABLE II
FEDERATED LEARNING IN TRAFFIC TARGET RECOGNITION.

Applications	Reference	Key contributions	Advantages
Road Target Recognition			
Pothole Detection	[29], [30]	Apply FL to pothole detection.	Address the limitations of time-consuming and prone to errors.
Road Damage Detection	[31]	Propose an adaptive FL strategy to facilitate robust model learning from diverse edges.	Provide fast responses with accurate results while preserving users' privacy.
Traffic Sign Recognition.	[32]	Employ FL and spike neural networks to traffic sign recognition.	Protect sensitive information and mitigating privacy risks.
Identify Vehicle Targets	[33]	Provide a federated method to identify vehicle targets in remote sensing images.	Protect privacy of remote sensing data.
Image Classification	[34]	Propose a selective model aggregation approach to select the most optimal local models for FL.	Reduce communication costs and ensure the privacy and security of the data.
Target Recognition	[35]	Propose an asynchronous federated aggregation protocol to select the most optimal local models based on the quality of each model.	Reduce communication costs and ensure the privacy and security of the data.
In-Vehicle Driving Assistance			
Steering Angle Prediction	[36], [37], [38]	Apply FL in steering angle prediction. Each vehicle acts as an edge computing device and trains local models using its own data.	Reduce communication costs and ensure the privacy and security of the data.
Driver Facial Detection	[39], [40], [41]	Use FL for driver status monitoring, only local in-vehicle training data is utilized.	Privacy-sensitive images of the driver do not leave the vehicle.

C. Federated Learning in In-Vehicle Driving Detection

FL has shown great potential for improving in-vehicle driving detection by addressing data privacy and computational challenges in machine learning tasks. Angle prediction, crucial for autonomous driving, requires machine learning models trained on vision-based datasets. However, transmitting raw sensor data, such as that captured by cameras and lidars, can be extremely bandwidth-intensive, imposing a significant traffic load on the wireless communication system. To reduce the central computational load and save bandwidth, FL has been applied in steering angle prediction [36], [37]. In this approach, each vehicle acts as an edge computing device and trains local models with data collected by its own vision sensors. The central server then updates the global model by aggregating local model parameters. Finally, the global model is shared with the vehicles for automatic steering control. This approach not only reduces the computational and communication costs, but also ensures data privacy and security. Zhang *et al.* [38] further explored model aggregation protocols. They noted that synchronous aggregation protocols

are inflexible and cannot adapt to dynamic environments and heterogeneous hardware. To overcome this, they proposed an asynchronous model aggregation protocol with a sliding training window. This approach can reduce communication overhead and accelerate model training while maintaining high accuracy.

Driver facial detection is also critical for ensuring road safety by preventing accidents caused by drowsiness or distraction. However, collection and sharing driver facial data raises privacy concerns. FL has emerged as a promising solution to address these concerns by enabling distributed model training without sharing raw data. FL can also help overcome the challenge of insufficient driver facial data by aggregating it from multiple industry entities, such as automotive manufacturers and ride-sharing services. These entities can collaborate in a privacy-preserving manner to improve driver facial detection accuracy, ultimately enhancing road safety. In the cited papers [39], [40], FL was used for driver status monitoring, with the main advantage being that only local in-vehicle training data is utilized, ensuring that privacy-sensitive images of the

driver do not leave the vehicle. Furthermore, the authors in [41] proposed a pre-learning mechanism of migration learning to improve the performance of the FL system for driver drowsiness detection. Furthermore, to enhance the security of the FL system, they selected a homomorphic encryption scheme with excellent computational speed. This approach can effectively protect sensitive driver data and provide more robust security guarantees. The results demonstrate that the proposed mechanism can significantly improve the accuracy and robustness of the FL system for driver drowsiness detection.

In conclusion, the utilization of FL in autonomous driving presents an innovative solution to address the challenges of limited data volume, communication efficiency, and data privacy protection. By enabling distributed model training among multiple vehicles or devices, FL enables local data processing while preserving user privacy. FL has shown promising results in various autonomous driving applications, including road target recognition and in-vehicle driving assistance. Further research in FL is expected to contribute significantly to the development of ITS and bring us closer to the realization of safer and more efficient autonomous driving.

V. FEDERATED LEARNING IN VEHICULAR EDGE COMPUTING

A. Vehicular Edge Computing

The current research proposes an intelligent-driven vehicular edge computing architecture to address the contradiction between limited network resources and massive user demands in the automotive environment [44]. By applying mobile edge computing to the connected vehicle, vehicular edge computing enables the decentralization of computing and storage capacities. This approach can provide and manage computational resources closer to vehicles and end-users, greatly relieving the network bandwidth pressure and providing lower latency service access. Therefore, vehicular edge computing, based on the motivation and foundation of edge computing, is a promising technology to support ITS [45], [46].

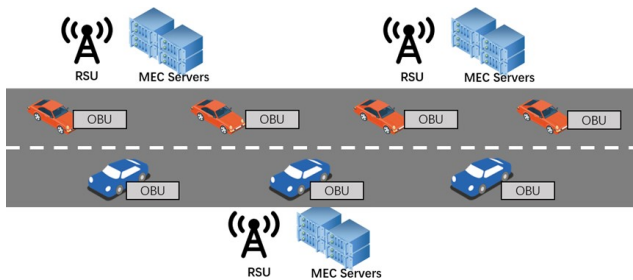


Fig. 9. Framework of VEC.

Autonomous driving systems are supported by the edge side, which comprises the On Board Unit (OBU), RSU, and Mobile Edge Computing (MEC) servers, as shown in Fig. 9. The OBU is responsible for environmental awareness, decision planning, and vehicle control, while the RSU provides the OBU with detailed information about the road and pedestrians. The MEC server is positioned close to the local device to reduce the

processing load of the system and mitigate the latency of data transmission, ultimately enhancing the overall efficiency of the autonomous driving system.

Collaborative perception is a prominent application of edge computing in autonomous driving. It allows vehicles to obtain sensor information from other edge nodes, thereby expanding their perception range. However, as autonomous driving levels increase and the number of smart sensors equipped on vehicles grows, an enormous amount of raw data is generated daily. This raw data needs to be processed, fused, and feature-extracted locally and in real-time. Given that most of these tasks need to be performed in-vehicle to ensure real-time processing and response, a robust and reliable edge computing platform is essential. As such, vehicular edge computing has emerged as a new research area of focus for autonomous driving systems. In the future, it is anticipated that more than 60% of data and applications will be generated and processed at the edge.

Vehicular edge computing has the following characteristics:

- 1) Low latency. By bringing computing resources closer to vehicles, vehicular edge computing reduces data transmission latency, enabling real-time responses.
- 2) Decentralized computing and storage. Vehicular edge computing allows for the decentralization of computing and storage capacity by applying mobile edge computing to the connected vehicle.
- 3) High bandwidth. Vehicular edge computing can provide high-speed, low-latency access to data and computing resources, enabling the processing of large amounts of data generated by autonomous vehicles.
- 4) Privacy and security. Vehicular edge computing can protect the privacy and security of user data by keeping the data within the vehicle or at the edge, reducing the risk of data breaches or unauthorized access.

Combining edge computing with FL represents a type of vehicular edge computing. In this methodology, edge devices utilize their own collected data to train their local DL models and upload only updated models to the central server [5]. This technique helps to minimize privacy and security risks by limiting the training data to the device side only. By utilizing FL, vehicular edge computing can support collaborative learning while ensuring data privacy and security, thereby improving the accuracy of the trained models without compromising user privacy [47], [48]. FL in vehicular edge computing is categorized into three main types: communication efficient improved FL, resource optimized FL, and security enhanced FL. Each type is designed to address specific challenges associated with FL in vehicular edge computing. In the following, we will elaborate on these categories.

B. Communication Efficient Improved Federated Learning

The communication overhead between edge devices and the central server has become a growing concern in FL, particularly in vehicular environments with limited network resources. This is primarily due to the large number of devices that send their local updates to a central server, which leads to communication bandwidth becoming a major bottleneck.

TABLE III
FEDERATED LEARNING IN VEHICULAR EDGE COMPUTING.

Applications	Key contributions Reference	Reference
Communication Efficient Improved FL	Reduce communication volume	Model Compression [49], [50], [51]
		Client Selection [52], [53], [54], [55], [56]
	Reduce communication rounds	[57], [55]
	Accelerate model update	[54], [55]
Resource Optimized FL	Structural Heterogeneity	[53], [58], [59], [60], [61]
	Fault Tolerance	[62]
Security Enhanced FL	Malicious Devices Detection	[63], [64], [65]
	Privacy Preservation	[65], [66], [67], [68]

To address this issue, reducing communication overhead has become a top priority. Various efforts are underway to improve communication efficiency, including reducing communication volume, minimizing the number of communication rounds, and accelerating model updates. These strategies are essential to handle the massive amount of data generated and ensure that FL can cope with the explosive growth of data in vehicular environments.

1) *Reducing Communication Volume*: In order to reduce communication overhead in FL for vehicular edge computing, several methods have been proposed in recent literature. One of these methods is model compression, which involves reducing the amount of data transmitted in both upstream and downstream. In [49], a method was proposed in which vehicles optimize their local ML model and then select a fixed percentage of randomly selected parameters to share with their neighbors in each training round. The use of quantization in the ML model further saves communication resources. Similarly, Shen *et al.* [50] proposed a local model training algorithm based on ternary quantization, which optimizes the quantization values of parameters for different local models. This strategy reduces the complexity of local model training and improves the overheads of upstream and downstream communication. Li *et al.* [51] executed optimization on both client and server sides. On the client side, they proposed a minimal squared quantization error quantizer design, while on the server side, they proposed a closed-form solution for the optimal aggregation weights assignment. This solution minimizes the weighted sum of squared quantization errors over all active clients. These methods demonstrate the potential of model compression and quantization techniques in reducing communication overhead in FL for vehicular edge computing.

Reducing the number of clients involved in the aggregation process is another promising strategy to alleviate communication overhead in FL. The traditional federated average

algorithm is a synchronous update algorithm, where all clients need to upload their model gradient information to update the server model simultaneously. As a result, the server side needs to receive most or all of the model data from the clients in each round of model aggregation, which greatly increases the data communication pressure on the server side. To address this challenge, various studies have proposed diverse client selection strategies. For example, in [52], the authors proposed a selective model aggregation method that selects models by evaluating their local image quality and computational power and sends them to the central server. Similarly, in [53], the optimal vehicle to participate in the learning task was selected based on position and speed. In [54], appropriate nodes were selected to participate in the aggregation process by computing their capacity, network capacity, and learning value of training samples. In [55], clients with large amounts of data were selected to participate in the aggregation phase. Finally, in [56], client selection takes into account vehicle velocity, vehicle distribution, and wireless link connectivity between vehicles. These studies show that careful client selection can significantly reduce communication overhead in FL.

In summary, communication overhead in FL can be reduced through model compression and client selection. Model compression can be accomplished through various techniques such as quantization and ternary quantization. The client selection optimizes the participation in the learning process based on their computational power, network capacity, and the learning value of training samples. By applying these techniques, the communication resources in FL can be saved, enabling FL to be more flexible and scalable in vehicular edge computing environments.

2) *Reducing Communication Rounds*: The communication overhead between the server and clients in FL is a critical challenge that needs to be addressed to ensure efficient data exchange. In this context, reducing the number of interactions

between edges and the edge server is crucial to minimize upload times and increase download speeds. To this end, a federated stochastic variance reduced gradient-based scheme was proposed in [57] to decrease the total number of interactions while ensuring the required accuracy. The proposed scheme optimizes the variance reduced stochastic gradient descent algorithm by employing a diagonal preconditioner and a thresholding operation to guarantee convergence. In [55], the authors aimed to strike a balance between local computation and communication overheads by customizing local training strategies for different clients. The approach allows varying local training epochs for clients, thereby improving the trade-off between local computation and communication overheads. Specifically, clients with high computation power are allowed to perform more local epochs, while clients with low computation power are permitted to perform fewer local epochs to meet the global accuracy requirement.

These studies demonstrate that reducing communication overhead in FL can be achieved by minimizing the communication rounds between the server and clients. By adopting these techniques, the number of interactions rounds between users and the edge server can be significantly reduced while still ensuring the desired level of accuracy in vehicular edge computing environments.

3) *Accelerating Model Update*: To reduce communication overhead in FL, accelerating model updates can be another important approach. In this regard, Liang *et al.* proposed a dynamic aggregation scheme in [54], which combines the advantages of both synchronous and asynchronous methods to perform semi-synchronous aggregation. The scheme adjusts the maximum server wait time dynamically based on the number of participating nodes in each round, allowing as many nodes as possible to participate in the aggregation process and hence reducing communication costs. Similarly, in [55], the authors proposed a flexible aggregation policy that drops clients who exceed the time limitation to dynamically adjust the number of clients during the aggregation phase, thus reducing communication overheads.

These techniques can help vehicular edge computing environments to achieve faster and more efficient model updates, significantly reduce communication overhead and enable FL to be more scalable and efficient in vehicular edge computing environments.

C. Resource Optimized Federated Learning

FL is a promising approach for collaborative machine learning that enables edge devices to train models in a decentralized manner. However, the heterogeneity of edge devices, including differences in computational power and network environment, can lead to imbalanced training times and inefficient global model aggregation. Straggler devices with weaker computational power may significantly delay the model aggregation, while devices with unstable networks may drop out of the training process, compromising the efficiency of FL. To address these issues, appropriate resource allocation and fault tolerance mechanisms need to be considered to minimize training time and improve FL's efficiency. Several studies have

proposed different optimization methods for formulating the FL process.

1) *Structural Heterogeneity*: Various studies have developed algorithms for efficient resource allocation in FL that account for the heterogeneous nature of edge devices. For instance, in [53], the authors considered the specific characteristics of vehicular edge computing environments, such as vehicle position and velocity, to formulate a min-max optimization problem. The objective was to jointly optimize the onboard computation capability, transmission power, and local model accuracy to achieve the minimum cost in the worst-case scenario of FL. By considering the worst-case scenario, this approach ensures robustness and reliability in FL training, even under challenging network conditions. In [58], the authors proposed an asynchronous FL scheme that aims to improve the efficiency of FL by selecting the participating nodes to minimize the total cost. This approach considers the computation, communication, and storage costs of the edge devices, and dynamically selects a subset of participating nodes in each round of FL based on their cost-efficiency scores. Similarly, in [59], a unified data and resource management framework was proposed to cluster vehicles on the road based on their mobility and resource characteristics. This framework partitions computationally intensive tasks' data and assigns them to individual vehicles in the cluster for parallel execution.

Additionally, some studies have proposed clustering clients. For example, in [60], a data and resource management framework was proposed that organizes vehicles on the road into clusters based on their mobility and resource characteristics, partitioning the computationally intensive tasks among the individual vehicles in the cluster for parallel execution. Furthermore, in [61], the authors designed an architecture and corresponding FL process for clustered FL in vehicular environments, aiming to enhance the scalability of FL. They formulated a joint cluster-head selection and resource block allocation problem taking into account mobility and data properties.

2) *Fault Tolerance*: To address the issue of stragglers in FL, Ji *et al.* proposed an edge-assisted FL approach that leverages edge computing to alleviate the computational burdens for straggler devices. The proposed approach allows stragglers to offload partial computation to the edge server and utilizes the server's computing power to assist clients in model training [62]. This approach not only reduces the time needed for stragglers to complete their tasks but also enhances the overall efficiency of the FL process.

By addressing the challenges of heterogeneous edge devices, appropriate resource allocation and fault tolerance mechanisms can significantly improve the efficiency of FL. These optimization methods can minimize training time and reduce energy consumption. Leveraging such approaches, FL has the potential to unlock the full potential of vehicular edge computing and pave the way for ITS.

D. Security Enhanced Federated Learning

1) *Malicious Devices Detection*: In FL, edge devices process their local data without sending it to the central server,

thus preserving user privacy. However, since the server has limited control over the edge devices, it cannot fully trust them. Some edge devices may have malicious intent and falsify or poison their training data, resulting in useless or even harmful model updates. Therefore, protecting the integrity and authenticity of the training data is a critical issue in FL. Several studies have proposed solutions to address this problem, including data poisoning detection, outlier detection, and secure aggregation techniques, which can help mitigate the impact of malicious edge devices on the FL process. These solutions enable the server to verify the authenticity and quality of the data provided by edge devices and ensure the overall reliability and security of the FL process.

To mitigate the risk of malicious devices participating in FL, various methods have been proposed. In [63], the authors addressed the issue of malicious mobile-edge computing servers and vehicles in FL by adopting blockchain technology to incentivize vehicles to contribute and reduce the influence of malicious participants. They also proposed a traceable identity-based privacy-preserving scheme to protect vehicular message privacy. In another study, Ghimire *et al.* [64] applied the quickest change detection technique to detect changes in the statistical properties of the model parameters sent by participating devices. This approach facilitates the identification of malicious clients. In [65], the authors proposed a blockchain-based FL scheme to detect misbehavior by coordinating multiple distributed edge devices while ensuring data security and privacy. These approaches aim to address the challenge of trustworthiness in FL by detecting and mitigating the influence of malicious devices on the training process.

2) *Privacy Preservation*: The adoption of FL offers a promising solution to mitigate the privacy leakage concerns. However, the challenge of indirect privacy leakages still remains significant. These indirect leakages can potentially compromise the privacy of user data, thereby making it imperative to address them effectively.

To enhance the privacy preservation of clients, differential privacy serves as a key strategy of protecting sensitive data. When querying data from a database, differential privacy reduces the chances of records being identified while maximizing query accuracy by introducing noise to the raw data [66]. In [67], the authors incorporated local differential privacy into FL to protect the privacy of updated local models. Similarly, in [65], differential privacy with the Gaussian mechanism was leveraged to provide strict privacy protection for the model on the blockchain.

Homomorphic encryption is another privacy strategy that is often applied in FL to prevent information leakage during the exchange of parameters between clients. It is an encryption mechanism that encodes parameters prior to an addition or multiplication operation, resulting in an equivalent result to a non-encoded function [66]. In [68], the authors proposed a privacy-preserving model aggregation scheme that uses a homomorphic threshold cryptosystem for key establishment and updates. The scheme leverages the homomorphic properties of the threshold cryptosystems to allow clients to perform secure addition and multiplication operations on the encrypted model updates, while ensuring the final aggregated model remains

encrypted.

In conclusion, security and privacy are critical challenges in FL. To mitigate these issues, a variety of methods, including blockchain technology and the quickest change detection technique, have been developed to detect malicious devices and prevent attacks. Furthermore, by incorporating differential privacy and homomorphic encryption, it is possible to further protect the privacy of clients' data and model parameters exchanged between clients. These security-enhancing techniques can increase the reliability and trustworthiness of FL, making it a promising approach for collaborative learning while ensuring privacy and security of the data.

VI. CONCLUSION

The integration of FL into ITS applications provides a collaborative training approach that protects data privacy. By performing distributed model training on local devices, FL ensures that sensitive user data is never leaked to other organizations or servers, thus satisfying the need for data privacy protection. This survey provides a comprehensive review of the current research hotspots in combining FL and ITS, including traffic flow prediction, traffic target recognition and vehicular edge computing, which can serve as a valuable resource for future work in this field. The application of FL in ITS has yielded promising results and has the potential to bring significant benefits. Our review highlights the potential of FL as a powerful tool for achieving sustainable and harmonious urban transportation systems.

REFERENCES

- [1] J. Zhang, F.-Y. Wang, K. Wang, W.-H. Lin, X. Xu, and C. Chen, "Data-driven intelligent transportation systems: A survey," *IEEE Transactions on Intelligent Transportation Systems*, vol. 12, no. 4, pp. 1624–1639, 2011.
- [2] L. Zhu, F. R. Yu, Y. Wang, B. Ning, and T. Tang, "Big data analytics in intelligent transportation systems: A survey," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 1, pp. 383–398, 2018.
- [3] Y. Lv, Y. Duan, W. Kang, Z. Li, and F.-Y. Wang, "Traffic flow prediction with big data: A deep learning approach," *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 2, pp. 865–873, 2014.
- [4] Q. Yang, Y. Liu, T. Chen, and Y. Tong, "Federated machine learning: Concept and applications," *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 10, no. 2, pp. 1–19, 2019.
- [5] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-efficient learning of deep networks from decentralized data," in *Artificial intelligence and statistics*, pp. 1273–1282, PMLR, 2017.
- [6] K. Bonawitz, H. Eichner, W. Grieskamp, D. Huba, A. Ingerman, V. Ivanov, C. Kiddon, J. Konečný, S. Mazzocchi, B. McMahan, *et al.*, "Towards federated learning at scale: System design," *Proceedings of machine learning and systems*, vol. 1, pp. 374–388, 2019.
- [7] Y. Lu, X. Huang, Y. Dai, S. Maharjan, and Y. Zhang, "Differentially private asynchronous federated learning for mobile edge computing in urban informatics," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 3, pp. 2134–2143, 2019.
- [8] D. A. Tedjopurnomo, Z. Bao, B. Zheng, F. M. Choudhury, and A. K. Qin, "A survey on modern deep neural network for traffic prediction: Trends, methods and challenges," *IEEE Transactions on Knowledge and Data Engineering*, vol. 34, no. 4, pp. 1544–1561, 2020.
- [9] S. Guo, Y. Lin, N. Feng, C. Song, and H. Wan, "Attention based spatial-temporal graph convolutional networks for traffic flow forecasting," in *Proceedings of the AAAI conference on artificial intelligence*, vol. 33, pp. 922–929, 2019.
- [10] B. Yu, H. Yin, and Z. Zhu, "Spatio-temporal graph convolutional networks: a deep learning framework for traffic forecasting," in *Proceedings of the 27th International Joint Conference on Artificial Intelligence*, pp. 3634–3640, 2018.

- [11] H. Wang, R. Zhang, X. Cheng, and L. Yang, "Hierarchical traffic flow prediction based on spatial-temporal graph convolutional network," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 9, pp. 16137–16147, 2022.
- [12] M. Xia, D. Jin, and J. Chen, "Short-term traffic flow prediction based on graph convolutional networks and federated learning," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 1, pp. 1191–1203, 2023.
- [13] C. Zhang, S. Zhang, J. James, and S. Yu, "Fastgmn: A topological information protected federated learning approach for traffic speed forecasting," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 12, pp. 8464–8474, 2021.
- [14] X. Yuan, J. Chen, J. Yang, N. Zhang, T. Yang, T. Han, and A. Taherkordi, "Fedstn: Graph representation driven federated learning for edge computing enabled urban traffic flow prediction," *IEEE Transactions on Intelligent Transportation Systems*, 2022.
- [15] Y. Qi, M. S. Hossain, J. Nie, and X. Li, "Privacy-preserving blockchain-based federated learning for traffic flow prediction," *Future Generation Computer Systems*, vol. 117, pp. 328–337, 2021.
- [16] C. Meese, H. Chen, S. A. Asif, W. Li, C.-C. Shen, and M. Nejad, "Bfrit: Blockchain federated learning for real-time traffic flow prediction," in *2022 22nd IEEE International Symposium on Cluster, Cloud and Internet Computing (CCGrid)*, pp. 317–326, IEEE, 2022.
- [17] M. Akallouch, O. Akallouch, K. Fardousse, A. Bouhoute, and I. Berrada, "Prediction and privacy scheme for traffic flow estimation on the highway road network," *Information*, vol. 13, no. 8, 2022.
- [18] J. Deng and G. Shen, "Federated learning-based privacy-preserving traffic flow prediction scheme for vanets," in *2022 4th International Conference on Communications, Information System and Computer Engineering (CISCE)*, pp. 374–378, IEEE, 2022.
- [19] Y. Liu, J. James, J. Kang, D. Niyato, and S. Zhang, "Privacy-preserving traffic flow prediction: A federated learning approach," *IEEE Internet of Things Journal*, vol. 7, no. 8, pp. 7751–7763, 2020.
- [20] C. Zhang, S. Zhang, S. Yu, and J. James, "Graph-based traffic forecasting via communication-efficient federated learning," in *2022 IEEE Wireless Communications and Networking Conference (WCNC)*, pp. 2041–2046, IEEE, 2022.
- [21] 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 *IEEE INFOCOM 2022-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, pp. 1–6, IEEE, 2022.
- [22] Z. Zhang, H. Wang, Z. Fan, J. Chen, X. Song, and R. Shibasaki, "Gof-tte: Generative online federated learning framework for travel time estimation," *IEEE Internet of Things Journal*, vol. 9, no. 23, pp. 24107–24121, 2022.
- [23] Y. Zhu, Y. Ye, Y. Liu, and J. James, "Cross-area travel time uncertainty estimation from trajectory data: a federated learning approach," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 12, pp. 24966–24978, 2022.
- [24] W. Wang, G. Yang, L. Bao, K. Ma, H. Zhou, *et al.*, "A privacy-preserving crowd flow prediction framework based on federated learning during epidemics," *Security and Communication Networks*, vol. 2022, 2022.
- [25] F. Z. Errounda and Y. Liu, "A mobility forecasting framework with vertical federated learning," in *2022 IEEE 46th Annual Computers, Software, and Applications Conference (COMPSAC)*, pp. 301–310, IEEE, 2022.
- [26] T. Zeng, J. Guo, K. J. Kim, K. Parsons, P. Orlik, S. Di Cairano, and W. Saad, "Multi-task federated learning for traffic prediction and its application to route planning," in *2021 IEEE Intelligent Vehicles Symposium (IV)*, pp. 451–457, IEEE, 2021.
- [27] S. M. Halim, L. Khan, and B. Thuraisingham, "Next-location prediction using federated learning on a blockchain," in *2020 IEEE second international conference on cognitive machine intelligence (CogMI)*, pp. 244–250, IEEE, 2020.
- [28] X. Huang, P. Li, R. Yu, Y. Wu, K. Xie, and S. Xie, "Fedparking: A federated learning based parking space estimation with parked vehicle assisted edge computing," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 9, pp. 9355–9368, 2021.
- [29] M. M. Rahman, M. A. Quader, M. A. Quader, and M. A. Razzaque, "Accurate identification of potholes on the road using federated learning," in *2021 3rd International Conference on Sustainable Technologies for Industry 4.0 (STI)*, pp. 1–6, IEEE, 2021.
- [30] S. Alshammari and S. Song, "3pod: Federated learning-based 3 dimensional pothole detection for smart transportation," in *2022 IEEE International Smart Cities Conference (ISC2)*, pp. 1–7, IEEE, 2022.
- [31] Y. Yuan, Y. Yuan, T. Baker, L. M. Kolbe, and D. Hogrefe, "Fedrd: Privacy-preserving adaptive federated learning framework for intelligent hazardous road damage detection and warning," *Future Generation Computer Systems*, vol. 125, pp. 385–398, 2021.
- [32] K. Xie, Z. Zhang, B. Li, J. Kang, D. Niyato, S. Xie, and Y. Wu, "Efficient federated learning with spike neural networks for traffic sign recognition," *IEEE Transactions on Vehicular Technology*, vol. 71, no. 9, pp. 9980–9992, 2022.
- [33] C. Xu and Y. Mao, "An improved traffic congestion monitoring system based on federated learning," *Information*, vol. 11, no. 7, p. 365, 2020.
- [34] D. Ye, R. Yu, M. Pan, and Z. Han, "Federated learning in vehicular edge computing: A selective model aggregation approach," *IEEE Access*, vol. 8, pp. 23920–23935, 2020.
- [35] H. Zhang, J. Bosch, H. H. Olsson, and A. C. Koppisetty, "Af-dndf: Asynchronous federated learning of deep neural decision forests," in *2021 47th Euromicro Conference on Software Engineering and Advanced Applications (SEAA)*, pp. 308–315, IEEE, 2021.
- [36] M. Aparna, R. Gandhiraj, and M. Panda, "Steering angle prediction for autonomous driving using federated learning: the impact of vehicle-to-everything communication," in *2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, pp. 1–7, IEEE, 2021.
- [37] H. Zhang, J. Bosch, and H. H. Olsson, "End-to-end federated learning for autonomous driving vehicles," in *2021 International Joint Conference on Neural Networks (IJCNN)*, pp. 1–8, IEEE, 2021.
- [38] H. Zhang, J. Bosch, and H. H. Olsson, "Real-time end-to-end federated learning: An automotive case study," in *2021 IEEE 45th Annual Computers, Software, and Applications Conference (COMPSAC)*, pp. 459–468, IEEE, 2021.
- [39] A. Zafar, C. Prehofer, and C.-H. Cheng, "Federated learning for driver status monitoring," in *2021 IEEE International Intelligent Transportation Systems Conference (ITSC)*, pp. 1463–1469, IEEE, 2021.
- [40] D. Y. Zhang, Z. Kou, and D. Wang, "Fedsens: A federated learning approach for smart health sensing with class imbalance in resource constrained edge computing," in *IEEE INFOCOM 2021-IEEE Conference on Computer Communications*, pp. 1–10, IEEE, 2021.
- [41] L. Zhang, H. Saito, L. Yang, and J. Wu, "Privacy-preserving federated transfer learning for driver drowsiness detection," *IEEE Access*, vol. 10, pp. 80565–80574, 2022.
- [42] Y. Chen, C. Wang, and B. Kim, "Federated learning with infrastructure resource limitations in vehicular object detection," in *2021 IEEE/ACM Symposium on Edge Computing (SEC)*, pp. 366–370, IEEE, 2021.
- [43] D. Jallepalli, N. C. Ravikumar, P. V. Badarinath, S. Uchil, and M. A. Suresh, "Federated learning for object detection in autonomous vehicles," in *2021 IEEE Seventh International Conference on Big Data Computing Service and Applications (BigDataService)*, pp. 107–114, IEEE, 2021.
- [44] R. Meneguette, R. De Grande, J. Ueyama, G. P. R. Filho, and E. Madeira, "Vehicular edge computing: architecture, resource management, security, and challenges," *ACM Computing Surveys (CSUR)*, vol. 55, no. 1, pp. 1–46, 2021.
- [45] L. Liu, C. Chen, Q. Pei, S. Maharjan, and Y. Zhang, "Vehicular edge computing and networking: A survey," *Mobile networks and applications*, vol. 26, pp. 1145–1168, 2021.
- [46] A. Hammoud, H. Sami, A. Mourad, H. Otrouk, R. Mizouni, and J. Bentahar, "Ai, blockchain, and vehicular edge computing for smart and secure iov: Challenges and directions," *IEEE Internet of Things Magazine*, vol. 3, no. 2, pp. 68–73, 2020.
- [47] 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 Journal of the Computer Society*, vol. 1, pp. 45–61, 2020.
- [48] W. Y. B. Lim, N. C. Luong, D. T. Hoang, Y. Jiao, Y.-C. Liang, Q. Yang, D. Niyato, and C. Miao, "Federated learning in mobile edge networks: A comprehensive survey," *IEEE Communications Surveys & Tutorials*, vol. 22, no. 3, pp. 2031–2063, 2020.
- [49] L. Barbieri, S. Savazzi, and M. Nicoli, "Communication-efficient distributed learning in v2x networks: Parameter selection and quantization," in *GLOBECOM 2022 - 2022 IEEE Global Communications Conference*, pp. 603–608, 2022.
- [50] S. Shen, C. Yu, K. Zhang, X. Chen, H. Chen, and S. Ci, "Communication-efficient federated learning for connected vehicles with constrained resources," in *2021 International Wireless Communications and Mobile Computing (IWCMC)*, pp. 1636–1641, 2021.
- [51] Y. Li, Y. Guo, M. Alazab, S. Chen, C. Shen, and K. Yu, "Joint optimal quantization and aggregation of federated learning scheme in vanets," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 10, pp. 19852–19863, 2022.

- [52] D. Ye, R. Yu, M. Pan, and Z. Han, "Federated learning in vehicular edge computing: A selective model aggregation approach," *IEEE Access*, vol. 8, pp. 23920–23935, 2020.
- [53] H. Xiao, J. Zhao, Q. Pei, J. Feng, L. Liu, and W. Shi, "Vehicle selection and resource optimization for federated learning in vehicular edge computing," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 8, pp. 11073–11087, 2021.
- [54] F. Liang, Q. Yang, R. Liu, J. Wang, K. Sato, and J. Guo, "Semi-synchronous federated learning protocol with dynamic aggregation in internet of vehicles," *IEEE Transactions on Vehicular Technology*, vol. 71, no. 5, pp. 4677–4691, 2022.
- [55] S. Liu, J. Yu, X. Deng, and S. Wan, "Fedcpf: An efficient-communication federated learning approach for vehicular edge computing in 6g communication networks," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 2, pp. 1616–1629, 2021.
- [56] W. Bao, C. Wu, S. Guleng, J. Zhang, K.-L. A. Yau, and Y. Ji, "Edge computing-based joint client selection and networking scheme for federated learning in vehicular iot," *China Communications*, vol. 18, no. 6, pp. 39–52, 2021.
- [57] D. Chen, C. S. Hong, Y. Zha, Y. Zhang, X. Liu, and Z. Han, "Fedsvrg based communication efficient scheme for federated learning in mec networks," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 7, pp. 7300–7304, 2021.
- [58] 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 Transactions on Vehicular Technology*, vol. 69, no. 4, pp. 4298–4311, 2020.
- [59] 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 Transactions on Vehicular Technology*, vol. 70, no. 6, pp. 5308–5317, 2021.
- [60] W. M. Danquah and D. T. Altılar, "Unidrm: Unified data and resource management for federated vehicular cloud computing," *IEEE Access*, vol. 9, pp. 157052–157067, 2021.
- [61] A. Taïk, Z. Mlika, and S. Cherkaoui, "Clustered vehicular federated learning: Process and optimization," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 12, pp. 25371–25383, 2022.
- [62] Z. Ji, L. Chen, N. Zhao, Y. Chen, G. Wei, and F. R. Yu, "Computation offloading for edge-assisted federated learning," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 9, pp. 9330–9344, 2021.
- [63] Y. Li, X. Tao, X. Zhang, J. Liu, and J. Xu, "Privacy-preserved federated learning for autonomous driving," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 7, pp. 8423–8434, 2021.
- [64] B. Ghimire, D. B. Rawat, and A. Rahman, "Data-driven quickest change detection for securing federated learning for internet-of-vehicles," in *2021 IEEE Global Communications Conference (GLOBECOM)*, pp. 1–6, IEEE, 2021.
- [65] P. Lv, L. Xie, J. Xu, X. Wu, and T. Li, "Misbehavior detection in vehicular ad hoc networks based on privacy-preserving federated learning and blockchain," *IEEE Transactions on Network and Service Management*, 2022.
- [66] L. Li, Y. Fan, M. Tse, and K.-Y. Lin, "A review of applications in federated learning," *Computers & Industrial Engineering*, vol. 149, p. 106854, 2020.
- [67] Y. Lu, X. Huang, Y. Dai, S. Maharjan, and Y. Zhang, "Differentially private asynchronous federated learning for mobile edge computing in urban informatics," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 3, pp. 2134–2143, 2019.
- [68] Q. Kong, F. Yin, R. Lu, B. Li, X. Wang, S. Cui, and P. Zhang, "Privacy-preserving aggregation for federated learning-based navigation in vehicular fog," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 12, pp. 8453–8463, 2021.



Rongqing Zhang (Member, IEEE) received the B.S. and Ph.D. degrees (with honors) from Peking University, Beijing, China, in 2009 and 2014, respectively.

From 2014 to 2018, he worked as a postdoctoral research fellow at Colorado State University, CO, USA. Since 2019, he has been an Associate Professor at Tongji University, Shanghai, China. He has authored and co-authored two books, two book chapters, and over 150 papers in refereed journals and conference proceedings. His current research

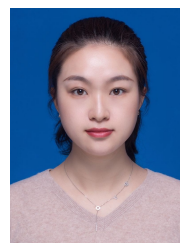
interests include vehicular communications and networking, UAV communications, and autonomous driving.

Dr. Zhang was the recipient of the Academic Award for Excellent Doctoral Students, Ministry of Education of China, the co-recipient of the First-Class Natural Science Award, Ministry of Education of China, and received the Best Paper Awards at IEEE ITST'12, ICC'16, GLOBECOM'18, and ICC'19. He was also awarded as International Presidential Fellow of Colorado State University in 2017. Currently, he is serving as an Associate Editor of *IEEE Transactions on Vehicular Technology* and *IET Communications*.



Hanqiu Wang received the B.E. and M.S. degree from Tongji University, Shanghai, China, in 2020 and 2023, respectively.

Her research interests include data mining and traffic flow prediction.



Bing Li (Member, IEEE) received the Ph.D. degree from Tongji University, Shanghai, China, in 2021.

She is currently an Assistant Professor with Tongji University, Shanghai, China. Her current research interests include UAV communications, wireless resource allocation, and relay communications.



Cheng Xiang (Fellow, IEEE) received the Ph.D. degree jointly from Heriot-Watt University and the University of Edinburgh, Edinburgh, U.K., in 2009.

He is currently a Boya Distinguished Professor of Peking University. His general research interests are in areas of channel modeling, wireless communications, and data analytics, subject on which he has published more than 280 journal and conference papers, 9 books, and holds 17 patents.

Prof. Cheng is a Distinguished Young Investigator of China Frontiers of Engineering, a recipient of the IEEE Asia Pacific Outstanding Young Researcher Award in 2015, a Distinguished Lecturer of *IEEE Vehicular Technology Society*, and a Highly Cited Chinese Researcher in 2020. He was a co-recipient of the 2016 IEEE JSAC Best Paper Award: Leonard G. Abraham Prize, and IET Communications Best Paper Award: Premium Award. He has also received the Best Paper Awards at IEEE ITST'12, ICC'13, ITSC'14, ICC'16, ICNC'17, GLOBECOM'18, ICCS'18, and ICC'19. He has served as the symposium lead chair, co-chair, and member of the Technical Program Committee for several international conferences. He is currently a Subject Editor of *IET Communications* and an Associate Editor of the *IEEE Transactions on Wireless Communications*, *IEEE Transactions on Intelligent Transportation Systems*, *IEEE Wireless Communications Letters*, and the *Journal of Communications and Information Networks*. In 2021, he was selected into two world scientist lists, including World's Top 2% Scientists released by Stanford University and Top Computer Science Scientists released by Guide2Research.



Liuqing Yang (Fellow, IEEE) received the Ph.D. degree in electrical and computer engineering from the University of Minnesota, Minneapolis, MN, USA, in 2004.

She is currently a Professor with the Hong Kong University of Science and Technology (Guangzhou). Before joining Hong Kong University of Science and Technology (Guangzhou), she has been a Faculty Member with the Department of Electrical and Computer Engineering, University of Florida (2004-2010), Colorado State University (2010-2020), and

University of Minnesota (2020- 2021). Her research interests include communications and networking subjects on which she has published more than 370 journals and conference papers, four book chapters, and five books.

She was a recipient of the ONR Young Investigator Program (YIP) Award in 2007, the NSF Faculty Early Career Development (CAREER) Award in 2009, and the Best Paper Award at IEEE ICUBW 2006, ICC 2013, ITSC 2014, GLOBECOM 2014, ICC 2016, WCSP 2016, GLOBECOM 2018, ICCS 2018, and ICC 2019. She is the Editor-in-Chief of *IET Communications*, a Executive Editorial Committee (EEC) Member of the *IEEE Transactions on Wireless Communications*, and a Senior Editor of the *IEEE Transactions on Signal Processing*. She has also served as an Editor for the *IEEE Transactions on Communications*, the *IEEE Transactions on Intelligent Transportation Systems*, *IEEE Intelligent Systems*, and *PHYCOM: Physical Communication*, and as a program chair, a track/symposium, or a TPC chair for many conferences.