Role of Federated Learning for Internet of Vehicles: A Systematic Review

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Abstract. The Internet of Vehicles (IoV) is one of the most exciting and practical ways that corporations and academics are interested in, especially by employing coordinated unmanned vehicles to explore areas like the automobile industry. To provide long-term possibilities for task investigations, the IoV connects vehicles, transportation networks, and communication infrastructure. Data privacy, however, may be compromised by the coordination of information gathering from numerous sources. Federated Learning (FL) is the answer to these concerns of privacy, scalability, and high availability. A well-distributed learning framework designed for edge devices is federated learning. It makes use of large-scale processing from edge devices while allowing private data to remain locally. In this work, different categories of federated learning have been discussed. A review of various systems implementing FL for IoV has been presented followed by the applications and challenges of FL in the IoV paradigm. The paper concludes by providing future research directions for FL in the IoV.

Keywords: Federated learning · Internet of Vehicles · Machine learning · Unmanned Arial Vehicles

1 Introduction to Federated Learning

Federated Learning (FL) utilizes a centralized aggregator and provides a solution to the issues associated with many Machine Learning (ML) clients. It ensures that training data for federated learning is decentralized to protect data privacy [1]. Two key concepts of local computation and model transmission have been introduced to lower the privacy risk and cost of centralized ML systems. In FL, participants train their models by using local data and then send the model to the server for aggregation, and the server disseminates model updates. In Fig. 1, FL's high-level map process has been given [2]. In FL, local models are trained on separate vehicles before aggregating them in the cloud to enhance security, accuracy and learning efficiency [3]. In two phase mitigating scheme, an intelligent architecture with FL provides data leakage detection [4] and intelligent data transmission [5] to improve security [6]. In Unmanned Aerial Vehicles (UAV) federated deep learning applications with wireless networks, the focus is to improve the learning efficiency, learning speed significance, conscious joint data selection, resource allotment algorithm [7], and content caching method for edge computing of FL in IoV.

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1.1 Categories of Federated Learning.

FL depends on five aspects which are heterogeneity, communication architecture, data partitioning, applicable machine learning models, and privacy mechanism [8]. Figure 2 depicts the classification of FL.

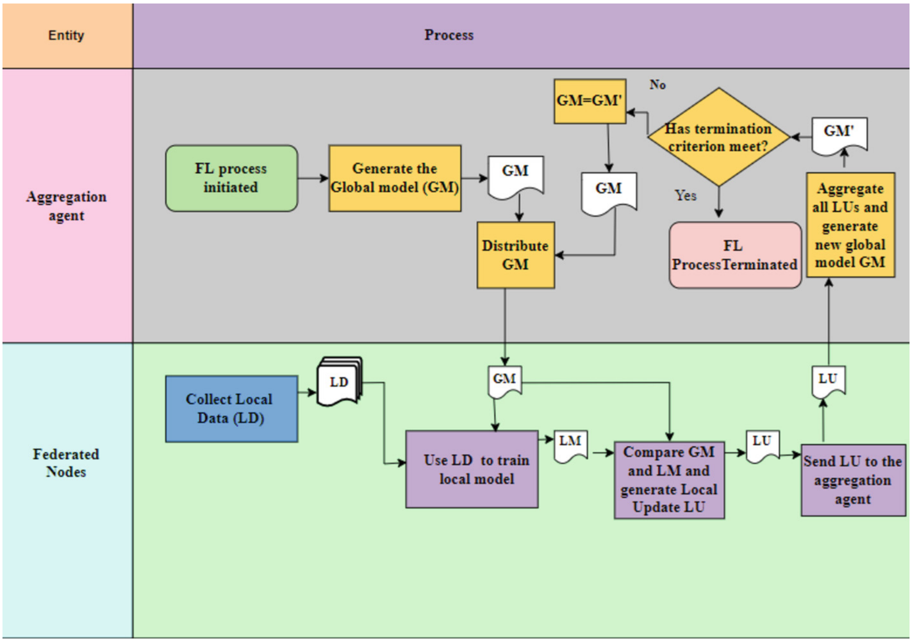

Fig. 1. Federated learning high-level process map

1.1.1 Data Partition

Based on various distributions of design, FL can be divided into the three types [9] i.e. horizontal FL, Vertical FL, and Federated Transfer Learning. Horizontal FL is employed where user attributes for two datasets overlay remarkably but user overlap is minimal. The data set is divided horizontally, with the same user attributes, but different users for training [10, 11]. In vertical FL (VFL), users are overlapped a lot and user features are overlapped a little. In VFL, data sets are divided vertically and a portion of data is considered for training wherever users are identical with different useful features [12]. In Federated Transfer learning (FTL) the users or the users' attributes are never segmented. However, it can be employed in cases when there is a lag of information or tags [13].

1.1.2 Privacy Mechanism

Using FL, clients can store data locally and transmit model information for target model training. In model aggregation, the only significant aspect of FL is model aggregation that trains their global model by integrating the model attributes from all clients thus prevent transferring the metadata throughout the training process [14]. The problems associated with calculating encrypted data have been resolved using homomorphic encryption key. In differential privacy, both ML and deep learning use gradient iteration [15], which incorporates the addition of noise to the result to implement differential privacy to safeguard user privacy [16].

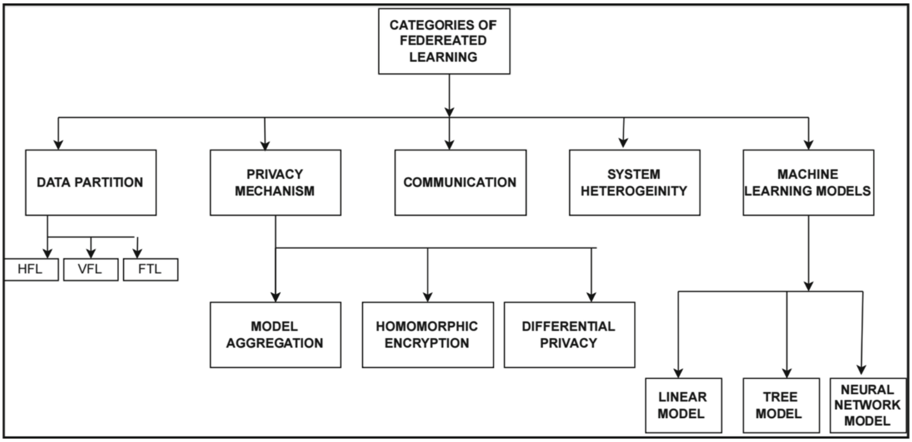

Fig. 2. The Classification of Federated Learning

1.1.3 Machine Learning Schemes

FL enhance the capability and security of the ML model. Neural network, decision tree and linear model are the three main ML models. In federated environment, the linear model of training that mitigates the security issues and attains the same accuracy as a non-private solution is proposed in [17]. The tree model in FL, random forest and gradient boost decision trees are utilized for both single and multiple decision trees [18]. The most famous model of machine learning is the neural network model that trains complex tasks. In autonomous vehicles using drones target location, trajectory planning, target recognition services plays a vital role [19]. Due to the drawback of regular connection between UAV group and base station, centralized training fails in real time but deep learning provides excellent efficiency with UAV group usually [20].

1.1.4 Communication Architecture

The problems of application scenario of FL are equipment computing and uneven distribution of user data [21]. All the participants that are under training are in touch with centralized server for the update of global model. The communication cost of FL is high for critical problems. To minimize the cost between server and local users the model data is compressed by secondary sample random rotation quantization [22].

1.1.5 Methods for Solving Heterogeneity

Different devices affect the accuracy of total training process. The diversions of heterogeneity are model heterogeneity, fault tolerance, asynchronous communication and device sampling [23]. The main factor of FL is the efficiency of unevenly distributed data from various devices. In FL, the processing of data from various devices affects the model. Asynchronous communication is the solution to many problems with dispersed devices in FL settings.

2 Related Work

This section discusses some of the related works of FL in IoV. For intelligent object detection, a two-layer FL model has been used in a 6G supported IoV environment [24, 25]. The use of a hybrid blockchain method in addition to FL by using DRL to select optimized participants which improve the learning efficiency has been proposed in [26]. Iterative model averaging is used by the deep network federated learning frame-work to train the global model by adding the local models in each round of updates [20]. For the selection of Smart Vehicles (SVs) for FL, local learners are adopted by using round robin, random scheduling using heterogeneous asynchronous FL networks [27–29]. In [30], the authors concluded that the Quality of Information (QoI) received by the SVs is dynamic and will affect the performance of FL. Therefore, to improve the QoI, the Vehicular Service Provider's (VSP's) responsibility is to select SVs of current location within important areas. With the combination of important areas and QoI, VSP can obtain beneficial on-road data [14] and trustworthy trained model updates [31] from the chosen SVs.

In a non-collaborative Stackleberg game model proposed in [32–34], the mobile devices have full information about the VSPs payment budget. For estimating the traffic with FL that more correctly captures the spatio temporal correlation of the traffic flow with the use of clustering, FedGRU approach proposed in [35] combines the GRU (Gated Recurrent Unit) to get the best overall model. A model proposed in [36] FedProx integrates the edge devices data of distributed training with the Federal Averaging (FedAvg) model maximization method that improves the reliability of the target task. In [37], Multiple Principal One Agent (MPOA) based contract optimization is being employed to maximize the revenue of VSPs in each iteration [38]. OBU in IoV can gather data and glean local knowledge. A model proposed in [39] replaces data as a service by know ledge as a service in IoV. Knowledge serves as real information and is incorporated into data intelligence. IoV cars learn about the environment and the roads in different locations using ML techniques, and they share their expertise [40]. In [41], a model has been proposed to maintain balance between the dataset computational resources and wireless resources that is affected by the combination of vehicle client selection resource and wireless resource. Table 1 gives the review of previous work done by various researchers with respect to implementation of federated learning for IoV.

3 Applications of Federated Learning

This section discusses the various applications of federated learning including its applications for IoVs.

Table 1. Review of the Federated Learning systems for IoVs

Ref no. Year	Method	Dataset/Parameters	Implementation	Outcome	Main Focus
[42] 2022	The design of federated learning collaborative authentication of protocol for shared data reduces the data leakages and propagation delay of data	Not Available	SUMO and OMNet + + platform	Authentication delay is lowest. Packet loss rate is reduced to 4.6%. Globally aggregated model is effective	Reducing the propagation delay and data leakages
[43] 2022	Hedonistic game theoretical model using horizontal based federated learning involved by fog federation	Road traffic sign dataset	SUMO and Images of traffic signs imported from Kaggle	Latency of the proposed approach is 18 ms, The. Quality of service (QoS) is improved with accuracy	Fog federation providers outperforms in terms of efficacy, scalability and stability
[44] 2022	Spike neural network which is fast training model and efficient energy with novel encoding method. Based on neuron receptive field to extract information from spatial dimension and pixel of traffic sign	Time step = T = 10, Leak rate = λ = 0.9 for Optimal settings	BelgiumTS (Belgium traffic sign) dataset	The outcome of FedSSNRFEE with accuracy approximately 95%	High accuracy and quick training for traffic sign in autonomous vehicles
[45] 2021	With the use of FL and Block chain this research develops the light weight encrypted algorithm called CPC	Not Available	TOSSIM simulator, TinyOS system	Communication cost = 13000bytes, Predicting accuracy = 84.25%, Computation time = 4000m	Predicting the road and traffic conditions

(*continued*)

Table 1. (*continued*)

Ref no. Year	Method	Dataset/Parameters	Implementation	Outcome	Main Focus
[46] 2021	The DGHV (Dijk-Gentry-Halevi-Vaikutanathan) algorithm has been enhanced	Data from Rancho Palos Verdes and San Pedro, California roads	Autonomous driving simulation in Python with the real-world Data	Reduced training loss by about 73.7%	Autonomous cars
[47] 2021	The set of intimate consensus nodes replaced neural network called GRU, differential policy, central server	Caltrans performance measurement system dataset	Consortium blockchain PySyft for FL framework	MAE = 7.96, MSE = 101.49 RMSE = 11.04	Traffic Flow Prediction
[48] 2021	Proposed three assaults, looked into the relevant defenses, and developed a privacy-preserving local model sharing algorithm using the LDP mechanism	MNIST dataset	The CNN model is adopted for model training, Python is used for implementation	Obtains the enhanced utilities, convergence strategies, QoLM (Quality of Local Model update) in federated learning process	Sharing high-quality models while protecting UAVs' privacy
[49] 2021	Promotes seamless service availability to end devices, the UAV and UGV cooperation procedure ensures constant power availability to UAVs	Data set on traffic taken from the U.S. Traffic Fatality Records	OMNET + +, Python and the scikitlearn ML library, NS-3, OverSim framework	97% of networks were covered, 89% less energy was used, and 90% of packets were delivered successfully	Energy used was 89%, less than that of other conventional methods
[50] 2021	Differential privacy (DP), Mobile Edge Computing (MEC) integrated with privacy preserving FL framework named BMFL	MNIST dataset	A cloud, 5 Mobile Edge Computing (MEC) servers and 50 devices with IoV system	Defends the backdoor attack successfully and maintains stability with an attack success rate of 9.54%	Lowering cloud communication costs and ensuring model training quality
[51] 2021	RSU infers the toxic model parameters by comparing the aggregation accuracy of various groups	KDDCup99	For deep learning Syft, Pytorch for federated learning	Epoch = 40, Accuracy = 96% for data size = 10000	To manage poisons attack

(*continued*)

Table 1. (*continued*)

Ref no. Year	Method	Dataset/Parameters	Implementation	Outcome	Main Focus
[36] 2021	CNN model is used as the local training model	MNIST dataset	Numerical simulation	Improves the accuracy of knowledge up to 18%	Knowledge Trading
[52] 2020	The RAOC-B rain drop optimization (RFO) algorithm is blockchain enabled	Simulation of urban mobility (SUMO) generated data	Network Simulator-2, SUMO	Highest throughput = 94%, maximum Packet delivery ratio = 0.9, End to end delay = 0.3 s for 100 nodes	Load balancing using cluster based VANET and communication by block chain to enhance privacy
[53] 2020	The supervised learning model Support vector machine (SVM) has been employed	Training data from Xiaojue Station of Shuohuang Railway to West Station of Dingzhou	SVM model based on the mixed kernel function	Federated learning accuracy is 94.21%	Intelligent control model for heavy haul trains
[54] 2020	ADMM-based algorithm	MNIST, CIFAR10 Datasets	Simulation parameters like road width, speed and road surface conditions have been considered	FL algorithms exhibits 10% increased accuracy	Sharing of knowledge in the IoV
[55] 2020	Long Short-Term Memory (LSTM) network has been used as the supervised learning model	Passenger flow data of Beijing Metro	Linux, EOS for blockchain and Node.js for test script	Optimal prediction using LSTM	Secure Railway passenger flow prediction model
[56] 2020	DRL-based node selection algorithm	MNIST dataset	Matplotlib, basemap toolkit	Improved of accuracy more than 90%	Secure Data sharing in IoV

3.1 Google Keyboard

The prediction of the next word is achieved while improving the quality of the keyboard with security and privacy [7, 57]. In building the recommended systems, building of language model is also attained.

3.2 Intelligent Medical Diagnosis Systems

In the centralized method of ML, the data gathering and processing for medical diagnosis becomes difficult because of privacy and security concerns. With FL, it is possible to use the data locally without any issues of privacy and train the model for diagnosis [57, 58]. For small and insufficient labels, federated transfer learning is the solution. To implement an integrated multi FL network on APOLLO network merges the interrelated medical system's longitudinal real world data with health outcome data for the help of doctors in forward-looking diagnosis of patients [57].

3.3 RSU Intelligence

IoV comprises of RSUs that are designed to receive data to process basic operations. Different varieties of data are received by RSUs and thus FL can be applied in various situations. One of the familiar approaches is in image processing. For autonomous vehicles, both onboard Vehicular Computing (VC) and RSU image processing is important. Collision detection and pedestrian detection also make use of image processing tasks [7].

3.4 Network Function Virtualization (NFV) Orchestration

NFV enabled network highlights the use of FL in making NFV orchestration in security/privacy services and in vehicular service delivery. Each of the networks is divided into sub-networks which may be further divided, utilizing network slicing techniques [59]. This added complexity supports the use of FL because NFV orchestrators from different network partitions can use cooperative ML training to create models capable of performing operations like VNF installation, scaling, termination, and migration. In MEC enabled orchestration of NFV, the RSU is placed near the network edge so that it can act as a network node to hold Virtual network functions (VNFs) [7].

3.5 Vehicular Intelligence

Vehicular intelligence in IoV has many applications such as forecasting the road conditions, image processing in lane detection and popular predictive maintenance [60]. The predictive maintenance uses operational data and alerts the user for maintenance of specific part by predicting the failure of the component through planned maintenance. With the use of FL, in addition to vast collection of data, predictive maintenance models have been built with greater efficiency [7].

4 Conclusions and Future Direction

Given the importance of communication in federated networks and the privacy risks associated with transferring raw data, it is mandatory to keep generated data local. In this situation, two things can be done to further minimize communication: one is to lessen the total number of iterations of communication rounds, and other is too minimize the size of message. In this paper, federated learning and its various categories have been discussed. A systematic review of different systems implementing FL in IoVs has been presented followed by applications of federated learning in different areas related to IoV. However, due to the heterogeneity of the VCs, system complexity is a major challenge. Thus, building privacy protection schemes depending on specific devices in IoV is the future direction. Resolving the tradeoff between communication cost and computational pressure is another challenge. Distributed FL is forthcoming research direction with heterogeneous data.

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