Federated Learning in Smart Cities: A Comprehensive Survey

Zhaohua Zheng\textsuperscript{1,2}, Yize Zhou\textsuperscript{2}, Yilong Sun\textsuperscript{2}, Zhang Wang\textsuperscript{2}, Boyi Liu\textsuperscript{3} and Keqiu Li\textsuperscript{1}

\textsuperscript{1}Tianjin University, China; \textsuperscript{2}Hainan University, China; \textsuperscript{3}University of Macau

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ABSTRACT
Federated learning plays an important role in the process of smart cities. With the development of big data and artificial intelligence, there is a problem of data privacy protection in this process. Federated learning is capable of solving this problem. This paper starts with the current developments of federated learning and its applications in various fields. We conduct a comprehensive investigation. This paper summarize the latest research on the application of federated learning in various fields of smart cities. In-depth understanding of the current development of federated learning from the Internet of Things, transportation, communications, finance, medical and other fields. Before that, we introduce the background, definition and key technologies of federated learning. Further more, we review the key technologies and the latest results. Finally, we discuss the future applications and research directions of federated learning in smart cities.

KEYWORDS
Federated learning; Smart city; Internet of Things;

1. Introduction

The current urban internet architecture is complex. And the concept of "smart city" provides a new idea for the problems encountered in the process of urban development. Smart city refers to the use of different types of electronic Internet of Things (IoT) sensors to collect data\cite{1}. Decision makers then use the insights gained from this data to effectively manage the urban area of assets, resources and services. The operating model of a smart city is to use IoT sensors to collect data. Furthermore, it can realize effective applications in a series of fields such as urban public services, resource allocation and communications. At the same time, smart cities have provided good solutions to key issues such as the development of the Internet of Things\cite{2}\cite{3}, medical care\cite{4}\cite{5}, transportation\cite{6}, communications\cite{7}\cite{8}, etc. Sensors will generate a lot of data\cite{9} in this large-scale information exchange process. These data are of great significance for improving the applications of the program and helping managers optimize decisions. However, a large part of the data is sensitive data. It involves user-generated personal privacy\cite{10}. Firstly, we must evade users' private data in data processing in smart cities. In addition, we will face the problems of low data resource utilization and network congestion\cite{11} in the process of data interaction.

At present, self-organization theory\cite{12}, machine learning\textsuperscript{2}\textsuperscript{6}, edge computing...
nodes\textsuperscript{13}, system simulation\textsuperscript{14} and other computing implementations all have large network bottlenecks in practical applications of smart cities. And it still has the problem of low efficiency in using network resources. Therefore, it requires a distributed learning paradigm. It can reduce network bottlenecks in this case. At the same time, it have solved the problem of users’ privacy while discovering valid data through the collaborative sharing model of IoT devices. Some examples of distributed organization computing are mentioned in the current smart city applications. But these practical applications (such as the realization of D2D communication\textsuperscript{8} and the realization of multi-layer fog computing for large-scale IoT data analysis \textsuperscript{15}) have not solved the problem of user privacy well.

Federated learning (FL) take advantage of solving the above-mentioned problems\textsuperscript{16}. Under the framework of FL, users can make use of the data without obtaining other participants’ data. The related data is stored locally\textsuperscript{11}. Users only periodically share their local model gradients with the coordination server for a period of time. The server organizes training data and measures the contributions of all participants\textsuperscript{17}. The server constructs a global model by averaging all gradients in the network \textsuperscript{18} at the server level. After that, the coordination server will distribute the new model update to all clients \textsuperscript{19}. Each client uploads its local model to the server. Users download new updated models and use cloud distribution to realize inference on the device. The coordination process of the entire server will continue until it stops \textsuperscript{20}. This is a complete operating principle of the federated learning algorithm.

Federated learning has been applied to smart cities. It has the advantages of distributed processing and effective privacy protection. Some common distributed communication devices (such as mobile phones and wearable mobile devices, etc.) have communication transfer problems. Federated learning proposes a federated domain adaptive method based on the domain transfer problem. This model solves the problem of data privacy and efficiency \textsuperscript{21}. On the other hand, Some scholars implement a blockchain federated learning (BlockFL) architecture. This architecture can realize the exchange and verification of local learning model updates. And it can describe the best block generation rate by considering communication and consensus delay issues \textsuperscript{22}. In addition, the vehicle network has low-latency communication (URLLC) and resource allocation (JTRA) issues. Some researchers propose a novel distributed method. It realizes the estimation of the tail distribution of the queue length \textsuperscript{23}. Related research results of federated learning have carried out many practices in the fields of the Internet of Things, communications and public services. These practices promote the update and development of applications in smart cities.

The organization of the rest in this article is as follows. The second part introduces the definition and key technologies of FL; The third part introduces the applications of federated learning in the IoT system of smart cities. The fourth part introduces the applications of federated learning in the transportation systems. The forth part introduces the applications of federated learning in the financial field of smart cities. The sixth part introduces the applications of federated learning in the medical field of smart cities. The seventh part introduces the communication of federated learning in smart cities field applications. The eighth part discusses the future developments and directions of federated learning in smart cities. Finally, we summarized.

At present, the popularization of federated learning in smart cities has not been widely used. This prompted us to conduct a comprehensive investigation. This work is as following contributions.

\begin{itemize}
  \item This work introduce the background, definition and key technologies of federated
\end{itemize}
This work classifies and summarizes the latest research on the application of federated learning in smart cities. At the same time, we review the key technologies and the latest results.

We discuss the future development of applications and research directions of FL in smart cities.

2. The definition and key technologies of federated learning

The concept of federated learning is now widely proposed [24][25][26]. It has been implemented and applied in various fields. Most of the existing large-scale work has been applied to distributed learning in the development of big data [27] and cloud computing [28][29][30]. Data pushed directly to the server can compromise user pri-
The core of federated learning is to build a machine learning model by using data distributed across multiple devices. This solves the problem of data privacy. At present, distributed computing agents are growing rapidly. FL has become an effective solution of protecting user privacy in the process of information and knowledge sharing\cite{20}. For example, smart behaviors currently exist on mobile devices. Mobile phones and tablets use image classification to predict pictures previewed multiple times\cite{31}. Federated learning is based on data and information processing to improve user experience. In addition, many insurance companies have always had great concerns about protecting their data. They are unwilling to share with other entities\cite{32}. In this case, they can use multi-party data in the FL framework. It solves the privacy problem in machine learning. Recent research improvements on federated learning are mainly aimed at statistical challenges in federated learning\cite{20,33} and security issues\cite{34,35}. At the same time, research work has made federated learning more personalized\cite{36}. These related research work are concentrated on the federated learning of distributed equipment. This process involves factors such as data interaction among distributed mobile users, unbalanced data distribution, and communication costs in equipment reliability. It can inspire researchers to continuously overcome challenges in data privacy, computational constraints and communication costs. This work is innovative. The concept of federated learning is extended to cover other collaborative learning programs between organizations. Here we make a preliminary explanation on the extension of the original concept of ‘federated learning’ to other distributed collaborative machine learning\cite{37}. In this article, we will further investigate the application of federated learning in smart cities. The work content will also include discussing its development status and future direction. In this section, we provide a more comprehensive overview of federated learning. This aspect considers the definition, privacy, training process and classification structure of federated learning.

2.1. Basic definition

We define $N$ data owners as $F_1, F_2, ..., F_N$. All of them hope to train their own machine learning models by merging their respective data $D_1, D_2, ..., D_N$. A conventional method that exists is to put all the data together. It uses $D = D_1 \cup D_2 \cup ... \cup D_N$ to train and obtain a model $M_{SUM}$. And federated learning is a systematic learning process. In this process, the owners of the data jointly train the model $M_{FED}$. No data owner $F_i$ will disclose his own data $D_i$ to others. In addition, the accuracy of $M_{FED}$ expressed as $V_{FED}$ should be very close to the performance of $V_{SUM}$ of $M_{SUM}$. In terms of expression, let $\varepsilon$ be a non-negative real number; if $|V_{FED} - V_{SUM}| < \varepsilon$, We can think that the federated learning algorithm has a $\varepsilon$ error accuracy.

2.2. The privacy of federated learning

Privacy management is one of the core elements considered in federated learning. The realization of this requirement requires some security model analysis. In this section, we briefly describe the different privacy technologies currently used for federated learning.

2.2.1. SMC model

The SMC security model involves data from multiple parties. It provides safety certification under a known and clear simulation framework. This is a model that
guarantees zero interaction of knowledge data. In this situation, apart from the input terminal and output terminal, neither user knows these information data. The “zero-knowledge” model formed under this condition is highly expected. However, this desired property requires a complex calculation protocol. And it has situations that may not be implemented effectively. With security assurances, we can consider that the knowledge can be partially disclosed. At present, researchs have shown that SMC can be used to establish a security model to improve computing efficiency under low security conditions[38]. In addition, the MPC protocol performs model training and verification. In this process, users do not need to disclose privacy-sensitive data[39]. This work has realized the sharing of participants’ data among servers.

2.2.2. Differential privacy

Existing researchs use differential privacy[40] or k-anonymity[41] technology to achieve the protection of data privacy[42][43]. The above methods complete the processing of the data. And they achieve the purpose of covering up certain privacy-sensitive attributes. This makes it impossible for third-party users to distinguish between users. This will make the data unrecoverable and realize the protection of user privacy. But the disadvantage of this method is that it needs to transfer the data to other places. This overrun will affect the accuracy of the data. Therefore, we need to make a trade-off between accuracy and privacy. At present, there are many applications implemented by this privacy processing method. Some researchers have proposed a differential privacy method for federated learning. They have realized of hiding customer contributions during the training process to protect client data[35].

2.2.3. Homomorphic encryption

At present, homomorphic encryption[44] has been widely used. Its operating model is the encryption mechanism in the machine learning process. It uses parameter exchange to protect the privacy of user data[45][46]. The difference between it and differential privacy protection is that the data and models themselves will not be transmitted. Their data will also be encrypted without being discovered. Therefore, its advantage is that the probability of leakage in the original data is very small. In practice, the additive homomorphic encrypt model[47] is widely used. At present, polynomial approximation is used to evaluate nonlinear functions in machine learning algorithms[48].

2.3. Typical architecture and training process of FL system

In the FL training system, the owner of the data participates in the FL system. Together, they train a shared model in the aggregation server center. In this architecture, a basic premise is that the data owners are honest and the data they provided is true. It requires data users to use their real private data for training. After the training is completed, the relevant parameters of local model training is submitted to the FL server.

Generally, the FL training process includes the following three training steps. We first define the local model as the model trained on each participating device. The global model refers to the model after the FL server is aggregated.

- Step 1. Realize the initialization of the task. The server determines the training task. That is to determine the target application and corresponding data
requirements. At the same time, the server specifies the global model and establishes the parameters in the training process, such as the learning rate. The global model parameter $W^G_0$ will be initialized by the server. And the training tasks are assigned to the participating users to complete the task assignment.

- **Step 2.** Realize the training and updating of the local model. The training is carried out on the basis of the global model $W^t_G$. $t$ represents the current iteration index. Each participating client uses local data and equipment to update the local model parameter $W^t_i$. The ultimate goal of participant $i$ in iteration $t$ is to find the optimal parameter $W^t_i$ that minimizes the loss function $L(W^t_i)$, namely $W^*_i = \arg\min W^t_i$.

- **Step 3.** Realize the aggregation and update of the global model. The server aggregates the local models of participating users. And it will send the updated global model parameter $W^{t+1}_G$ to the user who holds the data. The server continuously calculates the minimum global loss function $L(W^*_G)$ that is $L(W^*_G) = \frac{1}{N} \sum_{i=1}^{N} W^*_i$. Repeat steps 2-3 until the training global loss function converges or reaches the required training accuracy.

3. Application of federated learning in IoT system in smart city

In the smart city architecture in recent years, the development of the Internet of Things has provided technical support for the transformation and progress of smart cities. More and more intelligent products based on the Internet of Things appear in large numbers. The emergence of federated learning provides a good solution to the key problems in the development of the Internet of Things. There are a large number of data changes and information processing events in the Internet of Things. Many user privacy issues and information security issues have been exposed during this process. The framework model of “Federated Learning + Internet of Things” has solved many problems. The “smart city” architecture is therefore more complete. Federated learning builds a scalable production system for the field of mobile devices [49]. It improves the design of the system architecture. In addition, the combination of blockchain and federated learning constitutes a blockchain federated learning (BlockFL) architecture. It compares the performance between different terminals [50]. In the process of realizing these applications, the following factors need to be considered:

- Privacy. One of the core goals of Federated Learning is to protect the private information of participating users. Some recent research work has shown that participants or FL servers may be malicious in participating in the FL process. This situation may cause privacy and security issues. At the same time, this may damage the generated global model. On the other hand, it will damage the privacy of participating users during model training. In addition, FL does not need to exchange data for collaborative model training. Its maliciously participating users can still infer sensitive information (such as gender, occupation and location) based on the sharing models of other participating users. We use the FaceScrub dataset to train a binary gender classifier. In this process, the accuracy of inferring whether a participant’s input is included in the data set is as high as 90% by checking the shared model [51].

- Security. During the FL training process, participating users train the learning model locally and share the training parameters with other participants. It achieves the purpose of improving forecast accuracy. However, it is often vulner-
able to various attacks in this process. For example, data and models are missing or even poisoned. In this attack mode, malicious users may send wrong parameters or corrupted models. Thus it will provide a false learning model during the global aggregation process. The global model will update incorrectly. And the entire learning system will be damaged.

![Diagram of Federated Learning Training Model](image)

**Figure 3.** Framework of Federated learning training model for data transmission of multiple mobile devices in Internet of things

### 3.1. Data application scenarios under IoT

Currently, under the framework of the Internet of Things, federated learning based on device data has been widely deployed. At present, some scholars have proposed a novel federated learning framework for efficient communication and privacy protection. It improves the performance of IoV. After that, it stabilized the data flow dynamics through TCP CUBIC flow on the WiFi network. In the end we got a good training model[52]. On the other hand, some applications provide accurate video recommendation services. The creation of a joint cloud video recommendation framework based on deep learning for mobile Internet of Things meets the needs of users. At the same time, it uses quantitative methods to reduce the uplink communication cost and network bandwidth[53]. In addition, federated learning enables resource-constrained edge computing devices (such as mobile phones and IoT devices) to learn shared predictive models[33].

### 3.2. Blockchain federated learning (Block FL)

The development of blockchain provides a new development direction for the Internet of Things. BlockFL architecture has completed the update of the local learning model well. It uses the consensus mechanism in the blockchain. Therefore, on-device machine learning does not require any centralized training data or coordination. In the end, it performed a good performance data analysis[22]. In the industrial internet
of things, some researchers have designed a secure data sharing architecture authorized by blockchain. This process maintains data privacy well through the shared data model. It is compared with real-world data sets. The proposed data sharing scheme has good accuracy, high efficiency and safety\cite{54}.

3.3. Integration with edge computing

The current widespread application of edge computing has resulted in faster network service response. At the same time, it meets the basic needs of the industry in real-time business, application intelligence, security and privacy protection. At present, federated learning is combined with edge computing. It achieves a good practical application. We know that the use of edge and terminal computing can meet the needs of cloud capacity and equipment at the edge of the network. This process speeds up content delivery and improves the quality of mobile devices. Under this condition, Federated Learning has realized the application of the 4G/5G-based interconnected vehicle edge computing platform. This model completes the edge collaborative learning of real data sets collected by large electric vehicle (EV) companies. This method has the advantages of driver personalization, privacy services, reduced delay (asynchronous execution) and security protection. In addition, the personalized federated learning of the application of the intelligent Internet of Things can well alleviate the negative impact of heterogeneity in different aspects\cite{55}. At the same time, the framework design based on federated learning can utilize limited bandwidth resources. It effectively improves the communication efficiency and reduces the communication cost\cite{56}.

Currently, we need to combine deep learning techniques and federated learning frameworks with mobile edge systems at the same time\cite{57}. This can accelerate the applications of mobile edge computing.

The existing implementation mode of federated learning is to allow computing nodes to synchronize only the local training model in distributed training. And it does not synchronize the original data. This leads to the federated learning architecture relying on highly concentrated types and large server bandwidth. However, the network capacity distribution between nodes is highly uniform and smaller than that of a data center. In\cite{57}, the author proposed a method. It can make full use of the node-to-node bandwidth to speed up communication. The first point is that it is staff selection through segmented gossip aggregation and bandwidth awareness of the network. The second point is that it makes full use of the bandwidth between nodes and between workers and workers. This ultimately speeds up the convergence speed and reduces the number of communication rounds involved. Federated learning allows workers to train models using distributed data. The general federation learning system uses a central parameter server to coordinate a large federation of participating workers. Workers use their data set to train a local model. And they are regularly updated to a centralized server for synchronization. It achieves the same synchronization effect as the parameter server. But it consumes a lot of bandwidth resources. The model updates of all nodes in the system are sent to all other nodes. Performance will be severely reduced and costs will increase. So we use the model split level synchronization mechanism. In the first aspect, we “divide” a model into a set of segments-subsets containing the same number of model parameters. These parameters do not overlap. In the second aspect, the workers aggregate the partial divisions with the corresponding divisions of k other workers. Then it performs segmentation level update. In the third aspect, we divide other workers. This process maximizes the bandwidth capacity between workers. It
shares the communication cost and further accelerates the convergence speed.

In addition, the author also proposed in [57] to combine deep reinforcement learning techniques and federated learning frameworks with mobile edge systems. This can be used to optimize mobile edge computing. In this process, the “In-Edge AI” framework was designed. It can intelligently use the cooperation between the device and the edge node to exchange learning parameters. It finally achieves dynamic system-level optimization and application-level enhancement. Based on this process, unnecessary system communication load will also be reduced. The key and difficulty is that computing offloading requires wireless data transmission. This may cause congestion of the wireless channel, thereby affecting the effectiveness of the decision. The optimization of the entire communication and computing integration system—how to jointly allocate communication resources and computing resources of edge nodes. The author uses progressive reinforcement learning to jointly manage communication and computing resources. At the same time, it also uses floating and edge cache calculations between mobile edge computing (MEC) systems. In addition, federated learning [58][59] has also been introduced as a framework for training agents in a distributed manner. The effects of this method are as follows: 1) uploading through wireless channels greatly reduces the amount of data that should be used, 2) responding to the mobile communication environment and cellular network conditions, and 3) interacting with the actual cellular network Heterogeneous user equipment (UEs) adapt well, 4) protect personal data privacy.

| Reference | Year | Direction           | Framework | Contribution                  |
|-----------|------|---------------------|-----------|-------------------------------|
| (33)      | 2018 | Edge Computing      | FL        | Non-IID data training         |
| (49)      | 2019 | Mobile Devices      | FL        | Production system             |
| (50)      | 2019 | BlockChain          | BlockFL   | The block generation          |
| (51)      | 2019 | Information Security| FL        | Data breaches                 |
| (52)      | 2020 | IoT                 | FL        | The IoV scheme                |
| (53)      | 2019 | Mobile Devices      | JointRec  | FL algorithm                  |
| (54)      | 2019 | BlockChain          | BlockFL   | Data privacy sharing          |
| (55)      | 2020 | IoT                 | FL        | Impact of heterogeneity       |
| (56)      | 2020 | Network Computing   | BACombo    | Communication latency         |
| (53)      | 2019 | Edge Computing      | In-Edge AI| Communication load            |

4. Application of federated learning in intelligent transportation system in smart city

Transportation is an integral part of building a smart city. With the further development of deep learning, self-driving cars have gradually developed [60][61]. We can solve various problems in transportation systems through federated learning, such as communication delays, calculation data processing, and data privacy.

4.1. Combination of federated learning and vehicle system

The performance of emerging transportation applications largely depends on vehicle-to-vehicle (V2V) communication [62]. Therefore, the URLLC in the vehicle network is
Figure 4. Application of federated learning in transportation systems

an essential prerequisite for developing intelligent transportation systems [63][52]. For example, real-time navigation and avoiding obstacles depend to no small extent on low latency communication [64] and low loss rate. In this regard, Li et al. proposed q-fair federated learning (q-FFL), a new optimization goal [65]. This inspiration comes from the fair resource allocation in wireless networks and a fairer accuracy distribution across federated learning devices. Lu et al. proposed a solution for the intermittent and unreliable communication in the IoV and further improve data sharing’s reliability and efficiency [54].

Sumudu Samarakoon et al. describe the problem of joint power control and resource allocation in vehicle-mounted communication networks as a net-range power minimization problem constrained by URLLC. They utilized the concept of federated learning to propose a distributed learning mechanism; the vehicular users (VUEs) estimate the tail distribution locally with roadside units (RSU) [66]. The constraint of URLLC is characterized by extremum theory and modelled as a tail distribution of network scope queue length over a predefined threshold. It can effectively reduce delay and enhance reliability [67][23], and ensure reliable federated learning in mobile networks [68]. They proposed a distributed transmission power and VUEs’ resource allocation process based on Lyapunov stability. It can reduce unnecessary overhead by enabling VUEs to distribute the queue’s tail at the local learning network scope without sharing a sample of the actual queue length. The proposed solution is very accurate in estimating the parameters and dramatically reduces user vehicles’ queue length compared with the centralized learning module.

Nevertheless, it would be impractical to collect all the data to a centralized server due to delays in the vehicle-server network. Real-world applications, cloud-based learning methods are relatively slow. The author proposed a systematic IoT network design approach by [52] accelerating the learning process of data transmission protocols (such as TCP) that converts our vehicles into mobile data centers. This method performs federated learning to improve TCP performance, data transfer volume, and diversity of Internet performance. Their mathematical analysis based on equalization provides essential insights for the development of feasible federated learning algorithms for net-
4.2. Combination of federated learning and aviation system

The latest generation of aircraft has onboard computing power and links to data on the ground, different from vehicle systems. However, due to the large amount of data generated by the aviation system and the lack of computing resources, it cannot handle the aircraft’s fault prediction. Moreover, deploying additional airborne resources is very complicated and expensive. Therefore, in [69], the author proposed a method of combining active learning and federated learning. This method uses an active online decision tree based on confidence as the basic model of client learning [70] by sending it to the server. Finally, a single decision tree uses the integrated model from the server to mark the request. They can establish mechanisms for transmitting and identifying uncertain data under the communication budgets by classifying standard samples with minimum computational power. This method effectively achieves high communication efficiency and cheap calculation and is suitable for practical application cases.

Although federated learning can solve insufficient computing resources, high communication costs, and privacy involved in the IoT, communication inefficiency is the bottleneck of federated learning. UAV is increasingly used as the relay between ground base terminal and network base station [71] to improve network connectivity, and [72] extend coverage area and communication efficiency. [73] A joint formation method between cooperative UAVs is proposed to motivate UAVs to participate in federated learning training. This method achieves a stable coalitional structure and maximizes the allocation of profit.

| Reference | Year | Direction | Framework | Contribution |
|-----------|------|-----------|-----------|--------------|
| [23]      | 2019 | IoV       | FL        | A distributed resource allocation framework |
| [52]      | 2020 | IoV       | Math      | Design FL mechanism |
| [65]      | 2020 | IoV       | FL        | A communication-efficient method |
| [67]      | 2018 | IoV       | FL        | A novel joint transmit power and resource allocation approach |
| [69]      | 2020 | Aviation  | FL        | A new applied ML framework |
| [73]      | 2020 | UAV       | FL        | A joint auction-coalition formation algorithm |

5. Federated Learning in the financial field of smart cities

The financial sector includes banking, insurance, trust, securities and leasing. These criminal activities have been frequent in recent years. Some financial crimes can reach hundreds of millions of dollars, such as the mortgage crisis. These criminal activities have created a crisis for families and society as a whole. The financial industry also spends a lot of money every year to fight fraud, but not effectively.

In recent years, it has been necessary to use machine learning to reduce losses to banks and consumers. In deep learning, the sample size needs to be sufficient to train a better model. A single bank can’t provide enough information of a person’s
consumption and credit cards. And it is also difficult for one bank detect frauds. The proposal of federated learning gives the financial industry a new way to train models using deep learning[74]. The owner of each data can collaborate on the model without sharing the customer’s private information. The financial industry faces a number of challenges in reviewing user qualifications and screening quality customers. The combination of federated learning and finance can effectively address this challenge, while also protecting customers’ private information from disclosure.

Federated learning can be very effective in these areas. For example, Banks can use cameras to identify suspicious transactions, prevent malicious multi-party lending, and so on. Prevent malicious multi-party lending[76], and so on.

Federated learning can be very effective in these areas. For example, Banks can use cameras to identify suspicious transactions, prevent malicious multi-party lending, and so on.

![Figure 5. The processing framework of federated learning in the financial field. First, the collaborative group sends the key to the data source. Then encrypt the exchanged data to ensure data security. Finally, the learning model is updated in real time to perform model output for different application scenarios.](image)

### 5.1. Federated learning in the field of financial fraud

With the advent of the digital age, many transnational financial crimes have emerged in the world. Common sub-categories of financial crime are financial theft, fraudulent loan and money laundering. Credit card fraud will bring large losses to both banks and consumers. Yang et al. proposed a framework for training fraud detection models using behavioral features and federated learning[77]. They build a shared Fraud Detection System (FDS) by aggregating locally calculated fraud detection model updates. The result shows that the area under the curve (AUC) based on the federated learning FDS reaches 95.5%, which is about 10% higher than the traditional FDS. Chuan et al. also give satisfactory answers to some questions (Model Aggregation, Data Poisoning, Scaling Up Issue)[78]. In addition to improving federated learning, some researches combine federated learning with other algorithms. For example, Toyotaro Suzumura et al. [79] use federated learning and traditional graph learning methods to build a more...
accurate machine learning model. It can capture complex global money laundering activities across multiple financial institutions.

In recent years, privacy issues have gradually attracted attention. For the rich, they value whether their private information in the bank can be effectively protected. Due to the development of machine learning, more and more bank user data is analyzed and trained into relevant bank marketing models. However, protecting the private information of financial users is an important research direction. Feng Yan et al. [81] proposed a bilateral privacy-protected federated learning scheme, which also protects the iterative parameters during the training process. This scheme further protects model parameters from being acquired by external attackers on the basis of traditional federated learning only considering the privacy of the client. The asymmetric vertical federated learning proposed by Yang Liu et al. [82] can effectively protect the privacy of different bank users.

5.2. Federated learning in the field of insurance

Building a data service platform for the insurance industry requires integrating financial, medical, and other data from multiple parties. If an insurance company wants to improve its risk management capability and business development level, it needs to consider the impact of multi-party data. How to effectively use data without infringing on personal privacy is also an important issue facing the insurance industry. Malgorzata et al. [83] proposed that the key technologies that promote the insurance industry’s reform include federated learning and computable insurance contracts. Wang [84] explained the primary application of federated learning in the insurance industry and used Shapley values to explain the federated learning model. The results show that compared with the entire feature space results, the robust host features important results for part of the feature space. Yuan et al. [85] proposed a configurable FL benchmark suite FLBench. This kit can simulate various isolated data islands according to specific research requirements and covers areas such as insurance and securities.

When different insurance companies and multi-party data providers implement federated learning, how to measure participant contributions is also a more realistic problem. Wang et al. [82] proposed that the service model can use related models to use data models to integrate information to obtain better feedback. Yan et al. [86] proposed an online evaluation method that is more sensitive to the quality and quantity of data and compared it with the results obtained by Shapley Value in game theory. Besides, federated learning has more realizations in the insurance industry [87] [88] [89] [90].

6. Application of federated learning in the medical field of smart city

With the rapid increase of COVID-19 worldwide, the burden on medical staff has gradually increased. How to treat patients with effective methods is a major problem. Smart medicine is an area of future medical development, and this area is expected to benefit from the rise of federated learning technology. In the past, due to the independence of hospitals and the privacy of information, there was a lack of sufficient samples for machine learning. Federated learning can unite previously independent individual hospitals into a collective population, greatly increasing the sample size of model training. It can solve this problem well and improve the accuracy of the model [91].
Table 3. Research on the Contribution of Applied Federated Learning in the Field of Financial

| Reference | Year | Direction   | Framework | Contribution                                      |
|-----------|------|-------------|-----------|--------------------------------------------------|
| [77]      | 2019 | Financial   | FL        | Detection framework FFD                         |
| [79]      | 2019 | Financial   | FL        | Federated Graph Learning                        |
| [78]      | 2020 | Privacy protection | FL | An intelligent aggregation method               |
| [80]      | 2020 | Financial   | Secure multi-party learning | The desired security properties |
| [82]      | 2020 | Privacy protection | FL | Asymmetrical federated model training           |
| [91]      | 2020 | Bank        | FL        | Propose Open banking                            |
| [92]      | 2020 | Financial   | FL        | FL algorithms for vertically partitioned data   |
| [93]      | 2021 | Privacy protection | FL | The key exchange technology                     |

Figure 6. Comparison of training process between traditional machine learning on medical data and federated learning on medical data
6.1. The combination of federated learning and medical privacy protection

With the Precision Medicine Initiative in the United States and the emergence of a large amount of personal health electronic information, patient data is usually protected in localized silos. People want to merge data sets from different medical systems it’s difficult. Since the constraints of establishing a calibration model locally may limit the degree of improvement, Huang [95] proposed a safe multi-party calculation (SMC) method to establish a global isotonic regression calibration model. Fang et al. [96] proposed a method to reduce transmission bandwidth and protect privacy in distributed learning.

And it is worth noting that Praneeth et al. [97] further demonstrated how to minimize the distance correlation between the original data and the intermediary representation. Thereby reducing the leakage of sensitive raw data patterns during client communication while maintaining the accuracy of the model. It reduces the leakage of communication payload and original data in medical data. And M. A. P. Chamikara et al. [98] proposed a privacy-protected FL framework for multi-site functional MRI analysis, and studied the use of brain function connections to classify the communication speed and privacy protection of autism spectrum disorders and health control problems. In terms of privacy protection, there are also related methods to improve accuracy, efficiency and scalability [98] [99] [100].

6.2. Federated learning and drug development combined

FL has revolutionized leading fields such as health care technology. It has made outstanding achievements in many fields such as drug discovery. Artificial intelligence (AI) models usually require a large amount of high-quality training data, which is in sharp contrast to the small data currently faced by new drug discovery. The proposal of FL allows the drug development industry to use distributed data from different sources without leaking sensitive information of these data. This emerging decentralized machine learning paradigm is expected to greatly improve the success of artificial intelligence drug discovery [101]. Chen et al. [102] verified the feasibility of applying the horizontal federated learning (HFL). FL quantitative structure-activity relationship (FL-QSAR) under the HFL framework provides an effective way to break the barriers of pharmaceutical institutions in QSAR modeling. The solution promotes the development of collaboration and privacy-preserving drug discovery, and extends it to other privacy-related biomedical fields. Xiong et al. [101] demonstrated the application of FL in predicting drug-related properties. At the same time, they also emphasized its potential role in solving small data and biased data dilemmas in drug discovery.

6.3. Federated learning combined with disease prediction

Machine learning has been proven to be an effective way to help the medical industry make decisions and predict diseases. FL can further expand the sample size and protect privacy. In the medical field, more accurate judgments are often required for disease prediction and decision-making. For example, in the detection of lung nodules, the lung nodes are often too small to be detected. In actual tests, lung nodes are often confused with blood vessels and other small underlying biological structures. It is often mistakenly confused as tuberculosis. If it is wrongly tested, it is likely to reduce the patient’s chances of survival. Pragati et al. [103] proposed a method of using FL to effectively use medical and health records for disease prediction. This method
helps to use FL to maintain health records for disease prediction and strengthens the maintenance of patient privacy. FL helps to produce enhanced prediction results and can protect data privacy and security. It can help FL to make greater progress.

7. Application of federated learning in communication field in smart city

FL is trained through distributed machine learning. It allows distributed machines or users to cooperate in training machine learning models with the help of parameter servers. It also uses data sets from edge devices to train local models. At the same time, it regularly updates it to a centralized server to protect user privacy. But with the development of deep learning, in order to make machine learning and have better performance, we need a large number of data sets. In order to achieve the target accuracy, the participant and the server need several rounds of communication to achieve accuracy. This process may result in the need for millions of parameters. Communication costs have become very expensive. In addition, in this process, there are problems such as the delay of the Internet of Things terminal equipment, the instability of the communication link, and the lack of expensive data links and computing resources in aviation communications. The efficiency of this transportation system is also low and expensive. Therefore, it is necessary to improve communication efficiency, reduce delay, improve link availability, and reduce communication costs. At present, FL has made great breakthroughs in the field of multiple access channel communication. The views are as follows:

• Multiple access channels: One of the challenges faced by FL due to its iterative nature and large model size is communication overhead. A new method to alleviate the bottleneck of FL communication is to allow simultaneous display of user traffic on multiple access channels. This may make better use of communication resources. Or another way is to explore the superposition characteristics of the wireless multiple access channel to calculate the required function of the distributed local calculation update (that is, the weighted average function).

![Network interaction diagram of federated learning in communication](image)

**Figure 7.** Network interaction diagram of federated learning in communication
7.1. Federated learning solution for multiple access channel problem

Previous work relieved the communication bottleneck by compressing the gradient before transmission. Two commonly used gradient compression methods are (A) quantization and (B) sparse gradient quantization. It follows the lossy compression idea of using a small number of bits to describe the gradient. These low-precision gradients are transmitted back to the parameter server (PS). However, these independent compression techniques have not been adjusted to the underlying communication channel exchanged between the user and the parameter server. Channel resources may not be fully utilized. Another study of FL through wireless channels is the more general multiple access channel. The stacked nature of the wireless channel allows gradients to be clustered together in the air and allows more effective training. These methods can be roughly classified into digital or analog solutions. It depends on how the gradient is transmitted through the channel. In the simulation scheme, the local gradient is scaled and transmitted directly through the wireless channel. In the digital scheme, the slave users are decoded separately, but the transmission still occurs on the multiple access channel. Although in terms of bandwidth, the analog solution is better than the digital solution\cite{106}\cite{107}. Digital solutions have the following advantages:

- Backward compatibility, they can be easily implemented on existing digital systems.
- They are not easy to slow down users.
- They are more reliable because various error control codes can be used.
- Digital solutions do not require the tight synchronization required for analog transmission.

Driven by the above discussion, they considered the learning of federated learning on multiple access channels. It focuses on the design of digital gradient transmission scheme. The gradient of each user is the first quality conversion. This process is transmitted through multiple access channels and decoded separately on the parameter server. The conditions are: a) the informality of the gradient of each user; b) the underlying channel conditions; they proposed a stochastic gradient quantization scheme to optimize the quantization parameters according to the capacity area of the multiple access channel. The results show that, especially when users experience different channel conditions or different degrees of information gradient, the channel-aware quantization of federated learning is better than the non-perceptual channel quantization scheme (for example, uniform distribution). The difference between this scheme and the scheme in \cite{108} is that it allows each user to have their own quantitative budget. First, a scheme for arbitrary user \( M \) is proposed, and the convergence speed of the scheme is analyzed. The algorithm puts forward the general optimization problem of quantitative budget allocation based on multiple access channel capacity. Then, they showed an example with \( M=2 \) users and found the best quantitative budget and communication rate. To this end, they researched and analyzed a channel-aware quantization scheme that is superior to uniform quantization and other existing digital schemes.

7.2. Challenges and problems

Research on federated learning is still in early stages. It currently offers obvious opportunities from the edge to the core network. However, it has several key challenges in applying federated servers, as described in \cite{109}.
Security and privacy. It adopts a secure aggregation algorithm and does not need to transmit local sensitive data to the center. But the encrypted local model can reveal the local situation by analyzing the global model. In the case of federated learning, the model is trained through sensitive user data. The premise of these federated learning is to use users to effectively process data memory without revealing private information. Ultimately, this process can reduce the possibility of data disclosure in the event of an attack. At the same time, federated learning may be subject to reasoning attacks and confrontational attacks. The enemy embeds carefully designed samples into the data, effectively affecting the local training data set to manipulate the results of the model-polluting the federated learning process. Therefore, how federated learning can improve its own defense mechanism against these attacks should also be explored.

Considerations such as the optimal number of local learners participating in the global update, the grouping of local learners, and the frequency of local updates and global aggregation that lead to a trade-off between model performance and resource protection, are all application dependent and worthwhile the study. In addition, the scale of FL networks update can be very large for low-power devices such as IoT nodes. Therefore, the method of sparse and compressed model parameters has higher computational efficiency and reduces resource consumption.

| Reference | Year | Direction  | Framework | Contribution           |
|-----------|------|------------|-----------|------------------------|
| (102)     | 2019 | Communication | CMFL     | Communication overhead |
| (104)     | 2019 | Communication | CA-DSGD  | Reduce bandwidth       |
| (105)     | 2016 | Communication | Distribution | Network cost        |
| (106)     | 2020 | Communication | FL       | Wireless communication |

8. The future development and direction of federated learning in smart cities

FL has been continuously developed since it was proposed in 2016[11]. In addition to the main issues discussed at this stage (asynchronous[110], communication security[111] and privacy issues[19]), there are still the following key open directions to be explored.

Defense against attacks. Although FL can protect important information, if people deliberately launch a poisoning attack on distributed devices, it may also lead to the leakage of important information[112]. For example, due to the stochastic gradient descent (SGD)[113][114] in the actual application process, and the leakage of these gradients may actually leak data information[115]. Chuan et al. also studied the potential privacy and security issues in FL[78]. Therefore, how to effectively defend against privacy and security issues in FL is still an open challenge.

Algorithm efficiency. The rapid growth of network traffic has become the main technical bottleneck for the development of the IoT. Although FL can effectively connect distributed devices, optimization algorithms are also needed to better realize practical applications. For example, reduce time complexity[116]. FedAvg algorithm[117] is used for local calculation update and aggregation, and used for client-side differential privacy preservation federal optimization algorithm[35]. Due to the limitation of computing power, the related algorithms of FL still need to be optimized in face of massive data.
Technology application. FL has broad prospects in smart cities. It can involve almost all aspects, especially in the fields of finance, medical care, transportation and et al. FL can perform model training on data associated with multiple standards. Taking smart healthcare as an example, FL can train models that cannot be directly aggregated by hospitals. However, FL can fuse sensitive information without revealing privacy and overcome the data island. Combining more data can greatly improve the accuracy of the model. The practical application of FL will also make cities smarter.

The gradual development of FL has brought new vitality to all walks of life. This article introduces the application of FL in smart cities, including communications, life services and the IoT. It is expected that in the near future, FL will lead the further development of smart cities. FL will also be combined with all walks of life to form a good ecological community, so that everyone can benefit from it.

9. Conclusion

FL has been widely used and developed in various fields. This paper investigates the development achievements of FL in the field of Internet of things, transportation, communication, medical care and finance. Meanwhile, we think about the future research direction of FL in other fields of smart city. It will face heterogeneous, communication security and privacy issues. We also think about proposing certain ideas and implementations in defense against attacks, potential privacy security, algorithm efficiency, and broader application scenarios. Moreover, we put forward our future technology development prospects. After that, we will continue to conduct in-depth research on key technologies.

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