Sustainable Energy Technologies and Assessments 55 (2023) 102987

Contents lists available at ScienceDirect

Sustainable Energy Technologies and Assessments

journal homepage: www.elsevier.com/locate/seta

Federated learning for smart cities: A comprehensive survey ☆

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A R T I C L E I N F O

Keywords:
Smart city
Privacy preservation
Machine learning
Federated learning

A B S T R A C T

With the advent of new technologies such as the Artificial Intelligence of Things (AIoT), big data, fog computing, and edge computing, smart city applications have suffered from issues, such as leakage of confidential and sensitive information. To envision smart cities, it will be necessary to integrate federated learning (FL) with smart city applications. FL integration with smart city applications can provide privacy preservation and sensitive information protection. In this paper, we present a comprehensive overview of the current and future developments of FL for smart cities. Furthermore, we highlight the societal, industrial, and technological trends driving FL for smart cities. Then, we discuss the concept of FL for smart cities, and numerous FL integrated smart city applications, including smart transportation systems, smart healthcare, smart grid, smart governance, smart disaster management, smart industries, and UAVs for smart city monitoring, as well as alternative solutions and research enhancements for the future. Finally, we outline and analyze various research challenges and prospects for the development of FL for smart cities.

Introduction

The urban population has grown tremendously over the past few decades. As reported by the United Nations, the urban population surpassed that of the rural sector in 2007 [1]. Globally, the World Bank estimates that 53.7 percent of people will live in urban areas by 2020 [2]. In developed and developing countries, governments and municipalities allocate more resources and funds to urban areas than to rural areas, which in turn leads to more development of urban areas. Even though many opportunities are created in urban areas for the generation of income for the urban population, urbanization often faces several challenges such as overpopulation, unemployment, housing problems, traffic congestion, water shortages, urban planning, health hazards, degradation of the environment, and many others [3].

Smart cities rely heavily on sensors and Internet of Things (IoT) devices to collect and track data about vehicular traffic, waste, water, drainage, potholes, smart buildings, smart grids, burglaries, monitoring the environment, and sixth-generation (6G) networks [4]. Through big data analytics, machine learning (ML), and deep learning (DL) algorithms, hidden patterns in the data are revealed that can be used to make predictions. The administrator or city planner can use such

☆ This work was supported by the Korean Institute of Planning and Evaluation for Technology in Food, Agriculture, Forestry and Fisheries(IPET) through Digital Breeding Transformation Technology Development Program, funded by Ministry of Agriculture, Food and Rural Affairs (MAFRA) (322063-03-1-SB010). This work was also partially supported by NIH (NIGMS/P20GM109090), NSF under awards CNS-2016714, CNS-2104700, and CBET-2124918, the University of Nebraska Collaboration Initiative, and the Nebraska Tobacco Settlement Biomedical Research Development Funds.

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https://doi.org/10.1016/j.seta.2022.102987
Received 21 March 2022; Received in revised form 26 November 2022; Accepted 21 December 2022
2213-1388/

predictions to take necessary actions to improve the quality of life for residents [5,6].

Moreover, several smart city applications such as traffic prediction, smart industries, environmental monitoring, and disaster management require real-time decisions. Using technologies such as ubiquitous and pervasive computing, it is necessary to receive updates anywhere anytime. There is a risk of analytics being delayed due to latency issues in cloud-based storage [7–9]. IoT devices and sensors in a smart city generate huge amounts of data very rapidly [10]. Big data generated in smart city applications presents several challenges including loss of data, complex computations and communication, and a high energy demand [11].

Federated Learning (FL) is a recent development in machine learning, where the global ML algorithm itself is offloaded to the devices instead of transferring raw data captures from several sources to the central model [12]. The parameters from the local devices are transferred to the central ML algorithm for global training and predictions in FL [13]. In contrast to traditional ML, in which data is transferred to a central cloud server for training, in FL, the models are distributed to the device or location where the data was generated. FL can solve several issues of smart cities, including privacy preservation, and big data handling, enabling decision-makers to make real-time decisions [14,15]. An important aspect of FL is that it helps in training shared statistics using decentralized devices or servers. Even though data scientists and researchers use a similar model to train the data, FL eliminates the need to upload private data to the cloud or to exchange data with other scientists.

FL has been the subject of several surveys in recent years due to its importance. Recently the authors in [16,17] and [18] presented several comprehensive surveys on applications of FL for IoT. The authors in [19] presented a survey on several personalized techniques for FL, that work better for individual clients. Another interesting survey in [20] presented several applications, challenges, and design aspects of FL. In another interesting survey, the authors in [21] presented a comprehensive survey on privacy-preserving mechanisms of FL. The authors in [22] presented a detailed survey on the applications of FL for mobile edge computing. In another interesting study, the authors in [23] presented a detailed survey on privacy preservation aspects of FL. The authors in [24] presented a detailed survey of several sensing techniques through FL for a smart city. The study in [25] presented a survey on the applications of FL in UAV-enabled wireless networks. The authors in [24] presented a comprehensive survey on applications of FL for 6G of cellular networks. In another interesting survey, the authors in [18] have presented the applications of FL for blockchain and edge computing. The authors in [26] presented a detailed survey on applications of FL for healthcare. The authors in [27] presented a survey on applications of FL for DTs in smart city-based applications. The authors in [27] presented an extensive survey on applications of FL models integrated with DTs in a smart city setup. The authors in [28] reviewed the various developments of FL and its applications in versatile fields. The recent research applications relevant to FL implementation in smart city perspective are explored. Some of the prominent areas that were covered as part of the extensive review included IoT, transportation, communication and healthcare. The study in [29] emphasized on FL applications and the relevant system platforms, mechanisms, real-world applications and process contexts in details. The authors in [30] reviewed blockchain based FL applications for ensuring security in IoT devices. The existing enabling technologies in blockchain implementations are discussed and then the applications of these technologies in FL to achieve security in IoT are explored. In [31] the authors emphasized on the implementation of FL integrated with blockchain for preserving security and privacy for Smart Transport Infrastructure (STI). The survey initially explored the various aspects of Vehicular Ad Hoc Network (VANET) and STI and then presents an exhaustive review of blockchain and FL based real world implementations. Even though many researchers presented surveys on FL for different verticals, to the best of our knowledge there is no survey existing on FL for smart city-based applications, which motivated us to carry out this survey. Table 1 presents the summary of related reviews on FL for smart cities.

Motivation of FL for Smart Cities

The components of a smart city includes water supply management, Electricity Supply management, Sanitation & Solid Waste Management, Urban Mobility & Public Transport management, Affordable housing for the poor, robust IT connectivity & data collection, etc., In a smart city, IoT devices capture data related to various components of a smart city using sensors. The collected data is collated and analyzed to make appropriate decisions. These decisions will be sent to actuators of IoT devices for appropriate actions. It is very much crucial to create the most appropriate decision with IoT data and communicate the decision rapidly to the actuators for action. To make the most appropriate decision, AI and ML techniques are used. These AI and ML techniques consolidate results to provide better predictions for enhancing user experience. The traditional ML uses centralized machine learning approaches. In centralized machine learning, data is stored at a central location and Algorithms use training data (Sample data) to predict patterns and trends. But the centralized data in centralized machine learning has limitations such as limited access and security concerns. These precincts of traditional ML motivate us to carry out this comprehensive survey on Federated Learning for smart cities. The Federated Learning for smart cities enriches the user experience at various components of smart cities. In AI, FL paves a platform for a new trend of machine learning. FL creates a shared global modal rather than a central data model and uses multiple local datasets to train various ML algorithms without exchanging data. FL exploits both decentralization of data and computing power without compromising the privacy of data. All these discussions referred from the most recent, appropriate high-quality peer-review journals, conferences, symposiums, workshops, and books.

The main contributions of this survey are summarized as follows.

- First, we discuss FL and its importance for a smart city.
- Second, we examine the importance of FL for several smart city applications, including smart transportation systems, smart healthcare, smart grid, smart governance, smart disaster management, smart industries, and UAV for smart city monitoring.
- Next, we discuss several smart city-related projects using FL.
- Finally, we discuss several challenges and open issues of FL for smart city applications, as well as future directions.

The rest of the paper is organized as follows. Section “FL for Smart City Applications” summarizes the applications of FL for several smart city verticals along with recent state-of-the-art applications. Section “Research Projects and Use cases” discusses several interesting projects and use cases of FL-enabled smart cities. Several challenges and open issues associated with FL for smart cities along with future research directions are presented in Section “Lessons Learned, Open Issues, Challenges, Future Directions”. Finally, Section “Conclusion” concludes this survey.

FL for smart city applications

This section discusses the integration of FL with smart city applications and related use cases. Fig. 2 depicts FL for smart city applications.

FL for smart transportation systems

Smart transportation

Integrated into the transportation system, smart transportation ensures that traffic movements are convenient, cost-effective, and safe. Modern intelligent transportation systems monitor, evaluate, and manage transportation systems using various technologies, improving their efficiency and safety. Several applications of smart transportation can be seen in the following areas:

Table 1
Summary of related reviews on FL for smart cities.

Research	Contributions	Limitations
[28]	A review of FL in various fields, such as the IoT, transportation, communications, finance, and medicine.	The applicability of FL for smart cities was not explored.
[27]	A surveys on smart city applications where FL is integrated with Digital Twins (DTs).	The applicability of FL for smart cities was not explored in detail.
[24]	Smart city sensing approaches, challenges faced, advantages of FL.	The potential of FL for smart cities and vertical applications was not studied.
[18]	Emerging applications of FL in IoT, FL-IoT services.	Limited to the FL-IoT services like IoT data sharing, and data offloading, while applications of FL for smart cities were not studied.
[32]	FL techniques in the healthcare systems (e.g., drug development, clinical diagnosis, digital health monitoring, disease predictions and detection system).	Did not focus on the potential applications and enabling technologies of FL for smart cities.
[15]	The importance of FL in Big Data.	Focused mainly on FL for big data services and applications.
[33]	A review on integrating FL with IIoT in terms of privacy, resource and data management.	Did not focus on FL for smart cities and applications.
[34]	Highlighted the applications of FL.	Focused on different applications of FL, while the review of FL for smart cities was ignored.
[28]	Presented an extensive review of FL and its applications in IoT, Transportation, Communication and Healthcare.	Focused on FL implementations in various aspects on smart city but did not include issues pertinent to heterogeneous communication, preservation of privacy and security.
[29]	Emphasized on reviewing the role of FL in the privacy preservation of IoT devices.	Concentrated primarily on privacy preservation techniques, methods and applications relevant to FL implementation but the aspect of its plausible use in smart city was not explored.
[30]	The various enabling technologies that helped in the implementation of blockchain based FL implementation and the relevant architecture model was presented.	The primary focus was on privacy preservation application in general and smart city perspective was excluded.
[31]	The survey focused on blockchain integrated with FL applications in Vehicular (IoT) Networks.	Did not have an extensive review of versatile smart city applications while the scope of review was narrowed only to transportation.
Our survey	A comprehensive survey of FL for smart cities, societal, industrial, and technological trends driving FL for smart cities. We also discuss the concept of FL for smart city applications, including smart transportation systems, smart healthcare, smart grid, smart governance, smart disaster management, smart industries, and UAVs for smart city monitoring. We also highlight several key challenges and potential solutions to stimulate further research on this interesting topic.	–

- Navigation of cars: satellite navigation systems provide position data. As the vehicle's position is correlated with this data, the best routes are calculated.
- Control system for Traffic Signals: Modern traffic control systems work autonomously and respond to varying conditions and surroundings. Dynamic signaling systems assist in controlling traffic flow at different traffic hours.
- Automatic recognition of number plates: Vehicle registration plate images are analyzed using character recognition algorithms to read the numbers and provide vehicle location information. Law enforcement uses this data in exceptional circumstances as well as for regular electronic toll collection.
- Cameras for Speeding Vehicles: Vehicles exceeding the speed limit are detected using sensors and radar technology. A picture of the car is taken immediately and sent to the driver, preventing accidents and motivating safe driving.

The state-of-the-art FL methods for ST

FL for smart transportation has recently been the subject of several papers. Liu et al. in [35] proposed a privacy-preserving approach to predict the traffic of vehicle flow in smart cities based on FL. To predict traffic flow, the authors considered an FL-based gated recurrent unit neural network algorithm (FedGRU). Instead of sharing raw data directly among stakeholders, FedGRU updates universal learning models through a secure parameter aggregation mechanism.

Hua et al. in [36] proposed an approach based on blockchain and FL to realize collaborative ML to replace manual control with automated, intelligent control approaches in heavy haul railway systems. It is possible to perform distributed ML operations without the need for a trusted central server. In another study, Elbir et al. investigated how FL can facilitate the operation of ML-based applications in vehicular settings as well as identify future challenges and future directions [37].

In a similar setting, Yu et al. investigated the use of FL to enable proactive, mobility-aware content caching at the edge of the network [38]. The proposed content caching approach allows the network edge to dynamically add or evict content pieces based on vehicle mobility patterns. Furthermore, FL has been used to forecast the speed of vehicles while maintaining the privacy of the vehicles' current locations [39]. Manias et al. [40] discussed operation challenges and issues for the wide deployment of FL in smart transportation scenarios, while the authors also highlight the ability of an FL-based model deployed on roadside infrastructure to recover from faults by leveraging intelligence based on groups of connected vehicles. Chen et al. proposed a framework based on FL to enable elastic edge-to-cloud model aggregation from sensing data [41]. Finally, Yamany et al. proposed a quantum-based FL framework to defend against attacks in intelligent transportation systems [42].

FL for smart healthcare

Smart heathcare

Smart healthcare has evolved from IBM's "Smart Planet," first implemented in Armonk, NY, the USA in 2009. The smart planet is an intelligent framework with sensors that gather information, transmit it through the IoT, and then process it using supercomputers and cloud computing. A smart health system uses technology, including wearable devices, mobile internet, and IoT, to access information dynamically and integrate people, infrastructures, systems, and healthcare institutions. Actively managing the healthcare system and intelligently responding to all possible needs.

By analyzing their genetic makeup (genome), external appearance (phenotype), protein, and microorganism structures, ML algorithms can also detect disease early enough. Specifically, ML is used in healthcare for; (1) Health monitoring and prognosis of rare and critical diseases. (2) Imaging procedures, carcinomas, and metastases to identify anomalies earlier using various DL techniques. (3) Treatment decision support systems for transparent explanations to patients and their relatives. It also guides therapists in recommending the best therapies or surgical actions using AI tools avoiding unnecessary time delays and reducing potential risks for critically ill patients. (4) Prescribing medicine to chronically ill patients while minimizing stress and side effects.

Even though ML-based smart healthcare applications are numerous, they often suffer from various shortcomings. Its inapplicability outside of the training domain leads to biased and brittle solutions. Some of the major issues are: (1) insufficient data to develop specific algorithms, (2) implementation of research-based frameworks and technologies into clinical practice, (3) Lack of intuitive and user-friendly machine learning tools, (4) Exploitation of unreliable and unknown parameters that hinder the algorithms' generalization to new datasets, (5) Probability of adversarial attacks on algorithms, and (6) Excessively high training costs for healthcare data.

Due to scalability and privacy concerns, traditional ML techniques cannot be implemented in real-time healthcare applications due to centralized data collection.

Recent works on FL for smart healthcare

As a cost-effective and smart healthcare solution incorporating privacy protection, FL is considered a high potential and promising solution. FL is a step forward from traditional AI, as it utilizes a distributed AI approach that enables the training of AI models by averaging local updates received from various medical data clients, such as the Internet of Medical Things (IoMT) devices so that local data does not have to be accessed directly. In this way, sensitive user data and preferences are preserved and protected, preventing privacy leaks. In smart healthcare, FL is generally implemented through System Initialization and Client Selection, Distributed Local Training, and Aggregation of the model.

Scalability and generalizability are maintained with minimal loss of accuracy. Due to the elimination of the need to offload huge data volumes, network bandwidth is saved and network congestion is reduced. The study in [43] reported the implementation of a hierarchical FL system wherein the aggregation of the model was partially computed by the immediate hospitals. Also, a joint resource allocation and device association problem was created which was then solved using an iterative algorithm. In [44], the authors deployed an integrated computation and communication resource allocation framework for various FL services. This idea was motivated by scenarios wherein successful AI-based services and applications were simultaneously deployed on mobile devices and also on the network edge in the form of healthcare apps, virtual reality, and video streaming facilities. The study in [45] implemented a decentralized FL framework using a graph. In a distributed hospital setup, this system allowed local clients to include local updates and enabled peer-to-peer communication. The need to transfer the model to the remote server was eliminated, which reduced the delay in exchanging parameters and communicating among clients.

The concept of blockchain was reported in [46] integrated with a decentralized healthcare system that helped in preventing external and unsecured attacks. The authors also dissolved the need for a centralized server in hospitals or client locations wherein the IoMT devices competed with each other to perform block mining and then appended the new blocks to the local ledgers. The authors in [47] mentioned the irrelevance of raw data being sent to the central server. Also, the exchange of model updates with the huge IoMT devices lags bandwidth efficiency. The study presented in [47] proposed the fact that FL-based bandwidth-efficient frameworks ensured the privacy of data, especially in healthcare systems.

FL for smart grid

In a smart grid, electricity is supplied to consumers via a two-way digital communication system based on digital technology. By monitoring, communicating, analyzing, and controlling the electric supply chain, smart grid technologies reduce energy consumption and cost. Through the use of smart net meters, the energy supply chain can be made more efficient, transparent, and reliable, eliminating the challenges associated with traditional electric grid systems. Due to its potential to address prevalent environmental issues such as global warming, emergency resilience, and various energy-related issues, government organizations around the world are taking high initiatives to make extensive use of smart grid technology.

In smart grid implementations, artificial intelligence techniques have been popular choices. Modern power systems typically include distributed smart grid components, such as smart metering infrastructure, communication frameworks, and distributed energy sources that are further integrated with power systems encompassing huge power networks and communication systems. Since these components generate a large amount of data, AI approaches have an important role to play in such applications. Qiu et al. [48] proposed a hybrid incremental learning model that included a combination of the discrete wavelet transform, empirical mode decomposition, and random vector function link networks. Using this integrated ensemble model, short-term load forecasting in a smart grid framework was enhanced in efficiency and accuracy.

In [49], a smart grid system integrated with the CPS model was implemented. The power distribution units were the physical units of the system, and the ML module was its IT component. A multi-directional short-term memory technique (MLSTM) was used to predict the stability of the smart grid network. The study in [50] proposed an ML-based demand-side management system that helped in efficient energy usage as per preferences.

The authors in [51] proposed an ML-based energy management framework for smart grids that helped to reduce demand-side energy management issues. An efficient energy management model (EMM) was developed integrating Gaussian process regression (GPR) and ML. An optimized model for Prosumer energy surplus (PES), Prosumer energy cost (PEC), and grid revenue (GR) was used to calculate the performance parameters to be fed into the ML-based GPR system for training purposes. The proposed adaptive service level agreements (SLA) between the energy consumption and the grid benefited all the stakeholders involved. Although the use of ML in smart grids has promising benefits there are associated challenges as well. Firstly, there exists a lack of transparency in handling high-dimensional data and fulfillment of extensive memory requirements. It is also sometimes computationally expensive having very limited tolerance towards high dimensional data. Also, minor changes in data have the potential to make the implemented ML algorithm unstable. There are also issues with handling incomplete data, higher training time, and overfitting of the data.

Recent works on FL for smart healthcare

Using various mobile devices, Google proposed FL as a new paradigm for distributed learning. Both parallel and collaborative data processing can be implemented using the FL model. In each training epoch, the encrypted model updates were transferred, while the entire training data remained inside the individual devices. Data immobility and encryption ensured privacy. Electric load forecasts and energy demand predictions have been popular uses of FL in smart grid frameworks. The study in [52] proposed an FL framework in smart grids that addressed both vertical and horizontal separation of power traces. Additionally, ML models were used as an in-built learning tool. Zhuhai Power Grid in China used the framework to learn the various patterns of power consumption that helped predict collaborative power consumption. With the FL framework, the XGBoost algorithm was integrated with vertical linear regression to enhance prediction accuracy.

The authors in [53] developed a secured FL-based AI of Things (AIoT) framework for sharing private energy data in smart grids ensuring edge-cloud collaboration. In smart grids, this enabled efficient and secure sharing of user data. Additionally, non-independent and identical (non-IID) data distributions were considered and a local data evaluation mechanism was designed to address two optimization problems for energy data owners (EDOs) and energy service providers. The study in [54] evaluated the use of edge computing and FL as part of a decentralized ML scheme that helped to increase the volume and diversity of data in the training of the DL model without compromising data privacy. Based on real-time data collected from 200 houses in Texas, USA, the FL approach produced promising results. In the study in [55] an IFed framework was proposed that used an FL approach, allowing electricity to power IoT devices. Data utility, local differential privacy, and device resource consumption were all considered in the framework. ML model that transported data between electricity providers and customers was privacy-preserving. Users were categorized based on their individual needs, and sensitive users received enhanced privacy protection. Power Internet of Things users was satisfied with the model's ability to provide a secure IFed model.

FL for smart governance

The concept of smart governance refers to the use of technological innovations to improve decision-making and planning in democratic processes to provide transparency between the government and its citizens. Smart governance adapts emerging information and communication technologies (ICT) for intelligent decision-making to; (a) enhance citizens' quality of life, (b) monitor ecological aspects of the city's sustainable development, and (c) rapidly respond in cases of emergencies.

The applications of smart governance in smart cities can be visualized in the following areas:

(1) Smart e-billing systems: These types of billing management systems contain an online system that tracks the utility consumption of the consumers [56,57]. These systems save costs of manpower and reduce stationary costs. The meter value is fetched and transmitted to a central database. The report generation allows consumers to plan the usage of the utility. Moreover, these automated systems get rid of human error inaccuracy.

(2) Smart waste management: These systems are useful in managing waste in smart cities. Emerging computing and ICT technologies are used in providing a cleaner and healthier environment in the smart city. These systems are useful in locating the places of heavy waste, providing a map to the garbage collecting van, predicting future waste in specific areas, and monitoring the current state of waste in the city. This in turn helps inefficient waste management, reduction of manpower, reduction in fuel cost, planning the number of garbage collectors, and estimating the time of high waste production in the city [58–60].

(3) Smart bureaucratic governance: This approach allows the drafting and implementation of different policies and programs of the government simple, accountable, and transparent along with reducing hierarchical barriers. Moreover, it enables enhanced delivery of services by improving citizen participation, accountability, transparency, and administrative processes. This, in turn, brings automation of government processes, delivery of better QoS, reduction in procedural delay, integrity in administrative culture, accountability in services, empowerment in social development and effective strategic decisions [61–63].

Geng et al. [64] proposed an FL service system that provides flexible, reliable, and credible distributed access management using blockchain technology. Service access control is mainly based on a claim-based distributed identity management system integrated with blockchain technology. The identity scheme intelligently assists users in applying for digital identities as well as preventing misuse of the service. Furthermore, blockchain technology reduces human error and manual authorization processes.

In another work, Yin et al. [65] proposed an FL scheme to secure data collaborations for big data with private and public data centers along with a blockchain system. Data transmission outside the private cloud is not required since computations on multiparty data are performed on-premise. On the one hand, blockchain systems track multiparty communications to address security and privacy concerns, while on the other hand, FL paradigms address the concerns associated with large-scale multiparty collaborations. Lu et al. [66] proposed an FL-based model using DTs to make the communication between edge servers and end-users more reliable. A blockchain-enabled FL framework enhances the system's reliability, security, and privacy. DT association, training batch size, and bandwidth assignment form an optimization problem of edge association. Exploring multi-agent reinforcement learning provides an optimal solution to this problem.

FL for smart disaster management

As a result of smart disaster management, quick and effective responses can be provided during disasters such as earthquakes, floods, blizzards, tsunamis, cyclones, wildfires, and pandemics. It employs state-of-the-art paradigms and technologies for; (a) reducing action response time during disasters; (b) rapidly monitoring citizens' health during pandemic situations; (c) making intelligent decisions to effectively manage disaster scenarios.

The applications of smart disaster management in smart cities can be visualized in the following areas:

(1) Smart crowdsensing: Smart crowdsensing is an extremely powerful ubiquitous weapon during disaster management. One can address specific QoS requirements in extreme situations using embedded sensing technologies in smart mobile devices. Additionally, autonomous crowdsensing can be performed anytime and anywhere with reduced cost and rapid deployment [67–69].

(2) Hazardous zone detection: Detecting hazardous zones has become efficient in recent years due to the rich growth of technology. Enhanced image vision techniques applied to aerial images can accurately detect hazardous areas and their boundaries. These powerful hazardous zone detection methods require less human interference [70,71].

(3) Disaster prediction: Future disaster occurrence can be predicted by conducting risk analysis based on the occurrence, characteristics, and impacts of historical disastrous events. Thus, knowledge-based methods help in correlating the past events with the present scenario and thereby, help in predicting future disasters which in turn, save the all-important human lives and critical resources [72–74].

(4) Smart pandemic management: While pandemics such as COVID-19 (SARS-CoV-2) have shaken up the world, researchers have come up with different techniques for managing such epidemics. These techniques can help in monitoring patients' risk gradients, predicting health, predicting death rate, and efficiently strategizing further modes of action. This, in turn, helps in planning the country's critical healthcare resources and thereby saving human life [75–77].

Even though ML techniques can provide notable contributions in managing the disaster, they have the following limitations: (1) Gathering and processing data using mobile crowdsensing not only face privacy issues but also post a vital issue of communication overhead. (2) Operating on images with ML or CNN algorithms sometimes crashes the system even after the employment of dedicated high-end resources. (3) Central operations on complex big data raise latency issues and security issues. (4) Operating on pandemic data with ML algorithms can lead to privacy concerns, while operating on images may raise resource management issues. The potential of FL can be greatly explored by incorporating it with smart disaster management. We discuss below some of the recent state-of-the-art on FL applications for smart disaster management.

Chhikara et al. [78] presented an FL-based scheme to detect hazardous zones in a specific search space by monitoring the air quality index (AQI). FL incorporates swarm intelligence. It is suggested to integrate CNN-LSTM models with unmanned aerial vehicles (UAVs) for faster outcomes and minimal energy consumption. A given search space's AQI can be reliably and accurately forecasted using the proposed scheme.

In the other work, Wang et al. [67] proposed a secure FL framework for UAV-assisted mobile crowdsensing where a blockchain-based distributed approach is used for securely transmitting local updates and validating data without a centralized entity. Furthermore, a differentially private algorithm is proposed to preserve the privacy of shared local models. With reinforcement learning, the framework works efficiently and reliably in extremely uncertain situations. As a result of the proposed framework, efficient model sharing, optimal strategies, and reliable privacy preservation are demonstrated.

Feki et al. [79] developed and validated a collaborative and decentralized FL framework that allows several institutions to detect COVID-19 disease using chest X-ray images using DL. Sharing rich private data while preserving the privacy of sensitive patient information is possible with the proposed framework. The results show the significance and robustness of the proposed work in pandemic situations such as COVID-19. Ahmed et al. [80] proposed an active-learning-based FL framework for disaster image classification. The work shows how FL can prove beneficial in building a global model to manage unlabeled data at local nodes using active learning. Through extensive experiments, the authors show that the active-learning-based FL framework provides significant improvement in the classification of disaster images.

FL for smart industries

Around the world, especially in developed countries, Industry 4.0 is revolutionizing industries. The technological aspects of smart industries help in: (a) significantly reducing manpower; (b) greatly improving manufacturing efficiency; (c) increasing accuracy during product manufacturing; (d) improving resilience by forecasting a technical glitch.

The applications of smart industries in smart cities can be visualized in the following areas: (1) Smart manufacturing: These types of systems can bring complete transition in the manufacturing processes. This can bring operational analytics and revolutionize manufacturing efficiency. Additionally, this can help in developing equipment models for predictive maintenance. Thus, smart manufacturing automates industrial processes, improves efficiency, brings higher accuracy, and requires less manpower [81–83]. (2) Resource optimization: Smart industries can lead to optimization of communication as well as computation resources efficiently and robustly. This can help in optimizing transmission power, delay, computational cost, communication overhead, and energy. This, in turn, reduces the overall cost of smart manufacturing processes. Additionally, it helps in addressing the global warming challenges [84] [85]. (3) Failure prediction: The issue of defective products is one of the major concerns in manufacturing processes. Failure prediction systems can help in forecasting a glitch on the production line and thus, can drastically reduce the rate of failures. This, in turn, reduces production cost, increases production line robustness, and improves the overall resilience of the system [86–88].

ML methods can be very effective in smart industries which require working on big and complex data: (1) ML is proven as a potential paradigm for automating industrial processes in CPSs, improving product accuracy, and performing operational analytics of the processes based on the historically collected data. (2) Based on the past data in ML-based optimization techniques, product optimization can be performed along with resource optimization. (3) ML prediction algorithms incorporated in a predictive system can make the production system robust by improving resilience in manufacturing. While ML methods can play a major role in smart industries, they have the following limitations: (1) Operational analytics and predictive maintenance need collection and computation of big data which induces huge communication overhead along with privacy issues. (2) Resource optimization algorithms can sometimes cause the failure of the system due to heavy computation on a single machine. Additionally, it may cause cyber security concerns along with high communication overhead. (3) ML algorithms for predicting system/network failures can cause high computation overhead on a single machine. The incorporation of FL with smart industries can tremendously help the growth of a city. We discuss below some of the recent state-of-the-art on FL applications for smart industries.

Hao et al. [82] proposed an efficient and privacy-enhanced FL mechanism for handling sensitive data in industries such as healthcare and autopilot. In the presence of an adversary colluding with several benign entities, the proposed work provides improved privacy protection. Further, the mechanism provides improved aggregation oblivious security against collusion attacks. To address cognitive computing issues such as privacy leakage, inefficiency, and unreliability, Qu et al. [89] proposed a distributed framework integrating FL with blockchain. FL addresses efficiency and privacy issues, whereas blockchain addresses security issues like poisoning. Extensive experiments demonstrate the reliability and significance of the proposed approach in Industry 4.0. Khan et al. [84] devised a novel communication resource-optimization scheme based on a dispersed FL framework. Hierarchical decentralized schemes are proposed to optimize FL costs while introducing robustness to industrial systems. Several experiments show that the proposed scheme can be used for smart industrial solutions while protecting privacy.

Ge et al. [87] designed two distinct FL algorithms to show the applications of FL for intelligent manufacturing. Algorithms designed for production lines can predict failures. In addition to improving resilience, the proposed approach also enhances robustness and privacy protection. Liu et al. [90] carried out a literature review on FL for 6G communications. FL can be particularly useful for wireless applications to achieve ubiquitous and secure intelligence in 6G networks. It can be used for remote surgery, virtual events, holographic experiences, and decentralized infrastructure.

FL for UAV for smart city monitoring

In the context of smart city monitoring, several papers have been published on FL for UAVs. Zeng et al. in [91] proposed a framework for distributed FL in UAV swarms to identify obstacles and exploit common trajectories. UAVs train local FL models based on the data they collect, and then forward them to the leading UAV, which aggregates the data, generates a global model, and sends it to the following UAVs over the network created by the swarm of UAVs.

Zhang et al. in [92] studied the creation and use of networks of UAVs in the context of various applications, including smart city monitoring. In this context, FL is applied to reduce the communication cost and complexity between UAVs and ground fusion centers. Liu et al. proposed the use of FL on UAVs for the estimation of the Air Quality Index (AQI) in smart cities [93]. This is achieved through end-to-end learning from haze features of images taken by UAVs. Furthermore, Wang et al. proposed the use of FL on UAVs for mobile crowd-sensing [94]. Ng et al. discussed the use of UAVs as wireless relays to facilitate the communications between vehicles in smart cities and FL servers, thus improving the accuracy of the FL process [95]. Finally, Lim et al. suggested the idea of drones-as-a-service and the adoption of FL to enable privacy-preserving ML across a federation of drones-as-a-service in the context of the Internet of Vehicles (IoV) applications [96].

FL on smart buildings

Buildings today are more than just structures. As well as the technologies and systems that are available within it, customers can modernize and choose basic amenities like illumination, safety, warming, ventilation, and conditioning systems, as well as entertainment. In these applications, sophisticated technologies and energy saving should be given a higher priority. Due to both direct and indirect carbon emissions from high-energy buildings, society's ultimate focus is to achieve sustainable smart urbanization. Housing and construction account for 25%–35% of worldwide energy consumption, according to studies. To achieve energy efficiency and a cleaner environment, an intelligent building or residence is the only solution. To protect ourselves from strange happenings, we need a security system [97].

IoT can be used to implement an intelligent monitoring system by supplying CCTV images of various private spaces, which are then analyzed and assessed using sophisticated communication and processing technology. Despite their ability to reduce costs, carbon emissions, and energy waste, energy management systems have certain flaws, including their high cost, the difficulty of operation, and limited servicing options. Thus, smart buildings using modern IoT and big data analytics can benefit from improved power consumption. In many nations, especially in India, water scarcity has become a significant threat. As a result, water management systems are vital to preserving water resources. Using an IoT measurement system, a computerized method also helps estimate water consumption. Smart lighting is a critical characteristic of a smart home's appearance, feel, and functionality [98].

Commercial illumination systems can be selected based on design requirements, inhabitant conveniences, and interests. When fires occur, they can be catastrophic since residents are unaware of the situation and do not have time to evacuate. Using smart IoT technology, smart alarm systems can be implemented in smart houses, which provide notifications of unexpected precarious conditions, prompting people to leave or take appropriate action to put out the fire. Tracking senior members is essential to preserve them in effective communication with their smart home for tracking sickness, food, emergency calls, and other behaviors using smart devices, IoT, and enhanced wifi sensors [99].

Fig. 1 depicts the FL model training infrastructure. The system is composed of four layers: stakeholders' layer, ML models layer, interaction layer, and cloud computing layer. Stakeholders store data locally, but never transmit confidential information to the remote server or other stakeholders. Each member trains an ML model using their data. The energy usage patterns of buildings should also be quite diverse if their attributes are significantly different. To train a federated model, only vital information from identical buildings is used. Stakeholders and the cloud platform communicate information among ML models and the federated model through the interaction layer. A cloud computing layer stores the federated model [100,101].

Limitations of FL for applications

The limitations of FL applications are as follows:

- Providing adequate security in FL environments is challenging due to the collection of sensitive data related to people, vehicles, governments, and organizations.
- When performing real-time analytics in FL, poor decision making due to latency can reduce system throughput.
- Several challenges face FL systems, including increased latency, connectivity, bandwidth, and data migration.

Research projects and use cases

The purpose of this section was to discuss key research projects and use cases related to FL and its relevance to smart cities. Table 2 highlights the Contributions of global-level ongoing Projects concerning various technologies and applications.

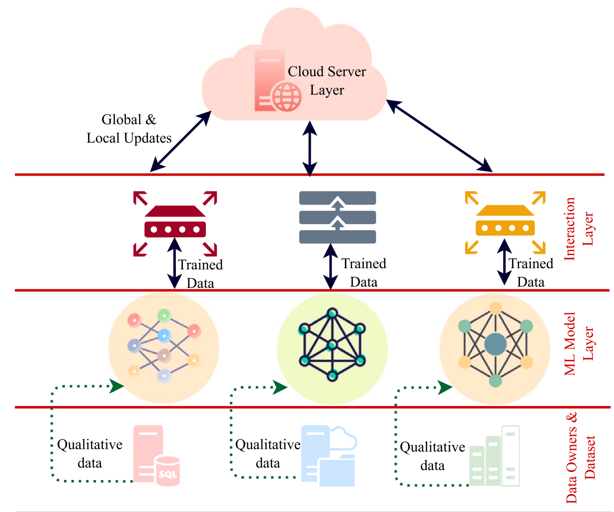

Fig. 1. Infrastructure of FL model training.

European Union (EU) projects

In the context of FL, the European Union has proposed several funding schemes and has a few ongoing projects.

FeatureCloud. The FeatureCloud project is primarily focused on developing FL methodologies for healthcare. For ease in aggregating data, FeatureCloud designs privacy preservation methodologies based on FL. Due to the rapid development of novel attack vectors, a privacy-preserving distributed system is required to prevent a variety of attacks. To minimize cyber threats in the design of secure smart city solutions, the FeatureCloud project applies the transformative security concept. The project is funded by the EU under the Horizon2020 framework [102].

IoT-NGIN. Under the H2020 Horizon scheme, IoT-NGIN is an EU-funded project widely referred to as European Next-Generation IoT for smart cities. As part of the IoT-NGIN project, meta-architectures for future IoT technologies are designed, as well as the concept of a European Next Generation Internet is envisioned. Using edge computing paradigms, the IoT-NGIN project optimizes existing IoT/M2M architectures and integrates 5G and beyond technologies. A privacy-preserving autonomous IoT system can be designed using FL and ambient intelligence methodologies. The project also envisions the concept of distributed IoT infrastructures integrated with meta-DTs [103].

Marvel. Fog and Edge-enabled pervasive and ubiquitous computing framework integrated with FL and AR/VR technologies. Marvel provides audiovisual data processing, multimodal learning, and smart city services to improve citizens' quality of life. It will also assist expert decision-makers in taking real-time decisions about traffic management, healthcare service management, protection against cybersecurity attacks, and many more. Marvel is an EU-funded project under the H2020 horizon scheme [104].

AI4HealthSec. AI4HealthSec is an EU-funded project under the Horizon 2020 program. The AIHealthSec solution integrates state-of-the-art federated machine learning methodologies with privacy and security features. In addition, it has built a large database of new cybersecurity threats and risks. Additionally, the project provides insights into integrating healthcare solutions with ambient technologies and ICT infrastructures, as well as privacy and security risk awareness for smart cities. Furthermore, AI4HealthSec is responsible for providing reliable and secure incident awareness and information to the citizens of smart cities [105].

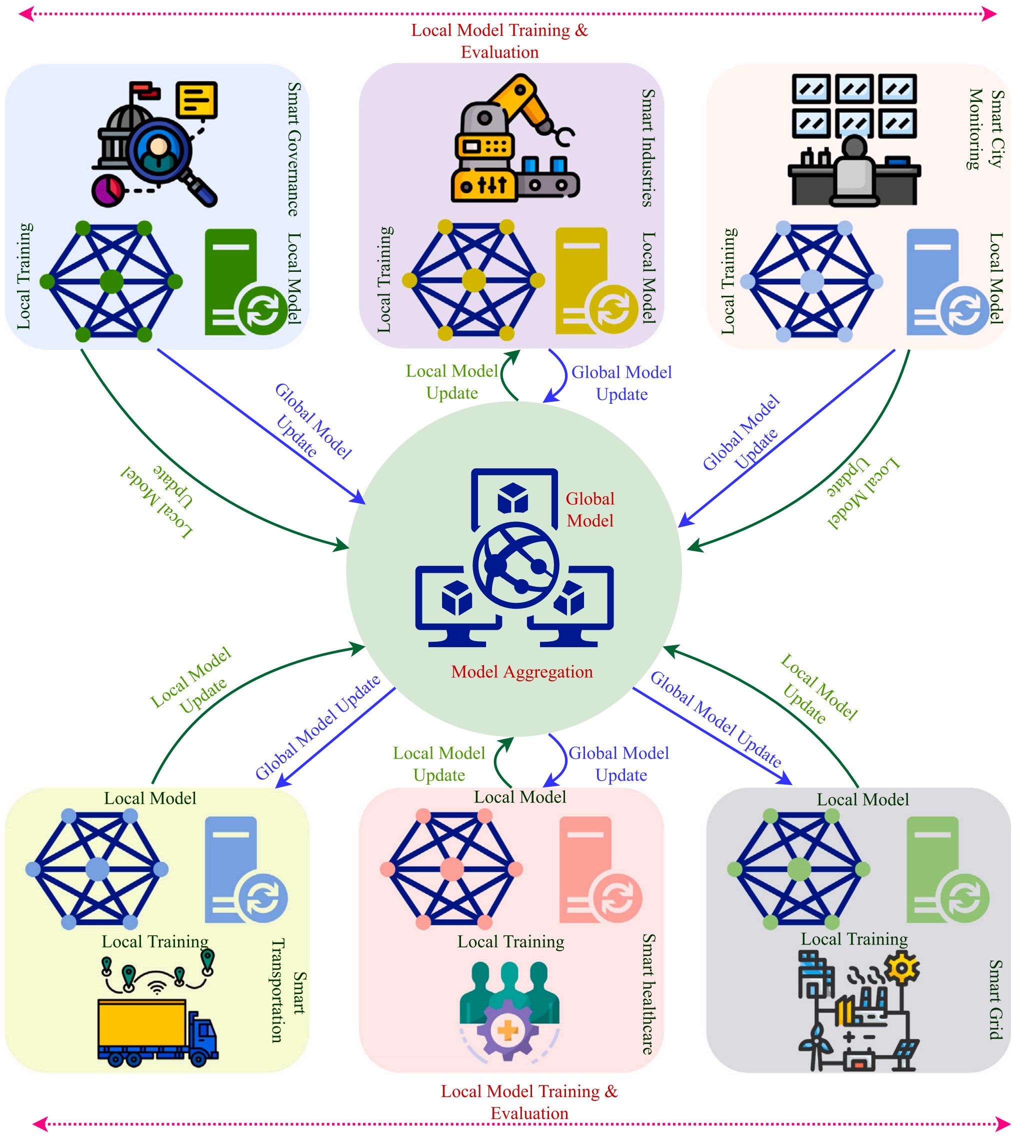

Fig. 2. FL for smart city applications.

MUSKEETER. MUSKEETER is a European Commission-sponsored project that aims to create a FL platform for industrial data. The MUSKEETER aims to create new ways to enable trust and security among data owners. Additionally, MUSKETEER aims to provide safe, secure, and privacy-protected advanced data analytics for a variety of industry scenarios, such as health and manufacturing. MUSKETEER builds numerous ML models for security and privacy scenarios, and trust and reliability enabled extendible architecture and infrastructure for fulfilling real-world industry demands [106].

GECKO. GECKO, an EU-funded project under the Marie-Curie scheme, is dedicated to designing and developing FL and explainable AI-enabled transparent ML models to envision green and sustainable smart cities. In GECKO, social and ethical practices are incorporated into federated AI algorithms to mitigate threats in poorly designed machine learning models. It is responsible for providing trustworthy, scalable, reliable, privacy-preserved, secure, and green solutions for smart cities [107].

INCISIVE. INCISIVE integrates a healthcare repository with a multi-modal AI toolbox. It is an EU-funded 42-months project, also known as “AI for Health images”. It is a large collection of federated repository of medical images. It has been designed to provide secure, ethical, transparent, and legal sharing of medical images. It also aims to design an AI toolbox for cancer classification and diagnosis which is integrated with FL and automated ML annotation methodologies. This platform provides 24 × 7 accessibility to medical datasets and allows access to experimentation-based AI-based methodologies [108].

GAIA-X. GAIA-X is designed for Europe and beyond. This project aims to create a trustworthy and secure data infrastructure for various industries and research organizations. Various sectors such as politics, science, health, business, transportation, and many others have collaborated on the project to design privacy-preserving, scalable, transparent, and decentralized data-sharing platforms. The industries and smart city citizens can also take control of their data and can also access the real-time status of the shared data [109].

Other projects and programs

Various projects and programs related to FL and its relevance to smart cities are highlighted in this section.

D3M. D3M (Data-Driven Discovery of Models) is a DARPA (Defense Advanced Research Projects Agency) funded program that automates ML model discovery. With the D3M program, non-technical experts can

Table 2
Contributions of global-level on-going projects.

Projects	Integration of FL with technologies										Integration of FL with applications										
	Explainable AI	Edge computing	Fog computing	5G and Beyond technologies/DLT	Blockchain	Industrial IoT	Augmented reality/Virtual reality	Industry 4.0	Mist computing	Quantum communication	Smart transportation	Smart healthcare	Smart governance	Smart grid	Smart disaster management	Smart cars	Smart industries	Smart traffic management	Smart buildings	Smart environment monitoring	Smart agriculture
EU projects																					
Feature cloud	✓	✓	✓	✓		✓		✓	✓	✓	✓		✓	✓			✓			✓	✓
IoT-NGIN	✓	✓	✓		✓						✓				✓		✓		✓		
Marvel		✓		✓		✓								✓	✓						
AI4HealthSec		✓	✓			✓					✓			✓	✓						✓
MUSKEETER	✓	✓	✓		✓	✓			✓		✓			✓	✓						
GECKO	✓	✓			✓		✓		✓				✓	✓	✓	✓	✓		✓		✓
INCISIVE	✓	✓			✓		✓		✓	✓	✓		✓	✓	✓	✓	✓		✓		✓
GAIZ-X	✓	✓	✓					✓							✓		✓	✓			
Other projects																					
D3M	✓	✓		✓		✓			✓	✓	✓		✓	✓	✓	✓	✓			✓	✓
LEAP	✓	✓		✓					✓	✓	✓	✓	✓	✓	✓	✓	✓				✓
FEDSCALE	✓	✓	✓					✓	✓		✓		✓	✓	✓	✓	✓		✓	✓	✓

easily execute complex empirical ML models. A person without a data-science background can execute machine and deep learning models with D3M's open-source ML tools.

Leap. University of British Columbia (UBC) researchers designed a privacy ML-based project called Leap with support from DARPA. For a variety of healthcare domains, the project aims to develop privacy-enabled, secure, transparent, and scalable systems. Endometriosis and pathology are the areas of focus for the project.

FedScale. FedScale is an FL evaluation platform designed by researchers at the University of Michigan. Benchmarking datasets for FL use cases are available on the platform. Various FL metrics can be executed on various CPUs/GPUs with the fee scale. Real-world FL deployments and privacy-preserving secure practices are the focus of the project.

AI and Mobility Lab develops one-shot learning-based FL platforms in countries such as South Korea. Samsung Medical Center has developed a clinical benchmark data platform for monitoring and evaluating FL algorithms. An Australian university has funded a project titled "federated competitive collaborative platform". The platform contains secret proprietary information from various Australian industries.

Lessons learned, open issues, challenges, future directions

FL can be used for a variety of smart city applications in this section. In addition, lessons learned from previous sections, challenges, and future research directions are discussed.

How FL has been helpful for smart city-based applications

FL can be a critical paradigm in smart city applications. We can summarize the following advantages of FL: (1) As a centralized server takes care of only local updates, the local data can be kept secure on the local devices. (2) FL can efficiently develop a secure, reliable, and sustainable system as per the General Data Protection Regulation (GDPR). (3) As data offloading to the server is tremendously reduced with FL, it reduces communication overhead and thereby saves bandwidth usage. (4) FL techniques integrated with DT paradigms can collect knowledge and patterns from various DTs and develop a global perspective in case of crisis management in any smart city applications. And (5) FL can be integrated with metaverse wherein the training of the AI model for various smart city applications can be performed on their local device before transferring the parameters or the gradient updates instead of transmitting the raw data. This would preserve privacy at the same time enhance the computational capability of the users.

What are the issues that have to be addressed to realize the full potential of Fl in smart city-based applications

To realize FL's full potential in smart cities, several issues must be addressed. Since FL-based solutions may run on resource-constrained devices, one of them is related to their energy efficiency. Security and privacy issues are also challenges, as we discuss further in this section. Additionally, there are still issues with FL algorithms' performance, data availability, and regulatory compliance. This section discusses all of these issues in detail.

Challenges and future directions

Since 2016, FL has continuously evolved and raised numerous challenges and issues, including privacy, security, interfacing, storage, exchange, etc. New challenges provide new opportunities for fellow researchers and motivate them to design and develop innovative methodologies and solutions. Several research challenges and open issues related to FL are discussed in this section, as well as possible alternative solutions.

Privacy issues in FL

As a result of privacy concerns, users tend to keep raw data on their local systems. During the training of the model, sensitive information of users may be disclosed to the main server where all raw data resides. To achieve privacy in FL integrated systems, methods such as differential privacy (DP), model aggregation FL, and secure multiparty computation (SMC) are used. Nevertheless, these privacy techniques are also subject to challenges, such as latency, efficiency, and performance degradation. Researchers have recently proposed integrating existing cryptography techniques with DP concepts. Nevertheless, these methodologies also suffer from individual-like challenges such as malicious third-party attacks, passive and active security attacks, etc.

Possible Alternative Solutions and Future Research Directions: It is generally our goal to address privacy challenges from both a local and global perspective. It is time to analyze and discuss granular privacy constraints and issues. Different devices, frameworks, and networks present different constraints and issues. Eventually, fellow researchers will be able to analyze proposed methodologies taking into account all levels of privacy concerns and constraints.

Security issues in FL

Even though FL protects the centralized server from a variety of attacks. Moreover, it exposes users to issues such as information leakage. Attackers can attack FL systems by poisoning, presenting, etc. Additionally, leakage of information may occur due to the vulnerability of algorithms such as gradient descent, which may leak sensitive information of users and expose the FL ecosystem to attackers. In addition, the defence mechanisms of FL systems need to be gradually improved to protect both centralized and distributed systems from a variety of security threats.

Possible Alternative Solutions and Future Research Directions: Researchers need to address the security concern of FL systems immediately. FL has been combined with Blockchain, cyber twin, and DT concepts in some research. Furthermore, FL ecosystems can be addressed by techniques such as privacy-preserving collaborative learning. Nevertheless, it is high time that the research community begins discussing these rudimentary issues and constraints and proposes suitable solutions and directions for the future.

Issues related to big and complex data

It is challenging to process big and complex data for a specific application due to their volume and complexity. Additionally, users must be able to understand noisy data. It becomes even more challenging when data are received from different sources and in different formats. Furthermore, the rate at which the data is created adds to the aforementioned challenges. Thus, the processing of such big and complex data is one of the major issues for FL solutions.

Possible Alternative Solutions and Future Research Directions: Handling high volume data with high velocity and diversity is a challenging issue. To address this issue, the pre-processing stage should be given higher importance. Additionally, small participants can be discovered who can effectively participate in building the training dataset. Furthermore, it is imperative to reduce redundancy in algorithms [14]. Furthermore, approaches such as geotechnical engineering and explainable AI (XAI) would assist in handling different types of complex data.

Issues related to performance of FL algorithms

Although FL algorithms have shown great promise in integrating distributed devices, they are not optimized to take into account limited computational resources. In addition, massive amounts of complex sensory data and high-velocity traffic have become major challenges for IoT. As a result, time complexity and optimization of algorithms have become key issues to realize practical FL solutions.

Possible Alternative Solutions and Future Research Directions: Optimization of FL algorithms is a burning issue. FL algorithms must be highly efficient by considering diverse aspects. Some promising future directions include: (a) how to optimize FL algorithms considering multiple constraints such as computational resources, transmission power, and local model accuracy [110]; And (b) how to ensure high performance while still taking into account the diversity, velocity, and quality of sensory data of IoT devices to enhance decision making by the algorithm.

Statistical heterogeneity in FL

FL has enormous potential in enabling smart sensing and smart city applications [111]. With FL, models can be trained with information from various disciplines, such as healthcare, smart manufacturing, transportation, and security. The biggest challenge for FL systems is dealing with heterogeneous systems with distributed data.

Possible Alternative Solutions and Future Research Directions: However, the research in this domain is in the infancy stage and requires the immediate attention of domain experts to propose innovative solutions. Researchers can consider integrating XAI with FL to address this issue of heterogeneous data.

Communication overhead in FL

There have been several approaches proposed for addressing communication overhead issues, including multi-channel access. Despite this, handling communication overhead and heterogeneous characteristics of data and systems remain open research questions.

Possible Alternative Solutions and Future Research Directions: The fellow researchers have tried to address communication overhead issues using methods such as sparse gradient, compressing gradient, and quantization [112]. However, identifying irrelevant network updates and preventing them from being uploaded would address the overhead issues for smart city applications.

Availability of data

For smart city applications, FL systems require enough data to train the model and achieve reasonable accuracy. Currently, FL systems suffer from data limitations.

Possible Alternative Solutions and Future Research Directions: To resolve issues such as limited data availability, fellow researchers can combine Big data-like methodologies with FL.

Regulatory compliance

FL approaches are evolving and transitioning with current technologies such as explainable AI, IoMT, Big data, Blockchain, etc. Developing suitable rules and regulations has remained an open research question.

Possible Alternative Solutions and Future Research Directions: Government authorities will be able to envision appropriate policies for combining FL with smart cities applications in the future.

FL for 5G and beyond technologies

The inclusion of heterogeneous smart devices in 5G and beyond networks increases computation complexity, as well as privacy and security concerns. As a result, FL systems can increase the scalability of training data and assure the security and privacy of sensitive user data. The fog and edge computing technologies enable FL to integrate with 5G and beyond technologies and provide resolution to issues such as computational complexity by processing the client data at the periphery of the network. Additionally, these technologies address resource-sharing issues by providing a few essential services at the edge.

Possible Alternative Solutions and Future Research Directions: By integrating deep reinforcement methodologies with FL systems, we can design and develop optimized solutions to achieve convergence and good accuracy [113].

Estimation deviation and energy-saving issues in FL integrated DT systems

Technology has paved the way for Industry 5.0, which enables collaboration between robotics and humans within a hyper-connected framework. Cybersecurity threats are associated with this process as it ensures automation and seamless information exchange across the business pipeline. These threats can be resolved using FL implementations which would provide privacy preservation during information exchange and local data processing. In a smart city setup, automation is inevitable, and individuals are invariably dependent on the collaborative work of robots and smart machines. By using technologies like IoT and big data, people can work better and faster. Thus, all of these frameworks are vulnerable to privacy risks, and FL is a plausible solution.

To envision Industry 4.0 and 5.0 advantages, the FL integrated DT solutions can be implemented to assist FL systems. The integration of DT with FL systems increases the possibility of deviations due to the deviations from the actual values of smart devices. This issue can be resolved using a trusted aggregation technique in FL that would help in the reduction of such deviations. The aggregation frequency of the FL can be tuned accordingly considering a Lyapunov dynamic deficit queue integrated with deep learning. This would help in enhancing the performance of the FL framework [114]. In addition to this, energy saving in DT integrated IoT systems is also a challenging issue.

Possible Alternative Solutions and Future Research Directions: With an adaptive clustering-based asynchronous FL approach, it will be possible to handle heterogeneous devices and deviations in FL integrated IIoT systems, and achieve high accuracy, energy efficiency, and convergence [114].

Conclusion

Recently, FL has emerged as an extension of distributed machine learning and is capable of contributing to the transition of smart cities and their applications. The latest trends and technologies, such as AIoT, Big Data, Fog, and Edge Computing, have created issues related to the protection and leakage of sensitive information in smart city applications. By integrating FL with smart city applications, sensitive information can be protected and preserved. In this paper, we presented a comprehensive survey on the state-of-the-art methodologies for FL for smart cities, various key enabling technologies, and FL integrated smart city applications. FL for smart cities was discussed in depth in the presented detailed study. Moreover, we highlighted the societal, industrial, and technological trends that drive FL for smart cities. Several FL-integrated smart city applications, including smart transportation systems, smart healthcare, smart grid, smart governance, smart disaster management, smart industries, and UAV for smart city monitoring, as well as possible alternative solutions, research enhancements, and current research developments, were discussed. As part of the presented review, data leakage and privacy issues were discussed for smart city applications such as smart transportation, smart healthcare, smart grid, smart governance, smart disaster management, smart industries, and UAVs for monitoring smart cities. Moreover, we discussed recent and future FL for smart cities projects, such as EU projects, DARPA projects, and industry and research projects. Lastly, we analyzed various research challenges and prospects for the technology development of FL for smart cities. Future research can examine FL's key enabling technologies in terms of security and privacy, as well as its applications.

The major contributions and concluding remarks of this survey are as follows:

- We firstly present a detailed introduction to FL and its advantages for a smart city.
- Secondly, we survey the importance of FL for several smart city applications including smart transportation systems, smart healthcare, smart grid, smart governance, smart disaster management, smart industries, and UAV for smart city monitoring.
- Thirdly, we discuss several reputed EU and DARPA smart city-based projects and use cases that use FL.
- Finally, we discuss several challenges and open issues of FL for smart city applications along with future directions for readers.

CRediT authorship contribution statement

Sharnil Pandya: Conceptualization, Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Gautam Srivastava:** Conceptualization, Investigation, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Rutvij Jhaveri:** Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **M. Rajasekhara Babu:** Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Writing – original draft, Writing – review & editing. **Sweta Bhattacharya:** Investigation, Formal analysis, Writing – original draft, Writing – review & editing. **Praveen Kumar Reddy Maddikunta:** Conceptualization, Supervision, Validation, Writing – original draft, Writing – review & editing, Visualization. **Spyridon Mastorakis:** Investigation, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Writing – original draft, Writing – review & editing. **Md. Jalil Piran:** Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Thippa Reddy Gadekallu:** Conceptualization, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

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