Federated Learning: A Cutting-Edge Survey of the Latest Advancements and Applications

Azim Akhtarshenas^a, Mohammad Ali Vahedifar^a, Navid Ayoobi^b, Behrouz Maham^c, Tohid Alizadeh^d, Sina Ebrahimi^e

^aDepartment of Electrical and Computer Engineering, University of Tehran, Tehran, Iran ^bDepartment of Computer Science, University of Houston, Houston, TX, USA ^cDepartment of Electrical and Computer Engineering, Nazarbayev University, Astana, Kazakhstan ^dDepartment of Robotics and Mechatronics, Nazarbayev University, Astana, Kazakhstan ^eCentre for Future Transport and Cities (CFTC), Coventry University, Coventry, UK

Abstract

Oppose Abstract

 In the realm of machine learning (ML) systems featuring client-host connections, the enhancement of privacy security can be effectively achieved through federated learning (FL) as a secure distributed ML methodology. FL effectively integrates cloud infrastructure to transfer ML models onto edge servers using blockchain technology. Through this mechanism, it guarantees the streamlined processing and data storage requirements of both centralized and decentralized systems, with an emphasis on scalability, privacy considerations, and cost-effective communication. In current FL implementations, data owners locally train their models, and subsequently upload the outcomes in the form of weights, gradients, and parameters to the cloud for overall model aggregation. This innovation obviates the necessity of engaging Internet of Things (IOT) clients and participants to communicate makes that additional research is imperative to address lingering knowledge gaps and effectively confront the intervorks but also enhances the protection of private data. This survey conducts an analysis and effectively confront the forthcoming challenges in this field. In this study, we categorize recent literature into the following clusters: privacy protection, resource allocation, case study analysis, and applications. Furthermore, at the end of each section, we tabulate the open areas and field.

 Keywords: Artificial intelligence, 6G, Machine learning, Federated learning, Deep reinforcement learning, Neural network, Internet of Things, Edge computing, Block-chain, Privacy preserving, Resource allocation

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 Netrotetion The superational capacity, necessitato and storing data in proximity to the IoT clients [1] In the realm of machine learning (ML) systems featuring client-host connections, the enhancement of privacy security can be

aggregate, store, and analyze the entirety of data generated by these devices. However, over the forthcoming years, the extensive proliferation of smart devices and the exponential surge in data traffic have posed substantial challenges in centralized and decentralized systems for both 5G and preceding generations of wireless communication networks. They encountered a significant latency in efficiently processing, storing, and transmitting the immense volume of mobile data, particularly in ultra-dense networks, owing to bandwidth constraints. In order to alleviate this latency and reduce the communication burden, edge servers were introduced as intermediate computational entities positioned between the central server and Internet-of-Things (IoT) devices. These edge servers are tasked with executing computa-

improved performance, higher quality of service (QoS), and enhanced quality of experience (QoE) within IoT-based mobile networks [3], [4]. The integration of Artificial Intelligence (AI) and Machine Learning (ML) into 6G networks offers enhanced network management orchestration performance by autonomously addressing optimization challenges. As an example, AI can enhance network power efficiency by dynamically activating and deactivating components in response to real-time operational conditions, thereby eliminating human-induced errors. Within the realm of AI model training, Federated Learning (FL) emerges as a promising technique that facilitates distributed learning. Employing a distributed framework, FL seeks to enable localized data training on users' devices, subsequently

transmitting solely model parameters to the server to safeguard against the potential exposure of sensitive raw data to untrustworthy servers [5].

1.1. AI and 6G Networks

AI has firmly embedded itself as an indispensable facet of home life, industrial, and academic environments. The pervasive influence of ML algorithms and techniques is discernible in the entirety of wireless networks, extending from smart cities to remote patient monitoring and smart robots. The incorporation of ML methods into the IoT and edge infrastructures has empowered the next generation of communication networks to exhibit ultra-reliable characteristics with reduced latency. ML models possess the capability to analyze link Signal-to-Noise Ratio (SNR), loss rate, delay, and packet loss in 6G and subsequent generations. Additionally, ML plays a crucial role for enhancing network efficiency, responding to the escalating network burdens caused by the proliferation of interconnected devices resulting from recent technological advances in wireless networks. In the context of traditional cloud-based machine learning services, the development process entails the central gathering of training datasets. Nonetheless, this training methodology confronts two primary concerns: 1) expensive communication and energy costs, and 2) compromised data privacy. In [6], the authors presented a comprehensive explanation of the foundations and supporting technologies of FL as a solution to the aforementioned issues. They also introduced a recently developed approach to bringing ML to edge servers. Baccour et al. [7] provided a unique platform architecture that deploys a zero-touch pervasive artificial intelligence (PAI) as a service (PAIaaS) in 6G networks, leveraging a smart system founded on blockchain technolog. Their platform is designed to standardize the integration of PAI at every architectural level and unify the interfaces, with the goal of facilitating service deployment across diverse application and infrastructure domains, alleviating user concerns regarding cost, security, and resource allocation, and concurrently meeting the rigorous performance criteria of 6G networks. Furthermore, they introduced a federated-learning-as-a-service use case as a proof-ofconcept to assess the capacity of their suggested system. Their model exhibits self-optimization and self-adaptation, aligning itself with the dynamic behaviors of 6G networks, thereby reducing users' perceived costs. The authors in [8] conducted a thorough analysis of AI-assisted 6G network slicing (NS) for network assurance and service provisioning. Their analysis includes an exploration of promising characteristics and AI-assisted approaches concerning core network (CN), transport network (TN), radio access network (RAN) slicing, management systems and slice extensions. Additionally, they suggested an elastic bandwidth scaling technique based on Reinforcement Learning (RL) that provides significant advantages in terms of increasing the request fulfillment rate and adjusting to environmental changes.

AI model is disseminated from the cloud server to edge computing nodes, wherein task nodes perform local processing and remote processing by offloading AI duties to cloud servers or other edge computing nodes in a 6G network. Li et al. [9]

tion offloading choices for each node. This optimization task is approached by solving a mixed-integer non-linear programming (MINLP) problem in order to reduce the overall computing time and energy consumption of all task nodes and increase the inference accuracy of AI tasks. They employed an alternate direction multiplier method (ADMM)-based approach to decompose this non-convex issue into manageable MINLP subproblems. Their proposed ADMM-based approach allows each task node to improve its computation mode and resource allocation by using local channel state information (CSI), which aligns well with the demands of large-scale networks. Utilizing Augmented Reality (AR) and Virtual Reality (VR) technologies, the authors in [10] unveiled an intelligent touch-enabled system for B5G/6G and an IoT-based wireless communication network. The core of touch technology, enriched by the incorporation of intelligence stemming from approaches like AI, ML, and deep learning (DL), is founded upon the tactile internet and NS. For the intelligent touch-based wireless communication system, an architectural framework is introduced, featuring a layered structure and interfaces, alongside its comprehensive end-to-end (E2E) solution. The forthcoming 6G network is envisioned to provide a diverse range of industries with the capacity to leverage AR/VR technology in applications within robotics and healthcare facilities, aimed at addressing numerous societal issues. Their study concluded by offering a set of use cases for the integration of touch infrastructure into automation, robotics, and intelligent healthcare systems in order to contribute to the diagnosis and treatment of widespread Covid-19 infections.

aimed to jointly optimize the resource allocation and computa-

The transition from the IoT to the Internet of Vehicles (IoV) is underway. Vehicles equipped with internet connectivity have the capability to perceive, communicate, assess, and make decisions. The extensive collection of vehicle-related data facilitates the utilization of AI and DL to deliver enhanced services for Intelligent Transportation Systems (ITS). However, AI/DLbased ITS applications require substantial computational resources, both during the training process and model deployment. A viable solution is exploiting the vast processing capacity that could be obtained by combining the computational power present in individual vehicles and ITS infrastructure. In [14], the authors presented the concept of a tangible vehicular fog computing (VFC) platform based on OneM2M, denoted as oneVFC. The oneVFC standard gains advantages from oneM2M by enabling interoperability and establishing hierarchical resource organization. OneVFC coordinats information flows and computational activities on vehicle fog nodes, maintaines dispersed resources, and reports outcomes to application users. The paper elaborates on how oneVFC efficiently manages AI-driven applications that are running on various machines within a laboratory-scale model comprising Raspberry Pi modules and laptops. Moreover, the paper demonstrates how oneVFC excells in significantly decreasing application processing time, especially in scenarios with elevated workloads.

Reference	Year	Accuracy of Used References	Mathematical Analysis of FL Averaging Algorithms	Challenges and Future Directions	Mostly Updated References from 2020 and Beyond
[5]	2023	1	×	✓	\checkmark
[1]	2023	×	×	×	×
[6]	2023	×	X	×	\checkmark
[10]	2023	×	X	×	×
[11]	2021	×	×	×	×
[12]	2021	×	X	×	×
[13]	2022	×	×	×	×

Table 1: Comparative analysis of existing surveys with the proposed survey on FL

1.2. Intelligent IoT-based and Edge Networks

IoT devices and associated clients contribute to the generation of a substantial data influx, necessitating both storage and analytical processes. Addressing the intricacies of large data computation and network optimization requires the development and implementation of systematic solutions. Data processing and structure optimization face significant demands due to the billions of data bytes generated at the network edge. Therefore, the combination of edge computing and AI, resulting in the development of edge intelligence, offers a promising solution. In the pursuit of this objective, Deng et al. [15] delineated a distinction between AI on the edge and AI for the edge (intelligence-enabled edge computing). The former entails leveraging AI technologies to provide more optimum solutions for the issues of edge computing, and the latter delves into the comprehensive execution of AI model development, encompassing model training and inference directly at the edge. The authors in [16] initiated their exploration by introducing sampling and data reduction methodologies. These methodologies facilitate a decrease in the volume of data sent for cloudbased processing. Nevertheless, it is crucial to acknowledge that the use of smaller datasets in ML algorithms may involve potential compromises in accuracy. An alternative and feasible strategy is to position ML algorithms in close proximity to data sources to minimize data transfer requirements. Within the framework of the Edge Computing (EC) paradigm, three primary modalities are employed to facilitate the execution of ML and data processing functions on intermediary nodes: deviceedge, device-cloud, and edge-cloud interactions. An assessment is conducted on these three cutting-edge procedures in conjunction with conventional methods, leading to a comprehensive discussion of their respective advantages and disadvantages. Furthermore, this paper [16] proposed a novel architecture, elucidating the potential application of EC within the Industrial Internet of Things (IIoT) for both data reduction and achieving successful predictive maintenance (PM). PM stands as a pivotal IIoT technology designed to continually monitor the health of machinery, enabling the prediction of component failures before they occur.

Numerous applications in edge computing, like federated ML and multiplayer AR games, require distant clients to engage in cooperative endeavors via message exchanges to achieve

common objectives. However, the effective deployment of such cooperative edge applications for the optimization of system performance throughout an entire edge network remains a subject of uncertainty. The authors in [17] discussed a formal analysis of the issue. To achieve a holistic system representation, offered a variety of cost models by presenting an iterative technique called ITEM based on a comprehensive formulation. In each iteration, they built a graph to encapsulate all the costs and change the cost optimization issue into a graph cut problem. By resolving a sequence of graph cuts employing available maxflow techniques, the lowest cost shortcut is found. They established the existence of a parameterized constant approximation ratio for ITEM. Moreover, they developed an online method called OPTS that is based on optimally alternating between partial and complete placement updates, driven by insights from the optimum stopping theory.

By balancing QoS and energy efficiency, Multi-access Edge Computing (MEC) enables IoT applications to locate their services in the edge servers of mobile networks. Prior initiatives have placed a primary emphasis on computational requisites, leaving the communication needs related to latency and bandwidth in the domain of IoT comparatively unaddressed. Additionally, the task of modeling Urban Smart Things (USTs), elucidating their connectivity with MEC networks, characterizing the multifaceted resource demands encompassing computation, communication, and IoT for application services, and modeling the federation of multiple MEC service providers in an urban environment poses a unique set of challenges for the smart city [18]. In response to these research gaps, the authors have presented the following solutions: i) The "UrbanEnQoSMDP" framework, tailored for optimizing service placement within the "Urban IoT-Federated MEC-Cloud" architecture to accommodate the computational, per-flow communication, and IoT requisites; ii) The " ϵ -greedy with mask" policy, crafted for the systematic selection of suitable USTs in advance to ensure the fulfillment of IoT requirements; and iii) "UrbanEnQoSPlace," a multi-action deep reinforcement learning (DRL) model that employs the outlined strategy to resolve the "UrbanEnQoS-MDP" problem by concurrently considering all services of an application that were created by the Dueling Deep-Q Network.



Figure 1: Comparison of three centeralized learning, decentralized learning, and federated learning structures

1.3. Motivation and Contributions

The inception of FL and its integration of privacy-preserving techniques has successfully persuaded a broad demographic, notably patients, to contribute their sensitive data for AI model training. This is achieved by transmitting model parameters rather than raw data, alleviating concerns regarding potential privacy risks. Furthermore, the advent of FL has provided a source of inspiration for wireless communication researchers and data scientists, motivating them to bring their previously incomplete practical or theoretical models to completion and operationalization within both academic and industrial domains. However, FL is currently in its early stages, holding immense potential for integration into our daily lives and various industrial sectors. Consequently, in order to foster its prudent development, an extensive volume of research and efforts must be dedicated to realizing substantial advancements in FL-assisted architectures. In accordance with the graphical depiction provided in Figure 2 in [12], the quantity of research publications in the past three years markedly surpasses that of publications up until the year 2020. In light of this accelerated pace of advancement, there arises an imperative to systematically direct and structure the contemporary trends within this domain.

The mathematical analysis of FL averaging algorithms is of paramount importance in the development and deployment of reliable and scalable FL-based schemes. It provides researchers with a systematic and technical means to calculate impactful parameters, subsequently guiding them in the design and development of their study model. Ultimately, serving as a roadmap, the identification of current challenges and prospective directions plays a pivotal role in offering guidance to researchers and scholars and expediting the ongoing progression within this domain. Taking into consideration all of these aspects, it is noteworthy that none of the prior surveys cited in Table 1 have provided exhaustive coverage of the aforementioned requirements, thereby highlighting a significant gap in this area. Consequently, driven by recent indicators of advancement within the FL domain and with the intention of addressing extant deficiencies, we present this comprehensive survey as a means to systematically bridge this gap through the incorporation of the latest advancements and applications in the FL field. In alignment with this goal, our initial focus centers on a comprehensive examination of 5G technology and its vulnerabilities, followed by an exploration of the capabilities inherent in 6G networks. We, then, delve into the intricacies of intelligent IoT, fog, and edge-based architectures. Moving forward, our research trajectory involves an in-depth examination of the extant literature pertaining to centralized learning, decentralized learning, and, most notably, federated learning. This survey paper contributes significantly by:

- Providing mathematical analyses and algorithmic frameworks for various federated learning averaging techniques.
- Outlining prospective research trajectories and unresolved queries pertaining to each specific FL area.
- Cataloging accuracy and AI/ML methods deployed by each cited reference for each focused aspect of FL.

1.4. Survey Outline

The remainder of the survey is structured as follows: Section 2 delineates decentralized learning, centralized learning, and FL. Section 3 provides a comprehensive exposition of FLbased structures. The security concerns associated with FL are discussed in Section 4. Sections 5 delves into the subject of resource allocation within FL systems. The applications of FL are presented in Section 6. Section 7 is dedicated to a comprehensive discussion on the scalability aspects of FL architectures. Finally, Section 8 brings the survey to its conclusion.

2. Centralized Learning, Decentralized Learning, and FL

2.1. Centralized Learning

Control and decision-making power are concentrated at one central location in a centralized system. This central authority must manage and coordinate all system-wide operations and resources. This system takes all significant decisions at the highest level, and power and knowledge are transferred from the central authority to the lower levels. The centralization of control makes coordination and standardization more effective, but it may also cause bottlenecks and delays if the central authority is too busy or becomes ineffective. For example, one type of crucial technology to address the limitations of wireless spectrum is spectrum sharing, specifically centralized spectrum. In a populated area, sharing performs well. However, this approach has significant computing costs. While optimizing, sophistication and problematic implementation targets are complicated, as is the whole system. A centralized solution for coordinated spectrum sharing based on reinforcement learning was studied in [19].

In multi-user wireless communication networks, the challenge of dynamic multichannel accessibility for transmission optimization was considered [20]. The centralized node examined all K channels at the start of each time slot and assigned one channel to broadcast a packet for each user. The centralized node received feedback signals for every user following each time slot, indicating whether the packet was properly delivered. Without any prior knowledge, the goal was to discover a multiuser approach that improved global channel use with a minimum impact in a centralized way. Due to the huge state and action space, finding the best solution for the centralized dynamic multichannel access challenge was challenging. To address this issue, the authors schemed a centralized dynamic multichannel access architecture using double-deep recurrent reinforcement learning.

Furthermore, IoT sensors' temporal data may be utilized to feed prediction algorithms continuously. This enables the development of programs that, for instance, forecast CO_2 levels in a particular area. The findings of these programs may be used to prototype health-related solutions. In [21], two ML approaches, FL and centralized learning, were contrasted to determine which was the best method for forecasting time series produced from data gathered by IoT sensors. While centralized learning imported data from IoT clients into a cloud and concentrated training on it, FL meant training the algorithms dispersed across devices. A long-short-term memory (LSTM) was employed to anticipate the time series, and their findings demonstrated that a centralized solution had an average mean squared error of 78% higher than that of an FL model when predicting five-time steps of a time series.

2.2. Decentralized Learning

Decision-making power and control are divided across several entities, or nodes, in a decentralized system. Each component, or node, in the system, has some autonomy and can make independent decisions based on local data. Local interactions and collaboration operate the system as a whole, yet there may

be specific standard rules or principles that all nodes adhere to. Compared to centralized systems, decentralized systems are frequently more robust and scalable. Since there isn't a single bottleneck or source of failure, they can cope with various changes and losses properly. However, there may be some concerns with consistency and synchronization due to more complex coordination and communication among nodes in ultradense networks. The challenge in decentralized learning is effectively coordinating decentralized learning while preserving data privacy and learning security across the board. In [22], the authors suggested SPDL, a privacy-preserving and blockchainsecured decentralized learning framework, to solve this problem. Through the seamless integration of Byzantine Fault-Tolerant (BFT) consensus, blockchain, BFT Gradients Aggregation Rule (GAR), and DP, SPDL ensured effective ML while guaranteeing data security, transparency, and Byzantine fault tolerance. The first privacy-preserving consensus-based technique for decentralized clients was offered to aggregate a decentralized global model in an area of considerable mobility, where participating learners and the connectivity graph among them might alter during the learning process. Specifically, anytime the communication graph changed, the Metropolis-Hastings algorithm was employed to update the weighted adjacency matrix according to the present communication architecture. Furthermore, Shamir's secret sharing mechanism was implemented to enhance privacy by obtaining agreement on the global model [23].

Mobile load balancing (MLB) attempts to address the issue of wireless networks' unequal resource consumption. Although wireless network dynamics are frequently complex and nonstationary, traditional model-based MLB approaches fall short of accounting for all possible outcomes. Without explicitly representing the underlying network dynamics, DRL can offer an adaptable structure for learning to distribute cell load equitably. In [24], Chang et al. enhanced a unique decentralized MLB technique based on DRL, where each of the cells had a DRL agent to learn its antenna tilt angle and handover parameters. The distributed structure divided the action space, making it more computationally efficient than its centralized equivalent as the number of cells rose. Additionally, their developed decentralized DRL architecture might accomplish a more balanced cell load distribution than the centralized DRL one by leveraging specific reward functions, and it just required data that was already publicly available and stated in current wireless protocols. A network model was designed closely adhering to the Third Generation Partnership Project (3GPP) requirements to give accurate ratings for performance.

2.3. Federated Learning

Data in FL is not centralized, gathered, or aggregated; instead, it stays on the machines or clients that produce it. Each gadget has its own local data. By retaining data on the devices, FL always worries about data privacy. In contrast with centralized and decentralized structures, sensitive data in FL structures is less exposed when devices submit model changes (updates and weights) to the central server rather than providing raw data. This strategy does not provide direct access to the

raw data but instead uses a central server to manage the model training process. To this end, it distributes the global model to the devices that train local models using their own data and transmit updated global models back to the central servers or edge servers. In contrast with centralized structures, FL structures dramatically minimize communication costs since only model updates, not raw data, are sent over the network. FL is also highly scalable, allowing many devices to participate in the model training process without centralized data storage. Finally, because the data is still decentralized and model changes are carefully pooled to ensure privacy protection, FL provides superior security and privacy [11, 12]. While FL allows devices to preserve their data and participate in model training by sharing just model parameters and weights, centralized learning collects data from many sources and sends it to a single central server for global model training (See Fig. 1).

3. Comprehensive Overview of FL

The transformation from centralized (cloud center) to distributed on-device learning (edge server) gave birth to a new paradigm called FL. This approach aims to maintain gathered data on local devices and servers to train local models while preserving privacy data and top-secret information. FL systematically mitigates storage and communication costs and presents a significant level of client-level privacy. At a glance, we may list the FL's benefits as follows:

- Offline operability
- Enhanced latency performance
- Enhanced accuracy
- · Privacy fortification
- Prolonged battery life
- · Localized model training

It is a decentralized strategy that protects privacy by keeping raw data on the devices and utilizing local ML training while cutting down on data transfer overhead. The built-in knowledge is then aggregated and shared among participants through a federation of the learned and shared models on a central server. The authors in [11] compared and contrasted several ML-based deployment models before delving deeply into FL. In contrast to previous evaluations in the area, they offer a new classification of FL issues and research domains based on careful examination of the primary technical difficulties and ongoing efforts in the field. In [12], the writers first outlined recent FL developments that have enabled FL-powered IoT applications. A set of measures, including sparsification, resilience, quantization, scalability, security, and privacy, were defined to assess the most current developments thoroughly. In the following, a taxonomy for FL across IoT networks was introduced and performed.

The conventional ecosystem of centralized over-the-cloud learning and processing for IoT platforms will face increasing challenges due to the high costs of transmission and storage, as well as privacy issues. The most promising alternative strategy to solve this issue is FL, which has been developed. Training data-driven ML models in FL involves several clients working together without needing the data to be transferred to a single location, which reduces transmission and storage costs and offers a high level of user privacy. The actual FL system implementation on IoT networks still faces certain obstacles. Manufacturing, transportation, energy, healthcare, quality and reliability, business, and computers are among those sectors. So, the advantages and disadvantages of FL in IoT systems are covered in [40, 41, 42, 43], as well as how it may support a variety of IoT applications. They specifically identified and analyzed several significant IoFL difficulties and described new, potential solutions to the challenges mentioned above.

In [13], a thorough analysis of the suggested intrusion detection systems for the IoT ecosystem was studied, which consisted of IoT devices and communications between the layers of cloud, fog, and the IoT. Although there were other survey publications, the three following aspects of this work are unique: (1) Explore the privacy issues of the IoT ecosystem, taking into account interactions across the IoT, fog, and cloud computing layers and IoT devices; (2) a unique two-level categorization system that first divides the literature into groups depending on the methods used to identify assaults and then subdivides each method into several techniques;(3) To provide future IoT systems with a robust defense against cyberattacks, we present a complete cybersecurity framework incorporating the ideas of Explainable AI (XAI), FL, game theory, and social psychology. The reliability of local models in FL for anomaly detection might be different. Several trained models, for instance, are likely to include the characteristics of abnormal data due to noise corruption or anomaly detection failure. Additionally, there is a chance that the training data or model weights might be contaminated since the communication protocol between edges could be abused by attackers. Consistent with this view, the authors in [44] carefully chose the local models participating in model aggregation while designing a federated training procedure. Their study used an observed dataset to compute prediction errors to filter out the poor local models from federated training.

Due to the prevalence of straggler devices, FL requires an inordinate amount of learning time. To address the heterogeneity issue in FL and increase communication and computation efficiency, a novel topology-optimized federated edge learning (TOFEL) technique is developed in this study. Huang et al. in [25] aimed to minimize the weighted sum of energy consumption and delay. Therefore, the problem of simultaneously optimizing the aggregation topology and processing speed was defined. They proposed a brand-new penalty-based sequential convex approximation approach to solve the mixed-integer nonlinear issue. Their approach converged on a stationary point for the primary problem under benign conditions. DNNs (DNNs) were trained offline to imitate the penalty-based technique to simplify real-time decision-making. The trained imitation DNNs were then deployed at the edge devices for online inference. Thus, the TOFEL architecture smoothly included an effective imitation-based learning strategy. Due to their limited computational capabilities and shoddy network connections, it

Reference	Year	Acc> 90%	AI/ML approach	Open Areas and Future Challenges and Directions
[25]	2021	1	TOFEL	_
[26]	2021	1	DNN/FL-PQSU	Testing FL-PQSU with new models/datasets and IoT devices, and alternative compression processes applicable to FL will be investigated.
[27]	2022	×	Semi-supervised	-
[28]	2021	✓	CNN	-
[29]	2022	X	FEDGS	-
[30]	2021	×	DNN	Exploring the effect of hyperparameters $(\alpha, \beta, and \gamma)$ to find the optimal Big.Little branch designs.
[31]	2021	1	DML	Enhancing E-Tree efficiency by additionally adjusting the number of layers and aggregation frequency with RL enhanced.
[32]	2021	X	FS	-
[33]	2021	1	E2E-FL	-
[34]	2020	X	semisupervised	-
[35]	2021	_	_	Developing a resilient control scheme for fuzzy-logic-based cooperative game theory and applying high-order control to a dynamic system.
[36]	2021	X	FFT	Replacing the router with another edge vehicle and involving secondary clients equipped with sensors to create an E2E edge device network.
[37]	2021	_	DQN	Using public infrastructure updates, multiple data migrations, and fault tolerance fulfill the needs of the vehicular edge networks (VENs).
[38]	2022	_	FedTDLearning	Studying a unique approach that combines self-supervised learning and deep RL to facilitate the convergence challenge in some areas.
[39]	2022	×	NN/DML	

is frequently impossible or extremely slow to train DNNs using the FL pattern on IoT devices. In [26], a brand-new, effective FL framework dubbed FL-PQSU was offered to deal with this issue. Structured pruning, weight quantization, and selective updating were the three stages of the pipeline. They were combined to lower the cost of computation, storage, and communication, which sped up FL training. The authors investigated FL-PQSU using well-known DNN models (AlexNet, VGG16) and publicly accessible datasets (MNIST, CIFAR10) and showed that it could effectively control the learning overhead while still ensuring training performance.

To make it easier to identify anomalous log patterns in massive IoT systems, the authors in [45] presented a configurable and communication-efficient federated anomaly detection technique (from now on referred to as FedLog). They first created a Temporal Convolutional Network-Attention Mechanismbased (TCN-ACNN) model to extract fine-grained features from system logs. To assist IoT devices in producing a thorough anomaly detection model in a cooperative and privacypreserving manner, they also designed a novel FL framework. Third, a masking approach based on a lottery ticket hypothesis was created to handle non-independent and identically distributed (non-IID) log datasets that are configurable and communication-efficient. Using two extensively used and publicly accessible real-world datasets (i.e., HDFS and BGL), they compared the performance of their suggested scheme to that of DeepLog (published in CCS, 2017) and Loganomaly (published in IJCAI, 2019) in both centralized learning and FL scenarios. Their results showed that their adopted FedLog method was helpful for log-based anomaly identification. Aouedi et al. in [27] presented a semi-supervised FL paradigm for IDS to deal with a high bandwidth overhead, poor device incentives to communicate their private data, and enormous computing and storage resources needed on the server side to label and process all this data. Additionally, they employed network software for deployment and automation. In their methodology, clients trained unsupervised models (using unlabeled data) to learn representative and low-dimensional features, while the server ran a supervised model (using labeled data). The authors in [46] provided an FL protocol for fog networking applications. The Internet Engineering Task Force's (IETF) concept is compatible with the fog networking architecture. The FL protocol was created and described to limit IoT devices that extend to the cloud through the edge. To this end, experimental experiments were conducted to evaluate their proposed distributed edge intelligence technology for particular application situations. Their outcomes showed the effectiveness of the suggested FL protocol regarding message latency and intelligence correctness. These protocols will be the foundation of the next generation of the Internet because they can more effectively distribute edge intelligence to the massive number of newly linked IoT devices.

Multi-Layer Hierarchical FL (MLH-FL), a unique method for FL, has been brought up in [47] along with a multi-layer architecture. MLH-FL made use of the traditional FL and MLH-FL techniques' accuracy. To this end, a hierarchical design at the edge to benefit from model aggregations at various levels was offered, in contrast to the conventional FL method. As a result, model aggregations could be carried out even when a set of edge nodes was not constantly linked to the cloud. Additionally, this strategy enabled model aggregations to communicate with the cloud less frequently, saving communication energy. The idea of a low-level round, which allowed aggregations to be repeated at the edge without transmitting updated models to the cloud each time, was also covered in their study. This kind of innovation made it possible to reduce the amount of communication energy.

nication going to the cloud.

The authors in [28] surveyed a method for diagnosing bearing faults based on FL. High-quality local models were chosen to participate in the model aggregation following the accuracy threshold adaptive algorithm to decrease the amount of communication.

Centralized learning and FL vary greatly in that data in the former should be offloaded, while in the latter it is taught locally. Guo et al. [48] explored the compute offloading issue for EC-based ML in an industrial setting, taking into account the ML models indicated above. In order to reduce the training latency, they defined an offloading issue based on ML. The issue was then resolved using an energy-constrained delay-greedy (ECDG) method.

For businesses enabled by 5G, the authors in [29] offered FEDGS, a hierarchical cloud-edge-end FL architecture, to enhance industrial FL performance on non-IID data. FEDGS employed a gradient-based binary permutation method (GBP-CS) to choose a subset of devices inside each factory and construct homogenous super nodes taking part in FL training using naturally grouped factory devices. The training process was then coordinated inside and across these super nodes using a compound-step synchronization approach that exhibited excellent resilience against data heterogeneity. The suggested guidelines saved time and could adapt to changing conditions without putting sensitive industrial data at risk through dangerous manipulation. They showed that FEDGS outperformed FedAvg in terms of convergence performance and then assumed a looser requirement under which FEDGS was more communicationefficient.

To overcome the computational and memory resource limitations that limit the capabilities of hosted DL models, the authors in [30] offered a collaborative Big.Little branch design to allow effective FL for artificial IoT (AIoT) applications. Their method installed DNN models across cloud and AIoT devices, drawing inspiration from BranchyNet's plan, which featured many prediction branches. The Big.Little branch of the tiny branch model, which is used to fit AIoT devices, was placed on the cloud for increased prediction accuracy. AIoT devices will turn to the large branch for additional inference when they cannot confidently make the prediction using the local, tiny branches. The authors adopted a two-stage training and coinference strategy that considered the local features of AIoT situations to improve the Big. Little branch model's prediction accuracy and early departure rate. In [31], Yang et al. presented a brand-new decentralized model learning method called E-Tree, which used an edge device-imposed, carefully designed tree structure. In order to increase training convergency and model correctness, the tree structure and the places and order of the aggregation on the tree were carefully planned. In particular, by taking into consideration the data distribution on the devices as well as the network distance, they built an effective device clustering technique, called by K-Means and average accuracy, for E-Tree.

In [49], the authors examined hostile attacks on time-series analysis in an IoT search engine (IoTSE) system. In particular, they utilized a simulated FL system to create the LSTM-Term Memory (LSTM) Recurrent Neural Network (RNN) as their basis model. They suggested the Federated Adversarial Learning for IoT Search Engine (FALIoTSE), which used the federated model's shared parameters to target adversarial example creation and robustness. The effect of an assault on FALIoTSE was shown under different levels of disruption using data from a real-world smart parking garage.

By establishing particular updating weights for each node based on the distinction between the global and local models, the authors in [32] created an elastic local update method that could train the customized models. Their approach considered both the local models' personalities and their overall consistency. Additionally, they provided an n-soft sync model aggregation technique that dramatically shortened training time by fusing synchronous and asynchronous aggregations. To address the end-to-end (E2E) reliability of FL communications, Chiu et al. in [33] focused on an intelligent, lightweight method based on the standard software-defined networking (SDN) architecture to manage the large FL communications between clients and aggregators. To represent the apparent network circumstances identified by the k-nearest neighbor (KNN) technique, the handling method modified each unique client's model parameters and batch sizes.

Math et al. [34] looked at an edge learning system based on FL and semisupervised learning to address data security and network bandwidth limitations. The system adapted FL technology to train AI models at edge devices using an upgraded semisupervised learning method and regularly uploaded the training results to the cloud server to create a single model. Then, they noticed that the data on the end devices is nonindependent and identically distributed (non-IID) in the actual world, which might lead to weight divergence during training and significantly lower model performance. To lessen the negative effects of weight divergence, they surveyed a novel operation termed federated swapping (FedSwap) to substitute partial FL operations based on a few shared data during federated training. By grouping the devices into equal-sized groups and choosing clients from each group equally, the authors in [50] developed a unique framework termed cluster-based federated averaging to obtain a fair global model. By doing this, the minority group's accuracy might be considerably increased at the expense of the majority group. They modified the training weights as features to split the users and guarantee that the customers' training data does not leave their devices to adhere to the FL's inclination for privacy protection.

To establish a reciprocal consensus between two distinct negotiating techniques: the weighted average solution and the constant elasticity substitution technique, the author in [35] came to an understanding while examining the mutual benefits. The primary innovation of their strategy was that it examined the dualinteractive bargaining process based on the interdependence between IoT devices and the tactical edge server. Moreover, to manage tactical edge-assisted job offloading services to the best of their knowledge, they jointly explored various negotiating strategies.

The optimization of client selection policies was clearly of interest in the literature, but the design of the actual execution of such policies with a focus on client discovery techniques has received less attention. To close this gap, an edge-based framework was proposed to enhance FL client discovery processes by utilizing (i) the purpose of the Message Queue Telemetry Transport (MQTT) protocol for FL client-server interactions was to find out what future clients' capabilities were, and (ii) the Lightweight Machine-to-Machine (LwM2M) standard from the Open Mobile Alliance (OMA) for the semantic definition of such capabilities[51].

Orescanin et al. in [36] presented two main contributions to address high communication costs for embedded applications: (1) To improve system security and model performance, the federated averaging algorithm's weight initialization phase should be improved. Additionally, the proportion of weights that may be averaged should be limited; and (2) deploying a realistic model employing an edge device as the server node (first for a federated system) to demonstrate the usefulness of the suggested approach. They employed a MobileNetV2 model centrally pretrained on the CelebA dataset for assessment. They used the modified federated averaging approach and FFT to record the model parameters sent over the network and to measure the CPU load, power use, device memory, and communication metrics. With MEC servers equipped with AI, the authors in [37] examined the problem of cooperative data sharing in vehicular edge networks (VENs). They also introduced a particular way of exchanging data collaboratively. Then, to ensure effective and secure data sharing in the VEN, they provided a unique collaborative data-sharing method using a deep Q-network and FL. Han in [52] considered FL with several local wireless edge servers. In a more realistic environment, their main goal was to expedite training. Utilizing clients in overlapped coverage areas between adjacent edge servers (ESs) was the core concept behind their approach. During the model-downloading stage, clients in overlapped areas received multiple models from various ESs, averaged the received models, and then updated the averaged model with local data. These clients used broadcasting to distribute their updated models to several ESs, which served as bridges for transferring learned models between servers. Even though certain ESs got biased datasets inside their coverage territories, the clients on the nearby servers' overlapping regions could help the training processes of those ESs. Consequently, compared to traditional cloud-based FL systems, their proposed technique greatly reduced the overall training time by eliminating the need for expensive connections with the central cloud server (placed at the upper tier of edge servers).

For order-and-driver matching, traditional studies used only pure combinatorial optimization models, which ignored the long-term benefits of the dynamic MOD decision-making process. To solve the problem mentioned above, the authors in [38] proposed a systemic paradigm of online matching with federated neural temporal difference learning, which included the learning and matching phases, with the goal of long-term optimization. The Markov decision process (MDP) was used to simulate the long-term matching process throughout the learning phase, and it was commonly addressed using data-driven reinforcement learning in an offline central training scheme. In-

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dustrial MOD systems would create enormous volumes of data on the network. Due to network bandwidth restrictions and security issues, transferring all of the large-scale industrial data to the cloud server for centralized model training was not viable. A general and novel form of federated neuronal Temporal Difference Learning (FedTDLearning) was postulated to accomplish long-term matching in a distributed way. A real-time bipartite matching optimization problem was created during the matching phase to maximize the acquired spatiotemporal value and reduce the pickup distance. This issue was expected to be reduced to the minimum-cost, maximum-weight bipartite graph matching problem. Based on the joint optimization of FedTDLearning and the combinatorial fractional programming technique, a distance-learned-value ratio algorithm was modeled to obtain optimal matching in the bipartite network. Additionally, to achieve the highest level of computing efficiency, they tackled the real-time matching issue by building a bipartite k-nearest neighbor (kNN) network in which kNN drivers connected each order. In [53], an asynchronously updating FL model for the edge nodes has been schemed to develop regional AI models for smart remote sensing with a use case for forest fire warning without the requirement for explicit data interchange with the cloud. Their scheme reduced network overhead while simultaneously protecting the privacy of data. To allow efficient and effective FL across heterogeneous IoT devices, the authors in [39] offered a unique framework called PervasiveFL. PervasiveFL installed one lightweight NN model called modellet on each device without altering the original local models. Modellets and local models could selectively learn from one another through soft labels using locally collected data by utilizing deep mutual learning (DML) and their entropy-based decision-gating (EDG) technique. Modellets could transmit the information they have gained among devices in a classic FL fashion since they shared the same architecture. This enabled the widespread application of PervasiveFL to any heterogeneous IoT system with high inference accuracy while reducing communication overhead. The future directions, open areas, and accuracy of references in FL-based structures are listed in Table 2 with details.

3.1. Mathematical Analysis of FL Averaging

Analyzing a great deal of raw data in cloud centers is infeasible due to the security challenges, latency, and adverse transmission impacts on the data. Therefore, can steering the IoT infrastructure and capabilities into intelligent edge centers considerably improve data processing and wireless networks? Functions. Intellectual edge centers help gather, process, optimize, and control traditional wireless networks. Specifically, the intelligent edge infrastructures have sped up all of the communication applications while maintaining data in local centers instead of sharing it with the main center. However, smart edges are in their birthdays and will have a lot to be improved; the following algorithms have already come up with different mathematical approaches to help significantly improve wireless network performance and security (see Table 3).

Table 3: Different Federated Averaging Algorithms

Papers	Algorithm
[54, 55, 56, 57]	Weighted
[58, 59, 60, 61, 62, 63, 64]	Adaptive
[65, 66, 67, 68, 69]	Momentum
[70, 71, 72, 73, 74, 75]	Secure
[76, 77, 78, 79, 80, 81]	Quantization

3.1.1. Weighted Federated Averaging

Recently, concerns regarding communication costs and data security have made it controversial to design a reliable central database system for local data aggregation in FL. To tackle this issue, an FL model equipped with dynamic weighted averaging was introduced in [54], where models were assumed to be trained to utilize local data, and then the model updates were forwarded to a central server for model aggregation. In the next step, the updated global model shared the last updates with the participants while ensuring data privacy. Their dynamic weighted averaging model carefully investigated the imbalance of distributed data and then effectively removed the impact of uncountable local updates (see Fig. 2).

The traditional federated averaging (FedAvg) methods employed by FL neglected the massive domain change among various FL clients, reducing their performance and applicability. To tackle this problem, a federated transfer learning (FTL) algorithm with discrepancy-based weighted federated averaging (D-WFA) was adopted in [55]. This algorithm received locally labeled source domain samples and unlabeled target domain samples to update local models with generalization capability. To this end, they designed an MMD-based dynamic weighted averaging algorithm to aggregate the updated local models, assuming the domain change and adapting the weights. Nevertheless, in actual industrial implementations, the domain transitions between the training customers (between the target participant and source or among many source participants themselves) were likely to be frequent. So, low-quality data from some clients might adversely impact the global model's performance if the customers were simply aggregated with a common weight. To best match the goal diagnosis job, a weighted algorithm should be created to assist the server in identifying "good" or "bad" clients. So, the fundamental goal of D-WFA in [55] was to penalize (lower weight) customers who were predicted to make a humble contribution and reward (more significant weight) clients who were expected to make a high contribution to the target global model. An MMD-based dynamic weighted technique was created to measure such assistance, which was prompted by the MMD distance in TL. They assumed that N clients were taking part in the federated training. Their proposed D-WFA had seven stages that must be followed when a new global training epoch begins, using the global training epoch as an example. The steps of their algorithms were as follows:

a) First, the source clients receive the model $w_{G,t-1}$ (a global aggregated model of the (t-1)th round).

b) The distributed model was trained using various local data



Figure 2: Weighted Federated Averaging

for numerous local epochs (local epochs) E_{local} , yielding various client models (client models), where k represents the k^{th} training client.

c) Step 3: The updated $w_{k,t}$ calculated the source feature vectors (the outcome of the final layer in the feature harvester) $f_{k,t}^S$. Once again uploaded to the server, $w_{k,t}$ and $f_{k,t}^S$ were then both present.

d) The target client downloaded the files $w_{k,t}$ and $f_{k,t}^S$, and the unlabeled target client data is used to compute the target feature vectors $f_{k,t}^T$. Then, $f_{k,t}^T$ are also returned to the server.

e) The MMD distances, MMD_i were computed with $f_{k,t}^S$ and $f_{k,t}^T$ by (6) [55].

$$L_m(x_i^S, x_i^T) = \left\| \frac{1}{n^S} \sum_{i=1}^{n^s} \varphi(x_i^S) - \frac{1}{n^T} \sum_{j=1}^{n^T} \varphi(x_j^T) \right\|.$$
(1)

f)The N MMD distances were turned into the weight vector, as follows [55]:

$$x_{k,t} = \frac{\frac{1}{MMM_{k,t}}}{\sum_{n=1}^{N} \frac{1}{MMD_{k,t}}}.$$
 (2)

where: $\sum_{n=1}^{N} \alpha_{k,t} = 1$

g) The final step is to aggregate the client's local models with the specified weight, as follows[55]:

$$w_{G,t} = \sum_{n=1}^{N} \alpha_{k,t} w_{k,t}.$$
 (3)

Notably, the MMD distance determined in (6) was assumed to be viewed as a numerical assessment of the degree of deep representational similarity in distribution between the target clients and the source. The degree of resemblance increased with decreasing distance. Additionally, federated training's overarching objective was to reduce domain inconsistency. Therefore, as a reward for correctly optimizing model parameters, more significant weight should be applied to a particular source client in this round if the data distribution of that client was more similar to the target client after the local training phase (lower MMD). On the other hand, if a client's MMD

Algorithm 1 Weighted Federated Learning 1:Input: $\mathbf{X}^{k,S}$, \mathbf{Y}^{S} , \mathbf{X}^{T} , E_{global} , E_{local} , β , B2:Server executes: Initialize $\omega_{G,0}$ 3: 4: For each global epoch t from 1 to E_{global} do: 5: For each client k in parallel do: $\omega_{k,t}, f_{k,t}^s \leftarrow \text{Client Local Train } (\omega_{G,t-1}, k)$ $f_{k,t}^T \leftarrow \text{Target Client Send Feature } (\omega_{k,t}, \mathbf{X}^T)$ 6: 7: 8: 9: 10 $\omega_{G,t} \leftarrow \sum_{k=1}^{N} \alpha_{k,t}^{\sim} \omega_{k,t}$ 11:**Client Local Train** $(\omega_{G,t-1}, k)$: 12: $\omega_{k,t-1} \leftarrow \omega_{G,t-1}$ For each local epoch *i* from 1 to E_{local} do: 13: 14: For batch do: $\omega_{k,t} \leftarrow \omega_{k,t-1} - \eta \nabla_1(\omega_{k,t-1}; b_{k,t-1})$ $f_{k,t}^S \leftarrow F_{\omega_{k,t}}(\mathbf{x}^{k,S})$ return $\omega_{k,t}, f_{k,t}^S$ to the server 15: 16: 17: 18: **Target Client Send Feature** $(\omega_{k,t}, \mathbf{X}^T)$: 19: $f_{k,t}^T \leftarrow F_{\omega_{k,t}}(\mathbf{X}^T)$ 20: return $f_{k,t}^T$ to the server 21:**Output:** Global Model ω_{global}

from the target client was still significant after local training, that customer should be given less weight. The Pseoudocode of their proposed method can be seen in (Algorithm 1). The local training period and the global training round were denoted by the variables E_{local} and E_{global} , respectively. The batch size of the local model and learning rate was, respectively, B and η (See Algorithm (1) in [55]).

The essence of discrimination among internal parameters of different client models plays an important role in the performance of FL-based structures. Consistent with this view, a new parameter-wise elastic weighted averaging aggregation method was introduced to handle the fusion of heterogeneous local models. Each local model assessed the significance of its model's internal parameters and estimated their essence coefficients correspondingly. The central server took these coefficients and carried out parameter-wise weighted averaging to perform the global model aggregation [56].

Current studies have focused on verifying the direct summation of updates received from local clients while ignoring the weighted average aggregation. To fill this gap, the authors in [57] offered a secure and efficient FL method using verifiable weighted average aggregation of the global model. Their method aimed to encrypt local updates and data size to guarantee the protection of updates through the model aggregation that security evaluations could confirm. This method also presented a verifiable aggregation tag and an efficient verification scheme to verify the weighted average aggregation.

3.1.2. Adaptive Federated Averaging

Conventional federated optimization approaches like Federated Averaging (FEDAVG) usually suffer from some main challenges regarding convergence behavior and tuning problems. So, researchers have aimed to employ adaptive optimization schemes that represent better performance in non-federated environments (see Fig. 3). For example, Reddi et al. [58] introduced federated versions of popular adaptive optimizers, namely ADAGRAD, ADAM, and YOGI. They intently focused on analyzing the convergence behavior of adaptive optimizers in heterogeneous data sets where the clients' training data may differ in various aspects, such as distribution, size, or quality, considering general non-convex problems. Their study lay in the intricate relationship between client heterogeneity and communication efficiency in FL. Heterogeneity in the data across clients can pose concerns in attaining appropriate convergence, as the model still needs to generalize well to different data sets and new labels. Furthermore, communication efficiency plays an integral role as the model updates are considered to be transmitted between the central server (cloud) and clients due to latency and bandwidth resource limitations.

Two main concerns in FL are the lack of adaptivity in SGDbased model updates and the significant transmission overhead caused by frequent server-client synchronization. То tackle both concerns mentioned above, different approaches, including Gradient compression and quantization techniques, have been adopted to overcome communication costs by forwarding compressed gradients between the central server and clients. Moreover, federated versions of adaptive optimizers like FedAdam have been applied to enhance the adaptation of the model updates. In [59], Wang et al. demonstrated a new method called FedCAMS (Communication-Efficient Adaptive FL) to solve these issues appropriately. FedCAMS offered a creative approach that integrated communication efficiency and adaptivity in FL. One of the main contributions of FedCAMS was to lower the communication overhead, resulting in improved communication efficiency of the FL process using several techniques such as gradient compression, quantization, or other communication optimization strategies.

In [60], the authors used Adaptive Federated Averaging, which aimed to diagnose and alleviate failures, attacks, and problematic updates contributed by clients during the collaborative model training process. To this end, they utilized the Hidden Markov Model, which modeled and learned each client's quality of model updates. This model ensured the updates' reliability and trustworthiness by identifying and filtering out harmful or malicious updates at each training iteration. Unlike traditional robust FL models, their method put forth a robust aggregation rule that identified and dropped undesirable updates, ensuring the maturity of the collaborative model. Moreover, a new protocol was considered to block unimportant clients, making it practical by improving communication efficiency and computational load. In [61], the Adaptive FL (AdaFed) method combined two key improvements to extend FL. Firstly, it dynamically assigned weights to the local models during the averaging procedure according to their local performance, where the



Figure 3: Adaptive Federated Averaging

higher weights assigned to every accurate model represented the significant contribution of the mentioned participant that shared better updates and developed global model performance. The adaptive weighting algorithm properly coped with variations in the trustworthiness and capabilities of different participants. Secondly, AdaFed evaluated and adjusted the loss function at each communication period under the training behavior monitored by the participants. With this method, AdaFed carefully captured the concerns and properties that the specific training data distribution faced in each communication period. Moreover, their adaptive loss function at each round helped their method mitigate unbalanced data distributions, leading to their resilience against malicious users.

The authors in [62] scrutinized traditional adaptive averaging methods, including peer-to-peer, publish-subscribe, and stream processing research, and explained that each method mentioned above had its deficiency in terms of communication cost and resource usage for FL aggregation. To address these problems, they suggested AdaFed, which leverages serverless and cloud-based operations to obtain adaptive and cost-effective aggregation. Their system model enabled dynamically deploying aggregation only on demand; its scalability allowed each client to join and leave the setting while satisfying fault tolerance from the aggregation operator's side. They highlighted that AdaFed not only substantially minimized resource requirements and communication costs but also had a minimal effect on aggregation delay. In the following, a prototype implementation was carried out according to Ray that ensured their system's scalability to thousands of clients and obtained a more than 90% reduction in communication costs and resource consumption. In their implementation part, they considered two FL deployment scenarios: cross-device and cross-silo. In the former scenario, a few clients with extensive processing capabilities contributed to tasks such as tumor and COVID diagnosis and detection. In the latter scenario, many clients with limited resources, such as mobile phones or IoT devices, collaborated with small amounts of data. These clients were less reliable, asynchronous, and susceptible to leaving and joining periodically. In [63], Wu et al. conflated adaptive gradient descent and differential privacy (DP) approaches tailored explicitly for multi-party collaborative modeling frameworks in the FL process. The adaptive learning rate approach was utilized to adapt the gradient descent process and avoid model overfitting and variations, resulting in improved model performance in multi-party computational frameworks. Furthermore, the DP mechanism was postulated to protect their system against various unwanted users and malicious servers to ensure a privacypreserving system. Unlike the existing studies, thanks to the federated adaptive learning rate gradient descent approach, they deepened their concentration on reducing the model's sensitivity to privacy issues and hyperparameters, leading to a flexible and robust model. The hyperparameters that must be specified before the ML process are the learning rate and the number of iterations. Due to the fixed learning rate, the conventional gradient descent approach, like SGD, frequently caused a slowdown in convergence and resulted in a local optimization solution. Given the shortcomings of SGD, the authors in [63] postulated the Fadam technique, which aimed to conflate the FL and an adaptive gradient descent algorithm. Fadam employs first and second-order momentum based on previous gradients to determine the gradient of the objective function given the parameters $\rho_t^1 = \varphi(\beta_1, \beta_2, \cdots, \beta_t), \rho_t^2 = \mu(\beta_1, \beta_2, \cdots, \beta_t)$. In each iteration,

these parameters were utilized to keep the global model updated as follows [63]:

$$\Omega_{t+1} = \Omega_t - \frac{1}{\sqrt{\rho_t^2 + \epsilon}} \rho_t^1.$$
(4)

The learning rate was reflected in the model convergence's gradient descent. Every local model trained typically at a certain learning rate forwarded parameters to the central server and lowered the loss function value to attain gradient descent. All local models received adjustments from the central server to increase their accuracy and generalizability. By changing the learning rate separately, the authors established adaptive gradient descent methods to prohibit model overfitting.

SGD could reach a minimal value, but it operated more slowly than other algorithms, and this issue may trap it at saddle points for non-convex functions. To solve this problem, the authors developed separate adaptive learning rates for various parameters using an optimization strategy that differed from the conventional gradient descent methodology, which technically computed the gradient's first-order momentum estimate and second-order momentum estimation. Their proposed scheme not only handled non-steady state issues of the function but also preserved the adaptive gradient algorithm's (AdaGrad) learning performance advantage over the root mean square propagation algorithm's (RMSProp) performance advantage and the gradient sparse datasets. Furthermore, because the second-order momentum in Fadam was measured across a fixed time window, it was challenging to find the best solution during the modeling training process because the data used for training may lose information if the time window changes. To tackle the problems mentioned above, the Adabound method was applied to the FL process and used a technique called Fadabound to get quicker learning speed in the early stage and higher generalization ability in the latter stage. In the Algorithm (2), the Fadabound process is presented [63]. η_l and η_u are the lower and upper bounds of the learning rate respectively and t denotes the number of iterations. The authors in [64] primarily put forth a deep theoretical scrutinization of the convergence bound for gradient-descent-based FL, assuming N.i.i.d data distributions along with a random number of local parameters. In the following, under-examined convergence bound, the authors adopted a control method that dynamically adjusted the oscillation of global aggregation in real time to diminish the learning loss under a constant resource budget.

3.1.3. Momentum Federated Averaging

A frequent optimization method in stochastic gradient descent (SGD) is momentum-federated learning. Contributing a portion of the past gradient to the current gradient update hastens the convergence of the learning process. This aids the optimization process in overcoming minute oscillations and accelerating convergence to the ideal result. The main goal of momentum FL is to include the momentum notion in FL. Similar to how momentum functions in SGD, while updating the local model on each node, the prior local gradient direction is Algorithm 2 Adaptive FL Algorithm

1:Input:Dataset, privacy budget ϵ , learning rate η **2:Output**: Ψ .

3:Begin set $\rho_0^1 = 0, \rho_0^2 = 0$.

- 4: For each round of iterations do:
- 5: Gradient descent at time step t: $\beta_t \leftarrow \Delta_{\Psi} f_t(\Psi_{t-1})$
- 6: Calculate the first-order mom: $\rho_t^1 \leftarrow x_1^t \rho_{t-1}^1 + (1 1)^{t-1}$
- 7: x_1^t) β_t
- 8: Calculate the second-order mom: $\rho_t^2 \leftarrow x_2 \rho_{t-1}^2 + (1 9)$: $x_2 \beta_t^2$
- 10: Clip learning rates by Clip: $(a/\sqrt{\rho_t^2}, \eta_l, \eta_u)$
- 11: Update the first-order mom estimation:

12:
$$\bar{\rho}_t^1 = \frac{\rho_t^1}{1 r^4}$$

13: Update the second-order mom estimation:

14: $\bar{\rho}_t^2 = \frac{\rho_t^2}{1-x_0^2}$

- 15: Until the model converges for the local dataset
- 16: Send the model parameters Ψ_t , of this iteration to the
- 17: central server
- 18: Central server calculates the contribution $\Psi^{i} \Psi^{i-1}$ of
- 19: the current iteration and delivers it
- 20: End.
- 21: **Return** resulting parameters $\Psi_1^i, \Psi_2^i, \cdots, \Psi_k^i$ from clients 22: to the central server.

also considered in addition to the current local gradient (See Fig. 4). In this figure, m(t) and β are momentum functions and momentum parameters, respectively.

The authors in [65] adopted a new method by blending model personalization and client-variance-reduction to upgrade the semi-supervised FL (SSFL) structure. However, one main concern of the SSFL was the interaction between participants' heterogeneity and label deficiency, which worsened their negative impacts. Traditional methods modeled for supervised FL were not directly implementable in SSFL, making it less likely to tackle these concerns adequately. To this end, they set the problem formulation according to pseudo-labeling and model interpolation. To properly resolve participant and data heterogeneity, they proposed a method called FedCPSL, which was assumed to combine momentum-based client variance reduction, normalized aggregation averaging, and other averaging strategies. To evaluate the resilience of their system to participant and data heterogeneity, they analyzed the convergence features of FedCPSL, which resulted in a sublinear convergence rate. Moreover, FedCPSL was envisioned to have a sublinear convergence rate for nonconvex objectives, fitting improved bounds and representing sustainability for participants and data heterogeneity.

Another similar method was adopted in [66] where the authors offered a new FL scheme called federated global and local momentum (FedGLOMO) to tackle the problems of participants and data heterogeneity, and compressed data communication. FedGLOMO reached a developed convergence rate with a complexity of $O(\epsilon^{-1.5})$ for smooth non-convex problems, compared to the complexity of previous schemes, which was $O(\epsilon^{-2})$. The major contribution of FedGLOMO was to



Figure 4: Momentum Federated Averaging

reduce the noise of local participant-level stochastic gradients and the high variance relevant to the central server aggregation phase. To this end, the authors postulated a variance-reducing momentum-based general update scheme at the central server and a variance-reduced local update scheme at the local participants. So, FedGLOMO technically mixed both schemes to appropriately address participant drift in heterogeneous data distribution environments, resulting in improved communication performance.

Kim et al. in [67] introduced a novel algorithm called FLwith Acceleration of Global Momentum (FedAGM) which developed the convergence and resilience of FL methods to address client heterogeneity and low participation rates. FedAGM aimed to forward a rapid model estimated with the global gradient to keep local gradients updated while developing the resilience of the central server-side aggregation setting. To this end, they merged global gradient data's momentum with clients and server weights. This method bridged the gap between local and global losses and obtained comparable taskspecific efficiency under fewer communication rounds. Moreover, FedAGM is considered a regularization term in the objective function of participants to improve the compatibility of local and global gradients. It was worth mentioning that FedAGM not only required the same memory and communication overhead, but it also was consistency with low-participation and large-scale FL settings.

To address the issue of data heterogeneity in FL, the authors in [68] put forth a clustered FL based on Momentum Gradient Descent (CFL-MGD) to improve the convergence rate of FL methods by incorporating cluster and momentum strategies and compared their results with existing approaches including kmeans clustering, cosine distance-based approaches, and userclustered algorithms. In CFL-MGD, participants with similar learning tasks fell into the same cluster according to their data. To update local model parameters, each participant in a cluster utilized its own data to update local model weights using momentum gradient descent. Their method integrated gradient averaging and model averaging for global average aggregation. They finally showed that the convergence of CFL-MGD for smooth and strongly convex loss functions was exponential.

Algorithm 3 Momentum Federated Learning Algorithm
1:Initialize global model: Ψ_t , number of rounds: t , Momentum
2: parameter: τ , Momentum update: ρ_t ($\rho_0 = 0$),Initialize
3:learning rate: η_l , batches: B, number of epochs: E.
4:For each round of iterations t do:
5: Select χ_t = random subset of clients $\chi(\chi_t < \chi)$
4: For each client $x \in \chi_t$ do:
5: For each local epoch i from 1 to E do:
6: For batch $b \in B$ do:
7: $\Psi_x^{t+1} = \Psi_t - \eta_l \Delta l_x(\Psi_t, b)$
8: end For
9: end For
10: end For
11: $v = \sum_{x=1}^{ \chi_t } \frac{n_x}{n} (\Psi_x^{t+1} - \Psi_t)$
12: $\rho_{t+1} = \tau \rho_t + (1 - \tau) v;$
13: $\Psi_{t+1} = \Psi_t + \rho_{t+1};$
14:end For

Another concern is that data heterogeneity among participants in FL gives rise to discrimination against unprivileged clusters assumed to have sensitive properties. To fill this gap, Salazar et al. in [69] offered a novel fairness-aware FL method (FAIR-FATE) to prioritize fairer models during global model aggregation and obtain group equality while ensuring higher utility. FAIR-FATE represents a fairness-aware aggregation algorithm that considers individual participants' fairness when performing global model aggregation using a fair Momentum term. The fair Momentum term overcame the fluctuation that occurred with non-fair gradients and claimed their method was the first method in ML to use a fair Momentum estimate for fulfilling fairness. In other words, FAIR-FATE tackled the concern of fairness in FL by facilitating collaboration among participants to create fair models while ensuring data protection. Technically, their method leveraged a verified set on the central server to examine the fairness and calculated fair Momentum weights utilizing a fraction of the average of participants' weights and previous fair weights, leading to higher fairness than the existing global and local models. When using momentum gradient descent, the oscillations of noisy gradients are overcome by using an exponentially weighted average of the gradients. It is quicker than DP because it better approximates the gradients.

The Federated Averaging with Standard Momentum (FedMom) method is represented by the algorithm 3 [69]. The Federated Averaging with Standard Momentum (FedMom) method is represented by the algorithm (3) [69]. The local weight was computed by deducting Ω_t from received Ω_{t+1}^k . In the next step, the local computed weights were averaged to build the global model weights, α . In the following, a summation of the former weights, ρ_t , was used to obtain the Momentum update, ρ_{t+1} , and the global model weight, α . To control the value of the previous weights, the authors defined τ , denoted the Momentum parameter. Eventually, the previous model was summarized to update the global model with the Momentum weight.

In the server, for every Ψ_{t+1}^k received, the local update is calculated by subtracting Ψ_t . Afterward, the local updates are averaged to form the global model update, ν . Then, the Momen-



Figure 5: Security Federated Averaging

tum update, ρ_{t+1} , is calculated by summing a fraction of the previous update, ρ_t , and the global model update, ν . τ is the Momentum parameter that controls the amount of the previous update. Finally, the global model is updated by summing the previous model with the Momentum update. In the Algorithm (3), the Fadabound process is presented [69].

3.1.4. Security Federated Averaging

Among other aggregation methods, security averaging is a cryptographic mechanism employed by FL to not only aggregate the updates received from clients but also guarantee a privacy-preserving model. It provides the following benefits:

- Preventing the server from learning the value and source of individual model updates.
- Protecting the FL system against inference and data attribution attacks.
- Compensating for the lack of parameter validation in the FL.

Cryptographic primitives and fully homomorphic encryption (FHE) suggest partial solutions for securitizing FL systems from sensitive information. However, both methods face deficiencies and scalability concerns. To solve these problems, FL has emerged to allow clients to train a shared NN without sharing their local data (see Fig. 5). To improve the security of FL, conflating the secure aggregation (SA) mechanisms has gained much attention. SA is assumed to be a robust defense mechanism against gradient inversion and inference attacks. SA enables clients to calculate the sum of their private parameters securely. Then, it receives the information from individual collaborations and conceals the source and location information of the aggregated data, ensuring client privacy. However, the authors in [70] showed that malicious servers could disturb the privacy properties of SA and exploit a vulnerability in the FL process. Malicious servers could tamper with model updates, planning a new attack vector called model inconsistency, where many clients use various views of the same model. Even after secure

aggregation, this inconsistency enabled the servers to extract information about users' privacy and their datasets. To clarify this vulnerability, the authors explored and applied two types of attacks that demonstrated the threat caused by the inconsistency attack vector. Both attacks represented how a malicious server could weaken the security created by current SA techniques. Individual model updates could be entirely identified from the aggregated data and correspondingly assigned to specific users, regardless of the number of involved users. Moreover, multiple strategies were adopted to put forth some solutions that helped integrate seamlessly with current SA techniques without compromising performance or utility to help alleviate this vulnerability caused by model inconsistency.

Another study was conducted to improve the privacypreserving system by employing secure multiparty computation (MPC) to aggregate the sum of model updates from clients confidently. Bonawitz et al. in [71] introduced a specific method called Secure Aggregation (SA), ensuring no party reveals their model update and sensitive parameters to the global aggregator or any other third party. The SA primitive enabled the private mixing of models' outputs locally to update a global model. This approach offers significant benefits, as users can share updates with the assurance that the service provider can only access the averaged updates after aggregation. The authors primarily focused on setting mobile devices in costly settings where dropouts were considered common. Compared to sending the parameter vector in simple text, their adopted model is intended to have less than twice the communication overhead. Furthermore, their mechanism was sustainable for dropout users at any point, while previous works did not adequately consider this combination of constraints [71]. Integrating DP with secure aggregation was suggested to model an E2E privacy-preserving system in FL. Secure aggregation enabled the combination of client weights without isolating any single client weight and updating it. DP algorithms mixed noise with client weights to prevent trained local and global models from exposing updates about the training data. Nevertheless, conventional secure aggregation approaches were extraordinarily complex and cost-effective. To shed more light on this topic, Stevens et al. in [72] adopted the FLDP mechanism, which used DP to provide precise, flexible, and effective FL without trusting on edge or cloud servers. The security of their scheme was according to the learning with errors (LWE) problem, where the noise mixed with DP also serves as the noise term in LWE. A main innovation of their study was offering a new algorithm that carefully utilized DP to fulfill secure model aggregation, which, in turn, resulted in a significant reduction of computational and communication overhead. In other words, their method significantly reduced the communications expansion factor and diminished the server's computation complexity. FLDP integrated the discrete Gaussian distribution and gradient clipping to ensure proper computational DP with well-organized, secure model aggregation. Their designed model obtained a high accuracy degree compared to central-model training methods under differentially private DL and enhanced efficiency and flexibility. Another application of DP was used in [73] by introducing a secure FedAvg approach that added Gaussian noise to the

Algorithm 4 Secure Federated Learning 1: **Input**: Initial model \bar{w}_0 and step size η_0 . The PS broadcasts \bar{w}_0 to all clients ($S_0 = [N]$). 2: for t = 0, 1, ..., T - 1 do: 3: **Client side**: for $k \in S_t$ in parallel do: 4: 5: if mod(t, Q) = 0 then: Set $w_k^t = \bar{w}_t$. 6: 7: end if 8: Sample a mini-batch ξ_k^t from D_k and calculate the 9: local gradient $g_k^t = \nabla F_k(w_k^t; \xi_k^t, b).$ if $\operatorname{mod}(t+1, \hat{Q}) \neq 0$ then: $w_k^{t+1} \leftarrow w_k^t - \eta_t g_k^t$. 10: 11: else if mod(t + 1, Q) = 0 then: $w_k^{t+1} \leftarrow (w_k^t - \eta_t g_k^t) + z_{kt}, \quad z_{kt} \sim N(0, \sigma_{t,k}^2 I_M).$ 12: 13: 14: Send w_k^{t+1} to the PS. end if 15: 16: end for for $k \notin S_t$ in parallel do: 17: $w_k^{t+1} = w_k^t.$ 18: 19: end for 20: Server side: 21: **if** mod(t + 1, Q) = 0 **then:** $\bar{w}_{t+1} = \frac{N}{K} \sum_{k \in S_t} p_k w_k^{t+1}$. Select a subset of clients S_{t+1} by sampling without-22: 23: 24: replacement, and broadcast \bar{w}_{t+1} to all clients. 25: end if 26: end for

shared updates. The authors' theoretical analysis showed that their approach achieved an O(1/T) convergence rate for local model parameters, where *T* denoted the overall number of SGD updates. Their analysis technically considered the interactions between the attainable privacy rate and system parameters, including mini-batch size, local epoch length, and the number of randomly selected clients using the amplification privacy theorem. To mitigate system complexity, they presented a proper trade-off between the convergence pace of their design and the chosen parameters. Finally, they investigated how different approach parameters could affect the communication efficiency of their approach. The secure FedAvg with standard security design is represented by an algorithm (4). [73]

Previous methods in secure aggregation primarily involved guaranteeing privacy within a single training round while neglecting massive privacy leakages through multiple rounds by assuming partial client selection. The authors in [74] overcame this problem by presenting a secure model aggregation protocol mainly aimed at ensuring client security during several consecutive training rounds. To this end, they offered a new metric in order to maintain privacy guarantees in FL secure aggregation within these rounds. Moreover, a systematic client selection mechanism, called Multi-RoundSecAgg, was adopted to significantly fulfill the long-term privacy of each FL client while providing proper fairness and allowing the average number of participants per round. In this regard, Kim et al. in [75] also came up with another solution by representing a new cluster-based secure model aggregation that carefully managed dropout nodes while improving computational and communication costs. They assumed an FL setting with heterogeneous devices with variable computing power and training data sizes distributed through diverse locations. Under their model, the cluster-based secure aggregation (CSA) mechanism grouped clients according to their response times, which were identified by their communication delay and local computing time. To this end, a grid-based clustering method was employed to cluster clients based on their similarity in processing scores and GPS information, allowing the edge or cloud server to approximate maximum latency for each cluster and determine dropout nodes more carefully. Over each cluster, the intermediate summations were performed for aggregation, and a novel additive sharing-based masking mechanism was schemed to preserve the actual local clients' weights through secure aggregation. Masking mechanism enabled elimination of dropout nodes without counting on (t, n) threshold factors, guaranteeing protected weights and data even when they were delivered after dropout nodes were exposed. Moreover, their mechanism included mask verification, allowing FL clients to publicly validate the exactness and loyalty of available masks utilizing a discrete logarithm problem.

3.1.5. Compressed and Quantization Federated Averaging

Blockchain has appeared as a distributed solution to ensure privacy-preserving FL-based systems; however, available blockchain methods suffer from several limitations regarding scalability and communication costs in large-scale networks (see Fig. 6). To address the downsides mentioned above, the authors in [76] innovated a cross-chain framework for flexible and scalable structures in AIoT. With this in mind, some applicable blockchain methods were used for particular FL tasks, guaranteeing security and performance. For example, a cross-chain approach allowed secure collaboration and interplay among blockchains, and accordingly, a model update compression method was used to carefully manage communication costs without compromising system precision. ML-based auctions as a dynamic pricing method were also offered for model training.

Another approach, compressed averaging, was used in [77], whichJoint privacy enhancement and quantization (JoPEQ) aimed to tackle communication efficiency and privacy in FL. JoPEQ blended privacy enhancement and lossy compression algorithms by leveraging vector quantization based on the random lattice, which was an applicable compression method. It showed statistically equivalent additive noise as a byproduct of distortion that was used to improve privacy issues by adding a dedicated privacy-preserving noise model involving two or more variable quantities to the model updates. They showed that JoPEQ obtains concurrent data quantization based on an appropriate bit rate while ensuring a proper privacy level without compromising the utility and accuracy of the global model. To this end, analytical guarantees were performed on convergence bounds, local DP, and the derivation of distortion. Moreover, JoPEQ revealed its efficiency in alleviating attacks that

took advantage of privacy leakage. The repeated exchange of local model weights and parameters between the participants and the central server (cloud) may result in communication bottlenecks and overload. To tackle this problem, a novel algorithm was introduced [78], called GWEP, a compression-based FL approach. GWEP incorporated joint quantization and model pruning methods to exploit the advantages of DNNs while carefully handling the limitations of resource-limited clients in FL. To enhance the scalability and feasibility of FL, GEWP facilitated the participation of low-end IoT clients in the FL setting by lowering the computational cache, complexity, and other network needs. Moreover, they mathematically showed the FL convergence to an optimal solution. Communication in FL can be performed in two scenarios: downlink and uplink. In uplink transmission, clients forward their updated weights to the central server, which usually brings about a tighter bottleneck than downlink transmission, which happens in the opposite direction. This is usually because of the limited upload bandwidth compared to download bandwidth and the demand for aggregating weights from many clients. To solve it, compressing uplink transmission is a key solution. To shed more light on the topic, a common adaptive quantization method is to apply lossy quantization supported by optional lossless compression. Adaptive quantization by constant change adapts the quantization rate and exploits the asymmetries, including variations in training time and client contributions according to local dataset sizes, to minimize transmission costs. For example, dynamic adaptations of the quantization level can significantly improve compression and quantization without compromising the quality of the trained model. The authors in [79] adopted a doubly adaptive quantization method (DAdaQuant) that dynamically adapted the quantization volume among various clients over time and consistently enhanced the client-server compression, improving non-adaptive baselines by up to 2.8 times in the FL process. Clearly, the client-adaptive quantization method technically assigned a minimal quantization rate to FL's clients, where the expected variance of quantized parameters was considered a quantization error metric. This decreased the volume of data transmitted from FL's clients to the central server (cloud) while controlling the quantization error.

Yongjeong et al. in [80] suggested a communication-efficient FL structure called FedQCS, supported by quantized compressed sensing. Their structure tackled the concerns of communication cost and transmission overhead without sacrificing the accuracy of gradient communication. This structure included dimensional reduction, sequential block sparsification, and quantization blocks for gradient compression. Their structure exploited quantization and dimension reduction to achieve higher compression ratios than one-bit gradient compression. For FL to carefully aggregate local updates from compressed signals, the authors presented an approximate minimum mean square error (MMSE) algorithm for gradient reconstruction utilizing the expectation-maximization generalized approximatemessage-passing (EM-GAMP) scheme. Moreover, their structure used a low-complexity method for gradient reconstruction based on the Bussgang theorem.



Figure 6: Compressed and Quantization Federated Averaging

To mathematically analyze the quantization method, the authors in [81] discussed a hierarchical FL called Hier-Local-QSGD where one cloud server, P edge servers, and N clients were assumed. D_i^l where $i = 1, \dots, M$ denoted the distributed training datasets. In their algorithm, there were two phases. The first one was frequent Edge Aggregation and Infrequent Cloud Aggregation, where periodic aggregation was considered an effective tool for communication costs. A big aggregation time slot, T, led to a small communication round while reducing the system's performance. This is because if local models underwent too many steps of local SGD updates, they would begin to come close to the local loss function $h_i(x)$'s optima rather than the global loss function h(x). To this end, before the cloud aggregation, each edge server effectively aggregated the models in its immediate vicinity many times. Each edge server averaged the models of its clients after every T_1 local SGD update on each client, to be more precise. Then, the cloud server averaged all edge servers' models after each T_2 edge aggregation. Thus, communication with the cloud occurred after every T_1T_2 local updates. In contrast to FedAvg with an aggregation interval of $T = T_1T_2$, the local model was thus less likely to be skewed towards its local minima. The second phase of the Hier-Local-QSGD was called Quantized Model Updates, where the DL model size, which defined the volume of data to be communicated in each communication cycle, also influenced the total communication cost in the FL process. The size of the model updates was frequently reduced using quantization techniques in each round. A low-precision quantizer significantly lowered the communication cost while adding more noise during the FL process, eventually decreasing the updated model's performance. In [81], the specific quantizers used on the model updates from the client to the edge server and the model updates from the edge servers to the cloud server were represented by Q1 and Q2, respectively. However, complex mathematical analysis was illustrated in [82Quan] with details. In the Algorithm (5), the Hier-Local-QSGD process is presented [81]



Figure 7: Federated Learning; Challenges and Applications

4. Security in FL

4.1. Block-Chain

Industrial IoT (IIoT) enables the collection of private data through a variety of smart devices, and the analysis of this data can guide decision-making at various levels. By delivering model updates across IIoT networks rather than private data, FL may be utilized to assess the gathered data while protecting user privacy. However, the FL framework is weak because hostile agents may readily interfere with model updates. To solve this security problem, the authors in [94] offered a unique chameleon hash algorithm with a configurable trapdoor (CHCT) for safe FL in IIoT scenarios. They thoroughly analyzed their CHCT system's security and created a redactable medical blockchain (RMB) that implemented the CHCT concept. Zhang et al. in [82] proposed a safe data transfer mechanism using the benefits of EC, FL, and the exceptional features of the blockchain. To improve learning efficiency, they first separated the local model updating process from the mobile device-independent process; next, they added an edge server so that most of the computation was done on the server; and finally, they used a distributed blockchain architecture.

Enhancing FL security and performance critically depends on preventing malicious nodes from impairing model training while motivating trustworthy nodes to participate in learning. In [83], the authors provided the BESIFL (Blockchain Empowered Secure and Incentive FL) paradigm as a contribution to the field. In particular, BESIFL used blockchain to create a completely decentralized FL system where efficient methods for incentive management and malicious node identification were fully incorporated. To assure data security and intelligent computation offloading in the Power IoT (PIoT) structures, Zhang et al. in [84] first discussed a blockchain and AI-based safe cloud-edge-end collaboration PIoT (BASE-PIoT) architecture. To solve the safe and low-latency compute offloading issue, they adopted a blockchain-enabled federated deep actor-criticbased task offloading method. Utilizing Lyapunov optimization, the long-term security constraint and short-term queuing delay optimization were separated to be managed appropriately. To address the security issue and latency problem in IoT-based networks, the authors in [85] represented a novel architecture called space-assisted PIoT (SPIoT), in which a satellite in low earth orbit (LEO) helped by broadcasting consensus messages to shorten the delay in block formation. To reduce the overall queuing time under the long-term security restriction, they specifically designed a Blockchain and semi-distributed learning-based secure and low-latency computation offloading method (BRACE). With Lyapunov optimization, server-side computational resource allocation and task offloading were first separated. Second, their proposed federated deep actor-criticbased task offloading technique resolved the issue. Finally, Lagrange optimization and smooth approximation were applied to resolve the resource allocation issue. Zhang et al. in [86] studied and designed a platform architecture of FL systems based on blockchain for IIoT failure detection, enabling verified integrity of client data. According to the design, each client produced a Merkle tree regularly, storing the tree root on a blockchain and each leaf node as a representation of a client data record. Additionally, they offered a unique centroid distance weighted federated averaging (CDW-FedAvg) technique that considered the distance between each client data set's positive class and negative class to solve the problem of data heterogeneity in HoT failure detection. Additionally, a clever contact-based incentive system was created to encourage users to participate in FL based on the volume and centroid distance of user data

Reference	Year	Acc> 90%	AI/ML approach	Open Areas and Future Challenges and Directions	
[82]	2022	1	_	Assessing the complexity of data transfer and developing a transmission security mechanism to cope up with significant network attacks.	
[83]	2021	1	BESIFL	Improving node-selection method to reduce iterations and considering model-variable gradient protection to increase learning reliability.	
[84]	2022	_	FDRL	Addressing Poor Scalability using lightweight hierarchical storage and Security threats with the integration of AI-based secure networks, zero-trust-based identity, and block-chain.	
[85]	2021	_	BRACE	DRL with adversary will be examined for their a Blockchain and semi-distRibuted leArning-based seCure and low-latEncy computation offloading algorithm (BRACE).	
[86]	2021	1	CDW-FedAvg	Improving the trustworthiness of node devices for the aggregation and modifying the model by relocating modules from node servers to node devices with storage facilities and better processing.	
[87]	2020	1	FL-Block	Expanding the model by maximizing the trade-off between efficiency and security and identifying the ideal conditions for computation and communication costs using the MDP and game theory.	
[88]	2022	1	HFL	_ .	
[89]	2022	X	_	Considering the non-cooperative game model in the industrial setting, training variables must be traded in a game theory way to enable distributed knowledge sharing.	
[90]	2022	1	BFRT/LSTM	Studying novel methods for online multi-output prediction, as well as experimenting using multiple blockchain designs to improve the FL process.	
[91]	2022	_	—	Assessing the structure's resistance against poisonous attacks.	
[92]	2021	_	DL/Triabase	The data integrity of transactions are protected by using binary hash trees, also known as Merkle trees, and only byte hashes are employed to construct a Merkle path from the root to a given transaction.	
[93]	2021	1	DL/Triastore	Exploring the performance of Triastore on edge DL datacenter with strong GPU cards and developing the Triastore with pervasive querying layers to conduct experiments with more datasets.	

Table 4: References on FL-based Block-Chain Structures

utilized for local model training. The authors in [95] looked into ways to synchronize the edge and the cloud to enhance FL's overall cost-effectiveness. Using Lyapunov optimization theory, they developed and analyzed a cost-effective optimization framework, CEFL, to make near-optimal control decisions for the dynamically arriving training data samples, such as admission control, load balancing, data scheduling, and accuracy tuning online. Their control framework, CEFL, could be adaptably expanded to include different design decisions and practical requirements of FL, like utilizing the less expensive cloud resource for model training with improved cost efficiency while facilitating on-demand privacy preservation. To enable the integration of security-focused offloading algorithms, Qu et al. [96] presented a unique simulation platform called ChainFL that creates an EC environment among IoT devices and is compatible with FL and blockchain technologies. ChainFL is interoperable and lightweight, and it can swiftly link devices with various architectural styles to create complicated network settings. Additionally, due to its distributed structure and incorporated blockchain, ChainFL can be utilized as an FL platform across various devices to enable FL with great security. By integrating a complicated offloading-decision model into the platform and using it in an industrial IoT setting with security issues, they proved the flexibility and efficiency of ChainFL. To anticipate cached files, the authors in [97] created a new CREAT method that performs the FL compression algorithm with blockchain assistance. Each edge node in the CREAT method uses local data to train a model, which is utilized to learn the properties of users and files and anticipate the most popular files to increase cache hit rates. They utilized FL to allow numerous edge nodes to participate in training while protecting the confidentiality of edge nodes' data without sharing it. Additionally, to lessen the burden on FL's communication system, their method helps compress the gradients that edge nodes upload to speed up communication. Additionally, they have included blockchain technology in the CREAT algorithm to guarantee the security of the communicated data. For decentralized entities, they created four smart contracts that track and confirm transactions to ensure data security. Qu et al. [87] adopted a unique FL-Block (FL facilitated by blockchain) approach. With a global learning model built on a blockchain and confirmed by miners, FL-Block enables local learning updates of end-device trades. Based on this, FL-Block uses the blockchain's Proof-of-Work consensus method to enable autonomous ML that maintains the global model without a centralized authority. Additionally, they evaluated FL-Block's latency performance and determined the ideal block production rate used for communication, consensus delays, and computing costs. Blockchain for data exchange was being studied in [98] technically as big data and blockchain technology advance. Studying blockchainbased data sharing models, they discovered that practically all of them suffer from some issues, including 1) It is challenging to safeguard users' data ownership rights and their privacy and integrity, 2) Blockchain lacks a system for handling data of various sorts and inconsistent forms, and its storage requirements are high, 3) The consensus procedure is inefficient or not very fair. They proposed an FL method to address these issues and designed a blockchain-based data-sharing privacy protection model (DS2PM). The authors in [88] provided a hierarchical FL (HFL) approach based on blockchain that maintains rapid, safe, and precise decision-making for commercial machinery. An FL technique with two stages was designed, the first involving clustering industrial devices for local ML training. Next, local models are sent to network edge devices, and Algorithm 5 Quantization Federated Learning Algorithm

1: initialize the model on the cloud server X_0 :

2: **for** k=0,1,··· ,K-1 **do**:

- 3: for $i = 1, \dots, s$ edge servers in parallel do:
- Set the edge model same as the cloud server model: 4:

5: $u_{k,0}^{i} = X_{k}$:

- for $t_2 = 0, 1, \dots, \tau_2 1$ do: 6:
- 7: for i in C^i clients in parallel do:
- Set the client model same as the associated edge 8:
- 9:
- 10:
- server model: $x_{k,t_2,0}^i = u_{k,t_2}^i$: **for** $t_1 = 0, 1, \dots, \tau_1 1$ **do**: $x_{k,t_2,t_1+1}^i = x_{k,t_2,t_1}^i \eta \nabla f_i(x_{k,t_2,t_1}^i)$ **end** 11:
- 12:
- Send $Q_1(x_{k,t_2,\tau_1}^i x_{k,t_2,0}^i)$ to its associated edge server: 13: 14: end

Edge server aggregates the quantized updates from the 15: clients:

- $u_{k,t_2+1}^i = u_{k,t_2}^i + \frac{1}{m^i} \sum_{i \in D^i} Q_1(x_{k,t_2,\tau_1}^i x_{k,t_2,0}^i)$ end 16: 17:
- Send $Q_2(u_{k,\tau_2}^i u_{k,0}^i)$ 18:
- 19: end

20: Cloud server aggregates the quantized updates from the edge servers:

21: $x_{k+1} = x_k + \sum_{i=1}^s \frac{m^i}{n} Q_2(u_{k,T_2}^i - u_{k,0}^i)$ <u>22:</u> end

FL averaging is used to build a collection of global models. Using an FL aggregating technique, a primary global model is built from the scattered first-stage global models in the second stage. The learned models are validated and verified on the edge using blockchain. To complete CPS tasks, Al et al. [89] discussed a cooperative blockchain-assisted resource and capability-sharing strategy. To support Next-Generation Networks (NGNs), their solution utilized Intelligent IoT (IIoT) devices that appropriately support FL. For CPS problems, local and global models are produced using a multi-stage clustering blockchain and FL algorithm. In each cluster, local models are developed in the first stage. Fog devices build fog models at a later time using federated averaging. The next step is utilizing Federated Aggregation to build a global deep model on the cloud. To record and validate the additional models and ensure that cyberattacks do not alter records, blockchain is employed. Given real-time data and EC, the authors in [90] concentrated on BFRT, a blockchained FL architecture for predicting internet traffic flow. Their method protects the confidentiality of the underlying data while enabling decentralized real-time model training at the edge of the IoT. Considering dynamically recorded arterial traffic data shards, they combined GRU and LSTM models and conducted comprehensive trials. On Hyperledger Fabric, they created a working prototype of their proposed permissioned blockchain network and performed extensive testing with virtual computers acting as the edge nodes. In circumstances where participatory organizations are thought to be completely capable of injecting low-quality model updates and are unwilling to submit their local models to any other entity for verification purposes, Ranathunga et al. [91] presented

a decentralized architecture based on Blockchain. Their proposed decentralized FL framework uses a cutting-edge hierarchical network of aggregators that penalize or reward organizations based on the quality of updates to their local models. Unlike cutting-edge methods, the architecture is adaptable and precludes a single entity from controlling the aggregated model in any FL round of training. In two Industry 4.0 use cases, namely, predictive maintenance and product visual inspection, their proposed framework is evaluated in terms of off-chain and on-chain performance.

Needless to say, mobile or IoT users must carry out numerous activities, including encryption, decryption, and mining, to add a transaction to the blockchain in MBNs. These activities need energy and computation power, which limits how well users of mobile and IoT devices may operate because they usually rely on batteries and have a limited computing capacity. The duties might be carried out virtually on common servers offered by mobile edge computing (MEC) or cloud computing as one potential option. It is possible to consider all the steps required to add a transaction to the blockchain as virtual blockchain functions that may run on common servers. The authors in [99] enhanced the blockchain function virtualization (BFV) architecture that enables MEC or cloud computing to carry out all blockchain tasks virtually. They also discussed the BFV framework's uses and the problems with resource allocation it creates in mobile networks. Additionally, they proposed an optimization problem to simultaneously reduce the cost of energy consumption and increase the incentives for miners.

The innovative idea of factory-as-a-service (FaaS) enables the production process to be quickly adjusted by recognizing the sector's supply chain and customer needs. Flexibility in networking and cloud services is essential for FaaS support. A third-party broker known as a 5G network slice broker (NSB) helps service providers and clients meet each other's demands for networking resources. To support FaaS, Hewa et al. [100] offered a safe NSB built on a blockchain. With the cooperation of slice and SSLA managers, their proposed secure NSB (SNSB) ensured secure, cognitive, and distributed network services for resource allocation and security service level agreement (SSLA) formulation. To compute the real-time and optimal unit pricing in SNSB, they put forth a federated slice selection technique that blends a Stackelberg game model with a reinforcement learning algorithm.

Through a shared ML model driven by blockchain technology and an FL framework dubbed iFLBC edge, the authors in [101] examined a method to deliver edge-AI to end nodes. Creating a technique known as the Proof of Common Interest (PoCI) to separate relevant data from irrelevant data tackles the problem of the dearth of pertinent data. A model is trained on the pertinent data, and when it is aggregated with other models to create a shared model, it is stored on the blockchain. Network members download the aggregated model, which they can use to give end consumers edge intelligence. Members of the iFLBC network can provide end-user intelligence services, making AI more pervasive.

This decentralized learning technique leaves the whole solution vulnerable to many types of assaults that can completely damage the correctness of the produced global model while not outsourcing sensitive data to cloud-hosted services and fragmenting the workload for data processing. In [102], Esposito et al. aimed to evaluate the effects of two well-known assaults on FL objectively and offered a provisional defense mechanism based on the blockchain.

To address the existing blockchain issue, reputation is used as a metric to assess the dependability and trustworthiness of edge devices. To solve the issue of task assignment between task publishers and reputable employees with high reputations, a many-to-one matching approach was presented in [103].

The authors in [92] and [93] surveyed Triabase, a unique permissioned blockchain database scheme that abstracts ML models into simple data blocks that are then saved and retrieved via the blockchain. Triabase is an ML application on the edge server. Because of the costly verification procedure, it does not keep extensive information on a medium like blockchains, which is inherently sluggish. Concerning its consensus process, Triabase uses technological innovations, specifically the Proofof-Federated-Learning (PoFL) concept. The Triabase prototype system was integrated into the Hyperledger Fabric blockchain architecture based on positive early results. The future directions, open areas, and accuracy of references in Block-chain FL-assisted systems are listed in Table 4 with details.

4.2. Privacy Preserving:

The limitations of the conventional centralized learning strategy (CL) include centralizing the data resources of several shipping businesses on a cloud server for model training due to privacy and commercial rivalry issues. Zhang et al. [104] presented the adaptive FL strategy (AdaPFL), which can bring together several shipping agents to construct a model by exchanging model parameters without any danger of data leakage for defect diagnosis in IoS. They first utilized two typical activities as examples to show that a tiny portion of the model parameters can disclose the shipping agents' unprocessed information. Based on this, the Paillier-based communication system was created to protect the shipping agents' original data. Additionally, a control technique was presented to adaptively alter the model aggregation interval throughout the training process to minimize the costs associated with cryptographic computation and communication for coping with the harsh sea environment.

To guarantee the context-aware privacy of task offloading, Xu et al. [105] presented C-fDRL, a model to enable context-aware federated deep reinforcement learning (fDRL). They performed this in three stages (CloudAI, EdgeAI, and DeviceAI). C-fDRL examines whether the privacy of low context-aware data is distributed at the EdgeAI and high context-aware data is preserved locally at the DeviceAI with the work being offloaded. To this end, C-fDRL employs a context-aware data management technique (CDMA) to decouple the context-aware (privacy) data from the tasks if a user requests to offload the data. This enables a novel scheduling method known as a "context-aware multi-level scheduler" that isolates the context-aware data from the job for local processing. To perform the computational process before the actual job execution, CDMA sets high context-aware data at local devices and low context-aware data at the edge device.

The authors in [106] studied a collaborative DDoS detection and classification strategy leveraging FL for dispersed and multi-tenant IoT settings. Through a joint effort, several tenants can improve their DDoS detection and classification skills across all edge nodes using this method while still retaining their privacy. Tenants exchange the model parameters with other tenants after training DL instances on locally scaled traffic data. Their proposed approach makes IoT operations safer and could be used in various applications. In [107], Ferrag et al. discussed creating the Edge-IIoT-set, a brand-new, comprehensive, and realistic cyber security dataset for IoT and HoT applications that ML-based intrusion detection systems can utilize in both centralized and FL modes. The dataset has a sizable representative set of IoT/IIoT testbed devices, sensors, protocols, and settings for the can and edge. The IoT generated data from more than ten IoT devices, including inexpensive digital sensors for detecting temperature and humidity, ultrasonic sensors, water level detection sensors, pH sensor meters, soil moisture sensors, heart rate sensors, and flame sensors, among others. The fourteen assaults the authors uncovered and evaluated are connected to IoT and IIoT communication protocols and are categorized into five types of threats: DoS/DDoS attacks, information-gathering attacks, a man in middle attacks, infiltration attacks, and malware attacks. They also extracted features from other sources, such as warnings, system resources, logs, and network traffic. In addition to the 1176 characteristics they collected, 61 features with strong correlations are suggested.

With unreliable users, the authors in [108] introduced an effective privacy-preserving FL (EPPFL) approach. Thev create a new method that ensures the targeted model is updated with high-quality data to lessen the detrimental effects of unreliable users. The FL model quickly converges with little communication and processing cost by iteratively applying its "Excluding Irrelevant Components" and "Weighted Aggregation". As a consequence, it is possible to maximize not only the model accuracy but also the training effectiveness. In the interim, they operate a secure framework based on the threshold Paillier cryptosystem, capable of rigorously safeguarding all user-related private data throughout the training procedure. Song et al. [109] presented FDA3, a powerful federated defense strategy that combines defensive expertise against hostile instances from several sources. Their presented cloud-based architecture enables the sharing of protection capabilities against various assaults across IIoT devices in a manner that FL inspires. In [110], Liu et al. presented a privacy protection FL system with staleness asynchronous updating to overcome the disparities brought on by vehicle heterogeneity and safeguard the confidentiality and privacy of vehicular training data. Additionally, to fully use the previously trained local model, their approach incorporates dynamic temporal weights according to various vehicles' computation and communication capabilities. This contrasts with the standard weighted average on the server side, which considers the number of samples. Their method can save network traffic and

increase learning efficiency, boosting security and privacy. An exploratory microservice placement approach was surveyed in [111] to enable improved microservice deployment depending on the computational capacity of the participants to address the latency issue of industrial cyber-physical systems (ICPSs).

For healthcare usage, the conventional training model fraud in the decentralized Internet of Medical Things (IoMT) is a serious study issue. To this end, an FL-based blockchain-enabled task scheduling framework (FL-BETS) with several dynamic heuristics was developed in [112]. The study considers several healthcare applications that, while executed on distributed fog and cloud nodes, had hard constraints (like deadlines) and soft constraints (like resource energy usage). To meet the deadlines of healthcare workloads, FL-BETS aims to identify and assure data privacy preservation and fraud at multiple levels, like local fog nodes and faraway clouds, with the least amount of energy and delay. The authors in [113] developed a generative convolutional autoencoder (GCAE) that aims to achieve accurate and individualized health monitoring by fine-tuning the model with a generated class-balanced dataset from user-specific data to deal with the unbalanced and non-IID distribution inherent in users' monitoring data. Additionally, the lightweight nature of GCAE makes it ideal for communication cost reduction in FedHome's FL. Xu et al. [114] concentrated on the elements of the system to enhance FL and provide FedMax, a highly effective and dependable distributed FL framework. By building FedMax with the characteristics of a genuine FL environment, they made novel contributions, such as a relaxed synchronization communication scheme and a similarity-based worker selection method. They constructed a FedMax prototype, tested it using many well-known ML models and datasets, and finally showed that FedMax greatly improves the resilience of an FL system and accelerates the convergence rate. Wang et al. [115] suggested the heterogeneous brainstorming (HBS) approach for real-world IoT item detection problems. With a novel "brainstorming" methodology and programmable temperature settings, their approach enables flexible bidirectional FL of heterogeneous models trained on remote datasets.

The authors in [116] built an F-DFRCNN-NE model for IoT privacy and security. The federated neural evolution framework investigates evolutionary computation-based neural architecture. It encodes network connections and modules, sets optimization parameters, makes a search space, uses evolutionary search techniques, and creates the required neural architecture. The federated environment guarantees information security during the federated neural development process. DP can be used to appropriately safeguard training data and prevent it from being misused. Convolution, pooling, and complete connection modules with their characteristics and parameters can be encoded by optimization variables, allowing for the flexible construction of neural architecture through evolution. This F-DFRCNNNE model can safeguard participants against cyberattacks while preserving their privacy. In [117], Zhao et al. focused on integrating FL with local DP (LDP) to help crowdsourcing applications develop ML models while avoiding privacy threats and lowering communication costs. They specifically focused on four LDP techniques to

disturb vehicle-generated gradients. When the privacy budget is limited, the Three-Outputs technique presents three alternative output choices to deliver high accuracy. To cut down on communication costs, the output options of Three-Outputs can be encoded with just two bits. Additionally, an ideal piecewise technique (PM-OPT) enhances performance when the privacy budget is substantial. Additionally, they provided a suboptimal technique (PM-SUB) with a straightforward formula and similar usefulness to PM-OPT. Then, they created a brand-new hybrid mechanism by merging Three-Outputs with PM-SUB. Finally, an LDP-FedSGD method is applied to jointly coordinate the cars and cloud server to train the model. The authors in [118] recommended a customized FL framework on a cloud-edge architecture for intelligent IoT applications. To deal with the heterogeneity challenges in IoT contexts, they looked into new customized FL approaches that could reduce the negative impacts of heterogeneity in several aspects. EC's strength enables the development of sophisticated IoT applications that need quick processing and low latency. Alotaibi et al. [119] offered a framework dubbed PPIoV built on Blockchain and FL technologies to protect the privacy of automobiles in the Internet of Automobiles. Since they were trained on data with local characteristics, most ML techniques are not well suited for distributed and highly dynamic systems like IoV. Therefore, they employed FL to train the global model while maintaining privacy. Additionally, their strategy is based on a plan that assesses the dependability of the automobiles taking part in FL training. Additionally, PPIoV is created on the blockchain to provide trust among several communication nodes. For instance, all transactions occur on the blockchain when the locally learned model updated by the cars and fog nodes communicates with the cloud to update the globally learned model. The authors in [120] put forth a workable technique for privacy protection in EC-based DL classification tasks based on bipartite topology threat modeling and an interactive adversarial deep network building. Their strategy is known as Privacy Partition. In deployment contexts like IoT smart spaces, where users like to be protected and also serviced by DL techniques, a bipartite topology with a trusted local partition and an untrusted remote partition presents an appropriate substitute to centralized and federated collaborative DL frameworks.

In an EC system based on FL and blockchain technology, the authors in [121] exerted a safe approach to exchanging MIoT data that protects node privacy by fusing its unique distributed architecture with the MIoT EC architecture. The blockchain works as a decentralized method for storing FL workers to ensure security and tamper-proof issues. They suggested using reputation and quality as selection criteria for FL employees. They created a quality proof technique called proof of quality (PoQ) and implemented it on the blockchain to improve the edge nodes recorded there. Additionally, a model of the maritime environment was developed in their study, and analysis based on this model extended its applicability to the marine environment. Zhou et al. [122] presented a real-time data processing architecture for multi-robots based on differential FL, known as the RT-robots architecture, to gain

huge data values via knowledge sharing while guaranteeing real-time data processing and data privacy. The robotic tasks are executed locally in real-time after a global shared model with DP protection is learned repeatedly on the cloud and disseminated to several edge robots in each round. In [123], Ghimire et al. focused on the security element and examined several methods for addressing performance difficulties like accuracy, latency, and resource limitations related to FL that affect the security and overall performance of the IoT. They went through the major current research initiatives, difficulties, research trends, and forecasts for how this new paradigm could develop in the future. The authors in [124] suggested an FL-enabled AIoT approach for private energy data sharing in edge-cloud collaborative smart grids. To be more precise, they first provided a communication-efficient and privacy-preserving user-sharing FL framework for edge clouds in smart grids. Then, by taking non-IID impacts into account, they developed two optimization issues for EDOs and energy service providers as well as a local data assessment method in FL. Additionally, to encourage EDO involvement and high-quality model contribution, a two-layer deep reinforcement-learning-based incentive algorithm was created owing to the absence of knowledge of multidimensional user private information in real-world settings.

For IIoT-enabled systems, Bugshan et al. [125] designed a reliable privacy-preserving FL-based DL (FDL) service By combining many locally trained models framework. without distributing any datasets among the participants, FL reduced the privacy concerns of the conventional collaborative learning paradigm. However, the FDL model can't be relied upon due to its vulnerability to intermediate findings and data structure leaks during the model aggregation phase. Their framework provided a Residual Network-based FDL with a DP service model for building reliable locally trained models and an edge and cloud-powered service-oriented architecture defining the major components. To assure reliable execution through privacy protection, the service model breaks down the functionality of the whole FDL process into services. Finally, they created a local model aggregation approach for FDL that protects privacy.

To accomplish model aggregation for FL while protecting privacy, the authors in [126] looked at using MultiParty Computation (MPC). Peer-to-peer model aggregation using MPC incurs significant communication costs and limits scalability. The authors aimed to create a two-phase system to solve this issue by 1) choosing a small committee and 2) making MPC-enabled aggregated model services available to more participants in the committee. The smart manufacturing IoT platform integrates the MPCenabled FL framework. It allows a group of companies to jointly train high-quality models using their complementary data sets on their own premises without sacrificing execution efficiency in terms of communication costs, execution time, and model accuracy compared to traditional ML methods and privacy.

The system's size makes it impossible to collect many logs. Sharing security records by the involved devices also gives rise to privacy issues; by outlining a novel IDS for EoT, the authors in [127] proposed a solution to these problems. The suggested IDS utilizes FL to let edge nodes share models rather than raw data and to aggregate the models made available hierarchically. Additionally, their method detects any individual or group efforts to undermine the IDS by disseminating false (poisonous) data. They used a Louvain technique to find collusive groups and an iterative voting procedure to assign trust to participating devices. In [128], new datasets, dubbed ToN IoT datasets, were described. These datasets comprise dispersed data sources gathered from Telemetry datasets of IoT services, Operating systems datasets of Windows and Linux, and Network traffic datasets. Their primary purpose is to describe the new testbed architecture that gathers Linux datasets from hard drives, memory, and process audit traces. The architecture creates edges, fog, and clouds at three dispersed levels. IoT and network systems are included in the edge layer, virtual machines and gateways in the fog layer, and data analytics and visualization tools in the cloud layer, which are interconnected with the edge and fog layers. The Network-Function Virtualization (NFV) and Software-Defined Networking (SDN) platforms VMware NSX and vCloud NFV control the layers programmatically. Several innovative federated and distributed AI-enabled security solutions, including intrusion detection, threat intelligence, privacy preservation, and digital forensics, can be trained and validated using the Linux ToN IoT datasets.

In the context of fog computing (FC), Liu et al. [129] adopted a safe aggregation mechanism based on effective additive secret sharing. Secure aggregation is widely used in FL training, so the protocol must have little communication and processing overhead. The first step is to provide local services that can help the cloud server aggregate the total data throughout the training process by using a fog node (FN) as an intermediary processing unit. Second, they created a simple Requestthen-Broadcast mechanism to ensure their protocol is resilient to clients who drop out. Moreover, their protocol also offered two straightforward new techniques for choosing clients. In [130], a unique edge intelligent computing architecture for picture categorization in the IoT was developed. Each edge device trains the autoencoder (an unsupervised method) before transmitting the acquired latent vectors to the edge server for training a classifier. The data of end users is protected, and transmission overhead is reduced. In contrast to FL, their proposed system allows the autoencoder to be taught individually at each edge device without the assistance of a server throughout the classifier training process. The developed technique does not experience high communication costs, as seen in SplitNN, a collaborative intelligence algorithm. Furthermore, the transmission of latent vectors protects the end-users' data privacy without incurring additional costs for encryption. In [131], the authors proposed an edge-cloud architecture that performs the detection duty directly at the edge layer, close to the attack source, enabling rapid reaction, adaptability, and lowering the workload of the cloud. They also introduced a multi-attack detection system dubbed LocKedge (Low-Complexity Cyberattack Detection in IoT Edge Computing) that is very accurate while still being easy to implement at the edge zone. To test the effective-

Table	5:	References	on	FL-based	Privacy	/-Preserv	ving	Structures
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Reference	Year	Acc> 90%	AI/ML approach	Open Areas and Future Challenges and Directions
[104]	2022	1	AdaPFL	Enhancing the FL's convergence pace, and creating and deploying an FL key distribution method in real-ship settings.
[105]	2022	1	fDRL	Examine the accuracy of the created FL scheme across DQN for numerous data points at different edges (local models) and add the associated processing cost of C-fDRL.
[106]	2022	×	DL	Examining model aggregation, hyperparameter customization, various attacks, computation time, and connectivity issues.
[107]	2022	1	—	-
[108]	2022		EPPFL	-
[109]	2021	×	DDN/FDA	-
[111]	2022	1	DL-Fed-TH	Investigating the load balancing in multi-cloud IIoT setups, installing a single threat intelligence (TI) microservice, and creating a trade-off between productivity and anonymity.
[112]	2021		FL-BETS	Focusing on mobility fraud awareness and intrusion detection for civil maritime usages and determining the cost functions for the system's scalability and security limitations.
[113]	2022	1	GCAE	_
[114]	2020	1	FedMax	_
[115]	2021	1	DL	Applying the asynchronous training for the fog/edge-based networks.
[116]	2022	_	F-DFRCNN-NE	To automatically optimize network to decrease cost, a multiobjective neural search method may be used and testing standards for FL can be further standardized due to its fast growth.
[117]	2021	1	LDP/SVM	Creating LDP protocols for cutting-edge FL systems.
[120]	2018	_	DL	Investigating the viability of deploying the model to large scale ML setups with integration of IoT hardware and software, and studying security issues and best invertibility situations.
[121]	2022	×	_	Creating methods to optimize the number of workers to save resources, as well as how to dynamically adjust reputation thresholds to reduce the adverse effects of malicious workers.
[122]	2018	×	DP	In addition to the real-world robotic identification work, they incorporate their architecture into future real-time IoT applications.
[123]	2022	_	_	IID, nonmodified, and equal data distribution will be used to address large-scale FL. The prevention of attacks on real FL stetting without compromising accuracy will be studied.
[124]	2022	1	DRL	In AIoT, the blockchain-based robust FL and the local model assessment framework will be examined according to DP-based gradient disturbance.
[125]	2022	—	FDL	Using real datasets for various DL models with smaller parameter sizes. Providing better protection for sharing parameters using various privacy methods like GAN-based policies.
[126]	2020	1	MPC-FL	TL and vertical FL will be examined. Improving efficiency and scalability by assuming a high number of parties and datasets on AWS-CrossRegion and AWS-SameRegion.
[127]	2022	1	FLACI	_
[129]	2022	—	—	Creating a safe aggregation protocol in a hostile environment, as well as a novel aggregation approach to identify corrupted new robust aggregation recipes and local models.
[130]	2022		DL/SplitNN	For image classifications, a comparison between federated learning and SplitNN in terms of classification accuracy vs. model complexity and transmission time will be performed.
[131]	2021	—	DL	Increasing the detection rate of Theft-Data-Typed Attacks by collecting more data sets and learning more about them.
[132]	2022	1	—	Taking into account the fact that certain malevolent individuals may also conduct poison attacks throughout the learning procedure.
[133]	2022	—	FLCH	Studying blockchain-enabled FL techniques for material storage to improve privacy, as well as studying a theoretical structure to examine the suggested method's convergence.
[134]	2021	1	DP	The topic of how to fully utilize DP in FL will be studied, and varied FL frameworks will be also investigated as it plays a role in industrial edge computing.
[135]	2022	1	TP-AMI/ATT-BLSTM	A hardware-based service platform is scheduled to be constructed, and the system will be able to better assess their proposed framework, particularly when transitory faults occur.
[136]	2022	_	_	To evaluate system efficacy, actual data is acquired by incorporating device variations including air, land, and undersea. NS will divide terrestrial IoT networks to discrete slices.
[137]	2021	_	_	Detecting the attack in the MEC cluster with the two LSTM stages without improving the DL model by performing the computationally expensive procedure for learning the model.

ness of the architecture from many angles, LocKedge is applied in two ways: centrally and through FL. Using the most recent BoT-IoT dataset, the effectiveness of their mechanism is contrasted with that of various ML and DL techniques.

While most previous techniques only considered the privacy of the local model, the authors in [132] employed additive homomorphic encryption and double-masking to simultaneously secure the user's local model and the aggregated global model. Linear homomorphic hashes and digital signatures are also employed to accomplish traceable verification. This allows users to confirm the accuracy of the aggregate results and pinpoint the incorrect epoch in the event that they are inaccurate. To shed more light on the topic, even if the cloud server colludes with malevolent users, their proposed protocol can realize the privacy of the local and global models and ensure verification traceability. Yu et al. [133] discussed FL-based cooperative hierarchical caching (FLCH) that uses IoT devices to build a shared learning model for content popularity prediction while storing data locally. To cache items with varying degrees of popularity, FLCH uses vertical cooperation between the baseband unit (BBU) pool and F-APs and horizontal collaboration between nearby F-APs. To further establish a stringent privacy guarantee, FLCH incorporates a DP method.

For industrial data processing, the authors in [134] proposed a novel federated edge learning architecture based on hybrid DP and adaptive compression. To fully protect against the transmission of gradient parameters in an industrial environment, it first completes the adaptive gradient compression preparation, builds the industrial FL model, and then uses the adaptive DP model to optimize. They can better defend terminal data privacy against inference assaults by maximizing hybrid DP and adaptive compression. In [135], a TP AMI service paradigm based on differentially private FL was modeled to balance the QoSs better and protect users' privacy. Their service model trains the neural network models locally and only shares model parameters with the central server instead of transmitting the private energy data to the cloud server. Additionally, individual identities are obliterated by including random Gaussian noise during the secure aggregate. The long-range dependency issue with traditional neural networks is also resolved using an attention-based bidirectional LSTM (ATT-BLSTM) neural network model. A residential short-term load forecasting (STLF) job is used in the case study to assess how well the suggested model performs. Uddin et al. in [136] established a strategy to prevent data breaches that could jeopardize the satellite-IoT architecture for space communication. To safely transmit sensitive data across IoT devices, the framework is built on softwaredefined networking and leverages FL techniques for distributed systems. It also applies deferential privacy when data exchange among devices occurs. To create a secure MEC environment, the authors in [137] represented a SecEdge-Learn architecture that uses DL and transfer learning methodologies. Additionally, they implemented the transfer learning technique to use the knowledge to address various attack situations by using blockchain to store the knowledge obtained from the MEC clusters. Finally, they deeply discussed the MEC environment's importance to the industrial environment and applications.

By utilizing FL approaches and creating reputation mechanisms, Zhang et al. [138] developed a reliable and privacypreserving QoS prediction strategy to handle this important topic. The future directions, open areas, and accuracy of references in FL-based privacy-preserving systems are listed in Table 5 with details.

5. Resource Allocation in FL:

IoT devices produce much data that requires transmission, storage, and analysis. To shed more light on the issue, IoT devices are equipped with tiny sensors to collect data from an area of interest (AoI), process it, and transmit it to the servers. Thanks to wireless technologies and the availability of sensors for end users, IoT structures are fully supported. However, one of the main concerns in this area is completing the assigned tasks properly during a specific time to fulfill the delay requirements on latency-sensitive platforms. Yin et al. in [139] offered a novel hybrid privacy-protecting method for FL to satisfy privacy and efficiency concerns. To this end, they primarily used an improved function encryption approach that protected both the characteristics of the data uploaded by each IoT device and the weight of each client in the global model aggregation. In the second part of their structure, they designed a local Bayesian DP in which the noise policy significantly developed the adaptability of various data sets. Moreover, the Sparse Differential Gradient was used to upgrade the efficiency of storage and data transmission in the FL procedure. In [140], Feng et al. considered the relay network when building a platform for cooperative communication that supports the sharing and trading of model updates. Based on their training data, the mobile devices updated the models in the system. The model owner was then informed of the modifications via the cooperative relay network. The owner of the model appreciated the educational service presented by mobile gadgets. The mobile gadgets demanded specific fees from the model owner in exchange. Rational mobile devices must pick their relay nodes and their transmission strengths due to the coupled wireless transmission interference among the mobile devices that utilize the same relay node. As a result, they created a Stackelberg game model to analyze how mobile devices interact with one another as well as with the model's creator. The outer point approach was utilized to examine the Stackelberg equilibrium. To deliver improved model accuracy with strict privacy assurances and excellent communication efficiency, the authors in [141] suggested PCFed, a revolutionary privacy-enhanced FL framework. To adaptively lower the communication frequency, they raised a sampling-based intermittent communication technique using a PID (proportional, integral, and derivative) controller on the cloud server. They also designed a budget allocation system to strike a compromise between model accuracy and privacy invasion. Then, considering the endless data streams on edge servers, they constructed PCFed+, an improved version of PCFed. In terms of communication effectiveness, privacy protection, and model correctness, extensive trials showed that PCFed and PCFed+ could surpass previous systems. Luo et al. in [142] developed an innovative

semi-asynchronous FL (SAFL) framework to address data security concerns and deliver effective model performance through multiple devices training a shared model, intending to lower computational and transmission latency while increasing the learning rate. They created a combined problem of terminal device selection and resource allocation within the SAFL framework to ensure communication effectiveness. They used a deep deterministic policy gradient (DDPG) approach to find the best answer to their proposed Markov Decision Process (MDP) problem. The authors of [143] looked at IoT-based EC applications and the related ML tools. One of the unresolved difficulties in FL was reliably completing the given work within the allotted time frame to satisfy the latency requirements of latency-sensitive applications. IoT devices frequently have limited processing resources. Therefore, they required assistance from backend computing equipment to do some of the complex operations. These backend devices, which were situated near the network's edge, were often not offloaded to the cloud to avoid considerable network delay. EC was the ideal solution for IoT applications that demand minimal latency. The authors in [144] showed that pooling the model parameters of all participating devices might not be the best course of action to improve FL-based content caching performance when the training data was non-IID. However, choosing an adaptive local iteration frequency when resources were scarce turned out to be more significant. It was impossible for FL to aggregate all participating devices simultaneously for model updates and adopt a fixed iteration frequency in the local training process due to the existence of non-IID data across clients and restricted edge resources. A distributed resource-efficient FL-based proactive content caching (FPC) policy was put out as a solution to this problem to improve resource efficiency and increase content caching effectiveness. The FPC problem was developed as a stacked autoencoder (SAE) model loss minimization problem while considering resource restrictions through a theoretical study. Then, an algorithm called the adaptable FPC (AFPC) was presented, which integrated DRL with two mechanisms: client selection and the choice of the number of local iterations. Tam et al., in [145], presented an adaptive model communication system for edge FL that includes virtual resource optimization. A self-learning agent could communicate with a network functions virtualization orchestrator and a software-defined networking-based architecture thanks to the use of a deep Qlearning algorithm in the scheme. In a virtualized infrastructure manager, the agent's goal was to optimize the resource control policies of virtual multi-access EC entities. Their presented method featured a learning model that was trained to determine the best course of action for particular network states. The approach considered different spatial-resolution sensing conditions during the exploitation phase and allocated compute offloading resources for aggregating global multi-CNN models based on congestion states. The authors in [146] showed an Energy-aware Multi-Criteria FL (EaMC-FL) model for EC. By combining locally trained models on chosen representative edge nodes (workers), their model aimed to facilitate the collaborative training of a shared global model. The edge

nodes (workers) were initially divided into clusters based on how similar their local model parameters were to achieve this. A small group of representative workers was chosen utilizing a multi-criteria evaluation for each training round. To assess its representativeness or significance, the study considered elements including the node's local model performance, energy consumption, and battery life. Zhao et al. in [147] developed a semi-hierarchical federated analytics framework in this article that incorporates the benefits of the various earlier described The framework does not require a central architectures. server or cloud architecture since it uses many edge servers to combine learned model weights and aggregate updates from IoT devices. They also added a new local client update rule to improve communication effectiveness by lowering the number of communication rounds between edge servers and IoT devices. They investigated the provided approach's characteristics and analyzed the convergence properties while considering variables like changing parameters, erratic links, and packet loss.

The authors in [148] looked into FL in a fog radio access network scenario, where several IoT devices worked together to train a common ML model. The devices could communicate with a cloud server thanks to dispersed access points (APs), which allowed for this. They suggested a rate-splitting transmission technique for IoT devices in light of the limited capacity of the fronthaul links that connect the APs to the CS. This strategy made decoding split uplink signals possible using both the edge and the cloud. They aimed to reduce the FL completion time, which they accomplished by improving fronthaul quantization techniques, rate-splitting transmission, and training hyperparameters, including precision and iteration rates. Xu et al. in [149] focused on a method for achieving effective EC in a heterogeneous wireless environment termed Cyber-Twin assisted asynchronous FL (AFL). The main goal was to properly utilize local computing capabilities, using the Cyber-Twin as a communication helper in the middle. First, during the AFL training process, they proposed the idea of Cyber-Twin as a communication coordinator to promote individual model aggregation between users and the cloud server. Second, Cyber-twin operated as an intelligent agent for EC resource optimization, considering both local computing and up-link transmission. They created an optimization problem for resources considering the various computer powers, data sizes, and available connection bandwidth. They used the block coordinate descent (BCD) method to get the best resource management answer.

A non-orthogonal multiple access (NOMA)-based joint resource allocation and IIoT device orchestration strategy for MEC-assisted hierarchical FL (HFL) was presented in [150]. This strategy used DRL to reduce overhead, optimize resource allocation, and produce a more accurate model. To reduce latency, energy use, and model accuracy while considering limits like the computational power and transmission power of IIoT devices, they developed a multi-objective optimization problem. To address this issue, they developed a DRL technique based on a deep deterministic policy gradient.

Communication quality among clients and servers is a crucial

issue through training rounds to manage available resources. For example, the authors in [151] showed that the time-varying link dependability in the wireless network of the smart grid could obstruct communication between clients and the server during the training rounds of FL. The model convergence rate was slowed, and resources, such as energy used during inefficient local training, were wasted. Considering the extremely dynamic nature of link reliability, this study examined a dynamic FL problem within a power grid mobile edge computing (GMEC) context. They created a delay deadline-constrained FL system to prevent overly long training delays. Additionally, they developed a dynamic client selection issue to enhance computational usefulness within this learning framework. To address the issue, they investigated two online client selection algorithms: climax greedy and uti-positive assurance. In this research, the authors in [152] introduced a novel prediction-assisted task offloading system for the IoT power grid, intending to make the best offloading decisions while maintaining privacy. By carefully choosing local servers, they developed an FL strategy to train a task prediction model quickly. They finally enhanced a dynamic prediction-assisted task offloading system based on the traffic loads of computation workloads at EC nodes and the behavioral traits of electrical users. The authors in [153] looked at a resource allocation strategy to lower FL overall energy usage in relay-assisted IoT networks. Their goal was to reduce IoT device energy usage while meeting the FL time restriction, which consists of wireless transmission latency and model training calculation time. To do this, they modeled a joint optimization problem that considered IoT device scheduling with relays, transmit power distribution, and computation frequency distribution. However, due to the problem's NP-hardness, developing a globally optimal solution was impossible. They consequently suggested using graph theory to find near-optimal and lowcomplexity sub-optimal solutions jointly. The authors in [154] introduced a Federated Adaptive Weighting (FedAdp) approach to quicken model convergence when nodes with non-IID datasets are present. This straightforward but powerful method significantly reduced the number of communication rounds, which dynamically rewarded positive node contributions and inhibited negative ones.

Yan et al. in [155] looked at distributed power allocation for edge users in decentralized wireless networks to preserve privacy while maximizing energy and spectrum efficiency within an FL framework. They chose an online Actor-Critic (AC) architecture as the local training model since wireless networks are dynamic and complicated. FL encouraged cooperation between edge users by distributing the gradients and weights produced in the Actor-network. They presented a federated augmentation mechanism employing the Wasserstein Generative Adversarial Networks (WGANs) method for data augmentation to solve the problem of overfitting brought on by data leakages in a non-IID data environment. Each device could reload its data buffer using a generative WGAN model thanks to this federated augmentation until it reached an i.i.d. training dataset. Comparing this strategy to direct data sample exchange approaches, the communication overhead in distributed

learning was dramatically reduced. The authors in [156] tackled the problem of simultaneously maximizing resource allocation and compute offloading in C-V2X networks. To do this, they suggested a hierarchical MEC/C-V2X network that considered the variety of computation offloading patterns and the dynamic changes of the vehicular network. Furthermore, they developed an offloading model for cooperative processing that accommodated various offloading patterns. Using the Markovian decision process as a foundation, they described the resource allocation and dynamic computation offloading problem as an ordered choice problem. They presented a DL system, named ORAD, based on the deep deterministic policy gradient algorithm that optimized offloading success levels in real-time, enabling intelligent and automated decision-making. To improve the accuracy of federated models in non-IID circumstances, the authors in [157] presented the FedCC algorithm in this study. The fundamental issue with FL is the extra communication required for parameter synchronization, which wastes bandwidth, extends training time, and may affect model accuracy. To solve this problem, the FedCC technique divides clients into groups based on how similar their data is, then chooses one model from each group to be uploaded to the cloud server for model aggregation. It should be noted, nonetheless, that using the FedCC algorithm resulted in a modest reduction in the federated model's test accuracy and an increase in the training phase of the federated model's communication cost.

To enhance the decentralized SGD (DSGD) algorithms, the authors in [158] designed generic digital and analog device-to-device (D2D) wireless implementations of the communication-efficient DSGD algorithms, using over-the-air computation (AirComp) for concurrent analog transmissions and random linear coding (RLC) for compression. To correctly manage the resource, they derived convergence bounds for both digital and analog implementations under the convexity and connection presumptions. The authors in [159] listed a set of application requirements for FL implementation in an IoT device architecture that was confined and unconstrained based on Internet Engineering Task Force (IETF) standards in this work. Initial configuration, distributed training, and cloud updates were the three phases of the FL protocols. They experimented with an IoT platform to gauge how well the FL protocols performed regarding accuracy, timing, cost-effectiveness, and latency. The authors in [160] introduced the Federated Synergy Learning (FedSyL) paradigm, which aimed to balance the risk of data leakage with the effectiveness of training. They looked at the intricate connection between local training latency and multi-dimensional training configurations and presented a method for uniformly predicting training latency using polynomial-quadratic regression analysis. Additionally, they raised an ideal model offloading approach, considering the resource constraints and computational heterogeneity of This method correctly assigned device-side end devices. sub-models to end devices whose capabilities varied. The FedSyL paradigm was put into practice and tested on an actual test bed of numerous heterogeneous end devices. Saha et al. in [161] developed the FogFL framework, which enabled FL

in resource-constrained IoT contexts and was especially useful for delay-sensitive applications. Although FL was a well-liked strategy, it had drawbacks, such as high computing needs and communication costs. The overall system was susceptible to malicious assaults due to its dependency on a single server for global aggregation in FL, which also caused inefficiencies in model training. They added geospatially positioned fog nodes as local aggregators to the FL architecture to address these problems. These fog nodes were in charge of particular demographics, enabling the transfer of location-based data between apps with related contexts. Additionally, they surveyed a greedy heuristic method for choosing the best fog node to act as a global aggregator in each exchange between the edge and the cloud. This lessens reliance on the operation of the centralized server, where FogFL incorporated fog nodes to decrease communication latency and energy usage of resourceconstrained edge devices without affecting the rate of global model convergence, thereby improving system reliability. The authors in [162] showed two crucial facets of an IoT network: security and easy connectivity for data transfer. To train ML models, they took advantage of the FL architecture, which used data and computational power appropriately on end-user devices. The study concentrated on FL ideas, notably caching, in the area of EC for IoT applications. The main goal in [163] was first to investigate FL for ultra-dense edge computing (UDEC), and it also offered a resource-effective inter-server FL method that made the servers and clients interact with each other collaboratively.

The difficulties of independent DRL training, deployment, and inference in the microgrid cluster scenario have not been studied previously. The authors of [164] suggested a distributed microgrid cluster-specific federated DRL-based request scheduling method where maximizing the system's long-term utility was the goal. The DRL model was also trimmed to improve its applicability for edge nodes with limited resources. The authors in [165] presented a novel market model of distributed learning resource management for various mobile-edge computing (MEC) operators to meet the budget and latency needs for data analytics from IoT devices. In "FL," a coordinator at the cloud effectively distributes sensing data from IoT sensors to numerous MECs; the focus is on a hybrid architecture (cloud-MEC) for distributed learning. The coordinator provides a shared model to each MEC, and each MEC then conducts local training using the acquired partial sensing data. To create a global model, the cloud coordinator then integrates the local training results from MECs. A Stackelberg game model was developed and solved to represent the hierarchical decision-making structure as market behavior. MEC operators take on the role of leaders, and a pricing strategy was developed to optimize their utility by considering the trade-off between revenue and energy usage. The coordinator follows and tries to strike a balance between cost and cost satisfaction in distributed learning. By coordinating IoT sensors to transfer sensing data via MECs, it complied with the decisions made by MEC operators. As a closed form, a distinct Stackelberg equilibrium (SE) point was obtained to enhance the utility of each market member. In

network to offer a hierarchical task offloading approach for delay-tolerant and delay-sensitive missions. To solve the enormous issues the IoT faces due to various application needs, heterogeneous multidimensional resources, and time-varying network settings, the goal was to assure user QoE, low latency, and reliable services. Their approach used a multi-agent deep deterministic policy gradient (MADDPG) to accelerate task processing, enable dynamic real-time power allocation, and reduce overhead. The MADDPG model was also trained using FL which increased system processing effectiveness and task completion ratio. The authors proposed a Dynamic Cooperative Cluster Algorithm (DCCA) in [167] to reduce delays in a problem that

[166], Hou et al. integrated EC and AI into a Cybertwin-based

rithm (DCCA) in [167] to reduce delays in a problem that has been shown to be NP-hard. D2D and opportunistic communication were also used for node-to-node communication. Clusters were set up using the DCCA approach based on the ability of several nodes to train models together and cut down on delays. In two steps, the DCCA algorithm was devised. An original dynamic cooperative cluster algorithm that was based on similarity was proposed in the first step. The dynamic cooperative cluster was adjusted in the second step using a different algorithm focusing on the core nodes' computing and transmission capacities. The authors of [168] sought to enhance the collaborative decision-making process for computing, device selection, and spectrum resource allocation. The objective was to maximize the effectiveness of distributed HoT networks using FL. A three-layer collaborative FL architecture was devised to enable effective FL over geographically distributed data and facilitate DNN training. To this end, locally, the devices' scattered data was used to train DNN models via industrial gateways. The associated edge servers at each FL epoch or a cloud server every few FL epochs could aggregate the local models to produce the global model. They developed a stochastic optimization problem to optimize the choice of participating devices and the allocation of computing and spectrum resources while minimizing FL evaluation loss. Resolving the issue using conventional optimization techniques was challenging due to the implied objective function of FL assessing loss and the temporally associated energy usage. To overcome this difficulty, they examined a decentralized strategy based on deep multi-agent reinforcement learning (MARL) called "Reinforcement on Federated" (RoF). The RoF scheme was implemented at edge servers to facilitate group decision-making for the best device selection and resource allocation. In addition, the RoF system included a device refinement subroutine to speed up convergence while efficiently preserving on-device energy.

Using Earth Mover's Distance to determine the weights of various node characteristics, the authors of [169] introduced a novel method for balancing the FL model. To prevent the FL model from showing bias towards certain distributed nodes in the dataset, reducing the impact of data non-independent identically distributed problems on the model was necessary. The research also studied a technique for condensing redundant communication between nodes and servers during training. To address the issue of standby energy reduction in residential

structures, the authors of [170] proposed a residential energy management system (EMS) with a personalized federated deep reinforcement learning framework. The solution was designed to protect privacy, enhance communication effectiveness, and do away with cloud services.

By eliminating the need for a centralized cloud server, Khan et al. [171] introduced a revolutionary FL framework that made FL possible. They first devised a social awarenessbased clustering method, and then they chose the cluster heads. The global FL time was reduced by formulating an optimization problem, which was the second step. Thev introduced a heuristic technique to optimize the total FL time after recognizing the NP-hardness of the optimization problem. To raise FL communication efficiency, the authors of [172] presented a unique 3-way hierarchical framework (THF). To reduce client communication costs, their structure included a cluster head (CH) corresponding with the cloud server through edge aggregation. According to this method, clients submitted their local models to their associated CHs, who then sent them to the appropriate edge server. Once edge precision was attained, the edge server applied model averaging and iterations. The edge models were then uploaded to the cloud server by each edge server for global aggregation. Through closer distances between source and destination, this 3-way hierarchical network structure optimized model downloading and uploading. The authors also established a shared communication and computation resource management framework by carefully choosing customers, lowering the FL's overall cost. The authors of [173] developed an efficient FL-based NIDS (Network Intrusion Detection System). They used the fact that network traffic data was tabular in nature and discovered that small value changes do not affect the data's fundamental properties. They applied data binning to extract feature data from clients. The classifier on the server was then trained using the extracted feature data. Techniques for data masking were also used to further improve energy efficiency and data privacy. Yu et al. in [174] enhanced an intelligent UDEC (I-UDEC) framework to develop resource allocation strategies and real-time, low-overhead computation offloading judgments. To this end, a novel two-timescale deep reinforcement learning (2Ts-DRL) method was proposed that combined a fast-timescale and slow-timescale learning procedure to achieve the goal. By optimizing compute offloading, resource allocation, and service caching placement, their approach sought to reduce total offloading time and network resource utilization while protecting edge device data privacy. The authors in [175] offered an adaptable and intelligent approach to federation construction using Genetic Algorithm and ML models and a novel architecture for the federated fog concept. The fog federations' main goal was to make it possible for fog providers to provide the necessary QoS. The idea allowed for effective load dispersion by sharing resources among various fog suppliers. As a result, the problem of QoS degradation brought on by local overloads was successfully resolved, enabling end users to experience real-time applications without delays.

practical implementation still has issues with reliability and communication efficiency, such as the negative impact of electromagnetic interference on digital twin (DT- reliability, the high communication cost of DT model training, and the uncoordinated resource allocation among cloud, edge, and device layers, The authors in [176] proposed a solution called C3-FLOW (Cloud-edge-device Collaborative reliable and Communication-efficient DT). Through a coordinated optimization of device scheduling, channel allocation, and computing resource allocation, C3-FLOW intends to reduce the long-term global loss function and time-average communication cost.

To achieve ubiquitous intelligence in 6G, the authors of [177] developed a decentralized and collaborative ML architecture for intelligent edge networks. They developed a compute offloading and resource allocation strategy supported by multi-agent DRL, realizing that energy efficiency was crucial to creating sustainable edge networks. The main goal was to reduce overall energy consumption while meeting latency demands. They devised a federated DRL system to overcome the issues of computing complexity and signaling overhead in the training phase. The authors in [178] introduced a technique dubbed Distilled One-Shot FL (DOSFL) to cut communication costs and reach parity in performance drastically. Each client condensed their dataset in a single round, sending fictitious information to the server to collectively train an international model. After model changes, the distilled data became unusable since it was meaningless for all model weights and just looked like noise. With up to 99% of the performance attained through centralized training preserved, this weight-free and gradient-free architecture produced a communication cost for DOSFL that was up to three orders of magnitude lower than that of FedAvg. The effectiveness of DOSFL was demonstrated using a variety of visual and language tasks using several models, including CNN, LSTM, and Transformer. It was noteworthy that an eavesdropping attacker could not train a successful model without knowing the baseline model weights, even given stolen distilled data. With less than 0.1% of the communication cost associated with conventional approaches, DOSFL offered a low-cost method to swiftly converge on a successful pre-trained model.

Channel fading and data-aware scheduling lead to distortions in the calculated gradient, which cause significant bias and have a detrimental effect on training performance. The authors in [179] focused on a dynamic approach for data and channel adaptive sensor scheduling and power regulation, using a residual feedback mechanism, to overcome these difficulties. Each sensor kept a local residual to keep gradients that were not sent to the central server instead of deleting them. They also used the Lyapunov drift optimization approach to examine the connection between training gain and resource allocation by connecting model update iterations to a dynamic evolution process. The decentralized optimum solution that resulted from this research was tailored to the knowledge about the channel condition and the significance of the data, allowing for efficient selection of transmission opportunities and important gradients. Tao et al. in [180] presented a data-driven

Due to the real-time electrical equipment management, the

matching methodology for vehicle-to-vehicle (V2V) energy management. In the offline step, they used DRL to discover the long-term benefit of matching actions using a formulated MDP. They also schemed an FL architecture that permitted collaboration across several EV aggregators while protecting the privacy of EV owners' information. In order to increase computing efficiency, a matching optimization model was developed and transformed into a bipartite graph problem during the online matching stage, assisting EV owners in lowering expenses and increasing revenues.

Akubathini et al. [181] described and evaluated ML algorithms along with various compression techniques built mainly for IIoT devices with limited resource availability and produced the lowest model size. The FL technique was highlighted, especially for applications involving time series data. The authors in [182] looked at a combined optimization issue comprising power control and multi-timescale job offloading. With regard to all Electricity Internet of Things (EIoT) devices, the goal was to reduce the queuing latency while maintaining a long-term energy consumption cap. They first divided the joint optimization issue into two smaller-scale power control optimizations and larger-scale task offloading optimizations. Then, for multi-timescale optimization, they introduced the federated deep actor-critic-based task offloading algorithm (FDAC). This technique used two actor-critic networks. The authors in [183] suggested a federated DRL framework to deal with a multi-objective optimization issue. The goal was to reduce IoT device energy consumption and the anticipated long-term job completion latency. Offloading choices, computing resource allocation, and transmit power allocation were all optimized to achieve this. The authors used the double deep Q-network (DDQN) technique and offloading decisions as actions to solve the mixed-integer non-linear programming (MINLP) issue as a multi-agent distributed DRL problem. Based on the selected offloading options, the transmit power optimization or local computation resource optimization was solved to determine the immediate cost of each agent. FL was added at the conclusion of each episode to speed up IoT devices' (agents') learning process. Scalability was increased, agent collaboration was promoted, and privacy issues were reduced thanks to FL. The authors in [184] tackled the issue of reducing energy and time consumption for job computation and transmission. In mobile-EC-enabled balloon networks. High-altitude balloons (HABs) operated as flying wireless base stations in the network design, using their processing power to handle computational tasks delegated by related users. Each user's work generated varying amounts of data over time; therefore, the HABs had to modify their resource allocation plans to satisfy user needs dynamically. In order to reduce the amount of energy and time needed for task calculation and transmission, the problem was phrased as an optimization problem. This was done by modifying the user association, service sequence, and job allocation algorithms. A support vector machine (SVM)-based FL technique was developed to proactively ascertain user associations to address this issue. Using the SVM-based FL technique, HABs might develop an SVM model collectively

without sharing user history associations or computational duties with other HABs. Each user's service sequence and job allocation could be improved to reduce the weighted total of energy and time consumption after the ideal user associations were projected.

In order to support certain computing workloads, the authors in [185] designed a Wireless Computing Power Network (WCPN) that coordinated the computing and networking resources of heterogeneous nodes; they created FedTAR, a task-aware and resource-aware FL paradigm, to allow intelligent services in WCPN. FedTAR sought to reduce the total amount of energy used by computer nodes by collaboratively optimizing each computing node's particular operating procedures and its cooperative learning methodology. Based on particular job needs and resource limitations, the optimization issue solution allowed for changeable NN depth and collaboration frequency across nodes. They also suggested an energy-efficient asynchronous aggregation approach for FedTAR to support heterogeneous computing nodes, which speeds up the FL in WCPN's convergence rate. The authors in [186] emphasized the frequent need for integrating both techniques in fog- and IoT-based scenarios and provided a framework for flexible parallel learning (FPL) that achieves both data and model parallelism. Additionally, they looked at how different methods of allocating and parallelizing learning tasks across the involved nodes produce various computing, communication, and energy costs. Shah et al. [187] proposed the space-terrestrial integrated network (STIN), a unique network control and resource allocation dilemma for huge IoTs. The authors used modern hierarchical deep actor-critic networks (H-DAC) to solve this issue. Urban regions were covered by the vast IoT networks, allowing for possible collaboration. This collaboration was used to develop a shared strategy for IoT networks to pay for spectrum per unit.

The integrated network control and resource allocation problem was defined as a utility maximization problem, and it was solved using deep actor-critic-based RL. The RL-based algorithms handled the data rate allotment for each IoT network and IoT device and the cost per unit spectrum for the federated cloud of IoT networks. Zhang et al. [188] looked into the dispersed IIoT networks' resource management issues for FL. To enable FL, they built a three-layer collaborative architecture in which DNNs were locally trained at chosen IIoT devices. In order to update the global DNN model, edge servers or cloud servers regularly gather the DNN model parameters. A careful distribution of CPU and spectrum resources was required to train and broadcast the DNN model parameters to enable effective FL in resource-constrained IIoT networks. They presented a combined device selection and resource allocation issue to minimize FL evaluation loss while strictly adhering to FL epoch delay and device energy consumption constraints to tackle this problem. They converted the joint optimization problem into an MDP after realizing the close relationship between judgments about device selection and resource allocation, and then a dynamic resource management plan based on DRL techniques was considered. The future directions, open areas, and accuracy of references in proper

Table 6: References on FL-based Resource Allocation

Reference	Year	Acc> 90%	AI/ML approach	Open Areas and Future Challenges and Directions
[141]	2022	X	PCFed/PCFed+	To extend their model, they are considering specific DP for FL devices with varied security resource allocations and examining its effects on communication and privacy issues.
[143]	2022	X	_	Studying FL methods in deeper depth, focusing on advancements while analyzing IID and Non-IID Data.
[144]	2022	1	AFPC	Using budgets effectively for collaborative learning in heterogeneous edge systems, and extending the AFPC to more non-convex optimization challenges with limited resources.
[145]	2021	1	CNN/DQL	In the edge FL models, NS for diverse spatial image classifications will be evaluated regarding power allocation, service cache placement, and computation offloading decisions.
[146]	2021	1	EaMC-FL	Further evaluating their proposed EaMC-FL system by investigating its viability on bigger scale actual datasets and various FL situations.
[147]	2022	×	_	Enhancing the actual efficiency of FL structures through tuning communication networks.
[148]	2022	×	_	The convergence rate determines the number of iterations necessary for convergence, although its analysis for broad sequential convex approximation methods will be performed.
[149]	2021	1	AFL	More research into the scalability, mobility, and connectivity of Cybertwin-assisted wireless asynchronous federated learning (AFL).
[150]	2022	_	HFL	Testing the effectiveness of our proposed solution on actual data and modifying it accordingly while employing DRL in the context of FL.
[151]	2021	_	_	Upgrading the specific diffusion/uploading latency paradigm connected with special access technology.
[153]	2022	1	JEADS-G	-
[154]	2021	1	FedAdp	_
[156]	2023	_	DRL/ORAD	Concentrating on decentralized ML-based resource consumption in Cellular Vehicle-to-Everything (C-V2X) structures.
[158]	2021	_	DSGD	Evaluating convergence bounds for non-convex wireless designs based on diminishing consensus rate and decreasing training step size.
[160]	2022	1	DNN/FedSyL	-
[162]	2021	_	_	Extending the mobile device cloud (MDC) Network in terms of scalability, self-organization, and automation, as well as using different datasets and FL methodologies.
[164]	2022	×	DRL	-
[166]	2021		MADDPG	Using FL and blockchain-based techniques to train their suggested framework in a decentralized manner for low training overhead and data privacy.
[167]	2021	_	HFL	Furtherly investigating clients' spontaneous cooperation and resource allocation difficulties.
[168]	2021	×	DNN	A data importance-aware device selection strategy is being investigated in order to optimize FL in large-scale IIoT systems.
[169]	2021	×	_	Determining whether or not part edge clients have the authorization to communicate with the parameter edge/cloud server.
[171]	2020	_	_	Considering the center client's distance from other clients, evaluating various scenarios, budget management, and learning methods for self-governing FL in multiple clusters situations.
[172]	2022	1	THF	The effect of implementing common approaches for strengthening privacy and an inquiry into the inclusion of adversaries in their suggested framework will be investigated.
[173]	2021	X	—	Incorporating a system of initial data feature extractors into their model, i.e., incorporating an FL-based feature extractor for initial packet data into the present data binning method.
[174]	2021	—	I-UDEC	Investigating the mechanism in which small cell cloud-enhanced e-Node Bs have private service caching policy to train their model with private data and the trained global model.
[176]	2022	—	C ³ -FLOW	To improve the efficiency of electrical equipment management, the computing resources and heterogeneities of device-side communication will be investigated.
[178]	2022	1	DOSFL	The accuracy of Distilled One-Shot Federated Learning (DOSFL) decreases from 10 to 100 users across both IID and non-IID. It is a DOSFL constraint that will be studied.
[181]	2021	1	FastGRNN	The resource limitations of edge nodes made that on-device retraining would be researched.
[182]	2021	_	FDAC	Concentrating on optimizing UAV distribution to increase AGE-IoT effectiveness.
[183]	2021		DDQN/DRL	-
[184]	2021	1	SVM	-
[185]	2022	1	WCPN/FedTAR	-
[186]	2022	×	FPL	Extending the performance evaluation of the flexible parallel learning approach to consider the junction layer's capacity to weight the input variously with more complicated DNNs.
[187]	2021	_	DL/DRL	Caching and service function chains are examples of specific applications of their proposed space-terrestrial integrated network, which may be developed for vehicular communications.
[188]	2022	X	DNN	A distributed learning resource-management system in large-scale IIoT will be studied.

resource-allocation FL-based systems are listed in Table 6 with details.

6. Applications of FL

6.0.1. Unmanned Aerial Vehicles (UAV)

FL promises to bring more than millions of IoT clients into cooperative learning, but dropouts and communication problems may result in inappropriate FL implementation. In other words, the connection between cloud/edge servers as ground servers and UAVs as space servers in IoT structures is not often guaranteed, particularly in ultra-dense networks with massive data. So, the previous cloud-centric or edge-centric methods were not applicable due to their extreme power consumption and significant latency. In addition, some inherent privacy problems associated with sharing medical records and data with the cloud server (central server) may dramatically introduce many protection concerns to the healthcare system, which poison patients? information and steal their identity. UAV-based applications facilitate data gathering and ML processes. Therefore, Drones-as-a-Service (DaaS) have become massively popular recently [189, 190, 191, 192, 193, 194].

In order to allow collaborative ML while protecting privacy across a federation of separate DaaS providers for the development of IoV applications, such as traffic prediction and parking occupancy management, the authors in [189] adopted an FL-based methodology. They used the self-revealing properties of a multi-dimensional contract to ensure accurate reporting of the UAV types while accounting for the various sources of heterogeneity, such as in sensing, computation, and transmission costs, given the information asymmetry and incentive mismatches between the UAVs and model owners. The Gale-Shapley method was then used to match the cheapest UAV to each subregion.

The FL model owner may use UAVs to offer mobile relays of the updated model parameters from data owners to the model owner and intermediate model aggregation in the sky. As a result, FL may now contact more data owners dealing with erratic network circumstances, enhancing communication effectiveness. Lim et al. [190] used the multi-dimensional contract incentive design as a case study to motivate the UAV service providers. The contract's incentive compatibility guaranteed that the UAVs only selected incentive packages appropriate to their nature, such as travel expenses.

For resource-constrained UAVs, the authors in [191] suggested a FDRL-based intelligent and decentralized job offloading method that could improve the operational capabilities of the multi-unmanned aerial vehicular systems (MUAV) systems. Additionally, FDRL could enhance the quality of offloading policies while protecting MUAV data privacy. However, backdoor attacks that might interfere with the system's normal functioning and quickly degrade its performance might target such intelligent systems. To test the robustness of the offloading strategy in the face of an adversary, they designed a unique triggerless backdoor attack technique for intelligent task offloading UAVs and assessed its effects. Aloqaily et al. [192] imagined a 5G network environment powered by blockchainenabled UAVs to balance the supply of network access with users' changing requests. The technology offered dependable and secure routing to and from end users, as well as decentralized service delivery (drones as a service). In order to provide a wide variety of complicated authenticated services and data availability, both public and private blockchains were placed within the UAVs, backed by fog and cloud computing devices and data centers. An emphasis was placed on contrasting their proposed solution's message exchange and data transfer success rates with those of conventional UAV-supported cellular networks.

The offloaded tasks from ground IoT devices could be cooperatively carried out by UAVs acting as an edge server and cloud server connected to a ground base station (GBS), which could be thought of as an access point, in an energy-constrained mobile edge-cloud continuum framework. A UAV was specifically fueled by the laser beam that a GBS transmits and could also wirelessly charge IoT gadgets. By maximizing the long-term reward subject to executed task size and execution time under constraints such as energy causality, task causality, and cache causality, an intriguing task offloading and energy allocation problem was studied. To learn the combined task offloading and energy allocation choices while lowering training costs and limiting privacy leakage during DRL training, a FDRL architecture was designed [193].

The authors in [194] modeled a non-orthogonal multiple access (NOMA) FL architecture for a UAV swarm made up of a leader UAV and many follower UAVs. To be more precise, each follower-UAV updated its local model using the data it had acquired, and all follower-UAVs then created a NOMA group to broadcast their individually trained FL parameters' or local FL models to the leader-UAV at the same time. In order to reduce the execution time for FL iterations till a certain accuracy was reached, they devised a combined optimization of the uplink NOMA transmission durations, the downlink broadcasting duration, as well as the calculation rates of the leader-UAV and all follower-UAVs.

The popularization of unmanned aerial vehicles (UAVs) has boosted various civil applications, such as traffic monitoring, in which the effective coordination of the UAV swarm plays a significant role in expanding the monitoring range and enhancing execution efficiency. However, due to the isolated local environments and the heterogeneous execution capabilities, it is challenging to achieve highly consistent actions. To coordinate the UAVs' maneuvers by interactively mimicking the leader UAV's actions, the authors in [195] combined the FL framework with the imitation learning approach. They used the generative adversarial imitation learning (GAIL) model to accurately follow the leader UAV's actions during the interagent global model download phase by reducing the biased estimations of imitation parameters. They employed the self-imitation learning (SIL) model during the intransigent local model training phase to rectify subtle imitation faults thanks to the follower UAVs' own historically significant experiences. Moreover, they regularly updated federated gradient to produce coordinated swarm policies and more effective distributed param-

Reference	Year	Acc> 90%	AI/ML approach	Open Areas and Future Challenges and Directions
[189]	2021	_	Gale-Shapley	Using wireless power harvesting to help the UAVs conduct continuous sensing and model training without returning to their bases.
[190]	2021	_	—	Integrating worker mobility into the FL supported by UAVs, where employees can move between subregions.
[191]	2022	1	FDRL	Expanding their federated deep reinforcement learning (FDRL) for many attackers with suitable adaptation for battery-limited UAVs.
[192]	2021	—	_	Using Off-Chain Blockchain Storage to manage large-size data and satisfy the consensus on the divisibility and location of services between the service providers.
[193]	2021	—	FDRL	Utilizing their federated deep reinforcement learning (FDRL) architecture to manage resource allocation and scheduling intelligently in accordance with various service needs.
[194]	2022	1	FDRL	_
[195]	2023	_	SIL	Extending generative adversarial imitation learning (GAIL) model by tackling obstacle-avoidance flight paths, swarm collaboration efficiency, and connection management using self-imitation learning (SIL).
[196]	2022	—	FLSDs	-
[197]	2022		DRL	_
[198]	2023	1	SSFL	Developing their method to better use unlabeled data and upgrading the theory of semisupervised FL (SSFL) to make it more applicable in real-life situations.
[199]	2023	_	HFL-LSTM/ MADDQN	-

Table 7: References on FL-based UAV-assisted Structures

eter interactions. Cheng et al. [196] examined a multiple FL service trading problem in networks supported by UAVs, where FL service demanders (FLSDs) sought to acquire various data sets from practical clients (smart devices, such as smartphones, smart vehicles), and model aggregation services from UAVs, in order to meet their needs. A trading market based on auctions was built to enable trade between three parties: FLSDs serving as buyers, scattered situated client groups acting as data-sellers, and UAVs acting as UAV-sellers. The auction aimed to maximize the income for all purchasers by examining winner selection and payment rule design. In particular, since two seller categories (data sellers and UAV sellers) were considered, an intriguing concept merging seller pairs and joint bids was developed, transforming various vendors into virtual seller pairs. One-sided matching-based and Vickrey-Clarke-Groves (VCG)based techniques were suggested, with the former achieving the best results but being computationally challenging. The latter, especially when taking into account a large number of players, might produce suboptimal solutions with low computing costs that were close to the ideal ones.

To allow sustainable FL with energy-harvesting user devices, the authors in [197] adopted a DRL-based system for cooperative UAV placement and resource allocation. Their goal was to maximize long-term FL performance while considering the network's limited bandwidth, collected energy, and energy budget for UAVs. They used the Lyapunov optimization method to convert a long-term energy restriction into a deterministic issue, reducing the complexity of the original problem. In order to solve the Markov decision process (MDP), they rephrased the optimization issue as the framework of a DRL-based method. The suggested approach could ensure the sustainable functioning of UAV-aided wireless networks by enhancing long-term network energy savings.

Data availability and data privacy issues will arise from such a strategy. The authors in [198] first looked at a semisupervised

FL (SSFL) framework for privacy-preserving UAV image identification to solve these problems. They specifically suggested a model parameter mixing technique known as federated mixing (FedMix), to enhance the combination of FL and semisupervised learning methods under two actual circumstances (labelsat-client and labels-at-server). Additionally, statistical heterogeneity, or the amount, characteristics, and distribution of local data acquired by UAVs using various camera modules in various situations showed notable variances. In order to address the issue of statistical heterogeneity, they suggested an aggregation method depending on the client's involvement in the training process, specifically, the FedFreq aggregation rule during training, which modified the weight of the associated local model in accordance with its frequency. Zou et al. [199] first, a dayahead energy scheduling problem for urban prosumers with access to UAV charging was investigated. The main goal was to optimize prosumers' overall energy satisfaction while preserving the QoS of the charged UAVs. They specifically divide the subject under consideration into two stages: the day-ahead energy need data prediction stage and the energy scheduling stage for each prosumer. Consequently, a hybrid technique was presented based on stochastic game-based multi-agent double deep Q-learning (MADDQN) with a community agent-independent approach. It is based on hierarchical FL (HFL) on LSTM architecture. In order to ensure data privacy, the HFL-LSTM technique was used in particular to anticipate each prosumer's energy need for data locally rather than centrally. Then, the specified problem was subjected to stochastic game analysis to identify the Nash equilibrium (NE) approach. Each prosumer's ideal energy scheduling approach was then achieved using MADDQN and a community agent-independent methodology. The future directions, open areas, and accuracy of references in FL-based UAV-assisted systems are listed in Table 7 with details.

6.0.2. Secured Healthcare System (SHCS)

Early dementia illness detection is becoming more accessible and economical because of the quick growth of the smart healthcare system. However, medical facilities are overstretched due to the coronavirus epidemic, requiring doctors to diagnose and treat patients remotely. For example, COVID-19 has raised people's awareness of the importance of their health, leading to a significant increase in the sales of IoT-enabled medical equipment. Cyber attackers were drawn in by the explosive growth of the Internet of Medical Things (IoMT) market. Consistent with this issue, medical information from sensors and wearable technology is gathered in many industrialized nations. While maintaining the security and privacy of individual health information, FL can facilitate the cooperative creation of health-related forecasting algorithms. For example, Shed et al. [200] suggested an FL method (FLM)-based effective and secure online diagnostic method for e-healthcare systems. In particular, they used FLM to first convert the data-sharing dilemma of the data owner into an ML issue. Training data sets' security could be effectively preserved by providing computed local model settings rather than real data. Next, they effectively categorized patients' medical information without compromising their security by utilizing a homomorphic cryptosystem and the SVM method. Additionally, they put forth a unique method to retrieve the SVM model's decision function that effectively stops model variable leaks.

Sakiba et al. [201] considered arrhythmia detection using ECG analysis a crucial application for heart activity monitoring. Utilizing the private ECG data collected within each smart logic-in-sensor deployed at the UltraEdge Nodes (UENs), they studied two FL architectures for categorizing arrhythmias. The envisioned paradigm enabled privacy protection while also enabling online knowledge exchange through lightweight, localized, and distributed learning. To further tailor their FLbased architecture for ECG analysis, a lightweight CNN-based AI model's shallow and deep model parameters were asynchronously updated to save critical communication bandwidth. The authors in [202] employed FL to enable scattered IoT users to train collaborative models at the network's edge while protecting user privacy. However, the FL network's members could differ in their willingness to participate (WTP), a secret the model owner was unaware of. Additionally, creating healthcare apps necessitates frequent long-term user involvement, for example, for the ongoing data-gathering process during which a user's WTP might alter over time. In order to explore a twoperiod incentive mechanism that fulfills intertemporal incentive compatibility (IIC) and maintains the contract's self-revealing mechanism throughout both periods, they used the dynamic contract design.

In order to identify COVID-19 infections using medical diagnostic image analysis, the authors in [210] looked at a unique dynamic fusion-based FL technique. In order to assess medical diagnostic pictures, they first designed an architecture for dynamic fusion-based FL systems. Additionally, they introduced a dynamic fusion approach that dynamically selects the participating clients based on their local model performance and plans the model fusion depending on the training duration of the participating clients. Additionally, they provided an overview of a group of COVID-19 detection-capable medical diagnostic image data sets that the ML community might employ for image analysis.

In order to enable privacy-enhanced COVID-19 detection with generative adversarial networks (GANs) on edge cloud computing, the authors in [203] offered a novel FL technique named FedGAN. They specifically designed a GAN in which a discriminator and a generator based on CNNs at each edge-based medical institution were trained alternately to match the genuine COVID-19 data distribution. Then, to improve the global GAN model for producing realistic COVID-19 pictures without the requirement for actual data sharing, they presented a novel FL approach that enables local GANs to cooperate and communicate learned parameters with a cloud server. They implemented a DP solution at each hospital institution to improve privacy in federated COVID-19 data analytics. Additionally, they suggested a new FedGAN architecture built on blockchain for safe COVID-19 data analytics by decentralizing the FL process and utilizing a novel mining technique for low running latency. The authors in [204] highlighted the FL-based system's role in the Internet of Medical Things (IoMT) fight against the COVID-19 epidemic. In particular, they first described the architecture of the smart healthcare system while emphasizing the fog layer. The preprocessing tasks that might be applied at the fog layer are then discussed, emphasizing ML and DL tasks. Following that, a report on the FL versus several COVID-19 scenarios was supplied. Gupta et al. [205] adopted an AD model based on FL that used edge cloudlets to run AD models locally without sharing patient data. Their study focused on a hierarchical FL that permits aggregation at several levels, enabling multiparty cooperation. Existing FL techniques executed aggregation on a single server, which restricted the scope of FL. We provide a unique disease-based grouping technique in which various AD models are categorized according to specific disorders. They also presented a novel Federated Time Distributed (FEDTIMEDIS) LSTM method to train the AD model. To illustrate their methodology, they designed a Remote Patient Monitoring (RPM) use case and showed how it might be implemented utilizing edge cloudlets and the Digital Twin (DT).

The authors in [206] put forth a unique method for protecting the privacy of electronic health records that combined DL and blockchain technology. The CNN method was used to classify normal and abnormal users in the processed dataset. Then, by integrating blockchain with a cryptography-based FL module, the anomalous users were dealt with and eliminated from the database, removing them from its accessibility for health records. In [207], Hierarchical FL (HFL) was made possible by a Dew-Cloud-based model. Dew-Cloud enhanced IoMT essential application availability and provided a higher level of data privacy. The hierarchical long-term memory (HLSTM) concept was implemented on distributed Dew servers with cloud computing as the backend.

In the context of 6G and IoMT, the authors in [208] discussed

Reference	Year	Acc> 90%	AI/ML approach	Open Areas and Future Challenges and Directions
[200]	2023	1	SVM	Assessing their online diagnostic e-healthcare scheme's resilience for Byzantine attack or lower-quality local gradients.
[201]	2021	1	CNN	-
[202]	2021	—	—	Putting a training-based reward system on top of the dynamic contract, such as DRL.
[203]	2022	1	FedGAN/CNN	Federated human activity analytics by expanding the FL-blockchain model, where wearable devices with sensors cooperate together to develop a common human activity.
[204]	2021	1	DL	Investigating of FL applications and examining their findings for the safety and performance of their fog-based smart healthcare system in the context of COVID-19.
[205]	2021	1	FEDTIMEDIS	Gathering of data, complete use of the Federated Time Distributed (FEDTIMEDIS) Long Short-Term Memory (LSTM) technique and an assessment of its effectiveness.
[206]	2023	1	CNN/DL	-
[207]	2022	1	hierarchical FL	The Dew-Cloud-based system may be expanded to incorporate the Gurobi optimization in order to decrease latency and improve accuracy.
[208]	2022	1	CNN/SMPC	Creating an encrypted inference technique based on SMPC that is more lightweight and can be executed on edge servers.
[209]	2021	_	_	Arousing interest in the development of the tele-biomedical laboratory among the industrial and scientific groups.

Table 8: References on FL-based Secured Healthcare Systems

a CNN-based FL architecture that integrated secure multi-party computation (SMPC)-based aggregation with encrypted inference techniques. They took into account various hospitals with mixed IoMT and edge device clusters that encrypt locally developed models. In the next step, each hospital sent its encrypted local models to the cloud for SMPC-based encrypted aggregation, which built the encrypted global model. Finally, each edge server received the encrypted global model back after further localized training to further increase model accuracy. Additionally, hospitals could use cloud computing or their edge servers to execute encrypted inference while ensuring the privacy of their data and models.

In a tele-biomedical laboratory, blood tests are carried out by patients themselves in their homes or by biomedical technicians in satellite clinical centers using IoT biomedical devices linked to Hospital Edge or Cloud systems that enable results to be sent to physicians working at federated hospitals for validation and/or consultation. For example, the goal of [209] was to present a comprehensive picture of the state of the art in the tele-biomedical laboratory while simultaneously noting existing problems and upcoming difficulties. In particular, the authors urged tele-biomedical laboratories to utilize IoT, edge, and cloud technologies. They first classified the primary biomedical equipment (taking into account invasive, non-invasive, minimally invasive, and noninvasive technologies) and then described many potential tele-biomedical laboratory situations. The future directions, open areas, and accuracy of references in FL-based secured healthcare systems are listed in Table 8 with details.

6.0.3. Smart Cities and Homes (SCH)

In smart cities, where energy efficiency and data protection are considered top priorities, deploying a large number of sensors and data-gathering devices helps FL find many uses, including traffic management, public safety, and environment monitoring, energy optimization, urban planning, and air quality monitoring. In order to identify the sensors that are present on each end-user device, the authors in [211] first introduced their new platform (which also included software and mobile app implementation). Gyroscope, ambient light sensor, temperature, magnetic field sensor, orientation sensor, game rotation vector, linear acceleration, relative humidity, gravity, geomagnetic rotation vector, and so on., were just a few of the many sensors they found. Given that the sensors were already built into the phone, employing them could be advantageous when taking into account the complexity, effectiveness, and cost of the entire system. Designing a system that could cause dispersed devices to self-activate and agree to generate all available sensor data was a problem. Additionally, since devices could provide a constant stream of data, the size of the data might increase and take on a random structure, making it difficult for us to distinguish one device's sensor data from another and come to a wise choice. To address these, the authors put up a distributed sensing solution to utilize a token to identify a device, activate dispersed end-user devices to send data to the cloud as needed, and store data on the cloud server while retaining the appropriate format. With this method, remote data collection was made possible using existing end-user devices, and the cost of adding new sensors for autonomous IoT applications was decreased. In order to provide dispersed intelligence across a network of smart devices, they expanded upon their effective sensing platform. To do this, they used the processing power of these devices for local decision-making, i.e., each smart device only interacted with a small number of nearby devices rather than broadcasting all sensing data to a centralized agent and solving a large-scale decision-making issue.

The authors in [212] provided a fog computing-based architecture for monitoring the environment that made use of multi-source heterogeneous data gathered from IoT sensors. They used local sub-classifiers to assess the data at each edge node and then used a DNN model to combine the results from the sub-classifiers. They set up an FL approach to

Table 9: Reference	s on FL-based	Smart Architectures
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Reference	Year	Acc> 90%	AI/ML approach	Open Areas and Future Challenges and Directions
[211]	2019	_	—	Creating decentralized learning methods specifically for use cases with the autonomous internet of things.
[212][2019	1	_	Enhancing the distributed model average method's efficiency and optimizing the consideration of variables like data dispersion and volume.
[213]	2020	×	Dual-CPMF	Examining a central video recommendation method that was coordinated by the edge-end-cloud, where the recommender is installed on the edge server close to the clients.
[214]	2021	1	CRNN	Personalizing clients' feedback models over a cloud server to keep local models updated with the most pertinent geographical data through neighboring update aggregation.
[215]	2019	_	ANN	Using several frequency ranges in the GPUs for clock frequencies and memory.
[216]	2022	—	FLITC	Enhancing the FLITC (FL-IoT-Traffic Classifier) by utilizing edge computing systems' functionalities.
[217]	2021	\checkmark		Testing their block-chain method using actual datasets, and determining the ideal ratio for global and local epochs.

simultaneously update homologous sub-classifiers at several edge nodes through model transfer. They assessed the fog computing-based architecture using multi-source, heterogeneous data gathered in Beijing.

The authors in [213] suggested JointRec, a framework for collaborative cloud video recommendations based on DL. JointRec enables federated training across dispersed cloud servers by integrating the JointCloud architecture into mobile IoT. They first schemed a dual-convolutional probabilistic matrix factorization (Dual-CPMF) model to undertake video recommendation. By utilizing user profiles and the descriptions of the films that users evaluated, each cloud might propose videos based on this model, offering more accurate video recommendation services. Next, they provided a federated recommendation approach that enabled each cloud to pool its weights and jointly train a model. Additionally, to decrease uplink communication costs and network capacity, they combined the 8-bit quantization approach with low-rank matrix factorization to address the high communication costs associated with federated training.

The FL paradigm technique was described in [214] for training air pollution prediction models using environmental monitoring sensor data. In the study, the authors provided a distributed learning framework to support group training among participants from various geographic locations, such as cities and prefectures. Convolutional Recurrent Neural Networks (CRNN) were trained locally in each area with the goal of forecasting the local Oxidant alert level, while an aggregated global model improves the distilled information from every part of a region. Their study showed that while CRNN's intended common elements may be fused worldwide, its predictive part's adaptive structure could capture various environmental monitoring stations' configurations in localized places. In order to enhance the accuracy of the whole FL system, certain experiment findings also pointed to strategies for maintaining the balance between local DNN training epochs and synchronous training rounds for FL.

New IoT and smart city applications are in high demand, and it is predicted that by 2020, there will be 20.41 billion linked devices worldwide. Numerous services and apps handle realtime data analytics with large amounts of data, necessitating

an effective computer infrastructure. This situation is made possible by EC, which reduces network saturation and service latency. The placement of multiple smaller data centers close to the data sources makes up this computing paradigm. The management of federated edge data centers would benefit from the use of microgrid energy sources parameterized by user needs. Energy efficiency is a major problem in executing this scenario. For example, based on the application's required data traffic, the authors in [215] provided an ANN predictive power model for GPU-based federated edge data centers. They verified their methodology by generating 1-hour-ahead power forecasts with a normalized root-mean-square deviation less than 7.4% when compared with actual measurements utilizing real traffic for a cutting-edge driving assistance application. The authors in [216] offered the FL IoT Traffic Classifier (FLITC), an IoT traffic classification method based on the MultiLayer Perception (MLP) neural network that kept local data on IoT devices intact by sending only the learned parameters to the aggregation server and ensured the privacy of traffic data.

The authors in [217] modeled an FL system using a reputation mechanism to aid home appliance makers in training an ML model based on consumer data in order to assist manufacturers in developing a smart home system. Manufacturers could then anticipate future consumer demands and consumption patterns. The system's operation was divided into two parts. First, users trained the manufacturer's initial model using a mobile device and a mobile-edge computing server. Customers used their phones to collect data from various household equipment, after which they downloaded and trained the basic model using local data. Customers signed and transmitted their models to the blockchain after generating local models. The authors substituted the centralized aggregator in the conventional FL system with the blockchain in the event that manufacturers or customers were hostile. Because blockchain records could not be altered, it was possible to track the actions of dishonest producers or consumers. In the second step, manufacturers chose specific individuals or groups as miners who could calculate the averaged model using the models they had received from consumers. One of the miners, chosen as the temporary leader at the completion of the crowd-sourcing work, uploaded

the model to the blockchain. The authors imposed DP on the retrieved characteristics and provided a new normalization method to safeguard customers' privacy while enhancing test accuracy.

Liu et al. [223] concentrated on IoT-based Maritime Transportation System (MTS) features and offered FedBatch, a CNN-MLP-based intrusion detection model trained using FL. FL protects the confidentiality of local data on boats by keeping model training local and only updating the global model through the sharing of model parameters. The peculiarities of communication among several vessels were first addressed in order to simulate the FL process while at sea. Then, the lightweight local model constructed by CNN and MultiLayer Perception (MLP) was established to reduce processing and storage overhead. Additionally, they presented Batch Federated Aggregation, an adaptive aggregation technique that suppressed the oscillations of model parameters during FL, to address the straggler issue during FL in MTS. The future directions, open areas, and accuracy of references in FL-based smart architectures are listed in Table 9 with details.

7. Scalability

In ultra-dense networks where we face quite a lot of clients geographically distributed in vast areas of interest, scalability, as an important economic property, plays an essential role in technically addressing model updating and control concerns. To address model updating and aggregation, combiners, and reducers are distributed in the area of interest, respectively. Combiners are assumed to be responsible for partial aggregation and load balancing, while reducers intend to be responsible for combiner connections and global model generation and enhancement. The following control mechanism is applied to monitor and provide service discovery among all clients carefully [218]. Another essential issue in scalability is entering clients and existing in the network, which enormously affects local and global model aggregation. The authors in [219] aimed to scrutinize a study case in which a large number of users are involved. To this end, they analyzed medical images utilizing accessible chest X-ray data sets to improve accuracy, loss, complexity, time, and privacy issues. Besides, the main purpose of their paper was to study the scalability of FL. Two important case studies are as follows: In one case study, intermittent clients may quit the training process but still participate in it. Another case study may occur when some medical centers no longer contribute to the FL process and stop sharing their medical records, or they may be better suited if the collaboration process were fully facilitated. Zheng et al. [220] explored the privacy and scalability to upgrade their system model economically. For the privacy issue, they modeled a Faithful FL (FFL) structure, a strategy in which deviation, obsession with relevant information, message passing, and computation may not benefit any client. FFL aimed to estimate the Vickrey-Clarke-Groves (VCG) payments in order to guarantee faithful implementation, voluntary contribution, and optimal conditions while controlling the complexity of their model. In the next step, the clients

were categorized into clusters that could approximate the scalability of the VCG structure. In the following, a salable and Differentially Private FFL (DP-FFL) scheme was designed in order for clients to perform three-way performance trade-offs among three essential issues in terms of the iteration demanded, payment precision loss, and protection.

COVID-19 screening check-up was federated and extended in [221], where the authors aimed to evaluate and develop a quickly client-friendly and scalable FL idea applied to hospital teams in the UK. Thanks to the emergency departments, they established an E2E solution to remove patients' data transformation by using and analyzing medical records, including vital signs and blood tests, which may take a while to reach out to the hospitals.

Fully decentralized FL (FDFL) was introduced in [222] based on a peer-to-peer network in order to develop the resilience and scalability of standard FL while guaranteeing proper convergence speed using global gradient methods. To this end, an aggregator-based model was designed that provided a client election process and scalability properties with respect to network size with respect to cache, computation, and communication to cope with client failures caused by decentralized systems. The future directions, open areas, and accuracy of references in the scalability of FL-based structures are listed in Table 10 with details.

8. Conclusion

The emergence of FL is deeply intertwined with the field of AI. FL leverages the power of decentralized data processing, allowing models to be trained across multiple edge devices without the need to centralize sensitive information. This approach addresses privacy concerns and opens new avenues for collaborative learning. In this survey, we conducted a comprehensive examination of FL, delving into its current challenges, applications, and future research directions. In pursuit of this objective, we meticulously examined and compared various FL structures, with a thorough investigation into their efficiency, accuracy, and privacy aspects, derived from the most recent FL research endeavors. We elucidated the persistent voids that remain unaddressed in prior surveys and articles. In response to prevailing gaps, this survey paper delivered substantial contributions by accomplishing some key objectives, including: 1) presenting mathematical analyses and algorithmic frameworks to facilitate a deeper comprehension of the fundamental principles governing FL, 2) providing research direction guidance and delineating unresolved queries to encourage researchers to venture into unexplored realms and explore novel avenues, 3) organizing previous studies according to their accuracy and the ML methods they utilized, thereby offering an invaluable resource to the scientific community. This resource enables researchers to gain deeper insights into the performance and methodologies employed across diverse FL contexts. Our research entailed an extensive scrutiny of the contributions and findings documented in published papers, focusing on three principal viewpoints: the security in FL-based structures, the optimization of resource allocation in FL networks, and the applications of FL

Table 10: References on Scalability of FL Structures

Reference	Year	Acc> 90%	AI/ML approach	Open Areas and Future Challenges and Directions
[218]	2021	X	FEDn	Improving the reducer that spends a large time downloading and loading models from the combiners.
[219]	2023	X	—	Exploring the advantages of their medical image classifier compared with the centralized classifier.
[220]	2021	1	Faithful-FL(FFL)	Exploring the effect of cost of ignoring processing and transmission cost.
[221]	2023	×	—	Implementing a fully-autonomous data extraction pathway through direct Electronic Healthcare Records (EHR).
[222]	2023	X	FDFL	Optimizing efficiency, security, and privacy by investigating the impact of many aggregator levels in fully decentralized FL (FDFL).

networks across various domains in both daily life and industry. Given FL's potentials to revolutionize various industries, the necessity for sustained research endeavors in this domain is undeniable. However, to expedite the realization of these transformative capabilities, it is crucial to highlight current gaps and challenges in the field. By doing so, researchers can be captivated and motivated to address these issues promptly, thereby unlocking the full potential of FL as swiftly as possible. Our survey serves as a valuable resource in this endeavor, offering a comprehensive overview of the field's current state and research directions. It provides a solid foundation for researchers to orient and refine their investigations, thereby expediting the advancement and application of FL.

Conflict of Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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