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APPLICATION OF SOFT COMPUTING

Blockchain for federated learning toward secure distributed machine learning systems: a systemic survey

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Abstract

Federated learning (*FL*) is a promising decentralized deep learning technology, which allows users to update models cooperatively without sharing their data. *FL* is reshaping existing industry paradigms for mathematical modeling and analysis, enabling an increasing number of industries to build privacy-preserving, secure distributed machine learning models. However, the inherent characteristics of *FL* have led to problems such as privacy protection, communication cost, systems heterogeneity, and unreliability model upload in actual operation. Interestingly, the integration with Blockchain technology provides an opportunity to further improve the *FL* security and performance, besides increasing its scope of applications. Therefore, we denote this integration of Blockchain and *FL* as the Blockchain-based federated learning (*BCFL*) framework. This paper introduces an in-depth survey of *BCFL* and discusses the insights of such a new paradigm. In particular, we first briefly introduce the *FL* technology and discuss the challenges faced by such technology. Then, we summarize the Blockchain ecosystem. Next, we highlight the structural design and platform of *BCFL*. Furthermore, we present the attempts ins improving *FL* performance with Blockchain and several combined applications of incentive mechanisms in *FL*. Finally, we summarize the industrial application scenarios of *BCFL*.

Keywords Blockchain · Federated learning · Smart Contract · Incentive mechanism · Industrial Applications

1 Introduction

The quality and security of data are the keys to the development of machine learning and artificial intelligence (*AI*). However, rich data is often privacy sensitive and large scale, which will hinder traditional methods to log into a data center and train there. Besides, most of the data and resources needed for effective training of machine learning models are owned by a few large technology companies, which is detrimental to privacy protection and further leads to centralization problems. Thus, a novel, distributed learning approach that allows large-scale joint modeling without publishing raw data becomes imperative. In this context, Federated learning (*FL*) proposed by Google (Konečnỳ et al. 2016; Aledhari et al. 2020; Konečnỳ et al. 2016; McMahan et al. 2017) has recently received great attention at both the research and application levels.

Specifically, *FL* is an emerging machine learning technology consisting of many mobile devices and a central storage server. This technology allows distributed model training using local datasets from large-scale nodes, such as mobile

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devices. *FL* updates the parameters without uploading the original training data and then builds a shared model by aggregating the locally computed updates (Xu et al. 2020). A typical example is the *FedAVG* algorithm, which is based on the iterative model averaging proposed in McMahan et al. (2017). This method is robust and allows to generate imbalanced and independent, and constant distribution non-IID data distributions. The basic design structure of *FL* is shown in Fig. 1. Based on this, *FL* offers promising privacy protection for mobile devices while ensuring high learning performance.

However, despite the many benefits mentioned above, *FL* still faces serious challenges. The gradient aggregation mechanism used for *FL* makes the entire algorithmic model dependent on the control of a central node. So we need to address two trust issues: one is to ensure that there is a central node that all participants trust, and the other is to ensure that information about the operations of the central node is transparent. First of all, *FL* relies on centralized databases and remains at risk of distributed denial of service *DDoS* attacks and privacy breaches. Again, currently, *FL* systems do not have suitable and transparent contribution evaluation mechanisms and incentive mechanisms to ensure continuous active training of training nodes. Finally, an effective distributed system needs to identify and prevent malicious nodes. However, the current *FL* system does not provide adequate mechanisms to implement these operations.

Interestingly, Blockchain technology provides an opportunity to address the above challenges of *FL*. More precisely, through the combination of chain structure, tree structure, and graph structure, the Blockchain ensures secure storage and data traceability (Liang et al. 2020). Besides, through the consensus mechanism of proof-of-work (*POW*), Blockchain realizes the untamperability of data. In more detail, due to the validation process of Blockchain local training results, the proposed *BCFL* framework can avoid the single point of failure (*SPOF*) and extend its federation scope to untrusted users in the public network. In addition, by providing rewards proportional to the size of the training samples, *BCFL* can realize effective incentives and thus facilitate the union of more devices with a large number of training samples. Therefore, the Blockchain can be seen as a perfect complement for *FL*, providing it with improved interoperability, privacy, security, reliability, and scalability (Liang et al. 2021).

Although many papers involve different aspects of the *BCFL* paradigm, there is no systematic investigation on this paradigm. In this article, we present a survey on a new paradigm for integrating Blockchain and *FL*. This survey denotes such a synthesis of Blockchain and *FL* as *Blockchain-based federated learning* (*BCFL*) framework. To present a complete picture of *BCFL*-related studies, we surveyed the related works focusing on structure design, performance enhancement attempts, incentive mechanism design, and industrial applications of *BCFL*, in a period ranging from 2016 to 2021. Given the previous work, we aim to (i) provide a conceptual introduction to *FL* and Blockchain technology, (ii) provide a systematic analysis of the potential of incorporating Blockchain into *FL*, and (iii) discuss the specific applications of *BCFL* in depth.

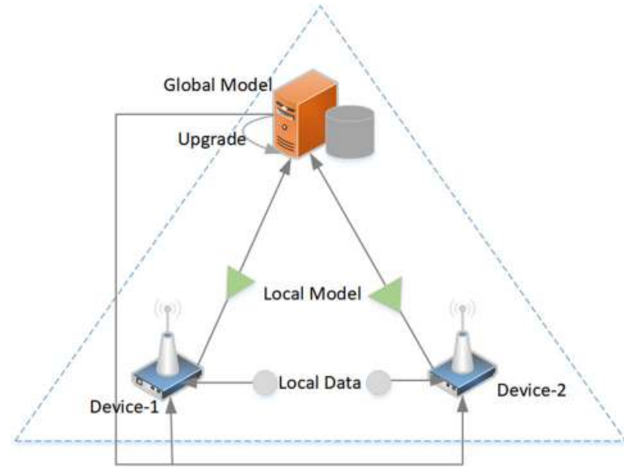
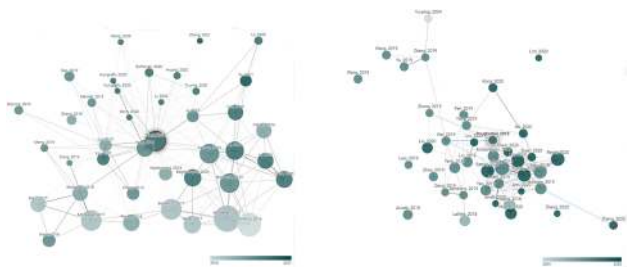


Fig. 1 The architecture of *FL*

In detail, the main contributions of this paper are summarized as follows.

- We provide an overview of the definition, architectural design, and deployed platform for Blockchain and *FL* convergence.
- We provide a systematic survey on the studies dedicated to improving the performance of *FL* by integrating block *FL* systems.
- We survey the existing studies on effective incentive mechanisms for training nodes using Blockchain.
- We summarize the current feasible applications for *BCFL* in industrial applications.

The rest of this article is organized as follows. We first introduce the related work in Sect. 2. Section 3 then introduces the background and fundamentals of *FL* and Blockchain. Subsequently, Sect. 4 presents the convergence architecture and deployment platform of *BCFL*. Section 5 then summarizes the attempts to make appropriate improvements to the *BCFL*. Section 6 discusses the transparent contribution recognition and effective reward for clients in *BCFL*. Section 7 next summarizes the feasible application of *BCFL*. Finally, Sect. 8 concludes the paper.



(a) Association of Yang's work **(b)** Association of Zheng's work

Fig. 2 The loosely related researches of Yang's work and Zheng's work

2 Related work

Currently, many studies have investigated the ideology, structure, and related research of *FL* and Blockchain, respectively. Particular, the works proposed in Konečnỳ et al. (2016), Konečnỳ et al. (2016), McMahan et al. (2017), Kairouz et al. (2019), Yang et al. (2019), Bonawitz et al. (2019), Yu et al. (2021), Li et al. (2020), Gu et al. (2019), Li et al. (2019), Mothukuri et al. (2021), Liang et al. (XXXX) comprehensively introduced the relevant information of *FL*, while the works proposed in Zheng et al. (2017), Kumar and Jaiswal (2019), Xiao et al. (2020), Gramoli (2020), Liang et al. (2020), Zhou et al. (2020), Saleh (2020), Li et al. (2020), Hewa et al. (2021), Liang et al. (2019), Xiao et al. (2020) summarized the main information concerning the structure and characteristics of Blockchain. In this work, we take Yang's work (Yang et al. 2019) and Zheng's work (Zheng et al. 2017) as baselines and organize the closely related research. As Fig. 2 shows, Yang's work is associated with more highly cited articles, and Zheng's work links more paper groups.

In conclusion, the technological development of *FL* has attracted much attention, and the related research has shown an explosive growth trend. However, as Table 1 shows, there is no existing survey related to the combination of Blockchain and *FL* in the literature. To fill this gap, we propose in this work the first survey that performs a thorough investigation of the relevant studies published in recent years on *BCFL*. Again, we systematically present the structural designs, deployed platforms, performance improvement, node incentive mechanisms, and the industrial applications of *BCFL*. Finally, based on the related works, Table 2 defines a list of acronyms and the definitions used in this survey.

3 Background

In this section, we provide all the background necessary to understand better and follow this paper. More precisely, we briefly introduce *FL* integration in Sect. 3.1 and present Blockchain ecosystem in Section 3.2.

3.1 Federated learning integration

FL refers to the calculation process that enables the data owner F_i to perform model training and obtain the model M_{FED} without giving their data D_i while ensuring that the gap between the effect V_{FED} of the model M_{FED} and the effect V_{SUM} of the model M_{SUM} is small enough. This calculation can be expressed as follows.

$$\omega_t^i = \& \arg\min_{\omega_t^i} F\left(\omega_t^i\right) \tag{1}$$

$$F\left(\omega_t^i\right) \& = \frac{1}{|\mathcal{D}_i|} \sum_{j \in \mathcal{D}_i} f_j\left(\omega_t^i\right) \tag{2}$$

Where $|\mathcal{D}_i|$ is an arbitrarily small positive value, $1 \le i \le n$, and n is the number of participants to the system.

3.1.1 Taxonomy of *FL*

The basis of *FL* is the data matrix. As shown in Fig. 3, based on the different distribution patterns of sample space and feature space of data, *FL* can be divided into three categories: horizontal federated learning (*HFL*), vertical federated learning (*VFL*), and federated transfer learning (*FTL*) which divide the dataset horizontally (i.e., user dimension), longitudinal (i.e., feature dimensions), and non-dimensionally, respectively.

3.1.2 The workflow of *FL*

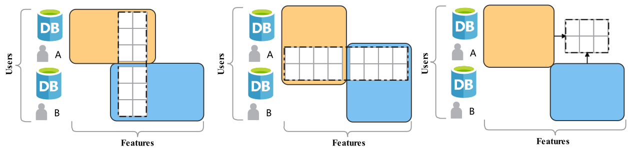
FL systems generally consist of data holders and central servers. The amount of local data or the number of features of each data holder may not be enough to support successful model training. Therefore, support from other data holders is required. Figure 4 illustrates the *FL* process for the client-server architecture.

In a typical cooperative modeling process of *FL*, the training of local data by the data holders occurs only locally to protect data privacy. Next, the gradients generated by the iterations are used as interaction information after desensitization and uploaded to a third-party trusted server instead of local data, waiting for the server to return the aggregated parameters to update the model. In detail, the steps of *FL* can be summarized as follows.

- *Step 1*. System Initialization. First, the central server sends the modeling task and seeks to participate in the client.
- *Step 2*. Local Calculation. After the joint modeling task is opened and the system parameters are initialized, each data holder will be required to perform local calculations according to the data locally first.

Table 1 The summary of selected overviews and surveys for *FL*

Category	Ref. no	Author(s)	Topic	Published
Fundamental architecture, algorithm, and model	Konečný et al. (2016, ?); McMahan et al. (2017)	Mcmahanet et al.	Concept and applications	2017.6-9
	Kairouz et al. (2019)	Kairouz et al.	Advances and open problems	2019.1
	Yang et al. (2019)	Yang et al.	Concept and applications	2019.2
	Bonawitz et al. (2019)	Bonawitz et al.	System design	2019.3
	Li et al. (2020)	Tian Li et al.	Challenges, methods, and future directions	2019.8
	Gu et al. (2019)	Gu et al.	Distributed machine learning	2019.9
	Li et al. (2019)	Qinbin Li et al.	Data privacy and protection	2019.11
	Mothukuri et al. (2021)	Mothukuri et al.	Security and privacy	2020.10
	Shen et al. (2020)	Sheng Shen et al.	Data privacy and security	2020.10
	Lo et al. (2020)	SK Lo et al.	A Software engineering perspective	2020.12
	Lyu et al. (2020)	Lyu et al.	Threats	2020.3
	Bellavista et al. (2021)	Bellavista et al.	Deployment environments	2021.2
	Zhan et al. (2021)	Yufeng Zhan et al.	Incentive mechanism design	2021.3
Performance improvement	Kulkarni et al. (2020)	Kulkarni et al.	Personalization techniques	2020.3
	Jin et al. (2020)	Yilun Jin et al.	Utilizing unlabeled data	2020.5
	Hu et al. (2020)	Sixu Hu et al.	Benchmark suite	2020.10
Embeding technology, and application	Cui et al. (2018)	Cui et al.	FL for Internet of things	2018.6
	Lim et al. (2020)	Bryan Lim et al.	FL in Mobile edge networks	2020.2
	Du et al. (2020)	Du et al.	FL for Vehicular internet of things	2020.4
	Saputra et al. (2020)	Saputra et al.	FL for Electric vehicle networks	2020.4
	Aledhari et al. (2020)	Aledhari et al.	Enabling technologies, protocols, and applications	2020.8
	Tan et al. (2020)	Tan et al.	FL in Vehicular networks	2020.8
	Wahab et al. (2021)	Wahab et al.	FL in Communication and networking systems	2021.2



(a) Horizontal Federated Learning **(b)** Vertical Federated Learning **(c)** Federated Transfer Learning

Fig. 3 The category of data partition for *FL*

- *Step 3*. Central Polymerization. After receiving the calculation results from multiple data holders, the central server aggregates the calculated values. In the aggregation process, efficiency, security, privacy, and other issues need to be considered.

Notably, the work of the *FL* central server is similar to a distributed machine learning server, which collects the gradients of each data holder and then returns a new gradient after performing aggregation operations in the server.

3.1.3 Applications of *FL*

Currently, *FL* has been integrated with other emerging technologies by many scholars to enable industrial applications, such as the efficiency improvement of mobile and wireless communication (Konecný et al. 2016; Sattler et al. 2020; Reisizadeh et al. 2020; Li et al. 2020; Niknam et al. 2020), edge computing (Wang et al. 2019; Doku et al. 2021; Lu et al. 2020; Fantacci and Picano 2020; Wang et al. 2019; Li et al. 2020; Lim et al. 2020), health care (Rieke et al. 2020; Bogdanova et al. 2020; Zerka et al. 2020), Internet of Things (Savazzi et al. 2020; Yang et al. 2020; Yuan et al. 2020; Qolomany et al. 2020; Briggs et al. 2020; Lim et al. 2020; Gao et al. 2020; Kamel and Mougy 2020; Imteaj and Amini 2019), Internet of Vehicles (Samarakoon et al., 2020; Hsu et al., 2020; Du et al., 2020), anomaly detection (Nguyen et al. 2019; Weinger et al. 2020), smart city (Jiang et al. 2020), financial fraud identification (Fan et al. 2020), visual object detection (Liu et al. 2020) and fog computing (Zhou et al. 2020; Cai et al. 2020). It can be seen that *FL* is prominent in industrial applications for privacy-sensitive data and the processing of non-IID data. Practical industrial-scale applications are not yet sufficient, but theoretical preparations are relatively well established.

3.1.4 Open-source frameworks of *FL*

There are currently a few open-source frameworks for researchers and developers to build *FL* systems. A summary of such frameworks is listed in Tab 3.

Table 2 The summary of acronyms and definitions

Acronym	Definition
FL	Federated learning
HFL	Horizontal federated learning
VFL	Vertical federated learning
FTL	Federated transfer learning
BCFL	The integration of Blockchain and federated learning
AI	Artificial intelligence
DDoS	Distributed denial of service
SPOF	Single point of failure
PoW	Proof of work
PoS	Proof of stake
DPoW	Delayed proof-of-work
DPoS	Delegated proof-of-stake
PBFT	Practical byzantine fault tolerance
dBFT	Delegated byzantine fault tolerance
PooL	Verify the pooling
IoV	Internet of vehicles
IoT	Internet of things
DTWN	Digital twin wireless network
5G	5th Generation mobile networks
6G	6th Generation mobile networks

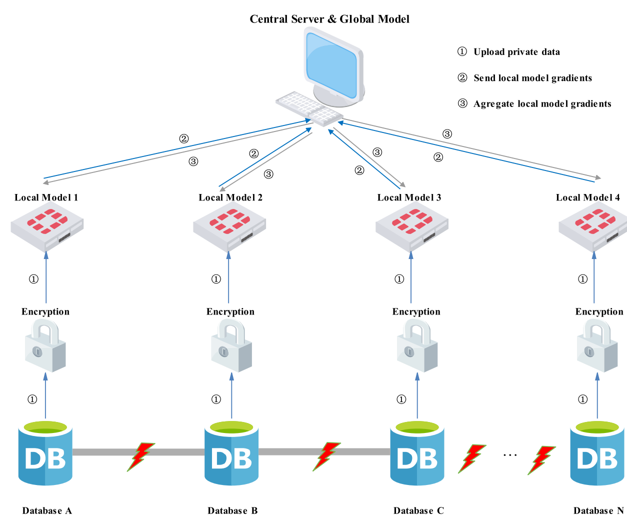


Fig. 4 The workflow of *FL*

3.2 Blockchain ecosystem

3.2.1 Overview of Blockchain

Blockchain is essentially a decentralized distributed database. All the interactive records (transactions) generated in the system are linked into chains as blocks and stored in each section in time. Furthermore, each transaction is guaranteed by cryp-

Table 3 The summary of open-source frameworks of *FL*

Project	Publisher	Framework	Open source	Refs.	Github
Tensorflow Federated	Google	Tensorflow	Code blocks	XXXX (XXXX)	https://github.com/tensorflow/federated
PySyft	Ryffel et.al	PyTorch	Code blocks	Ryffel et al. (2018)	https://github.com/OpenMined/PySyft
FATE	Webank	KubeFATE	API	XXXX (XXXX)	https://github.com/FederatedAI/FATE
PaddleFL	Baidu	PaddlePaddle	API	Ma et al. (2019)	https://github.com/PaddlePaddle/PaddleFL
FedML	University of Southern California	worker-oriented program	API	He et al. (2020)	https://github.com/FedML-AI/FedML

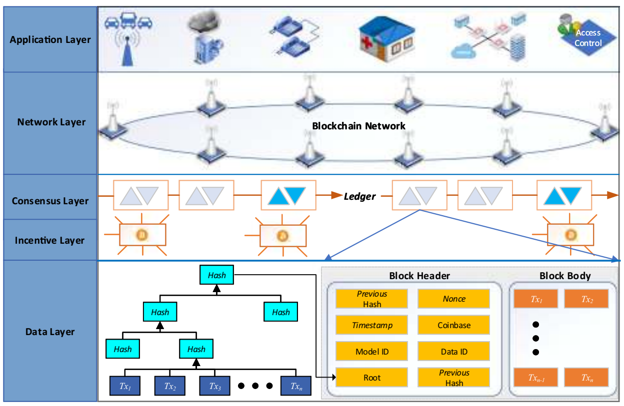


Fig. 5 The architecture of Blockchain

tography and *PoW* algorithms that cannot be tampered with or forged, so each node in the system can achieve secure peer-to-peer transactions. As Fig. 5 shows, a block consists of a *block header* containing metadata and some *transaction records*. These blocks are linked by the *hash pointer* of the block header to form a complete ledger, which is the narrow definition of Blockchain. More precisely, from the bottom to the top, the Blockchain is composed of the *data layer*, *incentive mechanism*, *consensus layer*, *network layer*, and *application layer* (Zheng et al. 2017; Fan et al. 2021; Zheng et al. 2018; Lu 2018; Liang et al. 2019).

Based on different application scenarios and designed systems, the Blockchain is generally divided into *public chain*, *consortium chain*, and *private chain*. Table 4 presents the comparison of three different types of Blockchain. Generally, different types of Blockchain are selected according to the requirements of different business scenarios (Liang et al. 2021). However, in a broad sense, only the public chain can meet the original design intention of the Blockchain.

3.2.2 Consensus mechanism

The most fundamental consensus mechanism of Blockchain is the proof-of-work (*POW*). A node chooses to store the hash value of a specific block in the current block and then mines it. Once successfully linked, it means that the node accepts the transactions of this block and all previous blocks linked by this block. In addition to *PoW*, there are many other types of consensus mechanisms. Table 5 lists several typical consensus mechanisms and gives a comparative explanation.

3.2.3 Smart contract

The smart contract can digitally verify the negotiated or executed contracts and allow trusted transactions without a third party. Besides, these transactions are traceable, and irreversible (Huang et al. 2019). Thus, the success of Ethereum has contributed to the realization of smart contracts. As shown in Fig. 6, it includes transaction processing and preservation mechanism and a complete state machine for accepting and processing various smart contracts. Smart contracts bring great versatility and adaptability to the Blockchain. It is because of the smart contract functionality that various algorithms, including *FL*, can be deployed on the Blockchain.

4 Structure design of *BCFL*

This section outlines the main characteristics of the Blockch ain-based federated learning (*BCFL*) framework. More precisely, in Sect. 4.1, we first introduce the *BCFL* architecture arising from the integration of Blockchain and *FL*. Then, we present the design of data storage and the deployed platform of *BCFL* in Sects. 4.2 and 4.3, respectively.

4.1 Architecture of *BCFL*

The first related research focused on the construction of *BCFL* has been proposed by Kim et al. (2018). The main concept underlying the *BCFL* is to solve the issues on private exchange and reward mechanisms by using Blockchain (Hieu et al. 2020). Subsequent related studies, such as Muguntha n et al. (2020), Kang et al. (2020), Ma et al. (2020), and Majeed and Hong (2019), have also built some contributions on this foundation, but only introducing some small-scale improvements. Besides, to make an intuitive display, a demo of *BCFL* has been proposed by Zhang et al. (2020). However, these follow-up studies all adopted this basic design structure, as shown in Fig. 7.

Specifically, the Blockchain mainly serves as a central database for the *FL* system, which is fully decentralized and privacy-protected. Therefore, the main goal is to reward the clients according to the quality of their contributions while

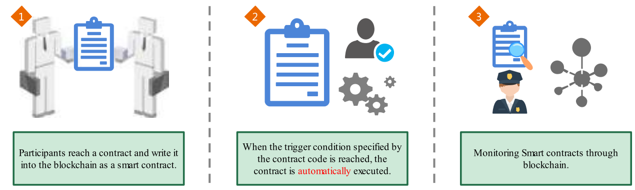


Fig. 6 Smart contract

Table 4 Taxonomy of Blockchain systems

Blockchain	Participants	Characteristics	TPS
Public	Anyone	Decentralized	3–20 data writes per second
Consortium	Authorized nodes	Partially centralized	1000 data writes per second
Private	Authorized nodes	Centralized	1000 data writes per second

Table 5 The summary of Consensus in Blockchain

Consensus	Merits	Weakness
PoW	Complete centralization, nodes free access	Waste of energy and difficult to reduce the confirmation time of blocks
	Simple algorithm	Prone to forking and need to wait for multiple forks to reach consistency
	The cost of destruction is huge(destroyer exceed 50%)	
PoS	cLow performance requirements for nodes	No final consistency, need checkpoint mechanism to compensate and finality
	Short consensus time	
DPoW	Significantly reduce the number of nodes involved in validation	Sacrifices the concept of decentralization, not suitable for public chains
DPoS	Energy conservation	Slightly more centralized, e.g., participants with high equity can vote to make themselves a validator.
	Rapidity	
PBFT	High consensus efficiency for high frequency trading	The existence of cryptocurrency and the incentive mechanism will create a Matthew effect making the poor poorer and the rich richer in the community
		The system will stop when only 33% of the nodes are left running
dBFT	Highly fault-tolerant with bookkeeping done by multiple nodes	The system will not be able to provide services when more than one-third of the bookkeepers stop working
	Every block has finality	
	The algorithm has a strict mathematical proof that it will not bifurcate	
PooL	No cryptocurrency required	Less decentralized
	Second-level consensus verification	

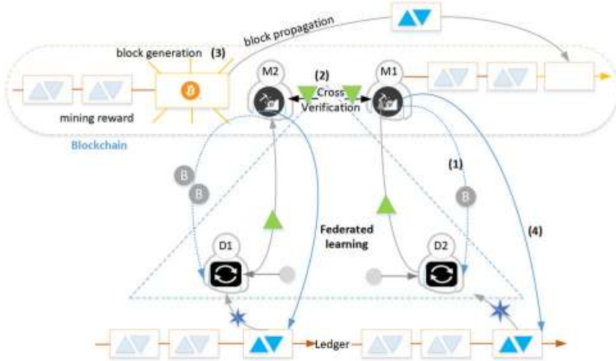


Fig. 7 The architecture of *BCFL*

protecting the privacy of the underlying dataset and fending off malicious adversaries.

4.2 Data storage

As with any distributed system, *FL* bears the privacy leakage challenge. For *BCFL*, the Blockchain plays a pivotal role in solving this problem (Liang et al. 2020). Indeed, the decentralized functioning of Blockchain enables to make *FL* fault-tolerant (Shayan et al. 2021), and can help to avoid attacks effectively. More precisely, to better solve the security problem of data storage, many studies try to make further improvements based on ordinary Blockchain. For example, a new ring decentralization algorithm (Hu et al. 2020), and an innovative committee consensus mechanism (Li et al. 2021) was shown to be feasible solutions for improving decentralized *FL* performance and reducing consensus computation, respectively. In summary, the Blockchain data storage model can protect the privacy of a single client update and maintain the large-scale performance of the global model.

4.3 Deployed platform

In *BCFL*, the functions of the Blockchain layer need to be implemented with the support of a platform. Different Blockchain platforms have different characteristics. For example, public chains provide stable performance, consortium chains provide robust security, and private chains provide more customization features. From a careful analysis of the literature, the current *BCFL* mainly adopts four platforms: Ethereum, Hyperledger Fabric, EOS, and Custom Blockchain. The features comparison of these platforms is shown in Table 6.

4.3.1 Ethereum

As the earliest programmable Blockchain, Ethereum is Turing-Complete (Buterin XXXX). The work proposed by Nagar (2019) deploys the *BCFL* platform using an unlicensed side chain, using a technique proposed by layer 2 extension. Moreover, based on smart contracts in Ethereum, Muguntham et al. (2020) proposes the *BlockFLow* architecture, which initially realizes accountable and privacy-preserving *FL* through a novel contribution scoring procedure. Similarly, *Baffle* (Ramanan et al. 2020) and *ChainFL* (Korkmaz et al. 2020) are both Etherium-based *FL* systems, which use smart contracts to coordinate round partitioning, model aggregation, and update tasks in *FL*.

4.3.2 Hyperledger Fabric

As an open-source project, Fabric is initiated by the Linux Foundation and maintained by several corporate organizations. Zhang et al. (2020) demonstrate *FL* training neural network model on *FL* client's physical distribution dataset. The underlying communication between the server and the client uses the new Blockchain-based protocol on the secure data exchange system.

4.3.3 EOS

The Enterprise Operating System (*EOS*) is a Blockchain-based operating system designed for commercial distributed applications (Grigg XXXX). For example, an *EOS*-based *FL* framework is proposed in Martinez et al. (2019), in which the model owner *O* has the total liability of payment for the device and producer work, as opposed to devices *D* needing to pay for their transactions.

4.3.4 Custom Blockchain

Although there are many well-established public chains or consortium chains on the market, many researchers still choose to load *FL* systems with Custom Blockchains. The main reason is that the Custom Blockchain allows better flexibility, programmability, and extensibility. In particular, the work of Kim et al. (2020) proposes *BlockFL*, an architecture based on a Custom Blockchain in which local learning model updates are exchanged and validated. Similarly, Lu et al. (2020) propose a system consisting of a dual-module containing a permission Blockchain module and a *FL* module.

5 Model improvement in *BCFL*

FL is essentially a kind of machine learning. Therefore, its learning performance, efficiency, and security are important aspects to take into account. For this reason, several studies have been proposed to make appropriate improvements to the *BCFL* and enhance the above model performance. Table

Table 6 The summary of Deployed Platform for *BCFL*

Platform	Blockchain type	Consensus	Identity	Recent studies	Refs.
Ethereum	Public	*PoW*, *PoS*	Anonymity	*BlockFLow*, *BAFFLE*, *Chain FL*	Nagar (2019), Mugunthan et al. (2020), Ramanan et al. (2020), Korkmaz et al. (2020)
Hyperledger Fabric	Consortium	*SOLO*, *Kafka*	Known identity	*DEMO*	Zhang et al. (2020)
EOS	Consortium	DPoS,BFT	Known identity	*BlockFL*	Martinez et al. (2019)
Custom Blockchain	Private	PBFT	Known identity	*BlockFL**, *Secure-DataSharing*	Kim et al. (2020), Lu et al. (2020)

7 summarizes the current effective attempts to improve the *BCFL*.

5.1 Performance improvement

FL is a distributed machine learning method that supports local storage of data. In this method, the client implements training through interactive gradient values. Therefore, the underlying idea for improving the accuracy of the model is similar to classical machine learning.

5.1.1 Fault tolerant enhancement

ChainFL proposed in Korkmaz et al. (2020) achieves encouraging results on the Modified National Institute of Standards and Technology database digit recognition task (*MNIST*) and Canadian Institute for Advanced Research image classification task (*CIFAR-10*). Such results demonstrate that the *BCFL* model can enhance the system fault tolerance without losing the corresponding model performance compared to the traditional *FL* model.

5.1.2 Solving non-IID issues

The ID labels of data samples have a significant impact on the accuracy of machine learning models. To address the problem that user-generated data samples across devices are likely to become non-IID, Jeong et al. (2018) proposed federated augmentation(*FAug*), a data augmentation scheme that collectively trains generative models on each device to enhance the local data to generate IID datasets.

5.2 Efficiency tracking and improvement

For industrial areas such as languages and games, large-scale computations still have high demands on overall algorithm performance (Ogiela and Ogiela 2009). Thus, the tracking and measurement of the algorithm's efficiency are therefore crucial.

5.2.1 Replace oracle service with chaincode

The efficiency of the database will have an appreciable impact on the efficiency of *FL*. Again, the smart contract function in the Blockchain can replace the oracle service to achieve the data access function. The work of Drungilas et al. (2021) uses chaincode in Hyperledger structures instead of oracle services in the database and compares the runtime of functions executed using either chaincode or oracle services, demonstrating that negligible differences between implementations justify the flexible choice of model.

5.2.2 Setting weight parameter

Blockchain allows the performance of algorithms to be securely stored and recorded, and in particular, the long-term trend of *FL* can be tracked, depicting the overall situation and future dynamics of algorithm efficiency during operation. Therefore, weights based on each client's local learning accuracy and weights based on each client's frequency of participation can be used to achieve higher stability and faster convergence times to target accuracy. For instance, Kim and Hong (2019) propose a local learning weighting method for node recognition. This method selects nodes according to the participation frequency and data and weights to achieve fast convergence and stable learning accuracy.

Table 7 The summary of performance enhancements in *BCFL*

Reinforcement	Proposed Model	Solutions	Simulation	Refs.
Performance	*Chain FL*	Classification Accuracy Enhancement	MNIST digit recognition task CIFAR-10 image classification task	Korkmaz et al. (2020)
	FAug	Solving non-IID issues	Non-IID MNIST dataset	Jeong et al. (2018)
Efficiency	*Smart Contract FL*	Replace Oracle service with chaincode	Synthetic 2D dataset EEG Eye State dataset	Drungilas et al. (2021)
	Dynamic Weighting FL	Setting weight parameter	MNIST dataset	Kim and Hong (2019)
Security	*CrowdSFL*	Re-encryption algorithms	FEMNIST dataset	Li et al. (2020)
	ReliableFL	Improved Consensus	MNIST dataset	Kang et al. (2020)

5.3 Security improvement

Existing schemes have proven that the Blockchain-based decentralized control mechanism of Blockchain can effectively prevent risks such as *SPOF* (Liu et al., 2020; Kim and Kim, 2020; Firdaus and Rhee, 2021; Dwivedi et al., 2021; Ruggeri et al., 2020), *DDoS* attacks (Li et al., 2019; Saad et al., 2019; Rodrigues et al., 2017; Houda et al., 2019; Elisa et al., 2020), and poisoning attacks (Liang et al., 2019; Barański and Konorski, 2020; Rathore et al., 2019). However, the considerable computing power and storage cost of standard solutions are still critical challenges.

5.3.1 Re-encryption algorithms

Another possibility to achieve low-cost security improvements is to use re-encryption algorithms (Han et al. 2020). For example, the work by Li et al. (2020) proposes a crowdsourcing framework called *CrowdSFL*, in which a re-encryption algorithm based on the ElGamal cryptosystem is designed to ensure that interaction values and other information are not exposed to other participants outside the workflow. In this way, users can realize crowdsourcing with less overhead and higher security.

5.3.2 Improved consensus

As mentioned in Sect. 4.2, the consensus mechanism in the Blockchain can better ensure the security and privacy of *FL*'s data storage. Therefore, the appropriate improvement of the consensus mechanism can make *FL* more suitable for different scenarios and data. A reliable worker selection scheme for *FL* tasks proposed in Kang et al. (2020) introduces the concept of reputation as a metric to identify trusted and reliable workers in joint to prevent unreliable updates.

6 Incentive mechanism in *BCFL*

FL participants pay for computational resources. However, the training and commercialization of models are not instantaneous, and therefore, there is some delay before the federation reimburses participants. In this section, we outline the incentive mechanism underlying the *BCFL*. More precisely, in Sect. 6.1, we summarize the current attempts to apply Blockchain technology in handling lazy clients, while in Sects. 6.2 and 6.3 we assess the client contribution and compelling motivation, respectively.

6.1 Handling lazy clients

Basic *FL* does not take into account the identification of lazy clients and lacks incentives for influential learning clients.

Some studies have already begun to try the node incentive of FL, such as Ng et al. (2020), Khan et al. (2020). However, since there is no actual token mechanism design, these studies mainly focus on documentation, detection, and simulation. In contrast, Block-FL's incentive mechanism deals with lazy nodes more practically. Typically, the works of Li et al. (2020) and Li et al. (2021) propose and evaluate the learning performance of *Blade-FL* with bounds that are convex concerning the total number of rounds K and optimize the computational resource allocation to minimize the upper bound.

6.2 Assessing client contribution

To sustain the long-term engagement of the high-quality data owners (especially enterprises), the *FL* system needs to provide appropriate incentives based on the accurate evaluation of computational contributions. The systems in *FL* can be synchronous or asynchronous, depending on whether they use communication or not. In practice, the system functionality of *FL* can be well realized only if the computational work of the participating nodes is reasonably and well evaluated. The current, reliable methods mainly include a joint learning framework based on Blockchain protocol (Ma et al. 2021) and a new measurement standard based on verification error (Martinez et al. 2019). Similarly, some of these methods introduce the concept of competition to prevent workers from deviating from the protocol (Ogiela et al. 2016), rewarding only those who contribute (Toyoda et al. 2020).

6.3 Effective motivation

Based on the contribution score assessment, part of the *BCFL* model attempts to incentive highly reputable mobile devices with high-quality data to participate in *FL* (Kang et al. 2019). The peer-to-peer payment system is a natural profit allocation mechanism in the Blockchain. Taking inspiration from that mechanism, the work of Liu et al. (2020) proposes a support vector machine-based profit allocation framework based on the proof of Shapley protocol. On the other hand, the framework proposed in Cai et al. (2020) is based on evaluating the fractions of the dataset for the corresponding share rewards and a framework of reasonable contribution scores generated by both protocols.

7 Industrial applications of *BCFL*

Due to the strong adaptability exhibited by *BCFL*, there is an increasing trend of its wide application. This section mainly studies the industrial applications of *BCFL*. As shown in Table 8, we divide these applications into nine areas and summarize the benefits and improvements brought by the corresponding research.

7.1 Data processing in health care

The health care industry is in a prominent position in using data to create value and improve human health. However, it has been proved that the traditional methods used to alleviate the privacy problems of health data are insufficient to protect personal interests. For this reason, it is easy to guess that medical data is highly privacy sensitive. *BCFl* can be an effective solution to mitigate the problems mentioned above since it can perfectly meet the data processing requirements in the field of medical and health care. In particular, *BCFl* not only completes the modeling requirements of physical therapy data but also avoids privacy leaks on relevant data. For instance, a new agent model based on *BCFL* is proposed in Dp et al. (2021), as a real-time medical data processing system. Again, to strengthen the privacy of health care data, the model proposed in Passerat-Palmbach et al. (2019) adopts the integration of unique privacy protection technology based on a protocol composed of protected hardware components and the native Ethereum cryptographic toolkit. Finally, the work of Passerat-Palmbach et al. (2020) also uses a similar model, and on this basis, it strengthens the incentive mechanism of data operation.

7.2 Anomaly detection in network security

Open networks and service sharing scenarios are complex and varied, leading to serious security challenges (Li et al. 2021). In the *FL* setting, adversaries have more opportunities to poison a local machine learning model with malicious training samples, thus affecting the results of *FL* and evading detection. However, the work of Preuveneers et al. (2018) shows that audit machine learning models using an anomaly detection algorithm that detects incremental updates recorded on a Blockchain ledger can effectively prevent attacks. For the same purpose, the framework proposed by Desai et al. (2020) uses smart contracts to detect and punish attackers through fines automatically.

7.3 Device failure and anomaly detection in IoT

Device fault detection is one of the most critical issues in the industrial Internet of Things (*IIoT*). However, in traditional *IoT* device fault detection, client devices need to upload raw data to a central server for model training, which carries the risk of leakage of sensitive business data (Zhao et al. 2021). Given the sensitivity, massive volume, fragmentation, and security of multi-party data computation in *IoT* environment, the works of Yin et al. (2020), and Rahman et al. (2020) both propose a *BCFL*-based learning approach for device

Table 8 The summary of industrial applications of *BCFL* in emerging domains

Application domains	Applicable data	Benefits	Related studies
Data processing in Health care	Covid-19 data	Data security, auditability, and incentives	Dp et al. (2021); Passerat-Palmbach et al. (2019, 2020); Kumar et al. (2020); Kuo and Ohno-Machado (2018); Aich et al. (2021)
	Transaction Metadata	Addressing data heterogeneity	
	Medical data	Model robustness	
Anomaly detection in network security	Automatic encoder for anomaly detection	Data Auditability	Preuveneers et al. (2018); Desai et al. (2020)
Device failure and anomaly detection in IoT	The movement data	High testing accuracy	Zhao et al. (2021); Yin et al. (2020); Rahman et al. (2020); Zhang et al. (2021)
		High communication efficiency	
		Complete privacy and anonymity	
Internet of vehicles For Trustworthy Vehicular Networks	Train running data Vehicle localization application data	High quality parameter collection	Otoum et al. (2020); Pokhrel (2020); Chai et al. (2020); Pokhrel and Choi (2020); Hua et al. (2020)
		High test accuracy	
		High communication efficiency	
		Anti-attack	
5G & 6G secure communication	LP solver with GMI Communication network data	System reliability and security	Liu et al. (2020); Hu et al. (2020); Lu et al. (2021); Rahmadika et al. (2021)
		Improved data privacy	
		Incentives and fairness	
Intelligent Edge Computing	MovieLens datasets CASIA-WebFace	High communication efficiency	Rehman et al. (2020); Cui et al. (2020); Shen et al. (2021)
		Bandwidth optimization	
		Privacy protection	
Fog Computing	Fog servers data	Decentralized Privacy	Qu et al. (2020)
		Poisoning Attack Proof	
		High Efficiency	
Cognitive Computing	CIFAR-10 dataset	Advanced validation	Qu et al. (2021)
		Fast convergence	
Defence framework for sustainable society	“Airplane,” “Bird,” “Drone,” and “Ship” from the different sources	Advanced validation	Sharma et al. (2020)
		Privacy protection	

fault detection in *IoT*. In particular, to solve the data heterogeneity problem in *IoT* fault detection, Zhang et al. (2021) proposed a novel centroid distance weighted federated averaging (*CDW_FedAvg*) algorithm. In detail, this algorithm effectively enhances the applicability and model accuracy by taking the distance between positive and negative classes of each client dataset as the basis for calculation.

7.4 Internet of vehicles for trustworthy vehicular networks

On the Internet of Vehicles (*IoV*), sharing data between vehicles for collaborative analysis can improve the driving experience and service quality (Xu et al. 2021). However, efficiency, security, and privacy issues have become obstacles for data providers to participate in the data sharing process (Meng et al. 2021; Pokhrel and Choi 2020; Zou et al. 2021). Fortunately, the *BCFL* framework is a suitable solution to the contradiction between large-scale data sharing and privacy protection. More precisely, the fundamental applications of *BCFL* deal with using the validation and consensus mechanisms within the Blockchain to secure IoV data and jointly ensuring trustworthy shared training for mutual machine learning models on decentralized end devices (Otoum et al. 2020). In detail, such operations are carried out by adapting instant block validation at the Blockchain level (Pokhrel 2020) and assessing the trustworthiness of vehicle observations during data collection (Chai et al. 2020). On this basis, the work of Pokhrel and Choi (Pokhrel and Choi 2020) uses the consensus mechanism of Blockchain to manage data without any centralized training or coordination. Meanwhile, the characteristics of controllable networks and *BCFL* parameters (such as retransmission limit, block size, block arrival rate, and frame size) can better capture their impact on system-level performance. Finally, some researchers have deployed *SVM* (Hua et al. 2020), and *DRL* algorithms to improve the efficiency.

7.5 5G and 6G for secure communication

In recent years, a large number of new applications requiring different network services have emerged. To secure *FL* in *5G* communication, the main current solutions are Blockchain authorization (Liu et al. 2020) and decentralized federated slicing architecture (Hu et al. 2020). Furthermore, the work of Lu et al. (2021) proposed a digital twin wireless network (*DTWN*) scheme which moved real-time data processing and computing to the edge plane by merging digital twins into wireless networks.

7.6 Intelligent edge computing

Edge computing architecture can quickly process the data collected by the Internet of Things (*IoT*) Zou et al. (2021). Based on the concept of Blockchain reputation perception for fine-grained *FL*, the model proposed in Rehman et al. (2020) can ensure credible collaborative training in mobile edge computing systems. Again, the work of Cui et al. (2020) proposes to apply a compression algorithm of *FL*, assisted by the Blockchain, to predict the content caching of files. On the other hand, as shown in Shen et al. (2021), a new attribute inference attack is proposed. This attack exploits the unexpected attribute leakage of *FL* aided by Blockchain in intelligent edge computing.

7.7 Fog computing

As an extension of cloud computing and the foundation of *IoT*, fog computing is experiencing rapid growth. Indeed, fog computing has the potential to alleviate some thorny issues, such as network congestion, latency, and local autonomy. However, privacy concerns and consequent inefficiencies are slowing down the performance of fog computing (Huang et al. 2019). *FL-Block* proposed in Qu et al. (2020) modifies the structure of the fog server by storing global updates on the Blockchain to secure the global updates, allowing the end devices to maintain the global model and coordinates based on distributed consensus.

7.8 Cognitive computing

Cognitive computing is used to teach a computer to think like a human brain, not just to develop an artificial system. In particular, with the success of AlphaGo and other AI algorithms, cognitive computing has also ushered in a vast development. In this context, the work of Qu et al. (2021) introduces a *BCFL*-based customized reward system to promote public equipment to participate in high-performance industries by deploying Blockchain as the underlying architecture.

7.9 Sustainable society

Defense organizations and armed forces are crucial elements for the protection and survival of a nation. However, ensuring these elements requires robust networks and computing power to coordinate intelligence and information processing efficiently. Moreover, given the highly classified nature of national data, Sharma et al. (2020) propose a distributed computational defense framework for a sustainable society using Blockchain technology and *FL* features. In particular, the proposed framework enables us to infer battlefield states while protecting the privacy of sensitive data.

8 Conclusions and future research directions

This paper presents a survey on the applicability and integration of Blockchain with federated learning *FL*. More precisely, we denote this integration as the Blockchain-based federated learning (*BCFL*) framework and provide a comprehensive survey of issues related to *BCFL* implementation. In this paper, we first provide a basic description of the definitions and ecosystems characterizing Blockchain and *FL*. Then, we present the structure design of *BCFL* as a whole and summarize the feasible deployment platforms. Next, we discuss the model improvement of *FL* through the introduction of Blockchain. After that, we survey the research related to Blockchain incentives as an element to improve *FL* systems. Finally, we summarize the full range of possible applications of *BCFL* in the industry.

In conclusion, the combination of Blockchain and *FL* is an auspicious research direction, as it can better ensure data security and privacy in the case of abundant data. In addition, this combination makes it possible for more application scenarios to adopt this distributed learning model that does not need to share raw data for joint modeling.

This survey aims to provide a clear view on this topic to ensure that more and more researchers would start working on it. Future research directions could deepen and develop the following aspects:

(1) This paper does not use a cross-referencing and quantitative measure to quantify the overall trends in relevant research. Therefore, future research could consider introducing these elements as a supplement.
(2) Future studies may consider summarizing and classifying the related works from a broader range of perspectives to uncover additional research information relevant to *BCFL*.
(3) *BCFL* may be applied to increasingly more industrial fields. Consequently, some research efforts may consider more application effects in different industrial fields and make more comparative studies.

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Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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