APPFLChain: A Privacy Protection Distributed Artificial-Intelligence Architecture Based on Federated Learning and Consortium Blockchain

Jun-Teng Yang, Wen-Yuan Chen, Che-Hua Li, Scott C.-H. Huang, *Member, IEEE*, and Hsiao-Chun Wu, *Fellow, IEEE*

***Abstract*—Recent research in Internet of things (IoT) has been widely applied for industrial practices, fostering the exponential growth of data and connected devices. Henceforth, data-driven AI (artificial intelligence) models would be accessed by different parties through certain data-sharing policies. However, most of the current training procedures rely on the centralized data-collection strategy and a single computational server. However, such a centralized scheme may lead to many issues. Customer data stored in a centralized database may be tampered with so the provenance and authenticity of data cannot be justified. Once the aforementioned security concerns occur, the credibility of the trained AI models would be questionable and even unfavorable outcomes might be produced at the test stage. Lately, blockchain and AI, the two core technologies in Industry 4.0 and Web 3.0, have been explored to facilitate the decentralized AI training strategy. To serve on this very purpose, we propose a new system architecture called APPFLChain, namely an integrated architecture of a Hyperledger Fabric-based blockchain and a federated-learning paradigm. Our proposed new system allows different parties to jointly train AI models and their customers or stakeholders are connected by a consortium blockchain-based network. Our new system can maintain a high degree of security and privacy as users do not need to share sensitive personal information to the server. For numerical evaluation, we simulate a real-world scenario to illustrate the whole operational process of APPFLChain. Simulation results show that taking advantage of the characteristics of consortium blockchain and federated learning, APPFLChain can demonstrate favorable properties including untamperability, traceability, privacy protection, and reliable decision-making. The throughput of APPFLChain can reach up to 2000 tps (transactions per second) in comparison with the popular Ethereum-based system whose throughput is just around 20 tps.**

***Index Terms*—Consortium blockchain, Hyperledger Fabric, decentralized AI, federated learning (FL), Internet of things (IoT), Industry 4.0, Web 3.0.**

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Manuscript received ”Month” ”Day”, 2022; revised ”Month” ”Day”, 2022; accepted ”Month” ”Day”, 2022; This work was supported in part by the Ministry of Science and Technology of Taiwan under Project MOST 110-2221-E-007-084-MY3, and in part by the Ministry of Science of Technology, Taiwan, Overseas Project for Post Graduate Research, under project number 110-2917-I-007-013. (Corresponding author: Jun-Teng Yang.)

I. Introduction

RECENT advancements in Internet of things (IoT) technologies (see [1]–[3]) have paved the way for realizing the blueprint of Industry 4.0 and Web 3.0. It was just estimated by [4] that there will be almost 6.5 billion consumer edge enabled IoT devices in 2030. Such edge devices include smartphones, security cameras, automotive sensors, etc. Therefore, various types of data including online purchasing behaviors, social-media interactive patterns, and personal health-care records could be collected and utilized by companies and organizations, which may infringe on individuals' privacy. In other words, it would not be appropriate to develop artificial intelligence (AI) models on a centralized computational server on the concern of privacy. Therefore, a critical challenge is how to design/develop a new decentralized AI framework by which users can train AI models right at their local devices without any need to upload the private data. In recent years, *federated learning* (FL) has become a promising decentralized approach for training AI models [5]–[7]. The FL allows different parties (companies or organizations) to share a global AI model to their connected IoT devices which can train the global model locally without sharing their own data with others. All these IoT devices need to do is upload the updated weights and parameters to the aggregation server until the training process of the global model is completed. Thus, users can not only enhance the data privacy but also save the communication resource (e.g., transmission bandwidth) by reducing the amount of data necessary to be transmitted. However, there still remain some problems in the current FL system. The learned weights may still reveal certain important information of private data [8]–[10]. Thus the FL system may be threatened by malicious hackers during data transmission, and those hackers can change or even steal the updated weights. Eventually, the hackers could recover the private data by use of the stolen information. In addition, the conventional FL system relies on a single server to aggregate the model parameters for updating the global model timely. It would inevitably lead to the *single point of failure* (SPoF) problem if such a server is attacked, which would shut down the functionality of an FL system [11]. Besides, a single server cannot support the aggregation of all weights keeping being uploaded by many active IoT devices. Therefore, another critical challenge is how to design/develop a secure and reliable decentralized FL framework without the need to rely

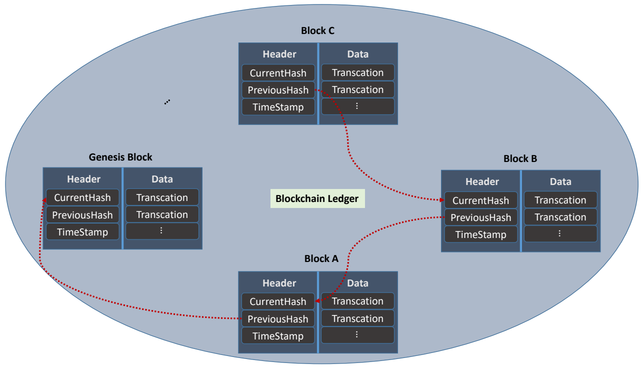


Fig. 1: The basic structure and the operational procedure of a blockchain ledger.

on a single server.

Since Satoshi Nakamoto proposed a peer-to-peer electronic cash system in 2008, the blockchain technology has been a major means for distributed data-storage and bookkeeping [12]. Blockchain is essentially a decentralized database facilitated by a decentralized network of peer nodes. The consensus protocols can be imposed to avoid the double-spending problem in a cost-effective manner, eliminate the requirement for a trusted third party, and verify the interactions and transactions between participants (nodes). In a blockchain, each transaction must be encrypted by a signature and verified by the mining nodes that hold the ledger, thereby creating a data storage environment with security, synchronization, and authenticity [13]. For example, the transactions stored in a blockchain ledger will be divided into multiple blocks. The data and time-stamps are stored in separate blocks, each of which contains the hash of the previous block, as illustrated by Figure 1. Most blockchains use the SHA-256 hash function in the secure hash algorithm (SHA) family to extract the digest of important data in a block to represent the 256-bit "CurrentHash" of the block. With this kind of structure depicted by Figure 1, blockchains are not vulnerable to malicious attacks. In summary, a blockchain is a shared ledger with decentralizability, traceability, and immutability. Due to the aforementioned advantages of the blockchain technology, it has been applied to many fields such as financial industry in [14], marketplace in [15], asset management in [16], and Internet of things in [17]. As a result, a blockchain-based FL model-training framework would be favorable as it can avoid the SPoF problem due to the corresponding implementation of the decentralized data ledgers. Besides, all participants (nodes) in a blockchain network have the ability to trace other users' action histories and update events in a transparent way.

The current blockchain technology can be split into three categories: (*i*) *public blockchain*, (*ii*) *private blockchain*, and (*iii*) *consortium blockchain* based on their openness and anonymity [18]. On the other hand, blockchains can also be characterized as *permissioned blockchains* and *permissionless blockchains*. A permissioned blockchain permits the access of some specific nodes; if a user (node) is interested in accessing data on a permissioned blockchain network, he/she needs to get approval from a central authority first. In contrast, a permissionless blockchain makes the access-right open to all nodes, and thus users can pseudo-anonymously join the network. Since a permissionless blockchain may have many nodes to validate transactions, they tend to be more secure than a permissioned blockchain. Nontheless, a permissioned blockchain would be rather verification-efficient due to the fact that all of its nodes have to be permitted for access and thus only few nodes gain such a right to verify transactions. Furthermore, research on the incorporation of FL and blockchain has been appealing to the science community. The incorporation of FL and permissioned blockchain was devised to facilitate a new privacy-preserving data-sharing mechanism for distributed multiple parties in industrial IoT applications [19]. A new consortium-blockchain-based crowdsourcing FL system for IoT device manufacturers was proposed to study the customers' behaviors [20]. A new EOS (electro-optical system) public blockchain was proposed to perform data security [21].

Although many AI training frameworks to rely on both FL and blockchain have been presented in the existing literature, the existing public-blockchain-based FL systems, as previously mentioned, still cannot meet the requirement of high verification efficiency. To address this verification-efficiency issue, we propose a novel FL architecture based on the Hyperledger Fabric consortium-blockchain in this work, namely "APPFLChain". Hyperledger Fabric established by the Linux foundation is an open-source enterprise-level distributed ledger technology (DLT) platform. The associated developers' community has grown to more than thirty-five organizations and two hundred developers now [22]. Since Hyperledger Fabric has a highly modular and configurable architecture, it has been widely used in the financial industry [23], insurance industry [24], healthcare [25], supply chain [26], electronic voting system [27], and Internet of things [28]. More details of Hyperledger Fabric blockchain will be introduced later in this paper. To the best of our knowledge, although a few papers addressed the distributed AI training system incorporating FL and Hyperledger Fabric blockchain in [21], [29], [30], no detailed (clear) manifestation of their architectures have been reported and thus the generalizability of these existing approaches is up in the air. In this work, we propose a novel FL system based on the Hyperledger Fabric consortium-blockchain and present the detailed information of each component in our proposed new APPFLChain system. The major contributions of this work can be highlighted as follows.

1) We design a novel FL system based on the Hyperledger Fabric consortium-blockchain, called APPFLChain. We also demonstrate a realworld scenario to illustrate the entire operational process of APPFLChain.
2) We take advantage of the characteristics of consortium-blockchain and FL to produce the favorable properties of APPFLChain including untamperability, traceability, privacy protection, and reliable decision-making.
3) We develop a new distributed AI training system with high scalability and high privacy-protectability. The generalizability is promising as users can deploy more peers,

channels, and ordering services (OSs) subject to individual needs. Therefore, our proposed novel APPFLChain system can be easily applied for many other scenarios without restriction.

The rest of this paper is organized as follows. Section II introduces the related works and background knowledge. In Section III, we formulate the focused problem in this work. In Section IV, we present our proposed new system architecture include a system overview, the required operations in the Hyperledger Fabric network, and the FL algorithm. Simulations are conducted for a realworld scenario to illustrate how to apply our proposed new APPFLChain system in Section V. Final conclusion will be drawn in Section VI.

II. Related Works and Background Knowledge

A. Blockchain

1) Public Blockchain: Public blockchain is also called permissionless blockchain since every transaction in a public blockchain is overt. Though public blockchain has advantages in decentralization and openness, it still operates more slowly and more costly than private blockchain and consortium blockchain. Well-known systems based on the public blockchain include Bitcoin [31] and Ethereum [32]. Ethereum inherits the concept of *smart contracts* for developers (users) to customize the pertinent blockchain logics, making such blockchain-oriented software (BOS) very flexible for further modifications [33].

2) Private Blockchain: To some extent, private blockchain is generally not open to ordinary people for access. If one wants to participate in a private blockchain network, he/she must be authorized to join as one of its nodes. Therefore, private blockchain is a permissioned blockchain. Compared to public blockchain, private blockchain tends to be a centralized system. Enterprises need to grant permission to whoever wants to access their blockchain ledgers. Private blockchain can serve as a medium for transferring the confidential data within a company or an organization as it can maintain higher privacy than public blockchain [34]. Although the architecture of private blockchain can effectively improve the efficiency for processing transactions, the security might be at risk due to only a bunch of nodes are allowed to verify transactions. The most famous private blockchain is Quorum [35].

3) Consortium Blockchain: Consortium blockchain can be adopted as a trusted platform for data circulation among parties in the same industry, allowing them to communicate with stakeholders at a low cost. Therefore, more and more people have tried to establish business-to-business (B2B) systems using consortium blockchains in recent years [36]. The degree of decentralization of consortium blockchain is between those of public blockchain and private blockchain. The advantage of consortium blockchain is that different enterprises can set the same data-sharing rules to facilitate efficient and low-cost data exchanges among stakeholders. The most popular consortium blockchain is Hyperledger Fabric proposed by the Linux foundation [22], which is also a permissioned blockchain because all participants have to be authorized.

4) Smart Contract: The concept of smart contract was first proposed by [32]. Smart contract is a special agreement containing the code functions that allow participants in a blockchain to interact with the blockchain ledger. Usually, the blockchain developers can customize the content of a smart contract. A smart contract may reduce the transaction costs compared to a traditional contract [37]. Smart contracts enable individual developers to independently develop blockchain logics so as to build BOS (see [33]) and decentralized applications (DAPPs) (see [38]).

5) Consensus Algorithm: Although the use of digital signatures can partially solve the authentication problem emerging from decentralization, it still cannot completely avoid the double-spending problem [39]. Satoshi Nakamoto proposed the proof-of-work (PoW) consensus algorithm in the Bitcoin system to achieve Byzantine fault tolerance (BFT) for resolving the double-spending problem [12], but it is very time-consuming to undertake the PoW consensus algorithm since users (miners) often need to check for many nonces to find the right solution [40]. Thus, the PoW consensus algorithm may not be a suitable method for consortium and private blockchains. On the other hand, the Raft consensus algorithm was proposed usually for consortium and private blockchains [41]. In this paper, we apply the Raft consensus algorithm in our proposed new APPFLChain system since its time-complexity is relatively low and it is easy to implement compared to the PoW consensus algorithm.

B. Hyperledger Fabric

Fabric is a type of permissioned blockchain that allows participants to know each other's identity. The Fabric network can operate according to the governance model established by the confidence among participants [42]. Fabric is also the first distributed ledger that supports common programming languages (e.g., Java, Go, and Node.js) for describing smart contracts, enabling people to develop smart contracts directly without spending time learning the new domain-specific language (DSL). Besides, Fabric is a plugable consensus protocol, allowing enterprises to customize the platform that best suits their requirements. However, when deployed in a single enterprise or operated by a trusted organization, a Fabric network using a fully Byzantine fault-tolerant consensus scheme would not perform well. To boost the system performance, the crash fault-tolerant (CFT) strategy should be adopted instead. On the contrary, if there are multiple organizations in a Fabric network, the conventional Byzantine fault-tolerant (BFT) consensus scheme would be appropriate. Now we would like to introduce the three major mechanisms involved in a Fabric blockchain, namely *Chaincode*, *Channel Mechanism*, and *Plugable Consensus*.

1) Chaincode: In Hyperledger Fabric, there is a mechanism similar to an Ethereum smart contract, which is called *chaincode*. Chaincode acts as a trusted distributed application in Fabric, and it also allows developers to customize the operation logics of the blockchain. For both permissionless- and permissioned-blockchain platforms, the order-execute architecture (Route A in Figure 2) is adopted in almost all

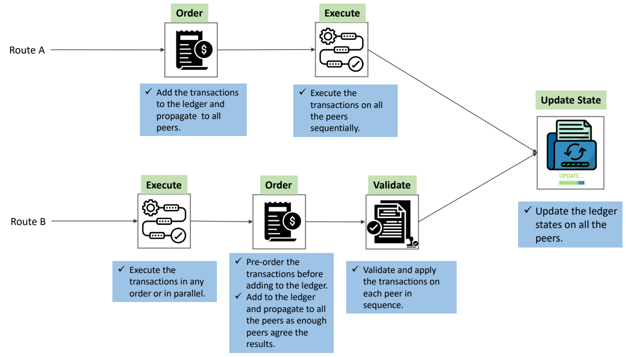


Fig. 2: The order-execute architecture (Route A) and the execute-order-validate architecture (Route B).

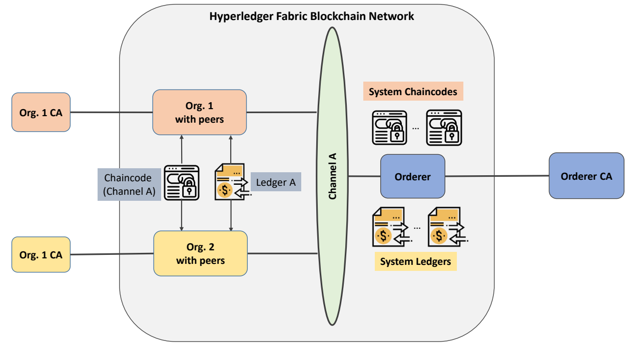


Fig. 3: Two organizations (Org. 1 and Org. 2) join Channel A on a Hyperledger Fabric blockchain network.

existing blockchain systems. The smart contracts running on the order-execute architecture must be deterministic; otherwise, they may never reach a consensus in the blockchain. In order to deal with practical non-deterministic situations, the majority of blockchain platforms require smart contracts to be written in a non-standard domain-specific language such as Solidity [43]. On the other hand, Fabric also introduces the execute-order-validate architecture (Route B in Figure 2) to solve the aforementioned non-deterministic problem along with the resiliency, scalability, performance, and confidentiality challenges the conventional order-execute architecture would often face. The application-specific endorsement policy specifies which nodes or how many nodes are required to guarantee a given chaincode (a smart contract) to be executed correctly in a Fabric network. Therefore, each transaction only needs to be executed by a subset of peer nodes required by the transaction's endorsement policy. The execute-order-validate architecture not only allows the Fabric network to execute in parallel for increasing the overall system performance but also eliminates any non-determinism because such an architecture can filter out inconsistent results before ordering. Since the Fabric network has the ability to successfully avoid non-deterministic problems, it can conveniently allow the usage of standard programming languages such as Java, Go, and Node.js.

2) Channel Mechanism: In Hyperledger Fabric, a *channel* is referred to as a private subnet established for the purpose of private and confidential transactions between one or more specific network members. Such a channel includes organizations, organization nodes, anchor nodes, blockchain ledger, on-chain applications, OS, and OS nodes. Every transaction on the network is executed by one or more designated channels, and each node that wants to join the channel must have an identity issued by a membership services provider (MSP). With the channel mechanism, Fabric can be converted from a private blockchain to a consortium blockchain. Channel mechanism enables the isolation and confidentiality of transaction information between unrelated groups and allows related groups to use a low-cost means to share data. Obviously, a node or an organization can register in multiple channels at the same time. Figure 3 illustrates a scenario for two organizations to join Channel A.

3) Plugable Consensus: The Fabric network has a variety of OSs that support different application requirements. The task of ordering transactions is delegated to a modular component OS to reach consensus. This modular component OS is logically separated from the peers that execute the transaction and maintain the ledger. Such a modular ("plugable") architecture allows the blockchain platform to rely on a comprehensive crash fault-tolerant (CFT) toolkit or a Byzantine fault-tolerant (BFT) toolkit. Fabric also provides a crash fault-tolerant OS implementation based on the etcd library of the Raft protocol [44].

C. Decentralized AI

Most existing machine-learning methods still rely on the centralized training strategy. For example, Google, Meta, and Amazon use their own servers to collect training data from their customers to build their AI models. The obvious disadvantage of such a centralized training database is that these training data may be tampered with or manipulated by people, so nobody can guarantee the provenance and authenticity of such training data. Therefore, a disruptive integration of blockchain and AI, a.k.a. "*decentralized AI*", was proposed in [45] such that the shortcomings of AI relying on the centralized training databases can be mitigated by the blockchain technology. AI models could produce more reliable outcomes if the integrity of training data is ensured. A public decentralized AI framework was proposed and built on the Ethereum platform [46], where smart contracts were established to develop certain machine-learning algorithms for participants to co-build a model using an incremental learning approach to update the models constantly. These models have been publicly shared on the Ethereum blockchain. Figure 4 illustrates how participants can collaborate on the development of an AI model using smart contracts on the Ethereum blockchain.

D. Federated Learning

Although AI methods have been widely explored in recent years, it is very challenging to collect sufficient and reliable training data for building robust AI models. For example, it is

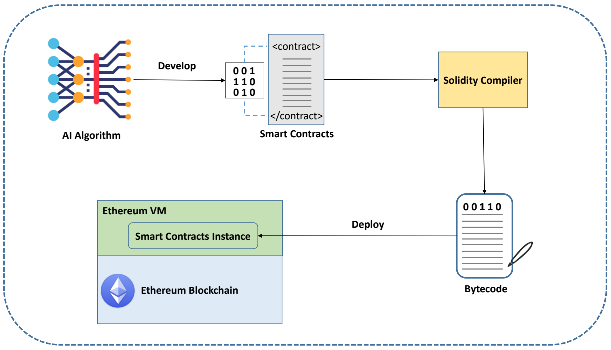


Fig. 4: Collaborative development of an AI model using smart contracts.

critical to acquire sensitive private information from users. To address the concern on users' privacy, FL was proposed by [6]. The FL approach eliminates the requirement of uploading the users' private data to the centralized database (at the data center) so users can locally train the AI model(s) on their own devices. The global AI model(s) will be established at the data center through a specific encryption mechanism, and the trained results of the local model(s) can be used to update the global model(s). In the FL approach, local data will only be accessible to individual users' devices for maintaining security and privacy.

The FL approach can be divided into three categories, namely *horizontal FL*, *vertical FL*, and *federated transfer learning* according to [7], [47] as illustrated by Figure 5. Among them, the horizontal FL approach is suitable for the practical situation that nodes almost have no data in common but the features they extract from those data would be similar in characteristics. In this work, we will focus on the horizontal FL scenario. In an FL framework, we assume that there exist N data contributors (nodes), say $\mathfrak{F}_1$, $\mathfrak{F}_2$, ..., $\mathfrak{F}_N$ and all nodes want to contribute their locally collected data sets $\mathcal{D}_1$, $\mathcal{D}_2$, ..., $\mathcal{D}_N$ to train an AI model. Without loss of generality, we specify the trained parameter set from a data set $\mathcal{D}$ subject to a given network topology $\mathbb{T}$ as $\Theta_{\mathbb{T}}(\mathcal{D})$. The conventional method is first to combine all training data sets into a set $\overline{\mathcal{D}} \stackrel{\text{def}}{=} \mathcal{D}_1 \cup \mathcal{D}_2 \cup \cdots \cup \mathcal{D}_N$. Then the parameter set of an AI model can be obtained as $\Theta_{\mathbb{T}}\big(\overline{\mathcal{D}}\big)$. In the FL approach, each node $\mathfrak{F}_i$ will produce a local parameter set as $\Theta_{\mathbb{T}}\big(\mathcal{D}_i\big)$, for i=1, 2, ..., N. Then the data center can merge these local models into a global AI model characterized by the global parameter set

$$\Theta_{\mathbb{T}}^{\text{global}} \stackrel{\text{def}}{=} \frac{1}{N} \sum_{i=1}^{N} \Theta_{\mathbb{T}}\big(\mathcal{D}_i\big). \tag{1}$$

III. PROBLEM FORMULATION

In this section, the functionalities, objectives, and challenges of the existing public-blockchain-based FL schemes. Then we will propose our new consortium-blockchain-based FL system (i.e., APPFLChain) to deal with the difficulties the public-blockchain-based FL schemes cannot resolve. A robust consortium-blockchain-based FL platform will also be introduced for business scenarios.

A. Challenges to Public-Blockchain-Based FL Systems

Although public blockchains have been very popular in recent years, many concerns emerge in practice. For example, companies often need to abide by the "*know your customer*" (KYC) rule to avoid transaction crimes and keep their trade secrets when conducting business transactions in the business-to-business (B2B) or business-to-consumer (B2C) mode [48]. However, these demands cannot be satisfied by public blockchains as they focus on the high degree of openness and transparency. Moreover, the verification efficiency (or transaction efficiency) of a public blockchain would be much lower than those of a private blockchain and a consortium blockchain. The transaction efficiency plays a very important role in the mergence of local training models into a global model in a blockchain-based FL system. Therefore, we propose a new consortium-blockchain-based FL system in this work.

B. Our Proposed Consortium-Blockchain-Based FL Approach

To deal with the challenges faced by the conventional public-blockchain-based FL systems as described in Section III, we propose a new FL architecture based on the Hyperledger Fabric consortium-blockchain in this work, namely "APPFLChain". Hyperledger Fabric consortium-blockchain has a highly modular and configurable architecture, which can serve for many practical applications. Hyperledger Fabric consortium-blockchain is also a permissioned blockchain, which means that participants know each other's identities. Hence, data contributors in a Hyperledger Fabric consortium-blockchain can abide by the KYC rule as they can maintain their local security. In addition, since participants in a consortium-blockchain network can establish separate channels to allow certain members to engage in different kinds of transactions, it can make the system more confidential. This channel mechanism not only protects trade secrets but also reduces the participants' communication cost. Hyperledger Fabric adopts the Etcd Raft consensus scheme [44]. Assume that N denotes the number of transactions, and t_i denotes the processing time of the i-th transaction. Thus the throughput τ is given by

$$\tau = \frac{N}{\sum_{i}^{N} t_i} \quad \text{transactions/sec (tps).} \tag{2}$$

If the consortium-blockchain is properly configured, one may have $\tau{>}2000$ tps. As a result, the throughput of Hyperledger Fabric is much higher than the Ethereum's throughput (around 20 tps). A more detailed analysis of Hyperledger Fabric can be found in [49].

However, contributors may not be willing to share their confidential data (e.g., facial information, location information, voice information, medical data, etc. [50]) even though Hyperledger Fabric can strengthen the security by the channel mechanism. Therefore, we deploy the FL algorithm on a

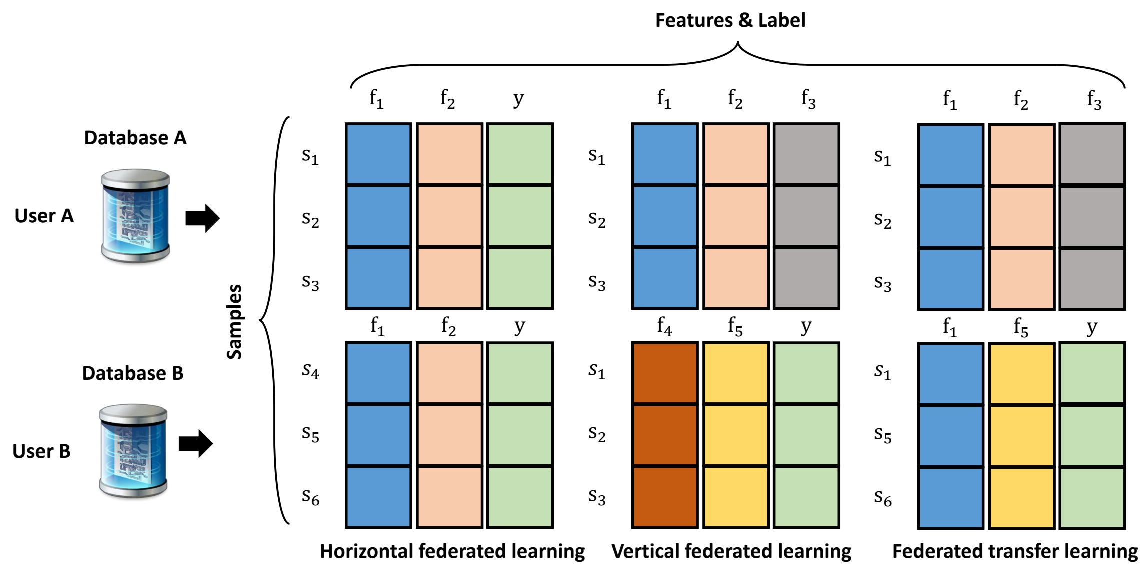


Fig. 5: Categorization of three federated learning (FL) approaches: horizontal FL, vertical FL, and federated transfer learning.

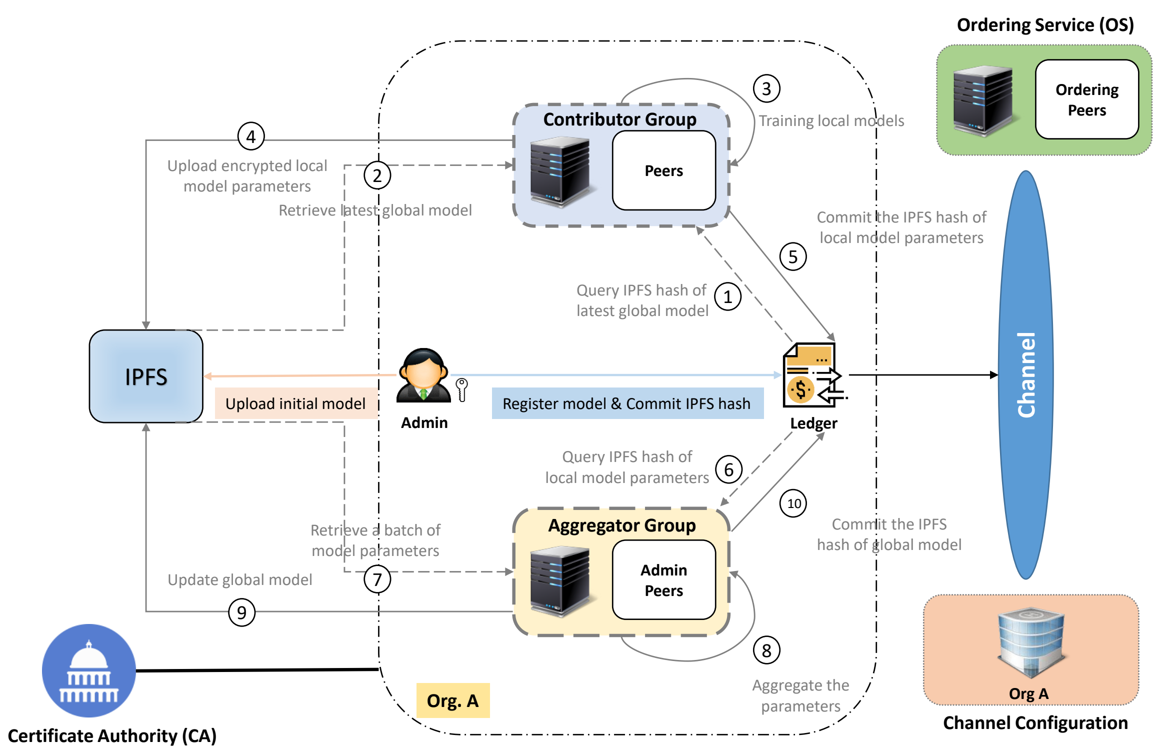


Fig. 6: The overview of our proposed new APPFLChain system.

Hyperledger Fabric blockchain to enable users to contribute their results from training the AI model(s) locally without any need to upload personal data to a distributed database. Consequently, not only the quality of the AI model(s) can be enhanced but also users can protect their own data from being exposed to the public, forming a win-win situation. In next section, we will manifest the architecture of our proposed new APPFLChain system in detail.

IV. Proposed System Architecture

In this section, we manifest how to construct a Hyperledger Fabric consortium-blockchain network and describe the functionality of each component therein. Besides, we will implement the FL algorithm on such a consortium-blockchain network and illustrate the corresponding operation flow.

A. System Overview

Figure 6 presents a simple example about how to apply our proposed APPFLChain system in the presence of a single organization (data contributor), a channel, and several important Hyperledger Fabric components. Note that this APPFLChain can be extended to a more complex scenario subject to the requirement by developers. In Figure 7, we focus on the operation flow of the underlying FL algorithm in the organization (Org. A). The administration/anchor peers in the organization need to initialize the parameters of a global model and submit them to the blockchain ledger before the decentralized FL process begins. Then the customers or contributors (client peers) can start to train the global model by sending a request to the local chaincode for contributing the information inferred by local data. In the meantime, the chaincode in each client peer (data contributor) will actively request the latest global model (parameters) from the ledger of the organization and use the local data to train the local model. After the local training process has been completed, the chaincode will submit the trained model (parameters) to the blockchain ledger. Finally, the aggregator that is composed of administration/anchor peers will aggregate the model-parameters in the ledger to update the global model (parameters). We call the aforementioned procedure a "*training round*". Next, we propose the APPFLChain architecture for executing the FL algorithm on a Hyperledger Fabric consortium-blockchain such that the decentralized AI can still maintain users' privacy.

B. The operations in Hyperledger Fabric Network

We will illustrate several essential components of our proposed APPFLChain network and their operation processes as depicted by Figure 8a.

1) Hyperledger Fabric Components: Several Hyperledger Fabric components, which can enable the consortium-blockchain network to operate in a secure, immutable, traceable, and confidential manner, will be introduced subsequently.

a) Configured Channel: To build the APPFLChain system, one first need to create a channel and establish the corresponding configuration. Once the configuration block is established, the channel formally exists. Organizations can determine which of them can join the channel by voting, how to make decisions, and how to control the mergence of local models, all through defining the configuration block. It is possible to create multiple channels in the APPFLChain system for dealing with more complicate scenarios. Each channel can be treated as a sub-blockchain by the involved organizations and OSs. Only those organizations who join the channel have the right to run the chaincode and access the blockchain ledger of the channel. Figure 8b presents an example for two organizations joining the same channel to share the chaincode and the ledger.

b) Certificate Authorities: Certificate authorities (CAs) in a blockchain network are responsible for issuing X.509 certificates, where X.509 is a common digital-certificate standard. An X.509 certificate contains critical information related to the certificate holder. An organization can approve a transaction result using the corresponding X.509 certificate to endorse the transaction. The roles (e.g., clients, administrators, and orderers) in a blockchain are encapsulated in the X.509 certificates to determine the permissions of different identities. In fact, each organization in the APPFLChain system has its own CAs and membership service provider (MSP), and all X.509 certificates issued by CAs in an organization will be stored in the MSP. Specifically, an organization can use the MSP to govern the rules for validating identities. Therefore, the MSP can use the X.509 certificates to recognize legitimate identities and encrypt these certificates using the public key infrastructure (PKI) hierarchical model according to the top graph of Figure 9. Furthermore, a pair of public and private keys for encrypting digital signatures will be generated when a CA issues an X.509 certificate. In the APPFLChain system, the SHA-256 function and elliptic curve digital signature algorithm (ECDSA) are adopted to sign and verify the digital signatures as demonstrated by Figure 9. Besides, a CA will generate an additional pair of RSA-2048 keys to encrypt local-model parameters.

c) Peers, Ledger, Chaincode, and Application: Peers in a Hyperledger Fabric blockchain can be classified into the following categories: *administration/anchor peer*, *endorsing peer* (*client peer*), *ordering peer* (*orderer*), and *committing peer*. Each type of peer has its own tasks. For example, the committing peers are responsible for receiving sorted blocks from orderers and connecting to the blockchain ledger. Therefore, a peer may have different identities in a transaction flow.

Ledger is a sorted and tamper-proof record of all transaction information in a Fabric network. The results of network participants invoking the chaincode to perform tasks through the application and software development kits (SDKs) are called *state transactions*. Each state transaction generates a set of asset key-value pairs to create, update, and delete data in the ledger. Furthermore, the ledger is maintained by all sub-blockchain participants because all peers in each channel have a ledger. Figure 10 shows the ledger architecture in our proposed new APPFLChain system.

Chaincode in Hyperledger Fabric is equivalent to the smart contract in Ethereum. It is a software module that defines the business logic of an organization. Besides, it can per-

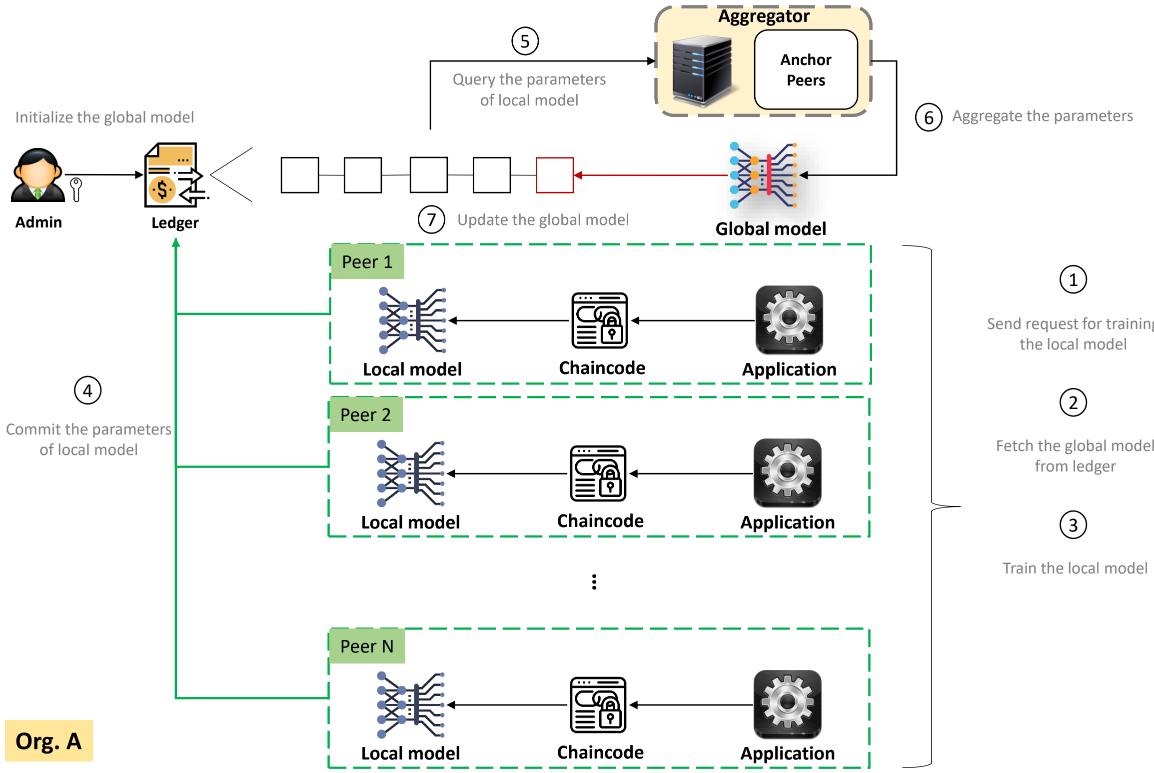
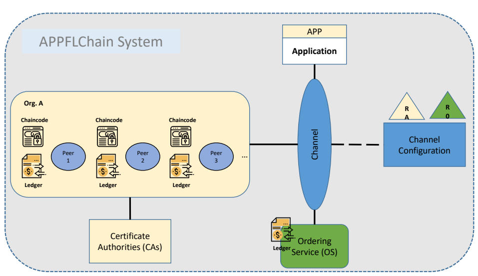
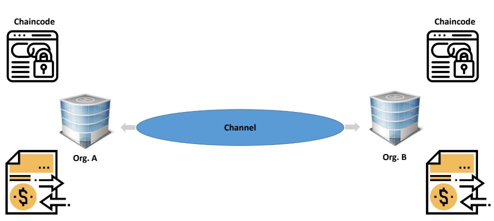


Fig. 7: The federated-learning flow in our proposed APPFLChain system.



(a)



(b)

Fig. 8: (a) Essential components in the APPFLChain architecture and (b) data-sharing between two organizations through a channel.

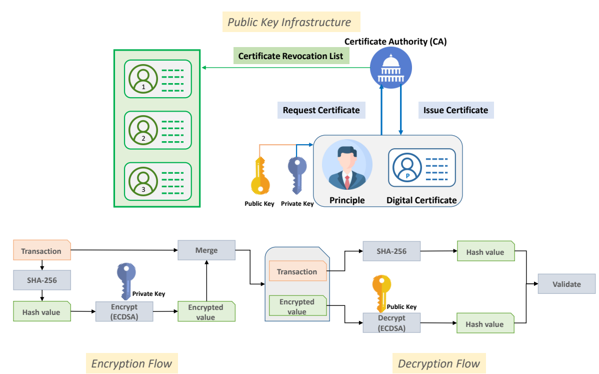


Fig. 9: The public key infrastructure (PKI) hierarchical model and the operation flow of digital-signature encryption and decryption.

form calculations, modify assets, and query assets through the application programming interfaces (APIs) provided by the Hyperledger Fabric core. Currently, developers can use Node.js, Java, and Go programming languages to design a chaincode. We use Node.js to develop the FL algorithm as the chaincode.

Application, the highest-level software in Hyperledger Fabric, allows clients to call functions in the chaincode through the Hyperledger Fabric SDKs. Developers in an organization can also design an application using programming languages, and here we use Node.js as well.

d) IPFS: In AI, the more complicated problem one encounters, the larger a deep-learning model one requires.

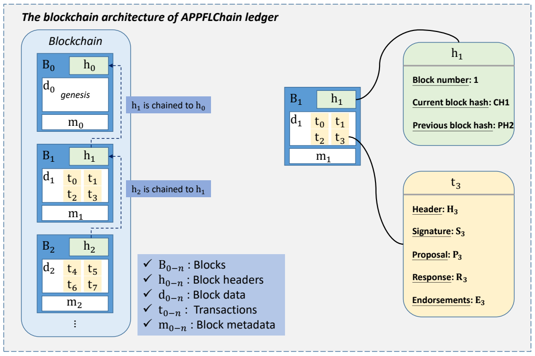


Fig. 10: The ledger architecture of our proposed APPFLChain system.

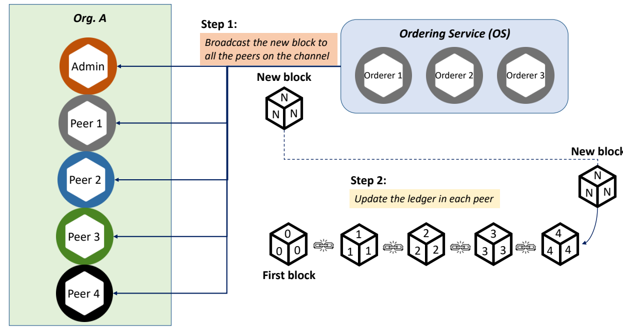


Fig. 12: The procedure for delivering a new block to all peers and updating each peer's ledger.

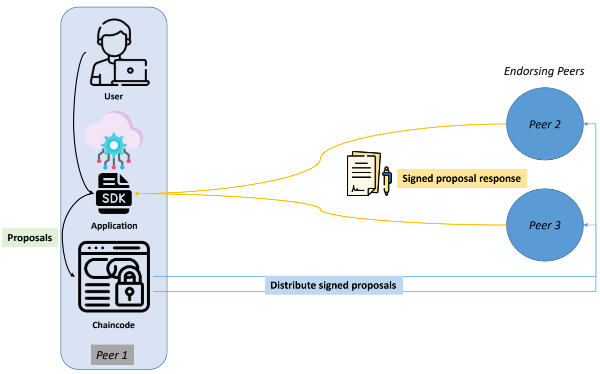


Fig. 11: The illustration of a process that Peer 1 to proposes a transaction while endorsing peers (Peers 2 and 3) verify the transaction.

It usually needs hundreds of megabytes of storage space to save a large deep-learning model in the floating-point format. Obviously, it is not efficient to use a blockchain-based ledger to store such a large model in the APPFLChain system. Instead, we use the InterPlanetary File System (IPFS) as our off-chain storage means. IPFS, a kind of peer-to-peer distributed communication protocol, can establish a content-based addressable file system using the distributed hash table (DHT). IPFS only produces a 46-byte hash digest to be archived by the blockchain ledger when a user uploads the information of a local model to it regardless of the model size. Thus the aggregators can query the hash digest from the ledger and use it to download the actual model from IPFS.

e) Ordering Service: In the APPFLChain system, the orderers in OS sort the transactions and generate blocks to form a deterministic consensus mechanism. Besides, the CFT sorting service implemented in Etcd based on the Raft protocol is deployed in our proposed APPFLChain system. More details of the Raft consensus algorithm will be presented in the next subsection. Assume that N denotes the total number of orderers in an OS. The number of faulty nodes that the Raft consensus algorithm can tolerate is given by

$$\aleph_{\text{fn}} = \frac{N}{2} - 1. \tag{3}$$

Eq. (3) infers that as long as more than 50% of orderers are normal subject to verification, an OS can implement the consensus service correctly. Eq. (3) means that the larger the value of N, the greater the number of faulty nodes ($\aleph_{\text{fn}}$) the system can tolerate. Consequently, we may have a massive decentralized system, which greatly enhances the security.

2) Hyperledger Fabric Transaction Flow: In this subsection, we present an example as illustrated by Figure 8a to show how a client peer calls a chaincode and makes a transaction proposal by use of certain application SDKs, how the endorsement policy of our proposed APPFLChain system will be invoked to endorse such a proposal, and how the consensus of a transaction can be reached in an OS using the Raft consensus algorithm. The system illustrated by Figure 8a contains a single channel, an organization, CAs, and an OS. The CAs will issue an X.509 digital certificate and a pair of keys to all peers, and the application SDKs deployed in the channel are used to make a proposal by a client peer. To manifest the details, we divide the entire transaction flow into the following four steps.

a) Step 1: Making a transaction proposal: Peer 1 in Figure 11 invokes the chaincode by use of application SDKs to make a transaction proposal. Then the chaincode will immediately conduct the corresponding task defined in the proposal. Furthermore, the chaincode uses the ECDSA private key to sign the proposal and distribute it to all endorsing peers selected by the endorsement policy of the channel.

b) Step 2: Verifying the transaction proposal: The developers can define an endorsement policy to select endorsing peers. Here, we simply define the endorsement policy by randomly selecting a half of the nodes active in the channel. Suppose that Peers 2 and 3 shown in Figure 8a to be the two endorsing peers. Then they need to verify (1) whether the format of the transaction proposal is correct, (2) whether there are repeated submissions (to address the replay-attack protection), (3) whether the contributor's digital signature is valid using MSP, and (4) whether the contributor has the authority to execute the proposal in the channel. If all of the aforementioned four conditions are verified, the endorsing peers will sign off the transaction proposal and send back a *signed proposal response* to the application SDKs of Peer 1 as illustrated by Figure 11.

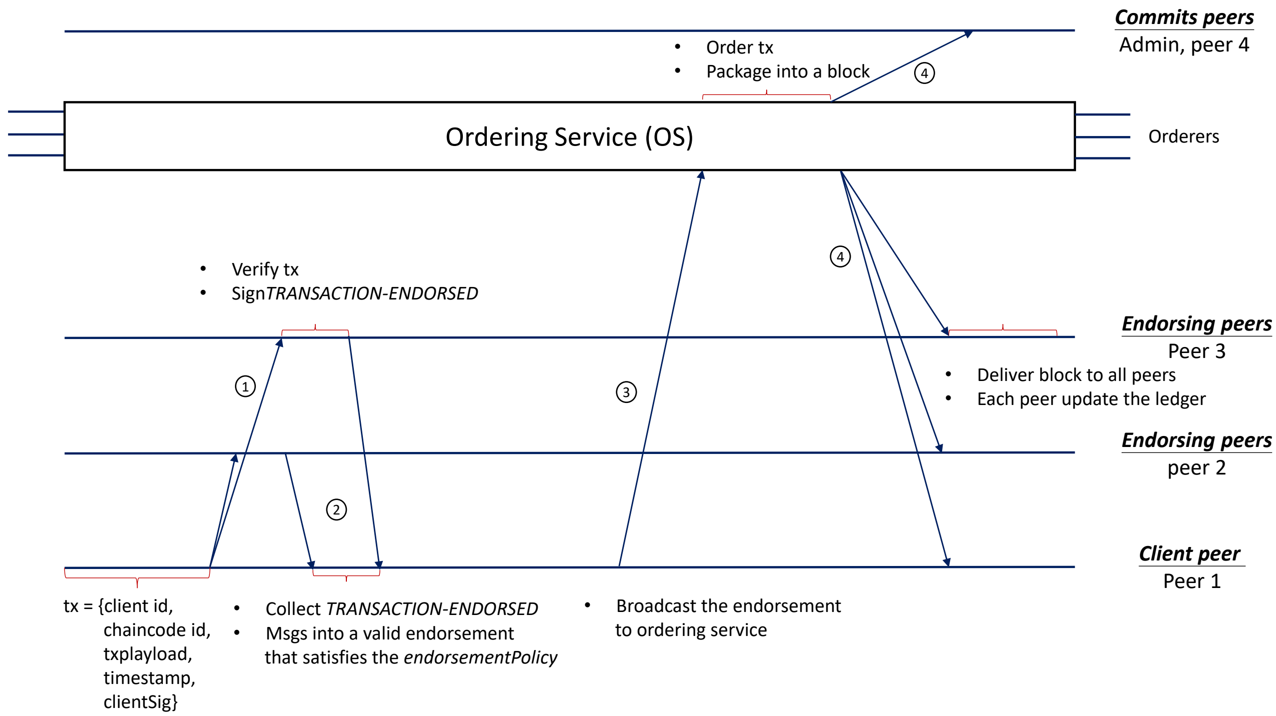


Fig. 13: The transaction-low swimlane diagram.

c) Step 3: Reaching the consensus in the OS: The Raft consensus algorithm are executed by orderers to determine which of them is responsible for sorting a batch of transactions and packing them into a block. There are three states, including "*follower*", "*candidate*", and "*leader*", to describe each orderer's status. Initially during a consensus process, the Raft consensus algorithm carries out the *heartbeat mechanism* to trigger the procedure of *leader election* while the states of all orderers are set to be "followers". Each follower will have a timer, which specifies its *election timeout* ranging from 150 to 300 msec. Whenever a follower's election timeout is reached, it will change its state to be a "candidate". Once more than 50% of the followers vote to approve such a leader the candidate's state will immediately switch to "leader". Then the leader will periodically synchronize its logs with all followers until it has sorted a batch of transactions and packed them into a block. The leader also needs to continuously send heartbeat signals to all followers to avoid triggering another election. As the leader collects a certain number of transaction requests, it will sort the transactions according to the corresponding timestamps and pack them into a block. Then the leader will conduct the process called "*log replication*" to send the block to all followers for updating their local logs. Finally, the orderers forward the latest generated block to all peers in the channel to update the peers' individual blockchain ledgers.

d) Step 4: Appending block to the ledger: The final step of a transaction flow is to append the block generated from Step 3 to the peers' existing blockchian ledgers. The authenticity of the newly generated block can be ensured due to the transactions within such a block have already been verified, endorsed, and digitally signed. In Figure 12, we show a schematic diagram of the OS sending a block to all peers in a channel for updating the ledgers. Besides, we use the swimlane sequence diagram (see Figure 13) to illustrate the transaction flow in detail.

C. Incorporating the FL algorithm into a consortium-blockchain

In this work, we deploy an FL algorithm in our proposed APPFLChain system to further address the requirement of data privacy. Thus, the data contributors can help the global AI model training without leaking the information of their local data. We present the following three steps to illustrate the training process of an FL algorithm on a Hyperledger Fabric consortium-blockchain.

1) Making Data-Contribution Proposals: The administration/anchor peers in an organization need to formulate the input data format and submit the initialized global model to the blockchain ledger before starting a training process. As the peers jointly maintain the ledger in the blockchain, each peer's ledger can store the initial global AI model. The peers may request data contribution to the local chaincode through the application SDKs. Then the local chaincode can fetch the global model from the corresponding ledger for training when it receives the request as illustrated by Figure 7.

2) Training and Contributing Local Models: After the local chaincode fetches the latest version of the global AI model, the client peer can use such local data and the defined training function in the chaincode to train the model and submit the trained local model. Besides, the local chaincode also submits the size of data used by the client peer in the local training process to the ledger. With the information of data size, the aggregator can know the proportion of data that a local model utilizes during this training process. Hence, the local chaincode does not leak any local data to the distributed database anytime. As a result, the sensitive information of the data contributors is kept in strict confidence.

3) Aggregating Locally Trained Results into the New Global Model: The aggregator is mainly composed of several administration/anchor peers. It aggregates the parameters of trained local AI models submitted by a batch of client peers into the latest version of global AI model. Consider a two layers fully-connected multilayer perceptron (MLP) composed by an input layer, a hidden layer, and an output layer. The total numbers of neurons at the input, hidden, and output layers are denoted by ψ, φ, and ϕ, respectively. To train an AI model, the gradient-descent method such as backpropagation can be adopted. Therefore, in the aforementioned case, we can iteratively update the two pairs of weights and biases

$$\boldsymbol{W}^1_{\psi\times\varphi} \overset{\text{def}}{=} \left[W^1_{k,j}\right]_{1\le k\le\psi, 1\le\varphi}, \quad \boldsymbol{b}^1_{1\times\varphi} \overset{\text{def}}{=} \left[b^1_j\right]_{1\le j\le\varphi} \tag{4}$$

and

$$\boldsymbol{W}^2_{\varphi\times\phi} \overset{\text{def}}{=} \left[W^2_{k,j}\right]_{1\le k\le\varphi, 1\le\phi}, \quad \boldsymbol{b}^2_{1\times\phi} \overset{\text{def}}{=} \left[b^2_j\right]_{1\le j\le\phi} \tag{5}$$

to make the output as close to the optimal solution as possible. Suppose that x_k, k=1, 2, ..., ψ are the features at the input layer, h_j, j=1, 2, ..., φ are the output values at the hidden layer. In a linear network, we have

$$h_j = b^1_j + \sum_{k=1}^{\psi} W^1_{k,j}\, x_k, \quad j = 1, 2, \ldots, \varphi. \tag{6}$$

In the presence of the nonlinear relu activation function "relu", Eq. (6) becomes

$$h'_j = \text{relu}\left(b^1_j + \sum_{k=1}^{\psi} W^1_{k,j}\, x_k\right), \quad j = 1, 2, \ldots, \varphi. \tag{7}$$

According to Eqs. (6) and (7), the crucial parameters in a neural network are weights and biases. Hence, in our proposed APPFLChain system, the aggregator will need to acquire the weights and biases of the trained local AI models and aggregate these weights and biases into the updated global AI model through the FL algorithm. Moreover, we create a new *block-listener function* in the aggregator to monitor the local ledger data. The organizations can determine when they need to execute aggregation based on their requirements.

V. Simulation

In this section, we demonstrate a realworld scenario to evaluate the effectiveness of our proposed novel APPFLChain system. We build two channels and accommodate three organizations in this system, where the channels are used to train deep-learning models based on the FL method. We will introduce the information of the training data to be utilized later on together with an APPFLChain prototype, the underlying FL algorithm, and the parameter settings related to the operation of the APPFLChian network. Finally, we will also compare the results from our APPFLChain system with those from two conventional FL methods, namely a centralized FL paradigm using a centralized database and a decentralized FL paradigm using the Ethereum public-blockchain. The specifications of our simulation environment are stated in the appendix.

A. Dataset

We use two sets of private medical data, namely the *liver disease dataset* from [51] and the *heart disease dataset* from [52], to simulate a practical scenario pertaining to sensitive data. There are 583 samples in the liver disease dataset and 1025 samples in the heart disease dataset. Here we would like to evaluate the effectiveness of our proposed APPFLChain system when it is applied to the situation that the number of data samples is quite limited as aforementioned. We put the liver disease dataset to Channel 1 (denoted by "C1") and the heart disease dataset to Channel 2 (denoted by "C2") to train the two pertinent detectors using the FL algorithm.

B. A Prototype APPFLChain System

A prototype APPFLChain system, which contains three organizations and two channels as previously described, is shown by Figure 14. Each organization has an administration/anchor peer, five data contributors, an aggregation peer, and a CA. Besides, C1 and C2 are equipped with an OS to sort endorsed transactions and generate blocks, and all peers in the prototype network have registered X.509 digital certificates with the CA of the affiliated organization. We associate Org. 1 with C1, Org. 2 with C2, and Org. 3 with both C1 and C2 as organizations may join multiple channels at the same time in reality. The participants in C1 and C2 are responsible for training the liver disease model and the heart disease model, respectively. In C1, we allocate 80% of 583 liver disease data samples to be the training data available to ten client peers while the remaining 20% of liver disease data are treated as the test data to cross-validate the trained model. A similar data-allocation strategy (80% for training and 20% for test) is applied for the heart disease data in C2 as well. After raising a contribution request, each client peer may use the allocated data to train its local model and submit the trained model to the local blockchain ledger, and the aggregator will acquire the local trained models from individual local ledgers to extract their corresponding parameters (e.g., weights and biases). Here, since we consider a three-layer MLP as the underlying learning-model topology, there are three weight-bias pairs $\left(\boldsymbol{W}^1_{\psi\times 16}, \boldsymbol{b}^1_{1\times 16}\right)$, $\left(\boldsymbol{W}^2_{16\times 8}, \boldsymbol{b}^2_{1\times 8}\right)$, and $\left(\boldsymbol{W}^3_{8\times\phi}, \boldsymbol{b}^3_{1\times\phi}\right)$ required to be trained. We can also extend this MLP to a more complex model as necessary.

In our simulations, we apply the horizontal FL algorithm in the APPFLChain system since the local data collected by each client peer are rather correlated. Moreover, we aggregate the local weight matrices $\boldsymbol{W}^1$'s, $\boldsymbol{W}^2$'s, $\boldsymbol{W}^3$'s and local bias vectors $\boldsymbol{b}^1$'s, $\boldsymbol{b}^2$'s, $\boldsymbol{b}^3$'s to produce the global model's weight matrices $\overline{\boldsymbol{W}}^1$, $\overline{\boldsymbol{W}}^2$, $\overline{\boldsymbol{W}}^3$ and bias vectors $\overline{\boldsymbol{b}}^1$, $\overline{\boldsymbol{b}}^2$, $\overline{\boldsymbol{b}}^3$ using the average scheme according to Eq. (1). Let $\aleph_{\text{ad}}$ denote the total number of training data samples available to all client peers

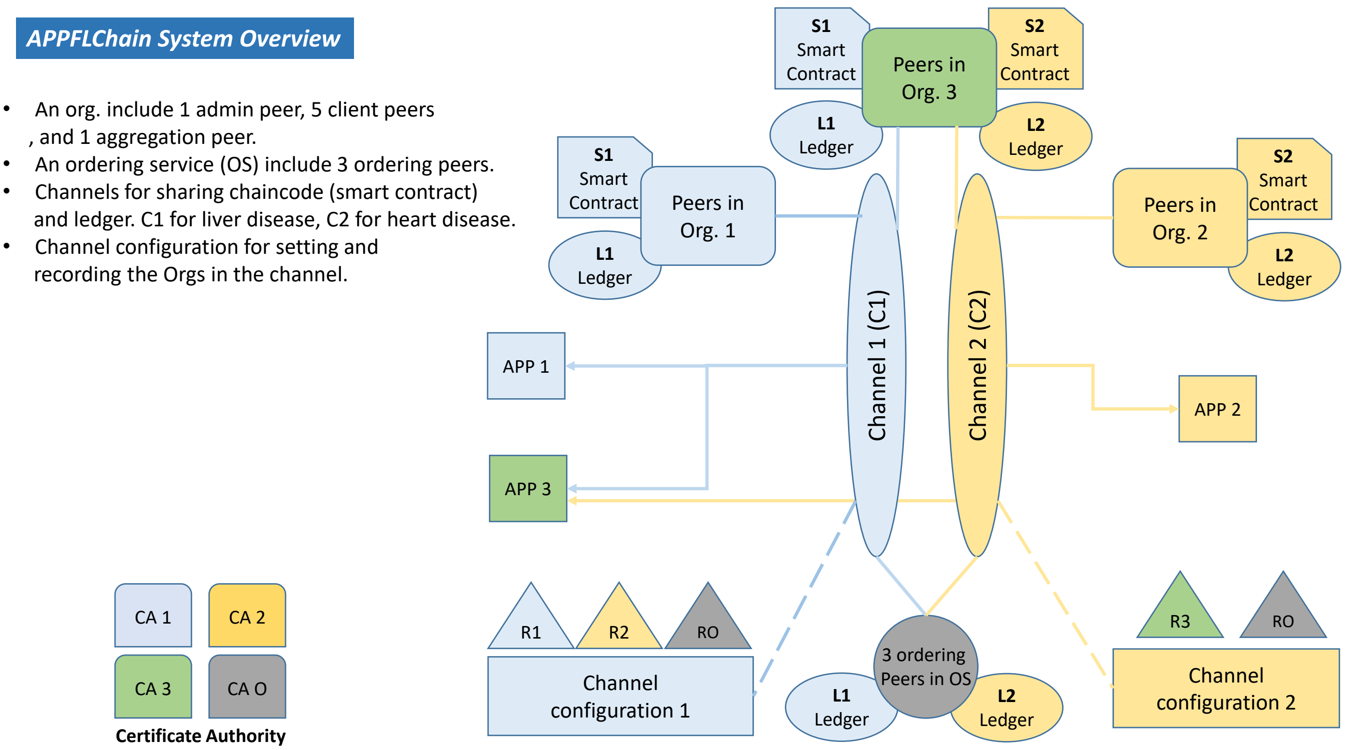


Fig. 14: An example to illustrate how our proposed APPFLChain system trains a disease-prediction model.

and n_p denote the number of data samples used by the p-th client peer to train its local model. Consequently, we have

$$\begin{aligned}
\overline{\boldsymbol{W}}^1 &= \frac{1}{\aleph_{\text{ad}}} \sum_{p=1}^{10} n_p \times \boldsymbol{W}_p^1, \\
\overline{\boldsymbol{b}}^1 &= \frac{1}{\aleph_{\text{ad}}} \sum_{p=1}^{10} n_p \times \boldsymbol{b}_p^1, \\
\overline{\boldsymbol{W}}^2 &= \frac{1}{\aleph_{\text{ad}}} \sum_{p=1}^{10} n_p \times \boldsymbol{W}_p^2, \\
\overline{\boldsymbol{b}}^2 &= \frac{1}{\aleph_{\text{ad}}} \sum_{p=1}^{10} n_p \times \boldsymbol{b}_p^2, \\
\overline{\boldsymbol{W}}^3 &= \frac{1}{\aleph_{\text{ad}}} \sum_{p=1}^{10} n_p \times \boldsymbol{W}_p^3, \\
\overline{\boldsymbol{b}}^3 &= \frac{1}{\aleph_{\text{ad}}} \sum_{p=1}^{10} n_p \times \boldsymbol{b}_p^3,
\end{aligned} \tag{8}$$

where $\boldsymbol{W}_p^1$, $\boldsymbol{W}_p^2$, $\boldsymbol{W}_p^3$ are the weight matrices submitted by the p-th client peer and $\boldsymbol{b}_p^1$, $\boldsymbol{b}_p^2$, $\boldsymbol{b}_p^3$ are the bias vectors submitted by the p-th client peer, p=1, 2, . . ., 10. As a result, the aggregator can construct the global model using these local parameters and commit it to the blockchain ledgers.

C. Results

Tables I and II describe the model summaries of the liver-disease and heart-disease detectors, respectively. Ten client peers in each channel (C1 and C2) collaboratively train the global AI model using the FL algorithm in the proposed APPFLChain system. We delineate the results after thirty training rounds from the APPFLChain system in Figures 15a and 15b.

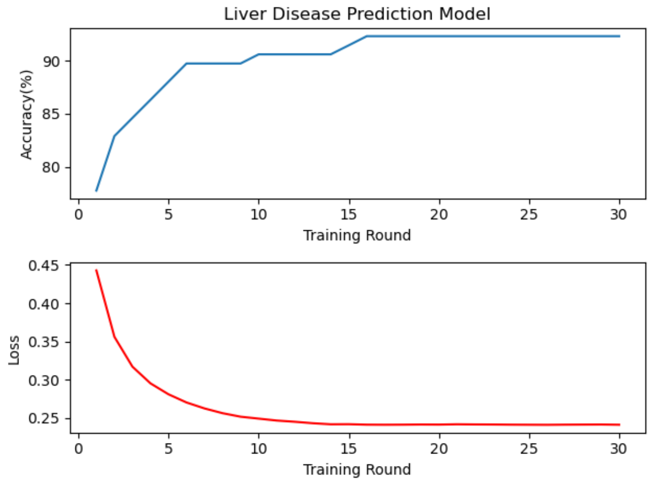
TABLE I: The Model Summary for Liver Disease Detection through C1

Layer (Type)	**Output Shape**	**Param #**
dense_Dense1 (Dense)	[null, 16]	176
dropout_Dropout1 (Dropout)	[null, 16]	0
dense_Dense2 (Dense)	[null, 8]	136
dropout_Dropout2 (Dropout)	[null, 8]	0
dense_Dense3 (Dense)	[null, 2]	18

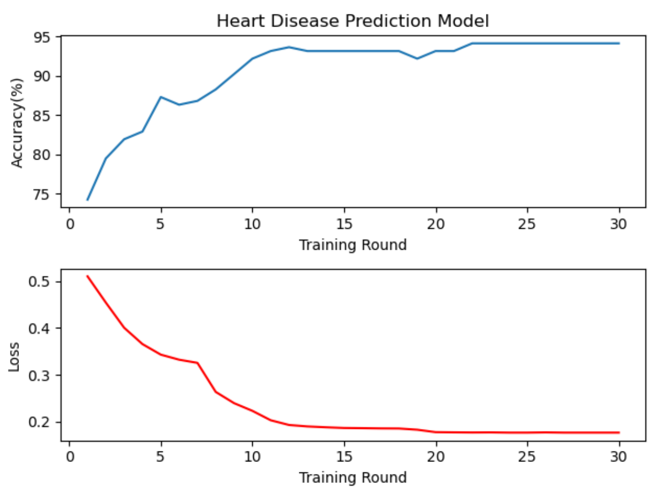
TABLE II: The Model Summary for Heart Disease Detection through C2

Layer (Type)	**Output Shape**	**Param #**
dense_Dense1 (Dense)	[null, 16]	224
dropout_Dropout1 (Dropout)	[null, 16]	0
dense_Dense2 (Dense)	[null, 8]	136
dropout_Dropout2 (Dropout)	[null, 8]	0
dense_Dense3 (Dense)	[null, 2]	18

Although its training results may not be optimal, our proposed APPFLChain system can train deep-learning models while maintaining the security and privacy of local data.



(a)



(b)

Fig. 15: The results from the first thirty training rounds for (a) liver disease detection through C1 and (b) heart disease detection through C2.

Furthermore, we also compare the system characteristics of our proposed new APPFLChain approach, the conventional FL approach, and the Ethereum public-blockchain-based FL approach by Table III. In general, both of the public-blockchain-based and the consortium-blockchain-based systems can employ cryptography, digital signatures, and consensus protocols to make the system more secure, tamper-proof, and traceable than the centralized systems. The difference between the public-blockchain-based system and the consortium-blockchain-based system is that we can apply the efficient Raft consensus algorithm in our proposed Hyperledger Fabric-based FL system to greatly speed up the verification time. The throughput of the verification and consensus process for our proposed APPFLChain system is around 2000 tps, which is much higher than that for the Ethereum-based system (around 20 tps). Consequently, simulation results also demonstrate that our proposed new APPFLChain system well incorporates the advantages of the consortium blockchain and the FL algorithm to have many favorable properties including untamperability, traceability, privacy protection, and reliable decision-making.

VI. Conclusion

In this paper, we propose a novel APPFLChain system which enables the federated learning using the Hyperledger Fabric consortium blockchain. We manifest the operation process of our proposed APPFLChain system, It can have favorable properties including untamperability, traceability, privacy protection, and reliable decision-making. Compared to the conventional public-blockchain-based federated learning approach, data contributors in our proposed APPFLChain system can train their local models without any need to share their local data to maintain the confidentiality throughout the training of a global model. Furthermore, our proposed APPFLChain system can lead to higher transaction throughput than the public-blockchain-based approach. Realworld medical data pertaining to liver and heart diseases are utilized to evaluate the effectiveness of our proposed APPFLChain prototype. Our proposed APPFLChain system is also highly scalable as it can be easily extended to accommodate much more peers, channels, and OSs subject to actual requirements. Therefore, our proposed novel APPFLChain system would be very useful to a lot of AI applications requiring collaborative training with local data privacy.

Appendix
Simulation Settings

In this appendix, we present the hardware configuration and operating system version of the workstation adopted for our simulations. We also illustrate the versions and purposes of the software used to implement the APPFLChain system. Note that errors or warnings may arise during the operation of the distributed database should one not adopt the same settings in this section.

A. Server PC

We use the Fujitsu PRIMERGY TX1320 M3 server PC to simulate the entire APPFLChain system. It is equipped with an Intel(R) Xeon(R) CPU E3-1220v6 processor, which has four cores, four threads, and a 16GB DDR4-2400 memory. Refer to Table IV for details. For implementing the APPFLChain prototype, we simulate all Hyperledger Fabric components and undertake the FL algorithm on the aforementioned server.

B. Hyperledger Fabric

We use the Hyperledger Fabric v2.3.1 package to facilitate the core distributed database in the APPFLChain prototye. Figure 16 depicts the current Fabric architecture. We develop the core of Hyperledger Fabric in Go. Besides, we use Node.js to build the chaincode and applications because it can allow us to use the module “TensorFLow.js” for model training. Table V lists the version numbers of Hyperledger Fabric and its prerequisites.

TABLE III: Comparison of Three Different FL Systems

	Conventional FL	Ethereum-based FL	**Proposed APPFLChain**
Core	Central server	Ethereum	**Hyperledger Fabric**
Centralization	Centralized	Decentralized	**Partially decentralized**
Architecture	Client-server	Public P2P	**Closed P2P**
Type	Permissioned	Permissionless	**Permissioned**
Consensus	None	POW/POS	**Raft**
Data persistence	Non-persistence	Immutable	**Immutable**
Chance of Failure	High	Low	**Low**
Confidentiality	Yes	No	**Yes**
Data privacy	High	Low	**High**
Throughput	$> 20000\,\text{tps}$	$\approx 20\,\text{tps}$	$\mathbf{> 2000\,tps}$

TABLE IV: Specifications of Fujitsu PRIMERGY TX1320 M3 Server PC

Item	**Equipment**
OS	Ubuntu Server 18.04 LTS (4.15.0-151-generic)
CPU	Intel(R) Xeon(R) CPU E3-1220v6 @3.00GHz
# of Cores	4
# of Threads	4
IGP	MGA-G200e 16MB
Memory	DDR4-2400 16GB
Active Power (max.)	231 Watt

TABLE V: Software Versions of Fabric and Prerequisites

Item	**Version**	**Remark**
Hyperledger Fabric	v2.3.1	The distributed database core of APPFLChain.
Fabric CA	v1.5.2	Register user info and issue digital certificates.
Node.js	v10.24.0	Develop chaincode and application.
Go	v1.16.7	Develop other related tools.
TensorFlow.js	v3.6.0	Develop federated learning algorithm.

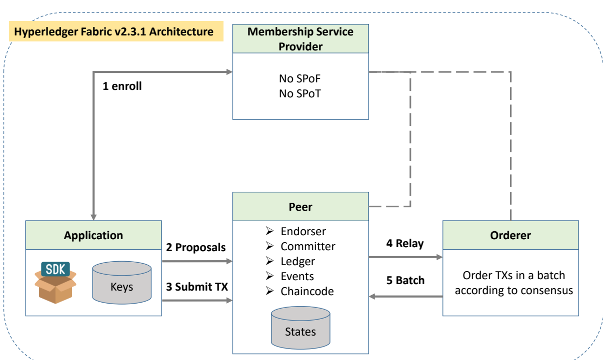


Fig. 16: The architecture of Hyperledger Fabric v2.3.1.

C. Docker and Docker Compose

As mentioned in Section V, we have three organizations and fifteen peer nodes to demonstrate the operation process of the APPFLChain system. Due to the limited number of available devices in reality, we use the open-source software Docker and Docker Compose tool, which can define and execute multiple docker containers at the same time, to emulate multiple devices on the Fujitsu PRIMERGY TX1320 M3 server. We create multiple Docker containers to enable the organizations and the peer nodes to interact on the APPFLChain. Refer to Table VI for more information. Finally, we establish many Docker containers, each of which operates an individual organization in the proposed APPFLChain system and uses the Alpine Linux OS with a simple instruction set. Table VII lists the version numbers of Docker, Docker Compose, and Alpine Linux OS.

Acknowledgment

We thank professor Yu-Hwa Lo for his valuable comments for this work. This work was supported in part by the Ministry of Science of Technology, Taiwan, under research project number 110-2221-E-007-084-MY3, and in part by the Ministry of Science of Technology, Taiwan, Overseas Project for Post Graduate Research, under project number 110-2917-I-007-013.

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TABLE VI: All Information of Peers Emulated by Docker

Group	Identity	Port
Ordering Service	Orderer 1	0.0.0.0 : 5051
	Orderer 2	0.0.0.0 : 5052
	Orderer 3	0.0.0.0 : 5053
Organization 1	Admin peer	0.0.0.0 : 7051
	Aggregator peer	0.0.0.0 : 7052
	Client peer 1	0.0.0.0 : 7053
	Client peer 2	0.0.0.0 : 7054
	Client peer 3	0.0.0.0 : 7055
	Client peer 4	0.0.0.0 : 7056
	Client peer 5	0.0.0.0 : 7057
Organization 2	Admin peer	0.0.0.0 : 9051
	Aggregator peer	0.0.0.0 : 9052
	Client peer 1	0.0.0.0 : 9053
	Client peer 2	0.0.0.0 : 9054
	Client peer 3	0.0.0.0 : 9055
	Client peer 4	0.0.0.0 : 9056
	Client peer 5	0.0.0.0 : 9057
Organization 3	Admin peer	0.0.0.0 : 11051
	Aggregator peer	0.0.0.0 : 11052
	Client peer 1	0.0.0.0 : 11053
	Client peer 2	0.0.0.0 : 11054
	Client peer 3	0.0.0.0 : 11055
	Client peer 4	0.0.0.0 : 11056
	Client peer 5	0.0.0.0 : 11057

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TABLE VII: Versions of Docker, Docker Compose, and Alpine Linux OS

Item	Version	Remark
Docker	v19.03.6	Create containers for APPFLChain.
Docker Compose	v1.27.2	Define and execute multiple docker containers.
Alpine Linux OS	v3.12.3	The simple OS for docker containers.

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