BPFISH: Blockchain and Privacy-preserving FL Inspired Smart Healthcare

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Abstract—This paper proposes Federated Learning (FL) based smart healthcare system where Medical Centers (MCs) train the local model using the data collected from patients and send the model weights to the miners in a blockchain-based robust framework without sharing raw data, keeping privacy preservation into deliberation. We formulate an optimization problem by maximizing the utility and minimizing the loss function considering energy consumption and FL process delay of MCs for learning effective models on distributed healthcare data underlying a blockchain-based framework. We propose a solution in two stages- first, offer a stable matching-based association algorithm to maximize the utility of both miners and MCs and then solve loss minimization using Stochastic Gradient Descent (SGD) algorithm employing FL under Differential Privacy (DP) and blockchain technology. Moreover, we incorporate blockchain technology to provide tempered resistant and decentralized model weight sharing in the proposed FL-based framework. The effectiveness of the proposed model is shown through simulation on real-world healthcare data comparing other state-of-the-art techniques.

Index Terms—Federated Learning, Blockchain, Stable Matching, Differential Privacy, Smart Healthcare.

1 INTRODUCTION

Smart healthcare system is likely to play a crucial role in our society. It can provide remote medical services, helps medical diagnosis and protect patients against dangerous infectious disease such as COVID-19 during personal visits to hospitals. Smart healthcare solutions are extremely helpful during the recent COVID-19 pandemic [1], [2]. However, there are still challenges in smart healthcare such as data unavailability due to privacy concerns of patients [3].

Federated Learning (FL) [4], an emerging framework is used to address the unavailability and privacy risks of sensitive healthcare data [5]–[7]. Since training data is not leaving the Medical Centres (MCs), this framework ensures privacy protection for all involved centres by sharing models instead of sharing sensitive raw healthcare data. However, there are still challenges in FL based healthcare architecture such as privacy leakage and single point of failure [5], [6]. Firstly, healthcare data is highly privacy-sensitive, thus the leakage of this sensitive information could destroy the reputation and finances of the patient. Secondly, the existing FL based healthcare architectures are suffering from a single point of failure risks due to the aggregation of the model in a central server and the unwillingness of MCs to participate in the FL process due to the lack of incentives.

To overcome the above-mentioned issues, we consider a blockchain and FL based smart healthcare framework (see Fig. [1]) in which MCs train a model locally using the data collected from patients and forward the model weights to the miner in a blockchain to build a robust model without sharing raw data. However, it is necessary to optimize both the utilities of miners as well as MCs and the FL loss function simultaneously to increase the accuracy and effectiveness of smart healthcare system while keeping privacy risks into consideration. Therefore, we propose a joint optimization problem by maximizing the utility and minimizing the loss function together, considering energy consumption and the model training delay at MCs for learning effective models. However, in blockchain-based FL, there is a need for a proper association between miners and MCs in order to increase accuracy and effectiveness of smart healthcare system. Thus, we offer a stable association algorithm between miners and MCs to maximize the utility of both miners as well as MCs in polynomial time and then solve the FL loss minimization using Stochastic Gradient Descent (SGD) algorithm employing FL under Differential Privacy (DP) and blockchain technology.

In this paper, we focus on developing a blockchain-based privacy-preserving FL framework for collaborative training across multiple MCs under differential privacy to solve privacy leakage problems in Healthcare Domain (HD). An adversary can use an inference attack to recreate the training data from the shared model. Therefore, we incorporate DP [9] to prevent privacy leakage while transmitting model weights during FL process. DP is a privacy protection technique that has been widely used in the field of privacy protection in deep learning models [9]–[11]. We also use blockchain as a way for decentralized architecture in model weights sharing. Blockchain provides a tempered resistant framework where each device verifies the transactions in the network and the miners perform Proof-of-work (PoW) to add new blocks. PoW is a proof of doing computation by the miner to add a new block to the blockchain. Therefore, we formulate a blockchain and FL based privacy-preserving smart healthcare framework by maximizing the utility and minimizing the loss function considering energy consumption and latency of MCs for learning effective models. Furthermore, to improve the utility and accuracy of the

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FL model, we offer a stable and computationally efficient association algorithm among miners and MCs. We also proposed an incentive mechanism to promote the MCs for participation in the FL process. Specifically, the contributions of this paper are summarized as follows:

- Formulate an optimization problem by maximizing the utility and minimizing the loss function considering energy consumption and FL process delay of MCs for collaborative learning on distributed healthcare data.
- Stable Miner-MC Association (MMA) algorithm is proposed between miners and MCs to maximize the utility with computational complexity of $O(N^2S)$, where $N$ and $S$ represent the number of MCs and the number of miners, respectively.
- Blockchain-based privacy-preserving FL framework that guarantees DP for decentralized collaborative learning from data stored across MCs is proposed, with communication complexity of $O(T|K|^2|w|)$, where $T$, $|K|$ and $|w|$ represent the number of global iteration, the number of participated MCs in the FL process and the number of model weights, respectively. An Incentive Mechanism (IM) is also proposed to encourage miners to verify and adding the blocks and MCs for participating as proportional to their data sample size.
- Through rigorous evaluations on Chest X-ray Images (Pneumonia) dataset we verify the effectiveness of the proposed model on various privacy parameters. Performance study demonstrates that proposed BPFISH framework surpass state-of-the-art schemes, achieving 11.18% better outcome on an average.

The rest of the paper is organized as follows: The relevant work is reviewed in Section 2. The system model and the problem formulation are discussed in Section 3. Miner-MC association and FL process are given in Section 4 and Section 5, respectively. Experiment results and analysis are given in Section 6. Finally, Section 7 provides the conclusion.

## 2 Related Work

In this section, we present the related works for FL with DP, blockchain, association and their combination in HD along with a comparative analysis in Table 1.

| Problem Focus | FL | DP | Block-chain | Association | IM | HD |
|---------------|----|----|-------------|-------------|----|----|
| Collaborative AI Model [8] | ✓ | × | × | × | × | ✓ |
| Smart Healthcare [12], [13] | ✓ | × | × | × | × | ✓ |
| Meta-Analysis of Brain Data [14] | ✓ | × | × | × | ✓ | ✓ |
| Health Research [15] | ✓ | ✓ | × | × | × | ✓ |
| Privacy Preserving [16] | ✓ | ✓ | × | × | × | ✓ |
| Multi-site fMRI Analysis [17] | ✓ | ✓ | × | × | × | ✓ |
| Prevent Information Leakage [18] | ✓ | ✓ | × | × | × | ✓ |
| Access Management [19] | × | × | ✓ | × | × | ✓ |
| EMRs Access Control [20], [21] | × | × | ✓ | × | × | ✓ |
| EMRs Management [22] | × | × | ✓ | × | × | ✓ |
| Resource off-loading [23], [24] | × | × | ✓ | ✓ | × | ✓ |
| Blockchain based Crowd-sourcing [25], [26] | × | × | ✓ | ✓ | × | ✓ |
| Patient-Physician Matching [27] | × | × | ✓ | ✓ | × | ✓ |
| Privacy Preserving FL [28] | ✓ | ✓ | ✓ | × | × | ✓ |
| Blockchain for Privacy Preserving [29] | × | ✓ | ✓ | × | × | ✓ |
| Privacy Preserving IoT [30] | ✓ | ✓ | ✓ | × | × | ✓ |
| Blockchain on-Device FL [8] | ✓ | ✓ | × | ✓ | ✓ | × |
| Decentralized aggregator free FL [31] | ✓ | × | ✓ | × | ✓ | ✓ |
| BPFISH (Proposed) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

### 2.1 FL with DP in Smart Healthcare

Recently, NVIDIA introduced Clara FL [5] for distributed, collaborative AI model training across multiple hospitals to develop a more accurate global model while maintaining patient privacy. In [12] and [13], authors developed a FL model for IoT based smart healthcare system. Silva et al. [14] also proposed an FL framework for securely accessing and analysing medical data stored at several institutions. These works consider central server for model aggregation in FL process but this causes inaccurate global model update if the server is malfunctioned or attacked. The adaptation of privacy-preserving techniques to conserve patient privacy with the use of FL has been demonstrated in clinical and epidemiological research [15]. In [16] and [17], FL based privacy-preserving method has been used for smart healthcare systems such as detection of Alzheimer’s disease and multi-site fMRI data analysis. In [18], K. Wei et al. proposed a framework under DP by adding Gaussian noises to the locally trained weights before sending it to the server. However, these works mainly focused on optimizing FL under DP by considering centralized model aggregation that is vulnerable to the single point of failure and did not consider incentives for participating in the FL process.

### 2.2 Blockchain in Smart Healthcare

In recent years, many research have proven that blockchain is a promising solution for ensuring the confidentiality, privacy preserving and distributed sharing of sensitive health information. Oscar Novo [19] focused on distributed access management based on blockchain in IoT. However, the work does not consider the privacy of Electronic Medical
2.3 Association in Smart Healthcare

Many studies had been done for user association in resource offloading considering UAVs and IoTs enabled edge computing framework [23],[24]. Smart user matching intersection with blockchain for stable matching in ultra-dense wireless networks had been proposed for computation offloading in [23]. M. Kadadha et al. [25] and J. An et al. [26] explored Gale-Shapley based matching algorithm for node selection in blockchain-based crowdsourcing model. R. Chen et al. [27] presented a matching algorithm by considering the preferences from both patients and physicians to reduce the waiting time of patient. However, the above stated works cannot be directly applied to the proposed framework due to ill posed nature of miners and MCs in blockchain and FL based healthcare architecture.

2.4 FL, DP and Blockchain for Smart Healthcare

C. Li et al. [28] and K. Gai et al. [29] proposed privacy-preserving data sharing architecture based on blockchain for industrial Internet of Things by integrating FL and blockchain technology. In [30], privacy protection schemes for data in blockchain have been applied using data perturbation techniques like DP. However, these works do not consider incentives and the privacy preserving technique in smart healthcare domain. In [8] and [31], blockchain-based FL for privacy-preserving had been applied to eliminate the centralized global model aggregation.

The above existing works mainly focused on improving the performance of learning algorithms in FL and they did not provide incentives to the MCs participated in the FL process. However, it is necessary to provide incentive since participating institutes in FL requires data collection and model training on the device itself. Users are unlikely to participate in FL activities unless they are rewarded because model training consumes energy and requires a constant network connection. Moreover, none of the existing approaches has considered privacy-preserving decentralized FL with association and incentive mechanisms altogether as shown in Table 1. In this paper, we proposed a blockchain-based privacy-preserving FL combined with incentive and association mechanisms for smart healthcare applications.

3 System Model and Problem Formulation

As shown in Fig. 1 we consider a smart healthcare scenario consisting of N MCs and S miners represented by $C = \{C_1, \ldots, C_n, \ldots, C_N\}$ and $M = \{M_1, \ldots, M_s, \ldots, M_S\}$, respectively. Furthermore, let $X_n = \{x_n^1, \ldots, x_n^d, \ldots, x_n^D_n\}$ be the set of $D_n$ data samples available at MC $C_n \in C$, collected from different patients admitted in the MC. MCs collaboratively train a shared model using their own data without sharing it to a central server. Specifically, each MC trains a model locally using their data and then send it to the miners for distributed aggregation [30], resulting in a global model. An MC is characterized by a tuple $<X_n, f_n>$, where $X_n$ and $f_n$ represent the available amount of data samples for local model training and available number of CPU cycles at MC $C_n \in C$, respectively. The above-stated scenario needs two-stage categorization as described in the following:

Stage 1: MMA: In this stage, each MC finds an association with a miner. The association is formed by considering the utilities of both the MCs and miners using deferred acceptance algorithm (discussed in Section 4).

Stage 2: Blockchain-based privacy-preserving FL: MCs train local model and send model weights to the associated miner without sharing the healthcare data. Thus, hereby preserving the privacy of the patient’s healthcare data. Miners add the models to the blockchain network. Blockchain provides distributed model weights sharing framework that is robust to the single point of failure (discussed in Section 5).

To set up the association between MCs and miners (Stage 1), there is a need for preference order of one over the other, depending on maximum utilities; described in the following.

3.1 Utility of Miner

The blockchain network provides mining rewards for verification and adding blocks to the blockchain. When a miner $M_s$ adds a block, its mining reward is provided from the blockchain network, as does in the traditional blockchain network [32]. Each miner adds the local models from MCs to the blockchain. However, miner $M_s$ adds local model from $C_n$ as a block to the blockchain if and only if $M_s$ and $C_n$...
are associated with each other. Specifically, the association between miner and MC is given as follows:

\[
y_{n,s} = \begin{cases} 1, & \text{if } \text{MC } C_n \text{ gets associated with miner } M_s, \\ 0, & \text{otherwise.} \end{cases}
\] (1)

Let \( R_s \) be the revenue of the miner \( M_s \) in the FL process and \( \mathcal{R} \) be the mining reward for adding a block to the blockchain \([32]\), which is the same for all the miners in the network. Each miner solves the PoW multiple times i.e., in every iteration. Therefore, the total revenue for a miner \( M_s \) is represented as follows:

\[
R_s = T \cdot h(\mathcal{R}),
\] (2)

where \( h(\cdot) \) is a monotonically increasing function for \( \mathcal{R} \) and \( T \) is the number of global iterations. For simplicity, we consider following function to define \( h(\mathcal{R}) \):

\[
h(\mathcal{R}) = \mathcal{R} \sum_{C_n \in \mathcal{C}} y_{n,s},
\] (3)

where \( \sum_{C_n \in \mathcal{C}} y_{n,s} \) is the number of blocks added to the blockchain by the miner \( M_s \) in each iteration which is equivalent to the number of MCs associated with the miner \( M_s \). Therefore, the total revenue of a miner can be rewritten as follows:

\[
R_s = T \mathcal{R} \sum_{C_n \in \mathcal{C}} y_{n,s}.
\] (4)

The reward is an essential component of an FL based framework for the MC to participate in the FL process. The reward of MC is related to the number of data samples available for training at MC, \( C_n \). We consider that the reward is linearly dependent on the number of data samples. Therefore, the reward offer to MC, \( C_n \) from miner \( M_s \) for training local model on data sample \( D_{n,s} \) is calculated as follows \([8]\):

\[
R_{n,s} = R_s \frac{D_n}{\sum_{C_n \in \mathcal{C}} D_n}.
\] (5)

We assume that the utility and the total revenue of a miner are linearly dependent. Therefore, the utility of a miner is defined as follows:

\[
U_{n,s}^{\text{Min}} = R_s - R_{n,s}.
\] (6)

### 3.2 Utility of Medical Center

We use the utility as a criterion to determine the preferences of the MCs and miners for the association. Since MC trains model in the FL process with the consumption of energy, we consider computation energy while defining the utility of an MC. Let \( f_n \) be the number of CPU cycles per second (computation capacity) of MC \( C_n \in \mathcal{C} \). Let \( \beta_n \) (cycles/sample) be the number of CPU cycles needed for computing one sample data \( x_{n,s}^d \in X_n \) at MC, \( C_n \). The energy consumption to calculate the total number of \( \beta_n D_n \) CPU cycles at MC, \( C_n \) can be derived as \([33]\):

\[
E_n = \kappa \beta_n D_n f_n^2,
\] (7)

where \( \kappa \) is a coefficient that depends on the chip architecture. In the FL process, an MC, \( C_n \) requires to compute \( \beta_n D_n \) CPU cycles in each \( I_n \) local iterations. Therefore the total energy consumption in local model training is given by:

\[
E_n^{\text{comp}} = I_n E_n = \kappa I_n \beta_n D_n f_n^2.
\] (8)

Moreover, the computation time taken by an MC, \( C_n \) to train local model can be defined as follows: \( T_n^{\text{comp}} = I_n \beta_n D_n f_n^2 / \kappa \).

Following the local model training, model is sent from the MC to the associated miner. For simplicity, we define the achievable data rate between MC, \( C_n \) and miner \( M_s \) as: \( v_{n,s} = QV \log_2 (1 + SINR_{n,s}) \). Here, \( V \) is the total number of allocated PRBs between MC and miner. \( SINR_{n,s} \) and \( Q \) are the signal-to-interference-plus-noise ratio (SINR) and the bandwidth of PRB allocated between MC and miner, respectively. The total transmission time \([35]\) for an MC in uploading the model weights of size \( H \) to the miner during the FL process is as follows: 

\[
t_{n,s}^{\text{trans}} = TH / v_{n,s}.
\] Given the same model across all MCs, the size of the local model remains constant, independent of the number of iterations or the amount of data available. The energy consumption in

1. PRB is the smallest unit that can be assigned to a device in the 5G network \([34]\).
2. For simplicity, we assume that the channel exhibits flat fading. However, this can be easily extended to frequency-selective fading channels as well \([34]\).
3. We assume that model download time between miners and MCs is negligible compared with the transmission time as usually the downlink bandwidth is significantly larger than the uplink bandwidth \([35]\).
the transmission of the trained local model can be defined as follows [24]:
\[ \zeta_{n,s} = E_{n,s}^{trans} = \tau_{n,s}^{trans} \mu_n, \] (9)
where, \( \mu_n \) is the transmit power of MC, \( C_n \).
Therefore, the utility, \( U_{n,s}^{MC} \) of an MC, \( C_n \) can be defined as follows:
\[ U_{n,s}^{MC} = R_{n,s} - \varphi(E_{n,s}^{comp} + E_{n,s}^{trans}), \]
\[ = R_{n,s} - \varphi(\kappa I_n \beta_n D_n f_n^2 + \zeta_{n,s}), \] (10)
where \( \varphi \) represents the cost per unit energy.

During the FL process, each MC has to upload the local model within a specified time. Particularly, to conduct FL process reliably and to find the feasible association candidates between miners and MCs, the time constraint needs to satisfy:
\[ \tau_{n,s}^{comp} + \tau_{n,s}^{trans} \leq \tau_{th}, \forall C_n \in \mathbb{C}, \forall M_s \in \mathbb{M}, \] (11)
where \( \tau_{th} \) is the predefined threshold.

3.3 Federated Learning

We define a vector \( w^{(n)} \) as weights related to the FL model for MC, \( C_n \). We introduce the loss function \( l(w^{(n)}, x_n^d) \) of the model, which indicates the FL performance over an input sample. The loss function varies depending on the learning problem. Different learning problems use different loss functions. In smart healthcare, loss defines how far the model’s prediction or the outcomes is from the actual outcomes of the health condition [36]. The FL local model training problem at MC \( C_n \in \mathbb{C} \) for miner \( M_s \), using its own data \( X_n \) can be formulated as follows [37]:
\[ \min_{w^{(n)}} \mathcal{L}_{n,s}(w^{(n)}) \min_{w^{(n)}} \frac{1}{D_n} \sum_{x_n^d \in X_n} l(w^{(n)}, x_n^d). \] (12)

In order to get better privacy, we integrate DP in the local model training. DP ensures that the output of a differentially private algorithm gives the same output with \( \epsilon \) error whether or not a local data sample is included in the input of the algorithm. \( \epsilon \) is the privacy budget that is bound on the loss of the privacy of the algorithm. We use the variant of DP definition introduced in [10], that satisfies \( (\epsilon, \delta) \)-DP, where \( \delta \) defines the bound that the privacy guarantee does not hold (which is preferably very small positive number).

Definition 1. A randomized algorithm \( Z : \mathcal{X} \rightarrow \mathcal{Y} \) with domain \( \mathcal{X} \) and range \( \mathcal{Y} \) satisfies \( (\epsilon, \delta) \)-DP if for any two adjacent datasets \( D' \) and \( D'' \) that differ by one data record and for any subset \( O \subseteq \mathcal{Y} \), the following probability condition holds:
\[ Pr[Z(D') \in O] \leq e^\epsilon Pr[Z(D'') \in O] + \delta. \] (13)

Privacy can be achieved in the algorithm by adding random noise to the gradient computation so that the resultant model is noisy. Therefore, we update the weights at \( i \)-th \((i \in [1, I_n])\) local iteration for optimizing the loss function as follows [10]:
\[ w^{(n,i+1)} = w^{(n,i)} - \alpha G'' \], (14)
where \( \alpha \) is the learning rate of the model. Moreover, \( G'' \) is calculated using Eq. (15):
\[ G'' = G' + N(0, \sigma^2 A^2), \] (15)
where \( N(0, \sigma^2 A^2) \) is the Gaussian noise, \( I \) is the identity matrix and \( G' \) is the clipped gradient using \( L_2 \) norm of the gradient calculated as follows:
\[ G' = \Delta \mathcal{L}_{n,s}(w^{(n)})/\max \left( 1, \frac{\| \Delta \mathcal{L}_{n,s}(w^{(n)}) \|_2}{A} \right), \] (16)
where \( \sigma = \sqrt{2 \log \frac{1}{\epsilon^2}}/\epsilon \) for \( \epsilon > 0 \) and \( A \) is the gradient bound. DP requires bounding the impact of each data sample on \( G'' \). So, each gradient is clipped in the \( L_2 \) norm, i.e., the gradient \( \Delta \mathcal{L}_{n,s}(w^{(n)}) \) is replaced by \( \Delta \mathcal{L}_{n,s}(w^{(n)})/\max \left( 1, \frac{\| \Delta \mathcal{L}_{n,s}(w^{(n)}) \|_2}{A} \right) \), for a gradient bound \( A \). This clipping ensures that if \( \| \Delta \mathcal{L}_{n,s}(w^{(n)}) \|_2 \leq A \), then \( \Delta \mathcal{L}_{n,s}(w^{(n)}) \) is preserved, whereas if \( \| \Delta \mathcal{L}_{n,s}(w^{(n)}) \|_2 > A \), gradient gets scaled down to be of norm \( A \). This gives the global minimization problem over the collection of all the loss functions from MCs. This global minimization problem is minimized by finding the optimal weights, \( W^T \) and is defined as follows:
\[ W^T = \min_{W} J(W), \] (17)
where \( J(W) \) is the total loss over the collection of all the MCs, given as follows:
\[ J(W) = \frac{1}{\sum_{C_n \in \mathbb{C}} \sum_{M_s \in \mathbb{M}} y_{n,s} \mathcal{L}_{n,s}(w^{(n)})}, \]
(18)
where \( W \) is the weights of the global model. \( \sum_{C_n \in \mathbb{C}, M_s \in \mathbb{M}} y_{n,s} \) gives the total number of MCs participated in the FL process. Moreover the descriptions of used symbols are given in Table 2.

3.4 Problem Formulation

We formulate a joint optimization problem having goal to maximize the utility of both the miner and MC and minimize the FL loss function while satisfying the FL process delay requirement. Utility of MC involves determining the miner associated with, amount of data present at MC for local model training, and the uplink transmit power of each MC for model update transmission to the miner. The utility of miner involves mining rewards for adding blocks to the blockchain. Therefore, the total utilities of miners and MCs is given by:
\[ U = \sum_{C_n \in \mathbb{C}} \sum_{M_s \in \mathbb{M}} y_{n,s}(U_{n,s}^{Min} + U_{n,s}^{MC}), \] (19)
where \( U_{n,s}^{Min} \) and \( U_{n,s}^{MC} \) are defined in the above Eq. (6) and Eq. (10), respectively.

The minimization problem of Eq. (17) is equivalent to the following maximization problem:
\[ W^T = \max_{W} \{-J(W)\}. \] (20)
As a result, we combine both the factors i.e., utilities of miners and MCs, and FL process loss function as follows:
\[ F = \rho U + \eta \{-J(W)\}, \] (21)
where \( \rho \) and \( \eta \) are the weights assigned to the utility and the FL loss function and \( \rho + \eta = 1 \).

Therefore, the optimization problem of the system model can be formulated as follows:

\[
\max_{y_{n,s}, \tau} F
\]

S. T.\begin{align*}
&1.1. \quad U_{n,s}^{MC} > 0, U_{n,s}^{Min} > 0, \forall C_n \in \mathbb{C}, \forall M_s \in \mathbb{M}, \\
&1.2. \quad \sum_{C_n \in \mathbb{C}, M_s \in \mathbb{M}} y_{n,s} > 0, \\
&1.3. \quad \text{Eqs. (I) and (II), (P1)}.
\end{align*}

\( \forall C_n \in \mathbb{C}, \forall M_s \in \mathbb{M} \). Constraint 1.1 tells that utility of MCs and miners should be greater than zero. Constraint 1.2 tells that at least one association between miners and MCs is possible in the FL process. Constraint 1.3 is described in the above Eq. (I) and Eq. (II), respectively.

The problem given in (P1) is challenging since it involves the optimization of utilities as well as FL loss values. We decouple this problem into the optimization of utility and optimization of FL loss and solve them separately. Firstly, the optimization of utility is solved for the Miner-MC Association (MMA) by applying Algorithm 1. Then the FL loss optimization is solved using Stochastic Gradient Descent (SGD) algorithm with DP and blockchain technology as described in Algorithm 2.

### 4 MINER-MC ASSOCIATION

Associations between miners and MCs are formed in coordination with a trusted entity as shown in Fig. 2. To perform the association, MCs and miners submit their computational power and data size, and amount of mining reward to the trusted entity, respectively. Here, computational power refers to the CPU cycles of each MC. Associations between miners and MCs are formally defined as follows:

**Definition 2.** MMA: An association between miner \( M_s \in \mathbb{M} \) and MC \( C_n \in \mathbb{C} \) is a mapping \( g: \mathbb{C} \rightarrow \mathbb{M} \), such that \( g(C_n) = M_s \), \( \forall C_n \in \mathbb{C}, \forall M_s \in \mathbb{M} \).

However, performing MMA in practice is subject to some constraints. To perform the FL process reliably, all the constraints 1.1, 1.2 and 1.3 need to satisfy. Thus, we define a feasible MMA as follows:

**Definition 3.** Feasible MMA: An MMA is feasible, if:

- \( \forall C_n \in \mathbb{C} \), each of its association with miner, \( g(C_n) = M_s \), should satisfy Eq. (11).
- \( \forall C_n \in \mathbb{C} \), there exists at most one association with miner, i.e., \( |\{g(C_n)\}| \leq 1 \).

The above Definition 2 implies that \( g \) is a many-to-one association, i.e., \( g(C_n) \) is not unique. The interpretation of \( g(C_n) = \phi \) implies that for some \( C_n \in \mathbb{C} \), there is no association due to non satisfactorily of constraints. The result of the function determines the successfully associated MC and the association between the miner and MC, e.g., \( K \) and \( \mathbb{Y} \), where

\[
K = \{C_n | y_{n,s} = 1, \forall C_n \in \mathbb{C}, \forall M_s \in \mathbb{M}\}
\]

and

\[
\mathbb{Y} = \{y_{n,s} | y_{n,s} = 1, \forall C_n \in \mathbb{C}, \forall M_s \in \mathbb{M}\}.
\]

### 4.1 Proposed MMA Algorithm

The proposed MMA is based on the deferred acceptance algorithm [38]. We modify the deferred acceptance algorithm in particular due to its feasibility and stability, allowing the proposed MMA algorithm to find a stable association result as described in the following.

In the beginning, miners and MCs select feasible association candidates that meet the criteria, i.e., \( \tau_{n,\text{comp}} + \tau_{n,\text{trans}} \leq \tau_{th} \) as defined in Definition 2 and \( U_{n,s}^{Min} > 0 \), respectively. Miner \( M_s \)'s and MC \( C_n \)'s feasible association candidates are denoted by \( \mathbb{A}_n \) and \( \mathbb{B}_n \), respectively (line 3). We arrange the utility lists of MC, \( C_n \) and miner, \( M_s \), in non increasing order, denoted by \( \Upsilon_n = \text{desc}\{U_{n,s}^{Min} \mid M_s \in \mathbb{B}_n\} \) and \( \Delta_n = \text{desc}\{U_{n,s}^{MC} \mid C_n \in \mathbb{A}_s\} \), respectively (line 4), where \( \text{desc}\{\cdot\} \) is to represent the ordered list in non-increasing order. Miners and MCs then construct their preference lists by arranging the utilities in non-increasing order based on

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**Algorithm 1 Proposed MMA Algorithm**

**Input:** Set of MCs \( \mathbb{C} \), set of miners \( \mathbb{M} \), number of data samples \( D_n \), CPU cycles \( f_n \), cycles per sample \( \beta_n \), threshold \( \tau_{th} \).

1. **Initialization:** \( U_{n,s}^{Min} \) and \( U_{n,s}^{MC} \), \( \forall C_n \in \mathbb{C}, \forall M_s \in \mathbb{M} \).
2. **while** \((|\mathbb{C}| \neq 0)\) **do**
   3. Find \( \mathbb{A}_n = \{C_n | \tau_{n,\text{comp}} + \tau_{n,\text{trans}} \leq \tau_{th}, \forall C_n \in \mathbb{C}\} \) and \( \mathbb{B}_n = \{M_s | U_{n,s}^{Min} > 0, \forall M_s \in \mathbb{M}\} \).
   4. Arrange the utility lists in non increasing order \( \Upsilon_n = \text{desc}\{U_{n,s}^{Min} \mid M_s \in \mathbb{B}_n\} \) and \( \Delta_n = \text{desc}\{U_{n,s}^{MC} \mid C_n \in \mathbb{A}_s\} \).
   5. Create preference lists \( P_n \) and \( P_s \) using \( \Upsilon_n \) and \( \Delta_n \).
   6. \( \mathcal{W}_s \leftarrow \phi \), \( \text{Rej}_s \leftarrow \phi \), \( \text{Rej}_n \leftarrow \phi \), \( \forall C_n \in \mathbb{C}, \forall M_s \in \mathbb{M} \).
   7. **for all** \( C_n \in \mathbb{C} \) **do**
      8. Find the miner \( M_s \) in \( P_n \) with the highest utility, such that the utility of which is \( U_{n,s}^{Min} \).
      9. **if** \( M_s = 0 \) **then**
         10. \( y_{n,s} = 0, \forall M_s \in \mathcal{P}_n \).
      11. **else**
         12. \( C_n \) applies to \( M_s \).
         13. \( M_s \) removes \( C_n \) from \( P_n \) and add it into \( \mathcal{W}_s \).
      14. **end if**
     15. **end for**

   16. **for all** \( M_s \in \mathbb{M} \) **do**
      17. Find the MC, \( C_n \)'s in \( \mathcal{W}_s \) according to \( P_s \) with the highest utility.
      18. \( g(C_n) = M_s, y_{n,s} = 1, \mathbb{Y} \leftarrow \mathbb{Y} \cup \{y_{n,s}\} \).
      19. \( y_{n,s} = 0, \forall C_n \in \mathcal{W}_s, C_n \neq C_n \).
      20. Remove MCs in \( \mathcal{W}_s \) (except \( C_n \)) from \( P_s \) into \( \text{Rej}_s \).
      21. Rejected MCs in \( \text{Rej}_s \) adds \( M_s \) from \( P_n \) into \( \text{Rej}_n \).
      22. \( \mathbb{K} \leftarrow \mathbb{K} \cup \{C_n\}, \mathbb{C} \leftarrow \mathbb{C} - \{C_n\} \).
      23. **end for**

   24. **if** No MCs are rejected **then**
      25. Break
      26. **end if**
     27. **end while**

**Output:** Association between miners and MCs i.e., \( \mathbb{Y} \) and successfully associated MCs i.e., \( \mathbb{K} \).
the feasible candidate list (line 5). The preference lists of miners and MCs present in \( Y_s \) and \( \Delta_s \) are given by \( P_n \) and \( P_s \), respectively. At the start of each association iteration, all waiting lists, \( W_s \) and miner \( M_s \)'s and MC, \( C_n \)'s rejection lists denoted by \( R_j \) and \( R_j \), respectively are initialized as empty lists (line 6) i.e., \( W_s \leftarrow \phi \), \( R_j \leftarrow \phi \), and \( R_j \leftarrow \phi \). The condition of nonexistence of blocking pairs.

Stability: An MMA is stable if it satisfies the Definition 5.

According to the definition of blocking pair, we define the stability of association, implying that the association is unstable. Based on the definition of blocking pair, we define the stability of the MMA in the following.

**Definition 4.** Blocking Pair: For every MC, \( C_n \), a pair \( (C_n, M_s) \) is defined as blocking pair if all the following conditions are satisfy:

- \( C_n \) associated with miner \( M_s \) \( \in \mathcal{M} \).
- There exists another pair \( (C_n, M_s) \), such that \( U_{n,s}^{MC} > U_{n,s}^{MC}, M_s \neq M_s, M_s \in \mathcal{M} \).

The higher utility can be obtained by blocking pairs. This indicates that the MC has a strong desire to change the association, implying that the association is unstable. Based on the definition of blocking pair, we define the stability of the MMA in the following.

**Definition 5.** Stability: An MMA is stable if it satisfies the condition of nonexistence of blocking pairs.

As a result, we can make Lemma 1 concerning the stability of the MMA formed by applying Algorithm 1.
Algorithm 2 Blockchain-based Privacy-preserving FL

Input: Training samples $X_n$, learning rate $\alpha$, batch size $B$, loss function $\mathcal{L}_{n,s}(w^{(n)}) = \frac{1}{B} \sum_{x \in X_n} l(w^{(n)}, x^d)$, number of global iteration $T$, noise scale $\sigma$, Gradient bound $A$.

1. Initialize weights $w^{(0)}$, $w^{(n)} \leftarrow w^{(0)}$
2. for each global iteration $t = 1, 2, \cdots, T$
   
   Local Model Training
   3. for each $C_n \in \mathbb{R}$ do \quad \text{//Perform in parallel}
      4. for each local iteration $i = 1, 2, \cdots, I_n$ do
         5. for each batch $b \in X_n$ do
            6. for each sample $x \in b$ do
               7. Compute Loss $\mathcal{L}_{n,s}(w^{(n,t)})$
               8. Compute gradient $G = \Delta \mathcal{L}_{n,s}(w^{(n,t)})$
               9. Gradient clipped $G' = G / \max (1, ||G||_2 / A)$
               10. end for
               11. Add noise to the gradient $G'' = \frac{1}{B} (\sum_{x \in b} G' + N(0, \sigma^2 A^2))$
               12. Updates local weights $w^{(n,t)} = w^{(n,t)} - \alpha G''$
               13. Upload $w^{(n,t)}$ to associated miner
               14. end for
            15. end for
         16. end for
      17. end for
   18. end for
   19. for each Miner $M_s \in \mathbb{M}$ do
      20. Perform PoW and adds candidate block to blockchain
      21. Broadcast the new block to all miners
     22. end for
   23. Model Aggregation
   24. MCs Update the local weights from the associated miner for $t$-th global iteration
   25. Initialize local weights as $w^{(n,t+1)} = w^{(n,t)}$
   26. end for

Output: Optimal model weights, $W^T$.

... every local iteration (lines 4-15). Each MC in the FL process performs lines 3-16 in parallel for every global iteration.

Miners add the local models from the associated MCs to the blockchain for distributed model weights sharing and provide an immutable framework. Miners verify the received weights and add them to the candidate block (lines 18-19). Miners perform PoW to add candidate block to the blockchain and broadcast the new block to all miners (lines 20-21). For model aggregation, MCs download local model from the associated miners and aggregate the model weights (lines 23-25) on-device in every global iteration. Each MC aggregates $||\mathbb{K}||$ local weights $w^{(n,t)}$ downloaded from its associated miner at $t$-th global iteration as follows:

$$W^{(t+1)} = \sum_{n=1}^{||\mathbb{K}||} p_n w^{(n,t)},$$

where $p_n = \frac{D_n}{D}$ is the weightage given to each MC, $C_n$, $w^{(n,t)}$ is the local model weights at MC, $C_n$ at global iteration $t$. Here $D = \sum_{n=1}^{||\mathbb{K}||} D_n$, and $||\mathbb{K}||$ is the number of MCs in the set $\mathbb{K}$ i.e., number of MCs participated in FL process.

After global model aggregation, each MC updates local weights using the global model for the next iteration (line 25). MC continues training using the updated local model weights and uploads them again to the associated miners for the next iteration. This process repeats in every global iteration (line 2-26). Finally, we obtained the optimal weights, $W^T$ after the FL process that gives the minimum value of loss function as given in Eq. (20).
TABLE 3: System parameters

| Parameters                  | Details |
|-----------------------------|---------|
| S                           | 5       |
| T                           | 10-100  |
| Iterations                  | T = 15, In = 10 |
| Cycle rate of MC $f_n$       | 1-2.6 GHz |
| Cycles per sample $\beta_n$ | $[1, 3] \times 10^4$ |
| Bandwidth $Q$               | 20 MHz |
| Number of allocated PRBs $V$ | 2-8 |
| $\text{SINR}_{n,s}$         | 13-20 dB |
| Transmit powers $\mu_n$     | 1-10 dB |
| $\kappa$                    | $10^{-28}$ |
| Batch size                  | 32      |
| $\varphi$                  | 10 units |
| Model weight size $H$       | 3.776 Kbits |
| Weight parameters           | $\rho = 0.5, \eta = 0.5$ |
| Threshold $\tau_{th}$       | 24 mins |
| Initial learning rate $\alpha$ | 0.01 |

Theorem 2. Communication complexity of Algorithm 2 is $O(T(|K|^2|w|))$.

Proof. We consider the number of model weights sent by every MC for the local model training to analyze the communication complexity of Algorithm 2. Let $|w|$ be the number of weights in a local model at each MC. In FL, the communication of weights during upload (line 13) and download of local model weights (line 23) from the blockchain is $|w|$ and $|K||w|$, respectively [40]. Therefore, communication per MC in each global iteration is $|w|+|K||w|$ i.e., $|K|(1+1)|w|$. Since $|K|$ number of MCs participated in the FL process, the communication required for MCs in each global iteration is $|K||S-1||w|$. Similarly, miners in the blockchain broadcast $|K|$ local models (line 21) and at least $(S-1)|w|$ communication is required to broadcast a local model. Thus, communication per miner in each global iteration is $|K|(S-1)|w|$. Lines 2-26 iterate over the total number of global iterations i.e., $T$. Therefore, overall communication required in $T$ global iteration is $T(|K||S-1||w|) + |K||w|S$ i.e., $T(|K|^2|w|+|K||w|S)$. Generally, the number of MCs participated in the FL process is more than the number of miners i.e., $|K| \geq S$. As a result, the communication complexity of the Algorithm 2 is $O(T(|K|^2|w|))$.

6 Performance Analysis

In this section, we present the performance of our proposed BPFISH framework through simulation analysis. The proposed framework is simulated using Python 3.9 and TensorFlow 2.0 on Windows 10 Home PC with Intel(R) Core(TM) i7-10750H @ 2.60 GHz processor and 16 GB memory.

We evaluate the performance of the proposed BPFISH framework on the Chest X-Ray Images (Pneumonia) dataset consisting of 5856 Chest X-Ray images [41]. The dataset is divided into 5270 training samples and 586 testing samples. Training data samples are partitioned into 5270/$N$ equal parts, with one part given to each MC. The images in the dataset have different resolutions, while our model needs a fixed dimension. Therefore, the images are down-sampled to a fixed resolution of 150 x 150 images. Our model uses a neural network that contains fourteen layers — the first ten layers are convolutional layers and the last four are fully connected layers. We use ReLU activation function in each layer except sigmoid activation function in output layer. The first convolutional layer uses 16 filters of size 3 x 3 with a stride of 1 pixel. The number of filters doubles every two convolution layers. Every two convolution layers are followed by batch normalization and max-pooling layer. The fully-connected layers have 512, 128, 68 and 1 neurons. The ‘dropout’ [42] rates of 0.7, 0.5 and 0.3 are used in the first three fully-connected layers to prevent overfitting. For the optimization of the convolutional neural network, we set the initial learning rate to 0.01 and reduced it by a factor of 0.3 once the loss stopped decreasing for two iterations.

In this experiment, cycle rate of each MC is set between 1 and 2.6 GHz, and cycles per sample $\beta_n$ are chosen uniformly from $[1, 3] \times 10^4$ [39]. Unless otherwise stated, we set coefficient $\kappa$ to $10^{-28}$ [39], transmit powers $\mu_n$ from 1 to 10 dB [39], model size $H = 3.776$ Kbits, bandwidth $Q = 20$ MHz and batch size $B = 32$. Number of allocated PRBs $V$ are chosen from 1 to 10 and $\text{SINR}_{n,s}$ are chosen from 13 to 20 dB. The common parameters used in the experiment are shown in Table 3.

6.1 Objective Function Analysis

We plot the value of F as a function of global iteration, shown in Fig. 3. We conduct the experiments by setting $N = 500$, $S = 50$, $T = 15$, $I_n = 10$, $\delta = 10^{-5}$, $\rho = 0.5$ and $\eta = 0.5$. To get a fair comparison, we apply random association for BlockFL [9] framework in which MCs select miners randomly. From the result, we can conclude that the proposed BPFISH is better compared to BlockFL and almost equal to non-private framework where non-private is the BPFISH without DP i.e., without adding noise to the gradient. The proposed BPFISH achieves 11.18% better results on an average. The reason for the better performance of BPFISH compared to BlockFL is that associations between miners and MCs in BPFISH are done more accurately using MMA algorithm in the proposed framework. The result of BPFISH is almost equal to that of non-private because both BPFISH and non-private framework used MMA algorithm and the difference in the value of loss function is small.

6.2 Accuracy and Loss Comparison

Fig. 4 compares the test accuracy and the value of loss function for 10 MCs with BlockFL and non-private framework using noise level $\sigma = 0.25$ and gradient bound $\delta = 8$. As we can see from Fig. 4, the test accuracy increases as compared to BlockFL and the decrease in accuracy for private BPFISH as compared to the non-private framework is small and has
little effect on the accuracy. In comparison to BlockFL, the proposed BPFISH obtains 10% higher accuracy on average. As we can see from Fig. 4, the value of the loss function decrease as compared to BlockFL but is higher than the non-private. The increase in the value of loss for private BPFISH as compared to the non-private framework is small and has little effect on the value of the loss.

Table 4 shows the best test accuracy obtained when different noise levels are applied. As observed from the table, the proposed BPFISH achieved accuracy comparable to that of non-private collaborative learning framework when we added small noise. However, large noise affects test accuracy severely. Therefore, it is important to find an acceptable noise level to achieve strong DP without compromising accuracy.

### 6.3 Computation Time Analysis

Fig. 5 shows computational time complexity analysis of the proposed BPFISH in comparison with BlockFL. For comparing computational time complexity, we set the number of MCs from 10 to 100 and the number of miners to 5. As we can conclude from the figure, the time taken by the BPFISH is increasing with the increased number of MCs. The reason is that the number of local models added to the blockchain increases as the number of MCs increases. The time taken of BPFISH is higher as compared to BlockFL because of the association formed by the MMA algorithm and the addition of noise in gradient calculation during local model training to ensure DP. However, the time taken of BPFISH is almost equal to the time taken of non-private because the addition of noise takes less time.

### 6.4 Effects of Different Privacy Parameters

In Fig. 6, we set $N = 10$, $S = 5$, $T = 15$, $I_n = 10$ and $\delta = 10^{-5}$. We take various noise levels such as $\sigma = 0.25$, $\sigma = 0.6$ and $\sigma = 1.0$ to illustrate the test accuracy and the value of loss function using gradient bound $A = 8$ as shown in Figs. 6a and 6b. We plot the test accuracy on various noise levels as a function of global iteration as shown in Fig 6a. As seen from the figure, the accuracy increases as the noise level decreases and attained the highest accuracy when the noise level is set to $\sigma = 0.25$. Fig. 6b compares the value of test set loss on various noise levels as a function of global iteration. We can see from the figure that the value of the loss function decreases as the noise level decreases and attained the best value when the noise level is set to $\sigma = 0.25$.

In Figs. 6c and 6d, we set different gradient bounds such as $A = 1$, $A = 4$ and $A = 8$ to illustrate the results of the test accuracy and the value of loss function using noise level $\sigma = 0.25$. Limiting the gradient bound destroys the true gradient value. Gradient bound destroys the true direction of gradient estimate if gradient bound is too small whereas a large gradient bound does not destroy true gradient. Therefore the clipped gradient becomes closer to true gradient estimates. As we can see from Fig. 6c, the test accuracy increases when the gradient bound increases from 1 to 8 and attained the best accuracy value when $A = 8$. Fig. 6d shows that the value of the test set loss function decreases when gradient bound increases from 1 to 8 and convergence performance of the proposed BPFISH obtained the best value when $A = 8$. We cannot compare BlockFL with BPFISH on various privacy parameters because BlockFL did not consider privacy parameters in their model.

### 7 Conclusion

In this paper, we have focused on decentralized privacy-preserving FL framework for learning effective models on healthcare data stored at different MCs. We have proposed a joint optimization problem as maximization of utility and minimization of FL loss function altogether in smart healthcare domain. We introduced a stable association algorithm to maximize the utility of miners and MCs in polynomial time complexity. Moreover, we leveraged blockchain technology to enable tempered resistant and decentralized local model weights sharing. Through simulation analysis using Chest X-Ray Images (Pneumonia) dataset, we have verified
Fig. 6: a) Effect of noise levels on test accuracy, b) Effect of noise levels on value of loss function, c) Effect of gradient bound on test accuracy, d) Effect of gradient bound on value of loss function.

Figures 7 and 8: A hardware-accelerated federated learning system for medical diagnosis.

Figures 9 and 10: A comparative analysis of various federated learning algorithms.

Table 1: Performance comparison of different federated learning techniques.

The effectiveness of the proposed BPFISH framework on various privacy parameters. The simulation results demonstrated that BPFISH achieves high accuracy under a strong privacy protection level. Performance study shows that our proposed BPFISH framework outperforms state-of-the-art methods, achieving 11.18% better results on an average.

In the future, we would like to consider other privacy-preserving techniques such as secure multi-party computation or homomorphic encryption. We would also like to work on energy efficient blockchain-based FL framework to reduce energy consumption during the FL process. In addition, we will consider state-of-the-art neural network architectures and different data augmentation techniques to observe the effects of privacy parameters on accuracy.

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