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Modified Artificial Bee Colony Based Feature Optimized Federated Learning for Heart Disease Diagnosis in Healthcare

Muhammad Mateen Yaqoob [1,*], Muhammad Nazir [1], Abdullah Yousafzai [2], Muhammad Amir Khan [3,*], Asad Ali Shaikh [4], Abeer D. Algarni [5] and Hela Elmannai [5]

1 Department of Computer Science, HITEC University Taxila, Taxila 47080, Pakistan
2 Department of Computer Science, University of Central Punjab, Lahore 54782, Pakistan
3 Department of Computer Science, COMSATS University Islamabad Abbottabad Campus, Abbottabad 22060, Pakistan
4 Computer Science Department, Faculty of Computer Sciences, ILMA University, Karachi 75190, Pakistan
5 Department of Information Technology, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, P.O. Box 84428, Riyadh 11671, Saudi Arabia
* Correspondence: mateenyaqoob@gmail.com (M.M.Y.); amirkhan@cuiatd.edu.pk (M.A.K.)

Abstract: Heart disease is one of the lethal diseases causing millions of fatalities every year. The Internet of Medical Things (IoMT) based healthcare effectively enables a reduction in death rate by early diagnosis and detection of disease. The biomedical data collected using IoMT contains personalized information about the patient and this data has serious privacy concerns. To overcome data privacy issues, several data protection laws are proposed internationally. These privacy laws created a huge problem for techniques used in traditional machine learning. We propose a framework based on federated matched averaging with a modified Artificial Bee Colony (M-ABC) optimization algorithm to overcome privacy issues and to improve the diagnosis method for the prediction of heart disease in this paper. The proposed technique improves the prediction accuracy, classification error, and communication efficiency as compared to the state-of-the-art federated learning algorithms on the real-world heart disease dataset.

Keywords: privacy aware; federated learning; healthcare; heart disease prediction; feature selection

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1. Introduction

Advancement in technologies like the Internet of Things (IoT) and wearable sensing devices enables the storage of records related to the health parameters of patients or people. The IoT in the healthcare environment has led to a new research domain of the Internet of Medical Things (IoMT). The IoMT-based solutions integrated with the healthcare system can enhance care services, and quality of life, and enable cost-effective solutions [1]. Biomedical data related to people like medical records, images, physiological signals, and many other forms are gathered using these technologies. The volume of this biomedical data is huge as it can easily be gathered from a huge number of people using modern technologies [2]. Wearable sensing devices, like smartwatches, wristbands, and many others, enable early detection and warnings of several diseases. The increasing trend in wearable devices helps in efficient data collection and the early detection of diseases. Healthcare is a system that is formed with the intention to prevent, diagnose, and treat various health-related problems in humans. As the advancement and development of healthcare-related technologies take place, data in huge amounts is available from various sources. The development of an efficient healthcare infrastructure system is one of the challenging goals of current modern society.

One of the primary health concerns faced worldwide is cardiovascular disease. According to the World Health Organization (WHO), approximately 18 million deaths occur yearly worldwide due to heart or cardiovascular disease [3]. Heart disease or cardiovascular disease (CVD) is based on various conditions that impact the human heart. Many factors cause heart disease including personal and functional behavior and genetic predisposition. Numerous risk factors include smoking, excessive consumption of caffeine, and alcohol, inactivity, stress, and physical fitness, as high blood pressure, obesity, pre-existing heart disease, and high cholesterol can also be a reason for heart disease. CVD is a serious condition that affects the function of the heart and causes problems such as strokes and reduced blood vessel function. Patients with heart disease do not reach the advanced stages of the disease and it is too late for the damage to be repaired. Early and accurate treatment of heart disease plays a significant role in avoiding death. Machine learning (ML)-based techniques provide a way forward for effective diagnosis of heart disease. A lot of research has been performed and various machine learning models have been used to make classifications and predictions for diagnosing heart disease. A hybrid technique based on random forest and a linear model is suggested in [4] to improve the prediction accuracy of heart disease. For the identification of heart disease in the E-healthcare system and to resolve the problem of feature selection, a system is proposed in [5] based on classification algorithms.

Machine learning (ML) models are frequently trained on sufficient user data in healthcare to track a patient's health status. Regrettably, today's healthcare faces two critical challenges. For starters, real data is frequently found as isolated islands. Even though there is a large amount of data in various organizations, sharing this data is impossible due to concerns about privacy and security. As a result, training powerful models with valuable data is difficult. In addition, the European Union through General Data Protection Regulation (GDPR) [6], China by China through China Cyber Security Law [7], and the United States with the California Consumer Privacy Act (CCPA) of 2018 [8], have recently enforced the protection of user data privacy through these regulatory procedures. Therefore, it is not possible to get huge amounts of user data in real-time healthcare applications. To overcome these challenges, federated learning is proposed recently by Google [9,10]. Recently, some new meta-heuristics techniques are proposed such as monarch butterfly optimization (MBO) [11], slime mold algorithm (SMA) [12], moth search algorithm (MSA) [13], hunger games search (HGS) [14], Runge Kutta method (RUN) [15], and Harris hawks optimization (HHO) [16], to further minimize the fitness function by keeping the size of the population unchanged, to improve the weight adaption rate, to enhance the local searching method, to optimize the dynamic fitness function computation, to avoid the local optimal solutions and increase convergence speed, and to cooperatively search for the optimal local solution, respectively. Several security and privacy challenges in an IoT environment with their use cases are outlined in [17,18].

The aim of federated learning is a privacy-aware collaborative learning mechanism of a shared model by keeping the data on the device. Hence, the users of federated learning will experience personalized machine learning and overcome privacy issues as well. Motivated by these highlighted issues of privacy in healthcare, in this paper, we propose a federated matched averaging with a Modified Artificial Bee Colony (M-ABC) optimization-based framework to overcome privacy issues and to improve the diagnosis method for the prediction of heart disease. The objective of our proposed framework is to develop an overall privacy-aware decentralized learning method for heart disease diagnosis which improves the feature optimization at the client end and the communication efficient global cloud model. We chose M-ABC optimizer because it is highly flexible and user-friendly, uses fewer control parameters than other algorithms such as genetic algorithm (GA) and particle swarm optimization (PSO), is easily hybrid with other optimization algorithms, and possesses strong robustness and a fast convergence rate. In addition, the M-ABC method can also accommodate a random cost objective function. This paper's contributions are as follows:

- We design and propose a privacy-aware framework for the prediction of heart disease in healthcare using an improved federated learning algorithm for cloud and user sites.

- M-ABC optimizer is proposed at the client end for the optimal feature selection of heart disease data. This optimizer enables improved accuracy of prediction and fewer classification errors.
- Federated matched averaging (FedMA)-based algorithm is explored for constructing a privacy-aware framework for a global cloud model.
- We validated and tested the proposed framework with a real-world heart disease dataset. Evaluation of the performance of the proposed framework in terms of prediction accuracy, classification error, and communication efficiency is performed with state-of-the-art federated learning algorithms.

The rest of the paper is organized as follows. Section 2 presents the review of related work. Section 3 explains the materials and the proposed framework. Section 4 is related to the evaluation of performance and results. The last section, Section 5, provides a conclusion and future work of the paper.

2. Literature Review

Privacy and security of data, and data in an isolated form are the two big challenges faced by the current machine learning research domain. Techniques based on machine learning require centralized training data for the model to be trained. Regulations are put into practice for data privacy throughout the world [6–8]. Hence data privacy is a big challenge for traditional machine learning techniques. Federated learning initially proposed by Google, federated stochastic gradient (FedSGD), and averaging (FedAvg) based algorithm brought a ray of hope to overcome these challenges [9]. A technique constructed on federated learning is proposed in [10] to overcome the issue of data isolation and privacy. They proposed a comprehensive framework based on federated learning to tackle the issues related to data security in the traditional artificial intelligence domain. Their proposed solution is categorized into two approaches i.e., horizontal, and vertical federated learning.

Technical aspects such as hardware, platforms, software, protocol, enabling technologies, and other features of the data privacy of federated learning are discussed by the authors in [19]. The authors discussed some of the optimization techniques for federated learning in their article by highlighting their features and performance. They also outlined some of the market implications of federated learning in order to anticipate them. Additionally, some of the advantages, issues, and challenges which refer to the design and deployment of federated learning are presented by the authors. In [20], the authors provide insight into the various machine learning deployment architectures such as centralized, distributed, and federated learning. They have outlined the evolution of machine learning architectures with comprehensive deliberation. Moreover, application areas for federated learning such as the IoT systems, healthcare, Gboard App, edge computing, cybersecurity, and many others were suggested by them.

In the paper [21], the authors developed a model based on federated learning for the prediction of hospitalization of health-related disease patients. They used electronic health records (EHR) data distributed amongst numerous sources or agents. The authors proposed the cluster Primal Dual Splitting (cPDS) algorithm to overcome the problem of large-scale sparse Support Vector Machine (sSVM) using a federated learning technique. Their proposed technique achieves analogous prediction accuracy of the classifier. Authors in [22], tested and evaluated the three federated learning-based algorithms on the MNIST dataset and used a Bayesian correlated t-test. According to their evaluation, FedAvg outperforms CO-OP and FSVRG algorithms when the uploads by clients are limited to 10,000. They have used balanced data distribution in which the clients have the same amount of data. An optimized version of FedAvg is proposed by authors in [23], in which they intend to enhance the accuracy and convergence rate of the state-of-the-art federated learning algorithm. They proposed the Federated Match Averaging (FedMA) algorithm based on the layer-wise federated learning algorithm to adopt Bayesian nonparameterized methods for heterogeneous data. Their proposed FedMA performs better than FedAvg in terms of convergence, and accuracy, and reduces the communication size. To optimize the convergence speed of federated learning, the authors in [24] proposed a fast-convergent algorithm that achieves intelligent selection of each device at every round of the training model. Their algorithm utilizes precise and effective approximation for communication of a near-optimal distribution of device selection to improve the convergence rate.

Authors in [25] have proposed an algorithm that assigns the weights according to the contribution of each class to the local models. The machine learning based algorithms can play their part in the detection of COVID-19 using a dataset of chest X-rays of the patients. A Federated learning-based technique is proposed by the authors in [26] to detect COVID-19 cases with improved model prediction accuracy and loss as compared with the traditional machine learning algorithms. For their work, the authors utilized two datasets which are descriptive datasets with COVID-19-infected cases from Wuhan and patients' chest x-ray radiography images with COVID-19, Pneumonia, and normal images. To resolve the issue of data privacy for the IoMT-based healthcare system, authors in [27] proposed a blockchain-based solution using federated learning. Their proposed algorithm is a hybrid approach based on federated learning and maximation of the Gaussian Mixture Model (FL-EM-GMM) and uses blockchain for model verification, and homomorphic encryption to overcome user data privacy issues. Their proposed method shows that the IoMT data training can be completed using privacy locally to prevent data leakage.

Traditionally, the cloud/server collects sensed data from IoMT devices and then performs the prediction of that sensed data. To develop a privacy-aware heart rate prediction technique, authors in [28] proposed a Bayesian inference federated learning with autoregression with exogenous variable (ARX) model. This FedARX method accomplishes accurate and robust heart rate prediction as compared with the traditional machine learning models. To effectively manage and optimize the computation offloading for IoT-based applications, authors in [29] proposed a meta-heuristic Artificial Bee Colony (ABC) optimization. Their technique intelligently manages the computation workload for resource-constrained IoT applications. Authors in [30] proposed the ABC algorithm for the optimization of numerical problems in a computing environment. For lightweight prediction of computational workload in an IoT-assisted Edge environment, authors in [31] proposed an artificial neural network-based framework. Their proposed multi-objective framework enhances workload management for computationally intensive applications. A long short-term memory (LSTM) based prediction of computational workload technique for offloading in IoT-assisted Mobile Edge Computing is proposed in [32]. A detailed survey of intelligent offloading of computational workload is prepared by authors in [33]. An extensive survey of open-source datasets for the COVID-19 disease is performed by authors in [34]. They categorized the datasets into four classes as the identification of COVID-19 from X-ray images, CT scans, and cough sounds, as well as transmission estimation, case reporting, and diagnosis from demographic, epidemiological, and mobility data.

Other methods were also introduced in the literature for heart disease prediction, such as a hybrid approach of linear discriminant analysis with the modified ant lion optimization for classification [35], a combination of Fuzzy logic algorithm and gradient boosting decision tree (GBDT) [36], a technique based on modified salp swarm optimization (MSSO) and an adaptive neuro-fuzzy inference system (ANFIS) [37], and multi-cost objective function [38]. Heart disease monitoring and prediction based on a hybrid classifier and deep learning centered modified neural network for IoT-assisted healthcare is proposed in [39–42]. Moreover, various methods are proposed for improving the classification error and accuracy, such as the higher-order Boltzmann-based model [43], performance evaluation of classifiers and optimizers for heart disease prediction [44], localization using two-stage classifiers [45], a hybrid classifier based on random forest and naïve bayes [46], hybrid recommender system [47], based on genetic algorithm and hybrid classifiers using the ensembled model with a majority voting technique [48], and Artificial intelligence (AI) based heart disease detection using electrocardiogram (ECG) signals [49].

3. Materials and Methods

A healthcare system built on the Internet of Medical Things (IoMT) makes it possible to collect patient data in real-time for the purposes of early disease diagnosis and treatment. Patients who are diagnosed and treated early have a lower risk of developing heart disease. With the emerging international privacy laws like GDPR [6], China Cyber Security Law [7], and CCPA [8], the traditional machine learning based techniques are unable to overcome the privacy issues as they require user data to be processed for model generation and diagnosis of disease. The IoMT-based sensing devices gather heart disease information from the patients before and after the initiation of heart disease. When it comes to the healthcare system, user data is impossible to share due to privacy and security issues. A federated learning framework for heart disease prediction in the healthcare system is proposed in this paper, which overcomes privacy issues and provides effective heart disease prediction in a privacy-aware healthcare system. The symbols used throughout the study are described in Table 1 below.

Table 1. Description of used symbols.

Used Symbol	Description
X_{ni}	Initialization vector for client sites
$\mathrm{C_{nie}}$	Candidate solution by employed bee
X_{pi}	Random local solution
$\mathrm{F_n}$	Fitness function
$\mathrm{C_{nio}}$	Onlooker bee's candidate solution
$\mathrm{C_{nis}}$	Candidate solution of scout bee
w_{jl}	l^{th} neuron studied on the dataset j
θ_i	Mean Gaussian
$c\ (w_{jl}, \theta_i)$	Similarity function
K	Number of client sites listed as k
B	Size of local minibatch
η	Learning rate
E	Number of local epochs
ω_o	Initial global cloud model
ω_k	Model of kth client

3.1. Dataset Description

We train and test our proposed framework on the heart disease dataset of UCI Cleveland. This dataset contains 303 records and 76 attributes. A detailed description of the dataset is illustrated in Table 2 below. This table shows the numerous risks of heart disease, their description, and the encoded values of these risks. The encoded values are utilized as the input to our proposed framework.

Table 2. Detailed Description of Dataset.

S#	Risk Name	Description	Encoded Values
1	Age	Age in years	>79 = 2, 61–79 = 1, 51–60 = 0, 35–50 = −1, <35 = −2
2	Sex	Female and Male	Female = 0, Male = 1
3	Blood pressure	In mmHg	Above 139 mmHg = High = 1 120–139 mmHg = Normal = 0 Below 120 mmHg = Low = −1

Table 2. *Cont.*

S#	Risk Name	Description	Encoded Values
4	Serum cholesterol	In mg/dL	>240 mg/dL = High = 1 200–239 mg/dL = Normal = 0 <200 mg/dL = Low = −1
5	Hereditary	Family members diagnosed with heart disease	Yes = 1 No = 0
6	Alcohol	Yes or No	Yes = 1 No = 0
7	Diabetes	Yes or No	Yes = 1 No = 0
8	Resting electrocardiographic	Normal, ST T, or Hypertrophy	Hypertrophy = 2 ST T = 1 Normal = 0
9	Angina induced by exercise	Yes or No	Yes = 1 No = 0
10	Fasting blood sugar	>120 mg/dL	True = 1 False = 0
11	Status of heart (thallium scan)	Reversible defect, Normal, fixed defect	Reversible defect = 7, Normal = 3, fixed defect = 6
12	Smoke	Yes or No	Yes = 1 No = 0
13	Diet	Good, Normal, Poor	Good = 1, Normal = 0, Poor = −1
14	Heart Disease	Yes or No	Yes = 1, No = 0

3.2. Optimal Solution Selection Using M-ABC Algorithm for IoMT Clients

An algorithm based on swarm intelligence, known as the Modified Artificial Bee Colony (M-ABC), has been developed and proposed in [50]. The scout bee, onlooker bee, and employed bee all appear in the M-ABC algorithm. Scout bees are responsible for exploring new food sources, while the onlooker bee chooses a food source based on the dance of an employed bee. As a result, the bees employed are protected from exploitation because they are linked to their food source. Neither the scout bees nor the onlooker bees are associated with any particular food source. They are referred to as "unemployed bees" as a result. The main aim of the fitness function is the optimal selection of classification error and communication efficiency of the received models from the IoMT client sites. The objective of the fitness function is to minimize the classification error and number of rounds consumed to achieve higher accuracy. Algorithm 1 below presents the generalized working of the M-ABC optimizer.

Algorithm 1: Working of Optimizer M-ABC Algorithm

1: IoMT sites initialization phase using Equation (1)
2: **Do Repeat**
3: Employed bees for new solution using Equation (2)
4: Onlooker bees candidate solution using Equations (3) and (4)
5: Phase of Scout bees' candidate solution using Equation (5)
6: Memorize the best solution you came up with
7: **until** maximum number of cycles reached

3.2.1. Initialization Phase

All the population of healthcare sites is initiated with vector X_{ni}. The initialization of IoMT client sites is done using the below Equation (1) with i ranges from 1 to NP:

$$X_{ni} = l_i + [(rand\ (-1{,}1) + 2i - 1) * \text{x}\ (u_i - l_i)]/2\text{NP} \tag{1}$$

The u_i and l_i represent the upper and lower bounds of the parameters, respectively.

3.2.2. Solution Search by Employed Bee

The employed bee scours the neighborhood for new solutions. Using this Equation (2), a new answer can be found. The function τ_{ni} produces a random number in the range of -1 and 1, and X_{pi} is a local random solution. The fitness of the new candidate solution by employed bee C_{nie} is calculated and in case the fitness is high then the solution is memorized. The candidate solution using the below equation of employed bee helps in obtaining an improved feature selection for IoMT client sites.

$$C_{nie} = \begin{cases} \tau_{ni} + \text{rand}\left(X_{ni}, -X_{pi}\right);\ \text{if } i = i', \\ X_{pi},\ \text{if } i \neq i'. \end{cases} \tag{2}$$

3.2.3. Candidate Solution by Onlooker Bee

Employed bees share their candidate solution with onlooker bee and after that, the onlooker bees probabilistically choose their candidate solution C_{nio} using the below Equation (3). To further improve the quality of the candidate solution, the C_{nio} by onlooker bee is utilized as represented by the below equation.

$$C_{nio} = \frac{F_{ni}\ (X_n)}{\sum_{i=1}^{m}(F_m)(X_n)} \tag{3}$$

The fitness function F_n is computed using the below equation.

$$F_n = \begin{cases} \frac{1}{1+F_{obj}},\ \text{if } F_{obj} \geq 0, \\ 1 + \text{abs}(F_{obj}),\ \text{if } F_{obj} < 0. \end{cases} \tag{4}$$

3.2.4. Scout Bee Phase

The scout bee in M-ABC ensures that the new solution is explored, and it chooses a candidate solution C_{nis} using the firefly algorithm as depicted in below Equation (5), where C_{nis0} is the initial solution. If an employed bee fails to improve its solution within a predetermined time frame, it becomes a scout bee.

$$C_{nis} = C_{nis} + e^{-{r_i}^2}(C_{nis0} - C_{nis}) + (rand\ (0,1) - 0.5) \tag{5}$$

3.2.5. Data Collection Using IoMT Clients

The IoMT devices are initially used to collect patient health information, and the connected devices communicate with one another when sending patient data. IoMT devices capture medical information from the patient's body after they are implanted, including the heart rate, blood pressure, glucose level, cholesterol, and pulse rate. Using the proposed M-ABC technique, these details are locally optimized within an IoMT local healthcare site, after which the local model from each IoMT local healthcare site is transferred to the global cloud. Patient data from the UCI repository is also used to assess the efficacy of the proposed technique.

3.3. Design of Proposed Framework

We briefly describe our proposed system model and technique in this section. Additionally, in this section, we provide a comprehensive overview of the federated matched averaging (FedMA) algorithm and M-ABC-based optimization for optimal feature selection and classification. The proposed system model is illustrated in Figure 1 below. We assume that there are five healthcare client sites and one cloud server, this setting can be scaled up for generalization. Our proposed framework consists of heart disease data collection devices that are located inside a healthcare site. Initially, a global model is disseminated by the global cloud towards the healthcare sites, after receiving the model from the cloud, the sites perform feature selection and classification using an M-ABC optimizer, after that perform training on the local data using the received model and then the healthcare sites upload their local model updates to the cloud. On receiving multiple updates of local models, a new global model is computed using FedMA, and this new model is then disseminated among the healthcare sites. In this way, all the training data remains on the device and the privacy concerns are overcome with increased prediction accuracy and less classification errors. The working of the proposed framework is illustrated in Algorithm 2.

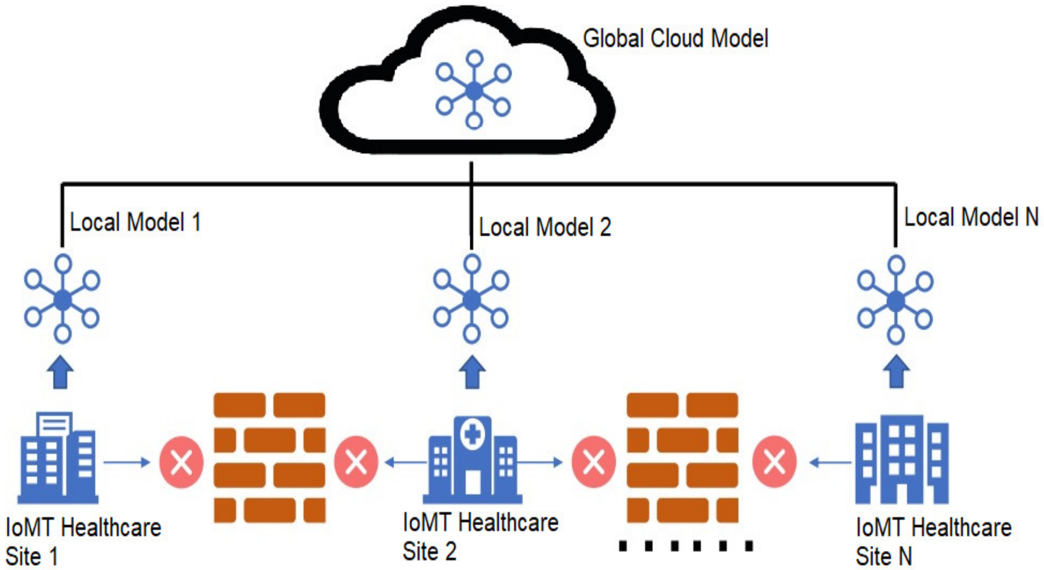

Figure 1. Overview of proposed framework.

FedMA calculates the Maximum Aposteriori Estimate (MAE) of a Bayesian nonparametric model using the Beta Bernoulli process (BBP) using equation 6 below. The w_{jl} be l^{th} neuron studied on the dataset j and $c(..)$ be an appropriate function of similarity. In case the client data sizes are imbalanced, then weighted averaging can be used instead of uniform. The similarity function $c\ (w_{jl}, \theta_i)$ is the subsequent posterior probability of j^{th} client neuron l generated from a Gaussian with mean θ_i. Due to the nonparametric aspect, their BBP-MAP inference approach allows a number of neurons in the federated model to mildly grow in comparison to the client model sizes. This matched averaging-based global cloud model helps in reducing the communication size to reach the target accuracy and the overall convergence rate of the model is also improved.

$$\min_{\{\pi^j_{li}\}} \sum_{\mathrm{i}=1}^{\mathrm{L}} \sum_{j,l} \min_{\theta_{\mathrm{i}}} \pi^j_{l\mathrm{i}}.c(w_{jl})\mathrm{s.t.} \sum_{\mathrm{i}} \pi^j_{l\mathrm{i}} = 1 \forall j, l;\ \sum_{l} \pi^j_{li} = 1 \forall\ \mathrm{i},\ j \tag{6}$$

Algorithm 2: Learning method of proposed framework for healthcare. The K number of users is listed as k, local minibatch size is shown by β, learning rate is represented by η, and local epochs are represented using E.

Input: Data from various healthcare users $\{U_1, U_2, - - -, U_N\}$
Output: Privacy-aware personalized model for each IoMT user ω_k
// Processing at the global cloud end:
1: Initialize a global cloud model ω_o
2: **for** every round $r = 1, 2, \ldots$ **do**
(i) $r \leftarrow 2190$ *maximum of* $(K, 1)$
(ii) $S_t \leftarrow$ (r is random number of clients)
3: **for** every client $k \in S_r$ **do in parallel**
(i) $\left\{\prod {}_{r}^{k}\right\} \leftarrow$ BBP-MAP ($\{k, C_n, \omega_r\}$)//call BBP-MAE to solve Equation (6)
(ii) $\omega_k \leftarrow \frac{1}{K} \sum_{k=1}^{K} \omega_r^k \prod_r^k$
(iii) $\omega_{r+1} \leftarrow \prod {}_{r}^{k} \omega_{k/}$/permutate the next weights
4: Distribute ω_k among all users
5: Repeat above steps with every evolving user data
// Working at Client End (k, ω)**:**
1: **for each** client in k
(i) $\beta \leftarrow$ (fragment each P_k to groups of β size)
(ii) Compute candidate solution C_n using M-ABC Optimizer using Equations (2), (3), and (5)
2: **for** every local round $i = 1 \ldots E$ **do**
(i) **for** group $b \in \beta$ **do**
(a) $\omega \leftarrow \omega - \eta \nabla l\ (\omega; b)$
3: return ω to the cloud

The proposed framework is devised for both client and cloud ends. This proposed framework is implemented into three stages as described below:

1. Initial Phase: Initially, all the connected IoMT healthcare sites obtain an initial global model ω_o from the cloud and are initiated with vector X_{ni}.
2. Working at Cloud End: To retrieve the weights ω_k of the federated model, the cloud first collects only the weights from the clients and performs matched averaging. The clients then train their local model using their local data while the matching federated is kept frozen once the cloud broadcasts these weights to them. Then, we repeat this process up until the final round of communication.
3. Working at IoMT Client Sites: After data collection using IoMT devices, the collected data is fragmented into local minibatch of size β. The candidate optimal solution C_n for each β is computed using the M-ABC optimizer and the weights of the local computed solution from every IoMT client site are returned to the global cloud.

4. Experimental Evaluation and Results

In this section, we will discuss the simulation process of the proposed framework, simulation environment, and experimental settings for analyzing the efficiency of the proposed framework as a whole and contrast its performance with that of the standard federated learning models.

4.1. Experimental Setup

To evaluate the performance of the proposed framework, we conducted the simulation compromising of 4000 rounds of communication using a python environment using *PyTorch* machine learning libraries on Intel ® Core ™ i7-8550 @ 4GHz system and all the experimentation is performed in this simulated environment. Table 3 below describes the simulation parameters and settings utilized for the experiments.

Table 3. Simulation parameters and settings.

Parameter	Value
Simulation environment	Python
Dataset utilized	UCI Cleveland
Number of communication rounds	4000
Local epochs	{10, 20, 40, 80, 100, 120, 140, 160}
Volume of communication (in GBs)	{0.2, 0.4, 0.6, 0.8, 1.0, 1.2, 1.4, 1.6}
Number of client nodes	5

4.2. Results and Discussion

The performance of the proposed framework for heart disease in terms of prediction accuracy, time to reach the accuracy, communication efficiency, and effect of local epoch on accuracy are measured and compared with state-of-the-art FedSGD, FedAvg, FedMA, and PSO optimizer with FedMA techniques. Figure 2 below shows the comparison of convergence rate with prediction accuracy on the heart disease dataset. The proposed framework achieves 92.89% accuracy on 3000 rounds of communication which is higher than the state-of-the-art FL and FedMA with PSO algorithms. Because our proposed framework utilizes the M-ABC optimizer for healthcare user sites and FedMA for the cloud model, this enables the model to achieve better accuracy faster than existing federated learning algorithms. In FedSGD, FedAvg, and FedMA, the cloud model tends to perform the simple gradient, averaging, and matched averaging, respectively, but their client model does not have any algorithm for feature selection and classification which results in higher convergence time for the cloud model. In PSO with FedMA, the learning rate is improved but the classification and feature selection consume higher convergence, whereas in our proposed framework the learning rate tends to increase faster after every round as compared with FedAvg and FedMA. Therefore, our proposed framework achieves higher accuracy in a lesser number of rounds.

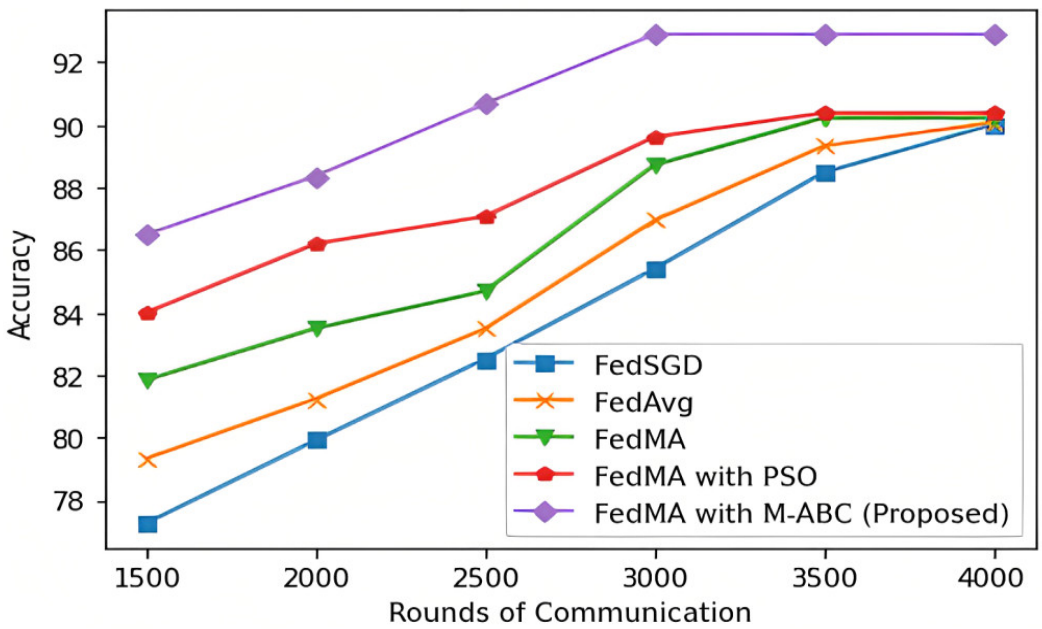

Figure 2. Comparison of communication efficiency.

We have conducted experiments on the effect of local epochs on the accuracy as compared to state-of-the-art FedAvg and FedMA algorithms on the heart disease dataset. We considered the local epochs E to be as {10, 20, 40, 80, 100, 120, 140, 160}. For every E, we evaluated the accuracy test of the proposed framework, FedAvg, and FedMA. The result is illustrated in Figure 3 below. We observed that training our proposed framework for a longer time favors the convergence rate because our proposed framework returns a better global model on the local model with higher model quality as our proposed technique utilizes a modified-ABC optimizer. For FedSGD, FedAvg and FedMA, both did not employ any optimizer, so their accuracy tends to deteriorate as they train for a longer period but in the case of PSO with FedMA, the accuracy remains constant after 80 local epochs which is due to the slow convergence rate of PSO algorithm. This result depicts that user sites can use our proposed framework to continue training their model's local users for as long as they wish.

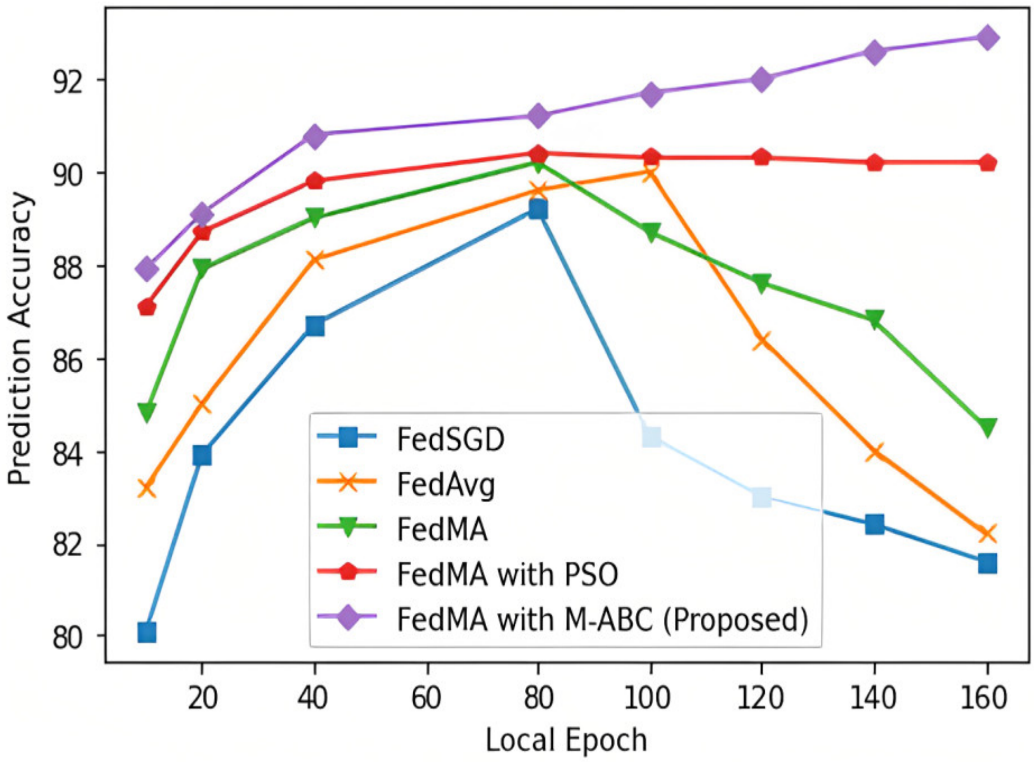

Figure 3. Effect of local epoch on accuracy.

We have evaluated and compared the performance of standard FL, PSO with FedMA and our proposed technique for the effect of prediction accuracy on the volume of communication. For this evaluation, we varied the volume of communication (in Gigabytes) as {0.2, 0.4, 0.6, 0.8, 1.0, 1.2, 1.4, 1.6} and recorded the prediction accuracy of each technique as shown in Figure 4 above. It is observed from the results that the proposed technique achieves better accuracy at both low and high volumes of communication as compared to standard FL and PSO with FedMA. Moreover, in Figure 5 below a comparison of the size of communication used to reach 90% prediction accuracy is illustrated. The proposed technique uses 20% less communication size (in GB) as compared to existing federated learning algorithms.

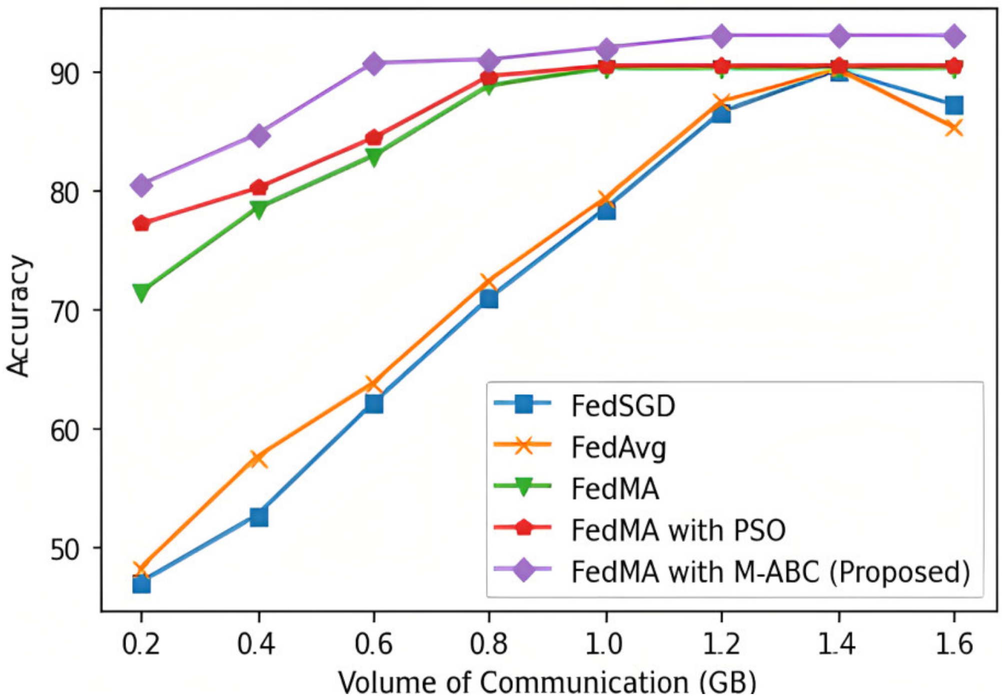

Figure 4. Effect of Accuracy on Amount of Communication.

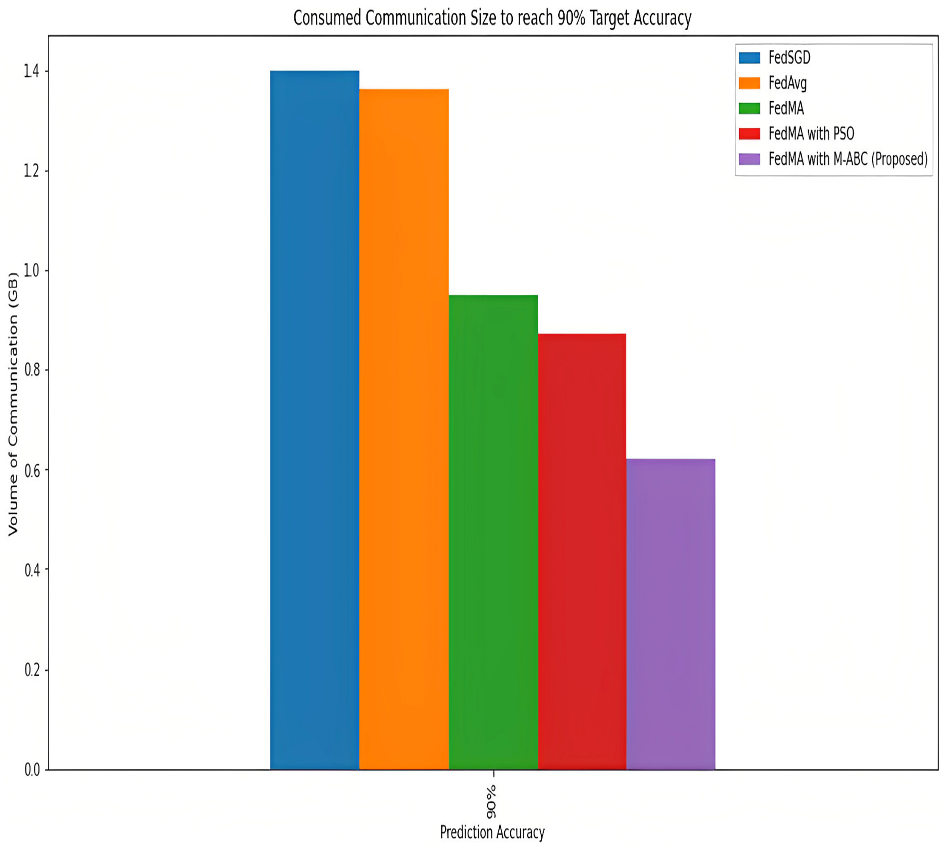

Figure 5. Comparison of communication size consumed to reach 90% prediction accuracy.

The performance metrics such as accuracy, precision, classification error, f-measure, specificity, sensitivity, and the number of rounds consumed to reach the highest accuracy are considered for the performance efficiency comparison of the proposed framework with FedAvg, FedMA, and PSO with FedMA. Accuracy in the context of machine learning means the percentage of all available instances that make the right predictions. Precision is defined as the percentage of correct predictions in the positive instance category. Classification errors are defined as the inaccuracies or percentages of errors available in the case. Three performance measurements are used to identify key features of heart disease. This helps to understand the behavior of different groups for a better selection of features. The results of these parameters are depicted in Tables 4 and 5. Our proposed framework achieves higher target accuracy in a lesser number of rounds as compared to vanilla FL, and PSO with FedMA for the heart disease dataset. As depicted in Table 4, our proposed method delivers a 22% reduction in the number of rounds as compared to FedSGD, FedAvg, and FedMA because the learning rate of our proposed model increases rapidly after every round which results in a 22% less number of rounds. As in Table 5, the proposed framework achieves better scores of prediction accuracy (92.89%), precision (94.2%), sensitivity (96.6), and specificity (81.8) as compared to existing FL algorithms on the heart disease dataset because the learning rate of our proposed model improves after every round of communication with less minibatch size. Hence our proposed framework is best suited for providing better heart disease prediction accuracy with privacy awareness as compared to existing FL algorithms. Moreover, the classification error of our proposed method is 11.8 which is less compared to FedAvg and FedMA due to the M-ABC optimization technique for feature selection and classification used in our proposed framework which results in less classification errors. The optimized features used for the M-ABC optimizer are shown in Table 6 with the details of achieved prediction accuracy. The M-ABC optimizer had 89% accuracy with five functions in the first experiment. Using the same dataset, the M-ABC optimizer with six features yielded 90% accuracy, and eight features achieved 92% accuracy.

Table 4. Time to reach the accuracy of model.

Technique	Accuracy after 4000 Rounds	# of Rounds to Reach 90%	Difference in # of Rounds
FedSGD	90	3988	–
FedAVG	90.07	3871	2.9%
FedMA	90.22	3495	12.4%
FedMA with PSO	90.38	3406	14.6%
FedMA with M-ABC (Proposed)	92.89	3018	24.3%

Table 5. Performance on full features set.

Technique	Accuracy	Precision	Classification Error	F-Measure	Specificity	Sensitivity
FedSGD	90	89.4	22.5	85.1	28.2	83.2
FedAVG	90.07	92.3	20.4	85.8	29.5	85.3
FedMA	90.22	90.1	18.6	86.6	52.5	89.5
FedMA with PSO	90.38	92.5	15.4	86.9	63.8	89.9
FedMA with M-ABC (Proposed)	92.89	94.2	11.8	90.1	81.8	96.6

Table 6. Optimized features with M-ABC optimizer.

Optimized Feature	Accuracy Achieved (in %)
Age, BP, Serum Chol., Rest ECG, Thallium Scan	89.82
Age, BP, Serum Chol., Hereditary, Rest ECG, Thallium Scan	90.72
Age, BP, Serum Chol., Hereditary, Rest ECG, Thallium Scan, Smoke, Diet	92.89

5. Conclusions

We proposed a privacy-aware decentralized federated learning framework for effective heart disease prediction in healthcare in this paper. The proposed framework is a hybrid method of FedMA and M-ABC optimization techniques to improve heart disease prediction while addressing privacy concerns in a healthcare system. The primary goal of this paper is to improve heart disease prediction accuracy as well as training time and communication efficiency. To ensure that our proposed framework is correct and valid, we evaluated and compared the performance in terms of various model prediction-based parameters and communication efficiency with the baseline federated learning FedAvg, FedMA, and with FedMA using PSO optimizer algorithms. The proposed framework indicated improved performance in terms of accuracy, classification error, precision, sensitivity, and communication efficiency. It is observed that the proposed framework provides 2.6% higher accuracy, 7% less classification error, 1.8% more precision, 7.1% higher sensitivity, and 12% fewer rounds are required to achieve the highest level of accuracy.

Our proposed model has some limitations, including the possibility of extending it for scalability in terms of the number of IoMT client sites with the effect of the learning rate on the overall model. In the future, we aim to further improve the privacy-aware healthcare predictive system by using other feature selection algorithms and optimization methods. The diagnosis, treatment, and control of health-related diseases is a major issue due to privacy concerns, hence, in the future, we will work on recovery and treatment of many other critical diseases such as breast cancer, diabetes, skin cancer, and Parkinson's Disease.

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