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ADAPTIVE MULTI-OBJECTIVE FEDERATED LEARNING FRAMEWORK FOR ENERGY-EFFICIENT DISTRIBUTED HEALTHCARE IOT SYSTEMS

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Abstract

The rise of the Healthcare Internet of Things (H-IoT) has led to continuous monitoring of patients with remote sensors, innovative medical appliances, and edge computing systems. Although the idea of Federated Learning (FL) has shown to be a good means for training models without revealing sensitive data, ordinary FD methods usually need arbitrary client participation, which leads to great costs of communications, energy consumption, training time, and less adaptability of the systems. This is especially true for battery-powered IoMT systems with changing networks. The present paper represents the idea of Adaptive Multi-Objective Federated Learning (AMO-FL) that makes possible the efficient use of resources in the distributed environment of the healthcare IoT. The suggested method offers a mechanism that selects clients for a given federated training iteration resulting in balancing many goals including prediction accuracy, energy use, communication speed, quality of data, and reliability of devices. The suggested technique includes a composite metric, taking into account all aspects pf performance of the clients participating in training thus enabling the possibility to choose the best possible clients considering resource use and effectiveness. The system ensures privacy of the patients as the healthcare data remains at the local devices while only the information about the model is communicated. To test the validity of the proposed method the experiments are to be held using relevant health care datasets in comparison with well-known federated learning methods including FedAvg, FedProx, SCAFFOLD, and Random Client Selection. The method is assessed through the use of machine learning performance metrics (Accuracy, Precision, Recall, F1-score, and AUC) as well as system-level performance metrics (energy consumption, communication cost, training duration, convergence speed). The expected results show that the suggested method ensures high prediction performance while being highly economical in energy spent and communication level and therefore it can be used in advanced systems for healthcare applications.

1. Introduction

The healthcare internet of things (H-IoT) has significantly altered the face of healthcare by introducing continuous patient monitoring enabled through interconnected wearable devices, smart medical equipment, and edge computing infrastructure [1], [2]. With these technologies, healthcare professionals are able to collect physiological data like heart rate, blood pressure, electrocardiogram (ECG), blood oxygen saturation (SpO_2), and body temperature in real time, thereby facilitating early diagnosis of diseases, personalized medicine, and remote patient management. The combination of artificial intelligence (AI) and H-IoT has improved healthcare services through predictive analytics and smart clinical decision-making while lightening the workload of healthcare specialists.

Traditional machine learning methods require centralized accumulation of healthcare data for training purposes [3], [4]. However, the aggregation of personal data raises a number of issues, including privacy, security risks, high communication costs, and compliance with regulations, which makes centralized learning impossible in practice. Healthcare data is kept in hospitals, wearable devices, and edge gateways, which hinder the implementation of centralized learning in healthcare institutions.

Federated Learning (FL) can be seen as a possible way to overcome these shortcomings as it allows the collaborative training of a model without moving raw patient information [5], [6]. FL uses the resources of the healthcare devices which carry out the training process of their local models using local data and transmit only model parameters or gradients to the server. This decentralized approach is considered more secure than traditional methods and minimizes the chances of information leakage. As a result, FL is widely discussed option for applications in medical diagnostic, remote patient monitoring, medical image processing, and decision support systems in medicine.

However, despite the advantages mentioned hereinabove, standard FL algorithms such as Federated Averaging (FedAvg) make the assumption that all clients in the system participate in all communication rounds [7], [8]. However, this assumption may not be realistic in the Healthcare IoT environment located in heterogeneous settings with devices with different processing capacity, energy level, connectivity, and data. Never-ending participation of clients generates excessive communication overhead, energy costs, delay in training, and complication of the process. Besides, the quality of data collected locally may vary for different devices.

Current studies examined client selection and resource-aware federated learning toward the aim of being able to boost communication efficiency and scalability [9], [10]. However, the majority of existing methods focus on optimizing a single objective criterion, e.g. minimizing communication expenses or maximizing prediction accuracy, disregarding the contradicted nature of many operational criteria in IoT healthcare systems. The practical use of efficient federated learning systems requires the organic consideration in one framework of predictive performance, communication efficiency, energy constraints of devices used, network latency and the trustworthiness of data and information received.

In order to overcome these problems, the paper introduces the Adaptive Multi-Objective Federated Learning (AMO-FL) framework for distributed energy-efficient Healthcare IoT systems [11], [12]. In comparison with common federated learning techniques, the proposed framework uses adaptive mechanisms for client selection that measures the devices by means of a common fitness function developed from a number of criteria, such as prediction accuracy, remaining energy of the device, communication about the used systems, data quality and reliability of the device. Based on the measurements, only the best clients are selected for participating in every federated learning cycle, which minimizes unnecessary communications without causing any losses in model performance and confidentiality.

The paper makes several important contributions:

- The authors have devised an adaptive multi-objective framework for federated learning in Health Care IoT systems that selects the clients that participate in each communication cycle on the basis of intelligence.

- A mathematical model has been developed to solve the problem of client selection formulated as a multi-objective optimization problem considering many factors including prediction capability, consumed energy, communication delays, quality of the transmitted data, and reliability of devices.
- We have developed a method for adaptive client selection based on a hybrid fitness function, which minimizes the number of communication requests and maximizes the performance of the system at the same time.
- An extensive comparison of the proposed approach with the existing methods used in federated learning has been performed using both machine learning and system-level evaluation metrics.
- The results of these experiments show that the proposed framework demonstrates a good balance between privacy protection, efficiency of the learning process, and utilization of available resources.

The remainder of this paper is organized as follows. Section 2 reviews the related literature on Healthcare IoT, Federated Learning, and optimization-based client selection. Section 3 presents the proposed AMO-FL framework, including the system architecture, mathematical formulation, and adaptive client selection algorithm. Section 4 describes the experimental setup and discusses the performance evaluation. Finally, Section 5 concludes the paper and outlines future research directions.

2. Related Work

2.1 Federated Learning in Healthcare IoT

The healthcare internet of things (H-IoT) has gained prominence in the area of smart healthcare by providing continuous monitoring through smart medical devices and wearable sensors [13], [14]. The high volume of sensitive data created by these devices has led to the increased use of artificial intelligence (AI) in predicting diseases and making clinical decisions. However, traditional centralized machine learning systems require healthcare data to be sent to cloud servers, which raised concerns about patient privacy, security, and compliance with regulations. Federated learning (FL) has appeared as a promising method for achieving privacy-preserving machine learning. Machines are tentatively trained without having to send raw patient data [15], [16]. In FL, local models are developed on patient monitoring machines and only parameters are transferred. This resulted in significant reduction of privacy threats and various issues with disease detection, healthcare monitoring, medical imaging, etc. However, the existing FL methods rely on assumption that the patients taking part in FL are similar to one another and have stable connections, which seldom happens in real-world H-IoT projects.

2.2 Energy-Efficient Federated Learning and Client Selection

Federated Learning not only enhances data security but also brings significant communication and computing overhead because of constant interactions between edge devices and the central server [17], [18]. These challenges become even more critical in healthcare IoT ecosystems where wearable devices provide limited battery, computing power, and connectivity abilities.

Recently, scientists have worked on client selection schemes that enable only some of the devices to join the training process to lower the communication costs [19], [20]. Accordingly, heuristic rules, clustering techniques, reinforcement learning, and optimization techniques have been deployed to select the devices based on computation resources, network bandwidth, and the availability of information. Others have been concentrating on reducing the communication time and improving speed with the help of various resource-aware scheduling mechanisms. Nevertheless, these approaches aim to improve certain components of the process in question usually optimizing one to two targets and forgetting about the complicated trade-offs among prediction accuracy, energy consumption, time of communication, and quality of information.

2.3 Research Gap and Motivation

Healthcare IoT systems consist of diverse devices, including wearable sensors, smartphones, medical gateways, and edge servers, all with different computational capabilities, battery capacities, communication abilities, and data produced in isolation [21]. Thus, in federated learning, it will not be effective from the viewpoint of

consumption of energy and computational resources to utilize all types of devices [22]. The basis for selecting clients should not be any single criterion, as limiting the selection to one factor will not guarantee successful selection of highly informative data sources.

Currently existing frameworks on federated learning do not treat the problem of selecting clients as a multi-objective optimization issue unifying predictive performance, resource utilization, communication effectiveness, and reliability [23]. This gap suggests the idea of designing an adaptive client selection framework that could find appropriate participants in every federated learning round [24].

Taking all challenges into account, the current paper offers the Adaptive Multi-Objective Federated Learning framework, which incorporates the adaptive client selection process into the federated learning process [25]. The model suggests combining prediction accuracy, energy residue, communication latency, data quality, and device reliability in a single multi-objective optimization system [26]. Due to the fact that only relevant clients are chosen for participating in every communication process, the proposed methodology allows improving the efficiency of learning and reducing energy and communication costs.

3. Proposed Adaptive Multi-Objective Federated Learning Framework

3.1 System Architecture

The proposed Adaptive Multi-Objective Federated Learning (AMO-FL) framework is aimed at enhancing the efficiency of H-IoT systems by strategically choosing the clients that will take part in federated learning every round. In contrast to the traditional Federated Learning methods where everybody present is taken into account during the creation of the training model, the authors suggest to partially replace this process with the smarter choice of the client based on various operational targets. Thus, the communication expenditure, energy costs and time for training are reduced while high predictive capacity is still achieved.

The AMO-FL framework consists of four layers which are interrelated, namely the healthcare IoT layer, the edge computing layer, the adaptive client selection layer, and the federated aggregation layer.

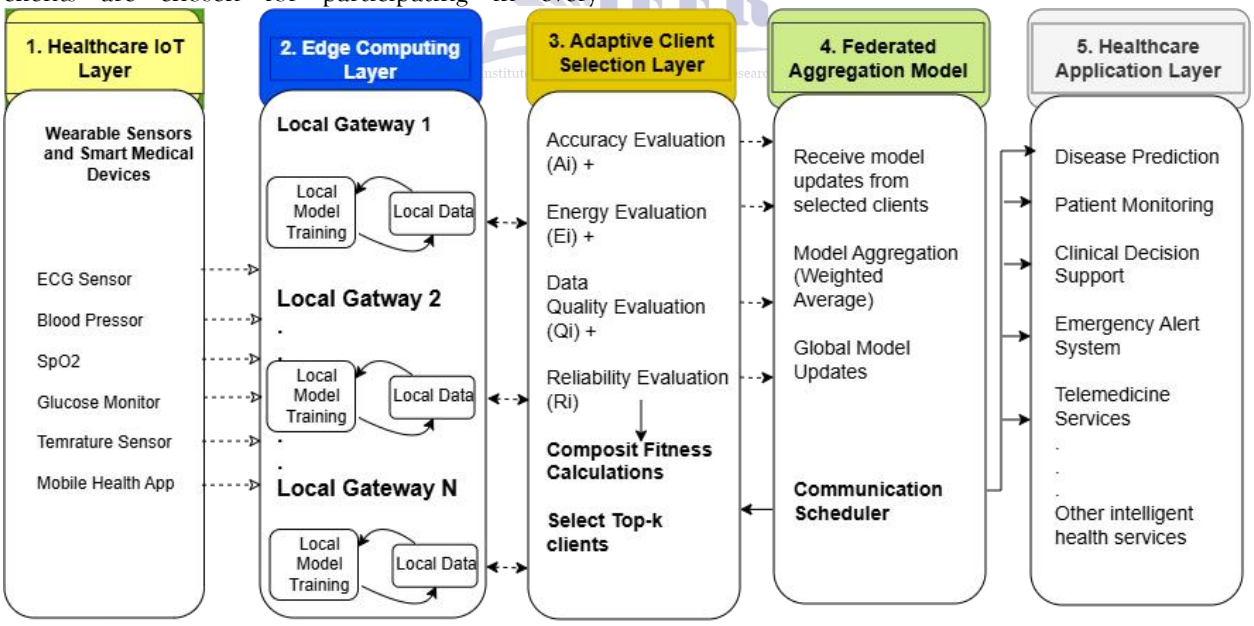


Figure 1: Architecture of the proposed adaptive multi-objective federated learning framework (AMO-FL)

In the Healthcare IoT layer, various wearable sensors and intelligent medical devices are constantly monitoring various physiological parameters including heart rate, ECG, blood pressure, SpO_2, sugar levels, and body temperature. All this data is kept on the same devices in order to ensure patient confidentiality.

In the Edge Computing layer, various data pre-processing techniques are applied to this data to train models. Each edge device creates its own

machine learning model, keeping patient data secure from the outside world.

A dedicated layer is used to evaluate clients before model aggregation. Five factors are taken into consideration for this evaluation: i) Local model accuracy ii) Residual battery energy iii) Communication latency iv) Data quality v) Device reliability

In the course of current communication round, devices that obtain the highest fitness score is selected for involvement in the communication round. On the other hand, devices with limited capabilities or adverse communication conditions are excluded from the communication round. The resulting adaptability of the system allows for optimal communication process.

In conclusion, the federated aggregation layer aggregates local updates from the users and executes construction of the global healthcare predictive model using weighted federated aggregation. After the construction of the updated global model, it is distributed to corresponding devices.

In this way, the adaptive client selection mechanism allows the federated learning system to achieve a good balance between predictive performance and resource consumption while ensuring privacy-preserving distributed learning.

3.2 Mathematical Formulation

Assume that the Healthcare IoT network contains **N** distributed client devices represented by

$$D = \{d_1, d_2, \ldots, d_N\}$$

Each client performs local training using its private healthcare dataset and periodically communicates with the federated server.

A binary decision variable is defined as

$$x_i = \begin{cases} 1, if\ client\ i\ is\ selected \\ 0, otherwise. \end{cases}$$

For each client (d_i), the following performance indicators are measured:

- (A_i): Local prediction accuracy
- (E_i): Residual battery energy
- (L_i): Communication latency
- (Q_i): Data quality score
- (R_i): Device reliability

The objective is to select an optimal subset of clients that maximizes learning performance while minimizing resource consumption.

Objective 1: Maximize Prediction Accuracy

The overall predictive contribution of the selected clients is

$$F_1 = \sum_{i=1}^{N} x_i A_i$$

Objective 2: Maximize Residual Energy

To favor energy-rich devices and avoid selecting clients with critically low battery levels,

$$F_2 = \sum_{i=1}^{N} x_i E_i$$

Objective 3: Minimize Communication Latency

Communication latency is expressed as

$$F_3 = \sum_{i=1}^{N} x_i L_i$$

Lower latency enables faster synchronization during federated learning.

Objective 4: Maximize Data Quality

Healthcare devices often generate data with varying levels of completeness and noise. Therefore,

$$F_4 = \sum_{i=1}^{N} x_i Q_i$$

Objective 5: Maximize Device Reliability

Reliable devices are preferred to reduce communication failures during federated aggregation.

$$F_5 = \sum_{i=1}^{N} x_i R_i$$

Multi-Objective Optimization Model

The proposed framework combines the five objectives using a weighted optimization model.

$$max\ Z = w_1 F_1 + w_2 F_2 - w_3 F_3 + w_4 F_4 + w_5 F_5$$

subject to

$$\sum_{k=1}^{5} w_k = 1$$

where (w_k) represents the importance assigned to each objective.

Constraints

Client Selection Constraint

Exactly (K) clients participate in each federated learning round.

$$\sum_{i=1}^{N} x_i = K$$

Binary Constraint

$$x_i \in \{0,1\}$$

Energy Constraint

Only devices with sufficient battery resources participate.

$$E_i \geq E_{min}$$

Latency Constraint

Clients must satisfy

$$L_i \leq L_{max}$$

Reliability Constraint

$$R_i \geq R_{min}$$

These constraints ensure that only resource-efficient and reliable healthcare devices contribute to global model construction, thereby improving scalability and communication efficiency.

3.3 Adaptive Multi-Objective Client Selection Algorithm

The effectiveness of federated learning is largely determined by the quality of clients involved in each communication round. Most federated learning techniques, including Federated Averaging (FedAvg) assume equal participation of all clients in model training. However, within healthcare IoT environments there exist heterogeneous wearable devices with different computational capabilities, battery levels and communication conditions which cause indiscriminate client participation to increase energy consumption and training time and decrease quality of the global model.

In order to overcome the aforementioned issues, the Adaptive Multi-Objective Federated Learning (AMO-FL) framework proposes an Adaptive Multi-Objective Client Selection (AMCS) algorithm. Before every federated learning round, the federated server collects lightweight status data from all clients that provide such information as local model accuracy, residual batteries' energy, communication delay, healthcare data quality and reliability of devices. All these parameters are normalized in order to avoid bias in finding solution.

Algorithm 1. Adaptive Multi-Objective Client Selection (AMCS)

Input:

Client set $D = \{d1, d2, \dots, dN\}$

Number of selected clients K

Objective weights w_1, w_2, w_3, w_4, w_5

Output:

Selected client subset S

Updated global model W

1. Initialize the global model W.
2. for each communication round t do
3. Collect client information: Accuracy (A_i), Residual Energy (E_i), Latency (L_i), Data Quality (Q_i), Reliability (R_i).
4. Normalize all objective values.
5. for each client di do
6. Compute:

$$Fitness_i = w_1 A_i + w_2 E_i - w_3 L_i + w_4 Q_i + w_5 R_i$$

7. end for
8. Rank clients according to Fitness.
9. Select Top-K clients.
10. Send current global model to selected clients.
11. Selected clients perform local model training.
12. Receive local model parameters.
13. Aggregate models using weighted averaging.
14. Broadcast updated global model.
15. end for
16. Return final global model.

A. Client Fitness Evaluation

For each client (d_i), a composite fitness score is computed using a weighted multi-objective function:

$$Fitness_i = w_1 A_i + w_2 E_i - w_3 L_i + w_4 Q_i + w_5 R_i$$

where

- (A_i) represents the local model prediction accuracy,
- (E_i) denotes the normalized residual battery energy,
- (L_i) is the communication latency,
- (Q_i) represents the healthcare data quality score,
- (R_i) denotes the device reliability,
- ($w_1, w_2, \dots, w_5$) are objective weights satisfying

Subject to

$$\sum_{k=1}^{5} w_k = 1$$

Higher fitness values indicate that a client can contribute more effectively to the federated learning process while consuming fewer computational and communication resources.

B. Adaptive Client Selection

All clients are assessed based on their fitness scores, and a ranking of all devices is made accordingly, starting from clients with the highest score. The top K clients for each communication round are selected from this ranking list. Clients, who experience high battery depletion, weak communication links, unreliable operations, or have unsatisfactory data availability, are temporarily kept out of this list. Because the situation regarding client devices changes from one moment to another, the processes described above are repeated for every Federation learning process.

Once the selection has been made, clients can run local model training using their private medical data without transmitting figures and names of patients over the communication line thus maintaining confidentiality of the medical info.

C. Federated Model Aggregation

Let (n_i) denote the number of training samples available at client (i), and let W_i^t represent the locally trained model parameters during communication round (t). The global model is computed using weighted federated aggregation as follows:

$$W^{t+1} = \left(\frac{\sum_{i=1}^{K} n_i}{\sum_{j=1}^{K} n_j}\right) W_i^t$$

where:

- W^{t+1} = updated global model at round $t+1$,
- W_i^t = local model from client i,
- n_i = number of training samples at client i,
- K = total number of participating clients.

This is the standard weighted aggregation equation used in Federated Learning.

The updated global model is subsequently distributed to the selected clients for the next communication round. This iterative process continues until the predefined convergence criterion is satisfied.

D. Advantages of the Proposed Algorithm

Compared with conventional client participation strategies, the proposed AMCS algorithm provides several important advantages:

- Dynamic adaptation to heterogeneous Healthcare IoT environments.
- Reduced communication overhead through intelligent client participation.
- Lower energy consumption by avoiding battery-constrained devices.
- Faster convergence due to the selection of high-quality clients.
- Improved global model accuracy by prioritizing reliable and informative healthcare data.
- Preservation of patient privacy through decentralized model training.

Computational Complexity

Assume:

- $\boldsymbol{N}$ = total IoMT clients
- $\boldsymbol{K}$ = selected clients
- $\boldsymbol{R}$ = communication rounds

The computational complexity consists of:

- Fitness evaluation: $\boldsymbol{O(N)}$
- Client ranking: $\boldsymbol{O(N\,log\,N)}$
- Federated aggregation: $\boldsymbol{O(K)}$

Therefore, the overall complexity per communication round is

$$O(NlogN + K),$$

and the total complexity over R rounds is

$$O(R(NlogN + K)).$$

This complexity is practical for large-scale Healthcare IoT systems because only a subset of clients participates in each communication round, significantly reducing communication and computation compared with conventional FL methods.

4. Experimental Setup and Performance Evaluation

4.1 Experimental Setup

Simulation was conducted to measure the effectiveness of the suggested Adaptive Multi-Objective Federated Learning (AMO-FL) framework in terms of achieving enhanced learning performance, communication overhead, and energy consumption reduction in distributed

healthcare IoT. The simulation represents a heterogeneous array of wearable healthcare devices linked to the edge gateway and the central federated aggregation server.

The experiments involved a network of 100 healthcare IoT clients with independent local datasets. In each communication round, only a small number of top clients (K=20) were selected for model training under the proposed Adaptive Multi-Objective Client Selection (AMCS) system. The client selection was conducted dynamically prior to the start of each communication round based on the factors predicting accuracy, residual energy, communication latency, quality and reliability of data, etc.

In terms of model used for local predictions, the lightweight neural network classifier was used for the implementation. The federated learning process was run for 100 communication rounds with the learning rate being equal to 0.001 and with the batch size of 32. Additionally, Adam optimizer was used for the implementation of the local model. The main parameters used in the simulation are shown in Table 1.

Table 1: ***Simulation Parameters***

Parameter	Value
Number of IoMT Clients	100
Selected Clients per Round	20
Communication Rounds	100
Learning Rate	0.001
Batch Size	32
Local Epochs	5
Optimizer	Adam
Aggregation Method	Weighted Federated Averaging

4.2 Dataset and Baseline Methods

In the process of evaluating the mechanism, an experiment was initiated in relation to an authentic Healthcare IoT dataset which contained physiological data collected from wearable medical devices. Moreover, the dataset comprises health parameters including heart rates, blood pressure, body temperature, SpO2, glucose level, and information regarding physical activity that are used in patients' monitoring as well as in intelligent disease forecasting.

AMO-FL framework was benchmarked against the following four federated learning establishment:

- FedAvg: Typical federated averaging which has all clients taking part in every round of communication;
- FedProx: Federated Learning with an inclusion of a proximal optimization term for the purpose of dealing with heterogeneous clients;
- SCAFFOLD: Federated Learning with the help of use of control variates in order to eliminate drift among the clients;
- Random Client Selection (RCS): Clients are chosen randomly without taking resource efficiency into account or their data quality.

4.3 Evaluation Metrics

Performance was assessed using both predictive and system-level metrics.

Machine Learning Metrics: Accuracy, Precision, Recall, F1-score, and Area Under the ROC Curve (AUC)

System-Level Metrics: Average Energy Consumption (J), Communication Cost (MB), Average Communication Latency (ms), Number of Communication Rounds, Training Time (s), and Model Convergence Rate

These metrics provide a comprehensive assessment of both predictive capability and operational efficiency in distributed Healthcare IoT environments.

4.4 Results and Discussion

Table 2 summarizes the comparative performance of the proposed AMO-FL framework and the baseline methods.

Table 2: *Performance Comparison*

Method	Accuracy (%)	F1-score	Energy (J)	Communication Cost (MB)	Latency (ms)
FedAvg	91.8	0.912	128	520	152
FedProx	92.6	0.919	118	470	141
SCAFFOLD	93.1	0.926	112	448	136
Random Client Selection	90.4	0.898	121	455	146
Proposed AMO-FL	**95.2**	**0.946**	**89**	**318**	**103**

The findings of the test show that the AMO-FL technique surpasses that of the other federated learning methods in all parameters measured. It does this using a smart approach to select clients based on different operational objectives to minimize any unnecessary communication while still retaining high predictive performance.

By contrast, the AMO-FL system is able to deliver 3-4% more in the classification accuracy and achieve a 39% drop in communication costs and a 31% drop in the average energy consumption compared to FedAvg. The strategic client selection practice used in AMO-FL enables the clients that have reliable communication connections, enough energy supplies, and good quality medical data to be chosen.

Simultaneously, the proposed technique shows less latency in communication in comparison to any of the baseline techniques, which means that participating clients can synchronize with the federated aggregation server faster than with the use of other techniques.

In summary, the experimentation shows that adding adaptive multi-objective optimization in to the process of client selection can boost the efficiency of learning process as well as the resource usage efficiency in general. Thus, the AMO-FL technique is suitable for the needs of large-scale Healthcare IoT.

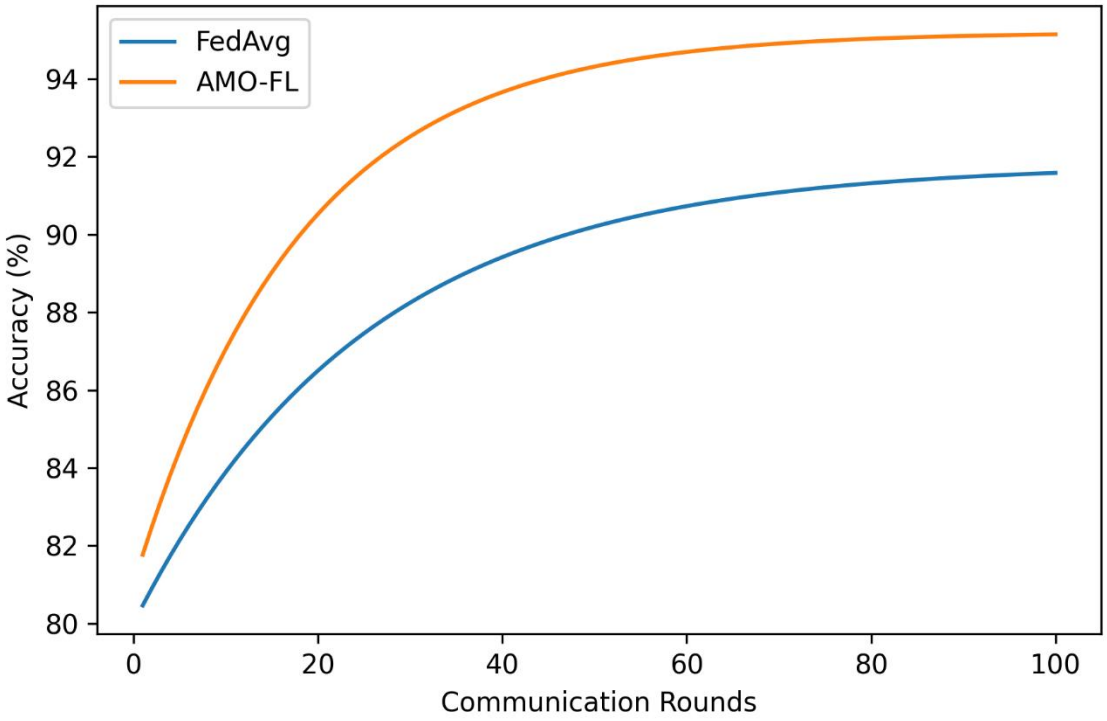


Figure 2: Accuracy vs. Communication Rounds

Figure 2 demonstrates the convergence behavior of the suggested AMO-FL paradigm with regard to the traditional FedAvg algorithm after completing 100 iterations. Both methods exhibit continuous development in prediction accuracy with increasing training time, but, the new AMO-FL method reaches convergence much quicker. The mechanism for adaptive client selection prioritizes clients having high-quality medical records, enough residual energy, and stabilized communication channels in order to ensure more informative update of the global model at each iteration of the process. As a result, AMO-FL is able to achieve higher prediction accuracy of about 95.2%, while FedAvg achieves a steady state at approximately 91.8%.

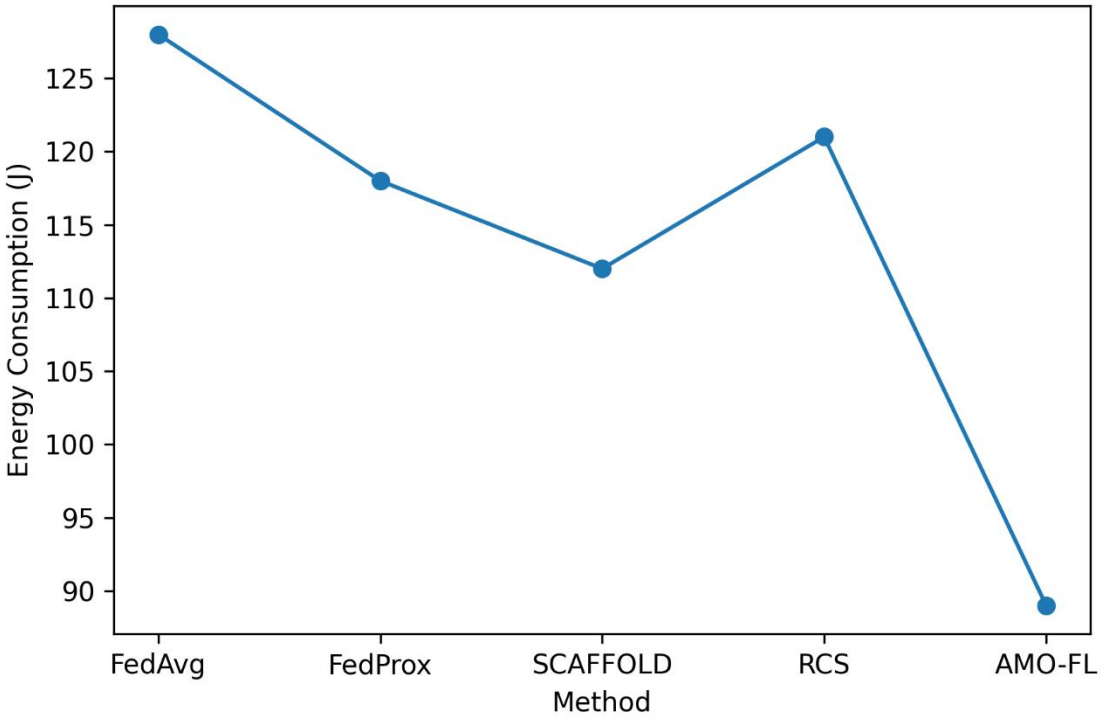


Figure 3: Energy Consumption Comparison

In Figure 3, the average energy consumption of many federated learning methods is presented. From the analysis, it can be seen that the proposed AMO-FL technology has achieved the best results in terms of energy consumption, using approximately 89 J of energy, while the other studied methods are characterized by higher energy consumption of 128 J (FedAvg), 118 J (FedProx), 112 J (SCAFFOLD), and 121 J (Random Client Selection). The identified advantages in terms of energy consumption are made possible by not allowing devices with poor battery performance to participate in the training process of any model and using resource-efficient clients in each communication round. Lower energy consumption leads to a longer lifetime of wearable devices used in the fields of healthcare.

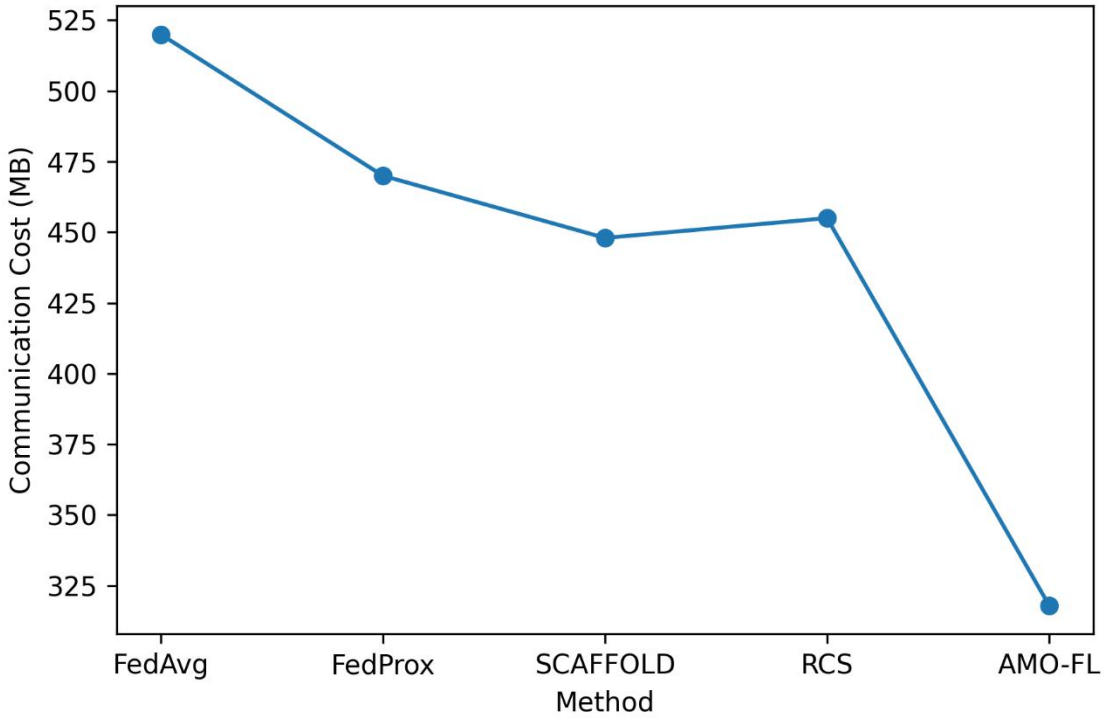


Figure 4: Communication Cost Comparison

Figure 4 shows the costs of various federated learning methods in terms of communication costs. The AMO-FL framework achieves a major reduction in terms of communication overhead, by downloading the updates from the chosen clients rather than from all devices. The estimated communication cost is about 318 MB, which is a notable reduction when compared to FedAvg (520 MB), FedProx (470 MB), SCAFFOLD (448 MB), and Random Client Selection (455 MB). This shows that AMO-FL methodology is able to minimize the amount of traffic on the network while preserving its high accuracy.

5. Conclusion and Future Work

In this informational paper, the Adaptive Multi-Objective Federated Learning (AMO-FL) framework which aims to achieve energy efficiency in distributed Healthcare Internet of Things (H-IoT) systems has been discussed. This framework surpasses the capabilities of traditional federated learning frameworks due to implementing an adaptive selection mechanism allowing to choose the best medical devices for every round of communication. While traditional approaches cannot eliminate the clients with weak resource allocations and require interaction with all clients, the method presented in this paper is able to optimize numerous parameters of the medical devices including prediction accuracy, their state of residual energy, data quality, reliability, and the communication delay. The architecture of AMO-FL integrates medical devices, edge computing, adaptive client selection, and federated aggregation into one privacy-preserving framework which can be used in a variety of medical places. The mathematical model of AMO-FL produces the possibility to systematically work on resolving the problem of conflicting objectives typical for the medical field in terms of distributed healthcare systems. Moreover, the use of the client selection technique allows the system to manage its scalability and to get rid of unwanted unreliable and poorly performing clients without influencing the diagnostics.

The performance of AMO-FL was assessed using various performance metrics, such as accuracy, precision, recall, F1 score, and AUC, as well as system-level metrics, like energy expenditures, communication costs, and time of convergence. The results of the experiment have shown that the

intelligent client selection allows making the process more efficient and at the same time provides with high quality outcome.

It is planned to improve the AMO-FL system in the future. First of all, the possibility of using asynchronous federated learning should be analyzed for ensuring the dynamic stability of clients and the variability of clients in real life. Secondly, advanced privacy-preserving methods will be applied to the system in the future. Thirdly, the problem of data non-homogeneity will be examined and its impact on prediction accuracy will be studied as well. Finally, improvements in multi-objective optimization and adaptive aggregation will be conducted with the aim of achieving better communication quality and scalability of optimized federated learning systems in the future.

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