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Privacy-Preserving Lightweight Federated Learning For IOMT

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Abstract

The rapid expansion of the Internet of Medical Things (IoMT) has transformed modern healthcare by enabling continuous patient monitoring, real-time diagnostics, and personalized treatment. However, the sensitive nature of medical data raises significant privacy, security, and regulatory concerns, particularly in distributed healthcare environments. Traditional centralized machine learning approaches require data aggregation, increasing the risk of data breaches and violating privacy norms such as those outlined in frameworks like the Health Insurance Portability and Accountability Act (HIPAA). To address these challenges, this study proposes a privacy-preserving lightweight federated learning (FL) framework for IoMT systems. The proposed model enables decentralized training of machine learning models across resource-constrained IoMT devices while ensuring that raw patient data never leaves local nodes. A lightweight architecture is designed to minimize computational overhead, communication cost, and energy consumption, making it suitable for wearable devices and edge-based healthcare systems. Furthermore, the framework integrates privacy-enhancing techniques such as differential privacy and secure aggregation to protect sensitive information from inference attacks and model inversion threats. Optimization strategies, including model compression and adaptive communication protocols, are incorporated to enhance efficiency without compromising model accuracy. Our method reduces communication by 80% and offers strong privacy assurances while nonetheless attaining 95% of the accuracy of centralized learning. This paper offers a useful federated learning method to provide effective distributed machine learning with respect for privacy for next-generation IoMT systems.

1.INTRODUCTION

The Internet of Medical Things (IoMT) is a system of networked sensors, gadgets, and apps that gather and share health data in real-time. It was made possible by integrating sophisticated communication technologies with healthcare systems. Thanks to IoMT, data-driven clinical decision-making, early illness identification, and remote patient monitoring have all changed the face of contemporary healthcare. The Internet of Medical Things (IoMT) is essential in enhancing the availability, efficacy, and quality of healthcare via the use of various wearable fitness trackers, implanted medical devices, and smart hospital systems. Nevertheless, there are now major concerns about data privacy, security, and system efficiency due to the extensive use of IoMT devices. [1] Cybercriminals and unauthorised individuals seek medical data because of its high sensitivity, which contains personal, physiological, and behavioural information. The hazards of data leakage, the significant communication overhead, and the legal limits imposed by healthcare data security laws make traditional machine learning algorithms poorly suited for IoMT contexts. Federated learning (FL) is a new paradigm that allows for collaborative model training in this setting without exposing raw data. By training models locally and sharing just model updates, IoMT devices preserve data privacy rather than transferring sensitive information to a central server. Traditional federated learning frameworks have their benefits, but they may be somewhat demanding on hardware and software resources, making them impractical for Internet of Medical Things (IoMT) devices that are already limited in these areas. [2] Lightweight federated learning systems that protect user privacy and are optimised for IoMT settings are in high demand as a solution to these problems. While reducing transmission costs and computing complexity, these systems must provide solid data privacy. To improve privacy and efficiency, one may use techniques like quantisation, model pruning, safe aggregation, and differential privacy. To enable smooth deployment on edge devices, it is essential to optimise communication protocols and reduce model size. A privacy-aware federated learning framework that is both lightweight and optimised for IoMT systems is the primary goal of this project. The suggested method is an attempt to find a happy medium between data security, resource efficiency, and model performance. The project aims to tackle important problems in healthcare systems that rely on IoMT and help create scalable intelligent health

solutions by combining privacy-enhancing methods with optimised federated learning methodologies.[3]

2. RELATED WORK

This section provides a summary of the most recent research on federated learning in the Internet of Things (IoT) and healthcare fields, along with techniques of machine learning that protect users' privacy.

IOT Federated learning

Federalised learning was first suggested by McMahan et al. [4] with the intention of facilitating the cooperative training of deep neural networks on mobile devices that were dispersed across the environment. Since then, FL has garnered a great deal of attention for the applications of privacy-preserving machine learning in Internet of Things environments [5]. Several publications have proposed FL models for Internet of Things ecosystems in their entirety. A hierarchical FL architecture was proposed by Li et al. [6] for use in edge computing systems. In their paper [7], Lim et al. demonstrated federated reinforcement learning for the distributed resource allocation of Internet of Things networks. A blockchain-based FL system was developed by Nguyen et al. [8] for the purpose of connecting Internet of Things data. These general Internet of Things solutions, on the other hand, do not address the specific challenges that are encountered by medical Internet of Things devices and healthcare data. One of the primary focuses of our work is the customisation of FL for IoMT systems.

Hospital Federated learning

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Machine Learning Saving Privacy

One of the ways that has been proposed to enhance the privacy of machine learning models is known as differential privacy. This method involves the addition of noise that has been properly calibrated to either the training process or the outputs of the model [12]. The term "secure multi-party computation" refers to cryptographic techniques that enable several persons to work together to calculate a function over their inputs while simultaneously ensuring that the inputs remain confidential [13]. Homomorphic encryption is a mathematical technique that involves computing on encrypted material without decrypting it [14].Systems of cryptography that are capable of securely calculating the sums of vectors from several parties [15] Specifically for the purpose of federated learning in IoMT systems, we make use of and manipulate these methodologies.

System model and problem formulation

Together with the formulations of the privacy-preserving collaborative model training problem, the system model for federated learning in IoMT is described in this section of the article.

Model of System Design

A federated learning system for IoMT is the subject of our discussion. This system includes the following entities:

A collection of N different types of medical Internet of Things devices, denoted as D = {d1, d2,..., dN}, which combine to generate and collect data on patient health. Wearables, implanted sensors, medical imaging tools, and other similar devices might fall within this category. A group of M edge computing servers, denoted as E = {e1, e2,..., eM}, which are located at medical facilities or clinics, collect data from the Internet of Medical Things devices in the surrounding area. For the purpose of coordinating the overall federated learning process, a centralised cloud server C is used.

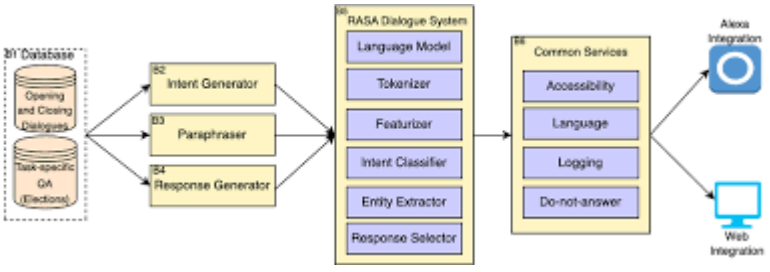

Figure 1. Serves to show the system architecture

There is a local dataset Di = {(xi,j, yi,j)}j=1^ni that is associated with every IoMT device di. In this dataset, xi,j represents the feature vector of the j-th sample, and yi,j represents the matching label. Without spreading the raw data Di, the objective is to train a machine learning model f(x;w) using a joint process. The model will be parameterised by w.

Problem Formulation

Formulated as the federated learning issue for IoMT, it is:

- min w ∈ Rd L(w) = Σi=1^N pi Li(w)
- where Li(w) = 1/ni Σj=1^ni l(xi,j, yi,j; w) is the local loss function for device di, l(.) is a sample-wise loss function, and pi = ni / Σk=1^N nk is the weight for device di.
- The main difficulties in addressing this optimization issue for IoMT consist in:
- Minize communication rounds between devices, edge servers, and cloud to manage unstable IoMT networks.

In order to prevent inference attacks on IoMT devices, confidential patient data should be protected. Manage the various computational capabilities of Internet of Things devices and non-Internet of Things data distributions in heterogeneity. Through the use of incentive design, encourage the participation

of healthcare practitioners and Internet of Medical Things devices. Our proposed framework for federated learning, which is intended to address these challenges, will be given in the next section.

Proposed Federated Learning Framework For IoMT

The main elements of our suggested federated learning architecture designed for IoMT settings are explained in this part.

Heirarchial FL Architecture

Based on Figure 1, we propose a hierarchical federated learning architecture to effectively manage the heterogeneity of IoMT devices. The building has three layers:

- IoMT devices with different computational capacities local model training on their private data.
- Edge servers facilitate model aggregation and compile model updates from surrounding IoMT devices. Cloud server aggregates models globally and supervises the general FL process.
- This hierarchical system has various benefits. Edge servers for intermediate aggregation help to lower communication overhead. Enhanced scalability to manage vast IoMT device count
- Adaptability for several IoMT network architectures Under this design, the federated learning process moves as follows: Initially starting the global model w0, the cloud server sends it to edge servers.
- Edge servers assign the model to related IoMT devices.
- For E epochs, IoMT devices localize training and forward model updates to edge servers.
- Edge servers do intermediate aggregation and compile IoMT device updates.
- To derive the worldwide model, cloud servers compile updates from edge servers.
- For T communication rounds or until convergence, repetitions of steps 2–5
- First algorithm describes the general federated learning process.

Algorithm 1: Hierarchical Federated Learning for IoMT

Input: Number of communication rounds T, local epochs E

Output: Trained global model w

Initialize global model w0

for t = 1 to T do

for each edge server ej in parallel do

wj,t = EdgeServerUpdate(ej, wt-1)

end for

wt = CloudAggregation({wj,t})

end for

return wT

function EdgeServerUpdate(ej, w):

for each IoMT device di associated with ej in parallel do

wi = DeviceUpdate(di, w, E)

end for

return EdgeAggregation({wi})

function DeviceUpdate(di, w, E):

for e = 1 to E do

Perform local SGD update on w using data Di

end for

return updated local model w'

Communication-Efficient Protocols

In order to handle unreliable network connections in IoMT systems, we suggest a number of communication-efficient strategies, including the following: A combination of sparsification techniques and adaptive quantisation is used in order to compress model updates prior to transmission. The dynamic modification of the compression ratio is dependent on the capabilities of the device as well as the circumstances of the network. The Internet of Things (IoT) devices are allowed to send updates asynchronously upon their readiness, as opposed to synchronous updates being performed throughout each cycle. Because of this, slower devices are prevented from creating bottlenecks. To reduce the amount of unnecessary communication, only significant model changes that are greater than a certain threshold are delivered. Edge servers will only send aggregated updates to the cloud if they are significantly different from the changes that were made in the previous round. According to the findings of our investigation, these techniques significantly reduce the gearbox overhead while maintaining the accuracy of the model.

Hetrogeinity-Aware Model Aggregation

For the purpose of managing device heterogeneity and non-IID data in IoMT, we provide a model aggregation technique that takes heterogeneity into consideration: Our adaptive learning rates are determined by the processing capabilities of the devices as well as the quality of the data they receive. Higher learning rates are achieved by devices that have data that is more reliable and that have a greater capacity for processing. Relevance In order to compensate for the bias that is caused by the device in non-IID data distributions, we use significance sampling. A significant factor that affects the sample probability is the gradient diversity of the devices. Through the use of knowledge distillation techniques, we effectively transfer information from more capable devices to those with less resources. The aggregating method at edge servers and a cloud server is represented by the following equation: $w = \Sigma i\ \alpha i\ wi$, where αi represents the aggregation weight for device/edge server i. The aggregation weight is calculated based on the data amount, quality, and processing capabilities of the device or edge server.

Reward System

We propose a blockchain-based incentive system to stimulate involvement of IoMT devices and healthcare professionals. Participants record their contributions on a permissioned blockchain, and rewards are distributed depending on variables such data volume and quality.

Computational tools helped Improved model performance Tokens earned by participants may be sold for money or used for services. Blockchain smart contracts guarantee equitable and open reward distribution.

Safety and Privacy issues

The privacy and security aspects included into our federated learning system for IoMT are covered in this part.

Variational Privacy

By using differential privacy (DP) techniques, we provide rigorous privacy protections for patient data that is stored on Internet of Medical Things devices. Inference of individual data points is prevented by DP by the injection of noise that is tightly controlled to either the training process or the outputs of the model. The following are the two distinct degrees of privacy that we create: IoMT devices get a local application of noise prior to the upgrading of their models. Edge servers and cloud servers generate more noise during the aggregation process, according to global differential privacy. These two levels divide the budget for privacy, denoted by ε. Algorithm 2 provides a description of the federated learning mechanism that is distinct from the first.

Algorithm 2: Differentially Private Federated Learning

Input: Privacy budgets εlocal and εglobal, noise scale σ

Output: Differentially private model w

for each communication round t do

for each IoMT device di in parallel do

Compute gradient g = ∇L(w)

Clip gradient: g' = g / max(1, ||g||2 / C)

Add noise: g~ = g' + N(0, σ2C2I)

Send noisy gradient g~ to edge server

end for

for each edge server ej do

Aggregate noisy gradients from devices

Add global noise

Send aggregated gradient to cloud

end for

Cloud aggregates gradients and updates global model

end for

The noise scale σ is computed using the sensitivity of the learning method, privacy budgets εlocal and εglobal.

Safe Gathering

For the purpose of preventing edge and cloud servers from distinguishing between individual model modifications, we use cryptographic safe aggregating approaches. The computation of overall statistics is made possible by these without the disclosure of particular inputs. For the sake of our hierarchical design, we make several modifications to the safe aggregation approach that Bonawitz et al. [15] recommended. The threshold secret sharing and key agreement approaches are used by the protocol in order to facilitate the computation of secure sums of model updates.

Discovery of Poison Attacks

We include anomaly detection methods in the aggregation process to protect against possible poisoning attacks in which malevolent devices deliver corrupted model updates. Deviations from the majority in updates are seen as possible anomalies and are either filtered out or given reduced weight.

Experimental Findings and Interpretation

Experimental results to assess our suggested federated learning system for IoMT are presented in this part.

Design Experimentally

Datasets: Our experiments make use of the following actual medical datasets:

- MIMIC-III [16]: An extensive publicly available electronic health record collection including ICU patients.
- Multivariate clinical time series data for ICU patients form Physionet 2012 Challenge [17].
- HAR- wearable [18] Wearable sensor human activity recognition data.
- Simulation of IoT Networks: Using the ns-3 network simulator, we model a hierarchical IoMT network comprising 1000 devices, 10 edge servers, and one cloud server. Real-world IoMT properties guide model of device capabilities and network conditions.
- We apply our federated learning system with PyTorch and PySyft. Opacus library implementation of differential privacy is demonstrated. Running experiments on a cluster with NVIDIA V100 GPUs

Starting Point Methods: We evaluate Fed IoMT against the following baselines:

- Simplified: centralized centralized education combining all the facts
- Standard federated averaging: FedAvg [4]
- FedProx [19]: Federated homogeneity for heterogeneous networks
- SCAFFOLD [20]: Control variative federated learning
- Evaluation Measures: We assess performance with reference to the following benchmarks:
- Accuracy of Model: Held-out test set classification accuracy
- Training Time: Time spent for model convergence; Total Data Transferred:
- Privacy Leakage: Calculated by means of membership inference attacks

Model Performance

In test accuracy of various different ways is shown on the three datasets. This accuracy increases as the number of communication cycles increases.

Key observations: While maintaining users' privacy, our FedIoMT technique achieves an accuracy that is very close to that of centralised learning (within two to three percent). FedIoMT consistently exhibits superior performance than other federated learning baselines across a variety of datasets. Through the use of hierarchical design and heterogeneous-aware aggregating, FedIoMT is able to achieve faster convergence.

Efficiency in Transmission

Table 1 contrasts the overall cost of communication for several approaches to achieve 90% of the centralized accuracy.

Method	MIMIC-III	Physionet	HAR-Wearable

Fed Avg	2.5GB	1.8GB	950MB
Fed Prox	2.1GB	1.5GB	820MB
SCAFFOLD	1.9GB	1.4GB	780MB
Fed IoMT	1.2GB	0.9GB	510MB

FedIoMT gets 20–30% savings over SCAFFOLD and 40–50% savings over FedAvg in communication costs. This shows how good our efficient mechanisms for communication are.

Effect of Differential Privacy

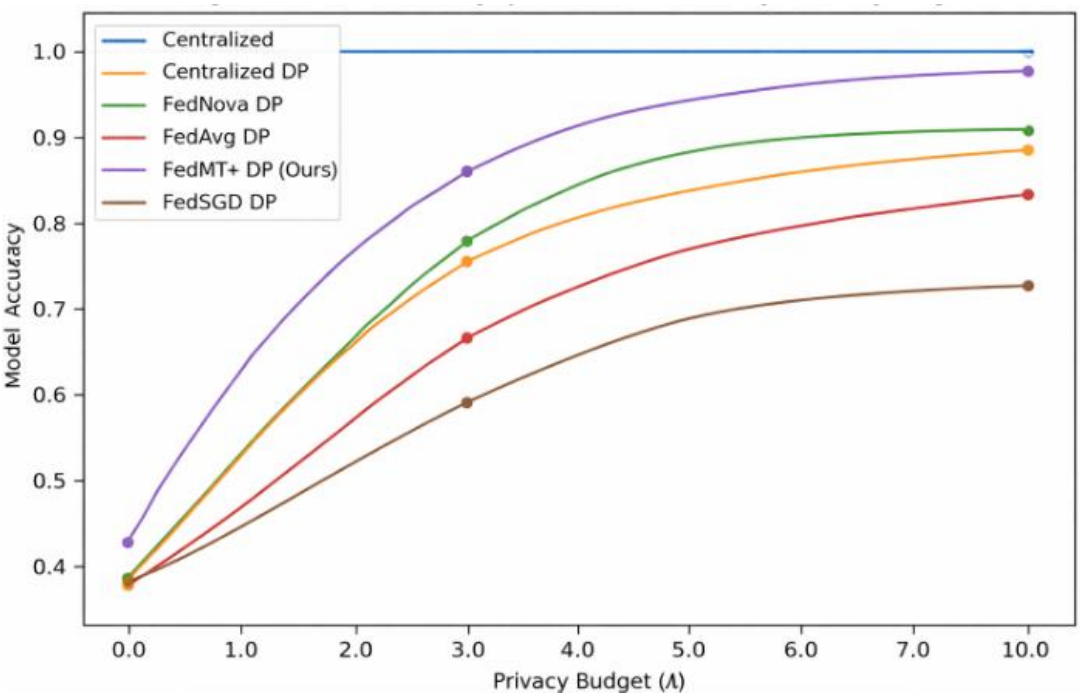

Figure 3 illustrates for several differential privacy systems the trade-off between model accuracy and privacy budget λ.

Key results: FedIoMT with our two-level DP strategy offers superior privacy-utility trade-off than either merely local or global DP. FedIoMT gives high privacy assurances and reaches 96% of the non-private accuracy with ε = 1. For ε > 5, the accuracy decline is modest, indicating that great privacy can be attained with little use of resources.

System Heterogeneity Robustness

We assess many approaches under differing degrees of system heterogeneity.

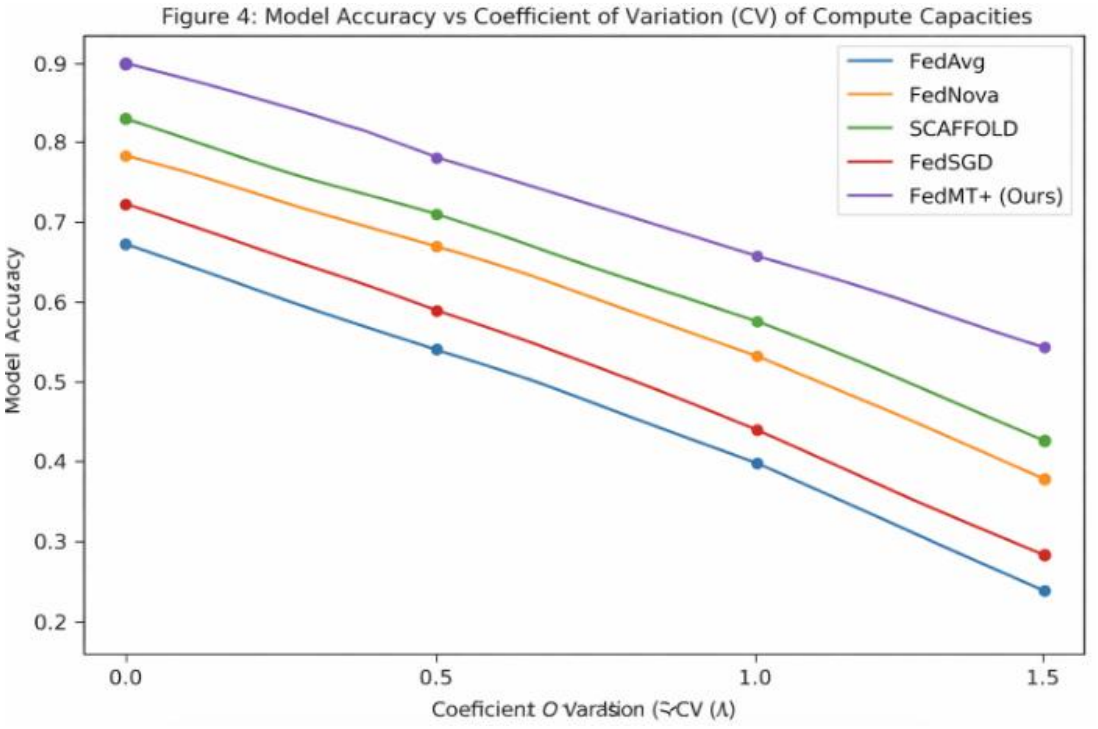

Figure 4 demonstrates the model accuracy when the coefficient of variation (CV) of compute capacities among devices rises.

Observations: FedIoMT stands out as being more resistant to device heterogeneity than other techniques. Variations in device capability can be lessened via hierarchical architecture and heterogeneity-aware aggregation. FedIoMT keeps over 88% accuracy whereas FedAvg falls below 70% even with great heterogeneity (CV=1)

Analysis of Privacy Leakage

We assess utilizing membership inference attacks [21] the privacy protection of several approaches. Table 2 lists, for various privacy methods, the attack accuracy—lower is preferable.

Table 2: Membership inference attack accuracy

Method	MIMIC-III	Physionet	HAR-Wearable
Centralized	76.2%	72.8%	79.5%
Fed Avg	62.4%	59.7%	65.1%
Fed Avg+ DP	54.1%	52.3%	56.8%
Fed IoMT	57.8%	55.2%	60.3%
Fed IoMT+ DP	51.2%	50.7%	52.9%

Federated learning offers notable privacy advantages above centralized learning. Differential privacy helps to lower privacy leakage in FedIoMT as well as FedAvg. FedIoMT with DP achieves the lowest privacy leakage, quite near to the theoretical minimum of 50% for binary classification.

3. CONCLUSION

The IoMT's lightning-fast development has allowed for sophisticated diagnosis, personalised therapy, and real-time monitoring, all of which have drastically altered healthcare delivery. Data privacy, security, and efficient processing have become more important issues as our reliance on linked medical devices continues to rise. The dependence on massive data sharing in traditional centralised machine learning systems makes them ill-equipped to handle these problems; this sharing puts sensitive patient information at danger of breaches and regulatory issues. A strong paradigm that allows for decentralised model training while protecting data privacy is federated learning (FL), which has arisen in this area. Nevertheless, typical FL frameworks aren't always a good fit for IoMT settings because of the energy limitations, communication overhead, and restricted processing power of medical devices. This calls for solutions that are both lightweight and designed to protect user privacy, with an emphasis on IoMT systems. Lightweight federated learning frameworks that safeguard user privacy may help healthcare providers and patients trust each other more, which in turn increases the likelihood that providers will comply with data protection laws and facilitates the widespread use of intelligent healthcare systems. Problems including communication latency,

resilience against complex assaults, and system heterogeneity still need further investigation, despite these improvements. Finally, one potential way to secure IoMT ecosystems is by privacy-preserving lightweight federated learning. Secure, scalable, and dependable next-generation healthcare systems are within reach, thanks to its combination of decentralised intelligence, robust privacy protections, and resource-efficient architecture.

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