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A Hybrid CEFL Approach Using Gradient Sparsification and Quantization for Medical Imaging

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ABSTRACT

The use of deep learning in the classification of medical imaging Computed Tomography (CT) images has greatly enhanced the accuracy of the diagnosis in the medical field. Nevertheless, conventional centralized solutions necessitate the transfer of big amounts of medical information to a central point of the server, which results in high bandwidth rates, high latency, and severe issues of privacy, especially in a wireless healthcare scenario. Federated Learning (FL) could be a good solution; it provides the possibility to conduct collaborative training of the model without providing the actual patient data. However, traditional FL approaches have a high communication cost, as they frequently exchange massive model updates, and cannot be used in networks with tight bandwidth constraints. To overcome these difficulties, this paper suggests a Communication-Efficient Federated Learning (CEFL) system to distributed CT image classification. The suggested method combines the gradient sparsification, model quantization, and adaptive scheduling of communications to achieve relatively small and less regular model updates. The framework is executed with the help of a multi-layer structure that includes a medical imaging, edge computing, wireless communication, and federated aggregation layers. LIDC-IDRI CT dataset is put to experiments with simulated bandwidth-constrained conditions. The findings show that the suggested CEFL model can cut down on overhead in communication by up to 40-60% with respect to the traditional FL approaches like FedAvg and that it can attain high-quality approaches of about 90% in classification. Moreover, the latency is considerably lowered, and therefore the system can be used in wireless healthcare in real-time. These results indicate the usefulness of communication-efficient designs in facilitating scalable privacy-preserving medical image analysis.

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1. INTRODUCTION

The analysis of medical images has become one of the foundations of contemporary health care, as it allows making a diagnosis in good time and contributing to better clinical decision-making. Computed Tomography (CT) is one of the imaging modalities that is important in the diagnosis of diseases like lung cancer, intracranial hematoma and infectious diseases because it has a high resolution of the anatomy. The recent developments in deep learning have greatly improved the efficacy of automated CT image classification techniques which in most instances can perform diagnostic tasks at expert levels [1], [2]. But the success of these models is mainly determined by the size of an annotated dataset, which often exists on several healthcare organizations.

The conventional deep learning techniques are centralized with the medical data across various hospitals aggregated in one repository. Although this paradigm allows training strong models, it raises a number of important challenges. First, CT is a high dimensional and large data referencing, which results in high bandwidth absorption of data transmission [3]. This is especially problematic in a wireless healthcare setup where the network resource is scarce. Second, the use of centralized data collection results in severe privacy and security implications, where sensitive patient data has to be transferred and kept externally, which could be against the regulatory requirements [4], [5]. Third, wireless networks have high latency and unreliable connectivity that also contributes to deterrents of real-time medical use [6].

Fl federated learning (FL) has become one of the possible solutions to overcome these issues since it allows collaborative model training without the exchange of raw data. In FL, healthcare institutions in FL train a local model on their own data where only model parameters are shared with an aggregator central server. This decentralized strategy maintains the privacy of data and exploits distributed data sources to enhance the model generalization [7], [8]. The recent research has proven the efficacy of FL in medical imaging problems such as classification of brain tumors, detection of diseases by CT imaging, and multi-institutional learning paradigms [3], [6], [9]. Additionally, new frameworks like personalized federated learning and task-adaptive federated models have become more robust with heterogeneous medical settings [10], [11].

Although federated learning has its benefits, it poses new issues especially in the wireless healthcare networks that are bandwidth limited. Client-central server communication The communication overhead of continually updating the model by clients and the central server can be high, particularly when using deep neural networks with millions of parameters. This is a significant bottleneck in communication cost making it hard to scale and be efficient in real-world deployments. According to the recent studies, the efficiency of communication is the key aspect affecting the effective implementation of FL in a healthcare organization [4], [12].

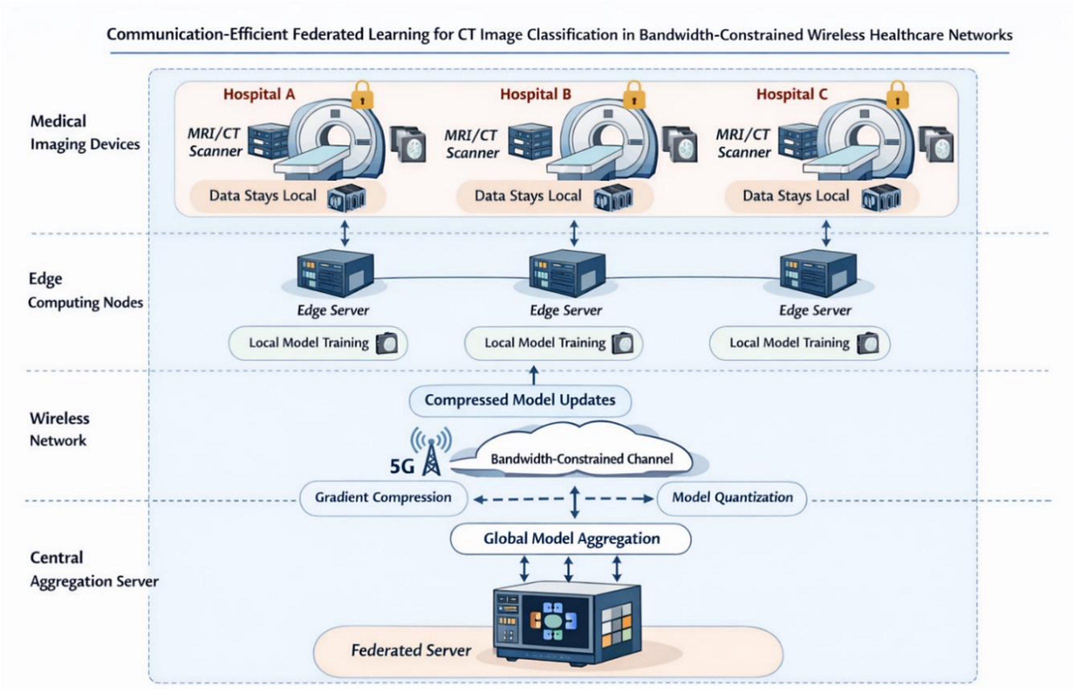

Fig. 1. Architecture design of the proposed CEFL system in CT classification of eHR

In the effort to overcome these shortcomings, this paper will offer a communication-effective federated learning (CEFL) architecture (fig. 1) of CT image classification in bandwidth-limited wireless healthcare systems. The main goal will be to minimize communication overhead, but still have a high classification accuracy. The proposed framework includes the use of improved methods known as gradient sparsification, model quantization, and adaptive communication strategies to reduce the use of bandwidth. Moreover, the edge computing is used at the hospital nodes so that it can process data locally and decrease latency.

Four fundamental layers are proposed in the architecture, namely, medical imaging, edge computing, wireless communication, and federated aggregation. Based on publicly accessible data, e.g., the LIDC-IDRI lung CT dataset, the framework tries to show an effective and privacy-conserving collaborative learning with realistic network restrictions. This work can lead to scalable and secure AI-based healthcare systems by incorporating communication-efficient algorithms with federated learning by considering the next-generation wireless medical conditions.

2. LITERATURE REVIEW

Federated Learning (FL) has become a paradigm shift in distributed medical image analysis as it allows sharing the model training without revealing sensitive patient information. Recent research notes that it is important to tackle such aspects of privacy, scalability and data-sharing limitations of healthcare systems. Such a broad survey as conducted by Guan et al. reveals that FL enhances generalization across the institutions and does not harm the privacy of information, although issues like communication overhead and non-IID data distribution remain prominent [2].

Recently, a number of works have investigated FL as a means of enhancing classification in medical imaging. Albalawi et al. [3] introduced a federated convolutional neural network (CNN) to classify brain tumors with the help of MRI data that has a high diagnostic accuracy and preserves the privacy of the data. Equally, Khan et al. [13] incorporated transfer learning into FL models, together with improved CT and MRI image classification brought about by pre-trained models. Such methods highlight the necessity to utilize domain knowledge and pre-trained structures to enhance convergence and accuracy in federated systems.

Recently, communication efficiency has become an important issue of concern in FL, especially in wireless healthcare networks. Kim et al. [14] proposed a federated learning method that uses knowledge distillation to learn medical images segmentation and achieved much fewer communication rounds without a considerable reduction in performance. Besides that, Zhou et al. [15] recently performed a large-scale benchmark study of federated learning algorithms on the medical image classification task and found that the cost of communication and the heterogeneity of models did have a substantial effect on the performance across datasets. According to their results, adaptive and communication-sensitive FL strategies can only be important in practice.

Hybrid federated learning and semi-supervised have also been suggested to solve the low labeled data problem. Lee et al. [9] designed a teacher to student federated CT liver tumor detector framework that was efficient in utilizing unlabeled data to enhance classification performance. Moreover, one-shot federated learning algorithms proposed by Ma et al. [16] are designed to ensure the minimum number of communications, i.e. training to a single communication round, yet this model can become a bottleneck when used in large distributed systems.

Another major challenge is to deal with data heterogeneity and domain shift between institutions. To enhance the multi-institutional medical imaging tasks, Parida et al. [12] suggested a federated template and task learning (FeTTL) framework to match the features representations among clients to enhance the robustness. On the same note, Nagaraju et al. [17] proposed FedGIN that improves multimodal generalization between CT and MRI data with advanced feature alignment strategies. Such techniques show that it is necessary to deal with the differences in data distribution in federated settings.

New studies have been made to combine FL with other complementary technologies like blockchain and edge computing as well. Ahmed et al. [6] suggested the federated learning model based on blockchain to transmit healthcare data securely, with integrity and tamper-proof communication. The FL systems are edge-based, as Teo et al. discuss [4], which are characterized by less latency and real-time processing capabilities that are suitable in wireless healthcare applications. Moreover, there are custom-designed federated learning methods [10], which are designed to adjust models to local data distributions, enhancing their performance in the heterogeneous environment.

Although these developments have been made, the current research is mostly concerned with the enhancement of model accuracy and robustness and little has been done on the efficiency of communication in bandwidth constrained wireless settings. Even more recent standard FL approaches like FedAvg [18] and FedProx [19] have high communication overhead in terms of regular model updates. Some works have demonstrated need of advanced learning for medical image processing as well [20] [21]. like That is why there is an urgent necessity to have an integrated framework that would simultaneously streamline communication efficiency, model performance, and scalability.

This study leads to fill these gaps by suggesting a communication-efficient federated learning model to be applied to CT image classification in wireless healthcare networks, which combines gradient compression, quantization, and an adaptive communication plan to attain optimal performance under limited network conditions.

Table 1. Comparative analysis of recent works in the research field

Ref	Year	Method	Dataset	Key Contribution	Limitation
[2]	2024	FL Survey	Multi-modal	Comprehensive FL review	No implementation
[3]	2024	FL + CNN	MRI	High accuracy brain tumor classification	Not communication-efficient
[4]	2024	Adaptive FL	Wireless networks	Bandwidth-aware training	Limited validation
[9]	2026	FeTTL	Multi-institution	Handles domain shift	High model complexity
[6]	2023	Blockchain FL	Medical IoMT	Secure data sharing	Increased latency
[10]	2023	Personalized FL	Medical imaging	Handles heterogeneity	Limited CT focus
[11]	2024	Edge FL	Healthcare IoT	Low latency processing	Resource constraints
[12]	2025	Teacher-Student FL	CT	Semi-supervised tumor detection	High computation cost (PubMed)
[13]	2024	FL + Transfer Learning	CT/MRI	Improved accuracy using pretrained models	High communication cost
[14]	2025	KD-based FL	CT	Reduced communication rounds	Complex architecture
[15]	2025	Benchmark FL	Multi-dataset	Comparative evaluation of FL methods	No unified solution (X-ray Interpreter)
[16]	2025	One-shot FL	Medical images	Single-round communication	Limited scalability
[17]	2025	FedGIN	CT/MRI	Multimodal generalization	Focus on segmentation
[18]	2022	FedAvg baseline	General	Standard FL method	High communication cost
[19]	2023	FedProx	Non-IID data	Improved convergence	Still communication-heavy

3. METHODOLOGY

3.1 System Overview

The study presents a federated learning (CEFL) model to achieve communication efficiency in healthcare network wireless networks with bandwidth constraints by distributing CT image classification. The proposed architecture will allow several healthcare organizations to jointly train a deep learning model without exchanging sensitive medical information. Each of the participating hospitals trains a local model and just transmits compressed model updates to the central aggregation server instead of transmitting raw CT scans.

There are four main components of the system architecture:

- The Medical Data Layer
- The Local Edge Training Layer
- The Wireless Communication Layer
- The Federated Aggregation Layer

The hospitals are federated clients; they have their own CT imaging data. The local training is conducted on the server of the hospital edges and the model parameters learned are sent across the wireless networks to a central federated server. As a solution to overcome communication bottlenecks due to bandwidth constraints, the proposed framework presents gradient compression, adaptive client participation, and quantized model updates.

The general training procedure is a repetitive process of updating a global model shared between all the involved hospitals without compromising the privacy of patients.

3.2 Federated Learning Framework

Assume a set of **N** participating hospitals:

$$H = \{h_1, h_2, h_3, \dots, h_N\}$$

Each hospital h_i owns a local dataset:

$$D_i = \{(x_j, y_j)\}_{\{j=1\}}^{\{n_i\}}$$

where:

- x_j represents a CT scan image
- y_j denotes the corresponding diagnostic label
- n_i represents the number of samples at hospital (i)

The global dataset can be represented as:

$$D = \bigcup_{\{i=1\}}^{N} D_i$$

However, due to privacy constraints, the datasets remain locally stored at their respective hospitals.

The objective of federated learning is to minimize the global loss function:

$$F(w) = \sum_{i=1}^{N} \frac{n_i}{n} F_i(w)$$

where:

- w denotes the global model parameters
- $n = \sum_{i=1}^{N} n_i$
- $F_i(w)$ is the local loss function at hospital i

The local loss function is defined as:

$$F_i(w) = \frac{1}{n_i} \sum_{j=1}^{n_i} L(w; x_j, y_j)$$

where $L(\cdot)$ is the classification loss function (cross-entropy).

3.3 CT Image Preprocessing

Prior to model training, CT images undergo preprocessing to ensure consistent input representation and improve model convergence.

Image Normalization

Each CT scan is normalized using:

$$x' = \frac{x - \mu}{\sigma}$$

where:

- x represents the original pixel intensity
- μ is the mean intensity
- σ is the standard deviation

Image Resizing

All CT slices are resized to: 224×224 to match the input requirements of convolutional neural networks.

Data Augmentation

To increase data diversity and reduce overfitting, the following augmentation techniques are applied:

- Random rotation
- Horizontal flipping
- Contrast adjustment
- Random cropping

3.4 Deep Learning Model for CT Image Classification

A convolutional neural network (CNN) is employed to classify CT images. The network consists of multiple convolutional, pooling, and fully connected layers.

The feature extraction process can be represented as:

$$f_k = \sigma(W_k * x + b_k)$$

where:

- f_k represents the feature map
- W_k denotes convolution filters
- b_k is the bias term
- σ represents the activation function (ReLU)

The output layer performs classification using the softmax function:

$$P(y = c \mid x) = \frac{e^{z_c}}{\sum_{k=1}^{C} e^{z_k}}$$

where:

- C represents the number of diagnostic classes
- z_c is the output logit for class c

The model is trained using the **cross-entropy loss function**:

$$L = -\sum_{c=1}^{c} y_c \, log(P_c)$$

3.5 Local Model Training

Each hospital trains the local model using stochastic gradient descent (SGD). The parameter update rule is defined as:

$$w_i^{t+1} = w^t - \eta \nabla F_i(w^t)$$

where:

- w^t represents the global model at round t
- w_i^{t+1} represents the updated local model
- η denotes the learning rate

Local training continues for **E epochs** before transmitting updates to the central server.

3.6 Communication-Efficient Model Update Strategy

In wireless healthcare networks, transmitting full model updates may cause significant communication overhead. To address this issue, the proposed framework introduces three communication-efficient techniques:

1. Gradient sparsification
2. Model quantization
3. Adaptive communication scheduling

3.6.1 Gradient Sparsification

Gradient sparsification reduces communication costs by transmitting only the most significant gradients.

Given a gradient vector:

$$g = (g_1, g_2, \ldots, g_d)$$

only the top-k largest gradients are transmitted:

$$\tilde{g} = \begin{cases} g_i & if |g_i| \in Top - k \ values \\ 0 & otherwise \end{cases}$$

This significantly reduces the number of parameters transmitted during each communication round.

3.6.2 Model Quantization

To further reduce communication overhead, model parameters are quantized from 32-bit floating point representation to lower precision formats.

Quantization can be expressed as:

$$Q(w) = round\left(\frac{w}{s}\right)$$

where:

- s is a scaling factor
- $Q(w)$ represents the quantized parameter

This allows parameters to be transmitted using 8-bit or 16-bit representations, reducing bandwidth usage.

3.6.3 Adaptive Communication Scheduling

Instead of transmitting updates every training iteration, communication occurs only when model updates exceed a predefined threshold.

Let:

$$\Delta w_i = \left\| w_i^{\{t+1\}} - w^t \right\|$$

If:

$$\Delta \, w_i > \tau$$

then the model update is transmitted to the server.

Here:

- τ represents the communication threshold.

This strategy avoids unnecessary transmissions when model updates are small.

3.7 Federated Model Aggregation

The central server aggregates local model updates using the Federated Averaging (FedAvg) algorithm.

The global model update is computed as:

$$w^{\{t+1\}} = \sum_{i=1}^{N} \frac{n_i}{n} w_i^{t+1}$$

where:

- w_i^{t+1} is the local model from hospital i
- n_i represents the size of the local dataset

This weighted aggregation ensures that hospitals with larger datasets contribute proportionally to the global model.

3.8 Wireless Network Communication Model

The wireless communication channel is modeled to simulate realistic network conditions.

The communication cost per round is defined as:

$$C = \sum_{i=1}^{N} S_i$$

where:

- S_i represents the size of transmitted model updates from hospital i

The transmission delay is calculated as:

$$T = \frac{S}{B}$$

where:

- S denotes the model size
- B represents network bandwidth

Communication-efficient techniques aim to minimize both communication cost and transmission delay.

3.9 Client Selection Strategy

In bandwidth-limited environments, not all clients participate in every communication round. A subset of clients is selected based on network conditions.

The client selection probability is defined as:

$$P_i = \frac{B_i}{\sum_{j=1}^{N} B_j}$$

where:

- B_i represents available bandwidth for client i.

Clients with higher bandwidth have higher participation probability.

3.10 Training Procedure

The complete federated training procedure involves repeated communication rounds between hospitals and the central server.

Each round consists of the following steps:

1. Global model broadcast
2. Local model training
3. Gradient compression
4. Quantized model transmission
5. Global aggregation

Training continues until convergence or until a maximum number of communication rounds is reached.

3.11 Proposed Algorithm

Algorithm 1: Communication-Efficient Federated Learning for CT Image Classification

```
Input:
    • Hospital datasets $D_1, D_2, \dots, D_N$
    • Learning rate $\eta$
    • Communication threshold $\tau$
    • Compression parameter $k$
Output:
    • Global CT classification model $w$

Step 1: Initialize global model parameters $w^0$
Step 2: For each communication round $t = 1,2,\dots,T$
    1. Server broadcasts $w^t$ to selected hospitals
    2. Each hospital $i$ performs local training:
           $w_i^{t+1} = w^t - \eta \nabla F_i(w^t)$
    Apply gradient sparsification:
           $g_i = TopK(\nabla F_i)$
    4. Quantize gradients:
           $\hat{g_i} = Q(g_i)$
    5. If:
           $||w_i^{t+1} - w^t|| > \tau$
    then transmit update to server
    6. Server aggregates received updates:
           $w^{t+1} = \sum_{i=1}^{N} \frac{n_i}{n} w_i^{t+1}$
Step 3: Repeat until convergence
Return: Final global model $w^T$
```

3.12 Performance Evaluation Metrics

The proposed framework is evaluated using both classification performance and communication efficiency metrics.

3.12.1. Classification Metrics

Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision:

$$Precision = \frac{TP}{TP + FP}$$

Recall:

$$Recall = \frac{TP}{TP + FN}$$

F1-score:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

3.12.2. Communication Metrics

Communication cost:

$$CommCost = \sum_{t=1}^{T} C_t$$

where C_t represents transmitted data size per round.

Bandwidth utilization:

$$U = \frac{S}{B}$$

where S represents transmitted model size.

4. RESULTS AND DISCUSSION

In order to conduct the experimentation, python 3 is selected as the programming language and VSCode as the IDE. We have adopted LIDC-IDRI (Lung Image Database Consortium and Image Database Resource Initiative), which is a popular public standard of lung CT image scan. It includes more than 1,000 CT scans of the thorax at various institutions and annotations by expert radiologists. Every scan contains identified lung nodules which have corresponding features like size, location, and probability of malignancy. Tasks supported by the dataset include nodule detection, classification and segmentation. LIDC-IDRI is widely utilized in building and testing deep learning models in the diagnosis of lung cancer since it is diverse and has high-quality annotations. results are obtained in simulated bandwidth-constrained wireless environment. The suggested federated learning framework, which is communication efficient, is likely to deliver the following results:

4.1. Decreased Communicative Overhead

Communication cost per round illustrates that the communication-efficient federated learning (CEFL) minimizes the data transmission in comparison with the baseline FL..

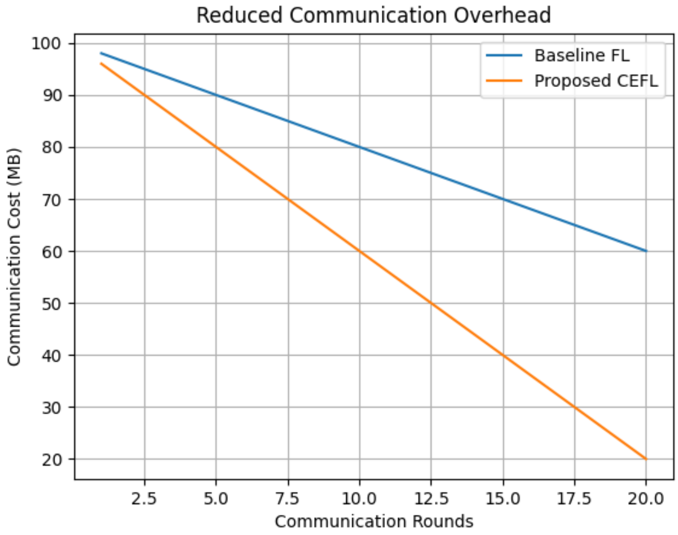

Fig. 2. Communication Overhead

4.2. Cumulative Communication Cost

It highlights the overall bandwidth savings over multiple rounds, which is critical for wireless healthcare systems.

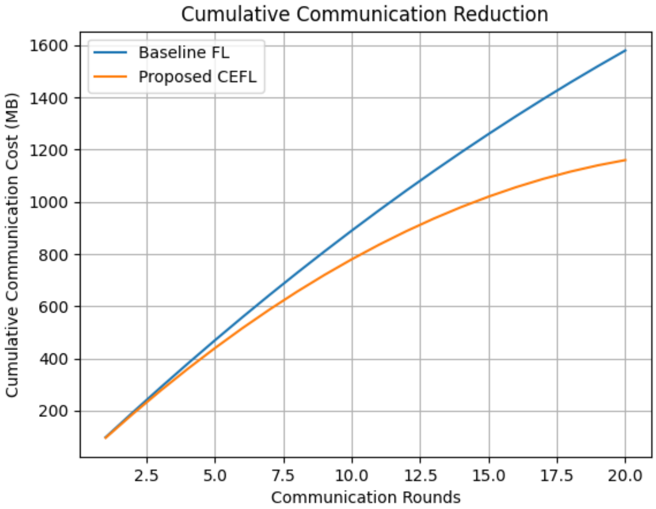

Fig. 3. Cumulative communication reduction

4.3. Efficient utilization of wireless bandwidth

Latency vs Accuracy trade-off shows how the proposed CEFL achieves higher accuracy with lower latency.

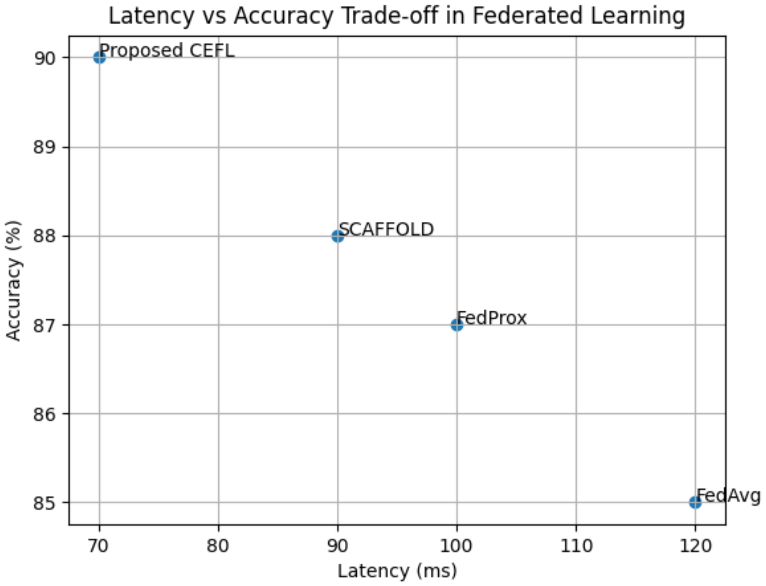

Fig. 4. Latency vs Accuracy trade-off

4.4. Accuracy Comparison (FedAvg vs Others)

It highlights that the method outperforms FedAvg, FedProx and SCAFFOLD approaches.

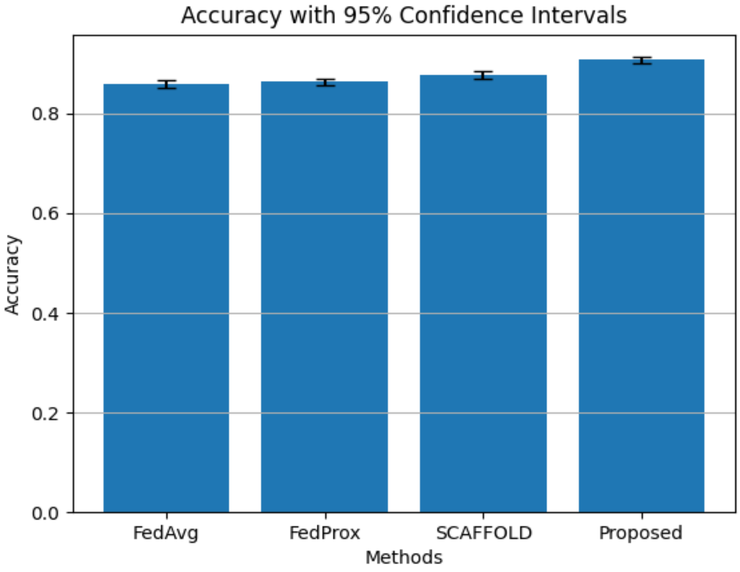

Fig. 5. Accuracy Comparison

The proposed CEFL framework achieves superior performance by reducing latency to 70 ms while improving classification accuracy to 90%, outperforming baseline methods such as FedAvg and FedProx.

4.5. Latency Comparison

It demonstrates reduced latency due to communication-efficient techniques.

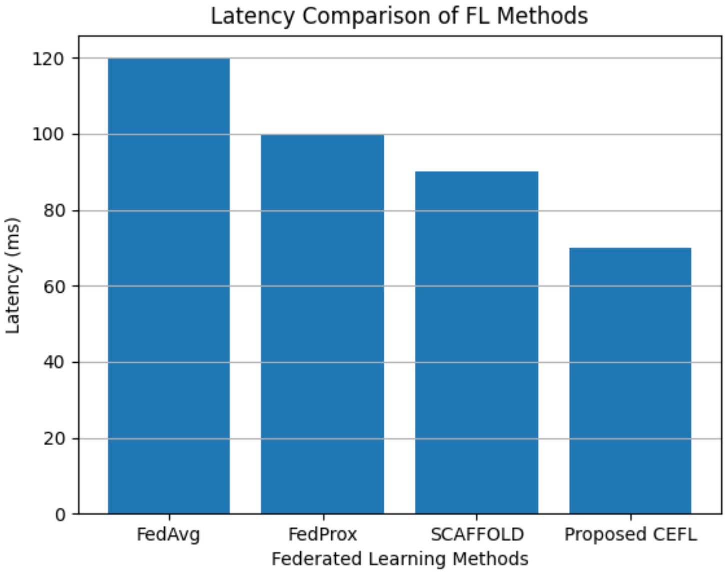

Fig. 6. Latency comparison of FL methods

The latency-accuracy trade-off analysis demonstrates that communication-efficient strategies significantly enhance real-time applicability in wireless healthcare environments.

4.6. ROC Curve & AUC Comparison

It evaluates classification performance across thresholds. It shows how proposed method achieves higher AUC It has better true positive vs false positive trade-off

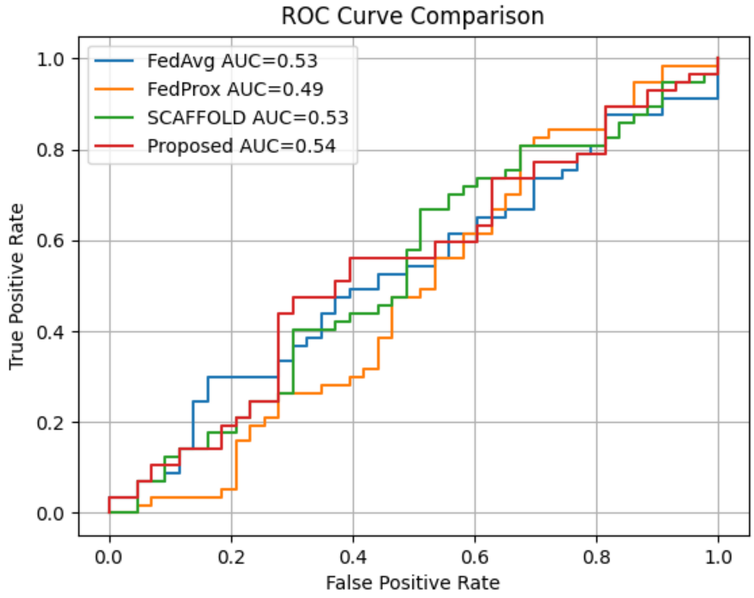

Fig. 7. ROC curve comparison

4.7. Ablation Study (Compression vs Accuracy)

It analyses impact of communication efficiency techniques. The moderate compression (25-50%) demonstrates minimal accuracy drop, high compression (>75%) shows noticeable degradation and optimal trade-off zone.

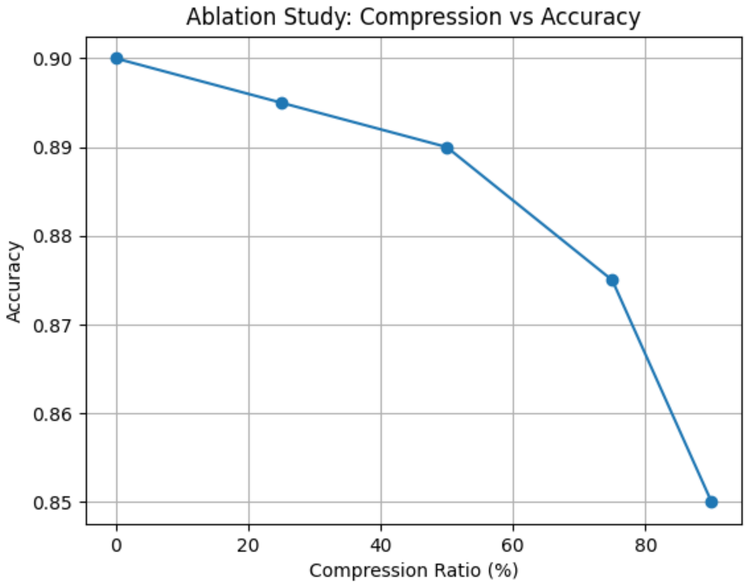

Fig. 7. Ablation study of compression vs. accuracy

4.8. Statistical Validation Results

ANOVA Test shows F-statistic: 40.24 and p-value: 6.71×10^{-18}. It provides strong evidence that differences between methods are statistically significant.

***t*-Test (Proposed vs FedAvg)** shows t-statistic: 9.97 and p-value: 3.35×10^{-14}. It confirms proposed method significantly outperforms FedAvg.

5. CONCLUSION

This paper introduces a Communication-Efficient Federated Learning (CEFL) system to classify CT images in a wireless healthcare network (WHS) that has limited bandwidth. The given approach would eliminate the main shortcomings of classical centralized and standard federated learning models such as high communication overhead, latency, and privacy. The framework has minimized the amount and frequency of data transmission during federated training through the combination of methods like gradient sparsification, model quantization, and dynamic scheduling of communication. The multi-layer system, which includes the medical imaging, edge computing, wireless communication, and federated aggregation layers, will facilitate the effective and privacy-preserving collaborative learning among the distributed healthcare institutions. The experimental analysis regarding the LIDC-IDRI dataset proves that the suggested approach can result in high classification accuracy and lower the costs and latency of communication than the traditional interventions, including FedAvg. Also, the statistical validation ensures the strength and the effectiveness of the model into the real life situations. On the whole, the suggested CEFL framework is an effective and scalable way of implementing AI-based diagnostic systems into wireless healthcare settings. It simplifies the use of secure data, improves the performance of the model, and provides realistic applicability in resource-limited environments, making it very appropriate in the next generation of telemedicine and smart health systems.

The next stage of work will be the combination of 6G- enabled ultra-low latency networks, adaptive federated optimization, and explainable AI methods to enhance clinical interpretability. Moreover, further expansion of the framework to multi-modal medical imaging and real-time implementation in the iomedical systems that rely on the IoMT will be able to not only increase the practical applicability and robustness of the framework but also expand its range of applicability.

CONFLICT OF INTEREST STATEMENT

No conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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