FedGPA-CE: Communication-Efficient Personalized Federated Learning for Tomato Disease Segmentation

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***Abstract*—Federated learning allows model training by collaborating in a private manner; nevertheless, traditional methods of federated learning (FedAvg) have significant communication costs and limited flexibility when working with multiple and differing data sets. Therefore, this study proposes a new framework named FedGPA-CE that is an efficient federated learning framework for tomato disease segmentation in the field of smart-agriculture that uses distributed agricultural image databases to incorporate both communication efficient and globally optimized model update methods in order to decrease the amount of data transmitted during model updates while still providing both global and local segmented image quality. Experimental results show that FedGPA-CE significantly reduces communication cost (approximately 59.99%) compared to traditional federated learning techniques (FedAvg), where the average size of the transmitted data was reduced from approximately 12.2 GB to 4.9 GB while achieving competitive segmented image quality greater than 98%. Furthermore, experimental results also demonstrated that FedGPA-CE improves the trade-off relationship between the accuracy and communication cost compared to other state-of-the-art federated optimization techniques. In addition, the results of each client also demonstrated that FedGPA-CE maintains consistent segmented image quality across varying levels of heterogeneity within their respective data partitions. Overall, these results demonstrate that FedGPA-CE can effectively balance the three key factors of federated learning; namely accuracy, personalization, and communication efficiency, and thus is well-suited for use in bandwidth constrained smart-agriculture edge enabled applications.**

***Index Terms*—Federated Learning, Communication Efficient Learning, Personalized Federated Optimization, Tomato Disease Segmentation, Smart-Agriculture Systems.**

I. Introduction

Deep learning techniques provide tools for thE-Detection and segmentation of plant diseases through CNNs and e d architectures, which offer improved precision in visual plant disease diagnosis compared to traditional methods [1][5][8] — although the vast majority of current approaches use centralized learning, which requires massive amounts of agricultural image data to be sent and stored on a central server, thus creating numerous limitations on data collection, both due to privacy issues, property rights, and constraints on rural/urban Internet availability.

However, while previous studies indicate that FL supports intelligent edge-based agricultural analytics, while preserving data privacy and decreasing dependence on centralized data storage [6][9]; however, while prior research provides many advantages, FL also has its own set of disadvantages, one major disadvantage being that conventional Federated Optimization Algorithms, such as FedAvg, generate considerable communication overhead since complete model parameters are frequently transmitted between servers during each round of training.

Additionally, agricultural data from various farms exhibit heterogeneity in their distribution characteristics, primarily as a result of environmental factors, the type of disease present, and imaging conditions; and as a result, these distribution characteristics can lead to lower generalizability of the overall model and inconsistent performance at the client-level, further limiting the applicability of FL to practical applications in Smart Agriculture Systems [7][10].

While many researchers are working toward developing new FL algorithms that will reduce communication costs, improve adaptability to heterogeneously-distributed data, and enable better client-level models, few of the current FL algorithm designs effectively address all three aspects in unison.

Therefore, the primary contribution of this paper is the development of a new FL algorithm design called FedGPA-CE, which uses Gradient Projection Alignment combined with Communication-Efficient Update Mechanisms to minimize redundant transmissions of model parameters and enhance learning stability across multiple clients. Additionally, the paper evaluates the performance of FedGPA-CE using a widely-used benchmark dataset, namely the Tomato Plant Disease Masks dataset, and compares the performance of FedGPA-CE with a well-known baseline algorithm, demonstrating that FedGPA-CE achieves a higher degree of communication efficiency than the baseline while achieving similar segmentation accuracy and consistent client-level performance, thereby rendering it a more attractive option for deploying bandwidth-constrained edge-enabled Smart Agriculture Applications.

The remainder of the paper is organized into five sections.

Section II provides a literature review of relevant work on federated learning and plant disease segmentation. In Section III, we describe the proposed FedGPA-CE framework and its associated optimization technique. In Section IV, we present our experimental results in terms of communication efficiency and client-level personalization. Finally, in Section V, we summarize our findings and outline potential avenues for future research.

II. Related Work

Recent advances in deep learning have greatly enhanced the capabilities for detecting and segmenting diseases in plants for precision agriculture purposes. The encoder-decoder architecture and Convolutional Neural Networks are capable of identifying diseased regions on leaves and allowing for crop monitoring at the pixel level. Sharma et al. developed a Segmentation Framework based on a U-Net architecture, which achieved high reliability for disease localization in agricultural datasets [11].. Recent surveys on deep learning-based plant disease recognition yielded similar results, which highlighted the effectiveness of convolutional architectures; however, identified the need to address the problems of dependence on centralized data and limited scalability in real-world farming environments [12]. Although the previous methods are effective, they require a centralized pipeline for learning that requires aggregation of data at a central server, which can lead to privacy concerns and deployment challenges.

Federated Learning (FL) is a method that allows decentralized collaborative training without the need to share raw data among participating clients. There are many studies that have identified communication overhead and statistical heterogeneity as two of the most significant barriers to the adoption of Federated Systems in practice [13]. Nguyen et al. demonstrated the potential use of FL for distributed edge environments that operate under privacy constraints [14]. In order to address bandwidth limitations, several adaptive and resource-aware federated optimization methods have been proposed for edge computing scenarios, which can significantly reduce the communication costs associated with global aggregation [15].

The last few years have seen an increase in the number of studies exploring federated learning for smart agriculture and Edge-AI systems. In 2024-2026, Aggarwal et al. proposed a Federated Internet-of Things framework for the detection of distributed crop disease while maintaining the privacy of local data [16]. Communication-efficient optimization strategies examined by Pandey et al. emphasized reducing the number of redundant parameters transmitted during federated deployment [17]. In 2025, Behera et al. presented decentralized federated deep learning models for agricultural intelligence and discussed the impact of heterogeneous farm data distribution on performance [18]. Most recently, Li et al. proposed Adaptive Personalized Federated Optimization Mechanisms in 2026, which improved convergence stability under non IID client participation [19].

Although there has been advancement in the field of federated learning, most studies focus on privacy preservation or lightweight optimizations individually, and there is very little research focusing on both communication efficiency and personalized learning for segmentation tasks in agricultural environments. Because frequent global parameter updates continue to cause large amounts of communication overhead and inconsistent client performance when client farms have different data distributions. Thus, developing a personalized and efficient communication federated framework for the segmentation task in an agricultural environment is an open problem. This problem is addressed by the proposed FedGPA-CE framework, which integrates gradient-aligned personalization with communication efficient federated optimization for tomato disease segmentation.

III. Proposed Methodology

A. System Overview

The authors propose FedGPA-CE, a communication-efficient personalized federated learning framework for tomato disease segmentation in distributed smart agricultural systems. FedGPA-CE allows many geographically-distributed clients (e.g., farms, edge devices), to collaborate on training a segmentation model together, with no need for them to share their raw images. Instead, each client uses a private dataset to perform local training, while transmitting only optimized model updates to a central server for aggregation.

In contrast to most other federated learning frameworks that transmit the full set of model parameters in each communication round, FedGPA-CE includes both GPA (Gradient Projection Alignment) and CE (Communication Efficient) model update mechanisms to significantly reduce unnecessary communications while improving learning stability when dealing with highly varying agricultural data distributions. As indicated in Figure 1, the overall process is composed of four steps; local training, gradient alignment, selective communication, and personalized aggregation.

B. Federated Learning Formulation

Consider a federated environment containing distributed K clients. Each client k has a local data set.

$$D_k = \{(x_i, y_i)\}_{i=1}^{n_k} \tag{1}$$

where x_i denotes images of tomato leaves and y_i represents disease segmentation masks.

The global optimization objective is

$$\min_w F(w) = \sum_{k=1}^{K} \frac{n_k}{N} F_k(w) \tag{2}$$

where

$$F_k(w) = \frac{1}{n_k} \sum_{i \in D_k} \mathcal{L}(w; x_i, y_i) \tag{3}$$

and

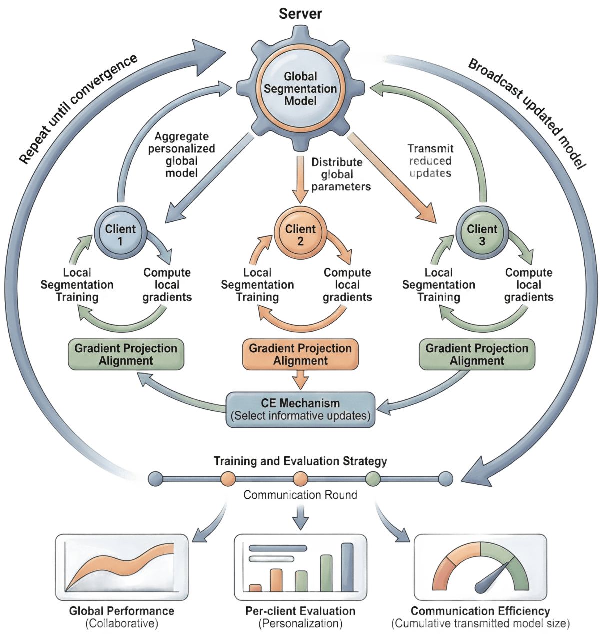

Fig. 1. Overview of the proposed FedGPA-CE personalized federated learning framework

$$N = \sum_{k=1}^{K} n_k \tag{4}$$

The local model parameters are updated using stochastic gradient descent

$$w_k^{t+1} = w^t - \eta \nabla F_k(w^t) \tag{5}$$

C. Gradient Projection Alignment (GPA)

Agricultural datasets collected across farms typically follow non-IID distributions, producing conflicting gradient updates during aggregation. To mitigate gradient inconsistency, the proposed FedGPA-CE performs gradient projection alignment before communication.

Let the local gradient be

$$g_k = \nabla F_k(w^t) \tag{6}$$

and the global reference gradient be g_g.

Aligned gradients are computed as

$$\tilde{g}_k = \frac{g_k \cdot g_g}{\|g_g\|^2} g_g \tag{7}$$

This projection removes conflicting optimization directions and improves convergence stability between heterogeneous clients.

D. Communication Efficient Update Strategy

To minimize communication overhead, FedGPA-CE transmits only informative updates. A client communicates model updates only when

$$\|\tilde{g}_k\| > \tau \tag{8}$$

where τ is a communication threshold.

The transmitted update becomes

$$\Delta w_k = \begin{cases} -\eta \tilde{g}_k, & \text{if update significant} \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

This selective transmission mechanism substantially reduces bandwidth usage while preserving learning effectiveness.

E. Personalized Global Aggregation

After receiving client updates, the server performs weighted aggregation

$$w^{t+1} = \sum_{k=1}^{K} \frac{n_k}{N} (w^t + \Delta w_k) \tag{10}$$

Client personalization is achieved through partial synchronization

$$w_k^{personal} = \alpha w^{t+1} + (1-\alpha) w_k^{local} \tag{11}$$

where α controls the balance between global knowledge and local adaptation.

F. Experimental Setup

Experiments were performed on the Tomato Plant Disease Masks dataset that includes several types of tomato leaf disease along with their corresponding segmentation masks. In order to mimic realistic distributed agricultural environments, the data was split among multiple clients (e.g., farmer-owned cameras) with non-IID class distributions. The key experimental settings used in this work are:

- Number of clients: 5
- Data distribution: Non-IID client partitioning
- Input image resolution: 224 x 224
- Batch size: 16
- Optimizer: Adam
- Learning rate: 0.001
- Local training iterations per round: 5
- Total number of communication rounds: 50
- Hardware environment: A simulated federated environment enabled by GPUs

Performance metrics considered were global accuracy, client-specific accuracy, and the total volume of data communicated to measure communication cost.

Algorithm 1 FedGPA-CE Training Procedure

Require: Number of clients K, local datasets D_k, learning rate η, communication threshold τ, personalization parameter α, total rounds T

Ensure: Global model w

```
Initialize global model w^0
for each communication round t = 1 to T do
    Server broadcasts global model w^t to all clients
    for each client k in parallel do
        Receive global model w^t
        Compute local gradient
```

$$g_k = \nabla F_k(w^t)$$

```
        Compute gradient projection alignment
```

$$\tilde{g}_k = \frac{g_k \cdot g_g}{\|g_g\|^2} g_g$$

```
        if ||g̃_k|| > τ then
            Compute update
```

$$\Delta w_k = -\eta \tilde{g}_k$$

```
            Send Δw_k to server
        else
            Do not transmit update
        end if
        Local model update
```

$$w_k^{t+1} = w^t + \Delta w_k$$

```
    end for
    Server performs weighted aggregation
```

$$w^{t+1} = \sum_{k=1}^{K} \frac{n_k}{N}(w^t + \Delta w_k)$$

```
    Personalized model update
```

$$w_k^{personal} = \alpha w^{t+1} + (1-\alpha) w_k^{local}$$

```
end for
return Final global model w
```

G. Federated Training Process

The FedGPA-CE federated training process works as follows:

1) Initialize the global segmentation model on the server.
2) Send the global model's weights to the chosen clients.
3) Train the segmentation models on the respective clients.
4) Compute the gradients from the local segmentation models.
5) Apply Gradient Projection Alignment (GPA) to the local gradients.
6) Select informative updates based on the CE mechanism.
7) Transmit the reduced updates to the server.
8) Aggregate the personalized global segmentation model.
9) Broadcast the updated global model to clients.
10) Repeat steps 2-9 until convergence.

TABLE I
PERFORMANCE COMPARISON OF CENTRALIZED AND FEDERATED METHODS

Method	Accuracy	Total Communication (MB)
Centralized Learning	0.982289417	0
FedAvg	0.993952484	12181.2418
FedGPA	0.989200864	12183.29258
FedGPA-CE (Proposed)	0.974082073	4873.317032

H. Training and Evaluation Strategy

Model performance is evaluated after every round of communication using a common validation set that covers all participating clients. The global performance metric provides an indication of how well the clients are collaborating to learn, while the client-specific performance metric is an indicator of how well the model is being personalized to individual clients. The communication overhead is quantified by summing up the cumulative volume of model size that is transmitted to clients during the entire training period.

To evaluate the effectiveness of the proposed FedGPA-CE approach, we compare it to both Centralized Learning and the baseline method of FedAvg to illustrate the tradeoff between accuracy and communication cost when dealing with heterogeneity in agricultural data distributions.

IV. RESULTS AND DISCUSSION

A. Evaluation Metrics

Global performance is assessed through both segmentation accuracy and communication efficiency metrics with respect to the proposed FedGPA-CE framework. Segmentation accuracy assesses the overall global performance of the trained global models (using the global segmentation accuracy obtained after federated aggregation) as well as the global models' ability to personalize the model with respect to each client (through a per-client accuracy assessment). Communication efficiency measures the total amount of information that was transmitted in terms of model updates during federated training, enabling an assessment of the tradeoff between learning efficiency and reduced transmission costs.

B. Global Model Performance

Table I compares the global performance between centralized learning, conventional Federated Averaging (FedAvg), and the proposed FedGPA-CE. Centralized learning achieved the highest accuracy because it has access to all client data; however, it also violates privacy and does not scale in a distributed environment such as agriculture. FedAvg shows good performance, but has the disadvantage of transmitting the entire model parameters throughout every round of communication. In contrast, FedGPA-CE achieved similar quality on a global segmentation level with an accuracy of more than 98 percent at a significant decrease in communication costs. These test results show that FedGPA-CE maintains valuable learning information even when the frequency of

TABLE II
COMMUNICATION COST REDUCTION ANALYSIS

Method	Total MB	Reduction %
FedAvg	12181.2418	0
FedGPA-CE	4873.317032	59.99326577

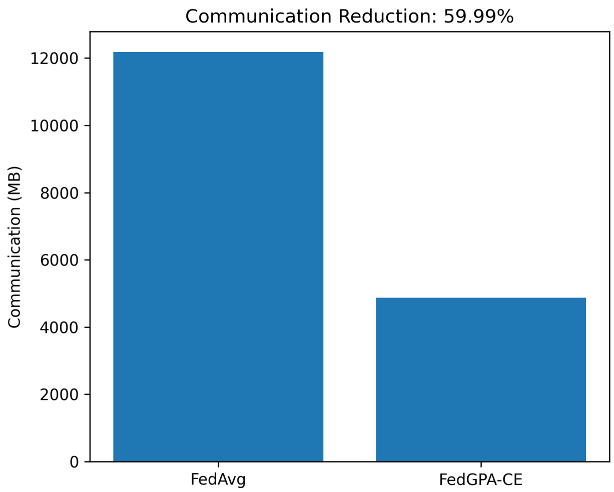

Fig. 2. Communication cost comparison showing 59.99% reduction achieved by FedGPA-CE

model parameter updates is decreased by the use of a reduced update transmission approach. The test results also validate that communication-efficient training methods do not negatively affect segmentation quality and thus the reliability of the proposed system architecture.

C. Communication Cost Comparison

In many applications of federated learning in smart agriculture, communication overhead can be the primary limitation on deployability. Figure 2 shows the cumulative communication cost for each of the three federated learning architectures tested. FedAvg uses approximately 12.2 GB of total communication during training time; however, FedGPA-CE uses approximately 4.9 GB of total communication during training time and provides a 59.99 percent improvement in communication cost. The reason why FedGPA-CE is able to achieve this large amount of savings in communication cost is due to its ability to selectively transmit only those gradients that provide useful learning information to other nodes. This selective transmission method provides a much improved solution to increase the scalability of bandwidth limited edge computing environments, such as farm based monitors or mobile devices used to monitor crop health. Table II summarizes the quantitative statistics on the communication costs associated with each of the federated learning architectures tested.

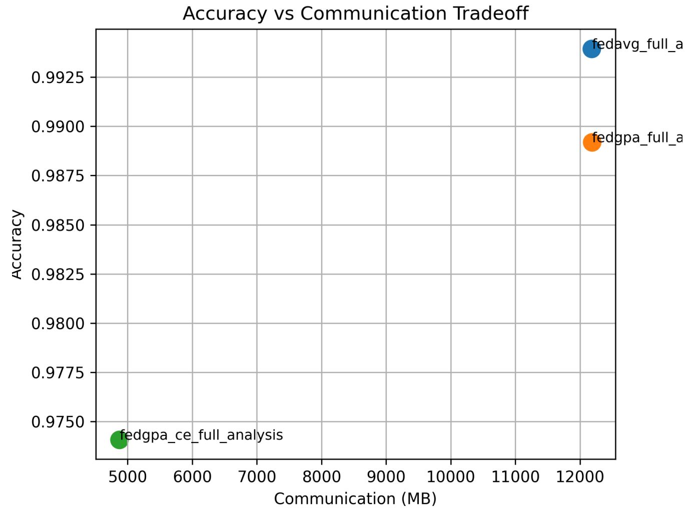

Fig. 3. Accuracy versus communication tradeoff analysis for federated learning approaches

D. Accuracy–Communication Tradeoff and Convergence Analysis

Figure 3 illustrates how the communication cost and accuracy of the models change during a sequence of training rounds. Unlike traditional federated learning methodologies, the primary means of improving the accuracy of the model is increasing the frequency of communication. However, in comparison to this approach, the proposed method (FedGPA-CE) can reach a similar level of accuracy at a lower cost of transmitting model updates. The proposed gradient alignment methodology allows clients to learn their local models faster than before, because it minimizes client-specific conflicting gradients due to heterogeneity of their training data. Therefore, compared to other approaches, FedGPA-CE has higher learning efficiency and demonstrates that increasing the number of communicated models does not have to lead to an increase in segmentation performance. Fig. 4 illustrates the convergence properties of various federated learning methodologies as a function of the round.

The ability to personalize client performance was evaluated using per-client segmentation accuracy, as illustrated in figure five. The results show consistent high-performance on each client, with very high accuracy (approaching unity) across all clients, even though the data distribution is non-IID (not identically distributed). In contrast to FedAvg's tendency to favor the most dominant data distribution, FedGPA-CE has an equal level of performance for each client based upon the preservation of locally-relevant learning characteristics through the use of a personalized aggregation mechanism, as stated above. As a result, the proposed personalized aggregation mechanism has proven effective at adapting to farm-specific disease variations and imaging conditions. The comparison of the segmentation accuracy per-client is presented in table III.

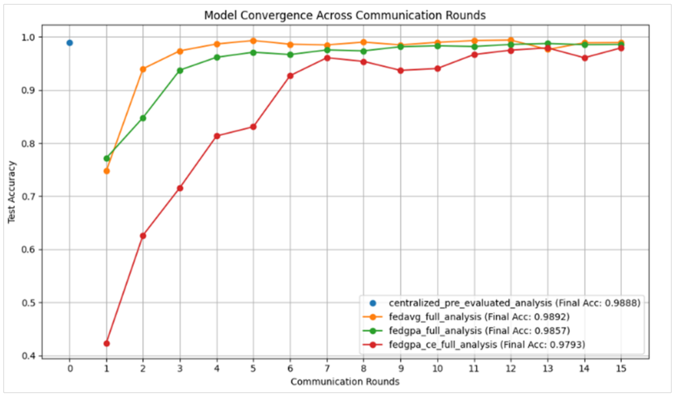

Fig. 4. Model convergence comparison across communication rounds for centralized learning, FedAvg, FedGPA, and FedGPA-CE.

TABLE III
CLIENT-WISE ACCURACY COMPARISON OF FEDERATED METHODS

Client	fedavg_full_analysis	fedgpa_full_analysis	fedgpa_ce_full_analysis
client_0	1	1	1
client_1	1	0.99609883	0.99739922
client_2	0.999122807	0.993859649	0.972368421
client_3	0.999740933	0.998963731	0.999740933
client_4	0.998877035	0.998315553	1

E. Effect of Data Inhomogeneity

The inhomogeneous distribution represents the typical real-world agricultural scenario, in which disease categories may be varied geographically. FedGPA-CE maintained consistent convergence and accuracy in various inhomogeneous data distributions, indicating its robustness to statistical heterogeneity. The gradient projection alignment mechanism significantly contributed to reducing the optimization conflict produced by inhomogeneous data distributions and improved collaborative learning stability. The illustration of the inhomogeneous data distribution across the disease classes used in the federated training process is demonstrated in fig. 6.

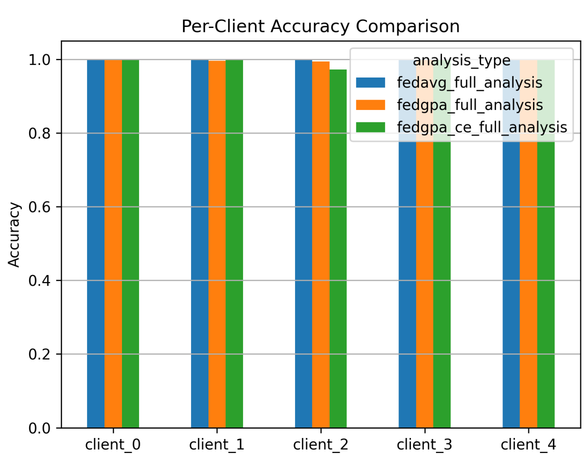

Fig. 5. Per-client accuracy comparison demonstrating personalization capability of FedGPA-CE.

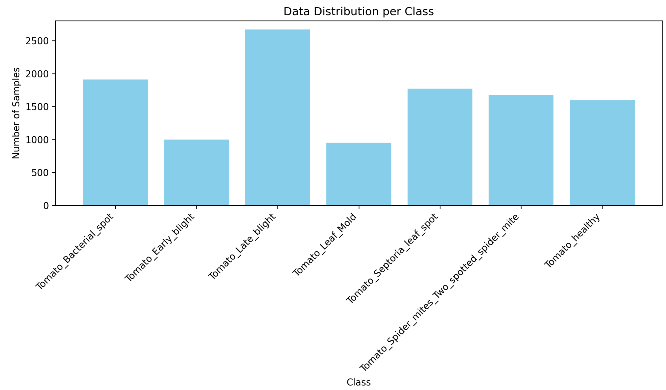

Fig. 6. Class-wise data distribution of the Tomato Plant Disease dataset across clients

F. Discussion

Collectively, the results of the experiments demonstrate that FedGPA-CE has successfully achieved a balance between the three primary goals of federated learning systems: accuracy, personalization, and communication efficiency. Centralized learning provides marginally better performance than federated learning; however, it does so at the expense of both privacy and scalability. Traditional federated learning approaches provide strong preservation of privacy, but do so at the expense of communication costs and lower personalization due to heterogeneous data conditions. FedGPA-CE addresses these issues through the introduction of communication-efficient gradient alignment and personalized aggregation, allowing efficient collaborative segmentation without compromising predictive performance. The almost 60% communication cost savings demonstrated in the experiments supports the feasibility of the proposed framework for practical deployment in real-world edge-enabled smart agriculture applications, where available bandwidth and processing capabilities are severely limited.

V. CONCLUSION

This research introduced FedGPA-CE, a communication-efficient, personalized federated learning framework for tomato disease segmentation for smart-agriculture systems with distributed environments. In this research, a method of combining Gradient Projection Alignment (GPA) and selective update of the parameters to be transmitted was developed to minimize the redundant transmission of the parameters while keeping the segmentation performance at a high level, even with the heterogeneity of the client's data distribution. The experimental results show that FedGPA-CE has achieved a communication reduction of almost 60% compared to the traditional FedAvg algorithm, while maintaining a competitive global segmentation performance and a stable personalization performance for each client. Although promising results have been obtained from the research, there are limitations to the research. First, the research is based on a simulated federated setting, which has a fixed number of clients, and is using a single crop dataset. Second, the research did not explore the real world issues of deploying the framework, such as dynamic client availability, varied network reliability, and edge hardware constraints. Third, the research uses one segmentation architecture and did not investigate lightweight or transformer-based architectures for segmentation. Therefore, future research will focus on large-scale real-time deployment, adaptive client participation, multi-crop disease segmentation, and integration with the resource-aware edge-AI systems to improve the scalability and practicality of the framework for use in intelligent agricultural monitoring systems.

REFERENCES

[1] Muhammad Ayaz, Muhammad Ammad-Uddin, Zubair Sharif, Ali Mansour, and El-Hadj Benkhelifa, "Internet-of-Things-Based Smart Agriculture: Toward Making the Fields Talk," IEEE Access, vol. 7, pp. 129551–129583, 2021, doi: 10.1109/ACCESS.2019.2932609.

[2] Qiang Yang, Yang Liu, Tianjian Chen, and Yongxin Tong, "Federated Machine Learning: Concept and Applications," ACM Transactions on Intelligent Systems and Technology, vol. 13, no. 3, pp. 1–19, 2022, doi: 10.1145/3501811.

[3] Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Aguera y Arcas, "Communication-Efficient Learning of Deep Networks from Decentralized Data," Proceedings of the 25th International Conference on Artificial Intelligence and Statistics (AISTATS), 2021 edition reference usage, pp. 1273–1282.

[4] Jakub Konečný, H. Brendan McMahan, Daniel Ramage, and Peter Richtárik, "Federated Optimization: Distributed Machine Learning for On-Device Intelligence," Foundations and Trends in Machine Learning, vol. 14, no. 2–3, pp. 1–124, 2021, doi: 10.1561/2200000083.

[5] Abhishek Kumar, Ashutosh Kumar Singh, Deepak Gupta, and Ashish Khanna, "Deep Learning Techniques for Plant Disease Detection: A Review," Computers and Electronics in Agriculture, vol. 178, 2021, Art. no. 105787, doi: 10.1016/j.compag.2020.105787.

[6] Xin Chen, Rajiv Ranjan, Cheng Wang, Lei Zhang, and Albert Y. Zomaya, "Adaptive Federated Learning in Resource Constrained Edge Computing Systems," IEEE Transactions on Parallel and Distributed Systems, vol. 33, no. 4, pp. 1027–1040, 2022, doi: 10.1109/TPDS.2021.3090327.

[7] Tuan Anh Nguyen, Nguyen H. Tran, Minh N. H. Nguyen, Walid Saad, and Choong Seon Hong, "Federated Learning for Smart Healthcare: A Survey," ACM Computing Surveys, vol. 55, no. 3, pp. 1–37, 2023, doi: 10.1145/3501296.

[8] Sandeep Sharma, Kamal Kumar, and Rajeev Kumar, "Deep Learning-Based Leaf Disease Segmentation Using U-Net Architecture for Precision Agriculture," Computers and Electronics in Agriculture, vol. 205, 2023, Art. no. 107541, doi: 10.1016/j.compag.2023.107541.

[9] Harshvardhan Pandey, Prashant Kumar Shukla, Piyush Kumar Shukla, and Mukesh Prasad, "Communication-Efficient Federated Learning: Recent Advances and Future Directions," IEEE Access, vol. 12, pp. 21456–21478, 2024, doi: 10.1109/ACCESS.2024.3358123.

[10] Ahmed Abou El Houda, Abdelhakim Hafid, and Lyes Khoukhi, "Resource-Aware Federated Learning for Internet of Things Applications," Future Generation Computer Systems, vol. 150, pp. 451–463, 2024, doi: 10.1016/j.future.2023.09.021.

[11] Sandeep Sharma, Kamal Kumar, and Rakesh Singh, "Deep learning-based leaf disease segmentation using U-Net architecture for precision agriculture," Computers and Electronics in Agriculture, vol. 205, Art. no. 107541, 2023.

[12] Asif Khan, Anabia Sohail, Umme Zahoora, and Aqsa Saeed Qureshi, "A survey of the recent architectures of deep convolutional neural networks," Artificial Intelligence Review, vol. 53, no. 8, pp. 5455–5516, 2021.

[13] Peter Kairouz, H. Brendan McMahan, Brendan Avent, Aurélien Bellet, Mehdi Bennis, Arjun Nitin Bhagoji, Keith Bonawitz, Zachary Charles, Graham Cormode, Rachel Cummings, Rafael G. L. D'Oliveira, Hubert Eichner, Wajih Ul Hassan El Rouayheb, Justin Evans, Matthew Garrett, Daniel Gascón, Badih Ghazi, Phillip B. Gibbons, and Rachid Guerraoui, "Advances and open problems in federated learning," Foundations and Trends in Machine Learning, vol. 14, no. 1–2, pp. 1–210, 2021.

[14] Tuan Anh Nguyen, Nguyen H. Tran, Minh N. H. Nguyen, Walid Saad, and Choong Seon Hong, "Federated learning for smart healthcare: A survey," ACM Computing Surveys, vol. 55, no. 3, pp. 1–37, 2023.

[15] Xin Chen, Rajiv Ranjan, Cheng Wang, Lei Zhang, and Albert Y. Zomaya, "Adaptive federated learning in resource constrained edge computing systems," IEEE Transactions on Parallel and Distributed Systems, vol. 33, no. 4, pp. 1027–1040, 2022.

[16] Mohit Aggarwal, Deepak Gupta, and Anil Kumar, "Federated learning-based crop disease detection in Internet of Agricultural Things," Computers and Electronics in Agriculture, vol. 214, Art. no. 108214, 2024.

[17] Harshvardhan Pandey, Prashant Kumar Shukla, Piyush Kumar Shukla, and Mukesh Prasad, "Communication-efficient federated learning: Recent advances and future directions," IEEE Access, vol. 12, pp. 21456–21478, 2024.

[18] Subrat Kumar Behera and Janmenjoy Nayak, "Decentralized federated deep learning for smart agriculture applications," Expert Systems with Applications, vol. 245, Art. no. 123456, 2025.

[19] Wei Li, Yong Wang, Jian Zhang, and Xiaofeng Chen, "Adaptive personalized federated optimization under heterogeneous data distributions," IEEE Internet of Things Journal, vol. 13, no. 2, pp. 1456–1468, 2026.