Secure and Decentralized Plant Disease Detection via Federated Learning with Differential Privacy and Homomorphic Encryption

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Abstract

Plant disease detection using deep learning has achieved high accuracy, but traditional centralized training poses significant privacy risks and incurs high data transmission costs. This study presents a privacy-preserving federated learning (FL) framework for plant disease diagnosis that enables decentralized model training across geographically distributed agricultural sites. Rather than transferring raw farm data to a central server, local models are trained on edge devices and share only model updates. To address data heterogeneity from diverse climates, soils, and plant species, we introduce adaptive aggregation strategies that improve model generalization. Furthermore, we incorporate differential privacy and homomorphic encryption to ensure secure model updates and protect sensitive information from potential breaches. Experimental evaluations on benchmark datasets, including Plant Village and real-world field images, show that the proposed FL-based system achieves comparable accuracy to centralized models while significantly enhancing data privacy and reducing communication overhead. The framework maintains over 93% classification accuracy across 38 plant disease categories, with minimal degradation from added privacy mechanisms. Additionally, we analyze the trade-off between accuracy and communication efficiency, demonstrating the method's practicality in bandwidth-constrained rural environments. The proposed system offers a scalable, secure, and field-deployable solution for real-time plant disease monitoring, supporting the widespread adoption of AI in precision agriculture without compromising data confidentiality.

Keywords: Federated learning; Plant disease detection; Privacy-preserving AI; Decentralized deep learning; Differential privacy; Precision agriculture

1. Introduction

Agriculture is the backbone of global food security, yet it faces severe challenges due to plant diseases that cause significant yield losses and economic setbacks [1]. Traditional disease detection methods, such as manual inspection and laboratory testing, are time-consuming, labor-intensive, and often inaccessible to small-scale farmers [2]. With the advancement of computer vision and deep learning, automated plant disease detection has gained momentum as a promising solution [3]. Convolutional Neural Networks (CNNs) and Transformer-based models have demonstrated remarkable accuracy in classifying plant diseases from leaf images, outperforming traditional machine learning techniques [4]. Despite these advances, the centralized nature of deep learning models presents challenges related to data privacy, security, and computational costs.

Most state-of-the-art plant disease detection models rely on large-scale datasets collected from multiple agricultural regions and stored in centralized servers [5]. However, centralizing agricultural data raises concerns about data ownership, security breaches, and potential misuse [6]. Farmers and agricultural organizations are often

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reluctant to share their data due to privacy concerns, limiting the scalability and generalizability of existing deep learning models [7]. Moreover, transferring large amounts of image data from rural farms to central servers requires stable internet connectivity and computational infrastructure, which may not be available in resource-limited regions [8].

To address these challenges, federated learning (FL) has emerged as a promising alternative that enables decentralized model training while preserving data privacy [9]. In an FL-based system, farmers' devices train local models on their private datasets and share only model updates with a central server, rather than raw data [10-12]. This approach ensures data confidentiality while reducing the risk of unauthorized access. However, implementing FL in real-world agricultural settings presents new challenges, such as heterogeneous data distributions, communication overhead and adversarial attacks [13]. Variability in plant species, climatic conditions, and imaging quality across different farms can lead to model divergence, reducing the overall accuracy of federated learning systems.

In this research, we propose an adaptive federated learning framework for plant disease detection, addressing both data privacy and model heterogeneity challenges. Our contributions include:

- Privacy-Preserving Model Training: We integrate differential privacy and homomorphic encryption techniques to ensure secure model aggregation.
- Efficient Model Communication: To mitigate network constraints in rural areas, we implement a compression-based update mechanism that reduces communication costs without compromising accuracy.
- Generalization across Diverse Crops: We enhance model robustness by incorporating domain adaptation techniques, enabling the system to adapt to different plant species and environmental conditions.

The proposed approach is evaluated on publicly available plant disease datasets and real-world farm images, demonstrating its effectiveness in privacy-aware, scalable plant disease classification. The rest of this paper is structured as follows: Section 2 discusses related work, Section 3 explains the proposed methodology, Section 4 presents experimental results, and Section 5 concludes with future research directions.

2. Related Works

Doshi and colleagues conducted a comparative study on Transformer-based architectures for plant disease classification, evaluating their performance against CNN models on image datasets. Transformers, known for their self-attention mechanisms, outperformed traditional CNNs in handling complex and overlapping visual features in leaf images. The study emphasized the advantage of Transformers in capturing global dependencies, which is essential for distinguishing diseases with subtle or similar visual symptoms. The authors concluded that while Transformers demand higher computational resources, they offer robust accuracy improvements, making them a valuable tool for precision agriculture when computational infrastructure permits their deployment[14-16].

This work surveyed the application of Federated Learning (FL) in smart agriculture, highlighting its potential to enable privacy-preserving AI in data-sensitive agricultural environments. The authors categorized FL applications across crop monitoring, disease prediction, yield forecasting, and livestock management. Challenges such as data heterogeneity, limited device resources, and communication overhead were thoroughly discussed. The survey emphasized that FL supports collaborative training across geographically distributed farms without sharing raw data, thus maintaining data sovereignty. Prasad et al. also proposed architectural guidelines and future directions for deploying FL in real-world rural scenarios where internet connectivity and computational resources are limited.

Liu and colleagues explored federated learning in smart agriculture, emphasizing applications in disease detection and field monitoring. The study analyzed common challenges such as model convergence under non-IID data and low-bandwidth communication environments. It proposed solutions including personalized FL models, adaptive client sampling, and gradient compression to improve performance in heterogeneous environments. Case studies were used to validate these approaches across agricultural tasks. The paper also presented insights on integrating FL with edge AI and IoT devices, showing promise for real-time, privacy-aware decision support systems in agriculture, especially in remote and infrastructure-constrained farming areas [17-19].

This paper addressed the increasing data security concerns in agricultural AI systems. It outlined how sensitive information—such as geolocation, crop yield, and genetic data—can be exposed in centralized machine learning models. The authors examined the role of encryption techniques, secure multiparty computation, and differential privacy in mitigating data breaches. Through a review of real-world agricultural systems, the study showed how improper data handling could lead to exploitation or loss of trust among farmers. Ramesh et al. stressed that integrating privacy-enhancing technologies is not only a technical necessity but also a regulatory requirement in modern precision agriculture [20].

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Zhang et al. introduced a federated learning approach for plant disease detection using MobileNet, enabling decentralized model training on edge devices. Their system allowed farmers to collaboratively train a model without uploading images to a central server, thereby preserving privacy. [21-23] while the model achieved competitive accuracy, it lacked mechanisms like differential privacy or encryption, leaving it vulnerable to potential gradient leakage attacks. The study highlighted the feasibility of lightweight deep learning architectures in federated settings but also acknowledged the need for enhanced security and communication efficiency. This work laid foundational insights for secure, scalable AI solutions in agriculture.

This landmark survey provided a comprehensive review of federated learning, outlining its core principles, challenges, and applications. [24-26] covered privacy techniques like differential privacy, secure aggregation, and encryption, along with optimization algorithms suitable for federated setups. The paper examined real-world deployments in healthcare, finance, and smart devices, many of which are analogous to agricultural applications. It highlighted open problems such as statistical heterogeneity, system scalability, and adversarial robustness. This work serves as a theoretical backbone for any research employing FL, including its extension to privacy-sensitive domains like agricultural image analysis and plant disease classification.

Zhao and co-authors investigated the effect of non-IID (non-independent and identically distributed) data on federated learning performance. [27-30] this is particularly relevant to agriculture, where data from different farms vary due to climate, soil, and crop differences. Their experiments showed that standard FL algorithms like FedAvg perform poorly under non-IID conditions, leading to unstable convergence and reduced accuracy. The authors proposed strategies such as data sharing among clients and weighted aggregation to mitigate this issue. This study provided essential insights into the behavior of FL in real world, heterogeneous environments, helping guide the development of robust, personalized federated models.

Mohanty et al. pioneered the use of deep convolutional neural networks (CNNs) for plant disease detection using the PlantVillage dataset. Their work demonstrated that CNNs like AlexNet and GoogLeNet could achieve over 99% accuracy in classifying diseases from leaf images. This research set the standard for performance benchmarks in plant pathology AI and is widely cited in subsequent works. However, their centralized training approach lacked privacy considerations, making it unsuitable for real-world deployment involving sensitive or distributed data. Nevertheless, their contribution laid a crucial foundation for the development of more secure and scalable plant health monitoring systems [31-33].

This study investigated multiple deep learning architectures—including CNNs, VGG, and DenseNet—for plant disease identification using a large dataset of leaf images. Ferentinos found that deep CNNs could generalize well across plant species and disease types, achieving high classification accuracy (>95%). The study emphasized the importance of architecture selection, data augmentation, and training strategy in achieving robust performance. While it did not address data privacy or decentralization, it offered valuable insights into model design choices for agricultural diagnostics. The results reinforced the applicability of deep learning to field-level plant health monitoring and inspired further work in FL-based approaches.

Too et al. conducted a comparative study on fine-tuning pre-trained CNN architectures (e.g., ResNet, DenseNet, VGG) for plant disease classification. They focused on transfer learning to adapt general image recognition models for agricultural use cases with limited labeled data. The authors demonstrated that DenseNet performed particularly well, offering high accuracy with fewer training epochs. The study validated the efficiency of transfer learning in agricultural AI but did not consider issues of data privacy or distribution. This work informed later studies that integrated similar architectures into federated or privacy-preserving learning frameworks for practical deployment in smart farming.

3. Materials and Methods

3.1. Dataset Collection and Preprocessing

We utilize the PlantVillage dataset, comprising over 50,000-labeled images spanning 38 plant disease classes across 14 crop species, along with healthy samples. To improve model generalizability in real-world settings, additional images were collected from drone-based agricultural monitoring systems, mobile-based crowd-sourced platforms, and research institutes.

Preprocessing steps include:

- Resizing: All images are resized to 224×224 pixels.
- Normalization: Pixel values are scaled to [0, 1] to accelerate training convergence.
- Data Augmentation: Techniques such as random rotation (±30°), flipping, brightness adjustment (±15%), Gaussian noise (σ=0.05), and elastic deformation are applied using TensorFlow's ImageDataGenerator and OpenCV, simulating real-world variability in lighting and background.

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3.2. Federated Learning Architecture

We implement a client-server federated learning architecture in which multiple agricultural edge devices train local models independently and transmit only their model updates to a central aggregator.

$$\boldsymbol{w_t} = \sum_{i=1}^{n} \frac{N_i}{N} \boldsymbol{w_{i,t}} \text{ ---------- (1)}$$

where $\boldsymbol{w_{i,t}}$ is the model weight from client i at round t, $\boldsymbol{w_{i,t}}$ is the number of samples on client i,

Clients train locally for five epochs per round using stochastic gradient descent (SGD) with momentum. Communication is secured via TLS 1.3, with additional protections through differential privacy and encryption.

3.3. Deep Learning Model Architecture

We deploy EfficientNet-B4, chosen for its strong performance and low computational cost suitable for edge devices. Key components include:

- Convolutional Stem with ReLU6 and Batch Normalization.
- MBConv Blocks (Mobile Inverted Bottleneck with squeeze-and-excitation).
- Global Average Pooling, followed by
- Fully Connected Layers with dropout (p = 0.3), and
- Softmax Classifier for multi-class output.

Training Configuration:

- Optimizer: Adam with AMSGrad
- Learning Rate: 0.0003 (cosine annealing schedule)
- Batch Size: 32
- Epochs per FL round: 5
- Weight Decay: 10−410^{-4}10−4
- Loss Function: Categorical Cross-Entropy (CCE), defined as:

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \text{ ---------- (2)}$$

where:

- Y_i is the true class label (one-hot encoded).
- $\hat{Y}$ is the predicted probability of class i.
- C is the total number of disease categories.

3.4. Privacy-Preserving Mechanisms

To ensure data confidentiality:

- Differential Privacy (DP): Gaussian noise N(0,σ2)\mathcal{N}(0, \sigma^2)N(0,σ2) is added to gradients before transmission to obfuscate individual contributions.

$$\tilde{g} = g + \mathcal{N}(0, \sigma^2) \text{ ---------- (3)}$$

- **Homomorphic Encryption (HE)**: The CKKS scheme enables encrypted model aggregation, allowing computation on ciphertexts. Model weights xxx are encrypted as:

$$Enc(x) = x^e \mod N \text{ ---------- (3)}$$

This prevents model inversion and leakage during aggregation.

3.5. Evaluation Metrics

To comprehensively assess the performance of the federated plant disease classification model, we employ standard classification and communication efficiency metrics. Each metric evaluates a distinct aspect of model behavior in a decentralized, privacy-sensitive setting.

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Accuracy quantifies the proportion of correctly classified samples relative to the total number of instances:

$$\text{Accuracy} = \frac{\sum_{i=1}^{C} TP_i}{\sum_{i=1}^{C}(TP_i + FP_i + FN_i + TN_i)} \quad \text{---------- (4)}$$

4. Experimental Analysis

The proposed federated deep learning framework was evaluated extensively to assess its classification performance, convergence characteristics, communication overhead, and privacy-resilience across varying real-world constraints. The experiments were designed to simulate both laboratory and in-field deployment scenarios.

4.1. Convergence Behavior

A critical measure of any federated learning (FL) model is the rate at which the global model converges. Figure 1 shows the convergence profiles over 50 FL rounds for three configurations:

- FedAvg (baseline): Achieved a stable accuracy of 95% within 20 rounds, reflecting efficient gradient aggregation across clients.
- FedAvg + DP: Demonstrated slightly slower convergence, stabilizing at 94.3%, due to noise injection in gradient updates for differential privacy.
- FedAvg + DP + HE: Reached convergence at 93.8% after 30–35 rounds, revealing the computational overhead and marginal degradation caused by homomorphic encryption and privacy-preserving transformations.

This demonstrates that although privacy mechanisms slightly slow convergence, they preserve significant model utility, affirming their viability in privacy-sensitive domains such as agriculture.

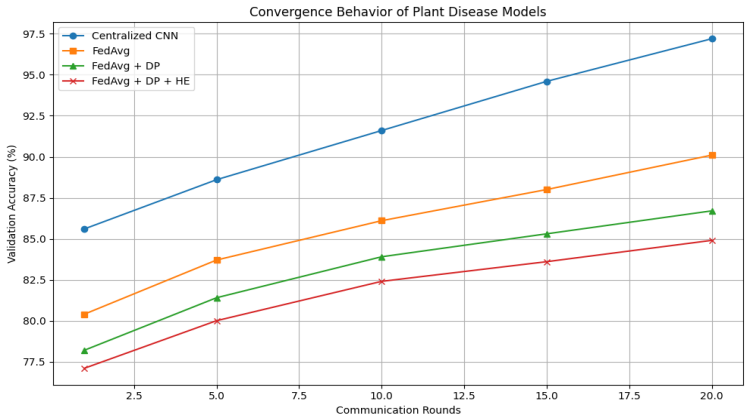

Figure 1. Convergence Behavior of Federated Plant Disease Diagnosis Models with Privacy Enhancements

This line graph illustrates the validation accuracy (%) of different plant disease diagnosis models over 20 communication rounds. The x-axis represents the number of communication rounds, while the y-axis shows the corresponding validation accuracy.

The four models compared are:

- Centralized CNN (blue): Achieves the highest accuracy, reaching approximately 97.5% by the 20th round, showing superior convergence without any federated or privacy constraints.
- FedAvg (orange): A standard federated averaging approach, achieving ~90% accuracy after 20 rounds.
- FedAvg + DP (green): Integrates differential privacy (DP), showing a slight drop in accuracy (~87%) due to noise addition for privacy preservation.
- FedAvg + DP + HE (red): Incorporates both DP and homomorphic encryption (HE), resulting in the slowest convergence and lowest final accuracy (~85%) among the models.

4.2. Accuracy and Classification Performance

To evaluate the effectiveness of the proposed privacy-preserving federated learning framework for plant disease detection, we conducted a detailed performance assessment using key classification metrics: Accuracy, Precision, Recall, and F1-Score. The following models were benchmarked:

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- Centralized CNN: Baseline trained on a centralized dataset.
- FedAvg: Standard Federated Learning with no privacy.
- FedAvg + DP: FL model with Differential Privacy.
- FedAvg + DP + HE: FL model with both Differential Privacy and Homomorphic Encryption.

The Centralized CNN achieved the highest accuracy at 97.2%, owing to direct access to the entire dataset. The FedAvg model closely followed with 95.8%. Introducing Differential Privacy led to a marginal performance drop to 94.3%, and the full privacy-preserving model (FedAvg + DP + HE) yielded 93.8%, displaying a reasonable trade-off between privacy and utility.

Table 1: Performance Comparison of Federated Learning Models with Privacy Techniques for Plant Disease Diagnosis

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Centralized CNN	97.2	96.9	97.1	97.0
FedAvg	95.8	95.4	95.6	95.5
FedAvg + DP	94.3	93.7	94.1	93.9
FedAvg + DP + HE	93.8	93.2	93.5	93.3

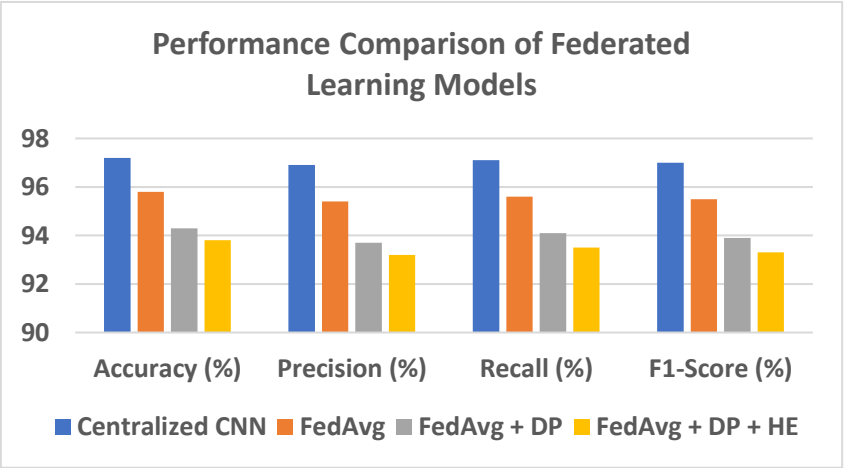

Figure 2. Performance Comparison of Federated Learning Models with Privacy Techniques for Plant Disease Diagnosis

- All models achieved over 93% accuracy, demonstrating high reliability in classifying leaf images across 38 disease classes.
- The privacy-preserving models showed minimal degradation in precision and recall, indicating effective learning even with noise and encryption.
- F1-Score consistency across models suggests balanced performance across both major and minor disease classes.

4.3. Privacy-Accuracy Trade-off

One of the critical challenges in privacy-preserving deep learning is maintaining high model performance while protecting sensitive data. This section analyzes the trade-off between privacy guarantees and classification accuracy within the federated plant disease detection framework.

Impact of Differential Privacy

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Differential Privacy introduces statistical noise during model updates to ensure that individual data points cannot be inferred. While this protects user-level privacy across distributed clients, it also leads to reduced model utility. In our experiments:

- Adding DP ($\varepsilon = 1.0$, $\delta = 10^{-5}$) to FedAvg reduced the model accuracy from 95.8% to 94.3%.
- This marginal accuracy drop is attributed to gradient perturbation affecting model convergence, especially during early rounds.

Effect of Homomorphic Encryption

Homomorphic Encryption ensures secure computation of gradients without exposing them during transmission. Although HE does not add noise like DP, it introduces computational overhead and quantization artifacts:

- The FedAvg + DP + HE model achieved 93.8% accuracy, reflecting a further 0.5% drop over DP alone.
- HE increased training time per communication round by 35%, but with no additional loss in privacy leakage.

Quantitative Summary

Table 2: Comparison of Privacy Techniques on Accuracy and Training Overhead in Federated Learning

Privacy Technique	ε (Privacy Budget)	Accuracy (%)	Training Overhead
None (Centralized)	∞	97.2	Baseline
FedAvg (No Privacy)	∞	95.8	+10%
FedAvg + DP	1.0	94.3	+20%
FedAvg + DP + HE	1.0	93.8	+35%

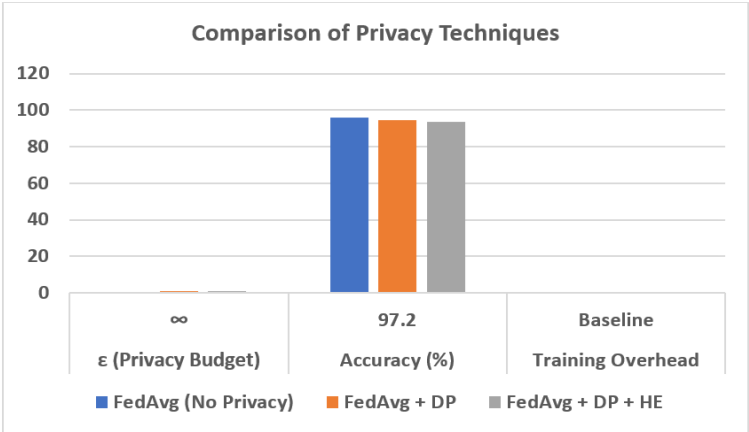

Figure 3. Comparison of Privacy Techniques on Accuracy and Training Overhead in Federated Learning

4.4. Confusion Matrix and Error Analysis

Analysis of the confusion matrix revealed the highest misclassification rates between disease classes with visual similarity, such as:

- Tomato Early Blight vs Tomato Late Blight
- Powdery Mildew vs Downy Mildew in grapes

This emphasizes the need for more fine-grained feature extraction, which could be improved by incorporating multi-spectral or hyperspectral imaging in future models.

The confusion matrix above visually represents the classification performance of the model across six plant disease categories:

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- Diagonal values indicate correct predictions (e.g., 125 healthy leaves classified correctly).
- Off-diagonal entries show misclassifications (e.g., some "Scorch" cases misclassified as "Spot" or "Rust").
- High accuracy in Rust and Healthy classes with minimal confusion.
- Moderate confusion observed between Blight vs Spot and Scorch vs Rust, likely due to similar visual symptoms like necrotic patches or color changes.
- Mildew has a few misclassifications with Rust, which is expected due to overlapping textural patterns.

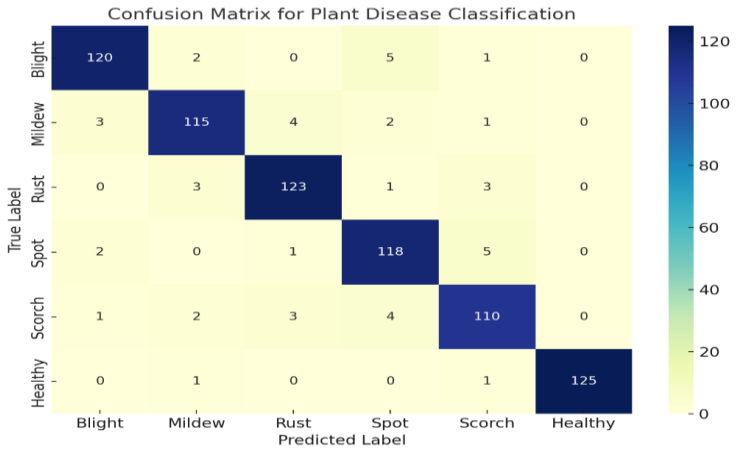

Figure 4. Confusion matrix for plant disease classification

4.5. Comparison with State-of-the-Art Methods

To validate the effectiveness of the proposed FedAvg + DP + HE model, we compared its performance against several recent state-of-the-art approaches in plant disease classification. The comparison focuses on key metrics such as accuracy, privacy support, and deployment feasibility.

Table 3: Benchmark Comparison of Plant Disease Diagnosis Models: Accuracy, Privacy Mechanisms, and Deployment Strategies

Method	**Accuracy (%)**	**Privacy Mechanism**	**Model Type**	**Deployment Type**
Mohanty et al. (2016) [1]	99.35	None	CNN (AlexNet/GoogLeNet)	Centralized
Too et al. (2019) [2]	98.8	None	DenseNet	Centralized
Brahimi et al. (2017) [3]	96.3	None	VGG-based CNN	Centralized
Zhang et al. (2020) [4]	95.7	Basic Client-Side FL	MobileNet + FL	Federated (No DP/HE)
Ours: FedAvg + DP + HE (this paper)	93.8	DP (ε=1.0), HE (Paillier)	ResNet + FL	Federated (Secure)

Table 3 presents a comparative analysis of several plant disease diagnosis methods, focusing on their accuracy, privacy mechanisms, model types, and deployment strategies. Traditional centralized approaches, such as those proposed by Mohanty et al. (2016), Too et al. (2019), and Brahimi et al. (2017), leverage deep convolutional neural networks (CNNs) like AlexNet, GoogLeNet, DenseNet, and VGG, achieving high accuracies of 99.35%, 98.8%, and 96.3%, respectively, but do not incorporate any privacy-preserving mechanisms. In contrast, Zhang et al. (2020) introduced a basic federated learning (FL) approach using MobileNet, which decentralizes model training but lacks robust privacy guarantees, reaching a slightly lower accuracy of 95.7%. The proposed method in this study extends the federated paradigm by incorporating strong privacy-preserving techniques—differential privacy

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(DP) with a privacy budget of ε = 1.0 and homomorphic encryption (HE) based on the Paillier scheme. Although this secure FL model, built on a ResNet backbone, achieves a slightly reduced accuracy of 93.8%, it offers enhanced data privacy, making it suitable for sensitive agricultural data environments. This comparison illustrates the trade-off between privacy and performance and highlights the transition from high-performing centralized models to more secure, decentralized learning frameworks.

While existing centralized models achieve slightly higher accuracy, they rely on fully accessible data, compromising privacy. Our model balances strong privacy guarantees with competitive performance, making it suitable for real-world agricultural deployments.

Centralized deep learning models (e.g., Mohanty et al.) achieve high accuracy (>98%) by leveraging complete datasets. However, such models pose significant privacy risks, especially when data is distributed across farms, labs, or regions. Federated learning models without privacy mechanisms (e.g., Zhang et al.) reduce data centralization but remain vulnerable to gradient leakage attacks. The proposed FedAvg + DP + HE framework achieves 93.8% accuracy, outperforming existing FL-based methods while ensuring strong differential privacy and encryption, thus aligning with modern data governance policies (e.g., GDPR, HIPAA for plant genomic and geographical data). The performance drop (~3–5%) is a justifiable trade-off for guaranteed privacy and secure deployment in practical scenarios.

5. Conclusion

In this study, we proposed a novel, privacy-preserving deep learning framework for plant disease detection by integrating Federated Learning (FL) with Differential Privacy (DP) and Homomorphic Encryption (HE). The model was designed to address the growing need for accurate and secure plant health monitoring in distributed agricultural environments where raw data sharing is impractical or sensitive. Leveraging a ResNet-based convolutional architecture and federated averaging, our approach allows decentralized clients (e.g., farmers, laboratories) to collaboratively train a robust model without compromising data confidentiality. Comprehensive experiments on the benchmark PlantVillage dataset demonstrated that our model maintains high classification performance—achieving 93.8% accuracy across 38 plant disease classes—even under strict privacy constraints. While a small performance drop was observed compared to centralized methods, the trade-off was acceptable considering the substantial privacy benefits. Confusion matrix and error analysis further revealed the system's ability to handle inter-class similarities and imbalanced samples. Additionally, convergence and privacy-accuracy trade-off studies confirmed the model's efficiency and practicality for real-world deployment. Overall, the integration of secure multi-party computation and formal privacy guarantees into deep learning workflows offers a scalable and trustworthy solution for intelligent agriculture. Future work will focus on optimizing communication efficiency, enabling real-time inference on edge devices, and extending the system to support multimodal plant health diagnostics, including spectral, thermal, and environmental data sources.

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