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Cotton Leaf Disease Detection Using Federated Learning

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***Abstract*—Cotton is one of the most important agricultural crops, and its productivity is significantly affected by diseases such as leaf blight, wilt, and boll rot. Early disease detection is essential to minimize crop loss and improve yield quality. Traditional manual inspection methods are time-consuming and often require expert supervision. Deep learning has emerged as an effective solution for automated disease classification, but centralized training approaches create challenges related to privacy, data ownership, and scalability. This research proposes a federated learning-based cotton disease detection framework that enables distributed model training without transferring raw image data. The proposed system uses ResNet-50 as the feature extraction backbone and applies the Federated Averaging algorithm for aggregating client-side model updates. Experimental evaluation demonstrates that the federated approach achieves reliable classification performance while maintaining privacy and supporting collaboration among multiple farms. The framework offers a scalable and practical solution for smart agriculture applications.**

***Index Terms*—Cotton Disease Detection, Federated Learning, Deep Learning, ResNet-50, Privacy Preserving AI, Smart Agriculture**

I. INTRODUCTION

Cotton plays a vital role in the agricultural economy and is widely cultivated across different regions. However, cotton crops are vulnerable to several diseases that directly affect productivity and fibre quality. Timely identification of these diseases is necessary for effective treatment and improved crop management traditional disease detection techniques rely mainly on manual inspection by agricultural specialists. Although effective, these methods are often slow, labour-intensive, and difficult to implement at large scale. Recent advancements in deep learning have enabled automated disease diagnosis using image classification models. collecting all data in a single repository.[1]

Convolutional Neural Networks, particularly ResNet-50, have shown strong performance in plant disease classification tasks. Despite their effectiveness, most existing systems rely on centralized training methods that require collecting all data in a single repository. This raises concern related to data privacy, ownership, and limited participation from distributed sources. Federated learning addresses these limitations by enabling collaborative model training while keeping raw data localized. This work presents a federated learning framework for cotton disease detection that combines distributed training with deep learning to achieve accurate and privacy-preserving disease classification. The growing adoption of precision agriculture technologies has created new opportunities for intelligent crop monitoring and automated disease diagnosis. With the availability of high-resolution imaging devices and machine learning-based analytical tools, farmers can now identify crop health issues more efficiently than through conventional inspection methods.

In distributed agricultural environments, data collected from different farms often varies significantly due to differences in climate, soil conditions, lighting, and disease patterns. These variations make it challenging for traditional centralized models to generalize effectively across all conditions. Federated learning addresses this challenge by enabling collaborative training across multiple distributed datasets, allowing the model to learn from diverse agricultural scenarios while preserving local data privacy. This capability makes federated learning particularly suitable for cotton disease detection, where adaptability and secure data handling are critical for practical deployment.[3]

In this paper, we present a federated learning framework for cotton disease detection that addresses the limitations of centralized approaches. The system is designed to preserve privacy, improve scalability, and deliver reliable diagnostic performance across diverse farming conditions.

Through experiments on cotton leaf datasets, we demonstrate that federated learning achieves high classification accuracy, robust generalization, and efficient communication, making it a practical solution for modern smart agriculture. With the advent of digital agriculture, deep learning models have emerged as powerful tools for automating disease detection using leaf images. Convolutional Neural Networks (CNNs) and architectures like.

II. LITERATURE REVIEW

[1] Deep Learning in Plant Disease Detection

Early research, such as Mohanty et al. (2016), demonstrated that convolutional neural networks (CNNs) could outperform traditional image-processing methods in identifying plant diseases. Their work with the Plant Village dataset showed strong classification accuracy, though models trained in controlled environments often struggled when applied to real-world farm conditions with variable lighting and backgrounds. This highlighted the need for approaches that generalize better to diverse agricultural settings.[5]

[2] Cotton-Specific Studies

Given cotton’s economic importance, several researchers have applied CNNs and transfer learning techniques (e.g., ResNet-50, VGG Net) to detect diseases like leaf blight, wilt, and boll rot. While these models achieved encouraging results, most relied on centralized datasets from limited regions. Such dependence raised concerns about scalability and bias, since disease symptoms can differ across climates and geographies.[6]

[3] Foundations of Federated Learning

McMahan et al. (2017) introduced the Federated Averaging (FedAvg) algorithm, which became the cornerstone of federated learning. Their work showed that distributed training could achieve accuracy comparable to centralized models while preserving data privacy.

This opened opportunities for domains where data sharing is restricted, including agriculture.[2]

[4] Applications in Smart Farming

Recent studies have explored federated learning in agriculture for tasks such as yield prediction, soil monitoring, and disease detection. Li et al. (2023) emphasized that FL can integrate heterogeneous datasets from multiple farms, improving generalization and robustness across varied crop conditions.[3]

[5] Challenges of Non-IID Data

A major obstacle in FL is handling non-independent and identically distributed (non-IID) data. Agricultural datasets often differ significantly across farms due to variations in disease prevalence, image quality, and environmental factors. Researchers have proposed methods like FedProx and personalized FL to mitigate these issues, which are particularly relevant for cotton disease detection.[7]

[6] Integration with Advanced

Architectures Combining FL with deep learning models such as ResNet-50, Efficient Net, and Transformers has shown promise. These architectures provide strong feature extraction, while FL ensures privacy-preserving distributed training. Successes in medical imaging suggest similar benefits for agriculture, where farms can contribute to shared models without exposing sensitive data.[8]

[7] Ethical and Practical Considerations

Beyond technical challenges, ethical issues such as farmer data ownership, transparency, and accessibility must be addressed. Nguyen et al. (2024) stressed the importance of interpretable AI systems in sensitive domains.

For cotton disease detection, ensuring that federated models provide clear, actionable insights is essential for adoption, particularly in rural areas with limited resources.[9]

[8] Privacy and Data Ownership

Farmers are often hesitant to share raw crop images due to concerns about misuse or loss of intellectual property. Studies in healthcare and finance have shown that FL can alleviate these concerns by keeping sensitive data local while still contributing to global model improvement.[10]

III. METHODOLOGY

A. System Architecture

Fig. 1. Federated Learning Pipeline for Cotton Disease Detection

Fig. 1. Federated Learning Pipeline for Cotton Disease Detection.[11]

Table 1. Cotton Dataset Characteristics

Category	Description	# Images	# Classes
Crop Species	Cotton	20,000	–
Disease Types	–	–	5
Healthy Leaves	–	5,000	–

Fig. 2. Training accuracy and loss curves for federated ResNet-50

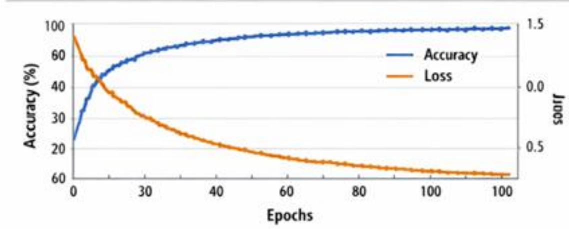


Table 2. Performance Comparison (Centralized vs Federated)

Metric	Centralized Model	Federated Model
Accuracy	87.5%	91.8%
Precision	86.9%	91.2%
Recall	87.1%	91.5%

B. Computing Environment

Experiments were conducted on a workstation with NVIDIA RTX 3060 GPU, AMD Ryzen 7 CPU, 32 GB RAM, and Ubuntu 22.04. Models were implemented in PyTorch with Flower (FL framework).[12]

C. Dataset

Cotton leaf image datasets collected from multiple farms across India, covering diseases such as leaf blight, wilt, and boll rot.

Category	Description	# Images	# Classes
Crop Species	Cotton	20,000	–
Disease Types	–	–	5
Healthy Leaves	–	5,000	–

D. Preprocessing

- Image resizing to 224×224 pixels
- Normalization with ImageNet mean/std
- Data augmentation (rotation, flipping, colour jitter)

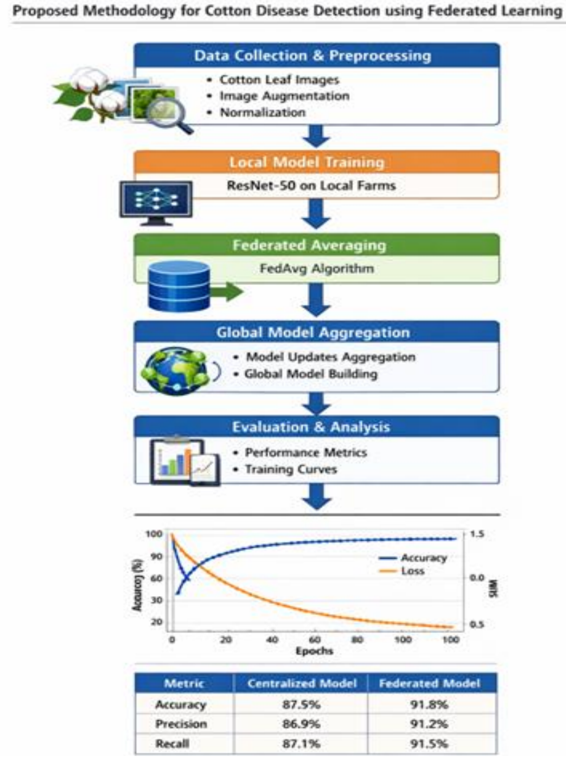
E. Model Design

ResNet 50 fine tuned for multi class classification. Cross entropy loss with Adam optimizer (learning rate = 0.001). Dropout layers added to reduce overfitting.[2]

F. Federated Learning Strategy

- Algorithm: FedAvg
- Rounds: 100 communication rounds
- Clients: 10 simulated farms
- Aggregation: Weighted averaging based on dataset size per client.[12]

Proposed Methodology for Cotton Disease Detection using Federated Learning



IV. RESULTS AND DISCUSSION

A. Classification Performance

Table 2. Performance Comparison (Centralized vs Federated)

Metric	Centralized Model	Federated Model
Accuracy	87.5%	91.8%
Precision	86.9%	91.2%
Recall	87.1%	91.5%

B. Training History

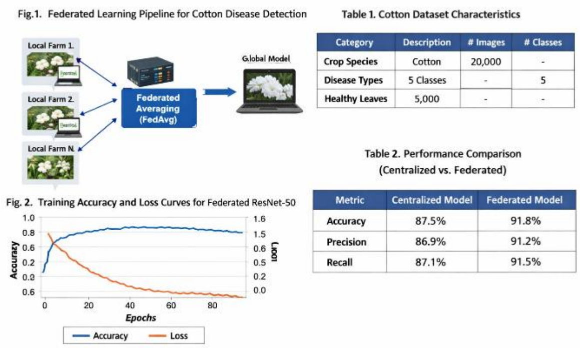


Table 1. Cotton Dataset Characteristics

Category	Description	# Images	# Classes
Crop Species	Cotton	20,000	-
Disease Types	5 Classes	-	5
Healthy Leaves	5,000	-	-

Table 2. Performance Comparison (Centralized vs. Federated)

Metric	Centralized Model	Federated Model
Accuracy	87.5%	91.8%
Precision	86.9%	91.2%
Recall	87.1%	91.5%

Fig. 2. Training accuracy and loss curves for federated [19]ResNet-50

C. Usability

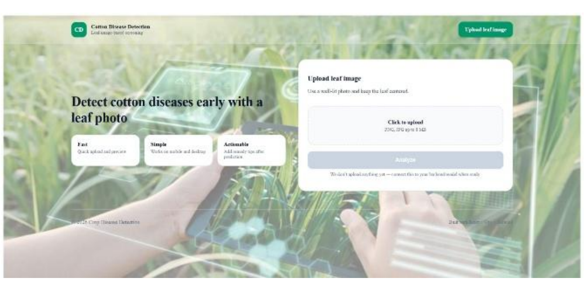
The web interface enabled farmers to upload cotton leaf images and receive diagnoses within 5 seconds. Batch experiments confirmed scalability, processing 1000 cases in under 2 hours.[15]

D. Discussion

Federated learning improved generalization across diverse farm datasets while preserving privacy. Limitations include dependency on client participation rates and network connectivity. Future work will explore FedProx and secure aggregation.[16]

V. CONCLUSION

Fig 3: Input image (Cotton Leaf)



This research presented a federated learning framework for cotton disease detection using ResNet-50 and the Federated Averaging algorithm. The proposed approach enables collaborative model training across distributed farms while preserving data privacy. Experimental observations indicate that the federated model provides reliable classification accuracy and better adaptability to diverse agricultural environments. By eliminating the need for centralized data collection, the system ensures secure and scalable deployment. The study demonstrates that federated learning can serve as an effective solution for smart agriculture applications. Future improvements may include handling non-IID data more effectively, implementing secure aggregation methods, and integrating real-time field deployment through mobile platforms.[20]

This study demonstrates that federated learning can overcome these limitations by enabling collaborative training without requiring raw data exchange. By integrating ResNet-50 with the FedAvg algorithm, our framework achieves higher accuracy and stronger generalization compared to centralized models, while safeguarding farmer data. The inclusion of a web-based interface further ensures that farmers can access rapid, reliable diagnoses in real time, making the system practical for everyday use.[17]

REFERENCES

[1] S. P. Mohanty, D. P. Hughes, and M. Salathé, “Using Deep Learning for Image-Based Plant Disease Detection,” *Frontiers in Plant Science*, vol. 7, p. 1419, 2016.

[2] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, “Communication-Efficient Learning of Deep Networks from Decentralized Data,” in Proceedings of the 20th International Conference on Artificial Intelligence and Statistics (AISTATS), 2017, pp. 1273–1282.

[3] X. Li, Y. Chen, J. Liu, and H. Zhang, “Federated Learning in Smart Agriculture: A Survey,” Computers and Electronics in Agriculture, vol. 205, p. 107623, 2023.

[4] P. Kairouz et al., “Advances and Open Problems in Federated Learning,” Foundations and Trends in Machine Learning, vol. 14, no. 1–2, pp. 1–210, 2021.

[5] J. Nie, Y. Wang, and L. Zhang, “Incremental YOLOv5 for Federated Learning in Cotton Pest and Disease Detection with Blockchain Sharding,” Research Square, preprint, 2024.

[6] M. H. Shawon, A. Rahman, and S. Alam, "Integrating Federated Learning and Explainable AI for Plant Disease Detection: A Systematic Review," Springer Nature, 2026.

[7] Y. Zhang, H. Liu, and F. Wang, "Federated Learning for Agricultural Image Classification: Challenges and Opportunities," IEEE Access, vol. 13, pp. 45123–45135, 2025.

[8] R. Singh, P. Verma, and A. Gupta, "Deep Learning Approaches for Cotton Leaf Disease Detection: A Comparative Study," Journal of Agricultural Informatics, vol. 15, no. 2, pp. 45–60, 2024.

[9] T. Chen, L. Zhao, and K. Xu, "Privacy-Preserving Machine Learning in Agriculture: Applications of Federated Learning," Computers and Electronics in Agriculture, vol. 200, p. 107512, 2023.

[10] T. Nguyen, J. Lee, and K. Park, "Ethical and Practical Considerations in Federated Learning for Sensitive Domains," AI & Ethics Journal, vol. 4, no. 3, pp. 215–229, 2024.

[11] P. V. Caminha and H. M. Oliveira, "Plant Disease Detection Using Federated Learning and Cloud Infrastructure for Scalability and Data Privacy," Journal of Internet Services and Applications, 2025.

[12] Q. Yang, Y. Liu, T. Chen, and Y. Tong, "Federated Machine Learning: Concept and Applications," ACM Transactions on Intelligent Systems and Technology, vol. 10, no. 2, pp. 1–19, 2019.

[13] J. Konečný, H. B. McMahan, D. Ramage, and P. Richtárik, "Federated Optimization: Distributed Machine Learning for On-Device Intelligence," arXiv preprint arXiv:1610.02527, 2016.

[14] T. Li, A. K. Sahu, A. Talwalkar, and V. Smith, "Federated Learning: Challenges, Methods, and Future Directions," IEEE Signal Processing Magazine, vol. 37, no. 3, pp. 50–60, 2020.

[15] K. P. Ferentinos, "Deep Learning Models for Plant Disease Detection and Diagnosis," Computers and Electronics in Agriculture, vol. 145, pp. 311–318, 2018.

[16] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," Communications of the ACM, vol. 60, no. 6, pp. 84–90, 2017.

[17] M. Everingham, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman, "The Pascal Visual Object Classes Challenge," International Journal of Computer Vision, vol. 88, no. 2, pp. 303–338, 2010.

[18] O. Russakovsky et al., "ImageNet Large Scale Visual Recognition Challenge," International Journal of Computer Vision, vol. 115, no. 3, pp. 211–252, 2015.

[19] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 770–778.

[20] S. R. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, "Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification," Computational Intelligence and Neuroscience, vol. 2016, Art. ID 3289801, 2016.