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Federated Learning for Crop Disease Detection: A Review of Lightweight Deep Learning Approaches

Review Paper on Smart Agriculture Using FL and XAI

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***Abstract*—**Crop diseases rank among the most serious threats to agricultural productivity and global food supply. In recent years, deep learning has gained traction as an effective means of automating plant disease recognition. However, conventional centralized training methods introduce significant challenges, including privacy vulnerabilities, high computational overhead, and limited suitability for resource-constrained farming environments. Federated Learning (FL) offers a decentralized alternative that supports cooperative model training without requiring local data to leave individual devices. This paper presents a comprehensive survey of recent research on FL-driven crop disease detection. Emphasis is placed on the use of lightweight convolutional models compatible with edge and mobile platforms, and on the contribution of Explainable Artificial Intelligence (XAI) to improving model transparency and user trust. The surveyed works are assessed for their strengths and limitations. Key technical challenges — including non-IID data distributions across participating clients, communication overhead during model aggregation, and the lack of real-world field validation — are analyzed in depth. The paper concludes by identifying open research problems and proposing directions toward scalable, privacy-preserving, and computationally lean disease detection systems.

Index Terms*—Federated Learning, Crop Disease Detection, Lightweight CNN, Explainable AI, Grad-CAM, Smart Agriculture, Deep Learning.*

I. Introduction

Agriculture forms the backbone of economic activity in many parts of the world, yet crop diseases continue to pose a severe and ongoing threat, leading to considerable losses in yield and jeopardizing food security. Early and accurate identification of such diseases is therefore essential for maintaining productive and sustainable farming practices. In recent years, deep learning models have demonstrated strong capability in detecting disease symptoms from plant images, opening promising pathways for automated field monitoring.

Conventional centralized training methods demand that raw agricultural data be transmitted to a central server, raising concerns about data privacy and compliance with regulations. Furthermore, the considerable computational requirements of large deep learning models render them unsuitable for rural deployments where devices are limited to low-power mobile or edge hardware. These challenges have driven interest in Federated Learning (FL), a distributed training approach that enables multiple devices to collaboratively train a shared model without sharing their local data, thus preserving privacy and reducing communication costs.

II. Background

A. Federated Learning

Federated Learning is a collaborative machine learning approach in which multiple client devices train a shared global model without ever exposing their raw data to a central server. In this setup, each client independently computes model updates using its local data and transmits only those updates — rather than the data itself — to a central aggregator. The aggregator merges the contributions from all clients to iteratively improve the global model.

B. Lightweight CNN Models

Models like MobileNet and EfficientNet have been specifically designed to deliver strong classification performance within tight resource constraints. Their reduced parameter counts and lower memory demands make them particularly well-suited for real-time inference on smartphones and edge devices — the kind of hardware most commonly available in agricultural field environments.

C. Explainable AI

Explainable AI (XAI) refers to a class of methods that make machine learning predictions interpretable to human users. Among these, Gradient-weighted Class Activation Mapping (Grad-CAM) is widely used to produce saliency maps that visually indicate which parts of an input image most strongly influenced a model's decision. These visual cues allow domain experts to assess model reliability and help build informed trust in AI-assisted diagnostic tools.

III. Literature Review

Recent research has increasingly examined the integration of deep learning and federated frameworks for automated plant disease diagnosis. Among notable contributions, the AGRIFOLD system introduced a federated architecture centered on compact CNN models, with a focus on achieving efficient inference under resource-limited agricultural conditions [1]. In a complementary line of work, Aggarwal et al. studied FL communication strategies optimized for IoT-based farming infrastructure, showing that bandwidth use could be substantially reduced without sacrificing classification accuracy [3].

Hari et al. addressed the non-IID data problem by developing adaptive knowledge transfer techniques that support better model convergence when data distributions vary widely across client nodes [2]. Other researchers have explored transfer learning methods [4], decentralized peer-to-peer FL topologies [5], and blockchain-based secure aggregation schemes to strengthen privacy protections [6].

In parallel, XAI research has highlighted the importance of interpretability in agricultural AI applications [7]. Techniques such as Grad-CAM and spatial attention mechanisms have been employed to pinpoint regions of infection and offer tangible insights to farmers and agronomists. Despite these advances, a recurring limitation in the literature is the tendency to address privacy, efficiency, and transparency as separate concerns. An integrated framework that satisfies all three simultaneously, and that has been validated in real farming conditions, remains an open challenge.

IV. Comparative Analysis

A review of the current landscape shows that FL has become the preferred approach for addressing data privacy concerns in disease detection workflows. AGRIFOLD confirms the suitability of compact convolutional architectures for edge-based deployment [1], while the framework by Aggarwal et al. illustrates how communication-conscious design can be effectively integrated into IoT-based agricultural systems [3]. The adaptive transfer learning approach by Hari et al. demonstrates improvements in model generalization across varied environmental conditions [2].

Nevertheless, important gaps persist. A large share of reviewed studies prioritize either speed or accuracy, without integrating XAI features, which limits the transparency of their predictions. Some frameworks also incur heavy communication overhead, making deployment impractical in bandwidth-constrained rural areas. Decentralized and blockchain-enhanced FL designs offer improved security and fault tolerance but tend to introduce significant implementation complexity [5], [6].

The comparative summary presented in Table I highlights the clear need for an integrated architecture that can simultaneously ensure data privacy, computational efficiency, and model interpretability — all of which are essential prerequisites for practical crop disease detection at scale.

TABLE I
Comparative Summary of FL Approaches

Approach	Privacy	Efficiency	XAI
AGRIFOLD [1]	High	Moderate	Low
Aggarwal et al. [3]	Mod.	High	Low
Hari et al. [2]	High	High	Low
FL + Blockchain [6]	High	Low	None
Proposed Dir.	High	High	High

V. Research Gaps

A careful review of existing literature reveals several structural shortcomings that must be addressed before FL-based crop disease detection can be practically deployed. Most notably, current research tends to treat privacy, model efficiency, and interpretability as separate objectives rather than designing systems that pursue all three together. This fragmented approach represents the most significant gap in the field today.

Additionally, the majority of experimental studies are conducted on curated benchmark datasets with relatively uniform distributions, which fail to capture the variability present in real-world agricultural settings. As a result, models often show a marked drop in performance when evaluated under actual field conditions. A related issue is that FL, while reducing direct data sharing, still requires frequent exchange of model parameters between clients and a central server — a process that creates significant communication bottlenecks, particularly in rural areas with unstable or low-bandwidth connectivity.

Furthermore, many published FL approaches still rely on architectures with high parameter counts that exceed the memory and processing limits of edge devices typically used by smallholder farmers, limiting their practical deployability. Explainability tools such as Grad-CAM have been incorporated only sporadically in FL-based detection systems, creating a transparency gap that undermines farmer confidence in AI-driven recommendations. Finally, nearly all existing approaches depend solely on visual image data, overlooking complementary data modalities whose integration could considerably enhance diagnostic precision. Table II provides a structured summary of these identified gaps.

TABLE II
Research Gaps in FL-Based Crop Disease Detection

#	Research Gap Identified
1	No unified framework covering privacy + compactness + XAI together
2	Benchmark datasets lack real-world agricultural diversity
3	Communication bottleneck in rural low-bandwidth environments
4	Parameter-heavy models exceed edge hardware capacity
5	Sporadic XAI adoption reduces farmer trust in AI decisions
6	Exclusive reliance on visual data; multimodal fusion unexplored

VI. Proposed Research Direction

Based on the gaps outlined above, future research efforts should target integrated frameworks that coherently combine federated training, efficient lightweight inference, and inherent explainability. Such systems should support privacy-preserving collaboration among distributed devices, operate within the hardware limits of resource-constrained field deployments, and generate outputs that can be meaningfully understood and trusted by end users such as farmers and agricultural advisors.

Specific research directions should include the development of robust model aggregation techniques capable of handling heterogeneous and non-IID data, the design of bandwidth-efficient communication protocols suited to low-connectivity rural environments, and the creation of energy-aware model architectures optimized for edge hardware. It is equally important to explore multimodal data fusion and to conduct thorough field-based validation studies in order to close the gap between controlled benchmark performance and real on-farm applicability.

VII. Future Scope

Future progress in this domain is likely to arise from the combination of advanced FL algorithms with highly efficient deep learning architectures, delivering improved scalability and lower latency in continuous disease monitoring applications. The incorporation of diverse data types — including microclimate sensor readings, drone-captured aerial imagery, and soil chemical measurements — has significant potential to enhance predictive accuracy beyond the limits of image-based approaches alone.

Converting research prototypes into practical, real-time mobile applications that can be deployed directly in agricultural fields will mark a critical step toward widespread adoption. At the same time, embedding robust XAI capabilities within these systems will be essential for building farmer trust in AI-generated diagnoses, while ongoing improvements in communication-efficient federated protocols will be key to achieving the scalability needed for broad agricultural deployment.

VIII. Conclusion

This paper has provided a structured survey of recent developments in federated learning for crop disease detection, highlighting the growing need for privacy-preserving and resource-efficient approaches in smart agriculture. The reviewed body of work demonstrates clear technical advancement in the field; however, unresolved issues related to data heterogeneity, communication overhead, and model interpretability continue to limit practical applicability.

Addressing these challenges through the thoughtful combination of federated learning, compact neural network architectures, and explainable AI holds the potential to produce systems that are both technically sound and practically usable in real agricultural settings. Such developments could contribute meaningfully to improving crop yields, minimizing unnecessary use of agrochemicals, and advancing the broader goal of intelligent, data-driven farming at a global scale.

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