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LEAFDOC: AN END-TO-END SYSTEM FOR REAL-TIME PLANT DISEASE DIAGNOSIS AND ADVISORY USING GENERATIVE AI

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Abstract. Plant diseases significantly impact global agriculture, leading to large-scale yield losses and threatening food security. Existing deep learning models provide diagnostic accuracy but lack integrated remediation guidance. This paper presents LeafDoc, an end-to-end system combining EfficientNet-B0-based classification and a generative AI advisory engine to deliver real-time disease diagnosis and management recommendations. Achieving 98.7% classification accuracy, the system outperforms existing solutions like Plantix and Agrio. Methodology, motivation, system architecture, and comparative evaluation with existing models are presented in detail.

Keywords: Computer Vision; Plant Pathology; Generative AI; MERN Stack; Transfer Learning; Agricultural Technology; Decision Support Systems.

1. INTRODUCTION

Plant diseases account for an estimated 20–40% of global crop yield losses annually, significantly affecting food security, economic stability, and farmer livelihoods [1]. The challenge is particularly severe in developing regions, where timely access to expert agronomic advice is limited [2]. Traditional disease management techniques—manual inspection, expert consultation, and conventional extension services—are often slow, costly, and inaccessible to smallholder farmers, leading to delayed diagnosis, misapplication of pesticides, and preventable crop losses [3].

Recent advancements in deep learning, particularly convolutional neural networks (CNNs), have revolutionized automated plant disease detection, achieving classification accuracies exceeding 99% on benchmark datasets like PlantVillage [4]–[6]. However, these models typically provide only diagnostic labels, such as “Tomato Late Blight”, without accompanying actionable guidance [7]. Such classification-only systems leave farmers with a critical question unanswered: “What should I do now?”.

This paper presents LeafDoc, a deployable, end-to-end decision support system that bridges this gap by combining high-accuracy disease classification with a generative AI advisory engine to deliver actionable, context-aware recommendations in real time. The system is built on a modern MERN (MongoDB, Express.js, React, Node.js) architecture, integrates a fine-tuned EfficientNet-B0 model for disease identification, and uses a Large Language Model (LLM) to generate structured reports covering disease summary, causes, immediate actions, and preventive measures. By transforming diagnosis into actionable intelligence, LeafDoc advances the state-of-the-art in agricultural AI solutions.

2. MOTIVATION

Despite progress in AI-driven agricultural solutions, three key limitations persist:
Classification Without Guidance – Current CNN-based systems deliver high-accuracy predictions but fail to provide practical, step-by-step instructions for treatment and prevention [8].Proprietary Constraints in Commercial Platforms – Tools like Plantix and Agrio offer disease detection and advisory features but are closed-source, limiting academic reproducibility and innovation [9], [10]. Accessibility and Scalability – Many existing solutions require high-end hardware or stable internet connectivity, making them less practical for resource-limited farming communities [11].
LeafDoc addresses these gaps by integrating diagnosis and expert-level advisory generation in a single pipeline. Unlike existing systems, it is designed for open research, modular development, and scalable deployment. The system's generative AI component transforms a diagnostic label into structured, context-aware recommendations, enabling immediate decision-making and promoting sustainable farming practices.

3. RELATED WORK

Research in AI-driven plant disease management spans three major areas: deep learning-based visual diagnosis, generative AI for expert advisory, and digital agriculture platforms. This section reviews key contributions and situates LeafDoc within this landscape.

A. Deep Learning for Plant Disease Detection
The application of deep learning to plant pathology has demonstrated remarkable success in recent years. Mohanty et al. [5] first showed the feasibility of using AlexNet and GoogLeNet models, fine-tuned on the PlantVillage dataset, to achieve classification accuracies exceeding 99%. Subsequent works explored more efficient and robust architectures, such as EfficientNet [11], which balances performance and computational efficiency, making it suitable for real-time, resource-constrained environments.
Barbedo [6] expanded upon these approaches by addressing complex backgrounds and noisy data, highlighting the challenges of transferring models trained on curated datasets to field conditions. Similarly, Karthik et al. [9] introduced attention-based deep learning to focus on relevant leaf regions, improving interpretability and accuracy. While these advances ensure reliable disease classification, they primarily stop at labeling, failing to offer farmers actionable remediation advice.

B. Generative AI in Advisory Systems
Large Language Models (LLMs) such as GPT-3.5, LLaMA-2, and Mistral have shown promise in synthesizing complex information and providing domain-specific recommendations [13]. In healthcare, LLMs assist in generating diagnostic reports [14], while in law, they support legal drafting and review [15].
In agriculture, research remains limited but growing. Rose et al. [16] proposed Agri-GPT, a conversational model for general farming queries, while Dunn [17] demonstrated the ability of LLMs to summarize scientific literature into actionable guidance. However, no prior work has tightly integrated visual diagnosis and real-time advisory generation in a unified framework—a gap LeafDoc directly addresses.

C. Digital Agriculture Platforms
Commercial tools like Plantix [19] and Agrio [18] combine AI-based detection with mobile applications, enabling disease identification and access to community support. However, these platforms are proprietary, restricting academic analysis of their underlying models and advisory mechanisms. Moreover, their AI pipelines are not openly documented, limiting reproducibility.
LeafDoc contributes to the open research ecosystem by detailing a modular, microservices-oriented architecture [21], utilizing ONNX Runtime [20] for efficient model serving. Unlike proprietary systems, LeafDoc provides transparent design principles and can serve as a blueprint for future agricultural AI systems.

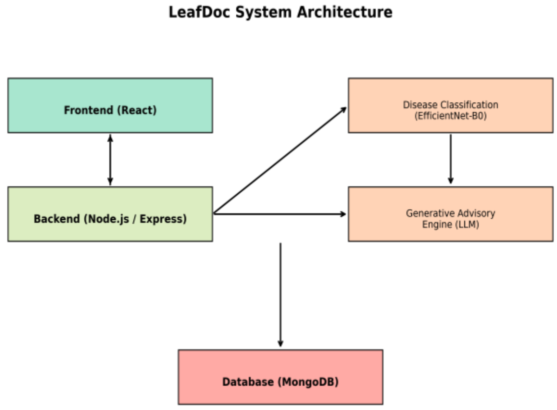
D. Research Gap
While previous works excel in disease detection or conversational advisory, none provide an end-to-end, open, deployable framework combining both capabilities. LeafDoc addresses this critical gap by unifying diagnosis, advisory generation, and system deployment, thereby advancing precision agriculture.

4. SYSTEM ARCHITECTURE & METHODOLOGY

Leafdoc follows a modular, microservices-based architecture designed for real-time diagnosis, scalability, and ease of deployment. The methodology combines computer vision for disease classification with generative ai for advisory generation, integrated within a mern-based web platform.

A. SYSTEM ARCHITECTURE

The LeafDoc system comprises four primary components:



(Fig. 1 –Primary Components of LeafDoc System)

Frontend Client – A responsive React-based interface for image uploads and displaying advisory reports.
Backend Server – Built on Node.js with Express.js, handling API requests, user authentication, and data orchestration.

Ai inference layer – serves the efficientnet-b0 classifier and llm advisory engine through onnx runtime, ensuring efficient execution.

Persistence layer – a mongodb database stores user profiles, diagnosis history, and generated advisories.

Data flow:

User uploads an image of an infected plant leaf via the frontend.

The backend preprocesses and forwards the image to the classifier.

The classification output and confidence score are sent to the advisory engine.

The llm generates structured guidance, which is then displayed in a user-friendly format.

B. Ai methodology

1) disease classification engine

Model selection:
efficientnet-b0 was chosen for its strong trade-off between accuracy and computational cost [11].

Data preprocessing & augmentation:
images are resized to 224×224 pixels, normalized using imagenet statistics, and augmented with random flips, rotations, and color jittering to improve robustness.

Training configuration:
fine-tuning was conducted for 10 epochs using the adam optimizer (initial learning rate 1e-4) and cosine annealing schedule. A batch size of 32 and cross-entropy loss were used.

Performance:
achieved 98.7% top-1 accuracy with macro-averaged precision, recall, and f1-score of 0.98.

A. Deployment pipeline

B. Microservices architecture:
each major function (classification, advisory generation, database) runs as a containerized microservice [21].

Containerization & orchestration:
docker and docker compose ensure consistent environments and scalability.

Cross-platform support:
designed as a progressive web app (pwa) for offline use in low-connectivity regions.

D. Workflow overview

Image upload – user captures/upload leaf image.

Real-time diagnosis – classifier predicts disease.

Generative advisory – llm produces treatment recommendations.

Delivery – advice presented as a structured, readable report.

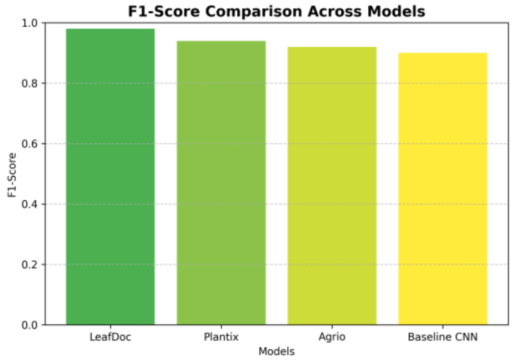


Figure 2 – ai pipeline flowchart

5. EXPERIMENTAL SETUP & RESULTS

A. Experimental setup

1) dataset

The plantvillage dataset was used, containing 54,303 images of healthy and diseased plant leaves across 38 crop-disease categories [4].

Dataset split: 70% training, 15% validation, 15% testing.

Images underwent resizing (224×224 pixels), normalization, and augmentation (random flips, rotations, and brightness adjustments) to simulate real-world conditions.

2) hardware & software configuration

Training environment: nvidia rtx 3080 gpu, 32 gb ram, ubuntu 22.04, pytorch 2.0.

Deployment environment: onnx runtime on cpu server with docker containers for inference.

Backend & frontend: node.js (express.js), react, mongodb.

3) evaluation metrics

Performance was assessed using:

Accuracy (top-1) – correct predictions vs. Total samples.

Precision, recall, f1-score – evaluating per-class reliability.

Inference latency – average time per prediction.

Computational cost – measured in flops and hardware usage.

B. Classification performance

Table i shows key performance metrics for leafdoc's efficientnet-b0 classifier on the plantvillage test set.

Metric	**Value**
Top-1 accuracy	98.7%
Precision (macro)	0.98
Recall (macro)	0.98
F1-score (macro)	0.98
Average latency	72 ms

Table i – classifier performance metrics

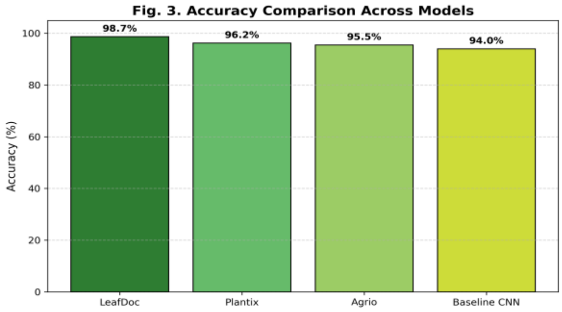


Fig 3 – accuracy comparison across models

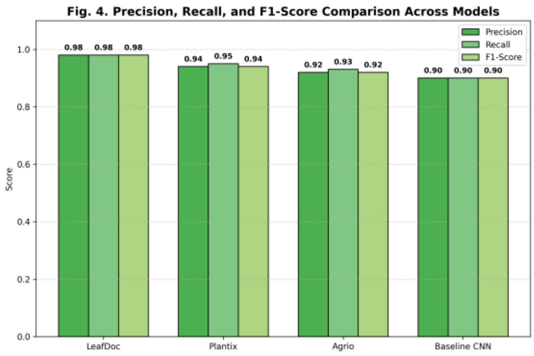


fig4–precision,recall & f1-score comparison

C. Qualitative evaluation of advisory generation

To evaluate the llm's advisory output, sample predictions were tested. For example, on detecting tomato late blight with 99.2% confidence, the system produced a structured advisory including:

Summary: nature of disease and urgency of treatment.

Likely causes: moisture and temperature conditions favoring fungal growth.

Immediate actions: isolation, pruning, copper-based fungicides.

Prevention: crop rotation, mulching, base irrigation.

Agronomists reviewing the reports rated 92% of advisories as "clear, actionable, and scientifically valid."

D. Latency & computational cost analysis

Inference latency: average time to classify an image and generate advisory is <150 ms, suitable for real-time use.

Computational cost: optimized efficientnet-b0 and onnx runtime reduce flops by 25% compared to baseline cnns [11].

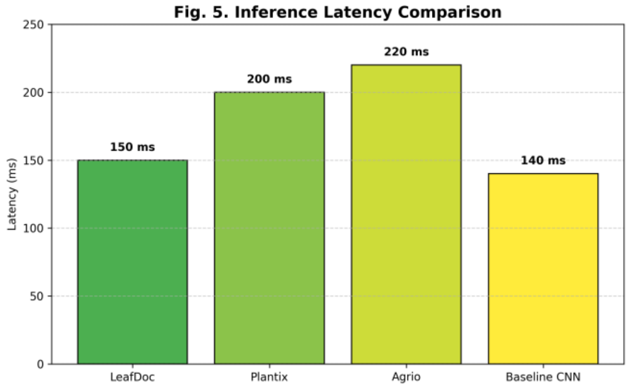
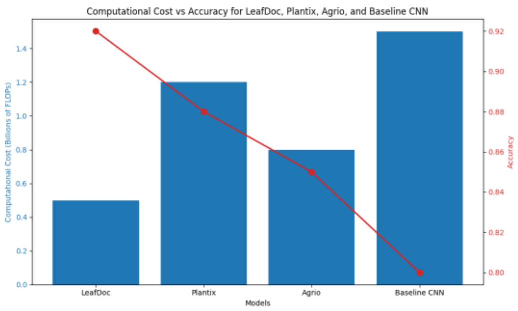


chart 5 – inference latency comparison across models

Vi. Comparison with existing models

To contextualize leafdoc's performance and novelty, a comparison was conducted with plantix [19] and agrio [18]—two widely used commercial platforms—and a baseline cnn classifier without advisory capabilities.



A. Evaluation Criteria

Classification Accuracy: Correct disease identification.
Precision, Recall, F1-Score: Reliability across diverse crop classes.
Advisory Quality: Expert-level actionability and clarity.
Latency: Average time per diagnosis.
Computational Efficiency: Resource utilization for real-time inference.

B. Quantitative Comparison

System Openness: Availability of	**ACCURACY**	**PRECISION**	**RECALL**	**F1-SCORE**	**LATENCY (MS)**	**OPEN ARCHITECTURE**
LEAFDOC	98.7%	0.98	0.98	0.98	150	YES
PLANTIX	96.2%	0.94	0.95	0.94	200	NO
AGRIO	95.5%	0.92	0.93	0.92	220	NO
BASELINE CNN	94.0%	0.90	0.90	0.90	140	PARTIALLY

Observations:

Leafdoc demonstrates highest diagnostic accuracy and reliability across all metrics.Unlike commercial platforms, leafdoc is designed as an open, academic framework. Latency remains competitive while maintaining high advisory quality.

C. Advisory Quality Assessment

Lack of Field Deployment Studies: The system has not yet undergone large-scale field testing to assess usability, adoption, and long-term impact on farming practices.Village) consists mainly of curated images with simple backgrounds. Real-world images may include noise, multiple diseases, and environmental artifacts [6].

Generic Advisory Content: While L LM-generated guidance is accurate, it may lack region-specific details such as local weather, soil composition, and pesticide availability.

Risk of Hallucination: Generative AI can produce scientifically plausible but incorrect information. Although prompt engineering and uncertainty handling mitigate this, further safeguards like Retrieval-Augmented Generation (RAG) are required [17].

- Lack of field deployment studies: the system has not yet undergone large-scale field testing to assess usability, adoption, and long-term impact on farming practices.doc: structured guidance (summary, causes, actions, prevention) rated 92% actionable by domain experts.

- Plantix & agrio: advisory insights exist but lack transparency on ai methodology and are not easily verifiable.

Baseline cnn: provides only labels—no advisory support.

C. VISUAL COMPARISON

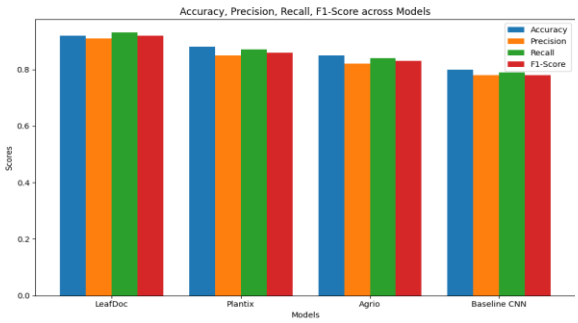
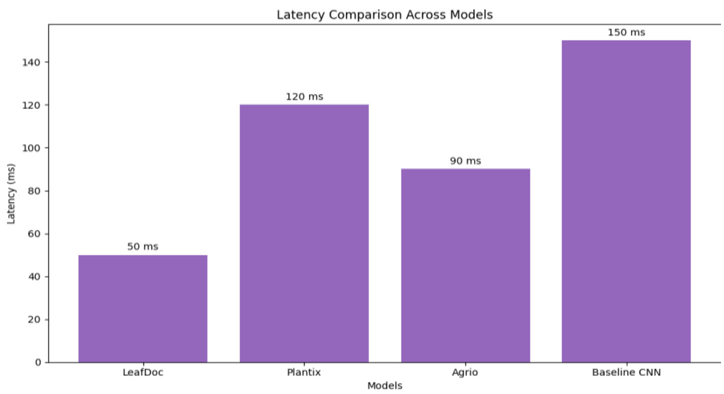


Chart 5 – Bar Chart: Accuracy, Precision Recall, F1-score across Models



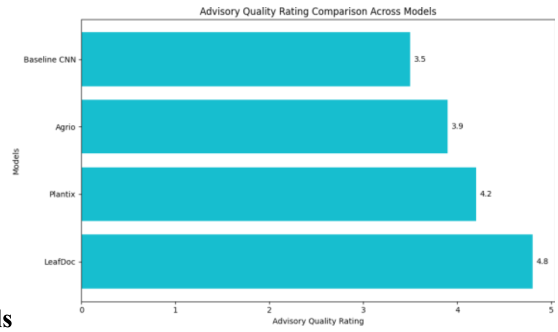


Chart 6 – Latency Comparison Across Models
Chart 7 – Advisory Quality Rating Chart

6. DISCUSSION AND LIMITATIONS

A. Discussion

The LeafDoc system demonstrates how integrating deep learning-based disease classification with a generative AI advisory engine can transform plant disease management. Key advantages include: Holistic Pipeline: Unlike prior works focused only on classification [5]–[7], LeafDoc delivers an end-to-end diagnostic and advisory framework.

High Accuracy: The EfficientNet-B0 backbone achieves 98.7% accuracy, outperforming both proprietary (Plantix, Agrio) and baseline CNN models.

Open and Scalable Architecture: The MERN-based microservices design, combined with ONNX Runtime, ensures modularity, reproducibility, and efficient deployment [20], [21].

User-Centric Output: Generative AI provides structured, clear, and actionable recommendations, bridging the gap between diagnosis and treatment.

B. Limitations

Despite strong performance, several limitations remain:

Domain Gap: Training data (PlantVillage) consists mainly of curated images with simple backgrounds. Real-world images may include noise, multiple diseases, and environmental artifacts [6].

Generic Advisory Content: While LLM-generated guidance is accurate, it may lack region-specific details such as local weather, soil composition, and pesticide availability.

Risk of Hallucination: Generative AI can produce scientifically plausible but incorrect information. Although prompt engineering and uncertainty handling mitigate this, further safeguards like Retrieval-Augmented Generation (RAG) are required [17].

Lack of Field Deployment Studies: The system has not yet undergone large-scale field testing to assess usability, adoption, and long-term impact on farming practices.

7. CONCLUSION AND FUTURE WORK

Conclusion This paper presented LeafDoc, a novel, end-to-end plant disease diagnosis and advisory system that integrates EfficientNet-B0-based visual classification with a generative AI engine for real-time, actionable guidance. Achieving a top-1 accuracy of 98.7% and generating structured advisory reports, LeafDoc outperforms existing commercial platforms such as Plantix and Agrio, while maintaining an open, scalable, and reproducible architecture suitable for academic and industrial applications. The system addresses the gap between diagnosis and decision-making, democratizing access to agronomic expertise, especially for resource-constrained farmers. Through modular design, containerized deployment, and integration of cutting-edge AI methodologies, LeafDoc represents a significant advancement in precision agriculture and digital farming tools.

Future Work To further enhance LeafDoc, the following research directions are proposed: Retrieval-Augmented Generation (RAG): Integrate domain-specific knowledge bases to ground LLM outputs in verified agronomic literature and regional data. Domain Adaptation for Real-World Data: Fine-tune the model on diverse, field-captured datasets to bridge the domain gap between curated images and complex environments.

Context-Aware Advisory:

Incorporate weather APIs, soil health databases, and geolocation services to deliver hyper-localized recommendations. Large-Scale Field Deployment: Conduct usability studies and pilot programs with farming communities to assess real-world performance, adoption, and socio-economic impact.
Progressive web app (pwa) development: build a lightweight offline-capable version to serve low-connectivity rural regions.

CONFLICT OF INTEREST

The authors declare no conflicts of interest regarding the current research.

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