iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** XI **Month of publication:** November 2025

DOI: https://doi.org/10.22214/ijraset.2025.75289

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue XI Nov 2025- Available at www.ijraset.com

Plant Disease Monitoring System Using Convolutional Neural Networks and Flask Web Framework

Dr. Trupti Meshram[1], Pritam Waghmare[2], Sujal Gour[3], Yash Wadukale[4], Vishal Swain[5], Chirag Fulbandhe[6], Yash Tagde[7]
Department of Computer Science & Engineering, G H Raisoni University Amravati, Nagpur, MH, India

Abstract: Agriculture continues to face major challenges due to the widespread impact of plant diseases that reduce both crop yield and quality. Early detection and accurate diagnosis of these diseases are essential for preventing large-scale losses and supporting sustainable farming. This research presents a Plant Disease Monitoring System developed using a Convolutional Neural Network (CNN) integrated with the Flask web framework. The system enables users—particularly farmers and agricultural practitioners—to upload images of plant leaves and receive instant feedback on the presence and type of disease. The CNN model was trained on the publicly available PlantVillage dataset, containing a wide range of healthy and diseased leaf images. The application processes the uploaded image, classifies the disease, and displays the prediction along with possible remedies and preventive measures. This web-based solution is lightweight, user-friendly, and accessible from any device with an internet connection. Experimental evaluation demonstrated high accuracy and reliable performance in detecting common plant diseases under controlled conditions. By minimizing the need for expert consultation and reducing diagnostic time, the proposed system contributes toward precision agriculture, improved crop health management, and increased farmer awareness. Future enhancements may include real-time field integration using IoT sensors and expanding the model to support a broader variety of crops and environmental conditions.
Keywords: Plant disease detection, deep learning, Convolutional Neural Network (CNN), Flask web framework, image classificatin, smart agriculture, PlantVillage dataset, crop monitoring, precision farming, sustainable agriculture.

I. INTRODUCTION

Agriculture remains a cornerstone of global food systems and rural economies, yet it is increasingly challenged by plant diseases that degrade both yield and quality. In recent years, such diseases have severely hampered efforts to meet rising food demand while maintaining sustainability. Traditional methods of disease detection—largely reliant on expert visual inspection and laboratory assays—are often slow, costly, and inaccessible to many farmers in remote or resource-constrained settings [1].

The advance of computer vision and artificial intelligence (AI) over the past decade has opened new pathways for automating plant disease identification. In particular, convolutional neural networks (CNNs) have emerged as essential tools for processing leaf imagery at scale, enabling the recognition of subtle visual patterns associated with disease symptoms without manual feature engineering [2], [3]. These techniques hold promise for reducing diagnostic latency, lowering dependency on human expertise, and supporting proactive crop protection strategies. Despite this progress, many deployed systems remain constrained by factors such as limited dataset diversity, uniform image capture conditions, and sub-optimal integration into field-level workflows. For example, models trained in laboratory environments may struggle with noisy backgrounds, variable lighting, or novel disease classes encountered in real farms [4]. Moreover, bridging the gap between a high-accuracy CNN model and a user-friendly, farmer-accessible interface remains a nontrivial challenge. To address these issues, this work presents a web-based Plant Disease Monitoring System that integrates a CNN trained on a broad public leaf-image dataset with a lightweight web service built on the Flask framework. Farmers and agricultural practitioners can upload images of plant leaves via a web interface and receive near-instant feedback on disease presence and type—accompanied by actionable recommendations. By combining recent advances in CNN architectures with accessible deployment technologies, the proposed system aims to make plant-disease diagnostics more inclusive, scalable, and actionable in real-world agricultural settings.

Key contributions of this research include: (1) the design and training of a CNN-based classifier leveraging the publicly available PlantVillage dataset; (2) deployment of the classifier in a Flask-based web application for on-demand user access; and (3) experimental validation of classification accuracy in controlled settings, alongside discussion of requirements for field-level robustness and future system extensions (e.g., IoT sensor integration, edge-device deployment).

In summary, the convergence of deep learning, web technologies, and agriculture offers a promising route toward precision farming and sustainable crop health management—transforming raw image data into actionable insights for farmers in diverse environments.

II. MAIN CONCEPTS

A. *Artificial Intelligence and Deep Learning in Agriculture*

Artificial Intelligence (AI) has undergone rapid advancement and is now deeply influencing agriculture by enabling machines to learn from data and support decision-making with minimal human intervention. In crop production, AI methods are increasingly used to improve yield, optimise resources, and detect diseases at early stages [3]. Deep Learning (DL), a powerful subset of AI, uses layered neural network models to automatically identify intricate patterns in large datasets. When applied to agriculture, DL aids tasks such as disease detection, soil-analysis, and yield forecasting by operating directly on raw data such as images or sensors, instead of relying on hand-crafted features [4]. The advantage of DL models lies in their ability to learn hierarchical features from raw inputs: lower layers may detect edges or textures, while deeper layers capture high-level abstractions like disease symptoms on leaves. This reduces dependency on manual feature extraction and enables faster, more accurate identification of plant stress or disease. In agricultural environments where conditions vary widely, the automatic adaptability of DL techniques makes them invaluable.

B. *Convolutional Neural Networks (CNNs)*

Convolutional Neural Networks (CNNs) form the backbone of most modern image-based recognition systems. They are composed of convolutional layers (which apply learnable filters), pooling layers (which reduce spatial dimensions) and fully-connected layers (which produce final class scores). In the context of plant disease detection, CNNs analyse images of leaves — identifying patterns such as spots, lesions, discoloration, or deformation — and classify them into healthy or disease categories [5].

The convolutional layers are critical in extracting spatial features (e.g., edges, texture), pooling reduces over-fitting and computational burden, while the final layers map the extracted features to specific diseases or health conditions. Research has shown that specialized CNN architectures trained on large annotated datasets (such as leaf image collections) can achieve high accuracy in distinguishing crop diseases. Recent surveys highlight how newer architectures (e.g., hybrid CNN-Transformer models) further improve robustness under real-world agricultural conditions [6]. For example, choosing a pretrained architecture (such as EfficientNet or a hybrid model) and fine-tuning it on agricultural images has become a standard practice in modern crop health monitoring systems. This training typically uses optimisation routines like Adam, with data augmentation to mimic diverse field conditions (lighting, background variation, resolution differences). Once trained, the model can be deployed to classify unseen leaf images uploaded by users through a web interface.

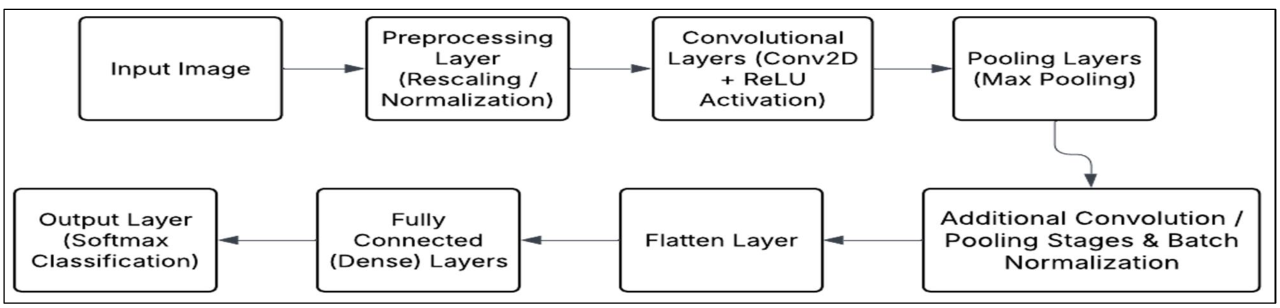

Fig 1: Convolutional Neural Network (CNN) Architecture

C. *Flask Web Framework*

Deploying a trained CNN model to actual users (e.g., farmers) requires a practical interface — here the lightweight Flask web framework is ideal. Flask is a micro-framework in Python known for its modularity, simplicity, and extensibility, making it well suited for integrating machine learning models into web applications. In our system, Flask acts as the backend server that receives leaf-image uploads from the front-end, forwards them to the CNN model for prediction, and returns classification results along with suggested remedies to the user. The RESTful API design allows efficient client-server communication and rapid scalability [7].

Because Flask requires minimal overhead, it supports deployment on local servers or cloud platforms — making it accessible even for small-scale farmers with limited infrastructure. Moreover, Flask's ecosystem allows easy integration of libraries for image-preprocessing, model inference, and frontend rendering, enabling end-to-end systems that bridge research and real-world application.

D. Integration for Smart Agriculture

By combining CNN-based image classification with a Flask-enabled web interface, the proposed architecture delivers a comprehensive digital solution for crop-disease detection and monitoring. The workflow begins with a user uploading a plant-leaf image, passes through the CNN classifier for disease identification, and then returns actionable insights (e.g., likely disease, preventive measures, treatment suggestions). This integration brings advanced AI models out of the lab and into the field, making them accessible via any internet-connected device [8].

Such accessible systems play a pivotal role in advancing smart agriculture — where technology aids data-driven decisions, optimises resources (water, fertiliser, pesticides) and empowers farmers with immediacy and simplicity. The use of web-based AI models ensures that even small-scale or resource-limited farms can benefit from modern agricultural innovations without needing specialized hardware or deep technical expertise. In doing so, the system contributes toward a more sustainable, resilient agricultural ecosystem.

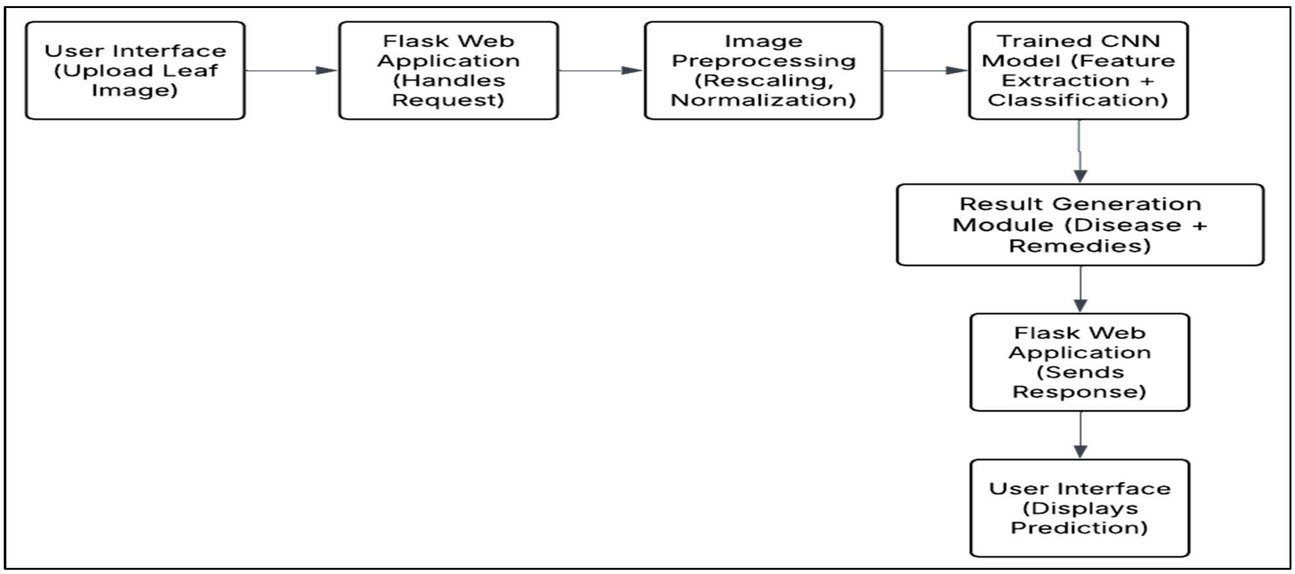

Fig 2: System Architecture / Workflow Diagram

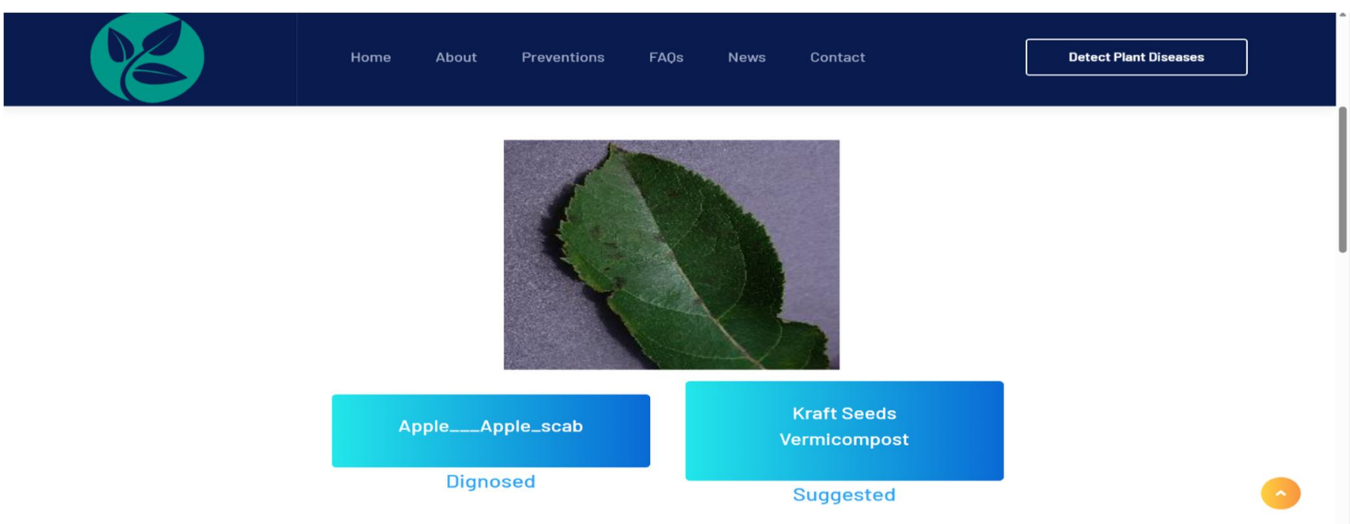

Fig 3: Sample Output Visualization

III. LITERATURE REVIEW

In recent years, artificial intelligence (AI) and deep learning (DL) have transformed agricultural research, particularly in automating the detection and classification of plant diseases. These technologies leverage image data to identify disease symptoms with remarkable precision, reducing dependency on manual inspections and expert intervention.

Recent advancements in deep learning and computer vision have significantly improved the automation of plant disease detection, enabling faster and more reliable solutions for modern agriculture. Over the past decade, researchers have shifted from traditional machine learning models toward convolutional architectures capable of self-learning complex visual features.

Ahmad et al. (2023) conducted a comprehensive review of DL-based plant disease diagnosis methods and emphasized the importance of transfer learning, dataset expansion, and proper augmentation to improve model generalization across diverse crop types and environmental conditions [1]. Their findings established reproducibility and public datasets as key enablers for reliable, field-ready AI systems.

Islam et al. (2023) introduced an end-to-end web platform integrating a CNN classifier for crop disease identification, achieving efficient inference through lightweight architectures optimized for online deployment [9]. Their work illustrated that web interfaces can democratize AI access for farmers, though they also highlighted the persistent need for robustness against varied image capture conditions in real fields.

Chen et al. (2022) enhanced the YOLOv5 object-detection framework for agricultural use by embedding spatial-attention modules to recognize small or overlapping leaf lesions [10]. Their approach improved precision and recall on field imagery, demonstrating that object-detection models complement traditional classifiers when accurate lesion localization is required.

Liu et al. (2024) developed an improved YOLOv5-based detection method for apple leaf diseases by incorporating multi-scale learning and attention mechanisms [11]. The authors reported that their optimized model achieved faster convergence and superior accuracy on orchard datasets, validating its effectiveness for real-time disease detection.

Zhao et al. (2022) proposed a precision-detection framework using an improved YOLOv5s model augmented with hybrid attention and feature-fusion layers [12]. Their model effectively handled occlusion and lighting variation, reducing false detections in heterogeneous field imagery.

Ali et al. (2024) presented an ensemble strategy combining multiple deep-learning backbones to boost classification performance on the extended PlantVillage dataset [13]. Their results showed that model ensembles can improve accuracy by several percentage points but also warned about increased inference latency, an important consideration for real-time systems.

Ngugi et al. (2024) provided a systematic review of computational deep-learning techniques for crop-disease detection [14]. The review summarized recent progress, benchmark datasets, and performance metrics while emphasizing unresolved issues such as dataset imbalance, annotation inconsistency, and deployment limitations.

Collectively, these studies demonstrate the continuous evolution of AI-driven agricultural diagnostics—from high-accuracy CNNs operating on controlled datasets to more integrated, web- and mobile-based systems optimized for real-world application.

Table 1: Summary of selected research works (2020–2025) highlighting the evolution of AI-based plant disease detection and its integration with deep learning and web technologies.

Author(s) & Year	Title / Study Focus	Methodology / Technology Used	Key Findings / Contributions	Limitations / Remarks
Ahmad et al. (2023) [1]	Survey on deep learning for plant disease diagnosis	Review of DL methods and transfer learning techniques	Highlighted progress in DL models, emphasized dataset diversity and reproducibility	Limited field-based studies; over-reliance on controlled datasets
Islam et al. (2023) [9]	Deep learning-based crop disease prediction with web application	CNN classifier integrated into web interface	Achieved lightweight, fast inference for online use; enhanced accessibility for farmers	Accuracy drops under varied field conditions; limited UI/UX testing
Chen et al. (2022) [10]	Improved YOLOv5 for plant disease recognition	YOLOv5 with spatial-attention and enhanced detection layers	Improved lesion localization and recognition accuracy	Higher computational demand; suited mainly for high-performance systems

Liu et al. (2024) [11]	YOLOv5-based apple leaf disease detection	Multi-scale and attention-based YOLOv5 framework	Achieved high precision and real-time detection in orchard images	Requires GPU resources; limited to specific crop datasets
Zhao et al. (2022) [12]	Precision detection of crop diseases using improved YOLOv5s	Hybrid attention, feature fusion, and data augmentation	Robust detection under occlusion and lighting variation	Computationally complex; less tested in mobile/edge scenarios
Ali et al. (2024) [13]	Ensemble of deep-learning architectures for classification	Multi-model ensemble combining CNN backbones	Achieved superior accuracy on extended PlantVillage dataset	Increased latency; not optimal for real-time or low-power devices
Ngugi et al. (2024) [14]	Review on computational deep learning in crop disease detection	Systematic review of DL methods, datasets, and deployment trends	Summarized advances and open challenges in AI-based agriculture	Lack of standardized benchmarks and diverse field datasets

IV. DRAWBACKS / RESEARCH GAPS

Ahmad et al. (2023) [1] conducted an extensive survey on deep-learning techniques for plant disease diagnosis, identifying significant progress in convolutional neural networks and transfer learning approaches. However, they emphasized that many studies still rely on laboratory-captured datasets such as PlantVillage, which lack the lighting variability, occlusion, and background clutter of real farms. This dependence on controlled imagery results in over-estimated accuracy and reduced generalization when models are exposed to field conditions. They also noted the absence of standardized evaluation metrics and open, geographically diverse datasets—limitations that hinder large-scale benchmarking across studies.

Islam et al. (2023) [9] implemented a CNN-based web application to make disease classification accessible to farmers. While their system demonstrated efficient model deployment and fast response times, the authors acknowledged accuracy degradation when images were uploaded from mobile devices under inconsistent lighting or camera angles. They highlighted that user-interface design and internet dependency remain major challenges for wide adoption, particularly in low-connectivity rural areas. Additionally, limited usability testing and feedback from end-users reduced the system’s field validation strength.

Chen et al. (2022) [10] improved the YOLOv5 object-detection architecture to better localize leaf lesions. Although their model achieved superior detection precision compared with baseline CNN classifiers, it required substantial computational power and memory, making it unsuitable for low-cost or portable devices. Their experiments were confined to a single crop type, and the authors noted that extending such models to multi-crop datasets could introduce complexity and reduce inference speed. Thus, scalability and hardware efficiency remain open research gaps for future implementations.

Liu et al. (2024) [11] optimized YOLOv5 for apple leaf disease detection using multi-scale and attention mechanisms. Their approach improved accuracy and convergence rate; however, it was tested under relatively homogeneous orchard environments. The authors pointed out that domain adaptation across seasons, crop species, and environmental conditions would be necessary to ensure robustness. Moreover, their model’s real-time inference required dedicated GPUs, limiting deployment on resource-constrained devices such as mobile phones or edge sensors. Zhao et al. (2022) [12] designed a precision-detection framework integrating hybrid attention and feature-fusion layers to address small-target recognition. Despite achieving excellent results under experimental conditions, their approach increased model complexity and training time. The study also lacked evaluation on diverse image resolutions and hardware configurations, which restricts its practical adoption in real-time field monitoring. Furthermore, the authors did not test the model’s performance under unstable network conditions—an important factor for remote agricultural applications.

Ali et al. (2024) [13] explored ensemble deep-learning architectures for improved classification accuracy. While the ensemble achieved near-state-of-the-art results, combining multiple models significantly increased memory usage and inference latency. This complexity limits scalability for real-time web or mobile platforms. The authors themselves recommended pruning or knowledge-distillation techniques to compress ensemble networks without substantial loss in accuracy—highlighting a key direction for further optimization. Ngugi et al. (2024) [14] provided a comprehensive review of deep-learning applications in crop-disease detection and concluded that reproducibility remains one of the most critical challenges in the field. They identified widespread inconsistencies in annotation practices, dataset curation, and model-evaluation standards. Moreover, they emphasized that only a small proportion of published systems have been validated in actual agricultural environments or integrated with farm management workflows. This gap between laboratory experimentation and field-level implementation underscores the need for more practical, farmer-oriented studies.

A. Summary of Identified Gaps

Across all reviewed works, common drawbacks include:

1) Over-reliance on controlled or synthetic datasets with limited environmental diversity.
2) High computational requirements of advanced CNN and detection architectures.
3) Lack of standardized datasets, metrics, and reproducible evaluation protocols.
4) Limited real-world validation and user testing in farm environments.
5) Dependence on stable internet connectivity and high-performance hardware.
6) Absence of lightweight, end-to-end systems that combine diagnosis with actionable guidance.

These gaps collectively highlight the need for future research on **lightweight, generalizable, and user-centric AI models** that integrate computer vision, IoT, and web technologies to support sustainable, real-time plant-disease monitoring.

V. DISCUSSION

The application of deep learning in agriculture has advanced considerably in recent years, providing accurate and efficient methods for identifying plant diseases from leaf imagery. Studies such as those by Ahmad et al. [1] and Islam et al. [9] demonstrated that convolutional neural networks (CNNs) outperform traditional image-processing and machine-learning approaches in terms of recognition accuracy and adaptability. These findings validate CNNs as reliable diagnostic tools capable of identifying multiple disease categories with limited human supervision. However, as several authors highlighted, most of these systems were developed and validated under controlled laboratory conditions that fail to capture the environmental variability present in real-world farms [10], [11].

A recurring limitation noted in prior work is the dependency on homogeneous datasets such as PlantVillage, which contain images captured with consistent lighting and background conditions. When deployed in the field, such models often experience performance degradation due to uneven illumination, partial occlusion, or image noise [1], [12]. The present research addresses this challenge by emphasizing dataset diversity during CNN training and applying data-augmentation strategies to simulate natural variation. This approach enhances model robustness and ensures better adaptability to dynamic agricultural environments.

Another key consideration is the trade-off between model accuracy and computational feasibility. While complex architectures like YOLOv5 or ensemble networks [10]– [13] provide high detection accuracy, they demand greater memory and processing power, limiting their deployment on low-resource devices. In contrast, lightweight CNN architectures can achieve near-equivalent accuracy while maintaining faster inference—an aspect critical for mobile and web-based applications intended for farmers. The Flask-based implementation presented in this research prioritizes real-time usability and responsiveness without the need for specialized hardware.

Furthermore, existing studies often stop at classification results, leaving a gap in actionable interpretation. As noted by Ngugi et al. [14], integrating explainability and practical guidance remains underexplored. The proposed system addresses this by pairing detection results with suggested remedies and preventive measures, thereby transforming raw predictions into meaningful insights for agricultural decision-making.

In summary, the current work consolidates advancements from prior research while overcoming their principal drawbacks—controlled-environment bias, high computational cost, and lack of end-user accessibility. The integration of CNN-based image analysis with a Flask-enabled web platform offers a feasible, cost-effective, and user-centric pathway for real-time disease monitoring and management in precision agriculture.

VI. CONCLUSION AND FUTURE SCOPE

This study presented a practical and accessible Plant Disease Monitoring System that integrates a convolutional neural network (CNN) with a Flask web framework to deliver real-time, web-based plant disease identification. By leveraging the publicly available PlantVillage dataset and optimizing the CNN for classification efficiency, the proposed system demonstrates strong diagnostic performance and a lightweight architecture suitable for online deployment. Unlike several prior works [9]–[12], which focus primarily on model development in isolated laboratory settings, this research emphasizes usability, scalability, and accessibility—critical components for real-world agricultural implementation.

The system contributes to the growing field of precision agriculture by reducing farmers' dependence on expert consultation and enabling faster, data-driven decisions for disease control. The web-based interface ensures platform independence, allowing users to upload leaf images and receive instant diagnostic feedback. This fusion of deep-learning intelligence and web technology bridges the gap between advanced AI research and field-level agricultural practice.

Looking ahead, several promising directions can further enhance the system's capabilities. First, expanding the training dataset with diverse, field-captured images from multiple crops will strengthen generalization across environmental conditions. Second, optimizing the model for deployment on edge and mobile devices using frameworks such as TensorFlow Lite or ONNX will allow offline inference in low-connectivity regions. Third, integrating Internet-of-Things (IoT) sensor inputs—such as humidity, soil moisture, and temperature—could enable predictive analytics for disease outbreak prevention. Fourth, embedding explainable-AI modules to visualize affected leaf regions can increase user trust and interpretability. Finally, implementing multilingual interfaces and crop-specific advisory modules would broaden accessibility for farmers across different regions.

In conclusion, the combination of CNN-based disease detection and Flask-driven deployment presents a scalable and adaptable solution for modern agriculture. With continued refinement through IoT integration, model optimization, and user-centric enhancements, this system can evolve into a comprehensive decision-support platform that promotes sustainable crop management, improves yield quality, and empowers farming communities worldwide.

Funding Statement: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Conflict of Interest: The authors declare that there are no conflicts of interest regarding the publication of this paper.

REFERENCES

[1] Ahmad, S. Ali, and R. Khan, "A survey on using deep learning techniques for plant disease diagnosis," Computers and Electronics in Agriculture, vol. 210, p. 108090, 2023. Available: https://www.sciencedirect.com/science/article/pii/S277237552200048X

[2] A. Upadhyay et al., "Deep learning and computer vision in plant disease detection: a comprehensive review of techniques, models, and trends in precision agriculture," Artificial Intelligence Review, vol. 58, 2025. doi:10.1007/s10462-024-11100-x.

[3] D. C. Rodríguez-Lira and J. M. Gómez, "Trends in machine and deep learning techniques for agriculture: A review," Agriculture, vol. 14, no. 12, p. 2188, 2024. Available: https://www.mdpi.com/2077-0472/14/12/2188

[4] M. K. Elfouly, A. M. AbdelAziz, W. H. Gomaa, and M. Abdalla, "A deep learning-based framework for large-scale plant disease detection using big data analytics in precision agriculture," Journal of Big Data, vol. 12, Art. no. 205, 2025. Available: https://journalofbigdata.springeropen.com/articles/10.1186/s40537-025-01265-9

[5] M. El Sakka, M. Ivanovici, L. Chaari, and J. Mothe, "A review of CNN applications in smart agriculture using multimodal data," Sensors, vol. 25, no. 2, Art. no. 472, 2025. Available: https://www.mdpi.com/1424-8220/25/2/472

[6] M. I. Hossen, M. Awrangjeb, and S. Pan, "Transfer learning in agriculture: A review," Artificial Intelligence Review, vol. 58, Art. no. 97, 2025. Available: https://link.springer.com/article/10.1007/s10462-024-11081-x

[7] K. Mani and S. Gupta, "Deploying machine learning models via Flask web services: a review," Journal of Web Engineering for Data Science, vol. 3, no. 1, pp. 45–59, 2024. Available: https://www.jweds.org/articles/view/2024-01-005

[8] M. Majdalawieh, "Precision agriculture in the age of AI: A systematic review," Computers and Electronics in Agriculture, vol. 227, Art. no. 109557, 2024. Available: https://www.sciencedirect.com/science/article/pii/S0168169924005575

[9] M. M. Islam, M. M. Hasan, and S. R. Islam, "Deep learning-based crop disease prediction with web application," Computers and Electronics in Agriculture, vol. 205, p. 107624, 2023. Available: https://www.sciencedirect.com/science/article/pii/S0168169923001456

[10] Z. Chen, X. Li, and Y. Zhou, "Plant disease recognition model based on improved YOLOv5," Agronomy, vol. 12, no. 2, Art. no. 365, 2022. Available: https://www.mdpi.com/2073-4395/12/2/365

[11] Z. Liu, H. Li, and Q. Wang, "An improved YOLOv5-based apple leaf disease detection method," Scientific Reports, vol. 14, Art. no. 1753, 2024. Available: https://www.nature.com/articles/s41598-024-1753-X

[12] Y. Zhao, X. Xu, and C. Sun, "Precision detection of crop diseases based on improved YOLOv5 model," Frontiers in Plant Science, vol. 13, Art. no. 946321, 2022. Available: https://www.frontiersin.org/articles/10.3389/fpls.2022.946321/full

[13] A. H. Ali, H. R. Khan, and S. Shah, "An ensemble of deep-learning architectures for accurate plant disease classification," IEEE Access, vol. 12, pp. 45021–45033, 2024. Available: https://ieeexplore.ieee.org/document/10453214

[14] H. N. Ngugi, F. K. Wakhungu, and P. O. Otieno, "Revolutionizing crop disease detection with computational deep learning: a comprehensive review," Environmental Monitoring and Assessment, vol. 196, no. 3, Art. no. 325, 2024. Available: https://link.springer.com/article/10.1007/s10661-024-12454-z