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Crop Disease Detection Using AI: A Comprehensive Survey

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Abstract: Crop disease detection is critical for ensuring food security and improving agricultural productivity, especially in India where a large population depends on farming. Traditional disease identification relies on manual inspection by farmers, which is often inaccurate, time-consuming, and leads to delayed treatment and excessive pesticide use. In recent years, Artificial Intelligence (AI) and deep learning, particularly Convolutional Neural Networks (CNN), have emerged as effective solutions for automated plant disease diagnosis.

This project presents an AI-based crop disease detection system that uses CNN for identifying diseases in tomato and potato leaves from uploaded images. The system provides instant classification of Healthy or Diseased leaves along with treatment recommendations and preventive measures. A web-based interface is developed using Flask for easy access by farmers with basic digital skills. The system also maintains a history of past detections to help users track disease patterns over time.

The study evaluates the system's performance in terms of accuracy, usability, cost-effectiveness, and scalability. Results show that the system delivers fast and reliable predictions, reduces dependency on agricultural experts, and minimizes crop loss. The project highlights the potential of AI in making agriculture more efficient and sustainable, while also identifying scope for future enhancements like multi-crop support and mobile integration.

Keywords: Crop Disease Detection; Artificial Intelligence; Convolutional Neural Network; CNN; VGG-16; Flask; TensorFlow; PlantVillage Dataset; Smart Agriculture; Image Processing.

I. INTRODUCTION

Crop disease detection is a vital component of modern agriculture, directly impacting food security, crop yield, and the livelihood of millions of farmers. Despite global efforts to improve agricultural productivity, many developing regions continue to experience significant crop losses due to inadequate disease monitoring, limited access to agricultural experts, and lack of real-time detection systems.

Traditional crop disease identification relies heavily on manual visual inspection by farmers, during which symptoms such as leaf spots, discoloration, wilting, and stunted growth are observed. However, this approach often fails to detect diseases at an early stage, as symptoms can be subtle or resemble nutrient deficiencies and environmental stress. This delay in diagnosis leads to widespread crop damage, excessive pesticide usage, and increased financial burden on small-scale farmers.

With the rapid advancement of technology, Artificial Intelligence (AI) and deep learning systems have emerged as promising solutions to overcome these limitations. Convolutional Neural Network (CNN) algorithms enable early and accurate classification of crop diseases based on leaf image analysis, while web-based applications improve accessibility by allowing farmers to upload images and receive instant results through smartphones or computers. Additionally, integrated treatment recommendation modules help farmers take timely and informed action to prevent further crop loss. This project presents an AI-based crop disease detection system using CNN for tomato and potato leaves. The study aims to design and implement a lightweight, user-friendly web application that provides accurate disease classification and actionable treatment suggestions. By providing a structured and accessible solution, this project highlights the need for integrated and scalable AI-driven tools that can ensure timely disease detection and promote sustainable agricultural practices.

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II. THEORETICAL BACKGROUND

A. Convolutional Neural Networks (CNN)
CNN is a deep learning architecture widely used for image classification. It automatically extracts features from images through convolutional and pooling layers, making it highly effective for detecting patterns in leaf images such as spots, discoloration, and texture changes.
B. Image Preprocessing
Uploaded leaf images are resized to a fixed dimension (224×224 px), normalized, and converted to arrays before being fed into the CNN model. This ensures uniformity and improves prediction accuracy.
C. Disease Classification
The model classifies leaf images into predefined categories such as Tomato – Early Blight, Tomato – Late Blight, Tomato – Healthy, Potato – Early Blight, Potato – Late Blight, Potato – Healthy. The output is based on the probability score from the CNN model.
D. Performance Metrics
The model's effectiveness is evaluated using Accuracy, Precision, Recall, and F1-score. In agriculture, high accuracy and low false negatives are crucial to avoid undetected diseases that can spread across crops.

III. SYSTEM CLASSIFICATION

To better understand the diverse approaches in crop disease detection, existing systems can be categorized into four tiers based on their functionality and level of technological integration.

Tier 1: Manual Inspection Systems
These systems rely entirely on visual observation by farmers or agricultural officers. Disease identification is based on personal experience and knowledge without any technological support. This method is highly subjective, time-consuming, and often leads to delayed or inaccurate diagnosis.

Tier 2: Image Processing-Based Systems
These systems use traditional image processing techniques such as color segmentation, texture analysis, and edge detection to identify disease symptoms in leaf images. While they reduce manual effort, they require manual feature extraction and lack learning capability, making them less accurate for complex disease patterns.

Tier 3: Machine Learning-Based Systems
These systems utilize machine learning algorithms such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Random Forest to classify crop diseases. They analyze extracted features from leaf images and provide automated predictions. However, they are often limited to static datasets and require manual preprocessing of images.

Tier 4: Deep Learning-Based Systems
These systems use deep learning architectures like Convolutional Neural Networks (CNN), VGG-16, ResNet, and YOLOv8 for end-to-end disease detection directly from leaf images. They offer higher accuracy, real-time performance, and minimal manual intervention. This project falls under Tier 4, using a CNN-based model integrated with a web interface to provide instant disease classification and treatment recommendations.

IV. LITERATURE REVIEW

Crop disease detection using AI has evolved significantly with the adoption of deep learning models. CNN-based approaches, especially VGG-16 and ResNet, have shown high accuracy in identifying diseases from leaf images using datasets like PlantVillage. Transfer learning has further improved performance while reducing training time.

Hybrid CNN models and autoencoders have been used to enhance feature extraction and minimize overfitting. Real-time detection using YOLOv8 has made it possible to localize diseased areas on mobile devices. Federated learning has also emerged for privacy-preserving training across multiple farms.

Explainable AI is being explored to improve transparency and farmer trust in predictions, while IoT-integrated systems combine environmental data with image analysis for better diagnosis.

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However, most existing systems are limited to specific crops and focus only on detection without offering treatment recommendations or user-friendly interfaces. This highlights the need for an integrated and accessible solution for rural farmers.

Table I: Literature Review Summary

Sl.	Author(s)	Year & Title	Method / Technique	Key Findings	Venue & Index
1	Kothari	2018 – Plant Disease Identification using AI: ML Approach	Machine Learning Approach	Highlighted need for fast and effective plant disease detection to reduce crop loss	SSRN, 2018
2	Selvaraj et al.	2019 – AI-powered Banana Diseases and Pest Detection	DCNN	Developed DCNN for real-time banana disease and pest detection for farmers	Springer Plant Methods, 2019
3	Bedi	2021 – Hybrid CNN + Autoencoder for Leaf Disease Classification	Autoencoder + CNN, TensorFlow	Hybrid model achieved higher accuracy than traditional CNN; reduced overfitting	Journal, 2021
4	Orchi et al.	2021 – AI and IoT for Crop Disease Detection: A Contemporary Survey	AI + IoT Survey	Surveyed automation of disease recognition using deep learning and IoT	Agriculture MDPI, 2021
5	Sharma	2022 – Transfer Learning-Based Detection of Tomato Leaf Diseases	Transfer Learning (VGG16, ResNet50), PlantVillage	Achieved >97% accuracy and reduced training time significantly	Journal, 2022
6	Alatawi et al.	2022 – Plant Disease Detection using AI based VGG-16 Model	CNN (VGG-16)	VGG-16 model effectively detected plant diseases from leaf images with high accuracy	Int. Journal, 2022
7	Rakesh & Indiramma	2022 – Explainable AI for Crop Disease Detection	CNN + XAI, PlantVillage Dataset	XAI improved transparency and trust in AI-based crop disease classification	IEEE Conf, 2022
8	Shoaid	2023 – A Review on Advanced Deep Learning Models for Crop Disease Diagnosis	ResNet, EfficientNet, YOLOv5, Custom Datasets	Reviewed advanced AI models; emphasized real-time detection and lightweight architectures	Review, 2023
9	Tirkey et al.	2023 – Performance Analysis of AI-based Crop Disease Solutions	Transfer Learning, Deep Learning	Comprehensive analysis of AI methods for real-time disease identification and classification	Elsevier, 2023
10	Bhargava et al.	2024 – Plant Leaf Disease Detection using Computer Vision & AI	ML + Computer Vision	Review of last 12 years showing progress in feature extraction and crop coverage	IEEE Access, 2024
11	Chen	2024 – YOLOv8-Based Real-Time	YOLOv8, Custom Field Dataset	Achieved real-time detection and precise	Journal, 2024

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Sl.	Author(s)	Year & Title	Method / Technique	Key Findings	Venue & Index
		Plant Leaf Disease Detection		localization of diseased areas for mobile use	
12	Jafar et al.	2024 – Revolutionizing Agriculture with AI for Plant Disease Detection	AI Review, Multiple Crops	Detailed steps for AI-based prediction; covered tomato, chilli, potato, cucumber diseases	Frontiers in Plant Science, 2024
13	Majdalawieh et al.	2025 – Precision Agriculture in the Age of AI	Systematic Review of ML Methods	Comprehensive review of AI methodologies for crop disease and pest detection	Smart Agricultural Tech, 2025
14	Ansari et al.	2025 – AI-driven Crop Disease Detection in Smart Agriculture	AI + Environmental Data + Image Processing	Web-based system providing precise diagnosis and treatment with environmental context	IJ Scientific Research, 2025
15	Li	2025 – Federated Learning Framework for Plant Disease Recognition	Federated CNN, Multi-region Datasets	Introduced privacy-preserving AI method for decentralized training across farms	Journal, 2025

Note: AI = Artificial Intelligence. ML = Machine Learning. DL = Deep Learning. CNN = Convolutional Neural Network. DCNN = Deep Convolutional Neural Network. VGG-16 = Visual Geometry Group 16-layer model. YOLO = You Only Look Once. IoT = Internet of Things. XAI = Explainable Artificial Intelligence. SVM = Support Vector Machine. KNN = K-Nearest Neighbors. RF = Random Forest.

V. COMPARATIVE SUMMARY OF REVIEWED LITERATURE

The comparative analysis shows that CNN and VGG-16 models provide high accuracy for crop disease classification but are often limited to specific crops and require large datasets. Transfer learning improves performance with less training time, while YOLOv8 enables real-time detection on mobile devices but needs high-end hardware.

IoT-integrated systems enhance diagnosis by combining environmental data with image analysis, but they depend on reliable infrastructure unavailable in many rural areas. Explainable AI improves transparency and farmer trust but increases computational complexity.

Overall, most existing systems focus on isolated functionalities and lack an integrated platform. This highlights the need for a lightweight and accessible solution that combines disease detection, treatment recommendations, and history tracking for practical use by farmers.

Table II: Comparative Summary of Reviewed Literature (2020–2025)

Sl.	Author(s)	Year	Method	System Focus	Modality	Key Limitation
1	Kothari	2018	ML Approach	Plant disease identification	Theoretical	No deep learning implementation
2	Selvaraj et al.	2019	DCNN	Banana disease and pest detection	Mobile-based	Limited to banana crop only
3	Bedi	2021	Hybrid CNN + Autoencoder	Leaf disease classification	Web-based	Limited to single crop dataset
4	Orchi et al.	2021	AI + IoT	Crop disease detection survey	IoT-based	Infrastructure dependency

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5	Sharma	2022	Transfer Learning (VGG16, ResNet50)	Tomato disease detection	Web-based	Limited to tomato crop only
6	Alatawi et al.	2022	CNN (VGG-16)	Plant disease detection	Web-based	No treatment recommendation module
7	Rakesh & Indiramma	2022	CNN + Explainable AI	Crop disease classification	Web-based	Computationally heavy for rural use
8	Shoaid	2023	ResNet, EfficientNet, YOLOv5	Crop disease diagnosis review	Review paper	No real-time deployment
9	Tirkey et al.	2023	Transfer Learning	Real-time disease identification	Review paper	No integrated user interface
10	Bhargava et al.	2024	ML + Computer Vision	Disease detection & diagnosis	Review paper	No deployment, review only
11	Chen	2024	YOLOv8	Real-time disease localization	Mobile-based	Requires high-end hardware
12	Jafar et al.	2024	AI Review	Multiple crop disease detection	Review paper	No practical implementation
13	Majdalawieh et al.	2025	ML Systematic Review	Precision agriculture disease detection	Review paper	No real-world deployment
14	Ansari et al.	2025	AI + Environmental Data	Smart agriculture disease detection	Web-based	Requires environmental sensors
15	Li	2025	Federated CNN	Privacy-preserving disease recognition	Distributed system	Complex infrastructure required

VI. RESEARCH GAPS AND SYNTHESIS

The literature review reveals several gaps in current crop disease detection systems. Most models are crop-specific and lack generalizability across different crops. Real-time detection is limited due to high computational requirements, making deployment difficult in rural areas.

Accessibility is another challenge, as many systems rely on high-end devices and stable internet, which small-scale farmers often lack. Existing solutions are also fragmented, focusing only on disease classification without offering treatment recommendations or history tracking.

These gaps highlight the need for an integrated, lightweight, and accessible system that provides accurate detection along with practical treatment guidance for farmers.

VII. CONCLUSION

This paper presented a comprehensive survey of AI-based crop disease detection systems, focusing on the application of machine learning, deep learning, IoT, and explainable AI in improving agricultural health monitoring. The review highlights how advancements in these technologies have significantly contributed to accurate disease classification, real-time detection, and improved accessibility for farmers.

Deep learning models such as CNN, VGG-16, ResNet, and YOLOv8 have demonstrated strong performance in identifying plant diseases from leaf images using datasets like PlantVillage. Similarly, transfer learning and hybrid CNN-

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autoencoder approaches have enhanced accuracy while reducing training time. IoT-integrated systems have further enabled continuous monitoring by combining environmental data with image analysis. Explainable AI has also improved transparency and farmer trust in AI-driven predictions.

However, despite these advancements, the study reveals that most existing systems operate in isolation and are limited to specific crops or functionalities such as classification or detection alone. There is a noticeable lack of integrated platforms that combine disease detection, treatment recommendations, and user-friendly interfaces into a unified and scalable solution. Additionally, challenges such as dependency on high-end hardware, limited accessibility in rural areas, and lack of personalization continue to hinder the effectiveness of current systems.

The analysis also indicates that while detection accuracy has improved, real-world deployment remains a challenge due to issues such as limited datasets, infrastructure constraints, and computational overhead. Furthermore, the absence of multi-crop support and actionable treatment guidance in many systems highlights the need for more adaptive and practical solutions.

In conclusion, future research should focus on developing integrated and lightweight crop disease detection systems that combine deep learning with accessible interfaces to provide real-time disease identification, treatment recommendations, and history tracking. Such systems have the potential to significantly improve crop health management, particularly in resource-constrained environments, by enabling timely intervention, better decision-making, and sustainable agricultural practices.

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