Survey on AI Powered Early Detection of Plant Disease

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***Abstract*— Global food security and sustainable farming practices are continuously jeopardized by recurrent outbreaks of pests and crop diseases. Conventional methods for identifying these issues, relying primarily on expert visual inspections, are fundamentally slow, resource-intensive, and too expensive for widespread, large-scale deployment. Deep Learning (DL) has recently materialized as a revolutionary solution, facilitating the automated, image-based diagnosis of crop health with notable accuracy. This review will showcase key advancements in applying DL to plant disease and pest detection, specifically synthesizing literature published since 2021. It documents the progression from earlier machine learning strategies that necessitated manual feature engineering to sophisticated modern deep architectures, such as Convolutional Neural Networks (CNNs). The subsequent discussion investigates crucial elements for optimizing performance, including the strategic use of transfer learning, the leveraging of pre-trained models, and the essential role of diverse and augmented datasets. Furthermore, the paper executes a comparative assessment of major DL frameworks, judging their precision, operational efficiency, and trustworthiness in practical agricultural settings. The final section offers conclusions on ongoing challenges and suggests future research pathways to sharpen the utility of deep learning within precision agriculture.**

Keywords— Advanced deep learning techniques, traditional machine learning methods, CNN-based image recognition, agricultural image processing, crop disease detection, neural network modeling, and transfer learning strategies.

I. INTRODUCTION

Global economic stability and food security for billions are highly dependent on agriculture, which acts as the backbone of global development [1]. Despite its importance, this sector constantly faces challenges such as unpredictable climate conditions, pest infestations, and plant diseases that severely affect productivity and crop quality [1], [2]. According to global studies, nearly 40% of crops are lost each year due to diseases and pests, leading to an estimated economic loss exceeding $220 billion annually [1]. Such alarming figures highlight the urgent need for reliable, automated systems that can detect plant diseases early and accurately to maintain sustainable food production [2].

Traditionally, disease diagnosis in crops has relied heavily on manual inspection carried out by experienced farmers or agricultural pathologists [3]. However, this method is prone to human error, subjectivity, and delay—especially when dealing with large-scale farms [4], [3]. Identifying diseases visually is not only time-consuming but also often inaccurate, as symptoms in early stages may be subtle or easily confused with nutrient deficiencies [3]. Moreover, incorrect diagnosis can lead to the misuse of pesticides, thereby harming both the environment and the economy. Consequently, the integration of automation and artificial intelligence (AI) into agriculture has become an essential step toward promoting sustainable and smart farming practices [1], [5].

Recent developments in computer vision and deep learning (DL) have dramatically transformed plant disease detection and diagnosis processes [6], [3]. These modern techniques allow machines to automatically interpret leaf images and identify disease symptoms that might be too subtle for the human eye to notice [5], [7]. Among DL models, Convolutional Neural Networks (CNNs) have shown outstanding capability in capturing intricate visual cues and distinguishing patterns linked to various crop diseases [6], [8]. By streamlining the entire diagnostic pipeline from image acquisition to final classification—DL-based systems significantly reduce manual effort, operational costs, and detection time compared to conventional methods [1], [2]. Moreover, these AI-driven approaches promote sustainable farming practices by enabling early intervention and reducing excessive pesticide use through precise, data-informed decision-making [6], [9].

This paper offers a systematic overview of the most current research pertaining to DL-based plant disease detection, spanning the period between 2020 and 2025. Its objectives include summarizing key developments, contrasting various methodologies, and identifying avenues for prospective research [1], [2]. The document starts by presenting an overview of conventional approaches, which utilize image processing and machine learning (ML) techniques. It then transitions to discuss modern deep learning (DL) approaches, examines commonly employed datasets, and concludes by providing insights into the critical challenges and future outlook within smart agriculture [2].

The increasing use of AI in agriculture marks a major transformation in how crop health is monitored and managed. Deep learning models can extract detailed hierarchical patterns from data captured by mobile devices, drones, or ground-based sensors [10], [7]. Such precision enables real-time, location-specific interventions like automated spraying, weeding, or yield prediction that improve resource utilization and enhance productivity [10]. The integration of DL systems into smartphone applications has also empowered farmers with on-field tools for instant disease diagnosis and corrective action [6], [2]. Ultimately, this transition to AI-powered agriculture represents a significant leap toward achieving global food security through smarter, sustainable, and data-driven farming [1].

II.LITERATURE SURVEY

A. Traditional Machine Learning and Image Processing

Before the emergence of Deep Learning (DL), researchers primarily relied on traditional image processing approached for the early Determining the specific pathology affecting crops [3]. These conventional systems typically involved a structured sequence of preprocessing, feature extraction, and classification stages [4]. During preprocessing, techniques such as Gaussian smoothing, based on two-dimensional convolution, were applied to minimize image noise and improve clarity by averaging adjacent pixel values [4]. Afterward, manual feature extraction was carried out to obtain visual descriptors representing the color, texture, and shape of diseased leaf regions [3]. Some studies also explored advanced configurations like 3D CNNs applied to hyperspectral imagery, achieving accuracies above 95% under laboratory settings, demonstrating strong performance in controlled environments [9], [3]. However, these traditional methods exhibited several shortcomings, including the need for extensive manual calibration, limited adaptability to environmental fluctuations, and inconsistent performance in real-world agricultural conditions [4], [3].

B. Deep Learning Based Approaches

The ascendancy of Deep Learning (DL), specifically Convolutional Neural Networks (CNNs), has fundamentally transformed the analysis of agricultural images. This revolution occurred by automating the feature extraction process and significantly enhancing classification performance [1]. This crucial capability eliminates the need for manually crafted features and extensive preprocessing procedures [1].

1) **Core CNN Architectures:** Researchers have employed various fine-tuned CNN architectures for this application.
2) **Pre-trained Models:** Initial studies in this field utilized fine-tuning of established pre-trained architectures like VGG, ResNet, GoogLeNet, InceptionV3, and DenseNet to improve model performance and accuracy in plant disease detection tasks [5], [2]. These architectures demonstrated high performance when retrained on agricultural datasets, improving both accuracy and generalization [5], [7].
3) **Optimized Models**: For agricultural applications that require real-time performance, researchers have designed compact CNN architectures specifically optimized for devices with limited computational resources. These target devices include smartphones and drones. For instance, models introduced by Hassan and Maji in 2022 showed both efficient performance and high accuracy, proving their suitability for practical field deployment [4].
4) **Advanced Techniques:** More recent research has introduced advanced techniques to further enhance detection accuracy.
    a) **Object Detection:** Beyond classification, object detection frameworks such as YOLO

variants (e.g., YOLOv5) have been adapted for real-time detection of diseased leaves or fruits in the field, showing strong precision and recall in several studies [10], [9].

b) **Feature Enhancement:** Model strength has been augmented through the inclusion of various architectural innovations, such as residual skip connections, depthwise convolutions, and squeeze-and-excitation (SE) blocks, which improve the differentiation and extraction of crucial features. Beyond architecture, the adoption of Explainable AI (XAI) tools like Grad-CAM and saliency maps provides enhanced visual justification for predictions. This improved visualization increases confidence in these automated systems for agricultural experts and farmers alike [2], [7].

III.DATASET

The following are some of the datasets frequently mentioned in recent research:

A. **PlantVillage**: The dataset is acknowledged as a foundational, extensively utilized benchmark in research for recognizing plant diseases. It consists of 54,306 images representing 14 crop types and 26 distinct diseases, organized into 38 classes. Despite its popularity, the dataset primarily contains images captured under uniform lighting and controlled backgrounds, which limits the ability of models trained exclusively on it to perform reliably in diverse, real-world farming conditions.

B. **PlantDoc**: The PlantDoc dataset offers a more realistic and balanced collection, with 27 plant disease categories captured under both laboratory and field conditions. It bridges the gap between controlled datasets like PlantVillage and the variability of natural farm settings, providing better generalization capability for deep learning models.

C. **DiaMOS Plant**: The DiaMOS Plant dataset consists of 3,505 field images of pear fruits and leaves affected by four diseases. Unlike other datasets, it focuses exclusively on field-acquired images, making it valuable for testing models in real-world deployment scenarios.

D. **Custom Datasets**: To overcome the limitations of existing public datasets, many researchers are now curating custom datasets by capturing images directly from farms or scraping them from online agricultural databases. These datasets often include variations in lighting, disease stages, and environmental noise, offering a broader perspective for robust model training and evaluation. This trend highlights the growing focus on domain adaptation and transfer learning to build resilient models capable of performing well in diverse agricultural conditions.

Table 1. Overview of Deep Learning Methods for Detecting Plant Leaf Diseases

Author	Year	Approach	Dataset & Details
Shruti Jadon [11]	2022	Few-shot learning (Stacked Siamese + Matching Net)	Two datasets: “mini-leaves diseases” + “sugarcane diseases”; achieved 92.7% & 94.3% accuracy.
J. A. Pandian et al. [12]	2022	Deep Convolutional Neural Network (14-layer DCNN)	Created dataset “PlantDisease59”: 147,500 images (58 classes).
M. Shoaib, B. Shah et al. [13]	2023	Review – Advanced DL models	Summarized datasets (PlantVillage, PlantDoc, DiaMOS).
P. K. Das, S. S. Rupa et al. [14]	2024	Systematic Analysis & Review of DL methods	Reviewed datasets and models (2020–2024).
Jiajia Li et al. [15]	2023	Data-Efficient Learning Methods in Agriculture	Discussed dataset scarcity, weak supervision, and labeling techniques.
Affan Yasin, Rubia Fatima [16]	2023	CNN comparative experiments for tomato & corn	Created dataset: 1,963 tomato + 7,316 corn images (PlantVillage subset).
H. P. Khandagale et al. [17]	2025	ourCropNet (CNN+ Residual Block+ Attention)	Dataset of Cotton, Grape, Soybean, Corn; 99.7 % (Grape), 99.5 % (Corn).

S. Saleem et al. [18]	2023	NASNetMobile +Few-Shot Learning	Utilizing NASNetMobile-Based Feature Extraction
Manjunatha Shettigere Krishna et al. [19]	2024	Multi-Dataset Deep Learning Approach	for Multi-Crop Leaf Disease Detection.
D. T. Nguyen, T. D. Bui, T. M. Ngo, U. Q. Ngo [20]	2025	YOLO-driven Detection with αSILU Activation Function	YOLOv5 (and related YOLO versions) on tomato & cucumber disease datasets

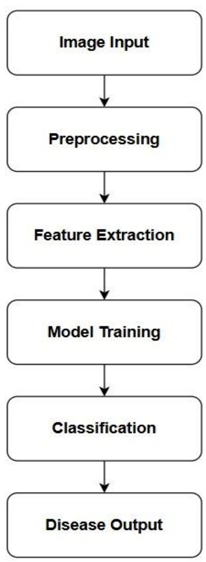

Fig 1. Proposed System Architecture (Adapted and Redrawn based on survey)

IV.CONCLUSION

This survey strongly confirms that models are the most effective and high-impact approach for recognizing automated plant diseases. By utilizing transfer learning and advanced feature automation, DL techniques consistently achieve superior accuracy and operational efficiency when compared to conventional image processing methods. The field's evolution is heavily focused on developing lightweight and optimized architectures (e.g., enhanced YOLO implementations). This critical refinement is necessary for achieving reliable, real-time deployment on edge devices like smartphones and drones. Looking ahead, future research must prioritize tackling persistent challenges related to generalization by utilizing diverse, large-scale field datasets and ensuring model transparency through Explainable AI (XAI) to foster user confidence.

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