Deep Learning with YOLO for Smart Agriculture: A Review of Plant Leaf Disease Detection

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Abstract

This paper presents a comprehensive review of the You Only Look Once (YOLO) framework, a transformative one-stage object detection algorithm renowned for its remarkable balance between speed and accuracy. Since its inception, YOLO has evolved significantly, with versions spanning from YOLOv1 to the most recent YOLOv11, each introducing pivotal innovations in feature extraction, bounding box prediction, and optimization techniques. These advancements, particularly in the backbone, neck, and head components, have positioned YOLO as a leading solution for real-time object detection across a variety of domains.

Keywords: You Only Look Once, Convolution Neural Network, Detection, Computer Vision

I. Introduction

Object detection, a fundamental aspect of computer vision, has witnessed significant progress in recent years, driven by the development of more efficient and accurate algorithms [1,2]. A major breakthrough in this field is the You Only Look Once (YOLO) framework, a pioneering one-stage object detection algorithm renowned for its real-time detection capabilities and high precision [3,4]. Unlike traditional multi-stage detection methods, YOLO performs bounding box prediction and class probability estimation in a single forward pass, ensuring both speed and efficiency [5–7].

The primary purpose of this survey is to analyze, evaluate, and synthesize current research on the use of the You Only Look Once (YOLO) object detection algorithm for plant leaf disease detection and classification. This includes a critical examination of the effectiveness, efficiency, and adaptability of various YOLO versions (YOLOv3 to YOLOv8) in agricultural settings.The survey aims to:

1. Review existing YOLO-based models used for detecting and classifying plant leaf diseases across different crops (e.g., tomato, rice, maize).

2. Compare model performance in terms of accuracy, processing speed, and real-time capability.
3. Identify commonly used datasets (such as PlantVillage and custom field datasets) and the types of diseases detected.
4. Highlight implementation challenges such as limited data, environmental noise, and computational constraints on edge devices (e.g., mobile, Raspberry Pi).
5. Recognize research gaps and propose future directions for applying YOLO in precision agriculture, including mobile deployment, hybrid models, and small object detection in real-world farm conditions.

II. YOLO model architecture for Plant Leaf Disease Detection

The YOLO (You Only Look Once) architecture is a one-stage object detection framework designed for real-time image analysis. It begins with an input image, typically a crop leaf photo, which is passed through the backbone network (like Darknet-53 or CSPDarknet) for feature extraction. This backbone captures important spatial and semantic information from the image. The extracted features are then fed into the neck component, such as PANet or FPN, which fuses multi-scale features to enhance object detection at different resolutions.

Next, the detection head interprets these aggregated features to predict bounding box coordinates and corresponding class probabilities for each grid cell. YOLO divides the input image into a grid and makes predictions for each cell, allowing it to detect multiple objects simultaneously. The final output includes class labels (e.g., disease types) and bounding box locations around affected leaf regions. Unlike multi-stage detectors, YOLO performs detection in a single forward pass, making it highly efficient. Its speed and simplicity make YOLO ideal for real-time plant disease detection in agricultural fields. Additionally, its newer versions (v4–v8) offer improved accuracy, lighter models, and better small object detection.

III. Literature Review

The agricultural sector increasingly leverages deep learning technologies to enhance crop monitoring and health management. Among these, the **You Only Look Once (YOLO)** algorithm stands out for its high-speed, real-time object detection capabilities. This section presents a comprehensive review of studies that utilize YOLO-based models for detecting plant diseases and pests, highlighting advancements, limitations, and prospects in this domain.

Liu and Wang employed an improved YOLOv3 model for detecting tomato diseases and insect pests under natural conditions. Their system achieved an impressive accuracy of **92.39%** within **20.39** ms, outperforming traditional models such as SSD, Faster R-CNN, and the original YOLOv3. However, enhancements in speed and accuracy are still required for practical agricultural deployment [8]. Morbekar et al**.** developed a YOLO-based real-time model trained on the PlantVillage dataset, achieving **98.5%** accuracy. The study focused on major Indian crops and primarily on leaf diseases, suggesting the need to expand coverage to stems, fruits, and other plant components [9]. Nihar and Raghavendra implemented a tiny_yolov3 model for rice disease detection, achieving **98.92%** accuracy. They proposed extending the model to pest detection, improving its flexibility for broader agricultural applications [10]. Agbulos et al. used YOLO for detecting rice leaf diseases, reporting an overall accuracy of **73.33%**. Despite effective identification of diseases like leaf blast and brown spot, hardware limitations (e.g., Raspberry Pi 3) and static image inputs restricted real-time implementation [11].Lippi et al. focused on pest detection in hazelnut orchards using a YOLO-based CNN model, achieving an average precision of **94.5%**. Although it performed well in real-time, scalability and depth-sensor resolution presented challenges for large-scale deployment [12]. Reddy and Deeksha developed a YOLOv4 model for detecting mulberry leaf diseases. The model demonstrated both speed and accuracy while offering post-detection pesticide recommendations, suggesting a viable direction for integrated disease management [13].Mathew and Mahesh applied YOLOv3 for early apple tree disease detection. They highlighted the model's real-time capabilities, while also identifying environmental interference and continuous monitoring as key areas for improvement **[14].**Verma et al. proposed a YOLO-based insect detection framework for soybean crops, achieving high mean average precision. Dataset size limitations and occasional misclassifications were noted, along with concerns over pesticide use ethics and environmental impact [15].Kundu et al. introduced a YOLOv5-based system for seed segregation and classification, reaching **99%** precision and recall. The model successfully handled pearl millet and maize seeds, but further investigation into mixed cropping systems and seed quality grading is recommended [16].Mathew and Mahesh extended their work to bell pepper plants using YOLOv5, achieving improved accuracy with a reduced model size. Their study suggests broader applicability to other bell pepper diseases for better yield prediction. [17] T.Nagarathinam et al. conclude that there are number of ways by which they can detect diseases in plant with the accuracy of 94 % and with each technique has some pros as well as limitation. [18].Soeb et al. employed YOLOv7 for tea leaf disease detection in Bangladesh. While the AI-based approach showed promise, limited annotated data and a lack of standard evaluation metrics indicated the need for further research [19]. Xue et al**.** proposed the YOLO-Tea model, which integrated advanced feature extraction and attention mechanisms to improve small-target detection in tea diseases. The results were promising, though additional real-world validation remains necessary.

IV. YOLO-Based Plant Leaf Disease Detection Studies- Overall Summary

The survey highlights the effective use of YOLO-based models for real-time detection and classification of plant leaf diseases across various crops like tomato, rice, and tea. YOLO variants (v3 to v7 and YOLO-Tea) demonstrate high accuracy, with some models achieving over 99%. Most studies used custom or PlantVillage datasets, though limited annotations and small object detection remain challenges. Real-time deployment was achieved in several cases, but hardware constraints (e.g., Raspberry Pi) affected performance. Future work should focus on expanding dataset diversity, improving robustness in field conditions, and integrating pest detection capabilities.

Author(s)	Year	Crop Type	Disease Type	Technique Used	Dataset	Accuracy	Real-Time?
Liu and Wang	2022	Tomato	Leaf diseases & insect pests	Improved YOLOv3	Field images	92.39%	Yes
Morbekar et al.	2022	Multiple Indian crops	Leaf diseases	YOLO	PlantVillage	98.5%	Yes
Nihar & Raghavendra	2023	Rice	Leaf diseases	Tiny-YOLOv3	Not specified	98.92%	Yes
Agbulos et al.	2021	Rice	Leaf blast, brown spot	YOLO	Static images	73.33%	No
Lippi et al.	2023	Hazelnut	Insect pests	YOLO-based CNN	Field dataset	94.5%	Yes
Reddy & Deeksha	2022	Mulberry	Leaf diseases	YOLOv4	Not specified	High	Yes
Mathew & Mahesh	2021	Apple	Leaf diseases	YOLOv3	Not specified	No	Yes
Verma et al.	2023	Soybean	Insect pests	YOLO	Not specified	High mAP	Yes
Kundu et al.	2022	Pearl millet, Maize	Seed classification	YOLOv5	Not specified	99%	Yes
Mathew & Mahesh	2023	Bell pepper	Leaf diseases	YOLOv5	Not specified	Improved	Yes
Soeb et al.	2023	Tea	Leaf diseases	YOLOv7	Limited annotations	No	Not clear

Xue et al.	2024	Tea	Leaf diseases & pests	YOLO-Tea + Attention Module	Not specified	Promising	Not clear

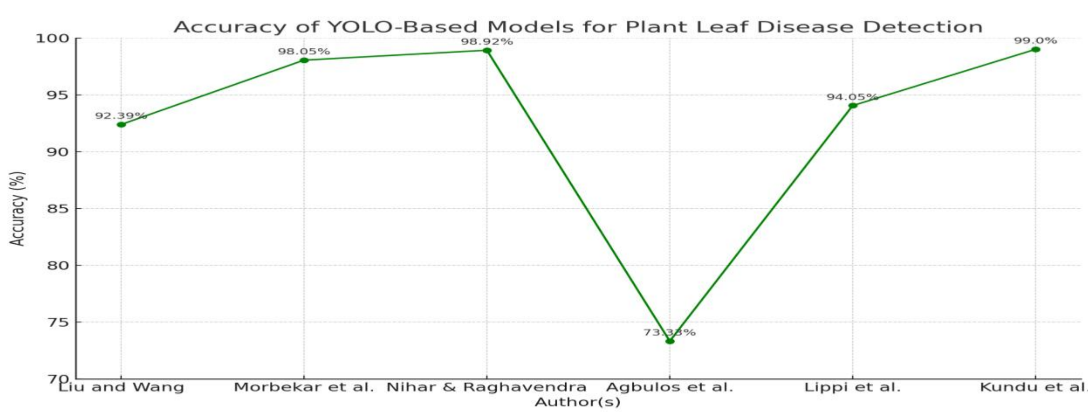
V. Best paper selection based on the accuracy

YOLO-based models have shown high accuracy in plant disease and pest detection, with results ranging from 73.33% to 99%. Models like Tiny-YOLOv3 and YOLOv5 achieved near-perfect accuracy for rice and seed classification tasks. Hardware limitations, such as using Raspberry Pi, affected performance in some cases like Agbulos et al.'s study.

S.No	Author(s)	Title / Crop Focus	Technique Used	Accuracy
1	Liu and Wang	Tomato disease and pest detection	Improved YOLOv3	92.39%
2	Morbekar et al.	Real-time detection on Indian crops	YOLO + PlantVillage	98.05%
3	Nihar & Raghavendra	Rice crop disease detection	Tiny-YOLOv3	98.92%
4	Agbulos et al.	Rice leaf disease detection (leaf blast)	YOLO + Raspberry Pi 3	73.33%
5	Lippi et al.	Pest detection in hazelnut orchards	YOLO-based CNN	94.05%
6	Kundu et al.	Seed segregation (pearl millet & maize)	YOLOv5	99.00%

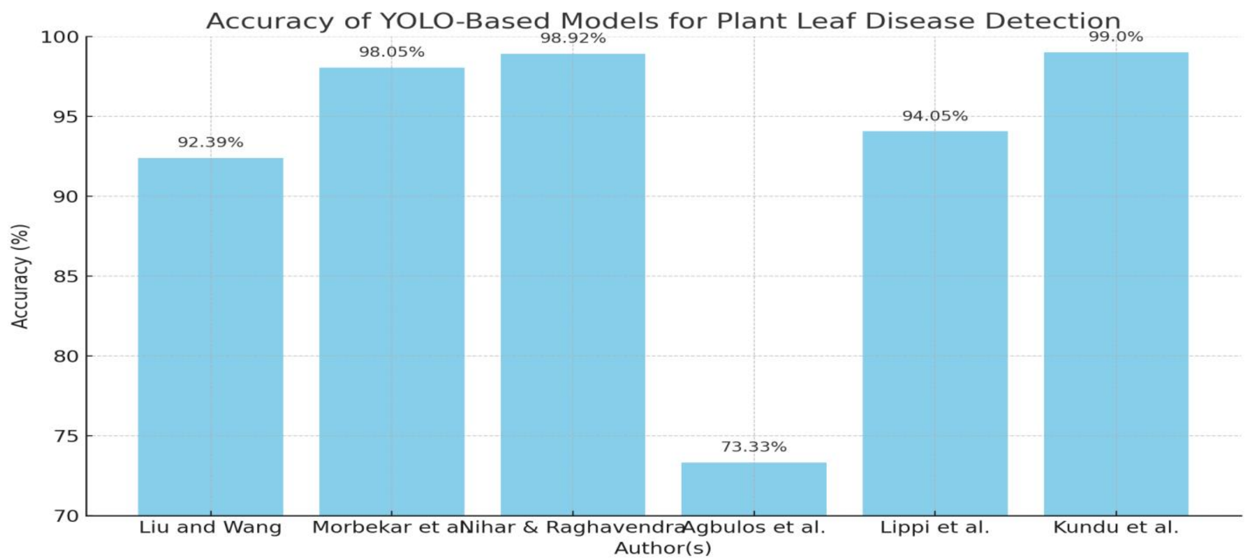
V.a. Line chart

Line chart showing the accuracy of YOLO-based models used by different authors for plant leaf disease and pest detection. Each point represents a study, highlighting how various YOLO techniques performed across different crops.



V.b. Barchart

The bar chart illustrating the accuracy of different YOLO-based models used by various authors for plant leaf disease and pest detection. Each bar represents a specific study and its reported model accuracy. Let me know if you need this exported or embedded in a document.



VI. Conclusion

This survey presents a comprehensive overview of recent advancements in using the YOLO (You Only Look Once) family of models for plant leaf disease and pest detection across diverse agricultural contexts. From improved YOLOv3 to YOLOv7 and customized architectures like YOLO-Tea, researchers have demonstrated significant accuracy gains (up to 99%) across a wide range of crops, including tomato, rice, maize, tea, apple, mulberry, and bell pepper. Studies also showed notable real-time capabilities, enabling timely disease identification crucial for early intervention and crop health management. Despite high performance, several challenges persist — such as limited annotated datasets, hardware constraints (as seen in Raspberry Pi-based deployments), and model generalization under field conditions. The studies also highlighted emerging trends, like integrating attention mechanisms, expanding detection to include pests and different plant parts, and exploring seed quality classification using YOLO.

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