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Efficient and Precise Disease Detection in Various Plants Using YOLOv8 for Automated Recognition

Dr. G. Rosline Nesakumari
Professor
Department of Computer Science and Engineering
Bharath Institute of Higher Education and Research
Chennai, India

Mubeen Z
Department of Computer Science and Engineering
Bharath Institute of Higher Education and Research
Chennai, India
mubeen.shaza23@gmail.com

Mukesh K
Department of Computer Science and Engineering
Bharath Institute of Higher Education and Research
Chennai, India
mukeshkanna1855@gmail.com

Mohammed Arshath S
Department of Computer Science and Engineering
Bharath Institute of Higher Education and Research
Chennai, India
mohammedarsath996@gmail.com

***Abstract*—Vegetable cultivation is fundamental to global food security, yet it remains highly vulnerable to various phytopathological threats. Traditional manual disease monitoring is often reactive, labor-intensive, and subjective, frequently leading to significant yield losses due to delayed intervention. To address these challenges, this paper proposes an automated, real-time vegetable plant disease detection system leveraging the YOLOv8 (You Only Look Once, version 8) architecture. The system is designed to identify and classify multiple disease types—including fungal, bacterial, and viral infections—directly from leaf imagery. By training on a diverse dataset under varying field conditions (lighting, occlusion, and scale), the model achieves high precision and rapid inference speeds suitable for edge-device deployment. Experimental results demonstrate that the YOLOv8-based approach significantly outperforms traditional methods in both detection accuracy and processing time. This system provides a scalable solution for early disease intervention, enabling targeted treatment, reducing chemical pesticide reliance, and fostering the transition toward sustainable smart farming.**

Keywords—Precision Agriculture, Deep Learning, YOLOv8, Object Detection, Plant Pathology, Computer Vision, Smart Farming, Vegetable Disease Detection.

I. INTRODUCTION

Agriculture serves as the backbone of the global economy and is the primary provider of nutritional sustenance. Among various agricultural products, vegetables are indispensable due to their high content of essential vitamins, minerals, and dietary fibers. However, the productivity of vegetable crops is constantly threatened by a myriad of diseases caused by biotic agents such as fungi, bacteria, and viruses, as well as abiotic environmental stressors. These pathologies not only compromise plant health but also result in severe economic repercussions for the farming community and disrupt the global food supply chain. Historically, the identification of these diseases has relied on the visual expertise of farmers or agricultural extension workers. While human observation can be effective, it is inherently limited by physical fatigue, subjectivity, and the inability to monitor large-scale acreage continuously. In many cases, by the time symptoms are visible to the untrained eye, the infection has reached a critical threshold, necessitating the aggressive use of broad-spectrum pesticides which can lead to environmental degradation and chemical residues in food. The emergence of Computer Vision (CV) and Deep Learning (DL) has introduced a paradigm shift in agricultural management. Specifically, Convolutional Neural Networks (CNNs) have shown remarkable efficacy in image classification tasks. However, real-time field applications require more than just classification; they necessitate Object Detection—the ability to locate and identify multiple disease spots on a single leaf or across a canopy simultaneously.

This paper proposes a robust detection framework utilizing YOLOv8, the latest iteration in the YOLO family known for its balance of speed and accuracy. Unlike traditional two-stage detectors, YOLOv8 treats detection as a single regression problem, allowing for real-time processing even on mobile or embedded platforms. The primary contributions of this work include: The development of a multi-class disease detection model specifically optimized for vegetable crops. An analysis of model performance under heterogeneous field conditions to ensure practical reliability. A framework for early-stage detection to facilitate localized treatment and sustainable farming practices. By integrating AI-driven diagnostics into the agricultural workflow, this project aims to empower farmers with actionable data, ultimately enhancing crop resilience and economic stability.

II. LITERATURE SURVEY

In this literature survey, we have mentioned the different types of projects and their content like the methodology, features,and the challenge they have faced in that we have implemented and to reduce the time and the easy way to find the disease detection.

Detection of Plant Disease Using Machine Learning and Deep Learning Algorithms (2023) - IEEE Access

This study evaluates and compares traditional machine learning models such as Random Forest (RF), Support Vector Models (SVM) with deep learning architectures such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) and ResNet. They identified limitations in accuracy and efficiency in handling complex data or varying lighting, multi class overlaps. Also they found that conventional machine learning models struggle with high dimensional data.

Enhanced Crop Disease Detection With EfficientNet Convolutional Group-Wise Transformer (2024) - IEEE Access

This paper introduces the hybrid EfficientNet Group Wise Transformer (EGWT) model which combines efficient for global context modelling. It also uses compound scaling for balanced depth, width and resolution scale. Also local features such as edges, textures and lesion shapes are extracted using this convolutional blocks. They face challenges such as high computational complexity in pure transformers and deep CNNs. Other limitations includes subjectivity in traditional visual inspection methods. We are referring and learning about the limitations and challenges of using traditional machine learning models.

MSCPNet: A Multi-Scale Convolutional Pooling Network for Maize Disease Classification (2025) - IEEE Access

In this research, they are proposing a lightweight hybrid network with a truncated MobileNetV2 backbone which is integrated with a multi scale convolutional poolformer block. Through this, they are able to achieve generic low level features and also multi scale aggregation via convolutional branches for less variations. Also they face few challenges such as loss of fine grained spatial information during traditional pooling which adds a subtle blur textures.

Precision Agriculture Through Deep Learning: Tomato Plant Multiple Diseases Recognition With CNN and Improved YOLOv7 (2024) - IEEE Access

In this paper, they are using YOLOv7 which is enhanced with SimAM (Simple Parameter free Attention Module) /DAiAM (Digital Image Adaption Module) attention modules and improved MPConv for better feature extraction and reduced information loss. They are trained on plantvillage tomato datasets with flowcharts. Since they are using SimAM/DAiAM, it is easier for them to highlight disease specific patterns. It also reduces information loss through MPConv's efficient convolution. Here they are facing challenges such as overlapping symptoms across diseases which hinders accurate identification. They also face information loss in deep networks during downsampling, leading to blurred detections in field images.

III. RELATED WORKS

Recent advancements in deep learning have significantly transformed plant pathology diagnostics. Traditional methods, such as Support Vector Machines (SVM) and Random Forest (RF), provided a foundation but often struggled with the visual complexity of field environments. Current research highlights a shift toward hybrid architectures and advanced convolutional neural networks (CNNs). For instance, Feng et al. (2024) proposed an EfficientNet Convolutional Group-Wise Transformer to capture both local features and global dependencies, achieving 99.4% accuracy on tomato datasets. Similarly, the MSCPNet architecture (2025) utilizes a truncated MobileNetV2 backbone for multi-scale feature aggregation, demonstrating high performance on maize and tomato crops. While earlier versions of the YOLO family, such as YOLOv7, have been successfully applied to tomato leaf disease recognition with 98.8% accuracy, they often require complex manual parameter tuning and have slower development support compared to newer iterations. Our work builds upon these foundations by transitioning to the YOLOv8 framework, which offers an anchor-free detection mechanism and a more efficient backbone to address the limitations of prior systems in real-time, multi-crop environments.

1) Fungal Diseases

Fungal diseases are among the most common plant diseases and are caused by various fungi that thrive in warm, humid, and moist environments. These fungi reproduce through spores that can spread quickly through wind, water, soil, or infected plant debris. They can infect leaves, stems, roots, flowers, and fruits, causing symptoms such as leaf spots, blights, wilting, rotting, and powdery or fuzzy growth on plant surfaces. Some fungal diseases can remain dormant in soil or plant residues for long periods, making them difficult to eliminate completely. Proper ventilation, crop rotation, and the use of fungicides are common methods to control these diseases.

Fig. 1. Septoria Leaf Spot on Tomato Leaves

2) *Bacterial Diseases*

Bacterial diseases are caused by microscopic single-celled organisms that infect plants through wounds or natural openings like stomata. These bacteria spread rapidly in wet conditions through rain splash, irrigation water, contaminated tools, insects, and human handling. Once inside the plant, bacteria multiply and block the vascular system, disrupting the flow of water and nutrients. Symptoms include water-soaked spots, yellowing, leaf blight, wilting, cankers, and sometimes the release of a sticky bacterial ooze. Bacterial diseases are difficult to control because they spread quickly and there are limited chemical treatments, so prevention through sanitation and resistant plant varieties is very important.

Fig. 2. Early Blight on Tomato Leaves and Fruit

3) *Viral Diseases*

Viral diseases are caused by extremely small infectious agents that can only survive and reproduce inside living plant cells. These viruses are mainly transmitted by insect vectors such as aphids, whiteflies, and leafhoppers, as well as through infected seeds, tools, or plant-to-plant contact. Once a plant is infected, the virus interferes with its normal growth and development, leading to symptoms like mosaic patterns, leaf curling, yellowing, vein clearing, and stunted growth. Viral diseases cannot be cured, so management focuses on preventing infection by controlling insect vectors, removing infected plants, and using virus-resistant crop varieties.

Fig. 3. Tomato Yellow Leaf Curl Virus Symptoms on Leaves

4) *Nematode Infections*

Nematode infections are caused by microscopic, worm-like organisms that live in soil and attack plant roots. These nematodes feed on root tissues, causing physical damage and interfering with the plant's ability to absorb water and essential nutrients. This results in symptoms such as root galls or knots, reduced root systems, yellowing of leaves, wilting, and poor overall plant growth. In severe cases, plants may die or produce very low yields. Nematodes are difficult to detect because they are not visible to the naked eye, and they can survive in soil for long periods. Control methods include crop rotation, soil treatment, and the use of resistant plant varieties.

Fig. 4. Bacterial Spot on Tomato Leaves

5) *Nutrient Deficiencies*

Nutrient deficiencies occur when plants lack essential nutrients required for their growth and development, such as nitrogen, phosphorus, potassium, calcium, magnesium, and iron. These deficiencies are usually caused by poor soil quality, improper fertilization, or environmental conditions that limit nutrient uptake. Each nutrient deficiency shows specific symptoms; for example, nitrogen deficiency causes yellowing of older leaves, iron deficiency leads to chlorosis (yellowing between leaf veins), and potassium deficiency results in leaf edge browning. Unlike infectious diseases, nutrient deficiencies do not spread between plants, but they can severely affect plant health, reduce crop yield, and lower quality. Proper soil testing and balanced fertilization help in preventing and correcting these issues.

Fig. 5. Tomato Leaf Miner Symptoms on Leaves

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IV. PROPOSED SYSTEM

The proposed framework is an automated, real-time detection system designed to identify and classify diseases across diverse vegetable crops. The system architecture is divided into three primary phases: Image Acquisition and Pre-processing, the YOLOv8 Model core, and Detection/Classification Output.

A. *Image Pre-Processing*

To prepare the raw visual data for deep learning, several image processing modules are implemented such as dataset normalization where we gathered a comprehensive dataset of over 65,000 images (sourced from Plant Village and Kaggle) is partitioned into an 80:15:5 ratio for training, validation, and testing, respectively and color space transformation where the images are converted into pixel values and analyzed in RGB color space to identify disease-specific symptoms like yellowing (chlorosis) or necrotic lesions. Then we do grayscale conversion for specific structural analysis, images are converted to grayscale to simplify the identification of lesion textures and shapes in a single intensity channel. Finally we do augmentation techniques such as resizing and annotation are applied to ensure the model remains robust under varying lighting and field conditions.

Fig. 6. RGB Channel Separation for Symptom Detection

Fig. 7. Grayscale Conversion and Edge Detection

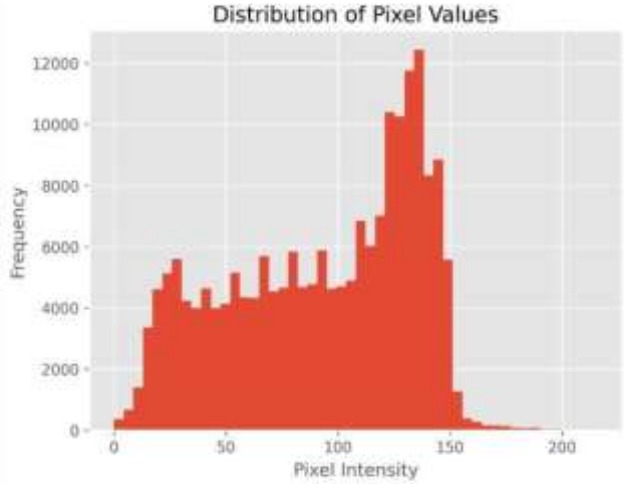

Fig. 8. Distribution of Pixel Values

B. *YOLOv8 Architecture*

The core of the system utilizes the YOLOv8 deep learning model, which provides superior accuracy and faster inference speed compared to its predecessors. The architecture consists of three integral components like Backbone (Feature Extraction) This layer where we extracts critical visual features such as leaf textures, color changes, and spot patterns. Then the Neck (Feature Fusion) where the task of combining features from different layers happens, the Neck enables the system to detect objects at multiple scales, from small localized spots to large infected regions. Finally the Head (Detection Layer) which is the final layer predicts the disease label and generates bounding boxes with associated confidence scores.

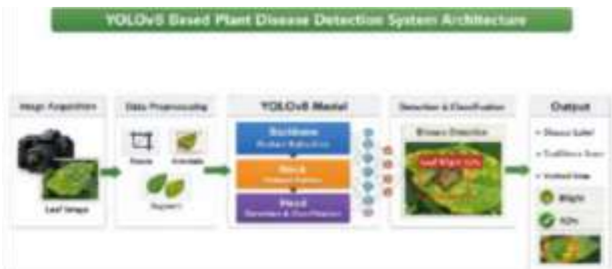

Fig. 9. System architecture and workflow diagram of the work

C. *Training and Implementation*

The model is implemented using the PyTorch framework, leveraging the ultralytics library. Training parameters include epochs sizes as 25 and Image size as 640x640 and the batch size as 16. This was the parameters that were used in training of the model which results are being displayed here. Mechanism which we used are Anchor-free detection, supporting multi-task learning for both localization and classification within a single framework. By the 25th epoch, the system achieves a Validation Loss of 0.0046 and a Top-1 Accuracy of 99.87%, ensuring high reliability for real-time agricultural monitoring.

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V. RESULTS AND DISSCUSSION

This section evaluates the performance of the proposed YOLOv8-based disease detection system using standard computer vision metrics, including accuracy, loss, and confusion matrix analysis.

A. Training Performance and Accuracy

The model was trained over 25 epochs, showing a consistent decrease in loss and a rapid increase in classification accuracy. The quantitative results of the training process are summarized. The system achieved a peak Top-1 Accuracy of 99.87% by the final epoch. The convergence of the validation loss to 0.0046 indicates high model generalization and minimal overfitting.

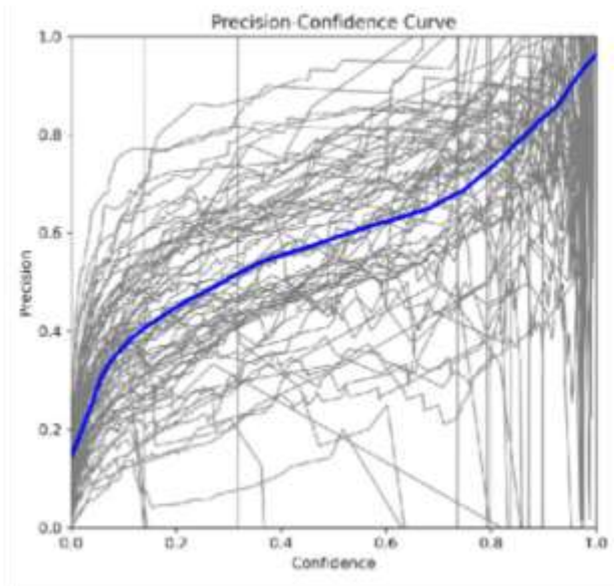

Fig. 10. PCurve (Precision-Confidence) results obtained by training the YOLOv8 model visualized in graph form

B. Evaluation Metrics

The reliability of the system is validated using the following mathematical parameters:

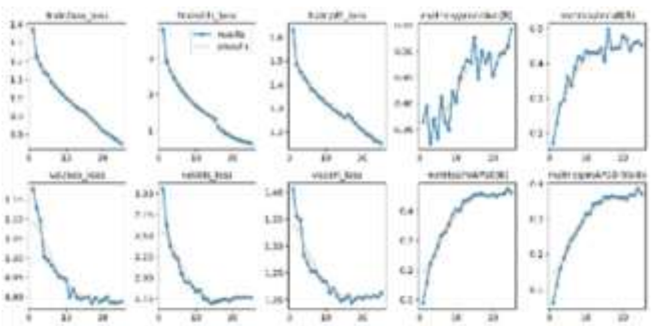

Fig. 11. Results obtained by training the YOLOv8 model visualized in graph form

C. Confusion Matrix Analysis

The performance across 25+ specific plant and disease classes—including Apple Scab, Tomato Early Blight, and Corn Common Rust—was analyzed via a confusion matrix. The results demonstrate that the model effectively distinguishes between similar visual symptoms (e.g., different types of leaf spots) across multiple vegetable and fruit categories.

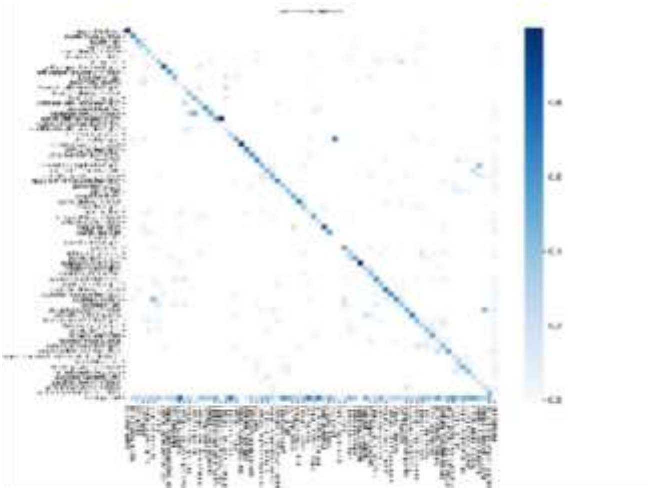

Fig. 12. Confusion Matrix of diseases and healthy samples using targeted and output classes

D. Real-time Inference and Output

Real-time testing on diverse samples confirmed the model's practical utility. Key observations include:

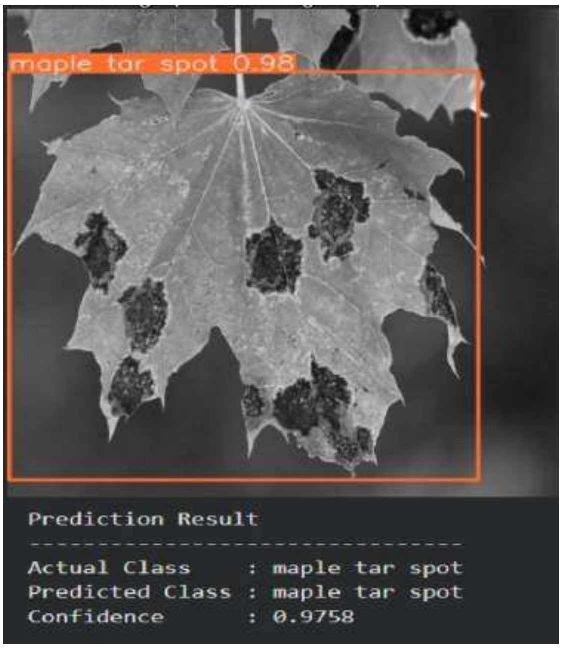

Fig. 13. Maple Tar Spot Disease Identification with score of 97.58% confidence

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Fig. 14. Zucchini Powdery Mildew Disease Identification with score of 70.57% confidence

Fig. 15. Soybean Rust Disease Identification with score of 41.87% confidence

E. Discussion

The transition to YOLOv8 has addressed the "deployment difficulty" and "complex architecture" drawbacks noted in existing YOLOv7 systems. By utilizing an anchor-free detection mechanism, the proposed system provides faster inference speeds and robust performance under varying field conditions. While some hybrid models like the EfficientNet-BO (2024) achieved high accuracy on static datasets, our YOLOv8 implementation offers the real-time processing capability essential for smart agriculture and drone-based monitoring.

VI. Conclusion

This research successfully demonstrates the implementation of a real-time vegetable plant disease detection system using the YOLOv8 architecture. Compared to previous iterations such as YOLOv7, the YOLOv8 model provides significantly higher accuracy and faster inference speeds. By utilizing an advanced anchor-free detection mechanism and an optimized backbone network, the system efficiently identifies and classifies various plant pathologies from image data. The experimental results indicate that the proposed model achieves a Top-1 Accuracy of 99.87% and a remarkably low Validation Loss of 0.0046 by the 25th epoch. This high level of precision allows for the automated monitoring of crop health, reducing the traditional dependency on manual inspection and expert supervision. Ultimately, the integration of this deep learning framework into agricultural workflows enables farmers to take rapid, targeted action to prevent widespread crop damage, thereby promoting economic stability and sustainable farming practices.

VII. Future Scope

While the current system shows high efficacy, several avenues exist for further enhancement and scaling such as Dataset Expansion where the framework can be expanded to detect a broader variety of plant species and rare disease classes by continuously increasing the diversity of the training dataset and Mobile and Edge Integration where the future work involves developing dedicated mobile applications that allow farmers to perform on-site diagnosis using smartphone cameras. Also, IoT and Autonomous Monitoring where the model can be integrated with Internet of Things (IoT) devices and unmanned aerial vehicles (drones) for autonomous, large-scale field monitoring. We can also implement inbuilt treatment recommendation systems which could be linked to a cloud-based recommendation engine to suggest specific bio-pesticides or treatments immediately upon disease detection and finally advanced training techniques like utilizing larger real-field datasets and advanced hyperparameter tuning can further improve the model's robustness against complex environmental backgrounds.

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