
Real-Time Tomato Leaf Disease Detection Using YOLOv7

Aditya Ramkrushna Mahale Puja Somnath Mahale Dr. A. S. Thorat Piyusha
Rajendra Mahajan Adarsh Pravin Patil

*Department of Computer Engineering, Amrutvahini College of Engineering, Sangamner
adityamahale53@gmail.com, pujamahale733@gmail.com, abhinav.th1990@gmail.com
piyumaha48@gmail.com aadarshpatil29604@gmail.com*

Abstract.

The devastating effects of tomato leaf diseases on crop yield and quality are so significant that it is necessary to detect early and accurately disease causes to provide good farm management. This study develops a real-time disease detection model from scratch using YOLOv7-tiny object detection. The model is trained with a dataset including 10 classes of 20,000 images from Roboflow Universe, including Bacterial Spot, Early Blight, Late Blight and Healthy leaves. The dataset has been divided in training, validation and testing set for good evaluation. As a last point, the model we propose has precision = 0.768, recall = 0.658 and mAP@0.5. Aside from detecting disease, the system estimates the severity of the disease and uses a web application to send an image along with automatic predictions. Findings showed the proposed method could be useful and relevant both for real time and applied use in agriculture, especially under conditions of scarcity of resources.

Keywords. Tomato leaf disease detection, YOLOv7-tiny, object detection, deep learning, precision agriculture, real-time detection.

1. INTRODUCTION

Tomato is a widely cultivated crop, but diseases such as Bacterial Spot, Early Blight, Late Blight, and Mosaic Virus can reduce yield and quality. Timely detection is essential for effective crop management. Conventional diagnosis relies on manual inspection and expert knowledge, limiting scalability. Computer vision and deep learning, particularly Convolutional Neural Networks (CNNs), have improved automated disease detection [1–4]. Other studies have explored feature-based methods, transfer learning, and advanced detection frameworks [5–7]. However, many approaches focus mainly on classification and provide limited disease localization [8,9]. YOLO models offer efficient real-time classification and localization [10].

Therefore, this study proposes a YOLOv7-tiny-based system for multi-disease detection and web-based prediction.

2. RELATED WORK

Machine learning and deep learning have been widely applied to plant disease detection. Mohanty et al. [4] demonstrated effective CNN-based plant disease classification on controlled datasets. Wang et al. [11] improved tomato disease detection using multi-scale feature fusion and attention mechanisms, while Pantazi et al. [6] explored image feature-based one-class classifiers. Phan et al. [7] applied YOLOv5 for real-time detection but provided limited localization. Karimanzira [2] emphasized context-aware detection for operational environments. However, lightweight models enabling real-time localization and classification on resource-constrained hardware remain limited.

Table 2.1: Comparison of Related Works with the Proposed Method

Method	Localization	Multi-Class	Real-Time	Deployment
[5]	Yes	Yes	Yes	Limited
[9]	No	Yes	No	No
[11]	Yes	Yes	Yes	Limited
[6]	No	Yes	No	No
This work	Yes	Yes	Yes	Yes

To address this limitation, this study proposes a lightweight YOLOv7-tiny model for multi-class tomato leaf disease detection, optimized for real-time deployment on resource-constrained hardware. Table 2.1 compares the proposed approach with existing methods in localization, multi-class support, real-time performance, and deployment suitability. The main contributions include: (1) disease classification and infected-region localization using bounding boxes; (2) disease severity estimation from detection outputs; and (3) integration into a Flask-based web application for real-time image upload and prediction.

3. METHOD, EXPERIMENTS AND RESULTS

3.1 Methodology

A YOLOv7-tiny object detection model was developed for tomato leaf disease detection using transfer learning with pre-trained weights to improve convergence and reduce training time. Data augmentation, including HSV adjustments, horizontal flipping, mosaic, and mixup, improved robustness to variations in lighting, occlusion, and leaf orientation. The model predicts disease classes with bounding boxes and class probabilities. Localization performance is evaluated using Intersection over Union (IoU), a standard object detection metric [10]. The complete system architecture is presented in Figure 4.1.

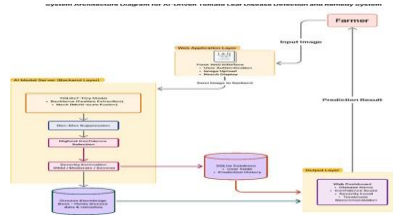


Figure 4.1. Complete system design for the YOLOv7-based tomato leaf disease detection system

The dataset contains approximately 20,000 annotated tomato leaf images across 10 disease classes in YOLO format. YOLOv7-tiny was trained for 25 epochs on an NVIDIA RTX 2050 GPU (4 GB VRAM) using batch size 2. SGD optimization used a learning rate of 0.001, momentum of 0.937, and weight decay of 0.0005. Performance was evaluated using precision, recall, mAP@0.5, and mAP@0.5:0.95.

3.2 Results

The YOLOv7-tiny model achieved a precision of 0.768, recall of 0.658, mAP@0.5 of 0.735, and mAP@0.5:0.95 of 0.465. Septoria and Late Blight showed higher AP values of 0.884 and 0.880, respectively, due to their distinct visual patterns. Leaf Miner achieved a lower AP of 0.456 because of its fine textures and smaller lesions. The confusion matrix and precision-recall curve are presented in Figures 4.2. Overall, the model provides reasonable multi-disease detection performance and inference efficiency on resource-limited hardware, although the 416×416 input resolution limits sensitivity to fine-grained features.

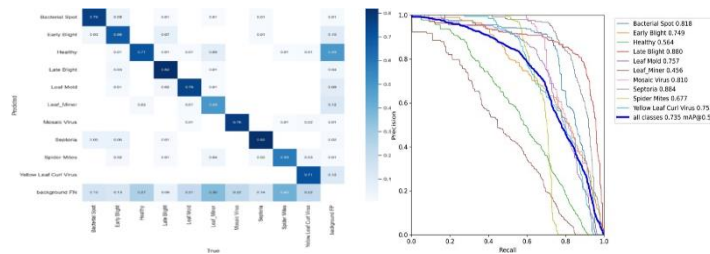


Figure 4.2. Confusion matrix and Precision-Recall curves.

4. CONCLUSIONS

The study addresses tomato leaf disease diagnosis, where manual inspection is time-consuming and dependent on expert knowledge. A transfer-learning-based YOLOv7-tiny model was developed for simultaneous disease classification and localization across ten disease classes. The model achieved 0.768 precision, 0.658 recall, and 0.735 mAP@0.5, with better performance for visually distinct diseases. Lower accuracy was observed for fine-textured diseases such as Leaf Miner. The 416×416 input resolution limits detection of small lesions and subtle patterns. Future work should explore higher-resolution inputs, advanced augmentation, improved architectures such as YOLOv8 or transformer-based models, field validation, and mobile deployment.

5. REFERENCES

- [1] K. P. Ferentinos. Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, 145:311–318, 2018.
- [2] D. Karimanzira. Context-aware tomato leaf disease detection using deep learning in an operational model. *Electronics*, 14(4):661, 2025.
- [3] J. Liu and X. Wang. Tomato diseases and pests detection based on improved yolov3 convolutional neural network. *Frontiers in Plant Science*, 11:898, 2020.
- [4] S. P. Mohanty, D. P. Hughes, and M. Salathe. Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*, 7:1419, 2016.
- [5] M. Umar. Precision agriculture through deep learning: Tomato plant multiple diseases recognition with cnn and improved yolov7. *IEEE Access*, 12:49167–49180, 2024.
- [6] M. C. Pantazi, D. Moshou, and A. A. Tamouridou. Automated leaf disease detection in different crop species through image features analysis and one-class classifiers. *Computers and Electronics in Agriculture*, 156:96–104, 2019.
- [7] Q.-H. Phan, T. N. Nguyen, and H. V. Le. Classification of tomato fruit using YOLOv5 and convolutional neural network models. *Plants*, 12(4):790, 2023.
- [8] P. Singh, R. Kaur, and H. Sharma. Explainable ai in agriculture: A model for interpretable plant disease detection using grad-cam. *IEEE Access*, 10:125980–125992, 2022.
- [9] L. Tan, J. Lu, and H. Jiang. Tomato leaf diseases classification based on leaf images: A comparison between classical machine learning and deep learning methods. *AgriEngineering*, 3(3):463–476, 2021.
- [10] C.-Y. Wang, A. Bochkovskiy, and H.-Y. M. Liao. Yolov7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors. *arXiv preprint arXiv:2207.02696*, 2022.
- [11] Y. Wang, P. Zhang, and S. Tian. Tomato leaf disease detection based on attention mechanism and multi-scale feature fusion. *Frontiers in Plant Science*, 15, 2024.

Biographies



Aditya Ramkrushna Mahale received the bachelor's degree in Computer Engineering from Amrutvahini College of Engineering, Sangamner, Maharashtra, India. His research areas include artificial intelligence, deep learning, computer vision, and real-time object detection, with a particular focus on developing intelligent solutions for agricultural applications.



Puja Somnath Mahale received the bachelor's degree in Computer Engineering

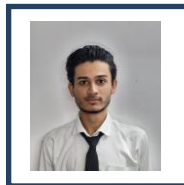
from Amrutvahini College of Engineering, Sangamner, Maharashtra, India. Her research interests include deep learning, computer vision, generative artificial intelligence, and real-time plant disease detection, with a particular focus on developing intelligent solutions for agricultural applications.



Dr. Abhinav Sudhir Thorat is an Assistant Professor in the Department of Computer Engineering at Amrutvahini College of Engineering, Sangamner, Maharashtra, India. He has over 12 years of teaching experience. His academic and research interests include Data Science, Big Data Analytics, Artificial Intelligence, Machine Learning, Generative AI, Data Mining, and Data Warehousing.



Piyusha Rajendra Mahajan received the bachelor's degree in Computer Engineering from Amrutvahini College of Engineering, Sangamner, Maharashtra, India. Her research interests include deep learning, computer vision, and plant disease detection.



Aadarsh Pravin Patil received the bachelor's degree in Computer Engineering from Amrutvahini College of Engineering, Sangamner, Maharashtra, India. His research interests include deep learning, computer vision, and real-time plant disease detection.