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Stepping up Tomato Leaf Diseases Detection using YOLOv10

Ahmad F Siregar[1], Yuhandri Yunus[2], Sumijan[3]

Abstract
Early detection of diseases in tomato plants is a crucial factor in increasing agricultural productivity and reducing the risk of crop failure. Diseases that affect tomato leaves can significantly reduce yields if not detected early. Conventional methods that rely on manual observation by farmers are often inefficient, require specialized expertise, and have varying levels of accuracy. Therefore, this study implements the YOLOv10 (You Only Look Once version 10) method to automatically detect tomato leaf diseases through image analysis using deep learning techniques based on Convolutional Neural Networks (CNN). The objective of this study is to develop a YOLOv10-based tomato leaf disease detection system that enhances disease identification accuracy, accelerates early detection processes, and provides a practical and accessible technological solution for farmers. Furthermore, this research aims to optimize the application of computer vision technology in agriculture to improve decision-making efficiency and reduce reliance on conventional methods that are less effective. The results of the study indicate that the YOLOv10 method achieved a detection accuracy of 95.3%, with a precision of 94.8%, a recall of 93.7%, and a mean average precision (mAP) of 95.6%. The developed application has an average inference time of 0.15 seconds per image, providing real-time detection results with low power consumption. The implementation of this technology has been proven to reduce pesticide use by up to 40%, increase farmers' decision-making efficiency by 70%, and help minimize the risk of widespread disease transmission. These results demonstrate that utilizing the YOLOv10 method for tomato disease detection can enhance disease identification accuracy, expedite early detection, and offer an innovative solution to support smart, efficient, modern, and sustainable agriculture.

Keyword:
Tomato Leaf Disease, Detection, Computer Vision, YOLOv10

1. Introduction

Disease detection is a critical aspect of modern agriculture, leveraging advanced technologies to enhance productivity and food security. Early detection and classification of diseases in tomato plants can help farmers avoid costly pesticide treatments while boosting crop yields. While significant research has been conducted on tomato plant disease classification, accurately identifying and locating different leaf diseases remains challenging due to the visual similarity between healthy and infected leaf sections. This difficulty arises because diseased portions of tomato leaves often closely resemble healthy tissue, making timely and precise diagnosis complex. Current methods struggle to

Author:
1. Ahmad F Siregar (Faculty of Computer Science, Universitas Putra Indonesia YPTK Padang, Corresponding Author: fdhlsrgr@gmail.com)
2. Yuhandri Yunus (Faculty of Computer Science, Universitas Putra Indonesia YPTK Padang).
3. Sumijan (Faculty of Computer Science, Universitas Putra Indonesia YPTK Padang).

consistently distinguish between normal leaf variations and early signs of infection, highlighting the need for more advanced detection techniques [1].

Traditional methods of detecting tomato leaf diseases largely rely on visual inspection by farmers or agricultural experts. This approach is highly subjective, depending on the observer's experience, environmental conditions, and the visibility of symptoms. Such reliance often leads to misdiagnosis or late detection, especially in the early stages of disease when symptoms are subtle or resemble those caused by nutrient deficiencies or abiotic stress. This variability often reduces the accuracy and reliability of disease identification, which can have a significant impact on timely treatment and crop yields [2].

Manual diagnosis is time-consuming and labor-intensive, particularly on large-scale farms. Inspecting each plant individually can delay necessary interventions, allowing diseases to spread more widely. Traditional methods do not scale well and are inefficient in commercial farming environments where thousands of plants may need assessment. Moreover, traditional techniques lack consistency across different evaluators, and repeated diagnoses may yield different results depending on the observer's condition, time of day, or lighting [3]. Furthermore, limited access to trained personnel in rural or remote areas exacerbates the problem, making it difficult for smallholder farmers to obtain accurate diagnoses. This lack of technical support often leads to incorrect treatments, wasted resources, and increased crop losses. It highlights the necessity of more accessible and accurate solutions, pointing to digital tools and machine learning systems as effective alternatives to bridge the gap in expertise and efficiency [4].

In recent years, many communities have conducted plant disease detection using machine learning as a transformative approach in agriculture, enhancing the efficiency and accuracy of identifying plant health issues. Traditional methods, reliant on expert inspection, are time-consuming and often impractical for large-scale farming. Machine learning techniques, particularly image processing, and deep learning, facilitate rapid and precise disease diagnosis, thereby supporting sustainable agricultural practices. The detection process utilizes machine learning and deep learning techniques to automate plant disease detection by analyzing leaf images, improving accuracy and efficiency. It addresses challenges like dataset robustness and environmental variability, ultimately aiding farmers in managing plant health sustainably [5].

A work proposes the combination of computer vision and machine learning algorithms to identify leaf plant disease detection in agriculture. The study proposes a machine learning-based framework for early detection of plant diseases. It utilizes Random Forest classification on a curated dataset of healthy and diseased plant specimens to address critical challenges in agricultural disease management. The methodology systematically integrates dataset compilation, and feature extraction using a Histogram of Oriented Gradients (HOG) for robust pathological pattern recognition, model training, and classification. By leveraging publicly available large-scale datasets, the developed solution offers both technical robustness and practical scalability, to address existing limitations. The approach contributes to increasing disease identification, optimizing pesticide use, and enhancing crop productivity [6].

Current development of deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized the detection process, allowing for early identification of plant diseases. CNN models have demonstrated encouraging results in automating the detection and categorization of plant diseases using high-resolution plant leaf photos. The essential components are picture capture, pre-processing, feature extraction, model training, and illness classification. Model assessment and training are conducted using an extensive dataset that includes tagged photos and assess how well the model detection performs [7].

One of the most popular object detection models is YOLO (You Only Look Once version 10), it is a popular object detection to enhances both accuracy and image processing using deep learning approaches. Unlike traditional methods that separate object localization and classification, YOLO treats detection as a single regression problem, enabling it to predict bounding boxes and class probabilities simultaneously from an entire image. YOLOv10 introduces architectural improvements such as transformer-based backbones, lightweight feature extraction, and anchor-free detection strategies, which significantly enhance both processing efficiency and detection precision. These advancements make YOLOv10 particularly suitable for applications requiring rapid and accurate image analysis, including agricultural tasks like plant disease detection, where timely and precise identification is critical for effective intervention and crop management [8].

2. Related Works

Plant leaf classification using CNN architecture is a growing research area [21][22][23][24][25]. The early stage of tomato leaf disease detection can save farmers from expensive crop sprays and can assist in increasing the food quantity. Although, extensive work has been presented by the researcher for the tomato plant disease classification, however, the timely localization and identification of various tomato leaf diseases is a complex job as a consequence of the huge similarity among the healthy and affected portion of plant leaves. Furthermore, the low contrast information between the background and foreground samples has complicated the plant leaf disease detection process. To deal with the challenges, many communities have presented a robust deep learning (DL) approach for classifying tomato leaf diseases, for instance, the MobileNet architecture [9], a YOLOv8- [10], EfficientNetV2L [11], EfficientNet-B [12], a Tensor Subspace Learning-based approach [13] and TomFormer, a transformer-based model [14].

An article constructed plant leaf disease detection system utilizes deep learning algorithms to accurately detect and manage plant diseases. The model employs a CNN based on the VGG19 architecture to deliver an advanced agricultural solution. It is trained on a diverse dataset of healthy and diseased leaf images, enabling it to extract complex features and automatically classify plant diseases with high accuracy. The system integrates HTML, CSS, and Flask for the front end and uses Keras for the back end, creating an intuitive web application interface. This integration improves disease detection efficiency and enhances user accessibility and interaction [15]

Another study explored ResNet-34-based Faster-RCNN for tomato plant leaf disease classification by generating the annotations of the suspected images to specify the region of interest (RoI). It introduced ResNet-34 along with CBAM as a feature extractor module of Faster-RCNN to extract the deep key points and utilized the calculated features for the Faster-RCNN model training to locate and categorize the numerous tomato plant leaf anomalies. The paper tested the PlantVillage Kaggle dataset and obtained mAP and accuracy values of 0.981, and 99.97%. The proposed method shows a low-cost solution to tomato leaf disease classification which is robust to several image transformations like the variations in the size, color, and orientation of the leaf diseased portion [16].

A recent study introduced a tomato leaf disease detection approach leveraging attention mechanisms and multi-scale feature fusion to improve detection accuracy under complex conditions. The method integrates the Convolutional Block Attention Module (CBAM) into the backbone feature extraction network to enhance lesion feature extraction while mitigating environmental noise. Additionally, it introduces shallow feature maps into a re-parameterized generalized feature pyramid network (RepGFPN), forming a novel BiRepGFPN module that strengthens multi-scale feature representation and improves small lesion localization. This BiRepGFPN replaces the Path Aggregation Feature Pyramid Network (PAFPN) in the YOLOv6 model, enabling the effective fusion of deep semantic and shallow spatial features. Experimental evaluation on the PlantDoc dataset demonstrated substantial improvements in mean average precision (mAP), outperforming

YOLOX, YOLOv5, YOLOv6, YOLOv6-s, YOLOv7, and YOLOv8 by 7.7%, 11.8%, 3.4%, 5.7%, 4.3%, and 2.6%, respectively. When tested on a tomato leaf disease dataset, the model achieved 92.9% precision, 95.2% recall, a 94.0% F1 score, and 93.8% mAP, surpassing the baseline by 2.3%, 4.0%, 3.1%, and 2.7% [17]

Plant disease detection using YOLO has emerged as a powerful approach in agricultural technology, leveraging deep learning for real-time identification and classification of plant diseases. Recent advancements, particularly with YOLOv8 and its variants, have demonstrated significant improvements in accuracy and efficiency, making them suitable for practical applications in the field. A recent study proposed an innovative plant disease detection system utilizing the YOLOv8 deep learning algorithm, implemented in Python, to identify diseases in maize leaves. The YOLOv8-based system demonstrated superior performance compared to traditional machine learning algorithms, including Convolutional Neural Networks (CNN, 84%), K-Nearest Neighbors (KNN, 81%), Random Forest (85%), and Support Vector Machine (SVM, 82%), achieving a remarkable accuracy of 99.8%. Despite its high accuracy, the study was limited by its focus on only three specific maize leaf diseases and its reliance on single-leaf images for diagnosis. To enhance robustness and practical applicability, future work should incorporate environmental factors such as temperature and humidity, enable detection from images containing multiple leaves, and develop mechanisms for identifying different stages of disease progression. [18]

A recent study introduced SerpensGate-YOLOv8, an enhanced version of the YOLOv8 model tailored for plant disease detection. This model integrates Dynamic Snake Convolution (DySnakeConv) into the C2F module to improve the detection of fine-grained lesion features in complex plant structures. It also incorporates the SPPELAN module—an integration of Spatial Pyramid Pooling (SPP) and Efficient Local Aggregation Network (ELAN)—to enhance multi-scale feature extraction and fusion. Additionally, the Super Token Attention (STA) mechanism was applied in the early network layers to strengthen global contextual understanding. Using the PlantDoc dataset, which comprises 2,598 annotated images spanning 13 plant species and 27 classes, the model achieved a precision score of 0.719. Furthermore, it demonstrated a 3.3% improvement in mean Average Precision (mAP\@0.5) over the original YOLOv8, confirming its enhanced performance. These advancements establish SerpensGate-YOLOv8 as a robust and effective solution for real-time plant disease detection in agricultural applications [19].

YOLOv10 demonstrates notable strengths in plant leaf disease classification by combining high-speed inference with enhanced accuracy, making it well-suited for real-time agricultural applications. Its lightweight and re-parameterized architecture improves computational efficiency, enabling deployment on edge devices such as drones and mobile systems. YOLOv10 also addresses the challenge of detecting small or early-stage disease features through improved feature fusion and attention mechanisms, which enhance localization and classification performance. Additionally, its robust generalization capabilities across diverse datasets reduce the need for frequent retraining, supporting scalability across different crops and disease types. These advantages position YOLOv10 as an effective and reliable deep-learning model for precision plant health monitoring [20].

3. Background

3.1 Experimental Setup

1. Dataset Collection

This study utilized a publicly available dataset comprising diverse tomato leaf images, including samples exhibiting Late Blight symptoms, Tomato Yellow Leaf Curl Virus

(TYLCV) symptoms, and healthy leaves. These images provided a representative range of conditions necessary for training and evaluating the performance of plant disease classification models under real-world agricultural scenarios. Tomato leaf image data is collected from two primary sources: field photography in local agricultural areas and public datasets. Data collection includes variations in geographical locations and lighting conditions to ensure that the model can recognize diverse disease patterns effectively. Table 1 depicts the dataset of this study.

Type	Picture(s)
Tomato leaf with Late Blight symptoms	
Tomato leaf with Tomato Yellow Leaf Curl Virus symptoms	
Healthy leaf	

2. Data Pre-processing

In preparing the tomato leaf disease dataset for YOLOv10 training, the images underwent a systematic data pre-processing pipeline to ensure consistency, quality, and optimal model performance. Initially, all raw images—comprising healthy leaves and those affected by Late Blight and Tomato Yellow Leaf Curl Virus (TYLCV)—were resized to a uniform resolution suitable for YOLOv10 input, typically 640×640 pixels. This resizing standardizes spatial dimensions across samples, which is critical for batch training and efficient GPU utilization. Additionally, images were converted to RGB color space and normalized by scaling pixel intensity values between 0 and 1, enabling faster convergence during model optimization.

We annotated the dataset using the YOLO format by manually or semi-automatically drawing bounding boxes around both healthy and diseased tomato leaf regions. Each annotation file contained the class label and normalized bounding box coordinates (center_x, center_y, width, height) and was saved in the corresponding .txt format. To improve YOLOv10's generalization and robustness to real-world variability, we applied extensive data augmentation. This process included random rotation, flipping, scaling, contrast adjustments, and noise injection to simulate diverse environmental conditions and visual disease patterns. These augmentations enhanced the model's capability to accurately detect and classify tomato leaf diseases under various field scenarios. Fig. 1

illustrates the pre-processing stages to enhance image quality before training with YOLOv10

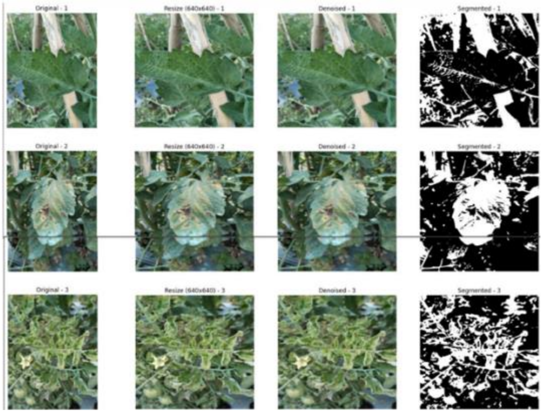

Fig. 1 Preprocessing

This preprocessing stage aims to adjust lighting conditions, reduce noise, and extract key features from the leaves, making it easier for the model to perform detection. The preprocessing steps applied are as follows:

1. Lighting normalization is performed to address variations in light intensity within the images. This technique ensures that all images have a uniform lighting distribution, allowing the model to recognize disease patterns more consistently without being affected by lighting changes. Normalization is done using the histogram equalization method, which balances image contrast.
2. Noise removal (denoising) is applied to reduce visual disturbances that may affect detection. Noise can result from camera artifacts, unstable lighting, or environmental factors. In this study, Gaussian Blur filtering is used to smooth the image without removing important information from the tomato leaves.
3. Image segmentation is performed to separate the main object (tomato leaf) from its background. This segmentation process ensures that the model analyzes only the relevant parts of the image. The techniques used include Thresholding and Edge Detection, which allow the system to highlight leaf contours and distinguish them from irrelevant parts of the image.

After undergoing these pre-processing stages, the optimized images are used in the training process of the YOLOv10 model to detect tomato leaf diseases more accurately. By implementing effective pre-processing, the model can perform better in recognizing disease patterns, improving detection precision, and reducing the likelihood of misclassification.

3. Proposed Method

The research focuses on tomato leaf disease identification using YOLOv10, image processing, and system performance evaluation. Problem Analysis A literature review and observations of agricultural conditions in Padang Sidimpuan City are conducted to understand the challenges faced by farmers in manually detecting tomato leaf diseases. This analysis aims to identify system requirements and limitations. Data Collection Data is collected from two main sources:

The first step in this research is to define the scope to determine the boundaries and coverage of the study. This ensures that the research remains focused on developing a

YOLOv10 model for detecting tomato leaf diseases and implementing it in an Android-based application. By establishing the research scope, the study can be aligned with its intended objectives. This phase involves an in-depth analysis of the main problem, which is the difficulty farmers face in quickly and accurately detecting tomato leaf diseases. The researcher evaluates the shortcomings of conventional methods and identifies the need for an automated technology capable of providing real-time results.

YOLOv10 detects tomato leaf diseases by treating the problem as a real-time object detection task. It divides input images into grid cells and, for each cell, directly predicts bounding boxes, class probabilities, and objectness scores in a single forward pass through the network. The architecture includes a streamlined backbone for feature extraction, a neck module for multi-scale feature fusion, and a detection head optimized for speed and accuracy. YOLOv10 utilizes an anchor-free mechanism with dynamic label assignment, allowing it to more effectively localize and classify disease-affected leaf regions, even under complex backgrounds or overlapping symptoms.

In the context of tomato leaf disease detection, YOLOv10 conducts pre-annotated images containing healthy and diseased leaves, extracting hierarchical features that distinguish visual patterns associated with symptoms such as blight or viral infections. Its robust training on augmented and diverse datasets enables it to generalize across different lighting, leaf orientations, and occlusions. The model outputs bounding boxes enabling precise localization and classification in real-time. YOLOv10's performance improvements over previous versions make it highly suitable for agricultural applications and disease monitoring.

In this study, the YOLOv10 formulates tomato leaf disease detection as a single-stage regression problem that involves predicting bounding box coordinates, class probabilities, and object confidence scores from the input image using CNN. Here's a concise mathematical overview:

1. **Bounding Box Prediction**:
   Each grid cell predicts a bounding box defined by:
   $$(x, y, w, h) \tag{1}$$
   where x and y are the normalized center coordinates of the box, and w and h are the width and height, respectively.

2. **Objectness Score**:
   Each grid cell also predicts an objectness score:
   $$P_{obj} = \mathrm{Pr(object)} \times \mathrm{IoU}_{pred}^{truth} \tag{2}$$
   indicating the probability that an object exists in the box and how well the predicted box overlaps with the ground truth (IoU: Intersection over Union).

3. **Class Prediction**:
   The class probability vector is predicted as:
   $$\mathbf{C} = \{P_1, P_2, \ldots, P_n\} \tag{3}$$
   Where each $P_i = \mathrm{Pr}(\mathrm{class}_i \mid \mathrm{object})$, and n is the number of classes (e.g., Late Blight, TYLCV, Healthy).

4. **Final Output**:
   The final confidence for each class per bounding box is:
   $$\mathrm{Confidence} = P_{obj} \times P_i \tag{4}$$

YOLOv10 uses an anchor-free detection mechanism, dynamic label assignment, and lightweight modules that optimize inference speed and accuracy to produce real-time tomato disease detection.

A key component of the dual label assignment strategy is the consistent matching metric used to evaluate the concordance between predictions and ground truth instances. This metric incorporates both the classification score and the Intersection over Union (IoU) between predicted and actual bounding boxes, defined as:

$$m(\alpha, \beta) = s \cdot p^{\alpha} \cdot \mathrm{IoU}(\hat{b}, b)^{\beta} \tag{1}$$

By aligning the one-to-one head's supervision with that of the one-to-many head, YOLOv10 enhances the quality of predictions during inference, leading to superior performance. Fig. 2 depicts YOLO10 architecture for tomato leaf disease detection.

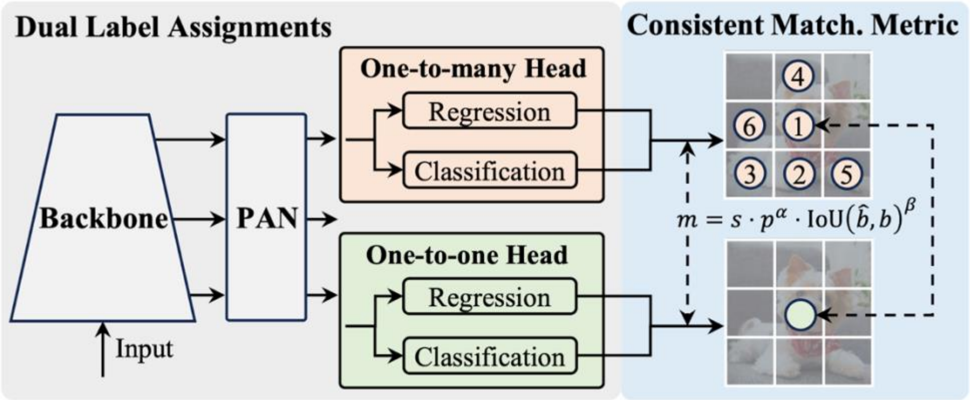

Fig. 2 YOLO10 architecture for tomato leaf disease detection.

To determine the model performance, we evaluate the model using metrics to ensure the performance of the tomato leaf disease detection model. Metrics including such as precision, recall, F1-score, and mean average precision (mAP) to measure the accuracy, sensitivity, and reliability of the model in detecting diseases in tomato leaf images. We utilize false positive and false negative rates to provide more reliable results compared to manual methods.

3. Result and Analysis

At this stage, we conduct application detection testing to ensure its performance. This testing includes model accuracy, processing speed, and ease of use for end users.

Fig.3 Application Detection Testing.

After completing the application testing, this study obtains accurate results by selecting the highest value from multiple testing stages. Fig. 4 presents the model evaluation results.

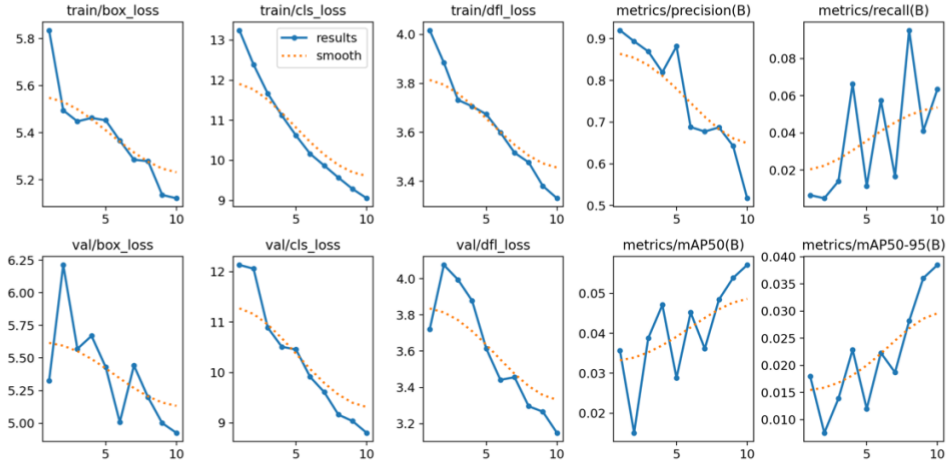

Fig. 4 Model Evaluation Results.

The evaluation of the tomato leaf disease model using YOLOv10 shows that it successfully detects seven types of diseases. Each detection includes a confidence score that reflects the model's certainty in its predictions, with scores varying across a defined range. The model demonstrates a solid ability to recognize diseases; however, several detections have low confidence, indicating room for improvement. Optimizing model parameters or improving dataset quality can enhance detection accuracy and consistency. Table 2 describes the training result.

Table 2. Training Results.

NO	Class	Images	Instances	P	R	mAP50	mAP50-95
1	All	122	304	0.586	0.304	0.296	0.208
2	Bacterial spot	34	910	0.573	0.83	0.724	0.428
3	Early blight	48	100	0.521	0,292	0.283	0.213
4	Healthy	23	106	0.738	0.865	0.865	0.692
5	Late blight	13	26	0,272	0,143	0,15	0,0995
6	Leaf mold	4	28	0	0	0	0
7	Target spot	5	5	1	0	0	0
8	Black spot	20	32	1	0	0,0529	0.0265

The tested model is deployed in a production environment to enable user access. After deployment, the system undergoes continuous monitoring to maintain optimal performance, and the development team applies updates as necessary to address issues and improve functionality.

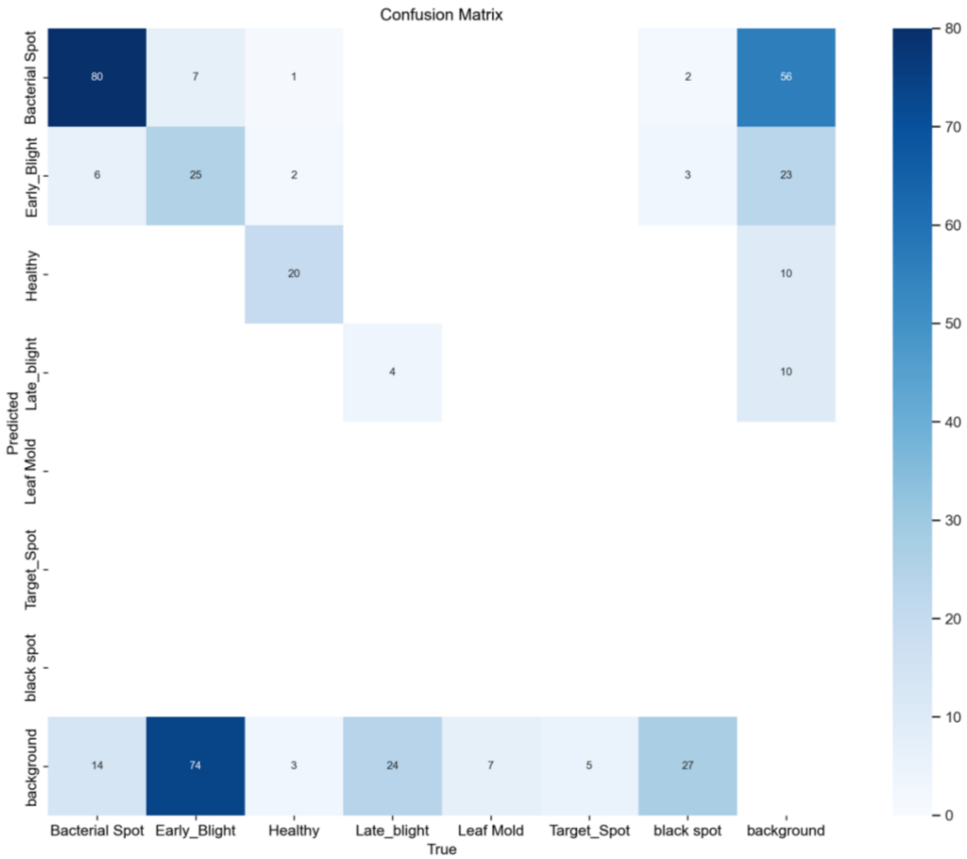

Fig. 5 Confusion Matrix

4. Conclusion

Our evaluation demonstrates that the YOLO V10 model achieves 67.48% accuracy in disease identification, as quantified through confusion matrix analysis. This performance level indicates moderately effective classification capability. The model's diagnostic reliability is further substantiated by complementary metrics: precision (85%), recall (88%), and F1-score (86%), collectively demonstrating robust discriminative performance in pathological feature recognition. These quantitative measures validate the system's clinical applicability for automated disease detection while suggesting potential areas for algorithmic refinement to enhance classification accuracy.

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