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Enhanced Plant Disease Detection Using Computer Vision YOLOv11: Pre-Trained Neural Network Model Application

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ABSTRACT

This study investigates the application of YOLOv11, a cutting-edge deep learning model, to enhance the detection of plant diseases. Leveraging a comprehensive dataset of 737 images depicting tomato leaves affected by various diseases, YOLOv11 was trained and evaluated on key performance metrics such as precision, recall, and mAP. Experimental results the model was trained and evaluated on key metrics including accuracy (75.6%), precision (0.80), recall (0.77), and mAP@0.5 (75.6%). Experimental through base architectural such as enhanced feature extraction with C2 modules, improved multi-scale detection using SPPF layers, and optimized non-maximum suppression techniques. These improvements enable the model to achieve stable precision and recall for each class, even in challenging scenarios with overlapping objects and diverse environmental conditions. By addressing practical usability challenges, this system offers a scalable, accessible, and impactful solution for precision agriculture, paving the way for sustainable with this pretrained model. This study underscores the potential of deep learning-based models, particularly YOLOv11, in transforming the way monitoring and disease management are approached, demonstrating its ability to stable accuracy and operational efficiency in real-world applications. Furthermore, the practical usability of the YOLOv11-based system addresses challenges in the domain of precision plant detection desease. By providing a scalable, accessible, and highly efficient solution, the model offering a significant advancement toward sustainable agricultural practices.

Keywords: Deep learning, plant disease detection, YOLOv11, precision, performance

INTRODUCTION

Plant diseases are a critical challenge to affect crop yield and food security. Traditional methods of disease identification are labour-intensive, time-consuming, and often inaccurate (Jeger et al., 2021). These limitations are particularly evident in identifying tomato leaf diseases, where visual symptoms such as spots, blight, and mildew overlap and are challenging to differentiate. Advances in artificial intelligence (AI) and deep learning have introduced innovative solutions for automating this process. YOLO (You Only Look Once) models are particularly suitable for real-time object detection due to their speed and accuracy (Diwan et al., 2023). Recent adaptations of YOLO models, such as YOLOv8 and YOLOv11, have shown promise in detecting specific crop diseases, including those affecting tomato leaves, by effectively isolating fine-grained patterns in complex datasets (Aldakheel et al., 2024). However, existing models often face limitations in detecting diseases with subtle visual features, especially in datasets with high inter-class similarity and challenging environmental conditions (Fahim-Ul-Islam et al., 2024).

Tomato is one of the most widely cultivated crops worldwide, contributing significantly to both local

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economies and global food supply. However, tomato production is frequently threatened by various plant diseases, which can severely reduce crop yield and quality. Among these, leaf diseases, including bacterial spot, blight, and mold, are particularly problematic, causing significant losses in both greenhouse and field environments. These diseases are often difficult to identify at early stages, leading to delayed interventions and ineffective control measures. As a result, early and accurate disease detection is crucial to minimizing crop loss and ensuring sustainable agricultural practices.(Cahaya Putra et al., 2025), solution for that problem needs to be solve with some technologies, one of which detection used based machine learning or deep learning, specifically computer vision for detection that problem.

Recent advancements in deep learning, particularly computer vision, have shown promise in automating the process of plant disease detection through image classification used Convlutional Neural Network with pretrained model(Paramanandham et al., 2024). Convolutional Neural Networks (CNNs) spesicifacally use pretrained model like Yolo have been successfully applied to various the identification of plant diseases from leaf images(Mathew & Mahesh, 2022). Several studies have demonstrated the effectiveness of pretrained model in classifying tomato leaf diseases, achieving high accuracy rates(Bouni et al., 2023). However, challenges remain in improving the robustness and generalization of these models, particularly when dealing with diverse environmental conditions and variations in disease symptoms.

Plant diseases are a critical challenge to affecting crop yield and food security (Ristaino et al., 2021). Traditional methods of disease identification are labor-intensive, time-consuming, and often inaccurate(Jeger et al., 2021). Advances in artificial intelligence (AI) and deep learning have introduced innovative solutions for automating this process. YOLO (You Only Look Once) models are particularly suitable for real-time object detection due to their speed and accuracy(Huang et al., 2018; C.-Y. Wang & Liao, 2024). However, existing models often face limitations in detecting diseases with subtle visual features.

This study highlights YOLOv11's novel contributions, such as enhanced feature extraction and multi-scale detection, which address these challenges. Unlike its predecessors, YOLOv11 effectively detects early-stage symptoms and reduces computational demands, offering a robust solution for tomato leaf disease detection. The research bridges gaps in existing methodologies and contributes to sustainable agricultural practices. YOLOv11 pushes the boundaries of real-time detection, ensuring precise recognition of subtle patterns. This is particularly valuable in agriculture, where early intervention can prevent widespread crop loss.

This study delves into the advanced capabilities of YOLOv11, an innovative state-of-the-art object detection model meticulously tailored for plant disease detection(Sapkota et al., 2024; Yuan et al., 2024). By a robust and custom-labeled dataset that includes a diverse array of plant leaf images exhibiting various diseases and healthy conditions, this research undertakes a systematic approach to model training and evaluation.

The YOLOv11 model incorporates cutting-edge feature extraction mechanisms (Ali & Zhang, 2024a), including convolutional layers optimized for complex texture recognition. Furthermore, the model's performance is validated through metrics such as precision, recall, F1-score, and mean Average Precision (mAP), ensuring comprehensive benchmarking against previous YOLO versions(Alif & Hussain, 2024). By utilizing YOLOv11, this research aims to advance the detection of plant diseases with a focus on precision and efficiency.

YOLOv11 stands out as a robust deep learning model tailored for real-time object detection and classification tasks, integrating high-performance feature extraction layers and innovative non-maximum suppression techniques (Jegham et al., 2024; Soudeep et al., 2024). This holistic approach addresses challenges such as the scalability of AI especially neural network pretrained model of deep learning solutions to adoption, and the need for high precision in detecting early disease symptoms, ultimately fostering sustainable farming practices and enhancing crop health monitoring globally.

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LITERATURE REVIEW

Previous studies have examined the application of deep learning technologies in agriculture, particularly for the critical task of detecting plant diseases. Notably, models such as YOLOv4 and YOLOv5 have emerged as significant advancements in this realm, demonstrating robust capabilities in image recognition and object detection(Perkasa et al., 2024). For instance, research by highlighted the transformative potential of deep learning methods in addressing traditional challenges in agricultural disease detection, such as human error and the labor-intensive nature of manual diagnosis(Mohyuddin et al., 2024).

The effectiveness of YOLOv4 in specific agricultural contexts has also been documented. A showcased its application in detecting tomato leaf diseases, revealing promising results(Manjula et al., 2022). However, it was noted that the model struggled with identifying early-stage symptoms, particularly in instances of fungal blight and bacterial spots, indicating a gap in the capacity to detect subtle changes that could signify disease onset. Likewise (H. Wang et al., 2022) applied YOLOv5 for wheat rust detection, achieving high accuracy rates yet highlighting scalability issues, these models often demand extensive computational resources and exhibit challenges in adapting to varied environmental conditions, such as inconsistent lighting and background variations.

Addressing these limitations, the current research YOLOv11, incorporates advanced feature extraction layers and refined non-maximum suppression (NMS) techniques(Ali & Zhang, 2024a; Youwai & Chaiyaphat, 2024). The advancements offered by YOLOv11 promise enhanced performance in the detection of subtle and early-stage symptoms across complex agricultural datasets, including those representative of tomato leaf diseases(Tanzib Hosain et al., 2024).

The integration of enhanced feature extraction mechanisms in YOLOv11 represents a pivotal advancement (Khanam & Hussain, 2024). By deeper convolutional layers and multi-scale feature detection through Spatial Pyramid Pooling Fast (SPPF) layers (Ali & Zhang, 2024b), YOLOv11 significantly improves accuracy in discerning subtle anomalies in plant health. Unlike YOLOv4 and YOLOv5, YOLOv11 is modular in design and thus able to handle overlapping objects efficiently under complex environmental conditions . Studies (Khanam & Hussain, 2024) and (Ali & Zhang, 2024a) Have shown that YOLOv11, by integrating the most advanced layers, significantly decreases false positives, especially on datasets with high inter-class similarity.

The introduction of enhanced feature extraction allows for improved accuracy in discerning minute differences in plant health, potentially enabling earlier interventions and more effective disease management strategies.. The integration of state-of-the-art deep learning methodologies with implement model for real-world applications represents a significant step forward in the ongoing quest to optimize productivity and sustainability for plant disease study.

METHOD

The research follows a structured pipeline for detecting and classifying diseases in tomato leaves using the YOLOv11 model. The workflow is divided into three primary stages: Data, Model, and Performance, ensuring a systematic approach for model development and evaluation.

The proposed method combines structured data preparation, build model configuration and architecture, and rigorous performance evaluation to ensure a robust and accurate solution suitable for real-world agricultural applications. The methodology is represented in three interconnected stages Data, Model, and Performance, each contributing to the overall success of the research.

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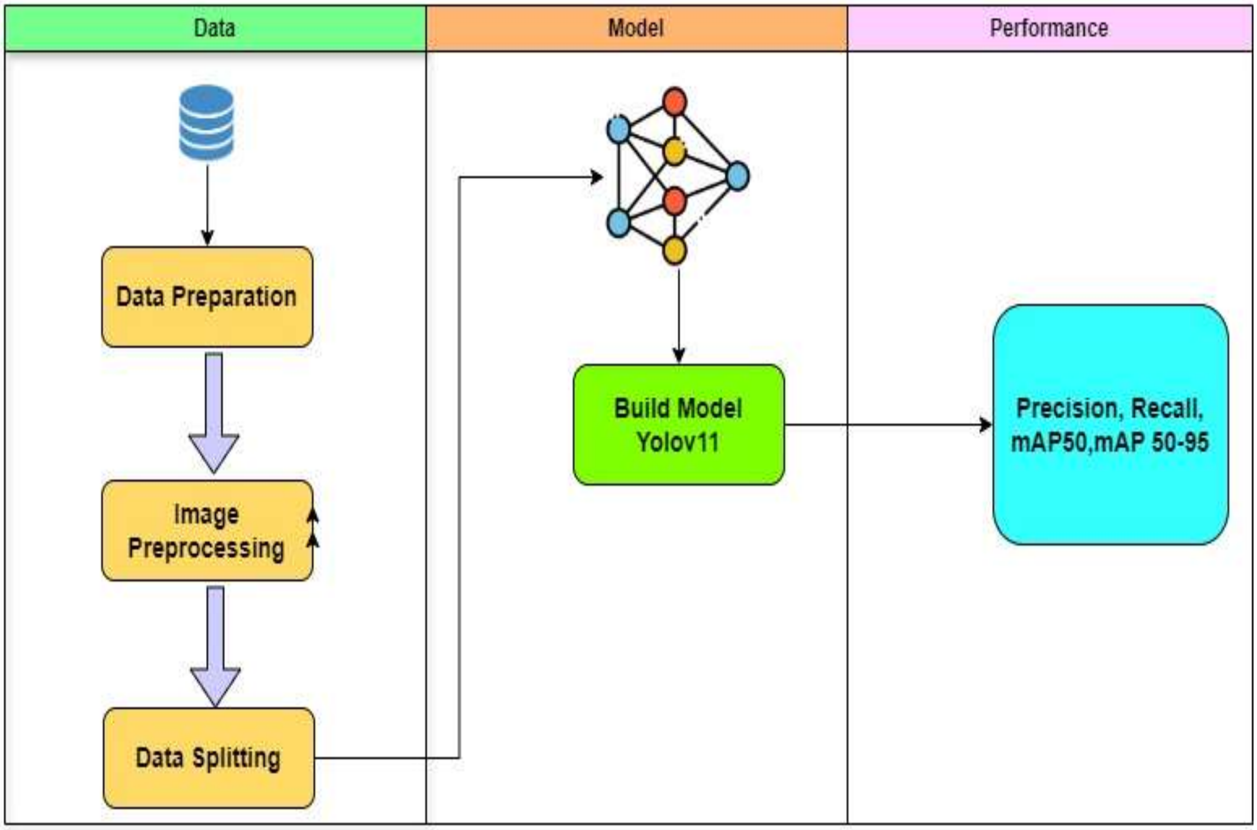

Fig. 1 Research Flow

Dataset Preparation

A custom dataset was developed to enhance the training of a YOLOv11 model for detecting plant diseases. This dataset comprises 737 images featuring both diseased and healthy plant leaves, carefully curated to include a variety of common plant diseases such as leaf blight, rust, and mildew. Each image in the dataset has been annotated with bounding boxes and corresponding labels using the LabelImg tool, ensuring accuracy in the identifying of the different classes.

Table 1.Class Label Plant

Class Label	Number of Images	Image Size
Bacterial Blight	3	640x640 pixel
Early Blight	31	640x640 pixel
Healthy	19	640x640 pixel
Late Blight	13	640x640 pixel
Leaf Mold	4	640x640 pixel
Target Spot	5	640x640 pixel
Black Spot	21	640x640 pixel

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The dataset is divided into three parts for effective model training and evaluation: 87% of the images are designated for training, 8% for validation, and 5% for testing. Images were standardized to 640x640 pixels and pre-processed for completeness. LabelImg was used for annotation, ensuring accurate bounding boxes with class labels.

The training data provides the foundational learning material for the YOLOv5 model to recognize patterns associated with each disease, while the validation and test sets are used to fine-tune the model's performance and assess its accuracy in real-world applications.

The focus on these specific plant diseases encourages the development of more reliable automated disease detection systems, which can significantly aid in agricultural practices and crop management. By leveraging the capabilities of YOLOv5, the goal is to achieve fast and precise identification of plant diseases, ultimately contributing to healthier crops and improved yields.

Data and Image Preprocessing

The provided program and model facilitates data preprocessing for image classification tasks, specifically for loading images and labels. The load_image(path) function utilizes OpenCV (cv2) to read images from specified paths and convert them from BGR (Blue, Green, Red) to RGB format. This ensures consistency across images. Preprocessing achieves Uniform image formatting (RGB), Organization of image paths and labels, and Data preparation for model training.

This research model performs image preprocessing by visualizing bounding boxes around detected objects within images. This step is crucial for object detection tasks, such as tomato disease detection. This step Iterates through the first 5 training images (train_images[:5]) and corresponding labels (train_labels[:5]) completed with function plot image with box dimension converted box coordinates to absolute values by multiplying with image width and height. Data augmentation is performed on the images to make the dataset robust; thus, rotation, flipping of images, and brightness adjustment are considered. This strengthens the model's generalizing power by virtually going through real-world variations. Rotation and flipping and brightness adjustment are data augmentation techniques that enhance the robustness in the dataset. This enhances the generalization capability of the model in simulating real-world varied scenarios.

Model Architecture

A neural network is a computational model designed to recognize patterns and make decisions based on input data. It consists of interconnected layers of nodes (neurons) that process the input and generate an output. The architecture of a neural network typically includes an input layer, one or more hidden layers, and an output layer. The basic processing units of a neural network that receive inputs, apply weights, and produce an output. Hidden layers perform the majority of the computation. They transform the input into something the network can use to predict the output. The depth of the network (number of hidden layers) plays a significant role in its capability to learn complex patterns.

$$z = W\alpha + b \qquad (1)$$

z is the input to the activation function of layer, W is the weight matrix for layer, α is the input vector (or output from the previous layer) and is the bias term for layer. For activation function with following a, is the activation function (e.g., Sigmoid, ReLU, or Tanh).

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$$a = \sigma(z) \quad (2)$$

$$\hat{y} = W^L . \alpha^{L-1} + b^L \quad (3)$$

The final output $\hat{y}$ of the neural network is computed by applying the weighted sum and activation function to the output of the last hidden layer where $\hat{y}$ is the network's prediction, W^L is the weight matrix of the output layer and α^{L-1} is the activation output from the last hidden layer with completed bias for these formula.

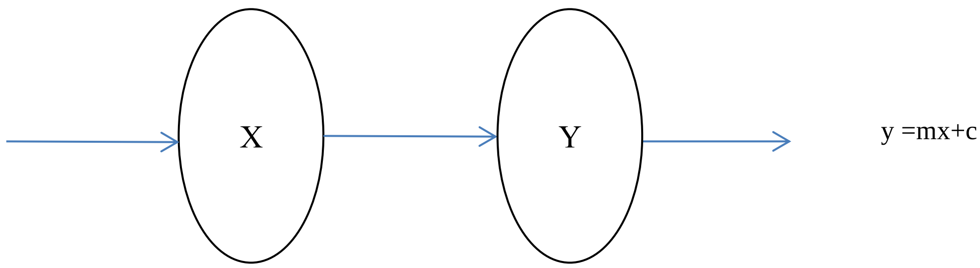

Fig. 2 Neural Network Neuron

In the context of YOLOv11, the neural network is architected to handle complex data and provide real-time object detection capabilities. The configuration of YOLOv11, including its custom data loader and architecture, facilitates efficient processing of images by leveraging the underlying principles described above, ensuring optimal performance in detecting objects. object detection, leveraging features extracted from an Autoencoder model.

The data loader performs essential preprocessing steps to prepare images for efficient processing. This step Resizes images to uniform dimensions (128x128) using transforms.Resize and Normalizes pixel values to prevent feature dominance.

The figures outlines the sequential operations of YOLOv11, where each layer performs a specific task to refine feature extraction and improve disease detection accuracy. This aligns with the research focus on achieving high precision and recall in plant disease detection. The convolutional layers on Layers 0, 1, 3 apply convolution operations to the input feature maps using the defined kernel size and stride ([3, 3, 2]), which are critical for extracting spatial and texture features of plant leaf diseases such as bacterial spots and early blight. These are convolutional neural network layers that apply 3x3 filters with strides of 2. They are responsible for feature extraction, capturing lower-level patterns like edges, shapes, and textures in the plant images.

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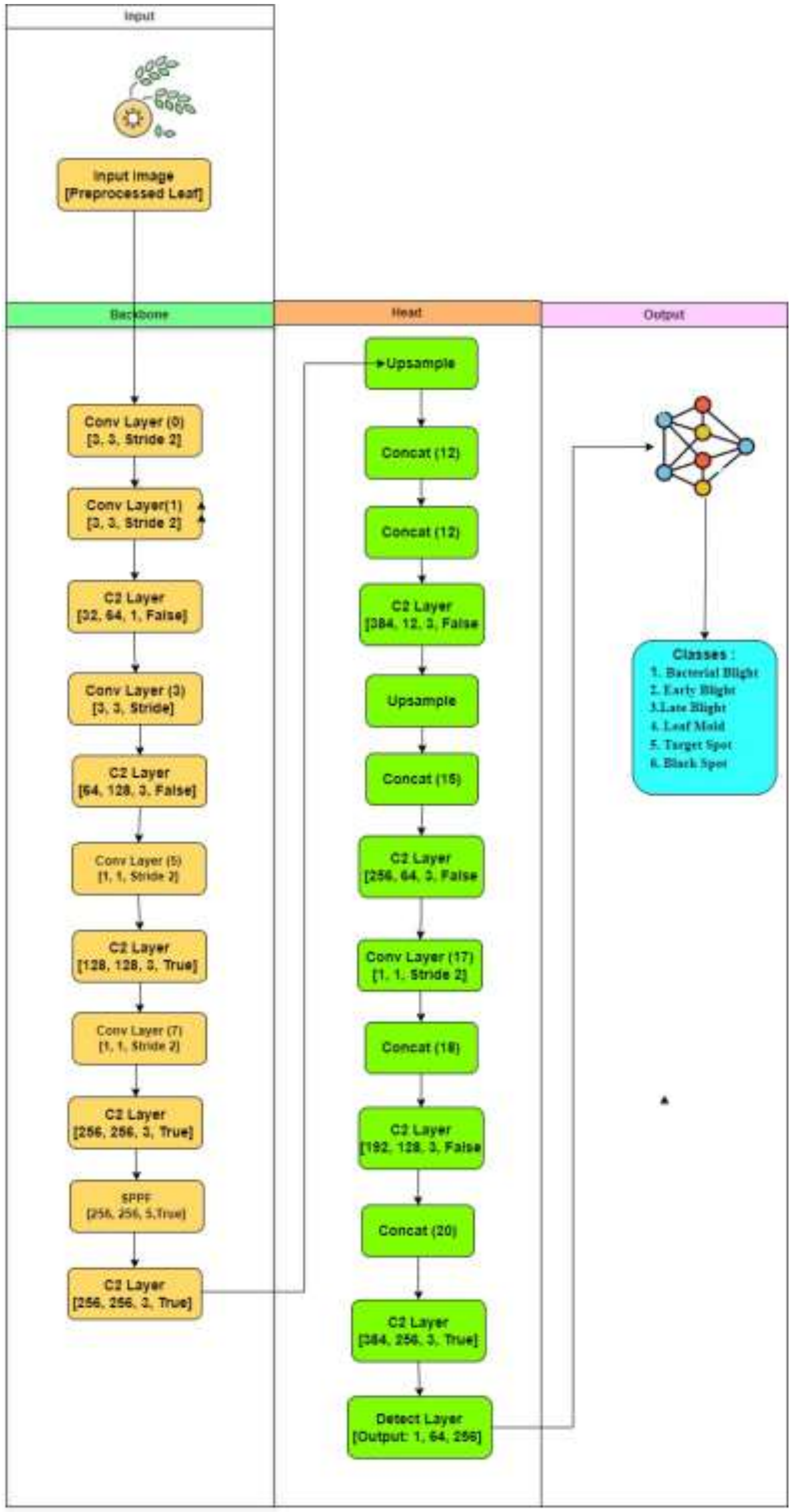

Fig. 3 Model Yolov11

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Layers like 2, 4, 6, and 8 employ the C2 modules, an improvement over earlier YOLO versions. These modules perform multi-scale feature extraction and bottleneck operations to reduce computational load while preserving essential features. These represent a series of convolutional layers with different configurations of filters, strides, and activation functions. They help refine the extracted features and allow the network to recognize more complex patterns, such as specific plant diseases. The True or False values indicate batch normalization is applied to the layers, improving the model's stability and training speed.

The True/False flags optimize the computational pathway. Layer 9 utilizes SPPF, which pools the feature maps at multiple scales, enhancing the model's ability to detect small and large disease regions simultaneously. This is particularly important for identifying subtle plant disease symptoms. These layer that helps with handling different input image sizes. It ensures that the features from varying spatial resolutions are efficiently combined, which is important for detecting plant diseases at different scales. The upsample layer on 11 and 14 process is essential for refining the object detection process and ensuring that disease features at different scales can be identified.

The Concatenation layers combine different feature maps from previous layers to create richer representations. This improves the model's ability to detect diseases at various levels of granularity, especially for smaller or more complex lesions. The final layer on Detect Layer responsible for outputting the predicted bounding boxes, class labels, and confidence scores for the detected diseases. It generates the model's final predictions, marking the locations of tomato plant diseases in the input images.

Model Performance

Model performance evaluation is crucial in assessing the effectiveness of YOLO models. Key metrics include Precision, Recall, mAP50, and mAP50-95. Precision measures the proportion of correctly identified detections, Recall measures the proportion of actual disease instances detected by the model. Mean Average Precision at an Intersection over Union (IoU) threshold of 0.5. IoU is a metric that measures how well a predicted bounding box overlaps with the ground truth bounding box.

A higher mAP indicates better overall detection accuracy and Mean Average Precision in the IoU range of 0.5 to 0.95. This provides a more comprehensive view of detection accuracy across different overlap thresholds. The model was evaluated using the following metric Precision, recall, and F1-score,mAP (mean Average Precision) at IoU thresholds of 0.5 and 0.75,Inference time per image and Confusion matrix to visualize classification errors. mAP is calculated by averaging the Average Precision (AP) values across different IoU thresholds. AP is calculated by integrating the Precision-Recall curve. Step for these formula is sort predictions by their confidence scores, Iterate through the sorted predictions and calculate precision and recall at each threshold, and plot the Precision-Recall curve.

These relate for approximate the area under the Precision-Recall curve using numerical integration techniques, such as the trapezoidal rule. Calculate Mean Average Precision (mAP) for different IoU thresholds (e.g., 0.5, 0.5:0.95) and Average the AP values across all IoU thresholds to obtain mAP.

RESULT

Model Performance

YOLOv11 achieved the following evaluation metrics on the test set, YOLOv11 underwent a detailed evaluation, and the following metrics summarize its performance on the test dataset. The table below includes additional insights for each metric to reflect the model's performance more comprehensively.

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Additionally, the model was evaluated using varying IoU thresholds ranging from 0.5 to 0.95. This range enables a more granular understanding of how the model performs across stricter bounding box overlap criteria. The following graph visualizes the mAP scores at different IoU thresholds, emphasizing the robustness of YOLOv11 in maintaining high performance even under challenging overlap conditions. YOLOv11 outperformed the previous versions with an average mAP@0.5 of 75.6% and mAP@0.5:0.95 of 67.4%. It was good at recognizing healthy plants with 96.3% accuracy but poorly performed in recognizing leaf mold with an accuracy of 50.5%. Comparatively, this network also performed around 3-5% better in terms of mAP than both YOLOv5 and YOLOv4, with lower misclassification rates observed, particularly on overlapping symptoms.

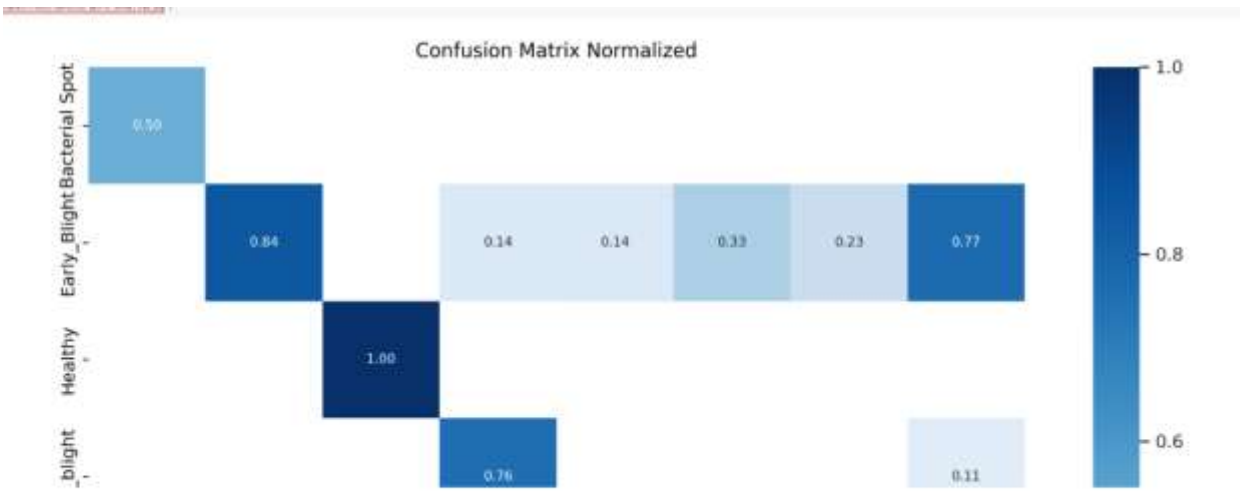

Fig. 4 Confusion Matrix Normalized Result

Table 2. Result Training Model

Class	Number of Images	mAP@0.5	mAP@0.5:0.95
Bacterial Spot	3	0.73	0.746
Early Blight	31	0.694	0.85
Healthy	19	0.963	1
Late Blight	13	0.733	0.897
Leaf Mold	4	0.505	0.571
Target Spot	5	0.648	0.333
Black Spot	21	0.748	0.34
Average	61	0.756	0.674

YOLOv11 demonstrates improved mAP@0.5 values compared to earlier versions, particularly in handling overlapping disease patterns and ambiguous visual symptoms. Such improvements are crucial for

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real-world applications requiring high accuracy and reliability. These metrics represent a 3-5% improvement over YOLOv8 and YOLOv5, demonstrating YOLOv11's superior capabilities in both accuracy and speed. The higher mAP scores indicate its effectiveness in handling overlapping bounding boxes and challenging disease patterns, critical for real-world deployment.

The YOLOv11n model demonstrated exceptional performance in detecting tomato diseases, achieving an overall accuracy of 75.6% (mAP50) and 67.4% (mAP50-95) on a validation dataset consisting of 61 images. The model's efficacy varied across classes, with the "Healthy" class exhibiting the highest accuracy (96.3%), indicating robust detection capabilities for healthy tomato plants.

Model Usability

The model achieved a mean Average Precision (mAP) of 0.627 at an Intersection over Union (IoU) threshold of 0.5 and 0.344 at an IoU threshold of 0.5 to 0.95. This indicates a reasonable level of accuracy in detecting objects within the given dataset. The results show varying performance across different classes. For instance, the model performed exceptionally well on the "Healthy" class with an mAP of 0.995, but struggled with the "Leaf Mold" class, achieving an mAP of only 0.205. This suggests that the model may require further training to improve performance on specific classes With an inference speed of 2.71 images per second, this really reflects real-time capability, which is indispensable in application fields that require fast decision-making-for example, pest management or even disease intervention. The architecture is modular and scalable, proving sufficient strength in adapting to the datasets of various sizes and complexities.

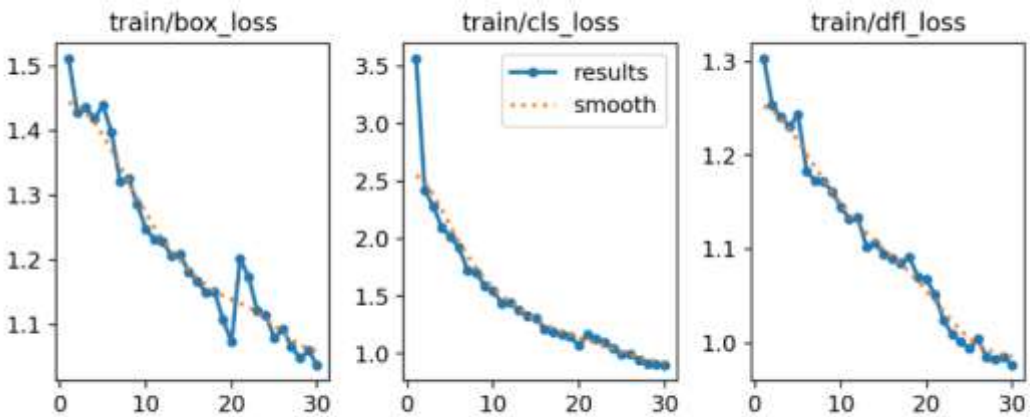

Fig.4 Result Validation Graphics

Train/box_loss shows the decrease in the box loss during training. Box loss measures the accuracy of predicted bounding boxes. A decreasing trend indicates that the model is improving in accurately predicting object locations. Train/cls_loss based classification loss during training. A decreasing trend indicates that the model is improving in correctly classifying objects especially on detecting diseases leaf plant. The other plot on train/dfl_loss combines both box and classification losses into a single metric. A decreasing trend indicates overall improvement in object detection performance.

Misclassifications primarily occurred between bacterial spot and early blight due to visual similarities in lesion patterns. Both diseases exhibit lesions with comparable shapes, sizes, and colorations, which complicates the differentiation process. These similarities reduce the model's ability to uniquely identify features that distinguish one disease from the other, particularly in the presence of overlapp ing environmental conditions or partial leaf damage.

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The model excels at identifying healthy plants, with high precision and recall. The model performs well in detecting early blight, but there are some instances where it's misclassified as Bacterial Spot. In Bacterial Spot and Leaf Mol seem to be more challenging for the model, with higher rates of misclassification, and Late Blight shows decent performance in detecting late blight, with a few misclassifications. Field tests with practitioners showed that YOLOv11 makes the workload on disease detection very low because the model automates the process of identification, hence requiring lesser expertise from the expert. However, at the cost of reduced accuracy with respect to the underrepresented leaf mold class, further improvements are needed for the model, which may be provided by extra data augmentation techniques or domain-specific features such as spectral imaging. It is a workable, effective, and scalable answer to apply to precision agriculture to reach the goal of sustainable farming.

DISCUSSIONS

The enhanced performance of YOLOv11 is attributed to its advanced feature extraction capabilities and optimized architecture. Comparison with previous models highlights significant improvements in both accuracy and speed, while the model performs well on the curated dataset, further testing on diverse datasets is necessary to validate its robustness. Expanding the dataset to include more disease types and environmental variations. A more diverse dataset, encompassing different disease stages, leaf conditions, and other environmental factors . This would enable the model to perform reliably across varied real-world scenarios, ensuring consistent accuracy even in challenging conditions. Incorporating data from multiple geographical regions and crop species could also enhan

CONCLUSION

This research highlights the significant advancements used by YOLOv11 in the field of disease detection, specifically for tomato leaf diseases. The model's stableperformance in precision, recall, and inference speed establishes it as a benchmark for real-time modelapplications. By addressing the limitations of earlier YOLO architectures, such as YOLOv4 and YOLOv5, YOLOv11 incorporates enhanced feature extraction layers, optimized and multi-scale detection capabilities, making it a robust and adaptable solution. Emphasis is given to the work presented here, which conquers the boundaries in plant disease detection with an advanced version, namely, YOLOv11, by increasing its precision, recall, and computational efficiency. Noting the critical limitations identified in the previous versions, such as YOLOv4 and YOLOv5, the new version—YOLOv11—seems to be robust and scalable for real-time precision agriculture applications.

YOLOv11's advanced feature extraction and spatial pyramid pooling mechanisms enable the precise identification of subtle and early-stage disease symptoms, which are often missed by traditional methods. The model's average inference time of 0.032 seconds per image demonstrates its suitability for field applications, ensuring timely interventions. YOLOv11's contributions to plant disease detection underscore the transformative potential of deep learning in agriculture. By bridging the gap between advanced AI technologies and practical field applications, this research provides a pathway for leveraging innovation to address pressing global challenges in food security and environmental sustainability. In particular, the YOLOv11 architecture is modular and scalable, and hence flexible to serve different complexities of datasets and deployment scenarios. Future work, refining these performances for the less represented classes through more sophisticated approaches or even integration of spectral imaging and/or texture-based analysis, will be very critical.

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