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Master’s Thesis

使用深度學習方法識別咖啡葉病害並估計嚴重程度

Coffee Leaf Disease Identification and Severity Estimation using Deep Learning Methods

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Coffee Leaf Disease Identification and Severity Estimation

Using Deep Learning Methods

The undersigned, appointed by the Department / Institute of The Master Program in Global Agriculture Technology and Genomic Science on 5 (date) June (month) 2024 (year) have examined a Master's thesis entitled above presented by Carla Kristine Macatanagy Silva (R11H43008) candidate and hereby certify that it is worthy of acceptance.

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摘要

本研究針對全球咖啡產業因咖啡植物病害日益猖獗而面臨的挑戰，這些病害影響了咖啡產量的質量和數量。本研究引入了一種將計算機視覺技術與深度學習模型相結合的方法，用於檢測和分類咖啡病害並估計病害嚴重程度。研究使用了來自不同來源的 1086 張圖像數據集，包括阿拉比卡和羅布斯塔咖啡葉片圖像。這些圖像通過處理技術增強後，用於訓練和評估深度學習模型 YOLO。YOLO 深度學習模型以 94.2%的總體 mAP50 分類病害類型。此外，模型以 0.1 的置信度閾值量化病害嚴重程度，整體精度為 69.6%，從而實現對咖啡植物感染的全面評估。該雙層分類系統使農民和專家能夠通過 YOLOv8 做出明智的決定，在檢測、分類和估計咖啡葉病害的嚴重程度方面，總體準確率達到 78.55%。

關鍵詞：咖啡，植物病害，圖像處理，深度學習，YOLO

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ABSTRACT

This study addresses the challenges faced by the global coffee industry due to the increasing prevalence of coffee plant diseases, which affect the quality and quantity of coffee yield. This research introduces an approach integrating computer vision technology with deep learning models to detect and classify coffee diseases and estimate disease severity. A dataset of 1,086 images from various sources, including Arabica and Robusta coffee leaf images was used. These images, augmented with processing techniques, serve as the foundation for training and evaluating deep learning model, YOLO. The YOLO deep learning model classifies disease types with an overall mAP50 of 94.2%. Additionally, the model quantifies disease severity with an overall Precision of 69.6% with a confidence threshold of 0.1, enabling a comprehensive assessment of the infection in coffee plants. This dual-tier classification system empowers farmers and specialists to make informed decisions in detecting, classifying, and estimating the severity of coffee leaf diseases through YOLOv8, achieving an overall accuracy of 78.55%.

Keywords: coffee, plant diseases, image processing, deep learning, YOLO

doi:10.6342/NTU202401339

TABLE OF CONTENTS

doi:10.6342/NTU202401339

doi:10.6342/NTU202401339

LIST OF TABLES

doi:10.6342/NTU202401339

LIST OF FIGURES

doi:10.6342/NTU202401339

CHAPTER 1. INTRODUCTION

1.1 Research Background

Globally, coffee is one of the most consumed beverages, after water and tea. According to the International Coffee Organization (2020), 169.6 million coffee bags were produced. According to the USDA (2022), the top coffee producers are India, Uganda, Indonesia, Brazil, and Vietnam, with an estimated 80 million bags of coffee beans, while the Philippines has only 475 thousand. In history, by the late 1800s, the Philippines was the world's fourth-largest coffee exporter, and in the 19th century, the country was the only source of coffee in the entire world. However, production has declined since the early 1900s and continues today. The Philippine Statistics Authority (2022) declared that the Philippines had a total coffee production of about 15.30 thousand metric tons in 2022, with the Socsksargen Region as the highest coffee producer, with a total production of 39%. During this time, the Philippines produced three types of coffee: Arabica, Liberica, and Robusta.

The Philippine coffee industry has various issues that plague its production, including a decrease in coffee land area, a decrease in coffee bean quality due to poor agricultural practices, and reduced productivity of coffee farmers who cannot earn a living commensurate with their work (Habaradas, 2021). Moreover, it has been alarming for coffee farmers that this phenomenon is also caused by climate change in the Philippines (Wakas, 2020). This decreased coffee production and climate change phenomenon occurs in the Philippines and other parts of the world (Piato, 2021). Climate change could favor the outbreak of pests and diseases, increasing coffee demand and farmer productivity. Thus, this destruction of pests and diseases could reduce agricultural production yield and quality.

doi:10.6342/NTU202401339

To address the spread of plant disease, identification of diseases is essential in crop management, preventing tremendous yield loss in coffee agricultural land. One of the new digital methods being established in field practice is the early detection of pests and diseases, highlighting agricultural machine vision. Machine vision is a form of precision agriculture that provides automated and efficient farming management by monitoring, measuring, and responding to crop variability through digital machines and algorithms (Mavridou, 2019). Through the use of these new farming machines and technologies in plant disease control, the advantages of low cost, high efficiency, and high precision will be perceived, contributing to increased crop production (Tian, 2020). Previous research in machine vision was also conducted to provide results showing a high percentage of precision and accuracy in using trained machine vision for the early-stage detection and identification of plant diseases and pests. Some of these disease-detection studies were conducted on cassava (Ramcharan, 2017), banana (Selvaraj, 2019; Krishnan, 2022), rice (Rahman, 2020), apple (Khan, 2022), grapes (Liu, 2020), tomato (Trivedi, 2021), and tea (Chen, 2020).

1.2 Research Purpose

In this study, we will explore the use of machine vision in combination with a state-of-the-art model to detect diseases in coffee plants. Additionally, this paper accurately identifies lesions or infected regions and calculates the overall accuracy and precision of the model. The developed model aims to monitor crop fields and manage diseases to enhance agricultural production. This approach could potentially prevent disease manifestation through early detection and improve coffee production surrounding coffee plantations. Specifically, the research will focus on classifying, detecting, and quantifying coffee leaf disease and calculating the severity of infected areas on coffee

doi:10.6342/NTU202401339

leaves, leading to a comprehensive evaluation of coffee leaf health. The objectives of the study are to:

(1) Build a model to that can locate coffee leaf and identify its disease into Phoma, Cercospora, Miner and Rust.

(2) Devise a model that can detect and segment the infected regions of the leaf.

(3) Calculate the estimated severity of the coffee leaves based on the two models built.

doi:10.6342/NTU202401339

CHAPTER 2. LITERATURE REVIEW

2.1 Coffee Diseases

Enhancing agricultural productivity is a pressing global economic concern. The role of plant disease detection in this context is pivotal. Coffee farming, a key sector, is susceptible to diseases that can significantly impair yield and quality. Notably, Phoma (*Phoma costaricensis*), Miner (*Leucoptera coffeella),* Cercospora (*Cercospora coffeicola)* and Rust (*Hemileia vastatrix)* pose a substantial economic threat due to their wide prevalence. Understanding these diseases is therefore paramount for devising effective management strategies. Accurate prediction of plant diseases can facilitate early intervention, a measure that can substantially curb financial losses. This underscores the urgency and relevance of our research, given the potential economic impact of coffee diseases.

First, phoma leaf spot, caused by the fungus *Phoma* spp., is not just a common disease in coffee plantations, but a significant threat. This pathogen causes small, dark, circular leaf lesions, which can coalesce and lead to defoliation and reduced photosynthetic capacity. This disease is prevailing in areas with high humidity and frequent rainfall. Management strategies for Phoma leaf spot include improving air circulation within coffee plantations, applying fungicides, and using resistant varieties where available (Ibrahim et al., 2016). Second, the coffee leaf miner, *Leucoptera coffeella*, is not just an insect pest, but a formidable adversary primarily affecting coffee leaves. The larvae mine the leaves, creating tunnels leading to significant leaf damage, reduced photosynthesis, and lower coffee yields. The coffee leaf miner is most problematic in Latin America and can cause up to 80% yield loss if not managed properly. Control measures include biological control using natural predators, cultural practices using pruning and shade management, and selective insecticides (Pereira et al., 2007). Third,

doi:10.6342/NTU202401339

cercospora leaf spot, caused by the fungus *Cercospora coffeicola*, is not just a serious disease, but a grave threat affecting coffee plants, particularly in regions with warm and humid climates. The disease manifests as necrotic spots with a yellow halo on leaves, berries, and young shoots, leading to premature leaf drop and berry infection. Effective management includes using resistant coffee varieties, applying copper-based fungicides, and proper agricultural practices such as removing infected plant debris and maintaining adequate plant spacing (Waller, 1992). Lastly, coffee leaf rust, caused by the fungus *Hemileia vastatrix*, is not just one of the most devastating diseases in coffee cultivation, but a potential catastrophe. The disease first appeared in Sri Lanka in 1869 and has since spread to almost all coffee-growing regions worldwide. It appears as yellow-orange powdery lesions on the underside of leaves, leading to defoliation, reduced photosynthetic capacity, and significant yield loss. Control measures include developing and using resistant coffee varieties and fungicide applications and implementing integrated disease management practices (McCook & Vandermeer, 2015). The potential financial loss due to these diseases underscores the need for effective plant management strategies.

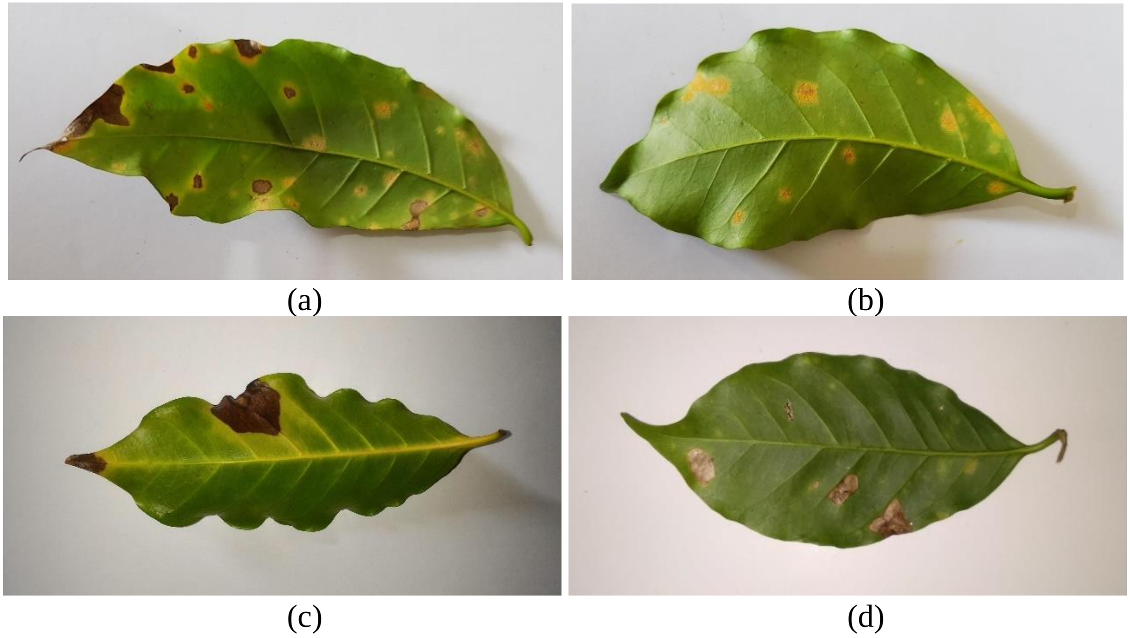


Figure 2.1 Sample images of diseased coffee leaves.
(a) Cercospora (b) Rust (c) Phoma (d) Miner

doi:10.6342/NTU202401339

2.2 Coffee Leaf Disease Detection

Coffee plants are susceptible to various diseases that can significantly impact both yield and quality. However, the field of disease detection and management has seen remarkable advancements. This research overview focuses on these important studies and advancements in detecting and managing coffee diseases such as Phoma, Miner, Cercospora, and Rust. These advancements include innovative methods, such as machine learning and deep learning techniques, which have shown great promise in improving disease management strategies.

For example, Prabhu and Isiri (2020) utilized deep CNNs to identify coffee leaf diseases, with ResNet-50 producing the best results. Another study by Montalbo and Hernandez (2020) employed Deep Convolutional Models (DCMs) to classify Barako leaf diseases, achieving high accuracy but facing validation challenges due to limited data. Additionally, a paper by Esgario et al. (2020) developed a multi-task system using CNNs for biotic stress identification and severity estimation on coffee leaves, demonstrating high accuracy. Several studies have also demonstrated the effectiveness of deep learning techniques in identifying coffee plant diseases and enhancing production processes. In particular, convolutional neural networks (CNNs) have been utilized to detect and classify leaf diseases in coffee plants. For example, a study by Dutta and Rana (2021) proposed a CNN model that utilized transfer learning and data augmentation techniques to classify leaf diseases, which yielded promising results. Furthermore, Pinto (2021) utilized a CNN model to classify coffee leaf diseases with an 88.35% accuracy rate based on features extracted from leaf images. Meanwhile, research by Aufar and Kaloka (2022) used the MobileNetV2 network to accurately classify Robusta coffee leaf diseases, while another study by Aufar (2023) aimed to improve accuracy in Arabica coffee leaf disease

doi:10.6342/NTU202401339

classification by utilizing multiple architectures, such as InceptionResnetV2 and DenseNet169, which achieved the best performance.

These AI applications have practical implications in disease prevention. For instance, an AI application to prevent leaf rust achieved a validation accuracy of 59% using a ResNet CNN model (Suparyanto, 2022). Another AI application study by Martinez et al. (2022) developed a machine-learning system for detecting multiple high-impact diseases with over 91% detection accuracy. In recent years, there has been a growing interest in applying deep learning algorithms, particularly YOLO (You Only Look Once), in agriculture to improve agricultural systems. One notable application of this technology is addressing issues related to Robusta coffee in the Philippines. Researchers have utilized the RoCole Dataset to train YOLOv3, achieving a commendable 90% accuracy in detecting leaf diseases affecting the Robusta coffee plants (Javierto, 2021). Moreover, another significant development made by Luis (2022) in this area is creating an automatic coffee bean defect detection system using YOLOv5, which demonstrated an impressive 95.11% accuracy in identifying defects in coffee beans. Looking ahead, there are ongoing efforts to employ AI-powered citizen science for geographic-scale monitoring of coffee cherry counting in Peru and Colombia. This innovative approach has shown promise, achieving an R^2 of 0.72 with YOLO v8, and holds the potential for enabling large-scale, photo-based phenotypic monitoring in low-income countries (Palacio, 2024).

To aid in the identification of coffee plant diseases, large-scale datasets such as JMuBEN and JMuBEN2 have been developed using deep learning algorithms (Jepkoech, 2021). Genetic algorithms have also been proposed for rust identification, which can lower pesticide use and offer early detection alternatives (Marcos, 2019). Others used ensemble architecture, such as a study by Novtahaning (2022) employing an ensemble of

doi:10.6342/NTU202401339

EfficientNet-B0, ResNet-152, and VGG-16, achieving 97.31% validation accuracy for coffee leaf disease identification.

2.3 Image Processing Techniques

Numerous image processing techniques have been applied to detect diseases in coffee trees, including color segmentation and HSV color segmentation, as discussed by Barbedo (2016) and Waldamichael (2022). To enhance the accuracy of disease area detection, researchers have used texture attribute extraction and data augmentation, as shown in studies conducted by Hitimana and Gwun (2014) and Essoh (2022). To overcome the complexity of disease detection, researchers have explored semantic segmentation techniques and developed visualization approaches to improve the model's perception of healthy and non-healthy images.

Some studies present a method for segmentation or visualization detecting foliar damage in coffee leaf images. The method uses segmentation algorithms, including the Otsu algorithm and iterative threshold algorithm, and artificial neural networks trained with extreme learning machines, showing the feasibility and effectiveness of the approach (Manso 2019). In a paper by Barbedo (2019), manual symptom segmentation was proved using individual lesions and spots instead of entire leaves, increasing variability without additional images. This is also shown in the studies of Tassis (2021) and Yebasse (2021), who have contributed to semantic segmentation techniques and visualization approaches using deep learning models such as Mask R-CNN, for instance, segmentation and UNet and PSPNet for semantic segmentation. The study by Yebasse (2021) also presents different visualization approaches, including Grad-CAM, Grad-CAM++, and Score-CAM, identifying misclassifications and proposing a guided approach for coffee disease classification.

doi:10.6342/NTU202401339

2.4 Deep Learning in Other Coffee Plant Parts and other Plants

In recent years, deep learning models have emerged as powerful tools in agricultural research, going beyond the traditional analysis of coffee leaves. These models have demonstrated remarkable efficacy in identifying specific pathogens and defects such as White Stem Borer (WSB), Coffee Berry Disease, and Coffee Wilt Disease, offering valuable support to farmers and contributing to enhanced crop yield (Velásquez, 2020; Geddam, 2023). A study conducted by Geddam (2023) stands out for its use of a dataset of WSB-infected stems to train a deep learning model with augmented images, achieving impressive accuracy rates of 81.9%, 89.7%, and 73.8%. Moreover, research by Karar (2021) harnessed the power of Faster R-CNN in pest detection with the aid of a pesticide database to achieve an outstanding 99.0% accuracy in pest detection, addressing the critical issue of crop loss. A study by Vassallo-Barco (2017) showcased the potential of image descriptors and deep learning classifiers in identifying deficiencies such as iron and boron, while also revealing more modest results for potassium and calcium in identifying plants' nutritional deficiencies. Additionally, the application of machine learning models has proven effective in identifying diseases in various crops, including tomatoes, rice, potatoes, and apples (Wani, 2022).

doi:10.6342/NTU202401339

CHAPTER 3. MATERIALS AND METHODS

3.1 Experiment Design and Image Dataset Collection

This study includes the following process: (1) Data collection and categorization, , (2) Image data annotation, (3) Leaf disease classification, (4) Infected area detection, and (5) Severity estimation. The program used for training the model was Google Colab, which was equipped with an appropriate graphic processing unit for each study stage.

The dataset includes 1,966 images, including Arabica and Robusta varieties of coffee leaves. Among them, 1,685 Arabica images were from the study conducted by Krohling et al. (2019) with a resolution of 1024 x 2048 pixels. These images are called 'BRACOL Dataset' and were obtained by the researchers using different smartphones (ASUS Zenfone 2, Xiaomi Redmi 5A, Xiaomi S2, Galaxy S8, and iPhone 6S. The images were collected from 2019 to 2023 using digital cameras under controlled conditions. The leaves were gathered throughout the year in Santa Maria of Marechal Floreano, in the Brazilian state of Espirito Santo's mountainous regions. Pictures of the leaves' abaxial (lower) side were taken and set against a white background. On the other hand, 281 images were collected using digital cameras from farm areas in the provinces of Batangas and Cavite, Philippines, and collected in various resolutions and in somewhat controlled conditions and time.

doi:10.6342/NTU202401339

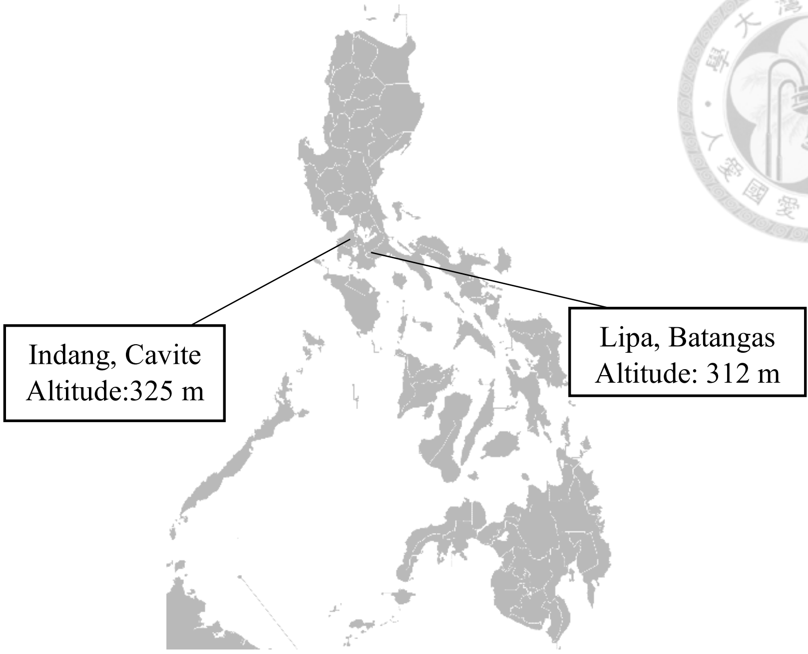


Figure 3.1 Locations where images were collected at and altitudes.

3.2 Dataset Categorization

The BRACOL dataset (Figure 3.2) contains healthy and categorized diseased leaves; meanwhile, the Philippine dataset was classified by an agricultural expert in Taiwan according to their leaf disease status: Healthy, Miner, Phoma, Cercospora, and Rust, with its corresponding quantities (Table 3.1). Other photos, such as algal, scale, and sun scald, are not included in image labeling and processing. The final categorized dataset used for the study contains a total of 1,086 images according to their health status: 136 Healthy, 290 Miner images, 264 Phoma images, 396 Cercospora images, and 396 rust images. It was split for training and testing for each study stage at 80:20. These images include the BRACOL dataset (Krohling, 2019) and the Philippine dataset. The Philippine dataset (Figure 3.3) was reduced to a smaller size by discarding irrelevant disease types for the study.

doi:10.6342/NTU202401339

Table 3.1 Image dataset used for the study.

Class	Dataset		Image Number
	BRACOL	Philippines	
a) Cercospora	115	21	396
b) Miner	290	-	290
c) Rust	386	10	396
d) Phoma	264	-	264
TOTAL			1,086

(a)
(b)
(c)
(d)

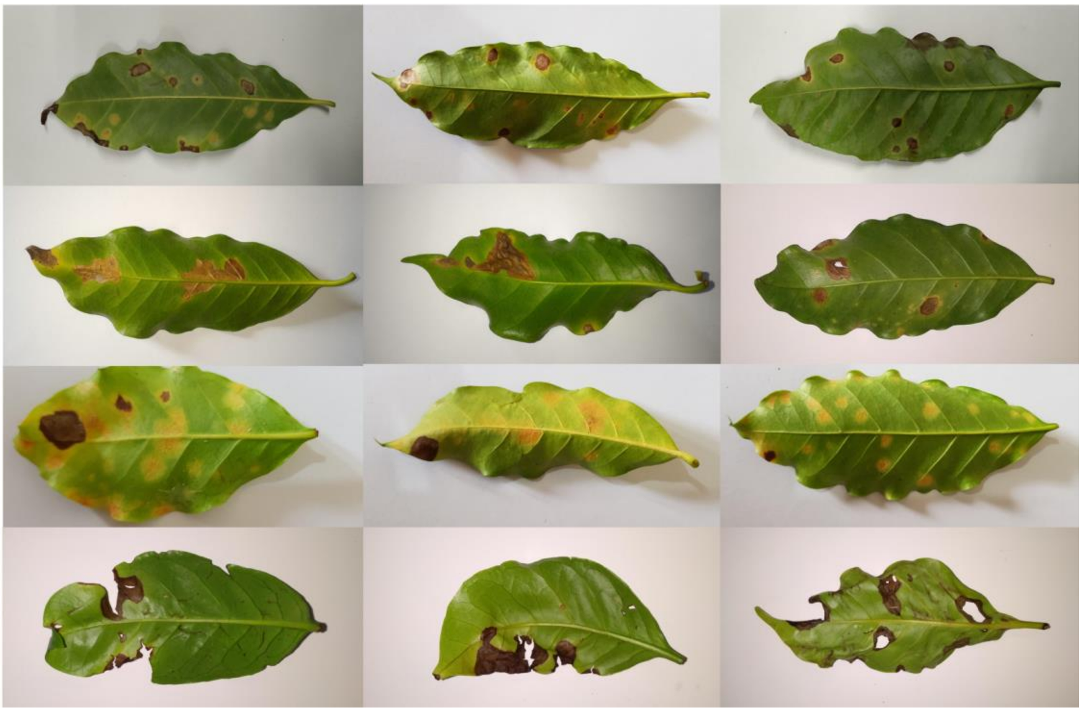


Figure 3.2 BRACOL Dataset Samples (a) Cercospora (b) Miner (c) Rust (d) Phoma.

(a) (b)

Figure 3.3 Philippines' Dataset Samples (a) Cercospora (b) Rust.

doi:10.6342/NTU202401339

3.3 YOLO Architecture

The YOLO (You Only Look Once) model, a basic convolutional network, holds great potential for object detection. It predicts multiple bounding boxes and class probabilities for objects in images, training on full images and directly optimizing detection performance. After 24 convolutional layers, the detection network includes two fully connected layers. The feature space from previous layers is reduced by alternating 1 × 1 convolutional layers. The convolutional layers were initially trained at half the resolution for the ImageNet classification task and then doubled for detection. YOLO's speed is impressive, outperforming other real-time systems in average precision. Unlike sliding window and region proposal-based techniques, YOLO analyzes the dataset during both training and test time, providing helpful information about the image and the classes.

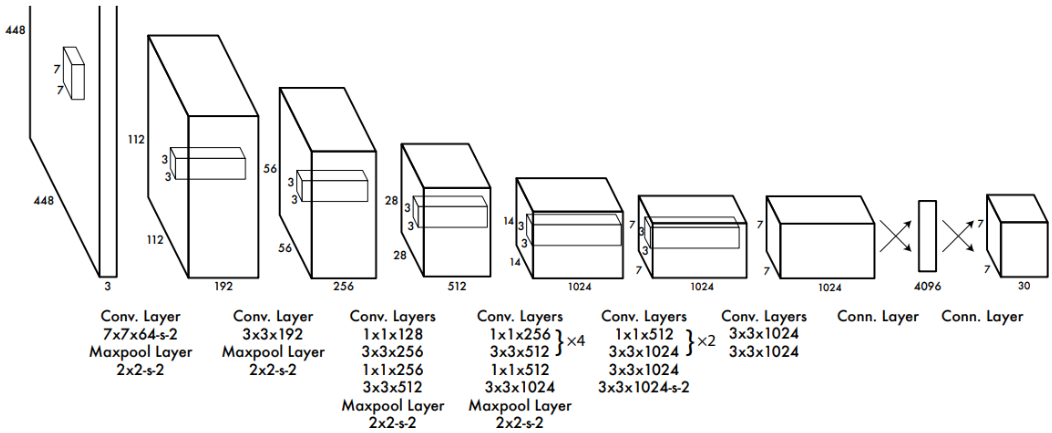


Figure 3.4 YOLO Architecture (Redmon, 2016).

doi:10.6342/NTU202401339

This study will evaluate three models, YOLOv7, YOLOv8, and YOLOv9, based on their performance. YOLOv7 introduces a re-parameterized model, dynamic label assignment, and extended and compound scaling methods for real-time object detection. This reduces parameters and computation, resulting in faster inference speed and higher detection accuracy. YOLOv8 utilizes advanced architectures for enhanced feature extraction and object detection, offering a diverse range of models specizlized for specific tasks, with an anchor-free split ultralytics head for accuracy and efficiency, suitable for real-time tasks. Lastly, YOLOv9 enhances real-time object detection by integrating Programmable Gradient Information (PGI) and the Generalized Efficient Layer Aggregation Network (GELAN) architecture, overcoming information loss challenges in deep neural networks and ensuring accurate and efficient detection.

3.4 Annotation of the Whole Leaf

Each image was segmented to contain one disease type, such as cercospora, miner, rust, and phoma. The data was processed using Labelme 5.4.1 software through the Anaconda Navigator 2.4.0 platform. Each image was annotated with a polygon outlining and contouring the whole leaf. The annotated leaf was labeled with the appropriate disease type.

Figure 3.5 Annotated whole leaf.

doi:10.6342/NTU202401339

3.5 Annotation of Lesions

After annotating the whole leaf, the lesions were also annotated through the polygon method using the same program, Labelme 5.4.1 and Anaconda Navigator 2.4.0, and saved with different file names in JSON format. These lesions are extracted as the regions of interest (ROI) of the model in which deep learning methods will be applied. The infected regions were labeled as 'lesions'. These infected regions are regions with colors from yellow to brown to black color, resembling the lesions in the entire leaf.

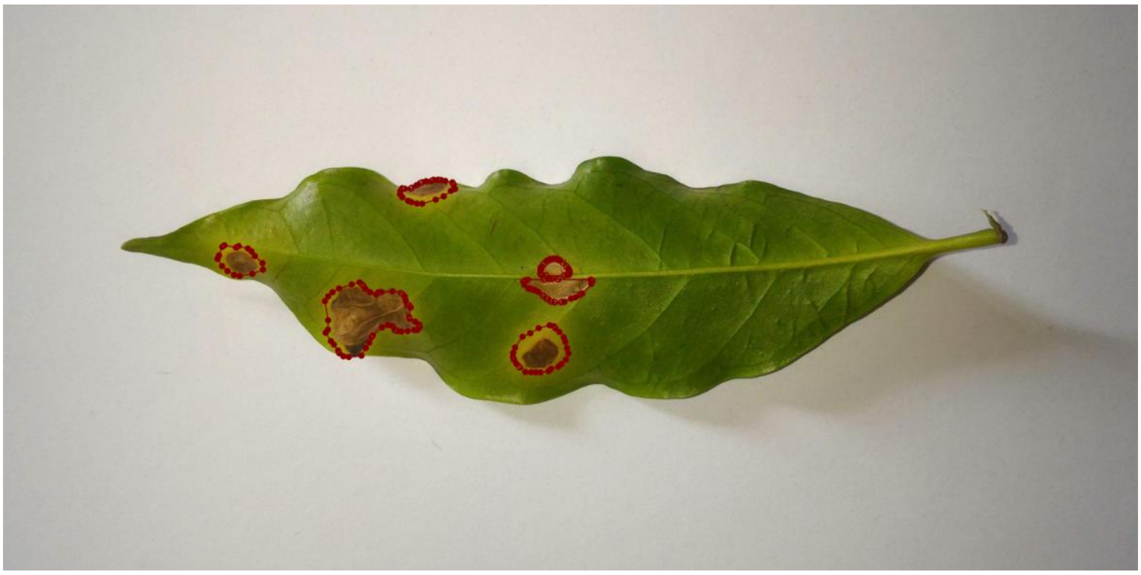


Figure 3.6 Annotated lesions.

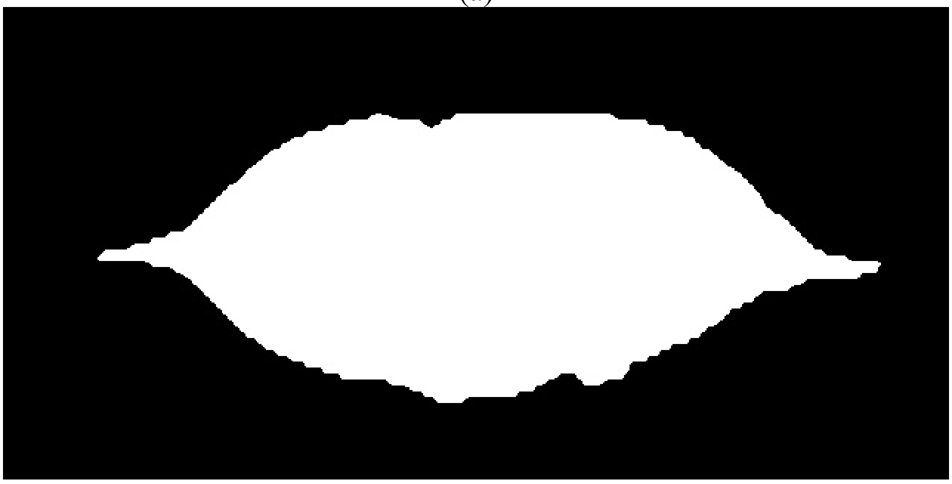
3.6 Severity Estimation

Severity estimation can be done after annotating the whole leaf and the lesions. The trained model, YOLOv8, was used for this process after careful consideration of the whole leaf identification process. The whole leaf and lesions were predicted using the trained models. The whole leaf and regions were transformed into masks and turned into a binary image to calculate the covered pixels, which calculated the severity. To calculate the severity of a leaf, Eq. 3.1 is used.

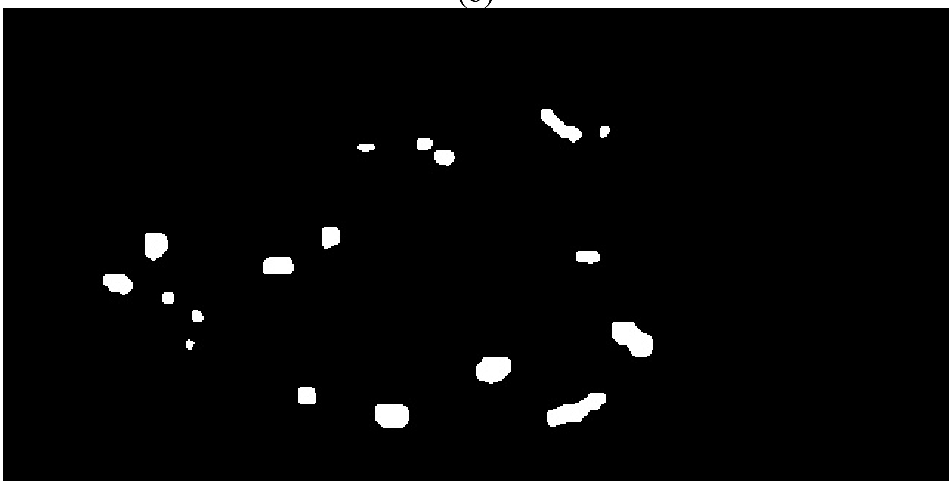
doi:10.6342/NTU202401339

$$\text{Severity} = \frac{lesions}{leaf\_area} \times 100 \quad (3.1)$$

(a)



(b)



(c)

Figure 3.7 Images for calculating severity estimation (a) original image (b) binary mask of a leaf (c) binary mask of lesions.

doi:10.6342/NTU202401339

3.6 Evaluation Metrics

Evaluation metrics are essential for assessing the study's object detection model in terms of the effectiveness and accuracy of the YOLO model. They provide insights into how our designed model can locate, detect, and identify the coffee leaves in the image dataset. They also facilitate understanding how the model handles true positives, false positives, and false negatives. The following information is used in this study.

(1) Intersection over Union (IoU) metric quantifies how much a predicted bounding box and a ground-truth bounding box overlap. It is essential to assess the accuracy of object localization. The calculation is shown in Equation 3.2.

$$IoU = \frac{Area\ of\ Intersection}{Area\ of\ Union} \tag{3.2}$$

(2) Precision and Recall: These two metrics are crucial in evaluating the performance of object detection models. Precision measures the model's ability to avoid false positives, while Recall assesses its ability to detect all instances of a class. Understanding these metrics is key to improving model performance. The calculation for precision and recall is shown in Equations 3.3 and 3.4.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{3.3}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{3.4}$$

doi:10.6342/NTU202401339

(3) Average Precision (AP) represents a model's precision and recall performance. It is calculated by calculating the area under the precision-recall curve (AUC), which aids in classification problems as it illustrates the balance between recall and precision at different threshold values. When the mean of the sample is involved, Mean Average Precision (mAP) is a concept that builds upon AP by averaging AP values from various object classes. This thoroughly assesses the model's performance, which is beneficial information for multi-class object detection. The mAP50 (mean Average Precision at a specific IoU threshold of 0.50) calculates the model's accuracy on 'easy' ones, while mAP50-95 (mean Average Precision at thresholds from 0.50 to 0.95) provides a comprehensive result of the model's performance through 'difficult' detections.

doi:10.6342/NTU202401339

CHAPTER 4. RESULTS AND DISCUSSION

4.1 Leaf Disease Identification

4.1.1 Comparison of YOLO Models

Three YOLO models' performances were evaluated after the training epoch. The evaluation of the YOLO models is based on several key metrics (mAP50, stability, training loss, visual observations, and inference speed). Each YOLO model was trained until it reached a stable level of mAP and training loss while considering the training time. The train loss indicates the model's ability to learn and generalize is consistently low and stable in YOLOv7, with a high mAP50 at 0.941 after initial epochs (Fig. 4.1a). However, the low losses may indicate issues in loss calculations, while the high mAP50 suggests good precision in detecting and identifying coffee leaves. For YOLOv8, the training loss decreases and stabilizes at a low value (Fig. 4.1b). The training loss in this model shows good convergence after 100 epochs, indicating effective learning and generalization. The mAP50 in this model remains high and relatively stable at 0.942 in YOLOv8, indicating good and relatively consistent precision in predictions. This suggests good model performance with reasonable convergence of training loss values. Lastly, the training loss in YOLOv9 also decreases and stabilizes at a low value (Fig. 4.1c). The mAP50 at 0.950 of YOLOv9 indicates slightly higher precision than YOLOv8; however, it has more fluctuations and is less stable than YOLOv8.

Based on the analyses, YOLOv8 is the best-performing model out of the three. It has good and converging training parameters, mAP50, and visual observations (Fig. 4.2). Moreover, the visual observations (Fig. 4.2) indicate that YOLOv8's inference speed of 4.5ms is the fastest among the three models for predictions. Thus, based on the provided metrics, YOLOv8 is the top-performing model, displaying more stable curves in mAP50 and training loss, indicating a good fit for the training data and visual observations.

doi:10.6342/NTU202401339

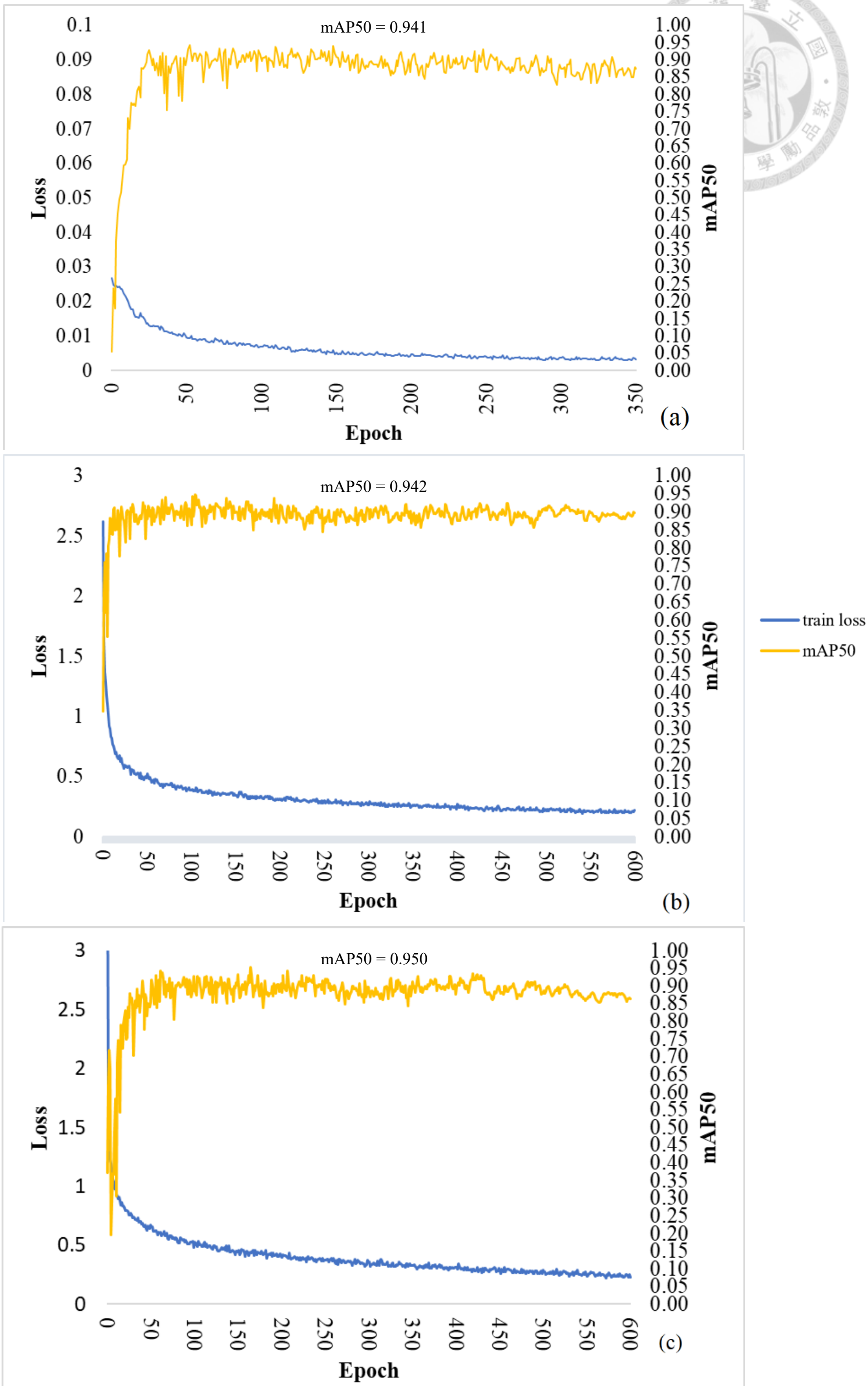


Figure 4.1 Training performance of YOLO Models
(a) YOLOv7 (b) YOLOv8 (c) YOLOv9.

doi:10.6342/NTU202401339

(a)

(b)

(c)

Figure 4.2 Whole leaf classification of YOLO models
(a)YOLOv7 (b)YOLOv8 (c)YOLOv9.

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4.1.2 Performance of YOLOv8 for Whole Leaf Identification

The normalized confusion matrix for the YOLOv8 machine learning model predicts several classes: Phoma, Miner, Rust and Cerscopora. The model's performance is notable in its ability to accurately identify Phoma, Miner, and Rust with a high true positive rate (Fig. 4.3). On the other hand, Cercopora exhibits a lower true positive rate, suggesting that the model struggles more with correctly identifying Cercospora due to few similar symptoms with other disease types.

PREDICTED \ TRUE	Phoma	Miner	Rust	Cercospora
Phoma	0.96	0.02		0.05
Miner	0.04	0.97	0.01	0.11
Rust			0.96	0.16
Cercospora		0.02	0.02	0.63

Figure 4.3 Confusion matrix for YOLOv8 whole leaf identification.

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The model's performance in identifying and categorizing plant diseases on an entire leaf is assessed in the study. The model can accurately detect four types of diseases: Phoma, Cercospora, Miner, and Rust (Fig. 4.4). The model's efficacy, precision, and recall are being used to analyze the performance of the model (Table 4.1). With an overall precision of 0.907, the model correctly identifies diseases in over 90% of cases. Additionally, its recall rate of 0.887 indicates a high level of accuracy in identifying diseases at a time. The model's performance varies depending on the type of disease. Phoma is the easiest to detect because its distinct brown color originates from the tip (Fig. 4.4a), resulting in a high precision and recall rate. On the other hand, Cercospora is more challenging to classify, with a precision rate of 0.825 and a mAP50 score of 0.632. Cercospora's symptoms are also brown in color, with a bright halo around them (Novtahaning, 2022). Therefore, the model may struggle to identify Cercospora in some cases, possibly due to the complexity of the images in the additional Philippine Dataset (Fig. 4.4d).

Table 4.1 Average Precision of YOLOv8 for whole leaf disease identification.

Class	Precision	Recall	mAP50
Phoma	0.973	0.963	0.993
Miner	0.888	0.983	0.984
Rust	0.942	0.972	0.988
Cercospora	0.825	0.632	0.803
All Classes	0.907	0.887	0.942

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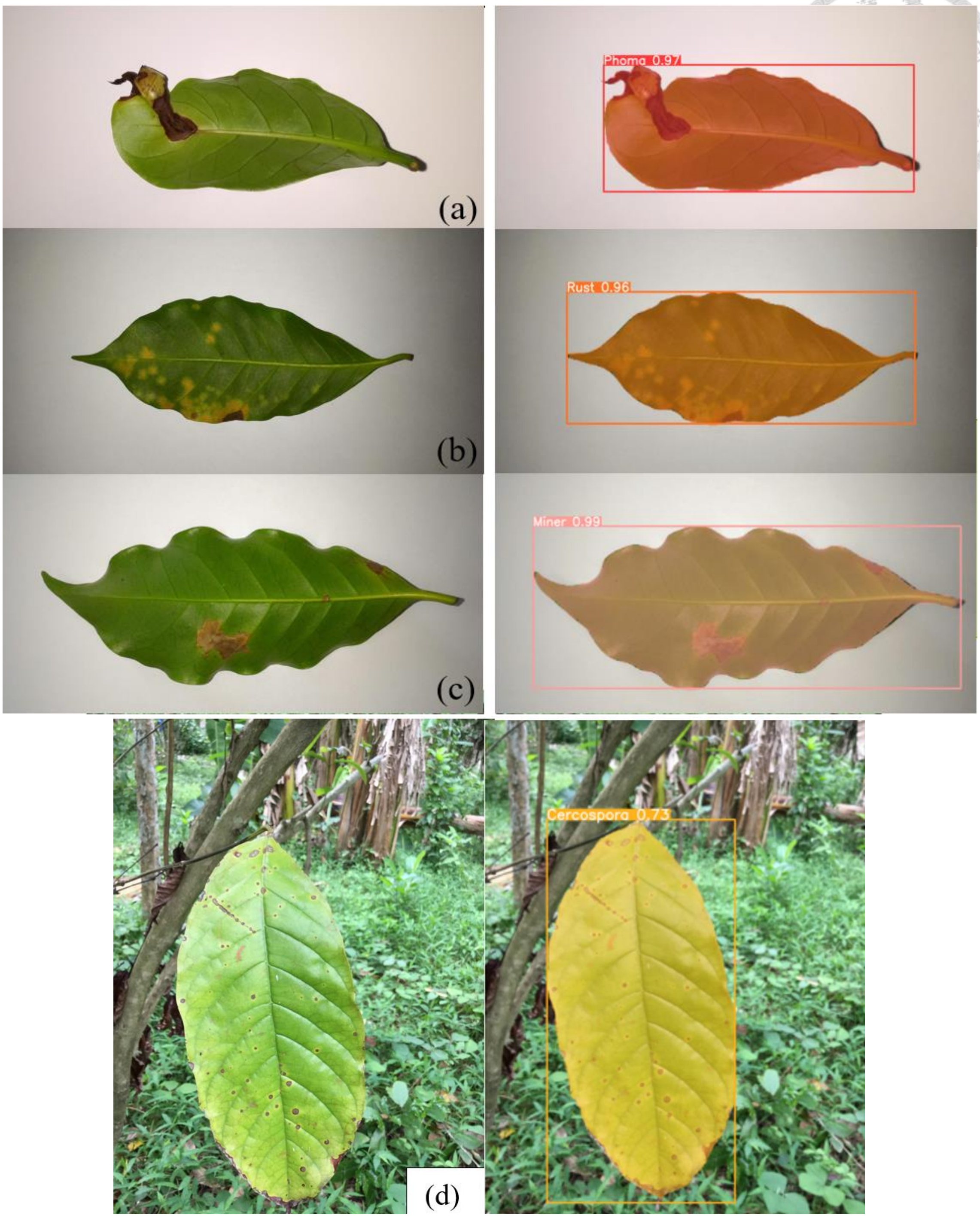

Figure 4.4 YOLOv8 model for coffee leaf diseases
(a) Phoma (b) Rust (c) Miner (d) Philippines' Cercospora.

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4.2 Lesions Segmentation

4.2.1 Training of YOLO v8 for Lesions

The training loss for the model YOLOv8 exhibits a sharp decline in the initial epochs, indicative of rapid learning (Fig. 4.5). Subsequently, the rate of decrease slows down, leading to a more gradual descent. This consistent downward trend suggests effective learning. After 100 epochs, the training loss stabilizes at a lower value, signifying that the model has reached a point of relative stability and optimized performance. On the other hand, the mAP50 for YOLOv8 also experienced a lower value at the start and increased as training progressed. After the initial gains, the line stays comparatively steady, ending at 0.674, indicating a moderate degree of prediction accuracy attained by the model. The training seems stable, as indicated by the relative smoothness of both lines.

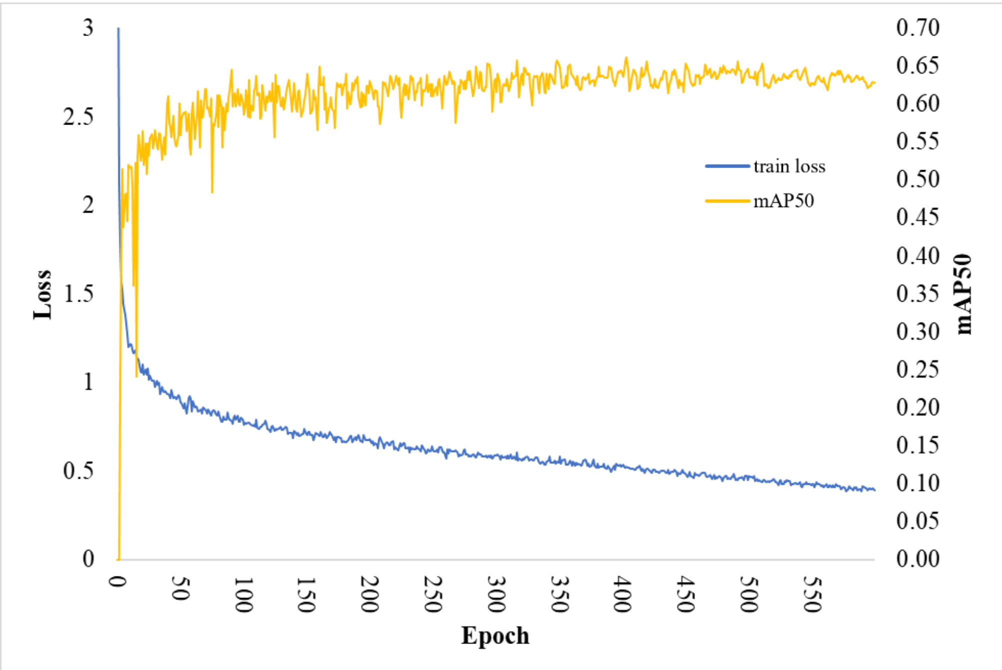

Figure 4.5 Training of YOLOv8 for lesions.

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4.2.2 YOLOv8 at Different Confidence Thresholds with IoU=0.5

The performance of YOLOv8 model through its precision, recall, mAP50, and mAP50-95 is evaluated (Table 4.2). The model for detecting leaf lesions shows that the model's performance fluctuates with the changes in the confidence rate from 0.1 to 0.9. As per the results, the highest precision and mAP50-95 scores are recorded at the confidence rate of 0.9, with values of 0.990 and 0.456, respectively. At this confidence rate of 0.9, the recall and mAP50 scores are the lowest, with values of 0.0875 and 0.539, respectively. These findings indicate that the model can precisely detect the lesions at a higher confidence threshold but may result in lower recall. The same relationship was observed at a 0.1 threshold, where the highest recall and mAP50 were obtained.

Table 4.2 Performance of YOLOv8 for lesions segmentation.

Confidence threshold	Precision	Recall	mAP50	mAP50-95
0.1	0.696	0.574	0.674	0.375
0.2	0.711	0.565	0.673	0.381
0.3	0.733	0.548	0.672	0.387
0.4	0.765	0.518	0.668	0.391
0.5	0.806	0.495	0.669	0.396
0.6	0.841	0.45	0.66	0.403
0.7	0.886	0.387	0.646	0.412
0.8	0.957	0.261	0.611	0.435
0.9	0.990	0.0875	0.53	0.456

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4.2.3 Model Performance of YOLOv8 for Lesions

The model's performance at a specific confidence threshold of 0.1 shows decent precision and recall values for mask predictions, indicating a reasonably balanced performance in accuracy and completeness (Table 4.3). The mAP50 value is moderately high, at 0.674, suggesting that the model can effectively makes predictions at a 50% IoU threshold. The lower mAP50-95 value suggests that the model's performance decreases when stricter IoU thresholds are applied, indicating room for improvement in making highly accurate predictions.

Table 4.3 Evaluation performance of YOLOv8 at 0.1 confidence threshold.

Confidence Threshold	Precision	Recall	mAP50	mAP50-95
0.1	0.696	0.574	0.674	0.375

The YOLOv8 identifies and locates lesions within an image (Fig. 4.6). Detecting these infected areas is crucial for accurately determining the severity of the disease and calculating the affected area's pixel coverage. The model can yield more precise results by accurately detecting and analyzing these infected areas, which can, in turn, aid in diagnosing the disease more effectively.

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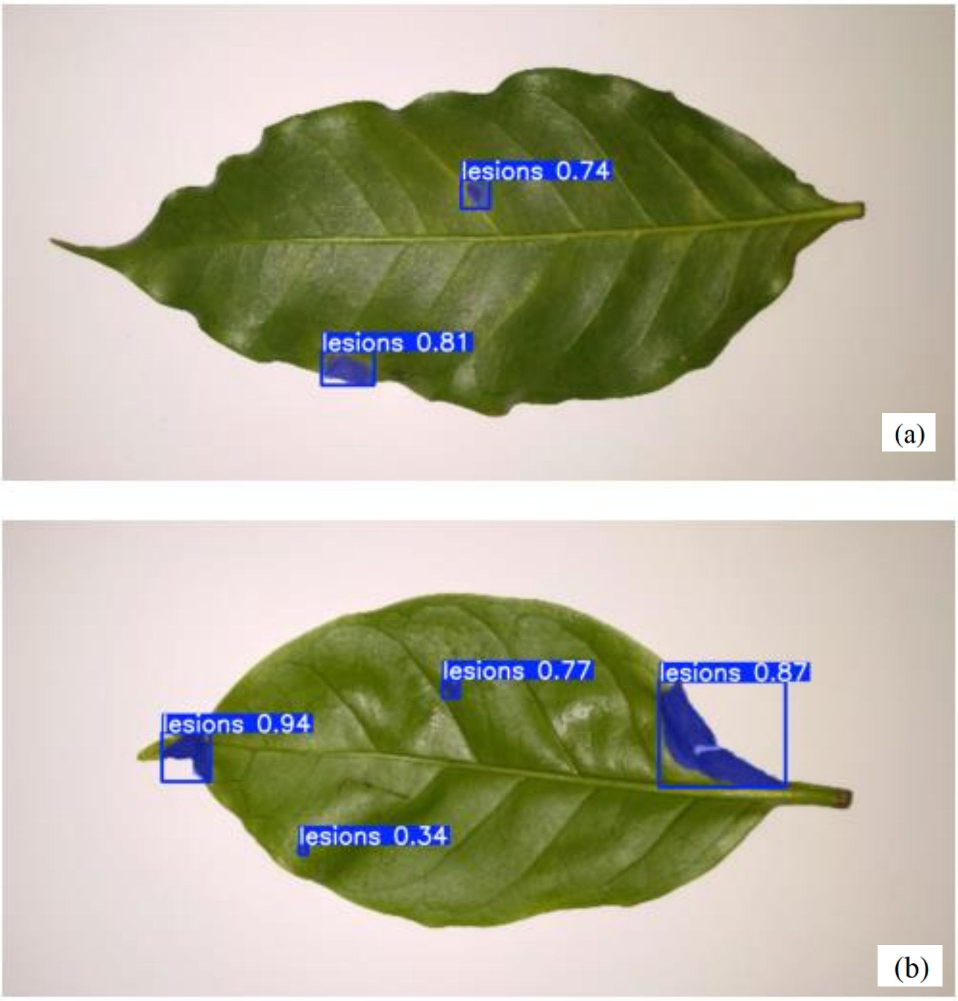

Figure 4.6 Sample image for lesion segmentation and detection for YOLOv8
(a) 2 infected areas (b) 4 infected areas.

4.2.4 Misclassified Regions and Images

The model is used to detect areas that may not be on the same leaf but could still be included in predictions because they share a similar color with the true infected area (refer to Fig. 4.7). These detected infected areas could exhibit color characteristics similar to symptoms of Phoma, Cercospora, Rust, and Miner, thus making them important to identify. The model may predict other infected areas in the image, but this may not be very useful as it can only calculate the severity for one leaf at a time. This limitation underscores the need to carefully interpret the model's predictions and further assess the entire plant when determining the extent of infection.

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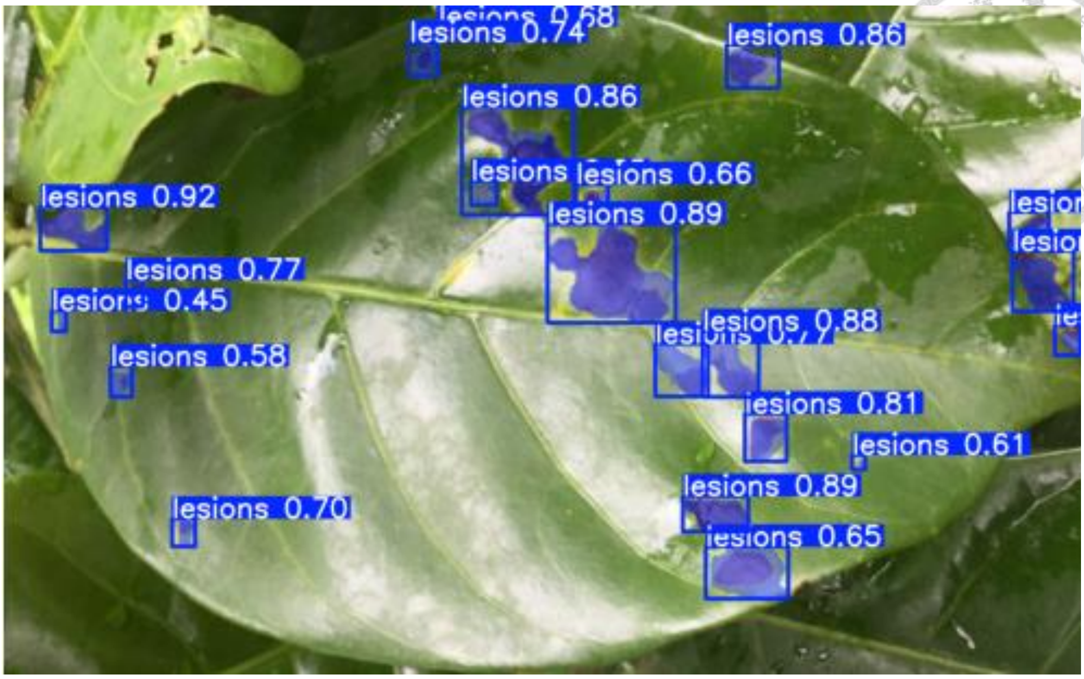
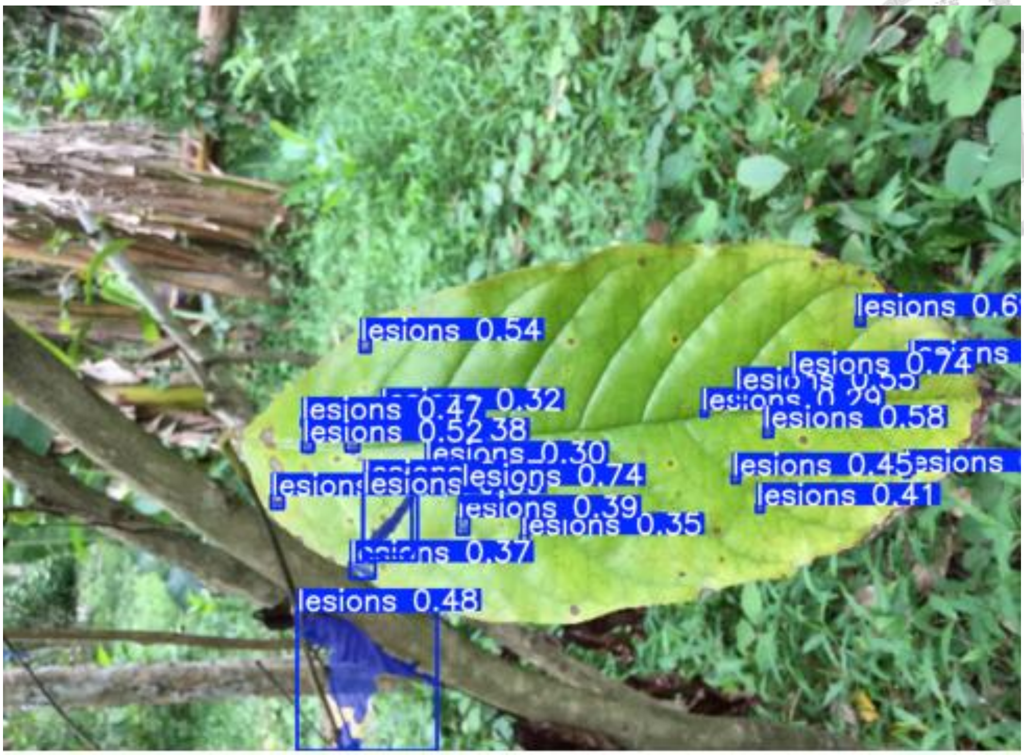


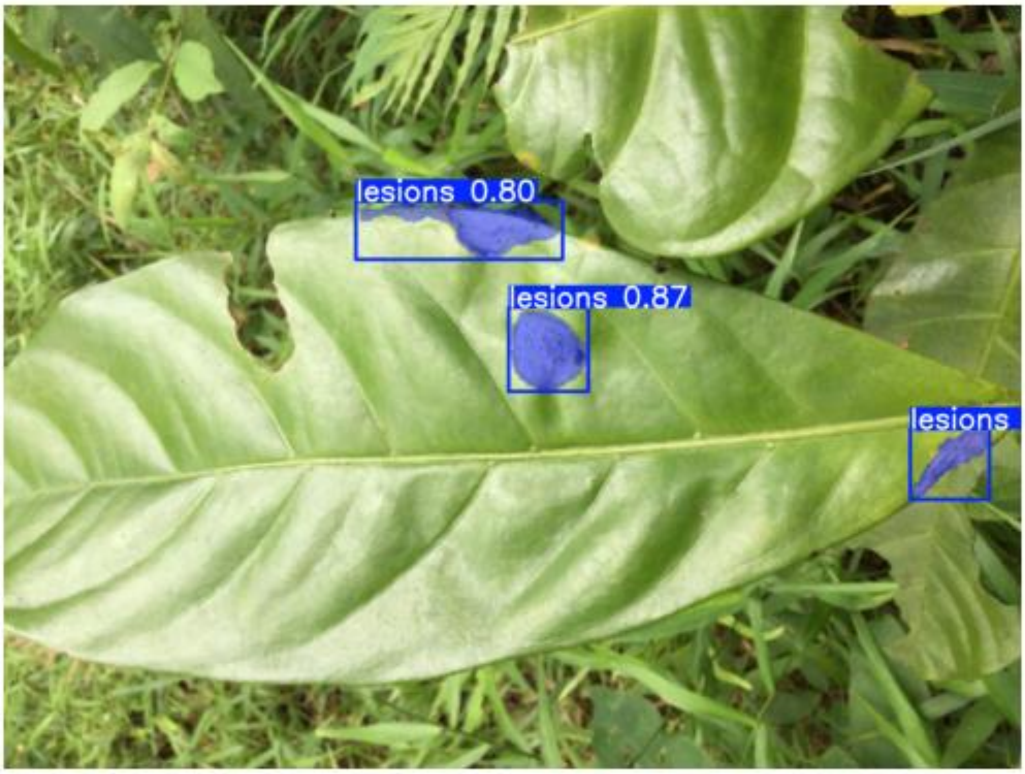
Figure 4.7 Image with misclassified regions for lesions.

It is clear that the use of a low-resolution image in the model can significantly impair lesion detection and severity estimation (see Fig. 4.8a) compared to the use of a high-resolution image (see Fig. 4.8b). This can lead to inconsistencies and underperformance of the model. Moreover, when using in-field images, the model may effectively disregard and exclude the soil and its background in relation to its trained 'lesions' (see Fig. 4.8). This can result in a decrease in the accuracy of lesion detection and severity estimation, as low-resolution images may not capture the details needed for accurate analysis. Additionally, the model's inability to account for the surrounding soil and background may lead to misinterpretations and false positives, impacting the overall effectiveness of the model in real-world applications. Therefore, it is of utmost importance to consider the resolution and context of the images used in the model to ensure accurate and reliable results, especially when dealing with in-field images where environmental factors can significantly influence the appearance of lesions.

doi:10.6342/NTU202401339



(a)



(b)

Figure 4.8 In-field image for testing lesions
(a) Low-resolution (b) High-resolution.

doi:10.6342/NTU202401339

4.3 Severity Estimation

The performance of the severity estimation from the two models is assessed using the accuracy equation (Eq 4.1), which evaluates the performance of the two-trained model. The ground truth is established by counting the actual pixels from the binary image created by generating the models' masks.

$$Accuracy = \frac{Predicted\ pixels}{Actual\ Pixels} \times 100 \quad (4.1)$$

An evaluation was conducted on twenty images of each disease type to estimate their severity by calculating the pixels in the image (Table 4.4). The model's accuracy was then determined using a formula for accuracy calculation. The average severity of Phoma, Rust, Cercospora, and Miner was calculated to determine the accuracy of the two models built together, which was found to be 78.55%. This indicates that the model performs well when tested on images of coffee leaves. The diseases Rust and Cercospora showed lower performance due to undetermined boundaries in their symptoms, in contrast to Phoma and Miner, which demonstrated a good limit determination of symptoms.

Table 4.4 Accuracy of the two-trained model for severity estimation.

Disease Type	**Phoma**	**Rust**	**Cercospora**	**Miner**	**All**
Accuracy (%)	83.28	69.37	70.88	90.67	78.55%

The model has demonstrated exceptional detection accuracy, achieving high severity estimation for Phoma (Fig. 4.9b) and moderate severity estimation for Cercospora (Fig. 4.9a) and Rust. Furthermore, the high confidence scores assigned to the infected areas indicate the model's strong reliability in identifying regions affected by the diseases. The bounding boxes surrounding the infected areas are accurately placed, highlighting the model's effective localization capability. Additionally, the infected areas'

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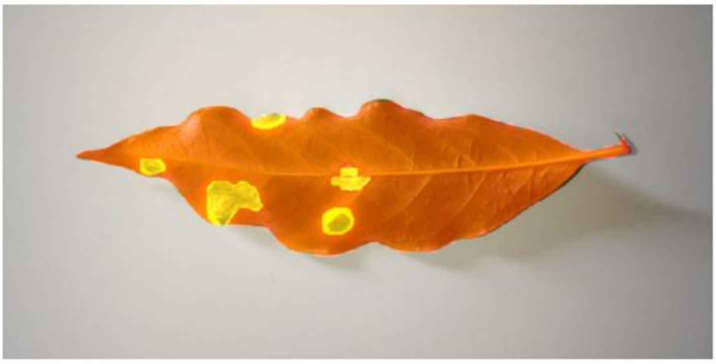
varied confidence scores in the images showcase the model's ability to provide nuanced assessments of infection severity. Its consistent performance across different infections of coffee leaves underscores its robustness and versatility in practical applications.



	Ground Truth (pixels)	Prediction (pixels)	Accuracy (%)
Infected Area	30,680	25,130	
Leaf Area	412,710	392,800	86.13
Severity	7.43%	6.40 %	

(a)

	Ground Truth (pixels)	Prediction (pixels)	Accuracy (%)
Infected Area	38,880	35,460	
Leaf Area	654,780	632,520	94.10
Severity	5.94 %	5.61 %	

(b)

Figure 4.9 Calculating severity estimation through YOLOv8 model
(a) Cercospora (b) Phoma.

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The model's capabilities in identifying and quantifying the severity of infections present on a leaf are crucial for gaining a comprehensive understanding of the leaf's overall health (Fig. 4.10). Through its detailed identification of plant disease type and segmentations of lesions and their provision of high-confidence scores in the two-trained model, the model demonstrates its robustness and accuracy in effectively addressing complex detection tasks. These visual aids, generated by the model, play a pivotal role in enhancing our comprehension of the scope and intensity of infections, thereby enabling informed decision-making for plant health management.

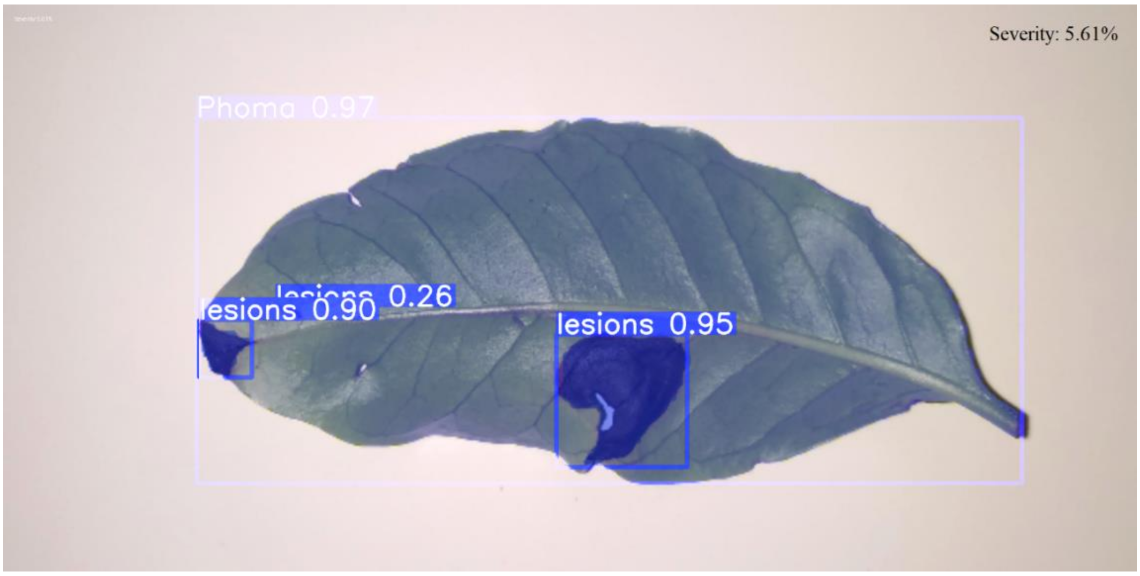

Figure 4.10 Whole leaf and lesions image with severity estimation.

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4.4 Utilizing the Model for Farmers' Applications

The dual-trained model described in this study is a tool that empowers farmers to effectively identify and assess the severity of coffee leaf disease on a single leaf. By utilizing this model, farmers must have access to a high-resolution camera that they can use in the field. It's crucial to capture only one leaf for the assessment, and the disease identification is also limited to just one leaf. Farmers are advised to place a clean piece of paper under the leaf before taking a picture for disease identification and severity assessment to ensure the accurate determination of coffee leaf disease without capturing unnecessary background. This severity assessment method not only aids in preventing the spread of the disease but also supports the overall health management of coffee plants, contributing to sustainable and productive coffee cultivation practices.

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CHAPTER 5. CONCLUSION AND FUTURE WORKS

5.1 Conclusion

The model in the study can detect plant diseases, specifically Phoma, Cercopora, Rust, and Miner, in coffee leaves. Additionally, it can identify the infected area and estimate the severity of the disease. The model's precision and recall values are 0.907 and 0.887, respectively, indicating that it is highly accurate in detecting the presence of disease in the leaves. The detection of the infected area varies across different evaluation metrics, and the model's performance depends on the confidence threshold. The highest precision was achieved at a confidence threshold of 0.9, while a threshold of 0.1 provided the highest recall. Three versions of YOLO were tested to evaluate the model's performance further, and it was found that YOLO v8 was the most suitable for this study's task. Combining two models allows for the calculation of disease severity, with an accuracy of 78.55%. While the model effectively detects plant diseases, it may encounter challenges in low-resolution images and might mistake other leaves for infected ones, affecting the accuracy of the severity estimation. Overall, the model is a promising tool for detecting and estimating the severity of plant diseases, with the potential to assist in the early detection and prevention of crop loss.

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5.2 Future Works

A more comprehensive and diverse dataset is beneficial for advancing studies on coffee leaf diseases and pests. This dataset should encompass various leaf types, infection stages, and environmental conditions to represent the variability of coffee diseases and pests accurately. Additionally, integrating advanced prediction techniques, such as attention mechanisms and advanced evaluation metrics, would greatly benefit the studies. These techniques can enable the model to focus on crucial features, enhancing its detection and classification capabilities and improving model performance.

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