Paradigm of YOLO: Exploring the instant Segmentation process in Lemon leaf disease detection

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This Report Presented in Partial Fulfillment of the Requirements for theDegree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

The paper entitled "Paradigm of YOLO: Exploring the instant Segmentation process in Lemon Leaf Disease detection", presented by Samsuddoha, the ID No: 201-15-3384 to the Department of Computer Science and Engineering, Daffodil International University, has been deemed satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering. It has been approved in terms of its style and contents. The presentation took place in July 2024.

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ABSTRACT

Efficient along with precise identification of plant diseases can significantly enhance agricultural productivity and overall crop yield, particularly for lemon trees and their foliage.[24] Algal Leaf Spot, Black spot, Citrus canker, Citrus pest, Citrus Scab, Dry leaf, Greening, Leaf Curl, and yellow spot are diseases that can significantly impair the health of lemon trees and reduce their fruit yield. These diseases typically develop on the leaves, leading to reduced fruit quality and output, sometimes by more than half.

Convolutional Neural Networks (CNN) have demonstrated promise in the field of lemon tree disease identification.[25] Nevertheless, there is a lack of research specifically focused on the identification of diseases in lemon trees, particularly in regions such as Bangladesh where lemon cultivation is widespread. Previous experiments in this field have primarily based on secondary data, limiting the depth of knowledge and practical application.

In order to fill these knowledge gaps, our research focused on collecting lemon disease leaves from well-known lemon-growing regions, such as Khagan and Ashulia in Bangladesh. I utilized advanced Convolutional Neural Network (CNN) techniques, specifically YOLOv8, to assess its effectiveness in identifying diseases. The trials I conducted highlighted the benefits of YOLOv8 in terms of its speed and accuracy, demonstrating its practicality for identifying diseases in agricultural settings.

Furthermore, our review of current literature uncovered a variety of machine-learning methods applied to publicly available datasets for lemon leaf disease diagnosis. By doing our experiments, I obtained a precision confidence curve score of 1.00, indicating a high level of confidence in the accuracy of our data. Various metrics, including precision, accuracy, and recall, were utilized to examine the performance of the model.

The findings of our research are intended to provide beneficial insights to agricultural authorities and lemon-growing communities, aiding in the creation of successful strategies for lemon disease identification and management via machine learning techniques. By utilizing advanced technology such as Convolutional Neural Networks (CNNs), lemon growers can enhance their capacity to swiftly identify and address illnesses, thereby ensuring the health of lemon trees and maximizing crop yield.

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CHAPTER 1

INTRODCTION

1.1 Overview

Citrus fruits, particularly lemons, are a crucial component of a healthy diet, delivering essential vitamins and antioxidants. However, their production confronts various obstacles, with illnesses providing a substantial danger to crop yields and economic sustainability for farmers. Among these illnesses, many afflictions especially target lemon leaves, greatly hurting the plant's health and fruit output. Early and precise diagnosis of these diseases is critical for implementing early interventions and reducing production losses. Traditional techniques of disease identification in lemon leaves often rely on visual inspection by knowledgeable farmers or agricultural specialists. While this technique offers the advantage of being reasonably affordable and non-invasive, it has drawbacks. Firstly, accurate diagnosis demands experience and qualified personnel, which may not be readily available in all locations or for small-scale farms. Secondly, visual inspection can be subjective and prone to human mistake, particularly in the early phases of illness development when symptoms might be modest. Additionally, traditional approaches are frequently time-consuming, delaying the execution of control measures and potentially allowing the disease to spread further. In recent years, technical breakthroughs have opened avenues for the creation of novel and more efficient technologies for disease detection in agriculture. Precision agriculture, a notion that harnesses technology to collect and analyze data for informed decision-making, has emerged as a promising option. One such technology with enormous potential in this arena is deep learning, a subfield of artificial intelligence (AI) that enables machines to learn from data and make accurate predictions. This research digs into the exploration of a deep learning technique dubbed You Only Look Once (YOLO) for fast segmentation of sick regions in lemon leaves. YOLO is an object detection algorithm noted for its speed and efficiency, making it appropriate for real-time applications. By applying YOLO to the task of segmenting unhealthy areas, I want to build a system that can overcome the limits of previous methodologies and contribute to a more efficient and objective disease detection procedure in lemon production. The following sections of this paper will elaborate on the methods adopted, including the acquisition and annotation of a lemon leaf picture dataset, the training process of the YOLO model, and the assessment criteria used to measure its performance. I will then give the quantitative analysis of the model's performance, comparing it to other commonly used segmentation techniques. Finally, I will evaluate the limitations of the existing technique and suggest potential avenues for further research. Through this investigation, I hope to not only contribute valuable insights into the potential of YOLO for instant segmentation in lemon leaf disease detection but also pave the way for the development of practical tools that can empower farmers and agricultural professionals with efficient and accurate disease detection capabilities, ultimately leading to improved crop health, yield sustainability, and economic benefits.

1.2 Background and Present State

The YOLO (You Only Look Once) paradigm revolutionized object detection in computer vision by giving a single neural network that predicts bounding boxes and class probabilities directly from complete images in real-time. However, applying this paradigm directly to the detection and categorization of lemon leaf illnesses contains various crucial concerns and issues.

Background on YOLO

YOLO is famous for its speed and ability to make predictions with a single forward pass over the network, making it excellent for real-time applications. The network divides the input image into a grid and predicts bounding boxes and class probabilities for each grid cell. This approach promises that YOLO can detect several objects in a single pass efficiently.

Applying YOLO to Lemon Leaf Disease Detection
Detecting illnesses on lemon leaves with YOLO takes multiple steps:

1. Dataset Collection and Annotation:

   First, a complete dataset of lemon leaf photos with various diseases (such as citrus canker, greasy spot, citrus black spot) needs to be collected and annotated. Annotations often entail putting bounding boxes around each affected area and naming it with the associated disease category.

2. Model Training:

   Once the dataset is prepared, the YOLO model needs to be trained using these annotated images. Training comprises loading the dataset into the YOLO network, adjusting the model's weights via backpropagation, and enhancing its capacity to accurately detect and categorize lemon leaf infections.

3. Model Evaluation and Fine-Tuning:

   After training, the model's performance needs to be evaluated using a separate test set of lemon leaf images that the model has not seen previously. Metrics including as precision, recall, and mean Average Precision (mAP) are often used to examine the model's accuracy and performance.
   Fine-tuning may be needed to boost the model's performance, such as adjusting hyperparameters, collecting more diverse data, or employing data augmentation techniques.

Present State

The current condition of utilizing YOLO to lemon leaf disease detection certainly faces numerous challenges:

- Dataset Quality and Quantity: Availability of a large and diversified dataset that adequately captures all types of lemon leaf diseases is vital. Limited or biased datasets can impact the model's capacity to generalize to new and unseen examples.

- Detection Accuracy: Ensuring high accuracy in illness detection is crucial. The model must distinguish between healthy and unhealthy leaf areas accurately, even in variable lighting conditions and angles.

- Real-World Deployment: Transitioning from controlled training environments to real-world situations brings obstacles such as fluctuation in lighting, leaf orientation, and background clutter.

- Interpretability: Understanding how the model generates decisions (interpretable AI) is vital for its practical implementation, especially in agricultural contexts where decisions based on model outputs need to be explainable and actionable.

1.3 Problem Statement

Most Of the People or lemon famers Of Our County are not aware lemon leaf Diseases. Additionally, they demonstrate a lack of motivation to begin any steps during the earliest phases of the sickness. In addition, it is tough to detect the specific state that the lemon leaf possesses. Consequently, lemon farmers are unable to perform the essential measures. There are several ailments of lemon leaves, one of them is Algal Leaf Spot, Black spot, Citrus canker, Citrus Scab, Dry leaf and more. These infections are highly dangerous since they limit the growth of lemon very quickly and damage the lemon as with the tree. So, if I provide a clear mechanism to detect these diseases it will be extremely helpful for the farmers and the induvial population. Identifying these illnesses provides a huge problem. That’s why, I am working on nine types of lemon leaf infection. Object identification has been a fundamental difficulty in computer vision, with deep learning algorithms playing a crucial role in boosting object recognition tasks. Researchers have widely explored and contributed to boosting the performance of object detectors, including object categorization, localization, and segmentation, using deep learning models. Object detectors are commonly categorized into two groups: two-stage and single-stage object detectors. Two-stage detectors frequently rely on sophisticated structures for selective area recommendations, while single-stage detectors employ simpler architectures for the simultaneous detection of things. Although two-stage detectors frequently demonstrate greater detection accuracy, single-stage detectors offer faster inference times. The advent of YOLO (You Only Look Once) and its variations has resulted to extraordinary advances in detection accuracy, frequently approaching that of two-stage detectors. YOLOs are commonly employed in numerous applications thanks to their rapid inference capabilities. For instance, whereas YOLO gets a detection accuracy of 63.4, Fast-RCNN obtains 70, although YOLO's inference time is over 300 times faster. This study gives a complete overview of single-stage object detectors, notably YOLOs, covering regression formulation, architectural alterations, and performance data. Additionally, it covers the comparative study between two-stage and single-stage object detectors, distinct kinds of YOLOs, applications based on two-stage detectors, and different variants of YOLOs, along with defining future research objectives.

In recent years, object detection has evolved substantially, particularly in processing difficult pictures such as X-ray images. However, extending existing feature extraction networks intended for traditional images to X-ray images remains hard due to their unique features. Researchers have examined numerous approaches, including attention processes and multiscale feature fusion, to improve feature extraction in X-ray photos. Despite development, issues such as item overlap and backdrop clutter persist. Inspired by the design idea of DOAM and its modules for increased edge detection and material awareness, fresh approaches such as edge and material feature extractors have been created to boost feature extraction from X-ray photos. Additionally, techniques like Soft-WIoU NMS have been employed to tackle issues such as overlapping occlusion in object detection findings.

The goal of this project is to construct a credible model for the early identification of lemon leaf disease, crucial for maintaining lemon quality and sustaining agricultural productivity. However, illness detection and segmentation are hard due to the intricate nature of diseases affecting lemon leaves. YOLOv8 delivers automated plant disease categorization and detection, allowing smart agricultural approaches. However, accurate identification and classification are challenged by the heterogeneous nature of visual data and noise in photographs, limiting classification accuracy. Additionally, considerable data collecting is necessary for accurate detection. Key ailments impacting lemon farming, such as citrus canker and black spot disease, indicate the importance of prevention and control for crop yield. The fundamental goal of this experiment was to design a tool leveraging the YOLO algorithm to diagnose lemon leaf disorders, aiding in effective disease control and preserving lemon yield.

1.4 Objectives:

The fundamental purpose of this research project is to develop a mechanism enabling individuals to independently identify diseases affecting lemon leaves. Detecting and detecting lemon leaf diseases is vital for effective disease control and sustaining the health of citrus trees. Similar to lemon leaf illnesses, diagnosing individual lemon leaf diseases can be problematic due to their similarity in look and characteristics.

To overcome this difficulty, I am researching the use of You only look once (YOLO) to accurately detect lemon leaf illnesses. YOLO are advanced deep learning object detection models noted for their performance in image identification applications. By integrating YOLO technology, our goal is to dramatically boost the accuracy of disease identification on lemon leaves. There are:

1. Algal Leaf Spot
2. Black spot
3. Citrus canker
4. Citrus pest
5. Citrus Scab
6. Dry leaf
7. Leaf Curl
8. Yellow spot
9. Healthy Leaf

Each category indicates a specific situation that can harm lemon trees, including major diseases and a category for healthy leaves as a reference point.

Through this research, I seek to empower citrus growers and researchers with a dependable tool for early disease diagnosis and rapid response, ultimately contributing to enhanced citrus tree health and crop output sustainability.

1.5 Scope and Limitations

lemon leaf disease detection, exploring the idea of YOLO (You Only Look Once) for instant segmentation is a substantial leap in computer vision and deep learning approaches. YOLO is recognized for its real-time object identification skills, which can be modified to rapidly identify and segment lemon leaf diseases from photos. Here's how this paradigm might be researched and utilized within the framework of a research paper:

1. Instant Segmentation with YOLO:

   - YOLO is designed to recognize objects in photos in real-time with a single transit across the network. This speed and efficiency are vital for applications where quick decision-making is essential, such as in agricultural settings where timely disease identification can minimize crop losses.
   - Unlike traditional segmentation approaches that may require numerous phases or sophisticated post-processing, YOLO provides a simplified approach by instantly predicting bounding boxes and class probabilities for items in an image.

2. Adaptation to Lemon Leaf Disease Detection:

    - Lemon leaf diseases exhibit unique visual characteristics such as yellowing, patches, or lesions. YOLO may be trained to recognize certain disease patterns by annotating photographs with bounding boxes around diseased areas and labeling them accordingly (e.g., Citrus Canker, Citrus Scab, Citrus Black Spot).
    - By training a YOLO model on a collection of annotated lemon leaf photos, the algorithm learns to recognize and separate these diseases in real-time. This capacity provides for quick assessment of disease frequency across big citrus orchards or individual trees.

3. Integration with Agricultural Practices:

    - Implementing YOLO-based rapid segmentation in lemon leaf disease diagnosis can transform agricultural operations by providing farmers and researchers with a valuable tool for monitoring plant health. Early detection of illnesses permits prompt intervention techniques, such as targeted pesticide spraying or trimming affected branches, to minimize the spread and effect of diseases.
    - The integration of YOLO into automated or semi-automated systems for disease monitoring can optimize resource allocation and increase overall crop management efficiency.

4. Research Paper Scope:

A research article examining the application of YOLO for instant segmentation in lemon leaf disease diagnosis would normally cover:

- Introduction to the topic of citrus disease detection and the relevance of early identification.
- Overview of YOLO architecture and its advantages in real-time object detection.
- Methodology showing how YOLO was converted and trained for lemon leaf disease diagnosis, including dataset preparation, model training, and assessment metrics.
- Results and performance analysis, comparing YOLO-based detection with standard approaches in terms of accuracy, speed, and practical application.
- Discussion on the relevance of the findings for agriculture, prospective improvements, and future research objectives.
- In conclusion, researching the paradigm of YOLO for fast segmentation in lemon leaf disease diagnosis represents a cutting-edge use of deep learning technology with tremendous potential to boost agricultural productivity and sustainability.

Our study has some limitations. That’s are, in data gathering area, dataset, pre-learning and technologies.

- Data collection area

I had collected our data from a certain place in (Bangladesh). But the illnesses are not similar of every plant if it’s cultivated in various place in the world.

- Dataset

My dataset has only 4155 photos. So, it is not enough for detect everything. A plant has also various diseases in other sections of plant, that’s are not included in my dataset.

- Pre-learning

I have read a few numbers of paper that’s are written by the other authors. So, a small study is nit proper to gain every type of knowledge.
Technologies I have employed only one technology for our research, So, in hare I have a significant research gap that I have used only one technology.

YOLO performance can be subject to hyperparameter tampering. Future studies should look into automated hyperparameter search methods to speed up this procedure. Second, YOLO are less accessible to researchers with minimal resources thanks to the large computational resources needed for training them. To overcome this difficulty, efficient training approaches, model distillation, or pre-trained models that have been improved on smaller datasets should be investigated. Third, while YOLO are good at capturing long-range dependencies, they might not be as powerful at addressing micro and local elements in images. Fourth, I have leveraged publicly available secondary dataset in our research, which makes it less perfect. Lastly, I have used free resources like Google Collab for doing experiment, which limits the study of multiple optimizers, hyperparameter tuning, and alternative base databases for transfer learning.

1.6 Report Organization:

This report is designed to give readers a broad overview of the system, its operations, and investigation findings. The report adheres to the prescribed DIU format for standard thesisreporting.

CHAPTER 1: Introduction

This section gives details about the topic, the Background and Present State of the study, Problem Statement of the study the study's objectives, Scope and Limitations of the report.

CHAPTER 2: Literature review

This chapter digs into the connected works, Comparison between existing works, and the Open Issues with the issue.

Chapter 3: METHODOLOGY/ REQUIREMENT ANALYSIS & DESIGN SPECIFICATION

This chapter gives an in-depth study of the research Proposed Methodology and Hardware/ Software Requirement, Hardware/ Software Requirement and Project Management and Financial Analysis.

Chapter 4: IMPLEMENTATION

This lesson contains the characteristics of the established system, training model of the system's diagrams and procedures.

Chapter 5: RESULT AND ANALYSIS

In this section, the consequences of the project on Simulation Result and Comparative Analysis.

Chapter 6: IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

In this chapter offers an outline of the research Impact on Life Impact on Society & Environment, Ethical Aspects, Sustainability Plan for the project.

CHAPTER 7: CONCLUSION AND FUTURE WORK

In this chapter presents an overview of the research the Further Suggested Works and the most importantly Limitations/ Conflict of Interests.

CHAPTER 2
BACKGROUND

2.1 Overview

This background study underlines the shortcomings in present detection methods, with a specific focus on the issues connected with illnesses affecting lemon leaves. It underlines the possibility of YOLO (You Only Look Once) as a new computer vision tool for the diagnosis of diseases. The purpose of this study is to present a quick summary by studying the historical backdrop of disease detection in lemon and the current condition of agricultural operations. Traditionally, the diagnosis of illnesses in lemon leaves has relied mainly on human inspection by experts. This technique is time-consuming, labor-intensive, and prone to human error. The introduction of machine learning and computer vision has brought about substantial breakthroughs, but many existing approaches still suffer with the necessity for extensive preprocessing and several stages of detection, which can restrict their efficiency and real-time applicability.

YOLO is an abbreviation for the term ‘You Only Look Once’. This is an algorithm that finds and recognizes numerous elements in a picture (in real-time). Object recognition in YOLO is done as a regression problem and delivers the class probabilities of the viewed photos.[26] YOLO method employs convolutional neural networks (CNN) to detect objects in real-time. As the name says, the technique requires only a single forward propagation through a neural network to recognize objects. This indicates that prediction in the complete image is done in a single algorithm run.[27] The CNN is used to forecast numerous class probabilities and bounding boxes simultaneously. The YOLO algorithm consists of several versions. Some of the common ones include tiny YOLO and YOLOv3.[28]

Advantages of YOLO:

- Speed: Several articles highlight YOLO's power to process photos quickly, even in real-time, which is vital for applications such as disease detection in crops. For example, the paper by Achyut Morbekar, Ashi Parihar, and Rashmi Jadhav (2020) [1] notes YOLO's capacity to process leaf images at 45 frames per second, offering real-time detection, which is faster compared to other object detection algorithms.

- Accuracy: YOLO algorithms, especially the latest versions like YOLOv5, have showed great accuracy in detecting and identifying plant diseases. Many of the studies you gave indicate outstanding results in terms of detection accuracy, often surpassing other detection approaches. For instance, the study by Shisong Zhu et al. (2023) [6] achieved a detection performance of 95.5% mean average precision utilizing YOLOv5 for apple leaf disease detection.

- Simplicity: The unified architecture of YOLO streamlines the detection process, minimizing the complexity associated with previous multi-stage approaches.

- Adaptability to Different Environments: The ness of YOLO to function well in varied environmental situations is another essential factor. Papers like the one by Yiwen Wang et al. (2022) [11] indicate the successful detection of apple leaf diseases under complicated backdrops, acquired from real-world settings.

I personally collect data or images from both field sources. Comprising 4155 images, the dataset includes eight categories of diseases as well as imagesdepicting a healthy state. In contrast to previously published models, this one is simpler, and the coding is notably straightforward.

2.2 Related Works

Md. Janibul Alam Soeb, Md. Fahad Jubayer, Tahmina Akanjee Tarin, Muhammad Rashed Al Mamun, Fahim Mahafuz Ruhad, Aney Parven, Nabisab Mujawar Mubarak, Soni Lanka Karri & Islam Md. Meftaul in 2023 they worked on "Tea leaf disease detection and identification based onYOLOv7 (YOLO T)" [3] A reliable and precise diagnosis and identification system is necessary to prevent and control tea leaf diseases. Tea leaf maladies are diagnosed manually, increasing time and impacting production quality and productivity. This study intends to offer an artificial intelligence-based solution to the problem of tea leaf disease identification by training the fastest single-stage object detection model, YOLOv7, using the diseased tea leaf dataset collected from four renowned tea gardens in Bangladesh. 4000 digital photographs of five kinds of leaf diseases are collected from these tea plantations, generating a manually annotated, data-augmented leaf disease image dataset. This work uses data augmentation methodologies to address the issue of limited sample sizes. The detection and identification findings for the YOLOv7 approach are supported by prominent statistical metrics like detection accuracy, precision, recall, map value, and F1-score, which resulted in 97.3%, 96.7%, 96.4%, 98.2%, and 0.965, respectively. Experimental results reveal that YOLOv7 for tea leaf maladies in natural scene photos is superior to existing target detection and identification networks, including CNN, Deep CNN, DNN, AX-Retina Net, improved DCNN, YOLOv5, and multi-objective image segmentation. Hence, this work is anticipated to lessen the load of entomologists and aid in the early diagnosis and detection of tea leaf diseases, thus decreasing economic losses.

Zhenyang Xue, Renjie Xu, Di Bai, and Haifeng Lin in 2023 they worked on "YOLO-Tea: A Tea Disease Detection Model Improved by YOLOv5" [4] Convolutional neural networks (CNNs) can automatically extract information from photos of tea leaves suffering from insect and disease infestation. However, images of tea tree leaves shot in a natural context contain challenges such as leaf shadowing, illumination, and small-sized objects. Affected by these difficulties, classic CNNs cannot have a sufficient recognition performance. To solve this difficulty, we present YOLO-Tea, an upgraded model based on You Only Look Once version 5 (YOLOv5). Firstly, we added self-attention and convolution (ACmix), and convolutional block attention module (CBAM) to YOLOv5 to enable our suggested model to better concentrate on tea tree leaf illnesses and insect pests. Secondly, to boost the feature extraction capabilities of our model, we replaced the spatial pyramid pooling fast (SPPF) module in the original YOLOv5 with the receptive field block (RFB) module. Finally, we lowered the resource utilization of our model by including a global context network (GCNet). This is critical particularly when the model operates on resource-constrained edge devices. When compared to YOLOv5s, our proposed YOLO-Tea improved by 0.3%–15.0% over all test data. YOLO-Tea's AP0.5, APTLB, and APGMB outperformed Faster R-CNN and SSD by 5.5%, 1.8%, 7.0% and 7.7%, 7.8%, 5.2%. YOLO-Tea has showed its promising potential to be applied in real-world tree disease detection systems.

Weishi Xu and Runjie Wang in 2023 they worked on “ALAD-YOLO: a lightweight and accurate detector for apple leaf diseases” [5] an accurate and lightweight model for apple leaf disease detection based on YOLO-V5s (ALAD-YOLO) is proposed in this publication. An apple leaf disease detection dataset is collected, encompassing 2,748 photos of sick apple leaves under a complicated environment, such as from diverse shooting angles, throughout various spans of the day, and under varying weather conditions. Moreover, different data augmentation strategies are utilized to increase the model generalization. The model size is compressed by introducing the Mobilenet-V3s basic block, which integrates the coordinate attention (CA) mechanism in the backbone network and replacing the ordinary convolution with group convolution in the Spatial Pyramid Pooling Cross Stage Partial Conv (SPPCSPC) module, depth-wise convolution, and Ghost module in the C3 module in the neck network, while maintaining a high detection accuracy. Experimental results reveal that ALAD-YOLO balances detection speed and accuracy well, attaining an accuracy of 90.2% (an improvement of 7.9% compared with yolov5s) on the test set and decreasing the floating point of operations (FLOPs) to 6.1 G (a drop of 9.7 G compared with yolov5s). In summary, this study proposes a reliable and efficient detection approach for apple leaf disease detection and other related fields.

2.3 Comparison between existing works

In this research I used raw dataset 4155. For image classification I YOLOv8. I divided the dataset into nine folders. 80% training, 20% testing. After training of the model, I have achieved validation accuracy from YOLO. In the summary, the study emphasizes the significance of responsibly integrating advanced technologies into agriculture by highlighting ethical considerations and a commitment to responsible AI. In general, the research provides valuable insights into utilizing CNNs to improve crop management and tackle challenges in the agricultural sector.

Table: 2.1: Summary of the related research work.

Author	Model	Accuracy	Contribution
Achyut Morbekar, Ashi Parihar, Rashmi Jadhav (2020) [1]	YOLO	-	Introduced YOLO for crop disease detection, achieving real-time processing and boosting speed and accuracy.
V Senthil Kumar, M Jaganathan, A Viswanathan, M Umamaheswari, J Vignesh (2023) [2]	Multi-scale YOLO v5 (with DenseNet-201 backbone)	82.8%	Developed a model for rice leaf disease identification with enhanced accuracy utilizing Bi-FAPN and depth-aware instance segmentation.
Md. Janibul Alam Soeb et al. (2023) [3]	YOLOv7 (YOLO T)	97.3%	Proposed YOLOv7 for tea leaf disease identification with high accuracy, combining data augmentation to overcome sample size concerns.
Zhenyang Xue, Renjie Xu, Di Bai, Haifeng Lin (2023) [4]	YOLO-Tea (improved YOLOv5)	-	Enhanced YOLOv5 for tea disease detection, incorporating self-attention, CBAM, RFB module, and GCNet for increased performance.
Weishi Xu, Runjie Wang (2023) [5]	ALAD-YOLO (based on YOLO-V5s)	90.2%	Proposed ALAD-YOLO for apple leaf disease detection with high accuracy and reduced model size and FLOPs.
Shisong Zhu et al. (2023) [6]	EADD-YOLO (improved YOLOv5)	95.5%	Developed EADD-YOLO for apple leaf disease diagnosis, boosting efficiency and accuracy with

			lightweight models and SIoU loss.
Shengjie Leng et al. (2023) [7]	YOLOv5-based lightweight models	87.5%	Proposed lightweight YOLOv5 models for maize leaf blight detection, incorporating attention mechanisms and transformer networks.
Phani Praveen et al. (2023) [8]	YOLO-based classification models	-	Introduced various attention mechanisms to improve grape leaf disease detection, with focus on real-time performance.
Midhun P. Mathew, Therese Yamuna Mahesh (2022) [9]	YOLO v5	-	Developed a model for bell pepper disease detection using YOLO v5, enabling early-stage disease diagnosis in big fields.
Gangadevi Ganesan, Jayakumar Chinnappan (2022) [10]	Hybrid model (ResNet + YOLO classifier)	99.81%	Proposed a hybrid ResNet-YOLO model for paddy leaf disease recognition, attaining excellent accuracy through optimization.
Yiwen Wang, Yaojun Wang, Jingbo Zhao (2022) [11]	MGA-YOLO	89.3%	Developed MGA-YOLO for apple leaf disease detection with high accuracy and real-time performance on mobile devices.

Dawei Li, Foysal Ahmed, Nailong Wu, Arlin I. Sethi (2022) [12]	YOLO-JD	96.63%	Proposed YOLO-JD for jute disease detection, attaining the greatest detection accuracy among state-of-the-art approaches.
Inchaya Kumpala, Nontawat Wichapha, Piyawat Prasomsab (2022) [13]	YOLO CNN	-	Developed YOLO CNN for sugar cane red stripe disease detection, achieving high accuracy and real-time diagnosis.
Guowei Dai, Lin Hu, Jingchao Fan (2022) [14]	Hybrid YOLO v5 Model (DA-ActNN-YOLOV5)	-	Proposed DA-ActNN-YOLOV5 for potato disease identification, attaining high accuracy and efficient resource utilization.
Dang Huu Chau et al. (2022) [15]	YOLO v5	81.28%	Developed YOLO v5 for plant leaf disease detection, achieving high detection and classification rates.
Yaping Li et al. (2022) [16]	Pruned-YOLO v5s+Shuffle (PYSS)	93.2%	Proposed PYSS for real-time melon leaf disease diagnosis, attaining excellent accuracy and efficiency in complicated situations.
Apu Shill, Md. Asifur Rahman (2021) [19]	YOLOv3, YOLOv4	-	Utilized YOLOv3 and YOLOv4 for accurate plant disease detection, demonstrating the usefulness of YOLO algorithms.

Midhun P Mathew, Therese Yamuna Mahesh (2021) [20]	YOLO v3	-	Developed YOLO v3 for apple leaf disease detection, enabling accurate identification of disease-affected regions.
Ma. Kristin Agbulos, Yovito Sarmiento, Jocelyn Villaverde (2021) [21]	Improved YOLO v5 (YOLO V5 + ShuffleNet)	-	Proposed YOLO V5 + ShuffleNet for peach leaf disease identification, attaining improved accuracy through feature additions.
Jun Liu, Xuewei Wang (2020) [18]	Improved YOLO V3	-	Improved YOLO V3 for tomato disease and pest identification, boosting accuracy and speed with multi-scale feature detection.
Rong-Zhou Qiu et al. (2022) [23]	YOLOv5l	85.19%	Developed YOLOv5l models for citrus greening disease detection, achieving high micro F1-scores for symptom recognition.

2.4 Open Issues

This study is centered on lemon leaf disorders which will facilitate everyone. However, lemon trees are many forms of diseases harming their leaves. I am working with only eight varieties of sickness and healthy leaf. It is a bit tough for us to deal with ailments other than the one I am dealing with in lemon leaf. Other than that lemon leaf diseases are quite complex and some of the diseases are very similar so there can be some challenges to detect the diseases properly. Some diseases of lemon leaves are so comparable and some diseases are difficult to direct for humans, due to which some intricate difficulty needs to be met while gathering infected leaves.

The key problem for this study is to acquire the right lemon leaf disease data. There are thousands of datasets available in the internet but very few can find in Bangladesh. So, I thought I would work with the raw dataset. I have 4155 raw data in my dataset. Then, training the model was also exceedingly tough. Because I don't have extremely powerful GPU set up. I trained our model in Google colab in GPU.

Effectively handling the entire process, from the initial data collection to on-field deployment, poses the most hard and intricate part of adopting YOLO for the diagnosis of lemon leaf diseases. Collecting the data with a modest capturing device is tough because the diseases are similar and looks same. After collecting the data, the annotations' component is too much time consuming and challenging. The management of the complete trip, ranging from start to conclusion, is where the ultimate difficulty lies. A thorough management plan is necessary to coordinate activities such as data gathering, model training, deployment, and continuing monitoring.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Overview

Object detection is a method in computer vision that comprises recognizing and finding specific items inside digital images or movies. The seen items include individuals, automobiles, furniture, rocks, structures, and live creatures.[29] Object detection encompasses numerous techniques, including rapid R-CNN, Retina-Net, and Single-Shot Multi-box Detector (SSD). While these approaches have successfully handled the difficulties of data scarcity and modeling in object detection, they are incapable of finding objects in a single algorithmic iteration. The YOLO method has become popular due to its higher performance compared to the previously discussed object detection algorithms.[30]

3.2 Proposed Methodology

YOLO is an acronym for the expression 'You Only Look Once'. This is an algorithm that detects and recognizes various items in an image (in real-time). Object recognition in YOLO is done as a regression problem and offers the class probabilities of the seen photographs. YOLO algorithm leverages convolutional neural networks (CNN) to detect objects in real-time.[31] As the name indicates, the approach requires only a single forward propagation through a neural network to identify objects. This illustrates that prediction in the full image is done in a single algorithm run. The CNN is used to forecast several class probabilities and bounding boxes concurrently. The YOLO algorithm consists of many variations. Some of the common ones are small YOLO and YOLOv3.[32]

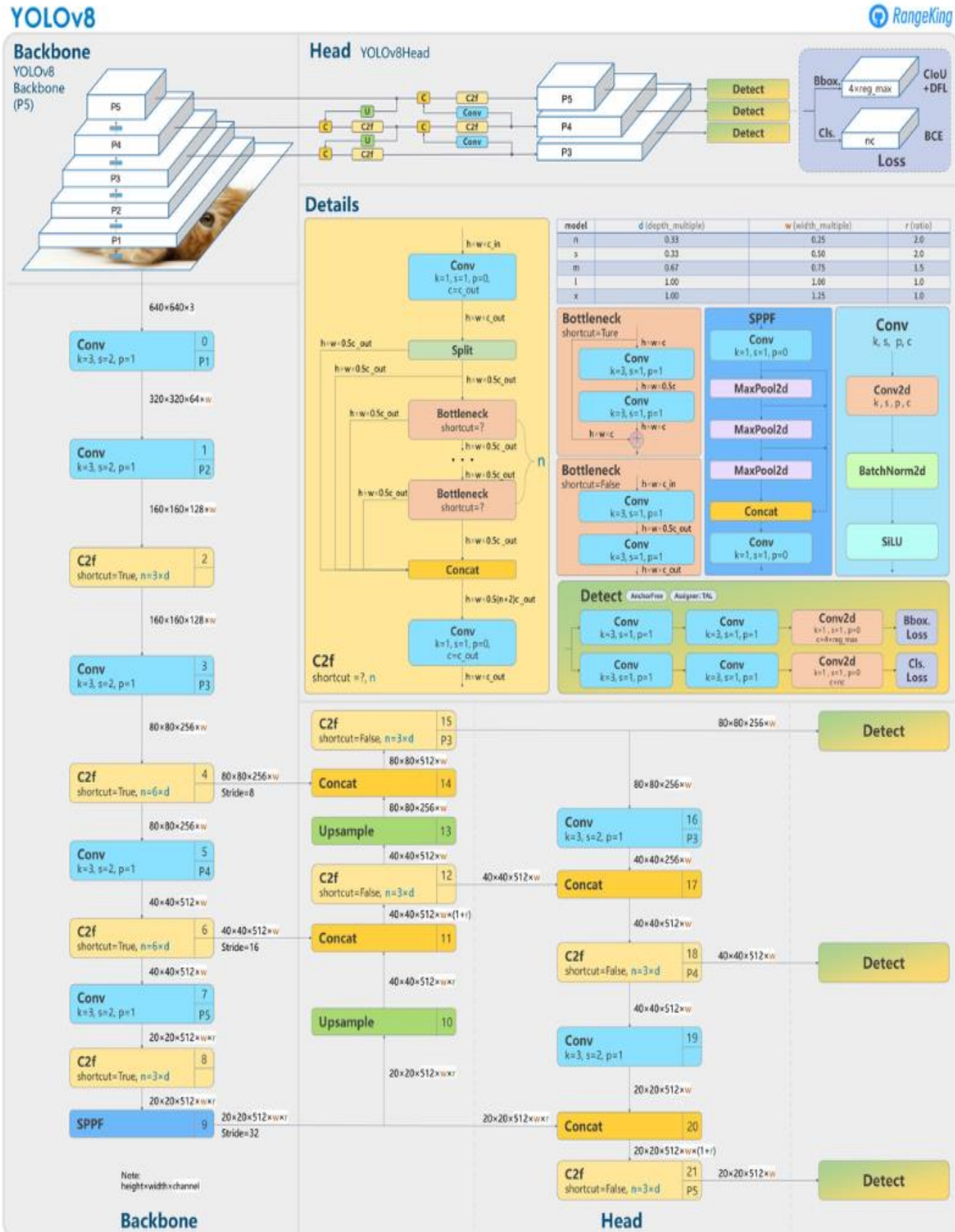


Figure 3.2(a): YOLOv8 Architecture [33]

How the YOLO algorithm works

YOLO algorithm operates utilizing the following three techniques:

• Residual blocks
• Bounding box regression
• Intersection Over Union (IOU) [34]

Residual blocks

Initially, the image is partitioned into many grids. Each grid has a size of S x S. The graphic below illustrates the process of dividing an input image into grids.

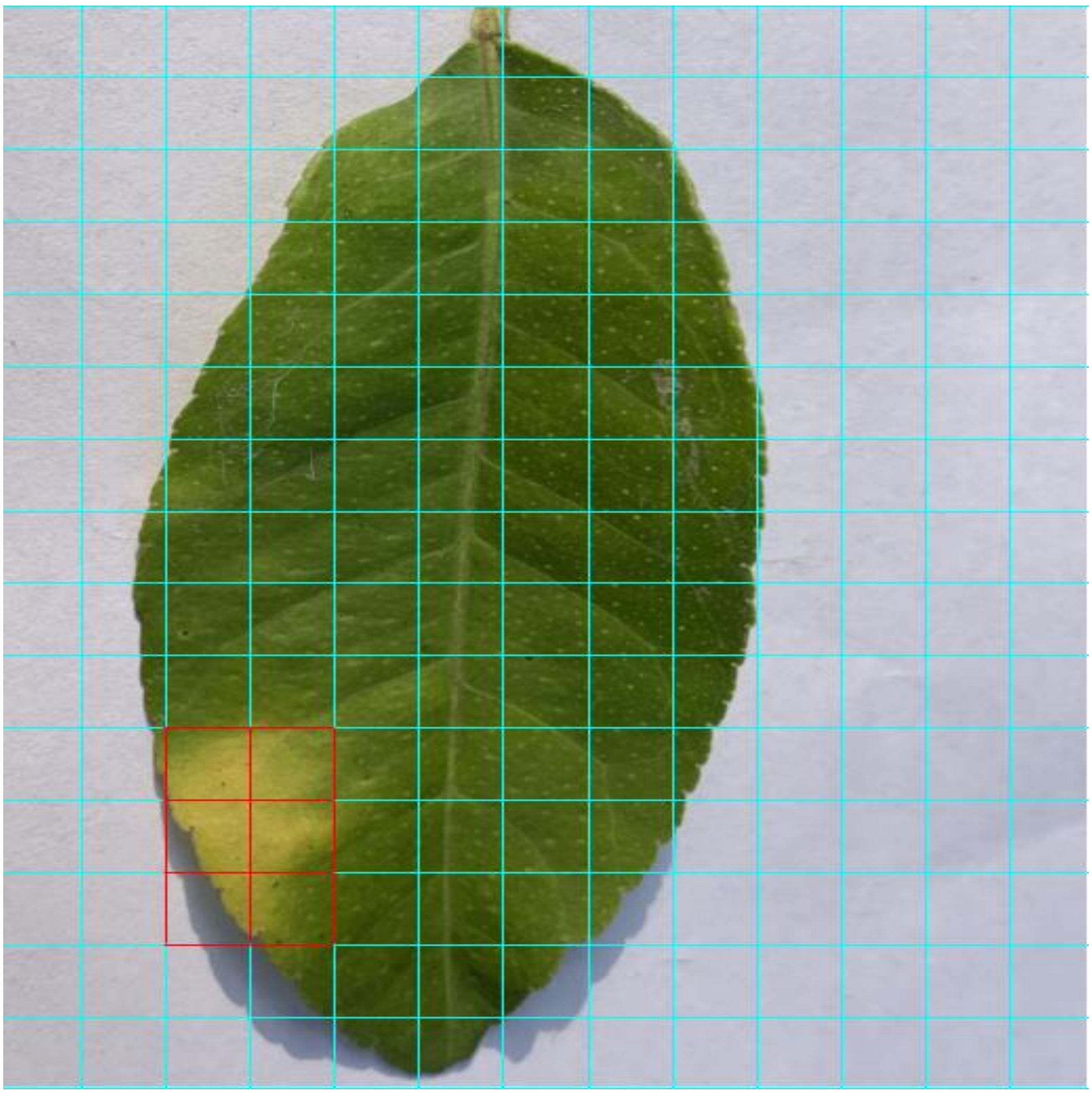


Figure 3.2(b): YOLO grid Example.

The image above contains several grid cells that are all of the same size. Each grid cell will detect any things that appear within it. If an item center is located within a specific grid cell, that cell will be responsible for detecting it.

Bounding box regression

Refers to the process of predicting the coordinates of a bounding box that tightly encloses an object in an image.

A bounding box is a delineation that enhances an object inside a picture.

Every bounding box in the image comprises of the following attributes:

• Width (bw)

• Height (bh)

• Class (for example, person, car, traffic signal, etc.)- This is represented by the letter c.

The center within the bounding box is denoted by the coordinates (bx, by).

Displayed below is an illustration of a bounding box. The bounding box has been indicated with a yellow outline.

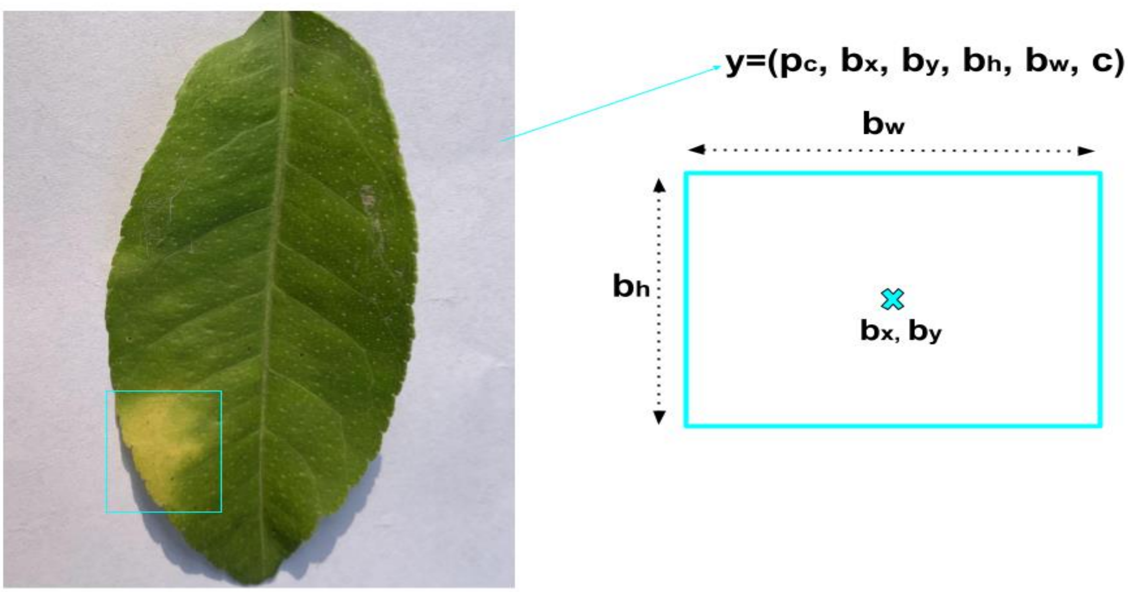


Figure 3.2(c): Bounding box regression example.

YOLO employs a single bounding box regression to predict the height, breadth, center, and class of objects. In the graphic above, represents the possibility of an object existing in the bounding box.

Intersection over union (IOU)

Intersection over union (IOU) is a phenomenon in object detection that determines how boxes overlap. YOLO uses IOU to build an output box that surrounds the objects correctly. Each grid cell is responsible for calculating the bounding boxes and their confidence ratings. The IOU is equal to 1 if the predicted bounding box is the same as the real box. This method eliminates bounding boxes that are not comparable to the genuine box. The following picture gives a clear description of how IOU works. [35]

Figure 3.2(d): Example of YOLO Intersection over union.

In the picture 3.2(d) above, there are two bounding boxes, one in green and the other one in blue. The blue box is the expected box whilst the green box is the genuine package. YOLO guarantees that the two bounding boxes are equal.

Combination of the three techniques

The following image depicts how the three procedures are applied to get the final detection findings.

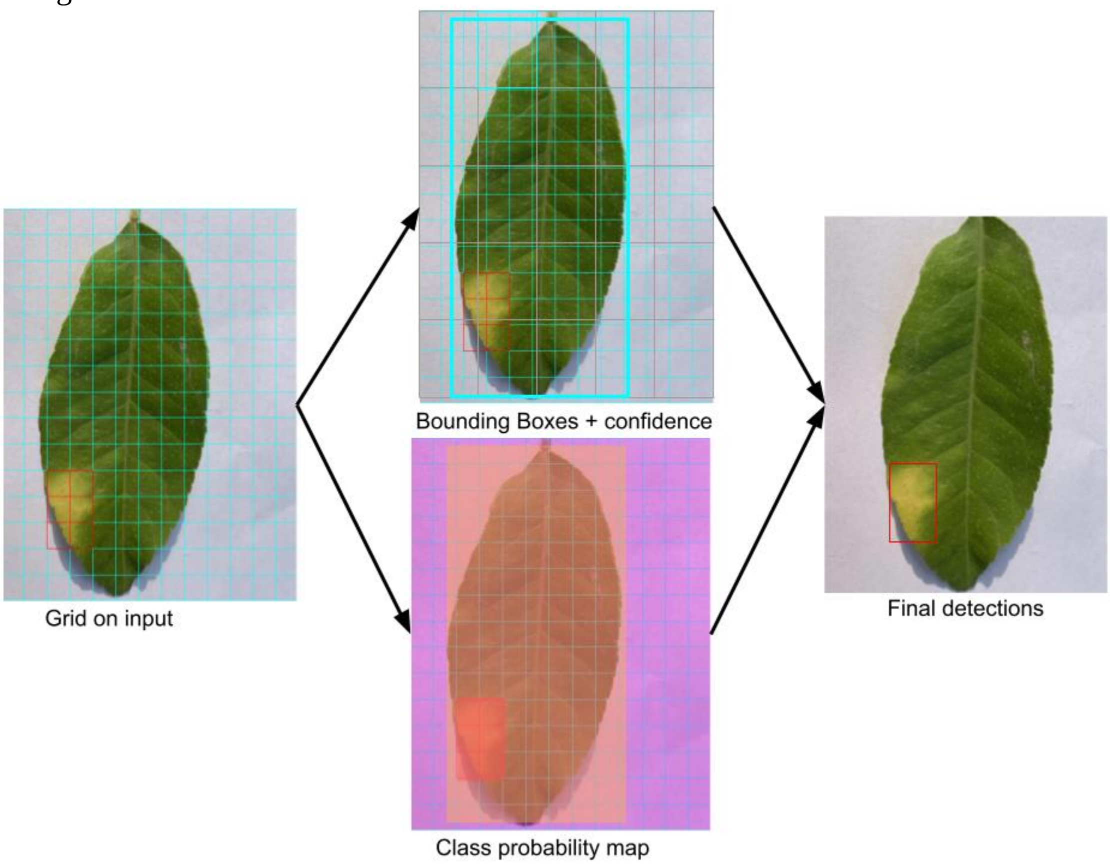


Figure 3.2(e): Combination of the three techniques.

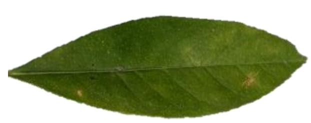
First, the image is divided into grid cells. Each grid cell forecasts B bounding boxes and provides their confidence scores. The cells anticipate the class probabilities to establish the class of each object.
For example, I can detect at least three categories of objects: a car, a dog, and a bicycle. All the predictions are made simultaneously using a single convolutional neural network. Intersection over union assures that the predicted bounding boxes are equivalent to the real boxes of the objects. This phenomenon lowers superfluous bounding boxes that do not satisfy the attributes of the objects (like height and width). The final detection will consist of unique bounding boxes that suit the objects accurately.

For example, the car is encompassed by the pink bounding box and the bicycle is enclosed by the yellow bounding box. The dog has been highlighted using the blue bounding box.

I have utilized the raw dataset. The data is taken from several disease affected leaves. A dataset is built by taken photos of leaves afflicted with different illnesses. I have taken 4155 sick lemon leaves photos in my data set. I have taken healthy and eight forms of lemon leaf illnesses in generating the data set. The illnesses are: Algal Leaf Spot, Black spot, Citrus canker, Citrus pest, Citrus Scab, Dry leaf, Leaf Curl, Yellow spot. I've divided the dataset into two segments: Test and Train. I maintained 80% of our data in the train 20% in the test. The training folder has 2800 images; test folder has 1355 images each.

In this study, the used raw dataset is a real-life dataset that is acquired from several credible sources, including agricultural sectors, and farmers in the field. This careful data collection technique ensures the precise portrayals of lemon leaf diseases in realistic and real-world circumstances. In addition, I intend to present a full and proper image of the diseases and farmers linked to lemon leaves in the fields of local ecosystems by merging information from these numerous sources. However, for reference, presents a schematic that depicts numerous lemon leaf diseases that I classify in our study.

Table 3.2(a): Overview of lemon leaf disease classification considered in this study.

Disease	**Preview**	**Description**
Algal Leaf Spot		Algal leaf spot is a fungal disease produced by different algae, creating circular patches on plant leaves.[36]
Black spot		Black spot is a fungal disease affecting roses, caused by the fungus Diplocarpon rosae.[37]
Citrus canker		Citrus canker is a bacterial disease caused by the pathogen Xanthomonas citri subsp. citri, infecting citrus plants. [38]
Citrus pest		Citrus pests cover a variety of insects, mites, and other organisms that infest citrus plants, causing harm and lowering productivity.[39]
Citrus Scab		Citrus scab is a fungal disease caused by the fungus Elsinoë fawcettii, damaging citrus trees. [40]
Dry leaf		Dry leaf is a symptom rather than a specific disease, generally caused by environmental stressors such lack of water, nutrient deficits, or fungal infections.
Leaf Curl		Leaf curl is a sign of numerous viral, fungal, or physiological illnesses, causing the leaves to curl and deform in shape.[41]
Yellow spot		Yellow spot is a symptom associated with different plant diseases, caused by factors such fungal infections, nutrient deficits, or environmental stresses.[42]

Here I use image of diseases lemon leaf and healthily as our data set. I have used eight categories of data in my research paper as training data and test data each of having 9 classes. The five categories' classes are: Algal Leaf Spot, Black spot, Citrus canker, Citrus pest, Citrus Scab, Dry leaf, Leaf Curl and Yellow spot.

Table 3.2(b): Several photos and the class index for each of those 8 classes.

Name	Class	Image size
Algal Leaf Spot	0	335
Black spot	1	340
Citrus canker	2	330
Citrus pest	3	320
Citrus Scab	4	310
Dry leaf	5	350
Leaf Curl	6	345
Yellow spot	7	306

3.3 Software Requirements

Software Requirements describe the important components and expertise necessary to accomplish a project or study. Researchers must acquire the essential expertise and assemble the relevant materials before initiating their investigation. As noted previously, my project falls within the domain of computer vision. To effectively complete this project, programming abilities, fluency in the Python language, and the utilization of several Python libraries like as PyTorch, Ultralytics, shutil, random, and os are needed. To undertake this project, a programming platform is necessary. I utilize Google Colab as my chosen programming platform. To identify "Lemon Leaf Disease," I devised a project.

Image Annotation

Annotation provides real-world data for training, detection, and assessment, a key stage in our model development. By recognizing the presence of disease in the image collection, I enable our proposed model to generate precise predictions and learn by itself. I label diseases for our annotation process using "MakesenseAI" program. In this application, the area of interest (disease-affected region) inside each image was manually marked using bounding boxes. Each bounding box defines the precise location where the illness was detected.

Python Programming Language

The current version of Python is 3.10.2. Recognized as a strong programming language, Python is high-level, open-source, and user-friendly. The sophisticated compositional structures of YOLO make it exceedingly tough to convert to another language. Python's built-in commands and functions are clear, making them easy for users to comprehend and utilize.

Google Colab

There is no necessity to utilize our personal computers as Colab, a hosted Jupiter environment, has been installed and set up, allowing me to access cloud resources throughmy web browsers. It functions a lot as Jupiter does. Since the Python kernel can substitutefor Jupiter in Collab, both are notebook-based, capable of including text, images, or code.

Software Requirements

- Operating System (Windows 10 or higher or Linux)
- Web Browser (Recent versions Chrome, Firefox, or Microsoft Edge)
- Hard Disk (At least 120GB)
- Ram (8 GB or more)
- GPU (Minimum 2GB)

CHAPTER 4
IMPLEMENTATION

4.1 Overview

Firstly, I need a data set for the experimental setup. I manually curated the dataset for our research. Validation, achieved by checking the model's performance on data not encountered during training, serves as a protection against overfitting and ensures its generalizability. Includes roughly 4155 photos of lemon leaf disease organized into 9 classes. The model was implemented using the Ultralytics API. The entire burden of this research was accomplished on a solitary computer. The hardware and software requirements are stated as follows: 32 GB RAM, an Intel(R) Core i7- 9700k CPU clocked at 4.70 GHz, NVIDIA RTX 3050 GDDR6 6 GB graphics card, and Windows 11 pro-64-bit operating system

4.2 Train Model/ Prototype Design

Designing a prototype for "Paradigm of YOLO: Exploring the Instant Segmentation Process in Lemon Leaf Disease Detection" comprises multiple processes, including data collection, preprocessing, model training, validation, and deployment. Below is a step-by-step tutorial to developing this prototype using YOLOv8.

Step 1: Data Collection

Collect Images of Lemon Leaves

- Gather a diversified dataset of lemon leaf photos, containing both healthy and sick leaves.
- Ensure photographs are excellent quality and include diverse lighting conditions and angles.

Annotate the Images

- Use annotation tools like MakesenseAI to construct bounding boxes around sick areas and label them.
- Save the annotations in YOLO format (.txt files).

Data Preparation

Prepare and preprocess the dataset for training, validation, and testing.

install ultralytics

!pip install ultralytics

Creating train-val split

Import required libraries

import os

import shutil

import random

!pip install tqdm –upgrade

from tqdm.notebook import tqdm

Training, test and validation path:

train_path_img = "/yolo/yolodata/images/train"

train_path_label = "/yolo/yolodata/labels/train"

val_path_img = "/yolo/yolodata/images/val"

val_path_label = "/yolo/yolodata/labels/val"

test_path = "/yolo/test_images"

4.3 System Testing/ Model Evaluation

Splitting the dataset and removing duplicate names

```
def train_test_split(path,neg_path=None, split = 0.2):
    print("------ PROCESS STARTED -------")


 files = list(set([name[:-4] for name in os.listdir(path)]))


    print (f"--- This folder has a total number of {len(files)} images---")
    random.seed(42)
    random.shuffle(files)

    test_size = int(len(files) * split)
    train_size = len(files) - test_size
```

Creating Required directories

```
        os.makedirs(train_path_img, exist_ok = True)
        os.makedirs(train_path_label, exist_ok = True)
        os.makedirs(val_path_img, exist_ok = True)
        os.makedirs(val_path_label, exist_ok = True)
```

Copying Image to train folder and removing duplicate names

```
    for filex in tqdm(files[:train_size]):
        if filex == 'classes':
            continue
        shutil.copy2(path + filex + '.JPG',f"{train_path_img}/" + filex + '.JPG' )
        shutil.copy2(path + filex + '.txt', f"{train_path_label}/" + filex + '.txt')



      print(f"------ Training data created with 80% split {len(files[:train_size])}
    images -------")

      if neg_path:
          neg_images = list(set([name[:-4] for name in os.listdir(neg_path)])) ##
```

```
removing duplicate names i.e. counting only number of images
        for filex in tqdm(neg_images):
            shutil.copy2(neg_path+filex+ ".JPG", f"{train_path_img}/" + filex +
'.JPG')

        print(f"------ Total  {len(neg_images)} negative images added to the training
data -------")

    print(f"------ TOTAL Training data created with {len(files[:train_size]) +
len(neg_images)} images -------")
```

Copying image to validation folder

```
for filex in tqdm(files[train_size:]):
      if filex == 'classes':
          continue
      # print("running")
      shutil.copy2(path + filex + '.JPG', f"{val_path_img}/" + filex + '.JPG' )
      shutil.copy2(path + filex + '.txt', f"{val_path_label}/" + filex + '.txt')

    print(f"------ Testing data created with a total of {len(files[train_size:])} images
----------")

print("------ TASK COMPLETED -------")
```

Training the Model:

```
train_test_split('C:\yolo\data')

!yolo task=detect mode=train model=yolov8l.pt
data=/content/drive/MyDrive/yolo/dataset.yaml epochs = 100 imgsz=640 batch=16
project=/content/drive/MyDrive/yolo/training_results name=res
```

I train the neural network across a number of epochs like—100, 125, 150, or even 200 for tweaking the model's parameters—weights and biases—in order to each epoch's loss function to be as minimal as possible. It appears that epoch value 200 in our suggested model (YOLOv8m) exhibits the middle performance in object detection and when epoch value is 200 the model exhibits the best performance in object detection. However, our constructed model's performance in object identification is routinely measured using a range of metrics that account both properly recognizing objects (true positives) and other kinds of mistakes.

CHAPTER 5: RESULT AND ANALYSIS

5.1 Image Annotation

Annotation provides real-world data for training, detection, and assessment, a key stage in our model development. By recognizing the presence of disease in the image collection, I enable our proposed model to generate precise predictions and learn by itself. I label diseases for our annotation process using "MakesenseAI" program. In this application, the area of interest (disease-affected region) inside each image was manually marked using bounding boxes. Each bounding box defines the precise location where the illness was detected.

Figure 5.1.(a): Image Annotations used for Training.

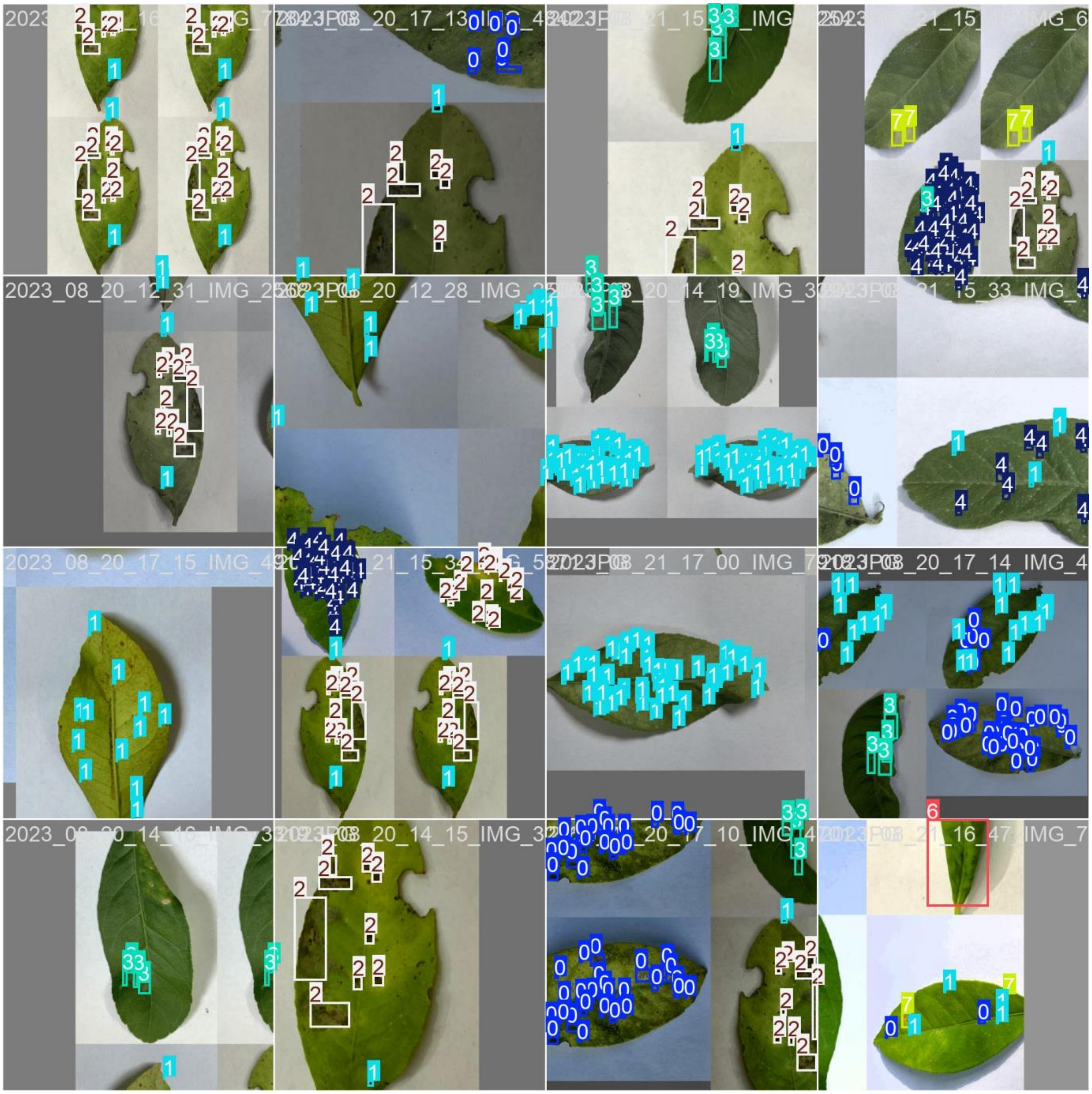


Figure 5.1(b): Image Annotations example used for training.

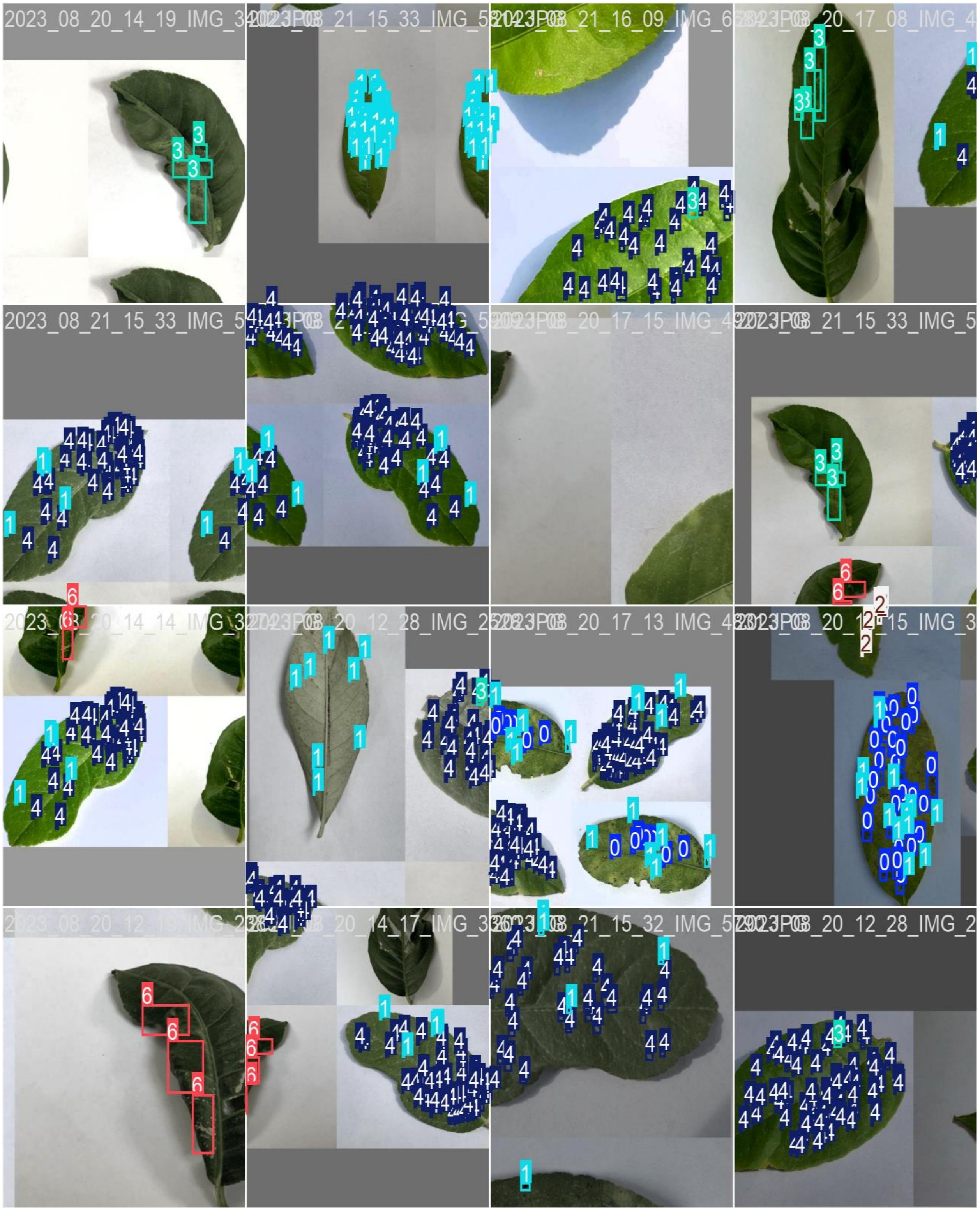


Figure 5.1(c): Image annotation examples of Lemon leaf used for training.

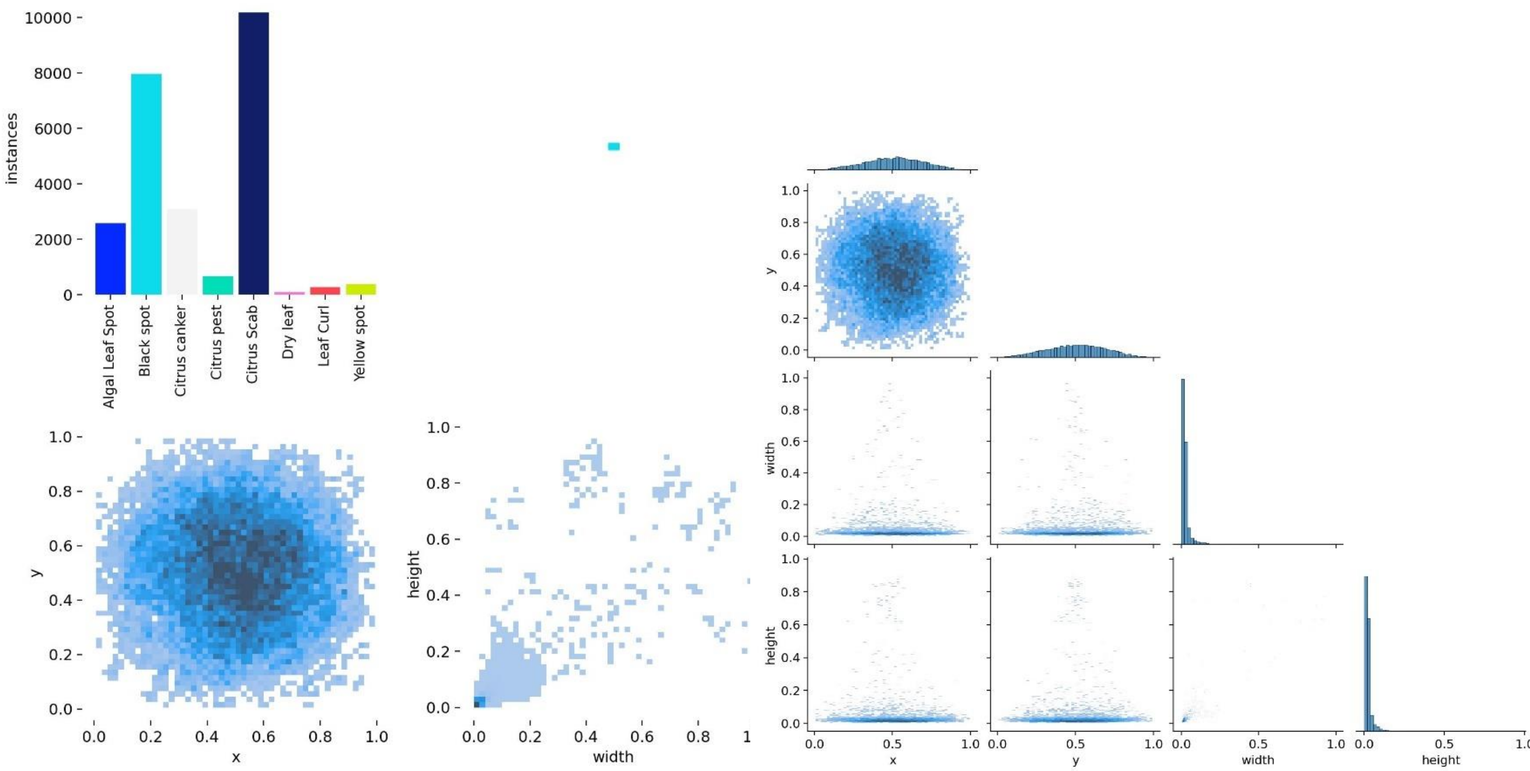


Figure 5.1(d): labels and labels correlogram.

Additionally, I added a label (Algal Leaf Spot, Black Spot, Citrus Canker, Citrus Pest, Citrus Scab, Dry Leaf, Leaf Curl, Yellow Spot) to the ticked bounding box to signal the existence of known diseases or anomalies to commence. These labels were designed to appropriately indicate the sort of disease being vaccinated against. Finally, to assist model training, parameter tuning and evaluation, the infected dataset was segmented into testing, targeting and subsets. The included dataset acts as the exercise and evaluation of our illness formation model, providing support for segmenting and segmenting disease forms or absences within the image.

5.2 Experimental Results & Analysis

5.2.1 Feature Extraction

In this instance, a format acceptable for machine learning is constructed from the annotated fields of interest. Nevertheless, I applied the YOLOv8 object identification model, which combines feature extraction and object recognition in just a single pass, to extract features from our dataset. It turns the unstructured raw image data into a format that allows our algorithm to accurately learn and categorize different diseases.

5.2.2 Classification

During the classification stage, I accurately classify the diseases by applying the features that I have obtained from the annotated photographs. Our classification model leverages features extracted from areas of interest (ROIs) of annotated photos as input data. The classifier is trained using an annotated dataset, where features are connected with their appropriate disease labels. To reduce classification mistakes, the model optimizes its parameters during training by learning to link the retrieved features according to disease class. To confirm the model's performance and generalizability, I test it on a validation dataset while keeping an eye on metrics like mAP score, recall, precision, and precision. And finally, our built system is finally assessed using a distinct testing dataset that was unobserved by the model before training and validation. However, this test step tests the model's capacity to reliably categorize diseases in real-world, unobserved data.

5.2.3 Disease Recognition

The disease recognition stage is the final phase in our technique, where the trained model applies what it has learnt to make predictions on new data. Here the deployed model receives input from unseen or test photos. Various sources, such as field observations, the aquaculture sector, or research programs, may have produced these test photographs or people collect them from the internet. Finally, given on all of the past information, our model will provide a forecast regarding whether the leaves have disease or not. Figure 4 shows the labels of photos that used for lemon leaf disease detection.

5.2.4 Experimenting with YOLOv8

I used the YOLOv8 (You Only Look Once) algorithm developed by Ultralytics for our Experimenting phase. Generally, a one pass technique is adopted by the object detection model YOLOv8, to complete both feature extraction and identification of an object. Usually, YOLO uses a convolutional neural network (CNN) as the base of its architecture to carry out feature extraction. I employed the YOLO network technique in our developed model for quick and reliable disease identification because it converts the input image into a series of feature maps that encode information at various scales and degrees of abstraction, from low-level insignificant details to high-level semantic features.

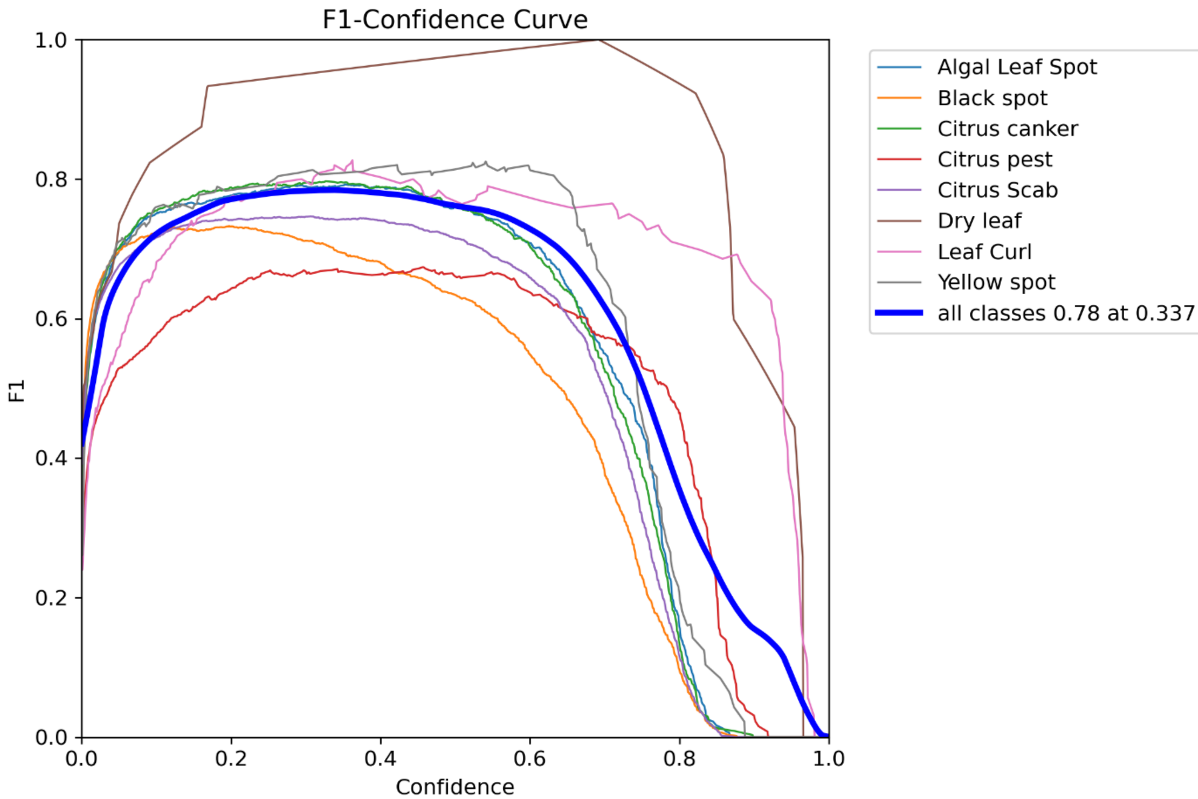


Figure 5.2.(a): The F1 Confidence Curve of training.

- X-axis (Confidence): This axis shows the model's confidence level in its categorization. It goes from 0.0 (not confident) to 1.0 (extremely confident).

- The Y-axis (All classes 0.78 at 0.337) represents the model's overall performance for all classes (namely, citrus leaf diseases) at a confidence level of 0.337. A Y-axis value of 0.78 corresponds to an X-axis confidence level of 0.337.

- Lines: The graph displays multiple lines, each reflecting a distinct classification of citrus leaf diseases.

- Model's Performance: By looking at the curves and the Y-axis label, I can get a sense of how well the model performs in classifying each citrus leaf disease. Ideally, the curves should be high on the Y-axis (above 0.8 or 0.9), suggesting great confidence in the classifications.

- Class Difficulty: The forms of the curves can also show which diseases would be more problematic for the model to categorize appropriately. Steeper curves suggest easier classification tasks for the model, while flatter curves can indicate more difficulty in identifying particular diseases from others.

5.2.5 Performance Metrics and Evaluation

Metrics like precision, recall, accuracy, and F1 score are utilized to assess the model's predictive performance. The following formula expresses accuracy.
Accuracy = Number of correct predictions / Total number of predictions

Precision:
Precision is the ratio of accurately predicted positive instances to the total instances predicted as positive.

Precision = True positive / (True Positive + False Positive)

Recall:
It indicates the precision of our predictions for positive classes, with elevated values reflecting a superior model quality.
Recall = True positive / (True Positive + False Negative)

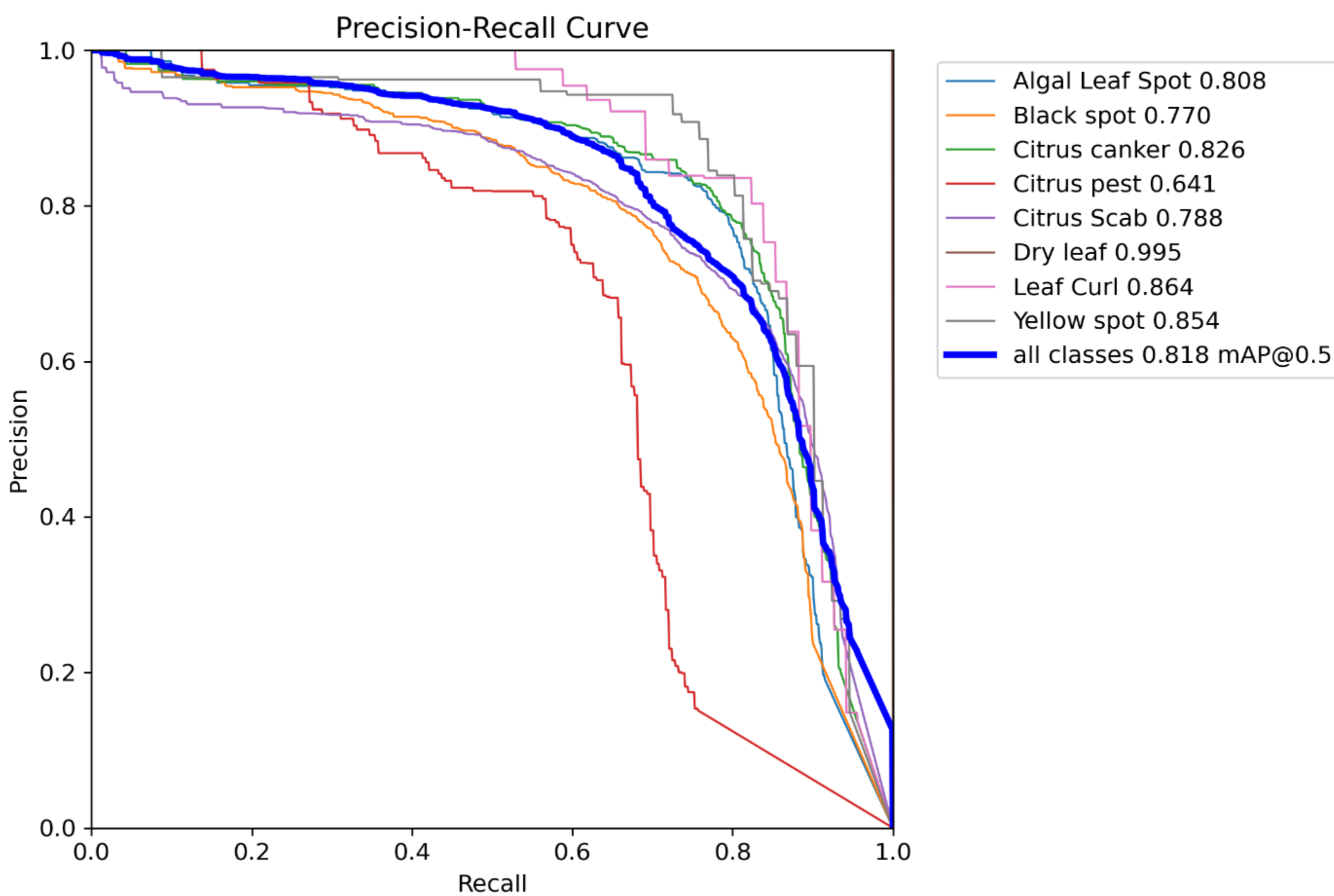


Figure 5.2(b): The Precision-confidence Curve of training.

The Precision-confidence

X-axis (Recall): This axis reflects the proportion of actual positive examples (objects) that were correctly identified by the model (true positives). A recall of 1.0 suggests the model found all the actual positive cases.

Y-axis (Precision): This axis reflects the fraction of the model's positive detections that were truly correct (true positives). An accuracy of 1.0 means all the objects identified by the model were genuinely present in the image.

Curve: The line in the graph displays the link between precision and recall as a threshold for the model's confidence score is modified. At higher confidence levels, the model is more certain about its detections, but it might miss some genuine positive cases (lower recall). Conversely, at lower confidence thresholds, the model can include some false positives (lower precision) but detect more true positive cases (higher recall).

Interpretation:

Ideal Curve: In general, I seek for a precision-recall curve that maintains high on both axes (near to 1.0) across a wide range of recall values. This shows the model can reliably identify most of the objects (high precision) while also capturing most of the real objects there (high recall).

Trade-off: The curve represents a trade-off between precision and recall. As you travel up the curve on the X-axis (raising recall), the precision often goes down (on the Y-axis) and vice versa. This is because the model is becoming more inclusive (capturing more items) but at the cost of including some false positives.
Additional Information in the graph:

mAP@0.5: This figure (0.818 mAP@0.5) represents the model's mean Average Precision (mAP) at a confidence threshold of 0.5. Average Precision is a measure that summarizes the precision-recall curve into a single value. In this example, a result of 0.818 implies good overall performance at a confidence level of 0.5.

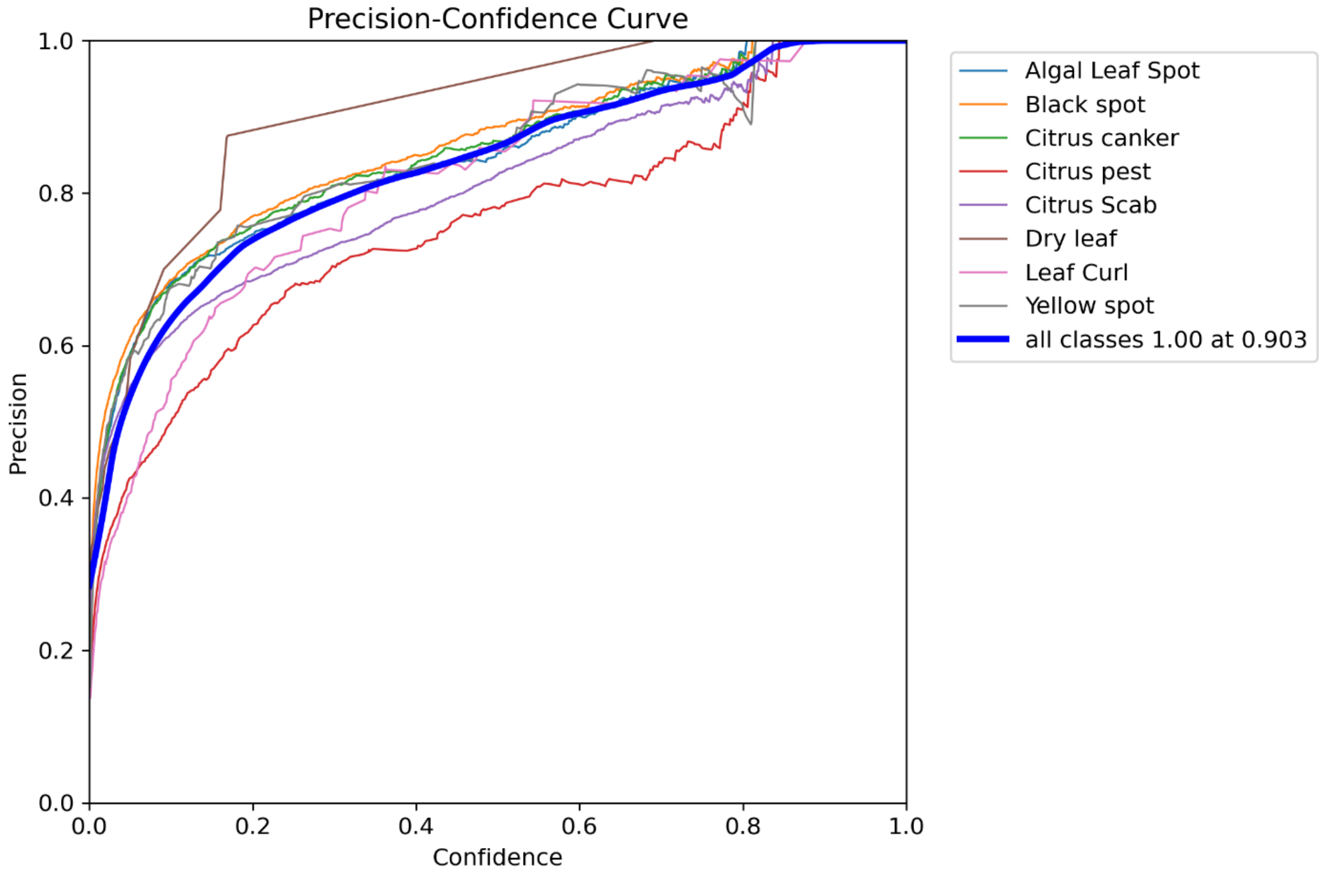


Figure 5. 2(c): The Precision-confidence Curve of training.

Precision-confidence Curve

X-axis (Confidence): This axis shows the model's confidence level in its categorization. It goes from 0.0 (not confident) to 1.0 (extremely confident).

Y-axis (Precision): This axis reflects the fraction of the model's positive detections that were truly correct (true positives). An accuracy of 1.0 means all the objects identified by the model as plastic waste were genuinely plastic waste in the image.

Curve: The line in the graph indicates the relationship between precision and confidence. As the model's confidence in its detections rises (going along the X-axis from left to right), the precision (Y-axis) generally increases as well.

Interpretation:

Model Performance: This curve helps analyze how well the model works at classifying plastic garbage objects with different confidence levels. Ideally, the curve should stay high on the Y-axis (near to 1.0) across a wide range of confidence values. This shows that the model is exact (usually correct) in its detections, especially when it has high confidence.

Setting a Confidence Threshold: A confidence threshold can be set based on the desired trade-off between precision and the number of detections. For example, if a very high level of precision is necessary (e.g., to avoid mistakenly taking actions based on false positives), a higher confidence threshold can be utilized, even if it means missing some actual plastic garbage objects (lower number of detections).

While the actual provenance of the graph isn't available, the title cites "plastic waste on water surfaces," implying the object detection challenge likely involves recognizing plastic waste objects in photographs or videos captured on water.
It's vital to highlight that accuracy is just one parameter used to evaluate object detection models. Other measures like recall (ability to locate all plastic trash objects) are also relevant for a complete understanding of the model's performance.

5.2.6 Training & Validation Loss

Our disease recognition model was trained using both training and validation loss values, which are crucial metrics for evaluating the model's performance. The training loss quantifies the accuracy with which a model fits the training dataset. It distinguishes between two predicted outputs of the model and the precise target values discovered in the training dataset. Reduction of this loss during training shows that the model is improving its ability to identify diseases in the training set. On the other hand, the validation loss is calculated using a distinct validation dataset that the model was not exposed to or seen during training. An important indicator of how effectively the model generalizes to new data is this loss. In order to track the model's performance and look for any possible signs of overfitting or under fitting, I regularly analyzed the validation loss.

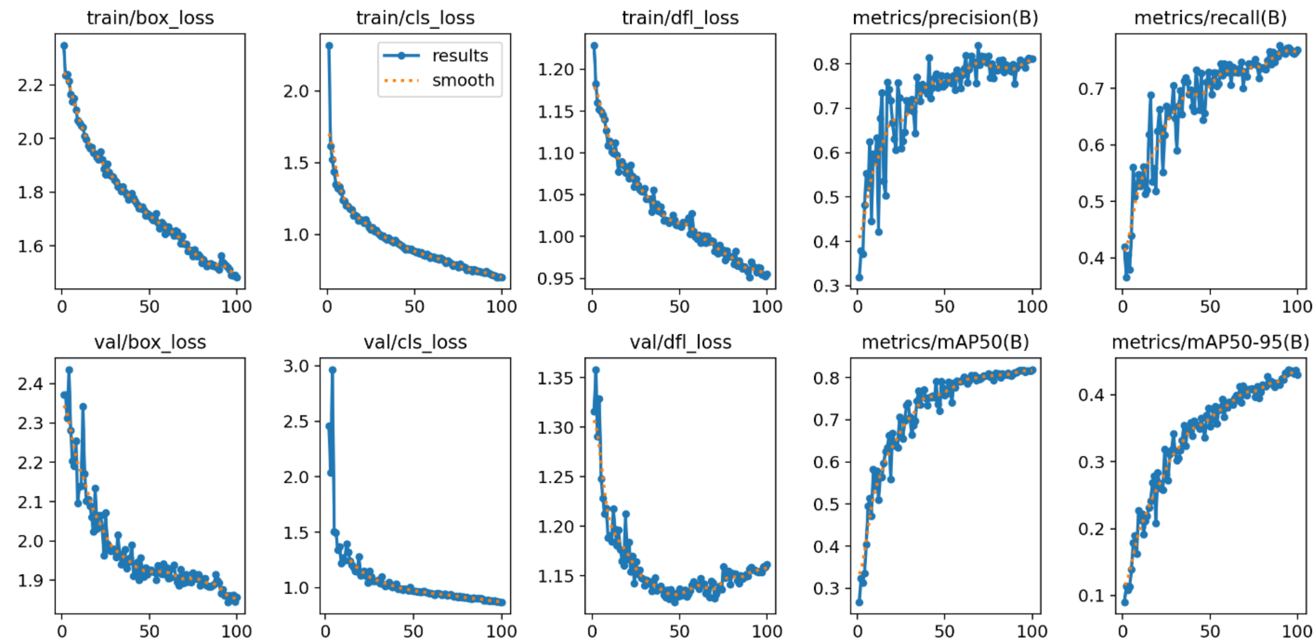


Figure 5.2(d): Training Box-Loss results.

The ideal situation is to achieve a balance where the model minimizes both the validation loss and the training loss. This balance depicts that the model is picking up useful patterns without being too dependent on the training dataset. By reaching this state of balance, the model is in a position to expand and perform as expected when applied to brand-new, untrained data.

5.3 Experimental Result

0% for validation data, and 80% for training data. I employed the pre-test team "YOLOv8" model to evaluate the learning power of the model to construct and connect the models according to their epizootics. The "Google Colab" environment, which has a hierarchically organized direct setup and pre-programmed computer vision and machine learning in Python, was taken as an experimental platform for the exercise. This environment can practice and test different models aimed at solving different scientific fields.

Figure 5.3(a): Detection test results of lemon leaves.

Figure 5.3(b): Detection test results of lemon leaves.

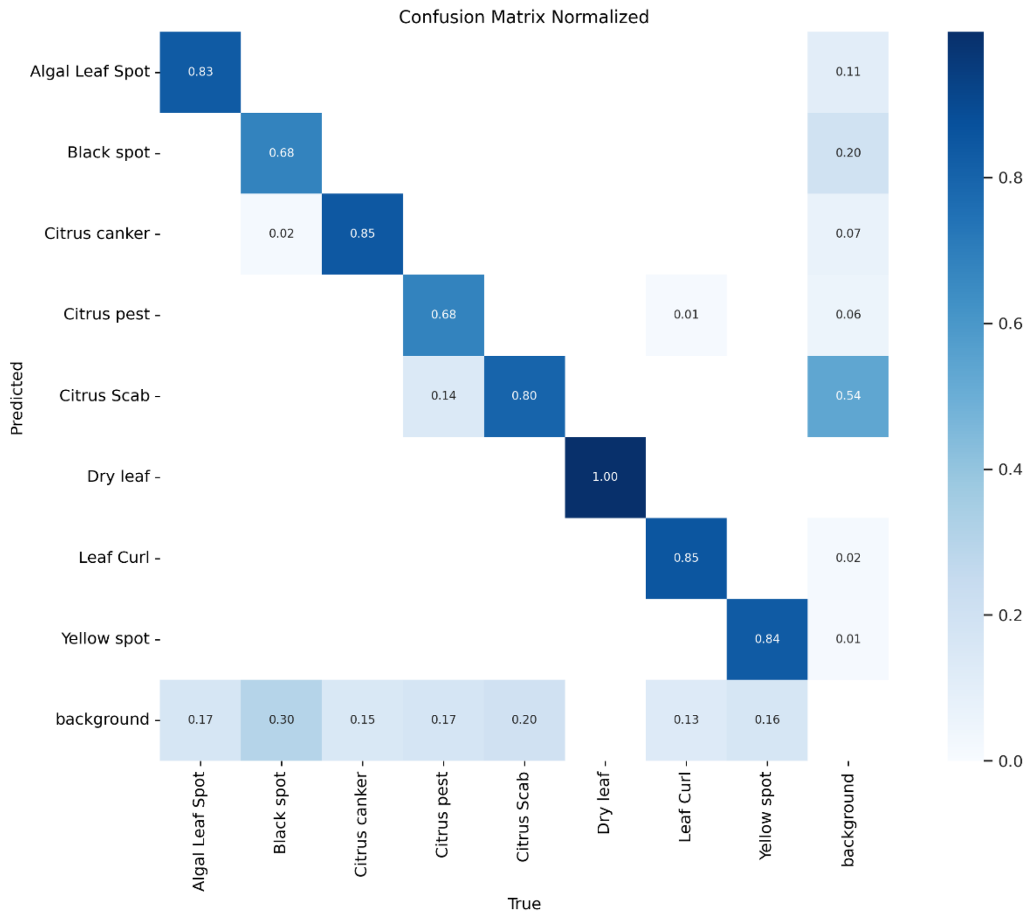


Figure 5.3(c): Confusion Matrix Normalized.

Algal Leaf Spot Recall: 0.83 (83% of actual Algal Leaf Spot incidences were properly anticipated)
Misclassifications: 0.11 (11% misclassified as background)

Black Spot Recall: 0.68 (68% of genuine Black Spot incidences were correctly predicted)
Misclassifications: 0.20 (20% misclassified as background), 0.14 (14% misclassified as Citrus Scab)

Citrus Canker Recall: 0.85 (85% of real Citrus Canker incidences were properly predicted)
Misclassifications: 0.02 (2% misclassified as Algal Leaf Spot), 0.07 (7% misclassified as backdrop)

Citrus Pest Recall: 0.68 (68% of real Citrus Pest cases were properly predicted)
Misclassifications: 0.01 (1% misclassified as background), 0.06 (6% misclassified as Citrus Scab)

Citrus Scab Recall: 0.80 (80% of actual Citrus Scab occurrences were properly predicted)

Misclassifications: 0.14 (14% misclassified as Black Spot), 0.54 (54% misclassified as backdrop)

Dry Leaf Recall: 1.00 (100% of real Dry Leaf cases were accurately predicted, showing flawless categorization)
Misclassifications: None (perfect classification)

Leaf Curl Recall: 0.85 (85% of actual Leaf Curl incidences were correctly predicted)
Misclassifications: 0.02 (2% misclassified as background)

Yellow Spot Recall: 0.84 (84% of real Yellow Spot instances were accurately predicted)
Misclassifications: 0.01 (1% misclassified as background)

Background Recall: 0.30 (30% of genuine background incidents were correctly predicted)
Misclassifications: 0.17 (17% misclassified as Algal Leaf Spot), 0.20 (20% misclassified as Black Spot), 0.15 (15% misclassified as Citrus Canker), 0.17 (17% misclassified as Citrus Pest), 0.13 (13% misclassified as Leaf Curl), 0.16 (16% misclassified as Yellow Spot)

Table. 5.1 Confusion Matrix Normalized.

Class	Recall	Misclassifications
Algal Leaf Spot	83%	11%
Black spot	68%	20%
Citrus canker	85%	9%
Citrus pest	68%	7%
Citrus Scab	80%	14%
Dry leaf	100%	0%
Leaf Curl	85%	2%
Yellow spot	84%	1%

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The application of the "Paradigm of YOLO: Exploring the Instant Segmentation Process in Lemon Leaf Disease Detection" might have a substantial impact on different sectors of life, particularly in the agriculture industry. Here are some significant areas where this technology can make a difference:

I. Improved Agricultural Productivity

- Early Detection and Treatment: By providing rapid and precise detection of lemon leaf diseases, farmers may take appropriate actions to treat damaged plants, reducing crop loss and enhancing total production.
- Precision Agriculture: The use of YOLOv8 for segmentation and detection enables for precision agriculture methods, where interventions (e.g., pesticide treatment) are aimed exclusively at afflicted areas, minimizing waste and cost.

II. Economic Benefits

- Cost Savings: Early detection eliminates the need for widespread pesticide use and enormous work for manual inspection, leading to significant cost savings for farmers.
- Increased Revenue: Healthy crops contribute to better quality produce and higher market pricing, thereby improving the revenue for farmers.

III. Environmental Impact

- Reduced Chemical Usage: Precision detection and focused treatment limit the overuse of chemicals, lowering the environmental impact of agricultural practices and minimizing the danger of soil and water pollution.
- Sustainable agricultural Practices: Encouraging the use of modern technologies for disease detection supports sustainable agricultural practices, contributing to long-term environmental health.

IV. Quality of Life for Farmers

- work Efficiency: Automation of disease detection decreases the physical work required for monitoring crops, allowing farmers to focus on other vital areas of farm management.

Reduced Stress: The dependability and accuracy of automated disease detection can lessen the stress and uncertainty associated with crop health, leading to enhanced mental well-being for farmers.

V. Research and Development

- Advancement in AI and Agriculture: The integration of YOLOv8 in agricultural practices can drive additional research and development in the field of AI and machine learning, leading to new breakthroughs and improvements.
- Data Collection and Analysis: Continuous usage of the detection system creates useful data on crop illnesses, which can be used for research purposes and to build even more successful agricultural technology.

VI. Food Security

- Expanded Crop Yields: By decreasing crop loss due to illnesses, this method helps assure a consistent and expanded supply of lemons, contributing to food security.
- Worldwide Impact: While initially focused on lemon leaves, the underlying technology can be extended for other crops, potentially enhancing food security on a worldwide scale by treating crop diseases in diverse agricultural sectors.

VII. Educational and Training Opportunities

- Knowledge Transfer: Farmers and agricultural workers can obtain training on using advanced AI tools, enhancing their technical knowledge and skills.
- Educational Programs: Institutions can include such technologies into their agricultural education programs, preparing future generations of farmers and agronomists with cutting-edge information.

6.2 Impact on Society & Environment

1. Environmental Impact

- Reduction in Chemical Usage: Targeted treatments based on accurate disease identification minimize the total usage of pesticides and fertilizers, minimizing the threat of soil and water contamination and encouraging sustainable agriculture practices.
- Biodiversity Conservation: Minimizing the use of toxic pesticides helps conserve beneficial insects, wildlife, and microorganisms, assisting to the conservation of biodiversity in agricultural settings.
- Climate Change Mitigation: Efficient agricultural practices and reduced chemical usage can lessen the carbon footprint of lemon production, aiding to climate change mitigation efforts.

2. Social Impact

- Empowerment of Farmers: Providing farmers with accessible and easy-to-use technology for disease diagnostics empowers them with information and skills to manage their crops more successfully. This can improve their life and lessen the stress associated with crop maintenance.
- Education and Awareness: The adoption of contemporary technologies in agriculture raises awareness about the importance of plant health and the possibility of innovative solutions in handling agricultural challenges.
- Community Health: Reducing the need on chemical therapies for illness management can lead to healthier living environments for farming communities, decreasing the possibility of exposure to hazardous substances.

6.3 Ethical Aspects

The ethical considerations of adopting YOLO for immediate segmentation in lemon leaf disease diagnosis involve maintaining data privacy, fostering fair access to technology, and avoiding any biases in the model. It's vital to collect and utilize data properly, respecting farmers' and landowners' privacy rights. Equitable access ensures that small-scale and resource-limited farmers can benefit from this technology, preventing a digital gap. Additionally, ensuring the model is trained on various datasets helps eliminate biases that could lead to inaccurate disease identification across different habitats and plant kinds, supporting fairness and accuracy in agricultural practice.

6.4 Sustainability Plan

The sustainability plan for applying YOLO in lemon leaf disease diagnosis focuses on continual data gathering and model update to assure accuracy and relevance. It involves educating local farmers and agricultural workers to use the technology successfully, encouraging local expertise. The approach includes cooperation with agricultural groups and governments to enable widespread adoption and integration into existing farming practices. Emphasis is made on eco-friendly methods, reducing chemical consumption through precision treatments. Regularly monitoring and analyzing the system's influence on crop health, yield, and environmental sustainability will assure long-term benefits and flexibility to changing agricultural condition.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusion

Future goals of the study include the creation of an Android-based mobile app or a web application for the identification of various lemon leaf diseases. Some of the key areas that also need some development include improving user interface and experience, providing real-time disease detection, integrating data analytics, assuring offline functionality, and updating the machine learning model.

In conclusion, our lemon leaf disease detection technology, based on YOLOv8 and real-world datasets, represents a significant step forward in disease management for aquaculture. Moreover, the research results emphasize the potential of YOLOv8 for early diagnosis for better production of lemon leaves and provide significant aquaculture insights. While acknowledging several limits, the study highlights the benefits of this technology for sustainable agriculture and global food security, as well as for advancing future advancements in the field. The sustainability plan for applying YOLO in lemon leaf disease diagnosis focuses on continual data gathering and model update to assure accuracy and relevance. It involves educating local farmers and agricultural workers to use the technology successfully, encouraging local expertise. The approach includes cooperation with agricultural groups and governments to enable widespread adoption and integration into existing farming practices. Emphasis is made on eco-friendly methods, reducing chemical consumption through precision treatments. Regularly monitoring and analyzing the system's influence on crop health, yield, and environmental sustainability will assure long-term benefits and flexibility to changing agricultural conditions.

7.2 FUTURE WORK

In terms of jobs that involve a comprehensive knowledge of the complete visual context, Vision Transformers (ViTs) offer amazing performance and enable flexibility in model construction. They come with decreased architectural restrictions and signal potential in transfer learning applications. In terms of large datasets ViTs acquire much accuracy than normal CNN models but it relies on the dataset. This research of grape leaf disease detection using vision transformers has the potential to help Sustainable Development Goal 2 (SDG 2) - End hunger, enhance food security and enhanced nutrition and promote sustainable agriculture. It can do so by enhancing agricultural yields, reinforcing food security, and aligning with SDG aim to eliminate hunger and enhance global food security through prompt and precise disease prevention for grapevine crops.

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