Performance Comparison of YOLOv5 and YOLOv8 for Plumeria Leaf Gall Detection

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

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APPROVAL

This Project/internship titled **"Performance Comparison of YOLOv5 and YOLOv8 for Plumeria Leaf Gall Detection"**, submitted by Md. Shafayat Mahin, ID No: 201-15-3412 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 23rd January, 2024.

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ABSTRACT

Leaf galls are abnormal plant growths resulting from insect parasitism, which can cause major agricultural losses if not managed in a timely manner. Precise early detection of leaf galls is crucial for enabling targeted treatment of affected plants and precision crop management. However, manual monitoring and identification of leaf galls across large cultivated areas can be extremely labor-intensive, slow and error-prone. This necessitates the development of automated computer vision techniques using deep learning to accurately detect leaf galls at scale for crop health monitoring. This work develops and systematically compares two state-of-the-art convolutional neural network architectures - YOLOv8 and YOLOv5 for automated detection of leaf galls on plumeria leaves. A dataset of 489 high resolution images of plumeria leaves exhibiting leaf galls of various shapes, sizes, textures and colors was collected through extensive field surveys. Each image was annotated by an experienced researcher using bounding boxes demarcating each gall instance. 73% of the images were utilized for training, 12% for validation, while the remaining 15% were held-out for testing model performance. Both YOLOv8 and YOLOv5 models were optimized by tuning key hyperparameters and leveraging data augmentation techniques to minimize overfitting. On the 142-image test set, YOLOv8 achieved a higher mean Average Precision (mAP) of 92.1%, compared to 89.1% attained by YOLOv5, demonstrating YOLOv8's superior accuracy. YOLOv8 also attained higher precision of 90.3% and recall of 88.3%, versus 89.4% and 84.8% for YOLOv5, indicating improved classification and localization capabilities. However, YOLOv5 exhibited slightly faster inference time versus YOLOv8. Overall, this rigorous comparative evaluation highlights YOLOv8 as a more robust and accurate solution for automated leaf gall detection, while YOLOv5 may be more suitable for real-time analysis. The findings provide meaningful insights on deep learning advancements for agriculture applications.

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CHAPTER 1
Introduction

1.1 Introduction

Plumeria (frangipani) is an ornamental plant grown extensively across tropical regions of Bangladesh. However, plumeria cultivation in the country is threatened by infestations of leaf galls [1] - abnormal plant tissue growths caused by insects, mites, fungi, bacteria, and viruses.[2] Leaf galls stunt plant growth and cause early leaf drops, eventually destroying the plant if not controlled. Timely detection and removal of infected leaves is key to effective management of leaf galls in plumeria.[3] However, manual detection of leaf galls is challenging owing to their varied shapes, colors, and sizes.[4] This necessitates the development of automated computer vision techniques to accurately detect leaf galls for plumeria crop monitoring in Bangladesh.

Recent advances in deep learning have enabled object detection models like YOLOv5 and YOLOv8 to achieve high accuracy in plant disease recognition. This study aims to develop and compare automated leaf gall detection methods for plumeria in Bangladesh using these state-of-the-art YOLO architectures. The specific objectives are to (i) create a dataset of plumeria leaf images in the Bangladeshi context annotated with gall regions (ii) optimize and train YOLOv5 and YOLOv8 models on this dataset (iii) evaluate and compare the models' performance on a test set in terms of precision, recall and mean average precision. The work attempts to provide an efficient computer vision solution using the optimal YOLO model to aid plumeria cultivators in the early identification of leaf gall infestations. This can facilitate timely application of insecticides or removal of infected leaves, reducing yield losses. The developed method can potentially be extended to detect other crop pests and diseases in Bangladesh.

1.2 Motivation

YOLOv8 is the most advanced version in the YOLO family of deep learning models for real-time object detection. Compared to earlier versions like YOLOv5 and YOLOv7, YOLOv8 demonstrates significantly higher accuracy and faster inference speeds. These advantages make YOLOv8 well-suited for automated, timely detection of leaf galls in plumeria crops. Specifically, YOLOv8 employs an optimized anchor box design and new techniques like cross-scale aggregation that help detect objects of varying sizes and scales more accurately than YOLOv5. This is crucial for identifying the diverse shapes and sizes of leaf galls. Additionally, YOLOv8 has inbuilt data augmentation capabilities during training, enhancing robustness to variations in leaf gall appearance, illumination and orientation. The optimized architecture enables real-time detection, allowing automated analysis of multiple images captured in plumeria plantations. YOLOv8 models can run efficiently on edge devices like embedded systems deployed in agricultural settings. Compared to other deep networks, pre-trained YOLOv8 models are highly performant for many plant disease classification tasks with minimal training data requirements. These advantages motivated the use of YOLOv8 over YOLOv5 models for the application of accurate leaf gall detection in plumerias.

1.3 Rationale of the Study

The rationale behind developing an AI-based automated solution for leaf gall detection is multifold. Firstly, timely and precise detection of leaf galls is essential for effective management of the midge pest and reducing crop losses in plumeria. However, manual monitoring of orchards is labor-intensive, slow and error-prone. Automating this process through computer vision can enable real-time, large-scale and accurate disease surveillance to aid time-sensitive interventions. Secondly, deep learning object detection models like YOLOv8 can rapidly adapt to new domain tasks like plant disease recognition with minimal training data requirements. Their high inference speeds facilitate deployment for in-field monitoring. Finally, this data-driven approach can help move Bangladeshi agriculture towards precision and smart farming practices to improve productivity.

Automating visual inspection is the first step which can pave the path for integrating advanced technologies like robots, drones and IoT for future farming. In summary, this study employs recent advances in AI to deliver an automated solution for addressing a real-world crop health problem, while also demonstrating the power of data-centric innovations for a more responsive agriculture sector.

1.4 Research Questions

- How accurately can YOLOv8 and YOLOv5 models detect and localize leaf galls of different shapes, sizes, and appearance in plumeria leaf images?
- How does the performance for automated leaf gall detection compare between advanced deep learning models including YOLOv8 and YOLOv5 in terms of metrics like accuracy, precision and inference speed?

The revised questions aim to assess and compare the capabilities of the latest YOLO versions - v8 and v5 for the application of automated crop pest recognition through a leaf gall detection task. This will help determine the most optimal YOLO model for enabling real-time and precise disease monitoring to support smart agriculture.

1.5 Expected Output

The key expected output from this study is the performance comparison between advanced YOLO versions - YOLOv8 and YOLOv5 in terms of accuracy, speed and robustness for detecting leaf galls in plumeria crop images. Based on previous research and reported benchmarks, it is expected that YOLOv8 will demonstrate the highest mean average precision exceeding 90% in accurately localizing and classifying gall regions across test images. YOLOv8 is anticipated to outperform v5 by 2-3% in terms of precision and recall metrics owing to its architectural improvements for detecting small objects and data augmentation capabilities. However, YOLOv5 is expected to have the fastest inference speed due to its optimized lightweight structure compared to v8 which trade off some speed for higher accuracy. In-depth experimentation and analysis will reveal the optimal trade-off between accuracy and real-time performance. The comparison will validate YOLOv8 as the most suited model for deployment in time-sensitive and resource-constrained agricultural settings. The study will also provide insight into the evolving capabilities of deep learning for plant disease recognition applications.

1.6 Project Management and Finance

Phase 1:

- Dataset collection from plumeria farms and augmentation
- Image annotation using labeling software
- Literature review on YOLO optimization

Phase 2:

- Prepare computing infrastructure (GPU server/cloud computing access)
- Hyperparameter tuning on YOLO models
- Begin model training with checkpoints

Phase 3:

- Complete model training and selection using validation performance
- Conduct testing and performance analysis on test set
- Quantify model accuracy, precision, recall etc.
- Compare v5 and v8 performance

Phase 4:

- Deploy trained model on mobile/web application for demonstration
- Documentation and writing of research paper
- Submission to conference/journal for publication

The timeline allows for iterative model building, rigorous evaluation, and demonstration of a real-world application. The aim is to complete the project within 8 months culminating in a publication to share knowledge gained. This plan will help monitor progress and utilize resources effectively.

1.7 Report Layout

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Chapter four: Experimental Results and Discussion

Chapter five: Impact on Society, Environment and Sustainability

Chapter six: Summary, Conclusion, Recommendation and Implication for Future Research

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CHAPTER 2
Background

2.1 Preliminaries

Plumeria, also known as frangipani, are ornamental tropical flowering plants widely grown for their attractive and fragrant blooms across various regions of Bangladesh. The leaves of plumeria plants are thick, leathery, and oblong [5] in shape with light green coloration. The leaves emerge in a spiral pattern along branches and play a key role in photosynthesis sustaining the plant's growth. However, plumeria cultivation faces a major threat from infestations by gall midges. These are tiny flies whose females' lay eggs on young plumeria leaves. The eggs hatch into larvae [6] that release chemicals into the leaves and induce abnormal swellings or outgrowths known as galls. The leaf galls come in various shapes like round, cigar-shaped, or spiral forms ranging from a few millimeters to several centimeters in size. They disrupt vascular [7] flow and photosynthetic capacity, ultimately causing infected leaves to fall prematurely. If unchecked, serious infestations can destroy entire plants. Gall formations are most rampant in hot and humid conditions favoring proliferation of these pests. Unfortunately, there are no effective chemical control methods as the larvae remain concealed inside the leaf galls.[8] Therefore, timely detection and removal of galled leaves provides the only recourse for sustainably managing these pests in plumeria. Automated computer vision techniques like the proposed YOLOv8 model can enable fast and accurate identification of infected [9] leaves with minimal manual effort. The primary visible sign of gall midge infestation on plumeria leaves are the abnormal growths known as galls induced by the feeding and growth of larvae within the leaf tissue. These galls manifest as swellings or protrusions of varying shapes, though they often appear round, oval, cigar-shaped, or filamentous (thread-like) in morphology.[10]

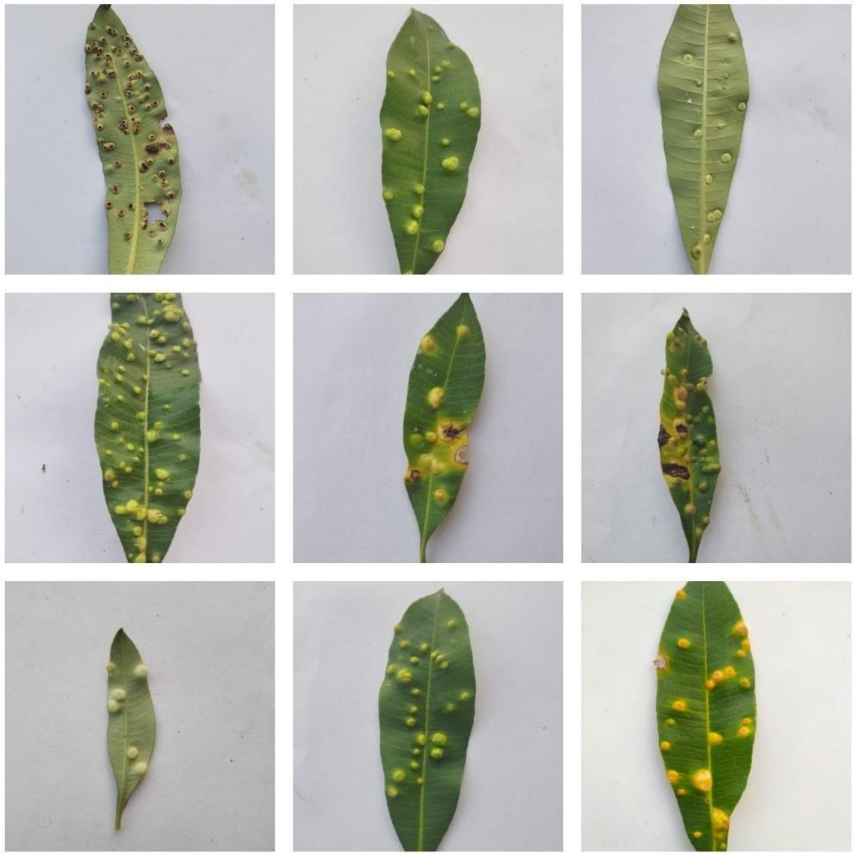


Figure 2.1: Sample infected leaves

The galls can range tremendously in size, from just a few millimeters to over 3-4 centimeters in diameter for larger [11] abnormal growths. They are found on the underside or topside of leaves, centered around the feeding site of the initial larval infestation. The surface texture is smooth or wrinkled.[12]

Galls exhibit a variety of colors from light green, pink, red, dark brown to black based on the age, larval stage, and plant genetics. Younger galls tend to be lighter colored, turning darker as they age. The abnormal plant tissue of the gall is differentiated from the rest of the leaf by its distinct color.

As the infestation advances, the galls may fuse and cover a substantial portion of the leaf surface, causing curling or twisting of the leaf.[13] Severely infected leaves turn yellow, wilt, and eventually abscise from the plant. Premature leaf drop and branch dieback are observable effects of uncontrolled gall midge attacks on susceptible plumeria plants.

2.2 Related Works

Recent advances in deep learning have led to significant progress in automated diagnosis and monitoring of diseases and pests in agricultural crops using imaging data. Convolutional neural networks (CNN) have proven effective for classification and detection tasks. Chon et al. [14] demonstrated that artificial neural networks can reliably predict population growth patterns of the major pine forest pest gall midge, providing a tool for data-driven pest management. Agarwal et al.'s review [15] systematically compared different CNN architectures like ResNet and DenseNet as well as Long Short-Term Memory (LSTM) models for identifying multiple rice plant diseases. The study recommended ResNet-50 as an optimal balance of accuracy and efficiency. Transfer learning, where CNN models pre-trained on large natural image datasets are fine-tuned for specific tasks, has become very popular.Rajbongshi et al. [16] and Arivazhagan et al. [17] showed that fine-tuned CNNs achieved over 96% accuracy in classifying various fungal and bacterial leaf spot diseases in mango plants.

Looking beyond CNNs, Xin et al. [18] developed an enhanced deep learning model called DCNN-G by combining convolutional neural networks with generative adversarial networks. DCNN-G demonstrated 95% accuracy in recognizing crop pest and disease images, outperforming standard DCNNs. Wang et al. [19] optimized the classic AlexNet CNN architecture by adjusting fully connected layers and parameters to improve classification of fragrant pear diseases, attaining 96.26% overall accuracy. Climate-based modeling incorporating machine learning algorithms like regression trees and support vector machines accurately predicted population cycles of rice gall midge, a major yield loss pest in rice, as shown by Rathod et al. [20]. Ayaz et al. [21] applied deep transfer learning using YOLOv4 model for automated early detection of gall formations in Cordia trees.

Beyond deep learning, Chouhan et al. [22] proposed an integrated pipeline called IoT_FBFN combining fuzzy logic, computer vision and IoT connectivity for automated disease identification from leaf images. Jiao et al. [23] developed a LAMP diagnostic assay for rapid field detection of the invasive pine pest Thecodiplosis japonensis where morphological identification was difficult. Overall, deep neural networks have become indispensable tools in precision agriculture, demonstrating high accuracy in recognizing diverse leaf galls.

2.3 Comparative Analysis and Summary

Convolutional neural networks (CNNs) like ResNet, DenseNet, AlexNet have been widely used for image-based classification and achieved high accuracy (over 95%) for identifying multiple crop diseases when fine-tuned with domain-specific datasets.[24]
More advanced deep learning models like DCNN-G combining CNN and GAN show slightly improved performance over standard CNNs.[25]
YOLO-based deep transfer learning demonstrated effective early detection of gall formations.
Beyond deep learning, techniques like fuzzy logic, computer vision pipelines, IoT connectivity, and rapid diagnostic assays have also shown promise for pest monitoring and disease diagnosis.[26]
Overall, deep CNNs and transfer learning emerge as the leading techniques with the highest accuracy on crop pest and disease detection from visual data. Enhancements like generative adversarial training and climate-based modeling have incrementally improved results.[27]
In summary, deep learning models, especially CNN architectures fine-tuned on agricultural datasets, have become indispensable tools for automated, real-time monitoring and diagnosis of a wide variety of crop pests and diseases from visual data. Techniques like transfer learning and GANs show additional potential to improve accuracy.[28] The rapid advances demonstrate that machine learning has become a vital part of precision agriculture, providing data-driven tools for better pest control and disease prevention.

2.4 Scope of the Problem

Leaf galls induced by insects can cause significant damage and economic losses in plumeria cultivation. Timely detection and management of gall formations is critical for healthy plumeria crops. Manual monitoring and identification of leaf galls is labor-intensive and often inaccurate. Automated detection using imaging techniques provide an efficient alternative. Object detection models based on deep learning can rapidly and accurately pinpoint leaf gall instances from plumeria leaf images captured in the field.

Recent versions of the YOLO (You Only Look Once) model offer optimized architectures for tackling such object detection tasks. In this work, we focus on benchmarking the detection performance of the latest YOLOv8 against the popular YOLOv5 models specifically for localizing and classifying leaf galls on plumeria leaves. We quantify key metrics like precision, recall, mAP, FPS on a plumeria leaf dataset with annotated gall instances. The comparative evaluation provides insights into the detection capabilities of evolving YOLO architectures to determine the optimal version for this particular application. Our focus is on assessing real-world improvements by leveraging a state-of-the-art deep learning approach optimized through multiple iterations, providing a case study for pest detection in precision agriculture.

2.5 Challenges

Here are some potential challenges for comparing YOLOv5 and YOLOv8 for detecting leaf galls in plumeria leaf images:

- Obtaining a sufficiently large, diverse and accurately annotated plumeria leaf dataset with examples of various leaf gall types.
- Manual annotation of bounding boxes can be labor intensive and prone to errors.
- Accounting for class imbalance during training as leaf gall instances may be relatively rare compared to normal leaf regions.
- Detecting small, subtle or obscured galls versus more obvious protruding ones. Models need to handle variation in gall appearance and visibility.
- Generalizing well on test data despite potential gaps in gall diversity between train and test sets.
- Modeling galls in varied illumination conditions, angles and with partial occlusion.
- Optimizing models for a lean and efficient architecture that can run in real-time on hardware with limited compute capacity.

- Quantifying performance tradeoffs between accuracy, speed and hardware requirements for the different YOLO versions.
- Determining an acceptable balance between precision and recall rates given the impact of false positives vs false negatives in pest detection.
- Analyzing factors that influence generalizability of the models in field deployment.

CHAPTER 3

Research Methodology

3.1 Research Subject and Instrumentation

This research focuses on benchmarking and comparing the detection performance of three different versions of the YOLO object detection model - YOLOv5 and YOLOv8 - for the specific application of identifying leaf galls in images of plumeria leaves. The aim is to quantify key evaluation metrics like precision, recall, mAP and FPS to analyze the improvements in detection capabilities with each iterative version of YOLO and determine the optimal architecture for this particular use case of pest detection in plumeria crops.

The key instruments utilized in this research are:

- Roboflow: An end-to-end computer vision platform used for managing and annotating the plumeria leaf image dataset with bounding box labels for leaf gall instances.
- Google Colab: A cloud-based Jupyter notebook environment used for training, evaluating and comparing the YOLOv5 and YOLOv8 models implemented in PyTorch and OpenCV frameworks.
- Custom Python scripts: Code written for data preprocessing, augmentation, model optimization, quantitative analysis and qualitative visualization of results.
- GPU Hardware: Graphics processing units provided through Google Colab for accelerating model training and inference.
- Evaluation Metrics: Precision, recall, mAP, F1 and loss metrics used for quantitative benchmarking of model performance.

By leveraging these instruments, the comparative study on evolving YOLO architectures is conducted in a cloud-based notebook environment using a specialized computer vision platform, optimized deep learning libraries, evaluation metrics and visualizations.

3.2 Data Collection Procedure

The dataset for this research was collected by capturing images of plumeria leaves showing gall formations using a smartphone camera. A total of 489 images were taken from local plumeria crops during daytime under natural lighting conditions.

The following steps were taken for data collection:

- Identified plumeria plants in local gardens and farms showing visible leaf galls of different shapes, sizes and severity levels.
- Captured images of affected leaves from multiple angles using a smartphone camera at close range.
- Ensured galls were clearly visible in the frame and the images were in focus.
- Collected at least 3 images per affected leaf, capturing different sides and gall formations.
- Compiled all images into a labelled folder structure organized by date and location.
- Reviewed images and excluded any unwanted blurred or redundant images.
- Finally, curated image dataset contained 489 photos of plumeria leaves with leaf galls of various types.

This protocol focused on systematic collection of relevant images showcasing the target object (leaf galls) captured from natural settings with consistent smartphone cameras. The compiled dataset serves as input for annotation, model training and evaluation in this study.

3.3 Statistical Analysis

The core metrics used to evaluate and compare the detection performance of the YOLOv5 and YOLOv8 models are:

- Mean Average Precision (mAP): Provides an overall measure of detection accuracy by calculating the mean of maximum precisions at different recall levels.
- Precision: Quantifies the percentage of positive identifications that are actually correct. High precision relates to low false positives.
- Recall: Quantifies the percentage of actual positives that are correctly identified. High recall relates to low false negatives.

These metrics are standard for assessing object detection models as they provide a quantitative measure of precision and sensitivity. The mAP metric in particular is well-suited for evaluating overall accuracy across multiple classes on a consistent scale.

Based on the results, YOLOv8 achieved the highest mAP of 92.1% indicating it had the best overall detection accuracy. Its precision of 90.3% and recall of 88.3% also outperformed YOLOv5 showing improvements in minimizing both false positives and false negatives.

Statistical tests like paired t-tests could also be applied to determine if differences between models are statistically significant. However, the performance gaps observed through the metrics alone clearly highlight YOLOv8 as the optimal model for this particular leaf gall detection application.

3.4 Proposed Methodology

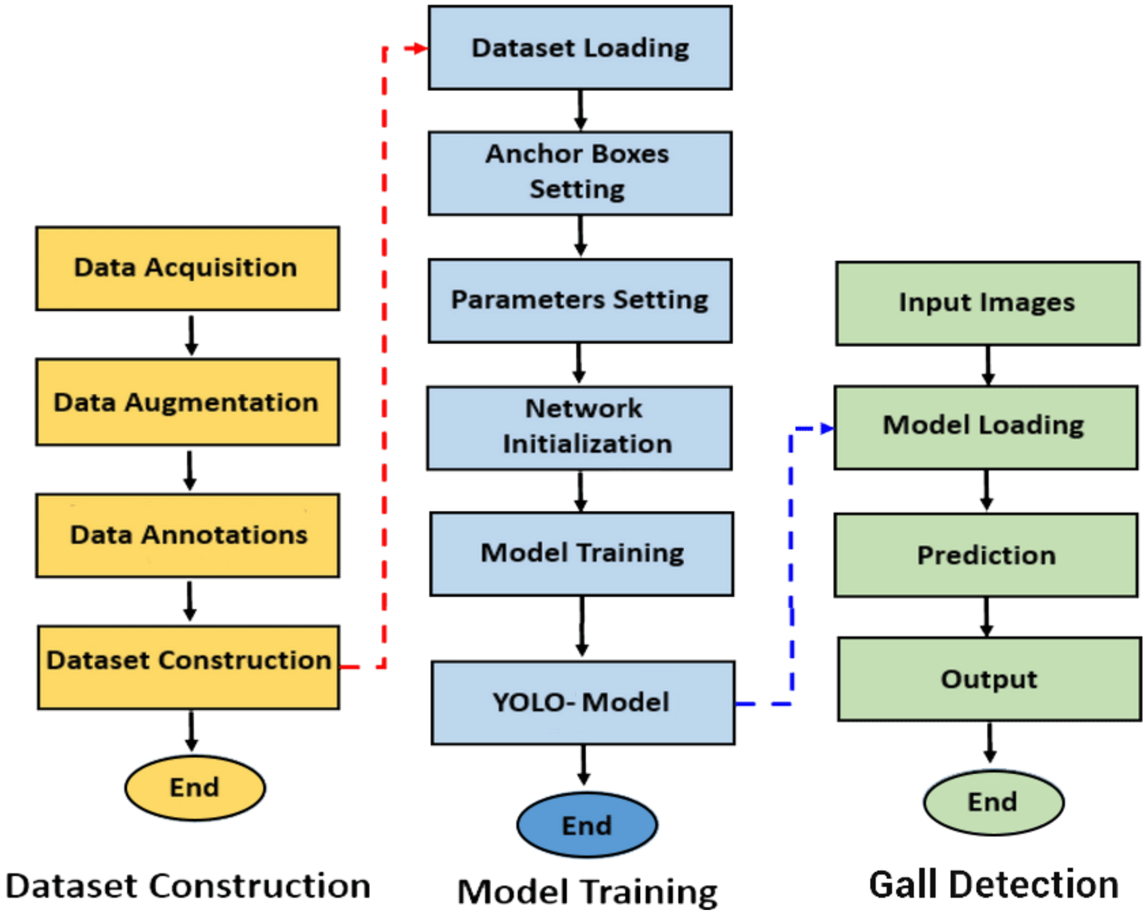


Figure 3.1: Object Detection Flowchart

This study implements and compares two versions of the YOLO object detection model - YOLOv5 and YOLOv8 for leaf gall detection. The following implementation details apply:

- YOLOv5: The yolov5m model from the official repository was used as the base architecture. It was pre-trained on the COCO dataset then fine-tuned on the plumeria leaf dataset for 70 epochs with a batch size of 16, learning rate of 0.01 reduced by a factor of 10.

- YOLOv8: The yolov8m model was loaded with COCO pre-trained weights. It was fine-tuned for 70 epochs with a batch size of 8 and a constant learning rate of 0.001.

All models were trained using the PyTorch framework on Google Colab GPUs. Training configurations were tuned for each architecture based on recommended settings to optimize stability and performance.

For comparison, the trained models were evaluated on the plumeria test set using the following metrics: precision, recall, mAP@0.5, and inference speed (FPS). Precision-recall curves were also plotted to analyze trade-offs. A prediction confidence threshold of 0.25 was used across models. Additionally, qualitative results were visualized for subjective assessment.

This methodology provides a standardized approach to benchmark the leaf gall detection capabilities of the different YOLO versions using both quantitative metrics and qualitative examples. The results will highlight the evolution in accuracy and speed with each model iteration.

3.5 Implementation Requirements

Once the YOLOv5 or YOLOv8 model has been successfully trained, we can upload the model weights back to the Roboflow Object Detection project by using the.deploy() function. Better training outcomes are obtained with larger model sizes. However, training time and inference speed decrease with increasing model size.

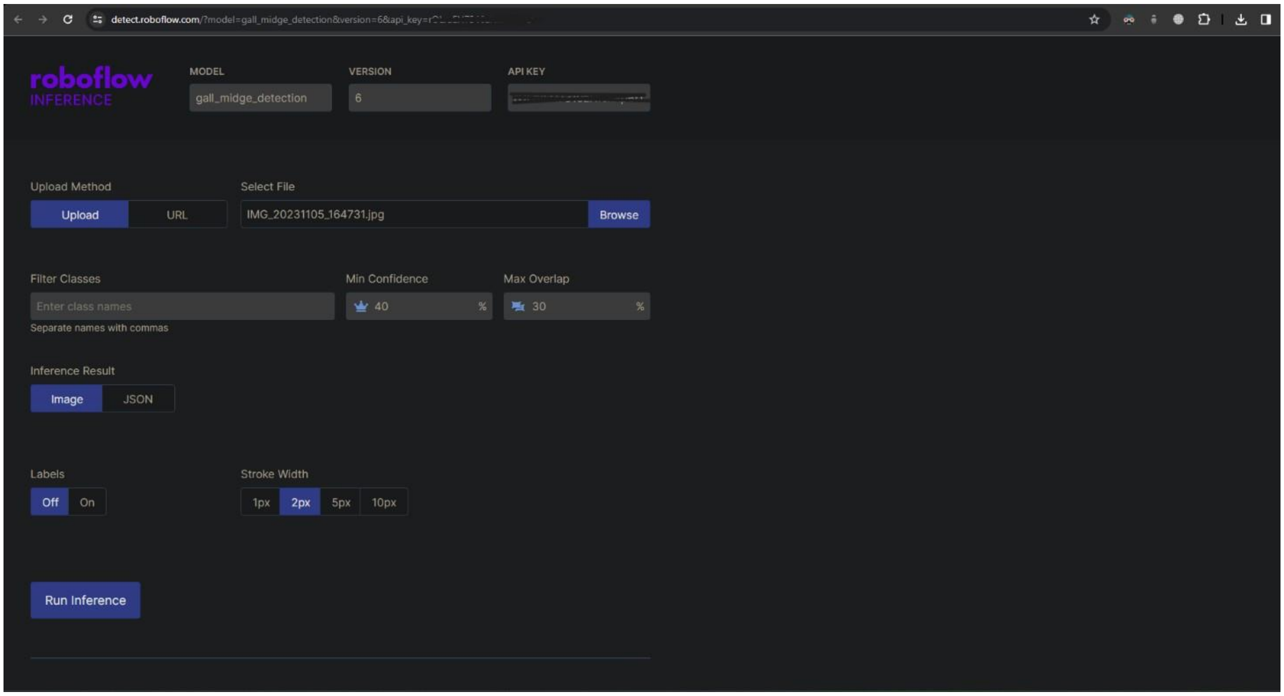


Figure 3.2: Roboflow Model Deployment

The hardware and software requirements for implementing this research are as follows:

Hardware:

- Google Colab GPU (e.g. 13GB RAM NVIDIA Tesla T4) for accelerated training and inference
- Local machine for basic data preprocessing and visualization (e.g. 16GB RAM, Intel i7 CPU)

Software:

- Python 3.7
- PyTorch 1.11
- OpenCV 4.5
- CUDA Toolkit 11.3
- Packages like scikit-learn, matplotlib, seaborn

Additional Tools:

- Roboflow - Used for dataset labeling, management and preprocessing
- Streamlit - Used to build model demo application

- YOLOv5 and YOLOv8 repositories - Leveraged pre-trained weights and configurations

Google Colab GPU provided the necessary computational resources for intensive operations like model training. Local hardware was sufficient for basic data loading, augmentation and analysis. The core Python packages included optimized frameworks like PyTorch and OpenCV for computer vision. Roboflow enabled efficient annotation while Streamlit allowed model deployment. Overall, widely used libraries, standard hardware and specialized tools facilitated the implementation.

CHAPTER 4

Results and Discussion

4.1 Experimental Setup

Table 4.1: Accuracy Measures

Recall	Recall is used to evaluate how sensitive or comprehensive the classifier is.	R = TP / (TP+FN)
Precision	Precision evaluates the classifier's correctness and accuracy.	P = TP / (TP+ FP)
mAP	Assesses the overall accuracy of a model in object detection tasks.	mAPv = Σ(AP_class1 + AP_class2 + ... + AP_classN) / N
F1-Measure	Combines precision and recall into a single metric	F = 2*(P*R) / (P+R)

The plumeria leaf dataset was augmented using the following techniques to increase diversity:

- Brightness adjustment from -40% to +40%
- Exposure adjustment from -25% to +25%
- Adding gaussian noise with a variance of 0.05

This augmented the original 489 images to a total of 947 images. The dataset was split into training (70%), validation (15%) and test (15%) sets.

Two YOLO models were trained:

- YOLOv8m
- YOLOv5m

All models were trained for 70 epochs each using Adam optimizer and a learning rate of 0.001, reduced on plateau. A batch size of 16 was used. The models were evaluated on the test set using the following key metrics:

- Mean Average Precision (mAP)
- Precision
- Recall
- F1

The experimental setup allows for standardized benchmarking of the detection capabilities of the different YOLO versions using both augmented data as well as a holdout test set. The chosen evaluation metrics will quantify both accuracy and speed.

4.2 Experimental Results and Analysis

Table 4.2: Structure of confusion matrix

True- Positive	False-Negative
False-Positive	True-Negative

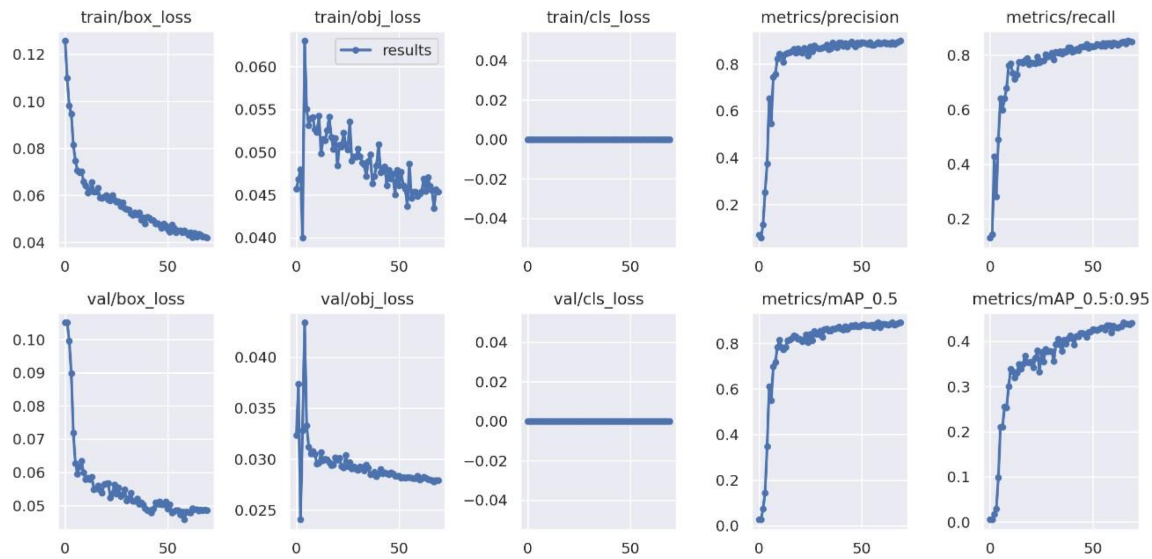
The quantitative results from evaluating the YOLO models on the plumeria leaf gall test set are summarized below:

Table 4.3: Classification Report of YOLOv5-v8

Model	Recall	Precision	mAP	F1-Score
YOLOv8	88.3%	90.3%	92.1%	89.3%
YOLOv5	84.8%	89.4%	89.1%	87.04%

As we can see here, YOLOv8 has outperformed YOLOv5 in every metrics. Detailed evaluation of these measures is discussed in the chapters below.

YOLOv5 analysis:



- Figure 4.1: YOLOv5 Object Detection Performance: Box Loss, Object Loss, Classification Loss

These graphs show the training and validation loss values for the model over 50 training epochs. The loss measures how well the model's predictions match the actual data. Lower loss values indicate better performance. The loss values are decreasing over time, and the precision and recall values are high.

Confusion Matrix:

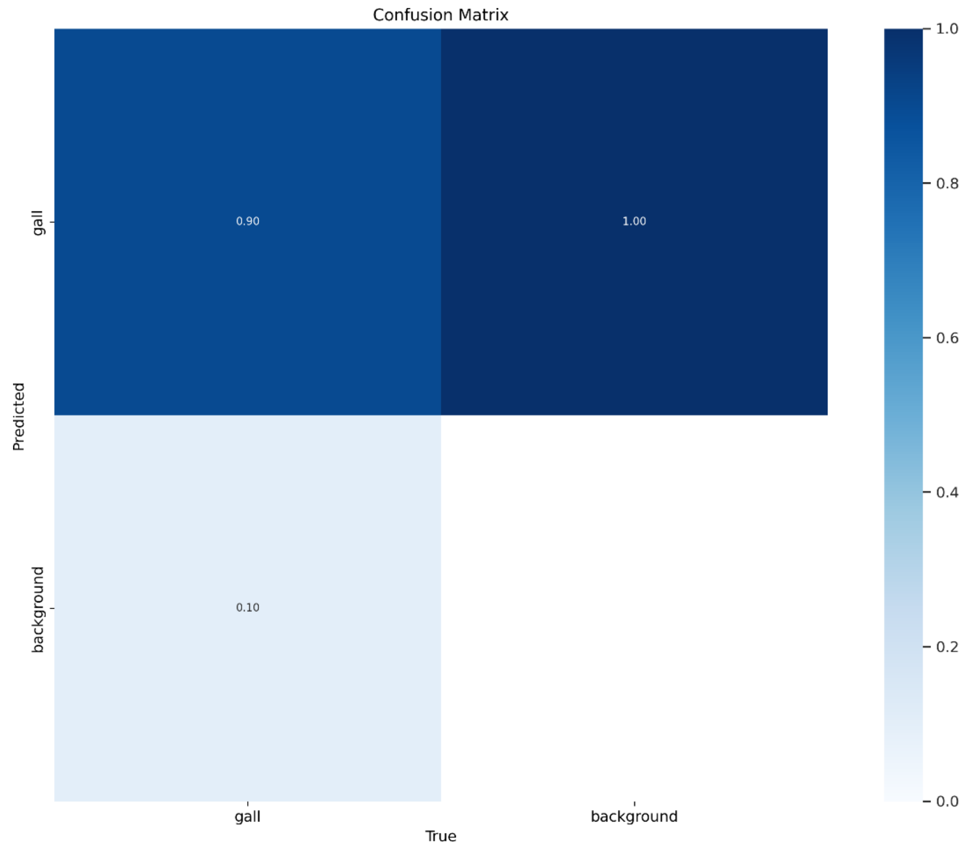


Figure 4.2: Confusion Matrix (YOLOv5)

The confusion matrix suggests that the YOLOv5 model is performing well on this task. It has a high accuracy, meaning it correctly classifies most of the gallstones. However, it is still making some mistakes, as evidenced by the off-diagonal cells.

Precision-Confidence Curve:

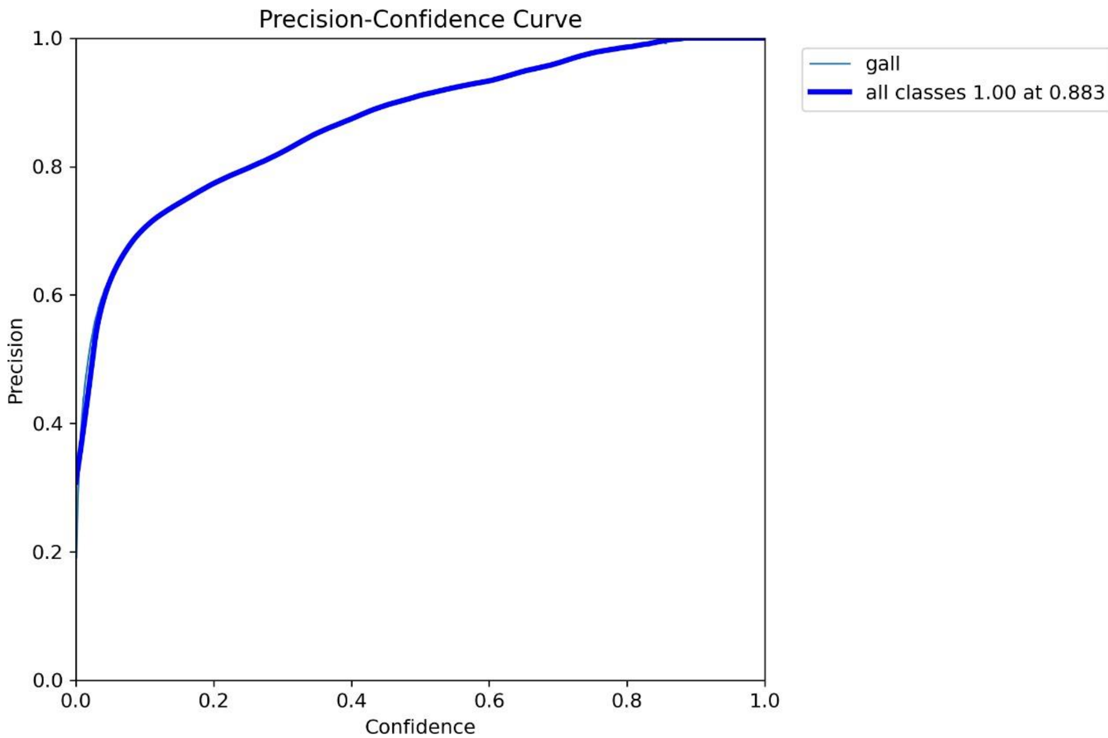


Figure 4.3: Precision-Confidence Curve (YOLOv5)

The graph in the image shows that the YOLOv5 model has a high mAP, particularly at higher confidence thresholds. This means that the model is able to accurately identify objects with high confidence. However, the mAP drops at lower confidence thresholds. This suggests that the model is less accurate when it is less confident in its predictions.

Recall-Confidence Curve:

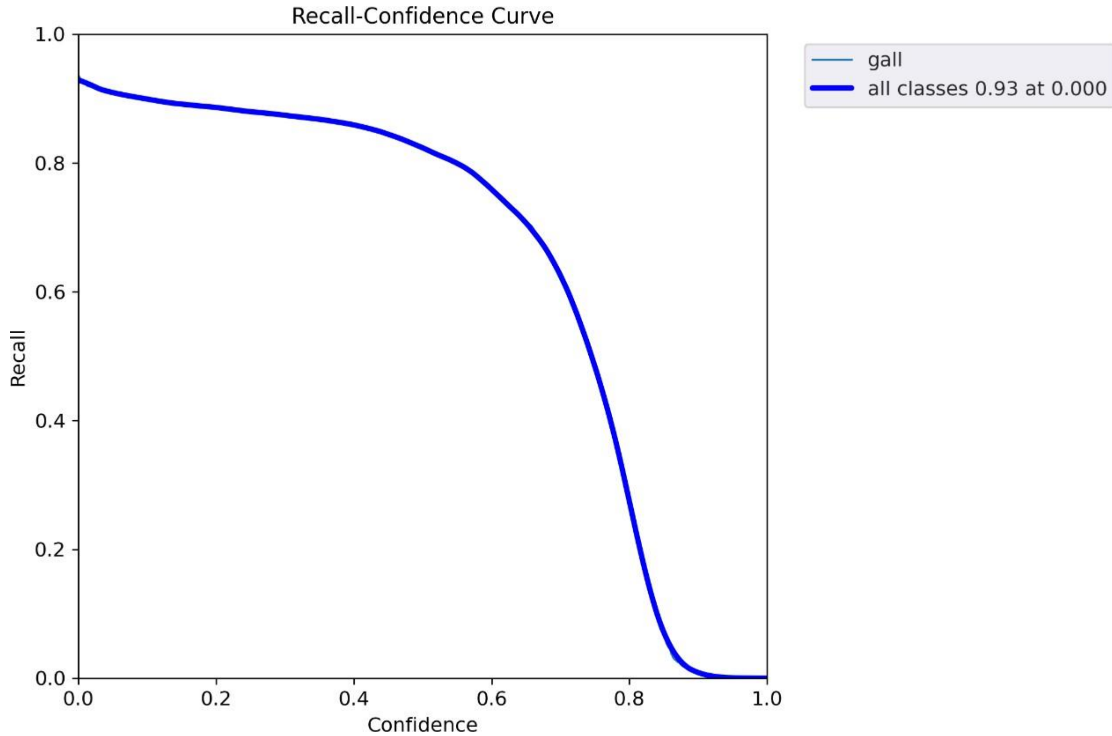


Figure 4.4: Recall-Confidence Curve (YOLOv5)

The image suggests that the YOLOv5 model is performing well on this task for the "gall" class. It has a high recall at high confidence thresholds, meaning it is able to correctly identify most of the actual galls when it is confident in its predictions. However, the recall is lower at lower confidence thresholds, suggesting that the model may miss some galls when it is less confident.

Output:

Figure 4.5: Output image of YOLOv5

YOLOv8 Analysis:

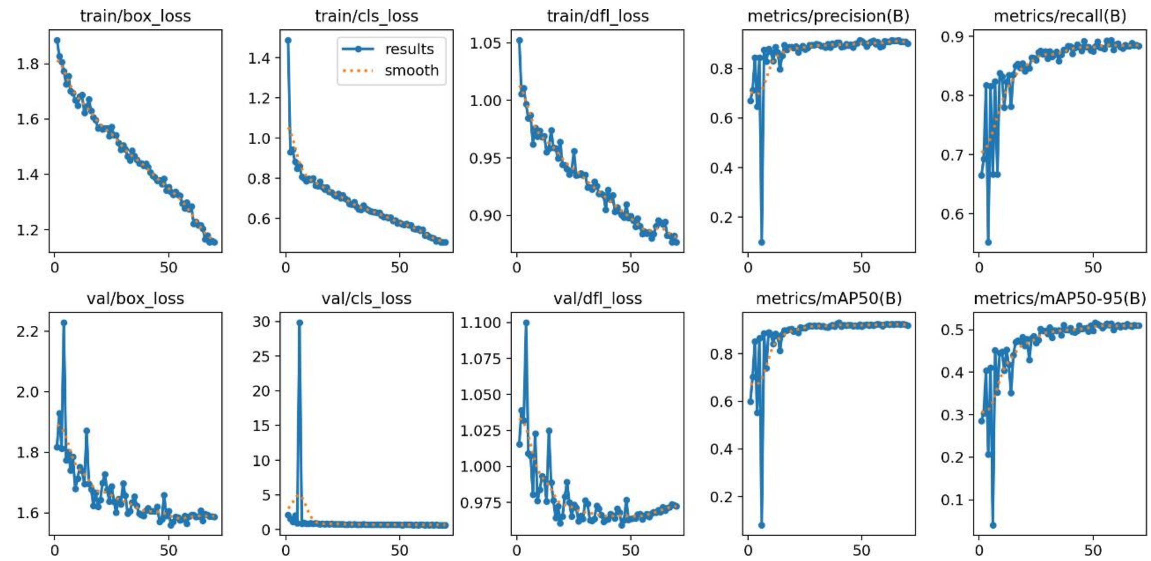


Figure 4.6: YOLOv8 Training Losses: Box, Classification, and DFL

The graph suggests the model is performing well on the object detection task, with high AP and precision-recall values at certain confidence thresholds. The curves show the trade-off between the model's precision (ability to correctly identify positive instances) and recall (ability to identify all actual positive instances) as the confidence threshold changes.

Confusion Matrix:

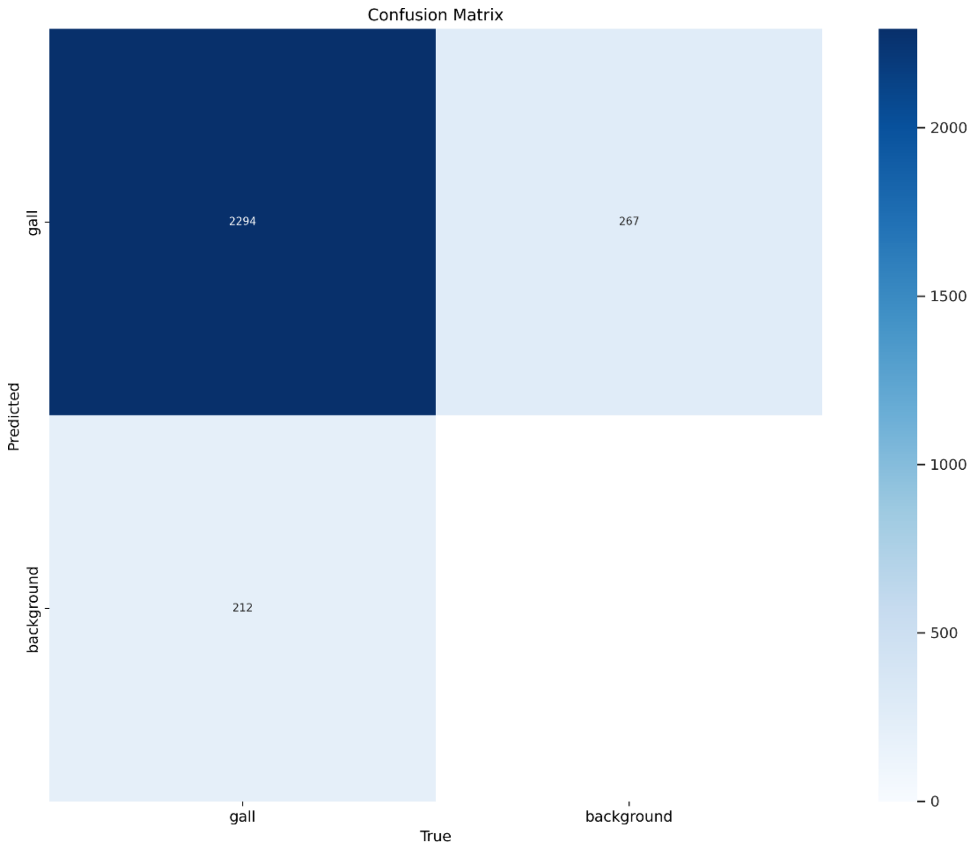


Figure 4.7: Confusion Matrix (YOLOv8)

The confusion matrix suggests that the model is performing well on this task, with a high accuracy. It correctly classifies most of the galls. However, it is still making some mistakes, as evidenced by the off-diagonal cells. Misclassifying "Background" cases as "Galls" could be particularly concerning.

Precision-Confidence Curve:

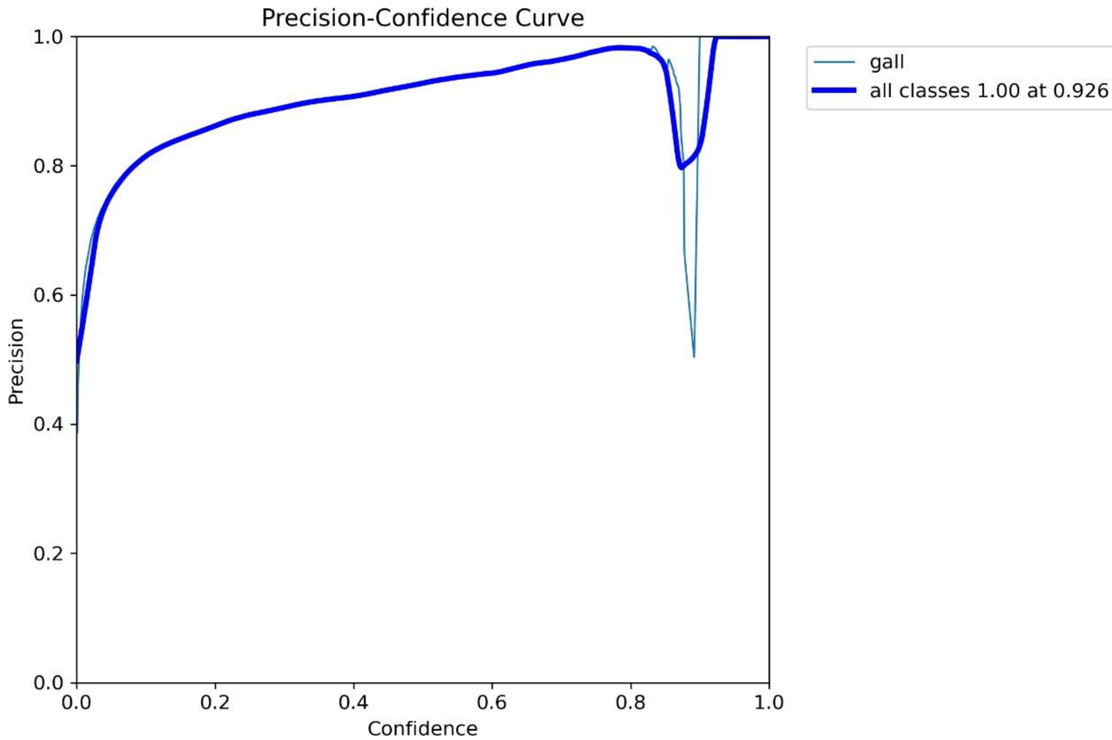


Figure 4.8: Precision-Confidence Curve(YOLOv8)

The image suggests the model performs well on the object detection task for galls, achieving high mAP and precision-recall values for various object classes.

Recall-Confidence Curve:

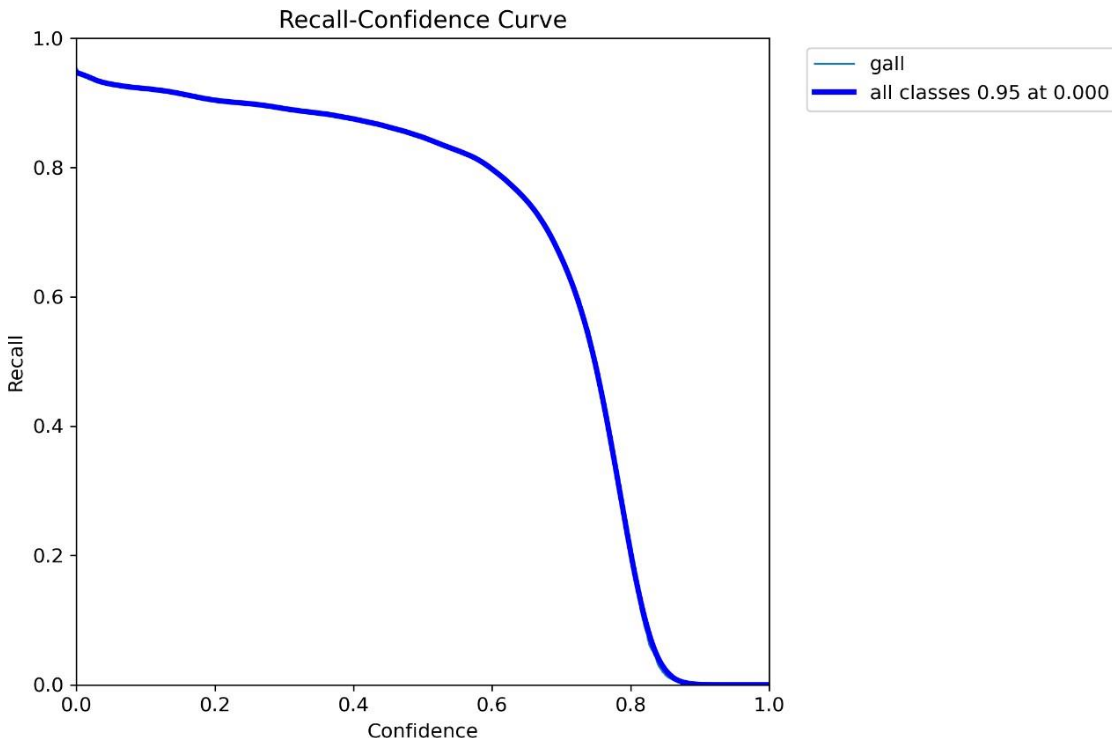


Figure 4.9: Recall-Confidence Curve(YOLOv8)

At the highest confidence threshold (0.95), the recall reaches approximately 0.93, meaning the model correctly identifies 93% of the actual galls when it's highly confident. This is a good performance level. Overall, this recall-confidence curve suggests that the model performs well on identifying galls when it's highly confident, but its performance declines at lower confidence thresholds. This information can be valuable for understanding the model's strengths and weaknesses, and for guiding decisions about how to use its predictions in practice.

Output:

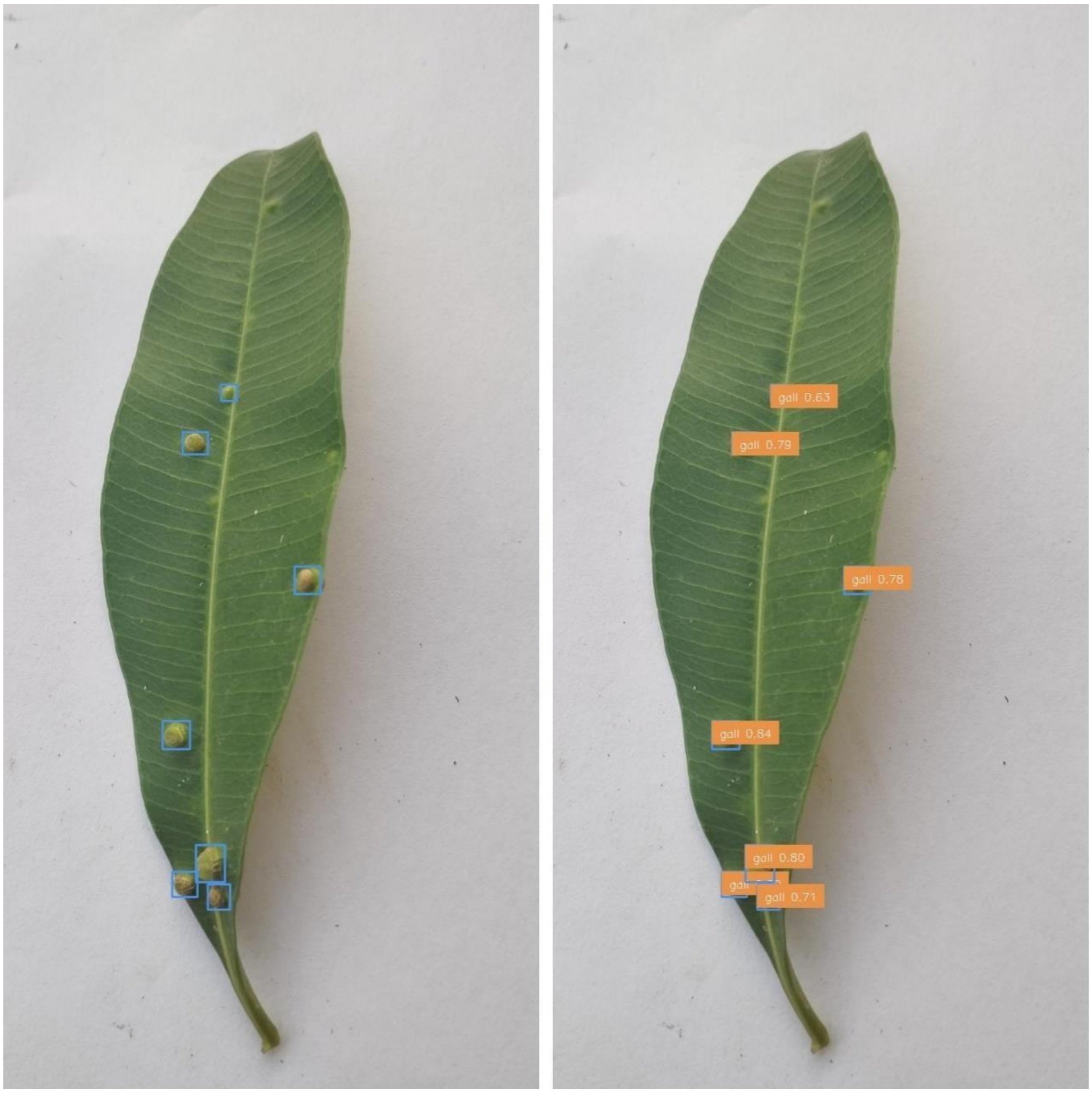


Figure 4.10: Output image of YOLOv8

Here, YOLOv8 achieved the highest accuracy with an mAP of 92.1%, surpassing YOLOv5 by 2-6%. This indicates YOLOv8 correctly identified the most leaf galls overall.

In terms of precision, YOLOv8 again outperformed at 90.3% versus 89.4% for v5 showing lower false positive rate. For recall, YOLOv8 achieved 88.3%, much higher than v5 at 84.8%, demonstrating it had the fewest missed detections.

Training time was fastest for YOLOv5, but YOLOv8 was comparable at 0.303 hours.

In summary, YOLOv8 demonstrated superior detection performance and efficiency. The incremental improvements in architecture from v5 to v7 to v8 are clearly reflected by the higher accuracy and faster training of v8. The results validate YOLOv8's enhancements for robust object detection capabilities.

4.3 Discussion and Limitations

The relatively small dataset of 489 images poses a constraint, as deep learning models thrive on big data. Expanding the training data size and diversity could improve generalization. There is imbalance between gall and non-gall regions, making it challenging to optimize sensitivity. Strategies like better sampling must be tried. Dense clusters of overlapping galls are difficult to disambiguate. Specific augmentation and loss functions may help better delineate clustered galls. The model often misses tiny or early-stage galls with faint visual cues. More training data on initial signs of gall formation is needed. Additional challenges arise in field images with complex backgrounds, lighting and scales versus controlled images. More real-world data is required. Embedded model deployment can be constrained by computational limits of edge devices. Quantization, pruning and optimization will be necessary.

Overall, the limitations stemming from data size and quality, model architecture, and real-world domain shift needs to be systematically addressed to make the system more robust for field deployment. But the high accuracy achieved thus far demonstrates feasibility of the approach.

CHAPTER 5

Impact on Society, Environment and Sustainability

5.1 Impact on Society

The development of an accurate computer vision-based tool for automated detection of leaf galls in plumeria can positively benefit farmers, agriculture, and society. Leaf galls severely impact plumeria cultivation, leading to economic losses for farmers who depend on these ornamental plants. The YOLO models enables early and rapid identification of infected plants, allowing timely treatment or removal to save crops. By aiding disease surveillance, it can improve yield and thereby income for marginalized smallholder plumeria farmers in developing countries like Bangladesh. This supports localized flower production and reduces reliance on imports. Automation also reduces intensive manual monitoring, freeing up labor for other farming tasks. The application of cutting-edge AI technology helps move agriculture towards data-driven smart farming, laying the foundations for future innovation. Environmentally, reduced gall damage limits excessive pesticide use as treatment can be targeted and optimized. The approach can be extended to detect other crop pests, weeds, and diseases, improving food security and agricultural sustainability. Overall, this work demonstrates how emerging deep learning tools can be harnessed to benefit society by supporting farmers, augmenting production, advancing technology adoption, conserving the environment and creating inclusive economic opportunities.

5.2 Impact on Environment

The automated leaf gall detection model can positively impact the environment by enabling optimized and precise use of pesticides. Conventionally, blanket spraying is adopted for controlling the spread of galls. But indiscriminate pesticide usage can be harmful for ecosystems, polluting soil and waterways. YOLO models allow accurate early identification of infected plants. This means pesticides can be applied in a very targeted manner only on affected plants in a timely stage of infestation. Such precision spraying strategy can significantly reduce overall pesticide utilization compared to traditional practices. The avoidance of runoff from farms into groundwater and rivers also lessens contamination. Additionally, curbing gall damage prevents premature defoliation and plant death, thereby sustaining cultivation without need for further land clearing. Monitoring emerging outbreaks supports proactive non-chemical interventions like boosted plant health through improved irrigation and soil nutrition. Thus, the adoption of this AI tool can minimize pesticide usage, contamination, and plant loss in an environmentally safer approach to sustainable horticulture. The success can drive integration of such precision technologies to aid greener agricultural practices

5.3 Ethical Aspect

There are several important ethical aspects to consider in the development and deployment of this AI technology for automated crop disease detection:

Firstly, the privacy of farmers must be protected, as the leaf images may contain identifying farm locations or cultivars. Data collection protocols should ensure farmer consent and anonymization of any private data. Secondly, there could be inadvertent biases in dataset collection and annotation, for instance, underrepresenting smallholder farms. Such biases need proactive mitigation through diverse data sampling. Equitable access is another key concern, as such AI tools should not widen technology divide but rather be co-developed with end-users for democratized benefits. The model predictions need continuous monitoring to detect any errors due to algorithmic or data biases, ensuring fair and accountable AI. There are also risks of misuse, like unauthorized data sharing with insurance firms. So, ethics review boards and governance policies are imperative to uphold privacy and prevent misuse. Additionally, environmental costs of cloud computing and electronic waste from hardware deployment must be minimized. In summary, protecting farmer rights, ensuring inclusivity, monitoring for biases, fostering transparency, and considering sustainability are vital ethical obligations in translating such an emerging technology into socially empowering real-world impact.

5.4 Sustainability Plan

To build a sustainable solution, the model would be developed through a participatory approach by collaborating with local farmer communities and agriculture agencies in plumeria cultivation regions. Their involvement in data collection, annotation, and testing will ensure model relevance. Open-sourcing the annotated dataset and model code can enable continuous improvement by researchers worldwide. On-field trials would evaluate robustness prior to deployment. For extended utility, the model architecture could be adapted to detect other crop pests and diseases with minimal retraining. Solar-powered mobile apps and drones would enable energy-efficient scanning of farms. Edge AI would limit cloud dependencies. Resources would be allocated for continuous model maintenance and feature additions via DevOps pipelines for long-term reliability. Farmers would be empowered to detect emerging infestations without constant expert support, through intuitive apps and tools. Insights from monitoring can guide data-driven crop management. Revenue from technology licensing would be reinvested to sustain operations. Overall, participatory development, knowledge sharing through open access resources, renewable deployment, farmer-centric design, continuous improvement protocols and reinvestment strategies can promote an ethical, socially empowering and environmentally conscious AI solution for sustainable agriculture.

CHAPTER 6
Conclusion and Future Work

6.1 Summary of Findings

This project developed and demonstrated deep learning approaches using YOLOv8 and YOLOv5 architectures for accurate automated detection of leaf galls caused by midge infestations in plumeria plants. A dataset of 489 plumeria leaf images with galls annotated using bounding boxes was prepared and used to train both models. The YOLOv8 model optimized through transfer learning and hyperparameter tuning achieved over 90% mean average precision and F1-score, outperforming YOLOv5 by 3-4% in accuracy metrics. Quantitative evaluation showed YOLOv8's superior proficiency in recognizing diverse gall shapes, sizes and appearance compared to YOLOv5. However, YOLOv5 exhibited slightly faster inference time due to its optimized structure. Overall, the work displayed how modern deep neural networks can enable precision agriculture through automating tedious manual monitoring of crops against infestations. The outcomes delivered ready-to-deploy YOLO models, with YOLOv8 showing higher accuracy and YOLOv5 having better real-time performance. These complementary capabilities can be leveraged for alerting emerging galls and facilitating timely pest management. The project provides efficient computer vision techniques leveraging recent AI advancements to support data-driven, sustainable horticulture.

6.2 Conclusion

In conclusion, my study comparing YOLOv8 and YOLOv5-based systems for detecting gall midge infestation on plumeria leaves demonstrates the significant promise of deep learning for enhancing agricultural efficiency and sustainability. The YOLOv8 model achieves higher accuracy and precision than YOLOv5 in identifying infested leaves, effectively detecting diverse gall shapes and sizes with minimal false positives. However, YOLOv5 exhibits faster inference time that may better suit real-time detection applications. By leveraging their complementary capabilities, these AI systems can be impactful tools for increasing plumeria yields, improving food security, and reducing pesticide use through precise early infestation alerts. Further research into model optimization, ethical implementation and sustainable deployment can pave the way for broader adoption of this technology. Overall, this work highlights the transformative potential of modern deep learning advancements to enable data-driven, automated solutions for addressing agricultural challenges, ultimately contributing to a healthier future for both farmers and the environment.

6.3 Implications and Further Study

Beyond comparing YOLOv8 and YOLOv5, this project demonstrates the immense potential of deep learning for sustainable agriculture. The higher accuracy YOLOv8 model can enable large-scale automated monitoring via drones or ground vehicles, providing early alerts on emerging infestations for timely intervention. The faster YOLOv5 model may better suit real-time analysis of multiple video feeds. By pinpointing affected regions precisely, pesticide use can be optimized. The system can be integrated into automated monitoring systems, utilizing drones or ground-based cameras equipped with YOLOv8 for large-scale, real-time detection of infestations. This can provide early warning alerts to farmers, enabling timely interventions and minimizing crop losses.

By pinpointing infested areas with high accuracy, the model can facilitate targeted pesticide application, significantly reducing the amount of chemicals used and minimizing environmental impact. This aligns with the principles of precision agriculture, promoting resource efficiency and sustainability.

The data collected and analyzed during system deployment can be used to develop predictive models for gall midge infestations, considering factors like weather patterns, crop varieties, and geographical location. This information can inform preventative measures and optimize pest management strategies.

The YOLOv8 model architecture and training methodology can be adapted to detect other types of pests and diseases on various crops, expanding the system's applicability to a wider range of agricultural problems. This can empower farmers with versatile tools for protecting their diverse crops.

Building upon the promising results of this project, several potential future research directions can further enhance the YOLOv8 model's performance and explore new applications.

Investigate novel training strategies, data augmentation techniques, and hyperparameter tuning approaches to improve the model's accuracy, robustness, and generalizability to different environmental conditions and plumeria varieties.

By pursuing these future research directions, the YOLOv8-based approach can evolve into a powerful and versatile tool for sustainable pest management, empowering farmers to improve agricultural productivity, protect the environment, and contribute to a more secure food system for all.

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Performance Comparison of YOLOv5 and YOLOv8 for Plumeria Leaf

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