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YOLOv8-Based Pest Detection for a Plant Treatment Spraying Machine in Agriculture

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Abstract. Whitefly infestations pose a significant threat to chili crop productivity, leading to reduced yield and increased pesticide dependence. The aim of project is to develop an automated pest spraying machine that can effectively control whiteflies using advanced sensors and camera-based detection systems. By using advanced sensors and cameras, the system applies pesticides precisely, minimizing labor, chemicals, and environmental impact. A functional prototype detects and eliminates whiteflies, supported by a YOLOv8-based machine learning monitoring system. The system uses 3,150 images with computer vision for fast, accurate whitefly and anthracnose detection. The performance matrices for the whiteflies and anthracnose dataset are divided into three subsets: precision, mAP, and recall. This study achieves 75.27% precision, 64.3% mAP, and 69.84% recall. The results demonstrate the effectiveness of the YOLOv8 (You Only Look Once version 8) approach. The results demonstrate that the YOLOv8 model ensures efficient, reliable pest detection and promotes sustainable, precise chili crop management.

Keywords: You Only Look Once version 8(YOLOv8), Artificial Intelligence (AI), Convolutional Neural Network (CNN), mAP (mean Average Precision), IoT(Internet of Things)

1. Introduction

To address the challenges associated with whitefly pest control on chili crops, Malaysia's agriculture sector developed a sophisticated mechanized insecticide-spraying model. Agriculture makes up a large part of the Malaysian economy. About 7.3% of the economy can be attributed to agriculture. It also provides jobs to 11% of the population. Chili plants grow well in Malaysia and are in high demand, both locally and internationally. Whitefly causes crop loss due to quantity and quality reduction on a large scale [1-4].

The whitefly sensor and automated spray technology target the rational application of preventive pesticides. The application of modern technology enhances the precision and effectiveness of the sprayer. Identification of plants and pests is done by integrated cameras and sensors. When this technology is applied, spraying pesticides can be reduced by up to 30%. This also improves profitability and reduces

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the burden on the environment. Compared to known techniques of hand spraying, the machine eliminates operator variability and preprogrammed algorithms ensure consistent pesticide application.

To ensure the machine reliability and effectiveness in the agricultural context of Malaysia, a detailed field-testing regime as well as prototype design and simulation are parts of the overall development process. To promote sustainability and productivity, the agricultural sector of Malaysia has been progressively adopting automation, and this machine epitomizes that advancement. Based on field research, the automated spraying insecticidal machine can achieve a reduction of labor costs by as much as 40% because it does not involve the traditional labor-intensive methods of pest control.

In summary, the Malaysian agriculture pest spraying machine is an important technological innovation which places Malaysian farmers at an advantageous position because of the practical and efficient methods to control pests. The use of advanced sensors and automation ensures better pest control while exposing farmers to lower health risks and reducing environmental damage. This invention assists Malaysia in realising the goal of improving agriculture sustainability and productivity, as it provides a solution to the unique challenges that local chili farmers experience. Structure of the paper

2. Methodology

The aim of this methodology section is to present a summary of the techniques employed during the image detection system's design, develop, and testing phases. This section will contain a block diagram, a flowchart, a system design, hardware creation, all the devices and components required for the project, software used in the project, a list of experiments, a work breakdown structure, and a Gantt chart.

2.1. Data Acquisition

The real-time whitefly and chili plant detection system using YOLOv8 focuses on achieving high precision, recall, and mean average precision (mAP) to ensure accurate and reliable pest detection. Precision prevents falsely detected whiteflies and chili plants (low false positive) and recall ensures that no chili plant infested with whiteflies is missed out (important but often not correctly classified). The mAP is used to measure the overall precision-recall balance it in terms of performance consistency across classes and systems. The system can achieve efficient real-time detection to improve pest management and crop health protection by optimizing the performance metrics.

Table 1. Comparison of R-CNN and YoLov8

Criteria	R-CNN	YOLOv8
Input Image Size	Fixed input size	Variable input size
Training time	Longer training time and need to train multiple components separately.	Faster training time and use a unified network for object detection and classification.
Inference speed	Slower inference speed and need to process region proposals.	Faster inference speed and can process the entire image at once.
Flexibility	More flexible and customizable due to the use of separate components for region proposal and classification.	Less flexible compared to R-CNN, but still offers some customization options.

2.2. Data Preparation

The focus is on the development of a pest monitoring device for the supervised classification whitefly, healthy chili and anthracnose. Previous studies can always enhance the application and improve chances of achieving the goals. The object-detection dataset consisted of three classes: Anthracnose, Healthy, and Whitefly (WF)**.** The Anthracnose class represents chili plants/fruits exhibiting visible symptoms of anthracnose infection; the Healthy class represents chili plants without visible pest or disease symptoms; and the Whitefly class represents visible whitefly insects present on the chili plant. All images were manually annotated using Roboflow before model training. However, during the pre-augmentation and pre-train in Roboflow the total images output is increased by 3 times, making the total of 5868 images.

Table 2. Total Number of Dataset

	Total dataset
Anthracnose	1000
Healthy	305
Whitefly	1845
Total	3150
Total after pre-trained	5868

2.3. Advancement in Agriculture

The project is vital because the automated pest spraying machine is expected to change the method of controlling whitefly, healthy chili and anthracnose, which is an issue faced within agriculture. There are plans to implement advanced sensors and precision spraying mechanisms into an automated pest spraying machine, which would ultimately increase the efficiency and effectiveness of how pesticides are applied. This form of innovation allows for decreased use of chemicals, which not only assists in environmental preservation but significantly cuts down the labour farmers must endure and lowers the health risks pesticides pose to humans. In a similar fashion, identifying a specific pest-crop pair is a great approach since it leads to improvements in productivity, sustainability, and resilience surrounding farming.

2.4. Deployment and output

For a pest spraying machine, there is a lot of hardware development that goes into it that involves the use of Raspberry Pi and cameras among other things. These components work collaboratively to take pictures of whiteflies found on chili plants and later, processes and analyses them to deliver the output. The integration of these devices allows the machine to work properly and efficiently. A list of each device's individual specifications is provided below the figure.

2.5. System Overview

Figure 1 illustrates the block diagram of the project, which consists of three main parts: input, process, and output, while the arrows represent the workflow of the system. Figure 2 shows the flowchart of the Pest Spraying Detection System, explaining the step-by-step operation of the proposed system. The project focuses on developing a real-time whitefly and chili plant detection system using YOLOv8 technology and computer vision methods.

The methodology began with collecting more than one thousand images of whiteflies and chili plants to create a diverse dataset. Each image was carefully annotated to identify whiteflies and chili plant conditions accurately, enabling the model to learn important visual features effectively. The annotated dataset was then used to train the YOLOv8 model, where the algorithm learned to distinguish whiteflies and plant conditions through repeated training processes.

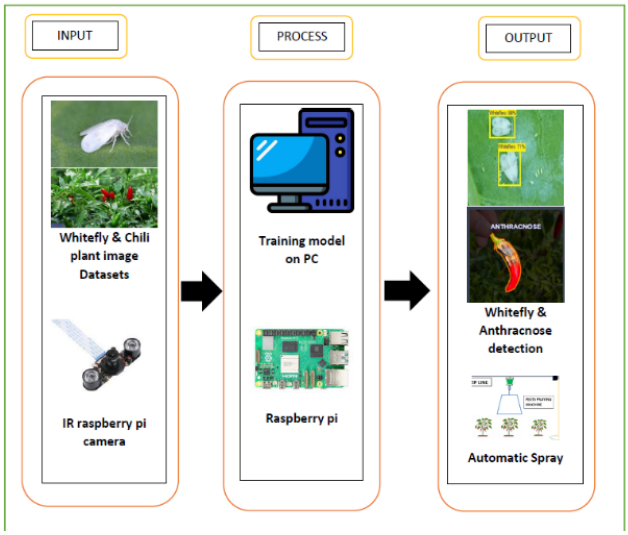


Fig 1. Block Diagram of pest spraying machine

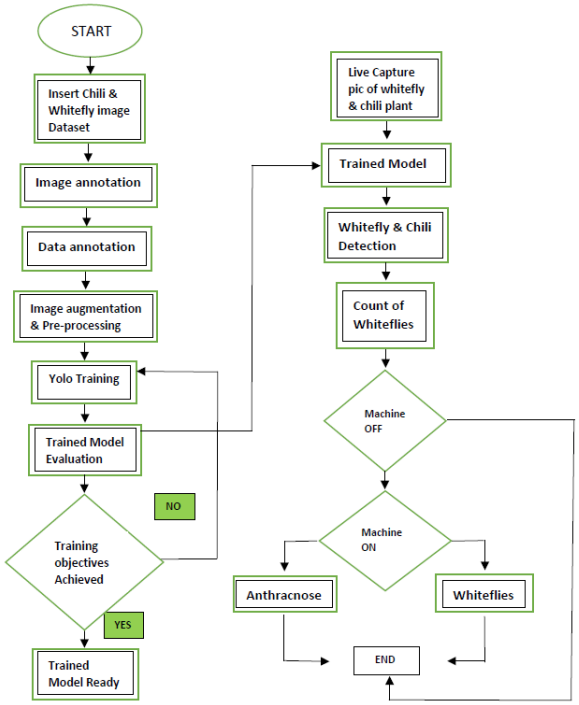


Fig 2. Flowchart of pest spraying machine

Data augmentation techniques such as rotation, scaling, flipping, and colour adjustment were applied to improve model robustness, reduce overfitting, and enhance detection performance under different environmental conditions. After training and evaluation, the model was deployed on a Raspberry Pi connected to an IR camera for real-time monitoring. The system continuously detected and counted whiteflies in greenhouse or field environments, and when detections exceeded a predefined threshold, an LED indicator alerted farmers to possible infestations. Detected images were also displayed on a monitor for verification before the system reset for the next 24-hour monitoring cycle.

3. Result and Discussion

The project focused on developing and applying computer vision techniques to identify whiteflies and anthracnose diseases in chili crops using YOLOv8. The objective was to train a pest detection model capable of recognizing whiteflies and anthracnose based on visual features in images. The model shown in Figure 4.1 was designed to accurately identify and label pest and disease symptoms to support early intervention, improve crop health, and enhance agricultural pest management while reducing the need for manual crop inspection by farmers.

In Figures 3 and 4, the image annotation process involved labelling the dataset using Roboflow so the model could learn to detect whiteflies and anthracnose effectively. Careful annotation of each image allowed the machine learning model to recognize important visual characteristics of pests and infected chili plants. Dataset augmentation was also applied to improve dataset quality and model performance. Techniques such as rotation, scaling, flipping, and colour correction increased dataset diversity and improved the model's ability to generalize under different lighting, scale, and background conditions. Augmentation also reduced overfitting and class imbalance, helping to create a robust, reliable, and effective real-world pest detection system.

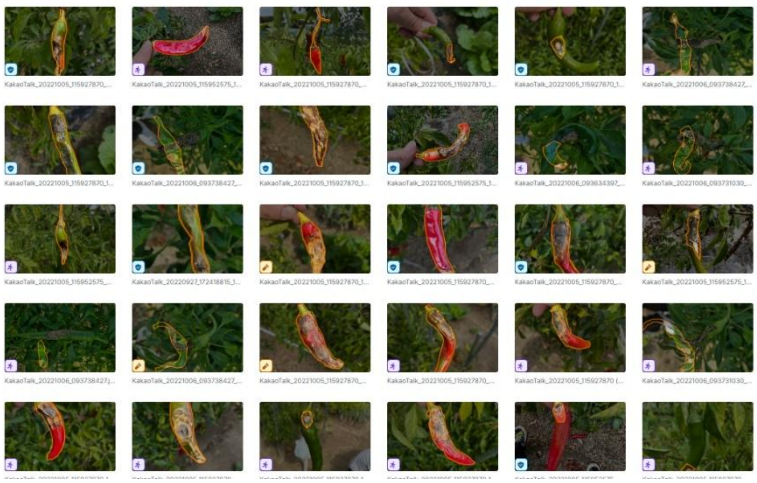


Fig 3. Annotate image of anthracnose using Roboflow.

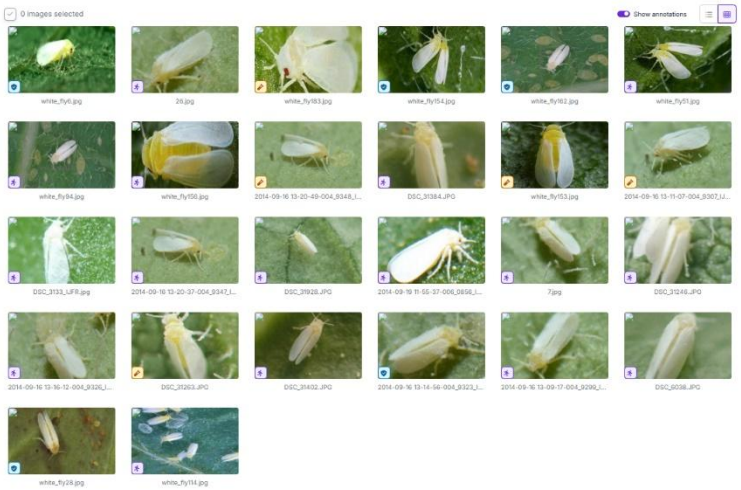


Fig 4. Annotate image of whiteflies using Roboflow.

The dataset is a combination of raw images of whiteflies and anthracnose were obtained from actual farms. A total of 3150 datasets were collected as in Table 2. And table 3 shows the roboflow's parameter for the augmentation dataset.

Table 2. Training details of YOLOv8

Input size	Software Language	Environment	Library	Epochs	Optimizer
1080 x 640	Pyhton	Anaconda	Ultralytics	100	Adam

Table 3. Roboflow's Parameter for Augmentation Dataset

Parameter for Augmentation	Value
Output per training	3
Flip	Horizontal, Vertical
90° Rotate	Clockwise, Counter-Clockwise, Upside Down
Crop	0% Minimum Zoom, 13% Maximum Zoom
Shear	± 10° Horizontal, ±10° Vertical
Greyscale	Apply to 15% of images
Hue	-15°. +15°
Saturation	-25%, +25%
Exposure	-10%, +10%

After augmentation of the dataset whose initial size was 3150 images, the new dataset now totals 5868 images. 5355 were set aside for training, including anthracnose and whitefly images, which make up about 91% of the total dataset. The validation subset accounted for 306, which is 5% of the total dataset images, while the remaining 207 images, which are 4% of the dataset, are reserved for testing as shown in figure 5. Once the images were in the requisite format, training commenced and was set for 80 epochs.

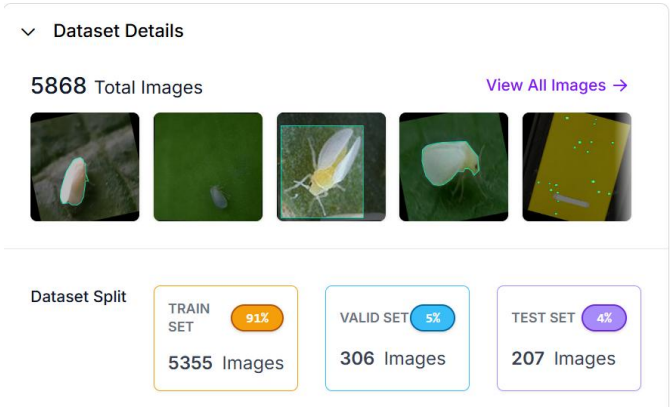


Fig 5. Dataset splitting for training using Roboflow.

Figure 6 presents the pest and disease detection system for chili pepper plants, which can identify whiteflies and anthracnose: anthracnose corresponds to black spots on plant leaves, while whiteflies are 1–2 mm long insects with powdery white wings that dwell on the undersides of leaves. Whiteflies reproduce rapidly and are prone to large-scale outbreaks, causing a wide range of harms. Early detection is the core of effective prevention and control. This system can accurately classify and identify pests and diseases, supporting timely intervention and reducing crop losses.

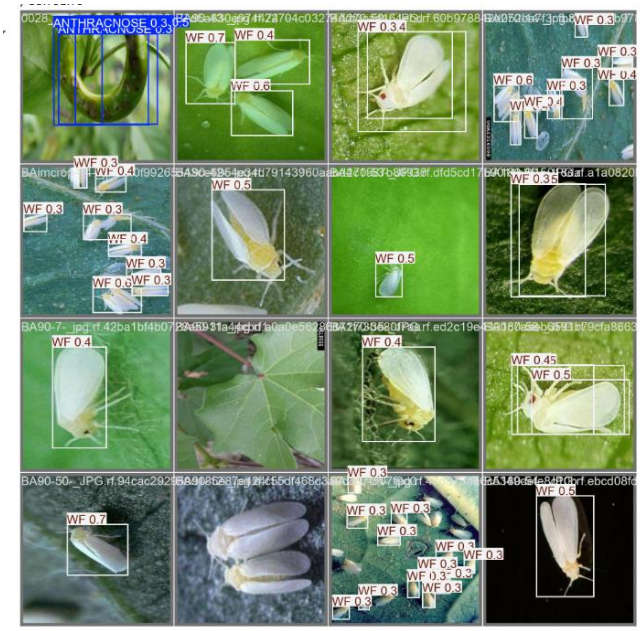


Fig 6. Result of the image detection for whiteflies and Anthracnose.

Figure 7 presents the confusion matrix for the three detection classes: Anthracnose, Healthy, and Whitefly. The model correctly identified 130 Anthracnose instances, 5 Healthy instances, and 1,067 Whitefly instances. Based on the confusion matrix, Anthracnose achieved a precision of 74.29% and recall of 89.66%, while Whitefly achieved a precision of 75.46% and recall of 68.97%. The Healthy class showed substantially poorer performance, with a precision of 62.50% and recall of 17.24%, indicating difficulty in distinguishing healthy samples from the other classes and background. Across all three classes, the micro-averaged precision and recall were 75.27% and 69.84%, respectively.

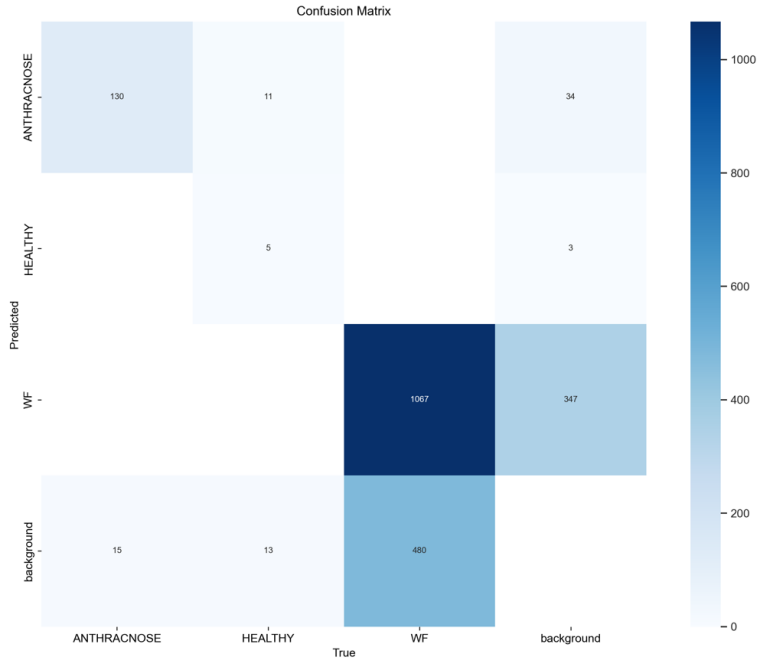


Fig 7. Confusion Matrix of pest spray machine

Figure 8 presents the Precision–Recall (PR) curve evaluating the model's performance in detecting Anthracnose, Healthy plants, and Whiteflies (WF). Recall (x-axis) measures how many actual instances are correctly detected, while precision (y-axis) measures how many predicted detections are correct. The class specific AP@0.5 values were 0.855 for Anthracnose, 0.429 for Healthy, and 0.645 for Whitefly. Their arithmetic mean gives an overall mAP@0.5 of 0.643 (64.3%).

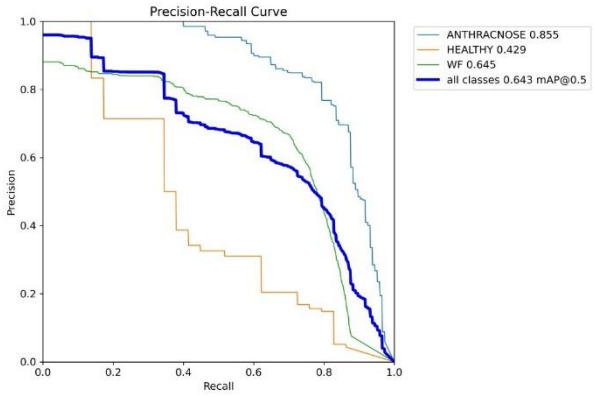


Fig 8. Graph of Precision-Recall Curve for Each Class.

Anthracnose therefore demonstrated the strongest detection performance, whereas the Healthy class was the most challenging. The results show that Anthracnose is detected most effectively, with strong precision and recall. Whiteflies are detected at a moderate level, but there is still room for improvement. However, the model struggles with correctly identifying Healthy plants, indicating misclassification issues in this class. Overall, the PR curve analysis highlights the model's strengths in disease detection

while also pointing out areas for improvement, particularly in distinguishing healthy crops from infected ones.

Figure 9 shows the training and validation performance of the YOLOv8 across multiple epochs. Training metrics such as box loss, classification loss, and distribution focal loss decrease steadily, indicating improved learning and better object detection accuracy. Training precision generally increases, although with some fluctuations. For validation, losses also decrease, showing better model generalization on unseen data. At the same time, recall, mAP50, and mAP50–95 increase, indicating improved detection performance and accuracy over time. Overall, the trends show that the model is learning effectively and becoming more reliable.

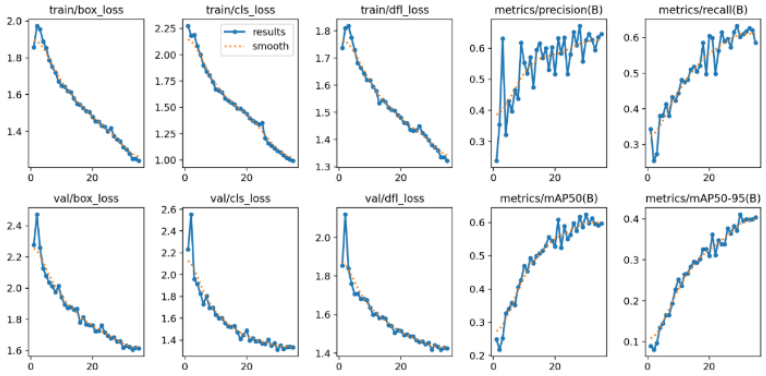


Fig 9. Results for the latest model trained.

3.1. Evaluation Metrics

Performance was evaluated using standard object detection metrics, the formula is as below:

i. Precision

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

ii. Recall

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

i. Accuracy

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

Table 4. Evaluation Metrics Results

Class	TP	FP	FN	Precision	Recall	F1-score	AP@0.5
Anthracnose	130	45	15	74.29%	89.66%	81.25%	85.5%
Healthy	5	3	24	62.50%	17.24%	27.03%	42.9%
Whitefly	1067	347	480	75.46%	68.97%	68.97%	64.5%
Overall mAP@0.5							64.3%

4. Conclusion

In this work, the project's goal is to design and launch an automated pest-spraying device that will successfully recognize whiteflies and track the health of chili plants in agricultural environments. The system monitors the health of chili plants according to preset criteria and detects whiteflies in real-time using sophisticated sensor technologies and machine learning algorithms like YOLOv8. The three performance matrix subsets for the whiteflies and anthracnose dataset are precision, mAP, and recall. This study achieves 75.27% precision, 64.3% mAP, and 69.84% recall. When whitefly populations above a threshold that is critical for crop damage, the machine acts on its own and initiates spraying mechanisms. Farmers can remotely monitor and control crop health thanks to its integration of cloud connectivity and IoT for data collection. Future developments will concentrate on increasing sensor precision, cutting expenses, and strengthening machine learning models to proactively forecast insect outbreaks. The project's objectives are to maximize crop output, reduce pesticide use, and promote global food security by fusing innovation with sustainable agriculture methods.

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