

Advanced Whitefly Detection System for Enhance Pest Control using YOLO8 and Deep Learning Model

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ABSTRACT

Whitefly infestations pose a significant threat to agricultural productivity, causing extensive crop damage that traditional pest control methods struggle to mitigate effectively. This study presents the development of a Whitefly Detection System leveraging image recognition technology to accurately and efficiently identify whiteflies. Underpinned by a deep learning approach, the system employs the YOLOv8 algorithm for image recognition, executed via Python software. The dataset comprises 1290 images, including self-captured and pre-existing images, annotated using the Roboflow platform. Following annotation, the dataset was augmented, and the model trained, with the Roboflow platform generating a YAML file for further processing with YOLOv8. The system achieved an average detection rate of 87.5%, facilitating immediate identification of whiteflies. This technological advancement significantly enhances pest monitoring and control, enabling early intervention and improved crop protection for farmers. Integrating this technology promotes precise and sustainable pest management practices, reducing reliance on chemical pesticides and supporting the overall sustainability of agricultural practices.

1. Introduction

In 2021, the agriculture sector in Malaysia contributed around 9.6 percent to Malaysia's gross domestic product (GDP) [1]. The vegetable industry specifically contributed 13.5 percent to the agriculture sector [2]. In Statista, Malaysia's Vegetable Industry GDP 2023 also stated that the value added of vegetable crops to the gross domestic product (GDP) in Malaysia was expected to reach 13.32 billion Malaysian ringgit in 2021, an increase from 12.15 billion Malaysian ringgit the year before [2]. In terms of consumption, it was estimated that Malaysia would consume approximately 2.91 million metric tons of rice in total in 2023 [3]. This is a slight increase in the annual consumption from the previous year [1].

The advancement of the agricultural industry has been accompanied by an increase in pest attacks, especially whiteflies, which hurt crop health and productivity [4]. In the article Whitefly-Transmitted Plant Viruses and Their Management, the author stated that whiteflies are destructive

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pests that harm various crops by consuming plant nutrients and spreading plant viruses [5]. Therefore, the demand for an effective detection system rises with the increasing infestation of whiteflies. This is crucial for ensuring the production of quality crops in the agriculture industry. Whitefly infestations can result in poor crop yield, stressing plants and leading to unmaturing growth, exposure to diseases, and eventually leading to plant death [6]. The increasing threat of whiteflies poses both short and long-term damage to crops, including disease infection [5]. This also shows the current manual detecting counting whitefly method on sticky traps. with the naked eye is slow and ineffective in keeping up with the rapidly increasing whitefly population [7]. This research aims to address this issue by developing a more efficient and reliable whitefly detection system. The system leverages advanced image recognition technology, by using a camera, and image recognition for accurate whitefly detection.

Whiteflies, scientifically known as *Bemisia tabaci*, are sensitive to their environment, especially to temperature because it can significantly affect the life of whiteflies [8]. Whiteflies can live in a variety of ecosystems, including farms, greenhouses, and gardens. In nature, adult whiteflies move within and between fields, seeking the best locations for whitefly offspring [9]. Female whiteflies are selective when laying eggs, ensuring the best conditions for their offspring's survival. The growth rate from egg to adult depends on the temperature [10].

With the rapid growth of farming in recent years, the number of harmful pests, especially whiteflies, has also increased. These pests could harm crops, making it challenging to grow healthy food and affecting both farmers and consumers [11]. Early detection of the whitefly is crucial. The implementation of Image recognition technology provides a reliable way to spot and count whiteflies, allowing farmers to take swift action and plan the next step after detection [12]. The system focuses on the notorious *Bemisia tabaci*, a common and destructive whitefly [11]. Smart algorithms in the software differentiate *Bemisia tabaci* from other insects on the traps, reducing false alarms and boosting accuracy. Precise whitefly detection is key to effective pest control.

Studies show that image recognition systems can surpass traditional methods in several ways. They allow for earlier detection of pests, reduce the amount of manual work required, and enhance the ability to plan and manage pest control more effectively. This method could minimize unnecessary pesticide use and protect the environment. Real-time monitoring with image recognition on sticky traps allows farmers to monitor whitefly populations, prevent infestations from spreading, and save crops. By acting early, farmers can save their money and ensure sustainable food production. This research thoroughly explores the current state and future of integrating image recognition into whitefly detection.

2. Related Works

This research paper presents a novel approach to pest detection and monitoring. The researchers used YOLOV3 to classify and detect objects, specifically whiteflies and fruit flies. This method greatly assists farmers in detecting and locating pests, even if they are very small or far from their farms. The results of this study showed that the model obtained an overall accuracy of 83.07% in classifying and detecting whiteflies and fruit flies. This indicates that the use of YOLOV3 for object detection in agricultural settings can be highly effective and accurate. Using an improved YOLOv4 deep learning network for accurate detection of whitefly and thrips on sticky trap images (2021) [13]. This article proposes a small object detection approach based on the YOLOv4 model. The researchers collected yellow sticky trap (YST) images using pest-monitoring equipment in a greenhouse. The experimental results showed that the mean average precision (mAP) for the detection of whitefly and thrips using the proposed approach was improved by 8.2% and 3.4% compared with the YOLOV3 and YOLOv4

models, respectively. This indicates that the proposed model has good robustness over a range of pest densities.

Insect Detection Research in Natural Environment Based on Faster-R-CNN Model (2020) [14]. This study focuses on utilizing the Faster R-CNN model to achieve real-time detection of Pests in the natural environment. An unsupervised augmentation algorithm was applied as pre-processing work for attaining the higher detection results of Faster RCNN. The proposed research is focused on utilizing the Faster R-CNN model to achieve real-time detection of Pests in the natural environment. Moreover, an unsupervised augmentation algorithm was applied as pre-processing work to attain the higher detection results of Faster R-CNN.

Field detection of tiny pests from sticky trap images using deep learning in agricultural greenhouse (2021) [15]. This article proposes a detection approach based on the YOLOv4 model for two common small pests (whitefly and thrips) in greenhouses. The experimental results showed that the mean average precision (mAP) for the detection of whitefly and thrips using the proposed approach was improved by 8.2% and 3.4% compared with the YOLOv3 and YOLOv4 models, respectively. The detection performance slightly decreased as the pest densities increased in the YST image, but the mAP value was still 92.7% in the high-density dataset.

Comparison of Single-Shot and Two-Shot Deep Neural Network Models for Whitefly Detection in IoT Web Application (2022) [16]. This article compares YOLOv4, a single-shot detector, to Faster-RCNN, a two-shot detector, for detecting and classifying whiteflies. The study found that Faster-RCNN achieved a higher level of performance than YOLOv4. The results of the study show that Faster-RCNN (precision 95.08%, F-1 Score 0.96, recall 98.69%) achieved a higher level of performance than YOLOv4 (precision 71.77%, F-1 score 0.83, recall 73.31%), and will be adopted for further development of the monitoring station.

3. Methodology

This methodology section provides an overview of the methods used in designing, developing, and testing the Whitefly detection system. This section includes a block diagram, a flowchart, system design details, hardware creation, a list of all components and devices needed for the research, the software utilized, a description of experiments conducted, a work breakdown structure, and a Gantt chart. This research involves three main experiments, described as follows:

3.1 Whitefly Detection Model

The first experiment is focused on designing a Whitefly detection system. The process begins with collecting a dataset, which involves gathering a substantial amount of data relevant to whiteflies. The dataset is obtained from 2 sources which are self-capture images on actual farms and images collected from the internet from the internet. After collecting the dataset, the next step is dataset preparation. This stage involves image annotation, dataset augmentation, and dataset splitting into training, validation, and testing. The final step in this experiment is model training. Here, the prepared dataset is used to train the deep learning model to accurately detect whiteflies.

Fig. 1 shows the block diagram of the proposed whitefly detection system. This research uses a camera to capture images of sticky traps. The camera can be activated manually via a bypass button or remotely through commands sent via the Telegram app. Once an image is captured, it is processed by a Raspberry Pi 4 Model B with 8GB RAM. This Raspberry Pi is equipped with a YOLOv8-trained model, which is used to detect the presence of whiteflies on sticky traps. The LCD monitor is primarily used for maintenance purposes. It will only be turned on to help the maintenance process if needed.

In addition to this, a motor power window mechanism is employed to roll the sticky trap. This ensures efficient monitoring and maintenance of the trap. The system also includes lights that are installed to attract whiteflies and provide enhanced visibility for the camera during image capture. The detection results are saved internally and sent to users remotely via the Telegram app. This ensures that the detection result is secure, and the user can monitor and respond to whitefly detections in real-time from any location.

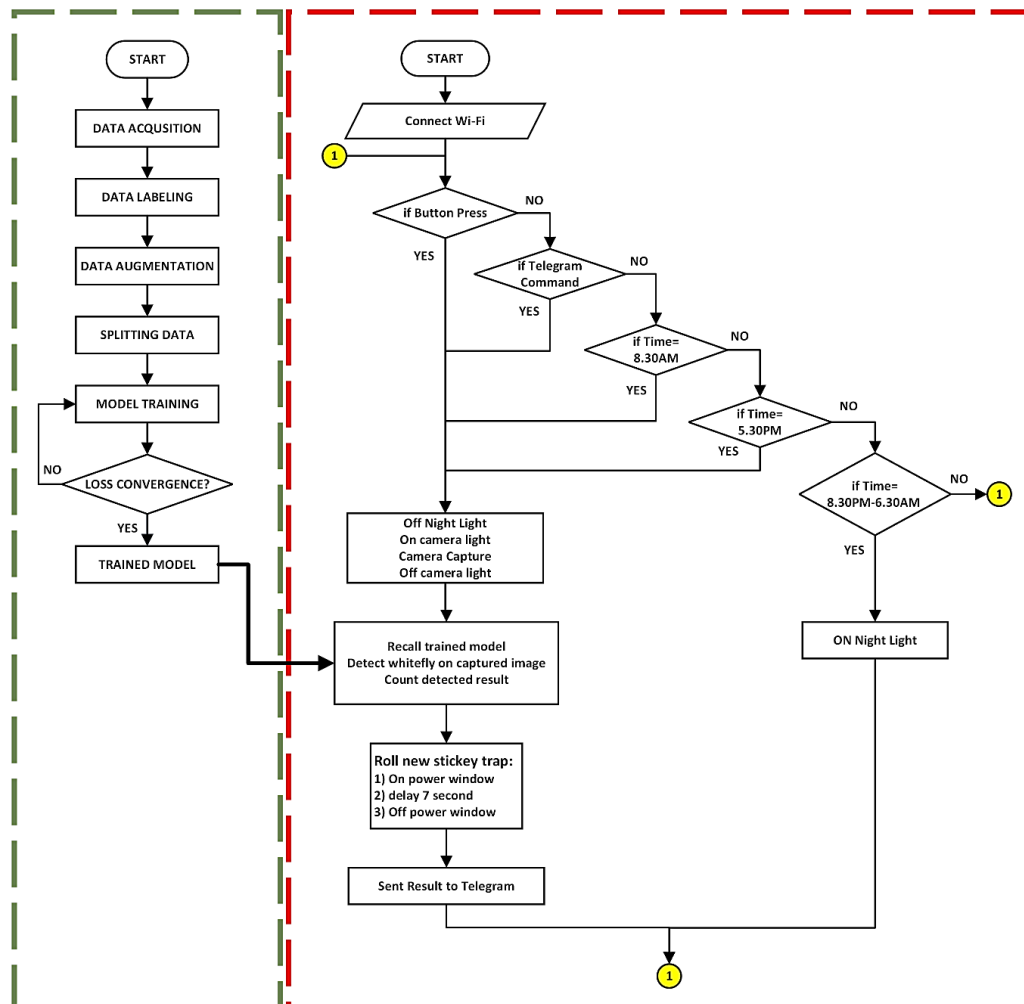


Fig. 1. The Flowchart for Development of IoT-Based Fertigation System in Agriculture

Fig. 2 shows the flowchart of the Whitefly Detection System. The flowcharts are split into 2, the first flowchart is the model training flowchart which outlines the process of obtaining a trained model for whitefly detection. The system begins with data acquisition, where 1290 raw images are collected to be used in the training of the model. These images are then labelled to identify and annotate the presence of whiteflies. Data augmentation follows, enhancing the dataset's diversity to improve model robustness and performance. The data is then split into training, valid and testing sets to facilitate model evaluation. The training process continues until loss convergence is achieved; this is to determine if the model has reached a state where further training will not substantially improve its performance. Then the trained model is obtained.

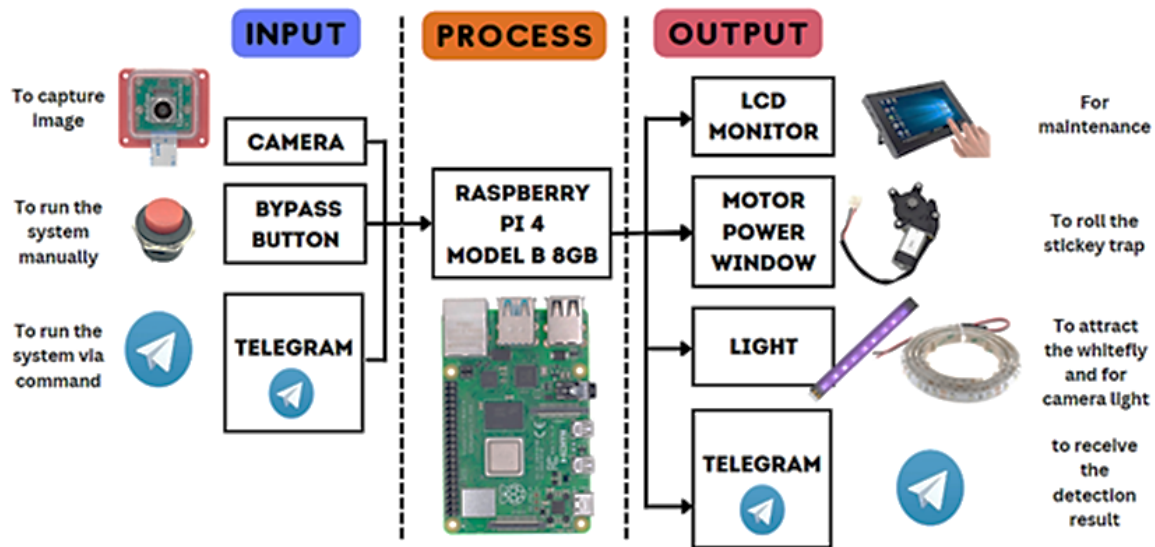


Fig. 2. The block diagram of IoT-Based Fertigation System in Agriculture

The second flowchart shows the system operations flowchart. The system starts by establishing a connection to Wi-Fi then enters the loop. The system activates if the bypass button is pressed, a Telegram command is received, or the time is either 8:30 a.m. or 5:00 p.m. Otherwise, it remains idle. If the time is between 8:30 p.m. and 6:30 a.m., the system stays idle, and the night light turns on to attract whiteflies. When the system is active, the trained model is utilized to detect whiteflies in the captured images. Upon successful detection and counting of whiteflies in the captured images, the results are saved. The power window is then turned on for 7 seconds to roll up the sticky trap to a new layer, then the power window is turned off. Results from each detection cycle are sent to users via a Telegram bot, ensuring real-time updates on whitefly activity levels.

This research is designed to detect whiteflies using computer vision. This is achieved by designing a model specifically adapted for whitefly detection. The design of the research begins with the collection of a raw dataset from farms infested with whiteflies in Tanjung Karang, Selangor. The dataset is a combination of raw images obtained from actual farms and a few sourced from the web as shown in Fig. 3. A total of 1290 datasets were collected. These datasets serve as the foundation for the subsequent stages of the research.

The next step in the research was image annotation. This involved manually labeling the collected dataset to detect whitefly using Roboflow as shown in Fig. 4. During the annotation process, every whitefly in each image is marked. These markings serve as a reference for the machine learning model to learn what a whitefly looks like and how to detect one in an image. This is a time-consuming and meticulous process as it requires a high level of precision each whitefly must be accurately marked to ensure the model is trained correctly. The model is trained to recognize the specific patterns and features that define what whitefly looks like based on the annotations provided.

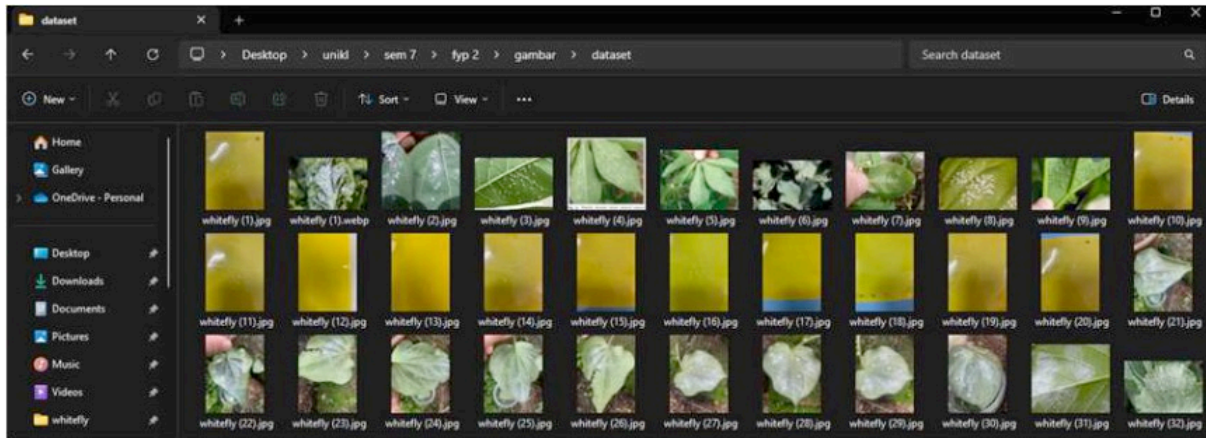


Fig. 3. Dataset collected.

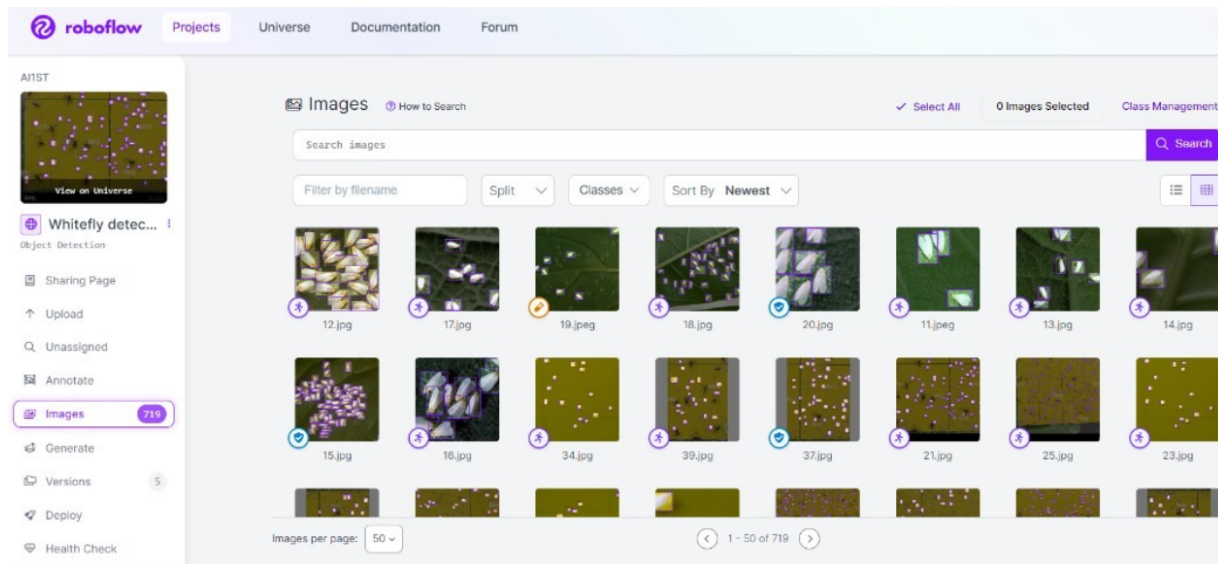


Fig. 4. Image annotation process using Roboflow.

The dataset, consisting of 1290 images, was augmented in terms of rotation, blurriness, brightness, and more. To improve the model, the dataset must be augmented. The augmentation techniques included rotation, blurring, brightness adjustments, and more. This process expanded the total dataset size to 3094 images, giving more sets of data for the model to learn from. The next step involved dividing the dataset into three subsets which are training, validation, and testing. The training subset contains 2707 images, which is equal to 87% of the total dataset. This subset is used to train the model, allowing the model to learn and recognize whiteflies. The validation subset, which included 256 images or 8% of the dataset, is used to fine-tune the model parameters to prevent overfitting and ensure the model's performance is the best. The remaining 131 images, which are equal to 4% of the dataset, were set aside for testing as shown in Fig. 5. This testing subset is crucial as it provides an unbiased evaluation of the final model, reflecting its performance in real-time.

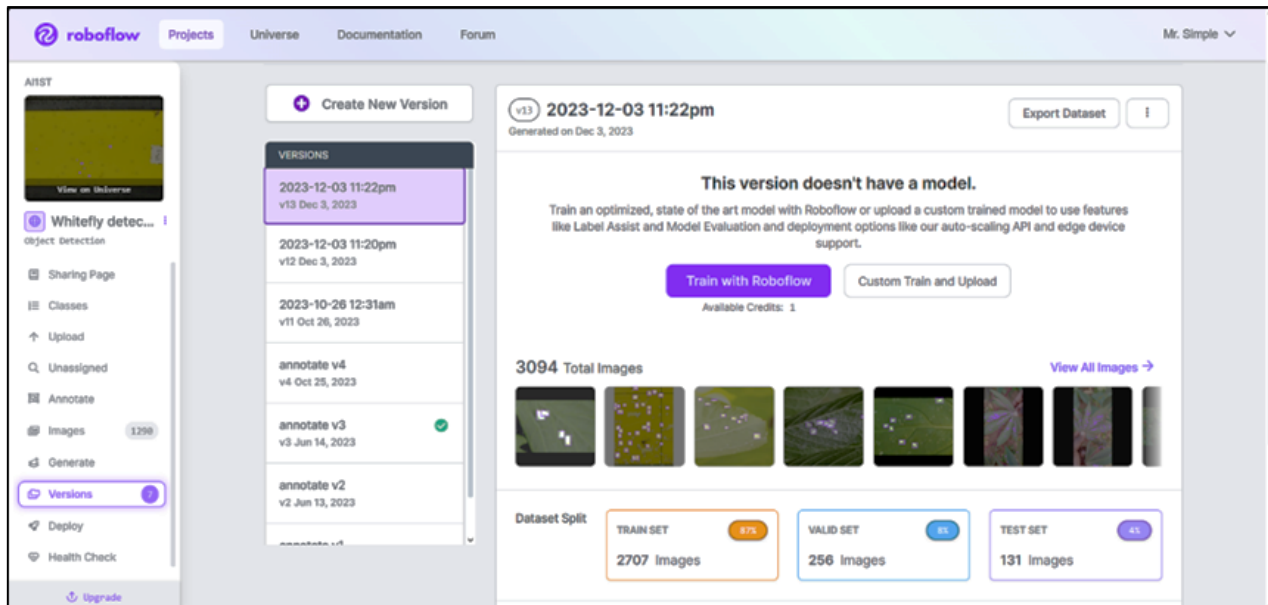


Fig. 5. Dataset splitting for training using Roboflow.

3.2 Hardware Modeling of Detection System

Experiment 2 aims to develop a functional internal and external prototype design for a whitefly detection system. This starts by analyzing earlier articles and research related to the research's prototype design then proceeds to build the prototype internal and external parts.

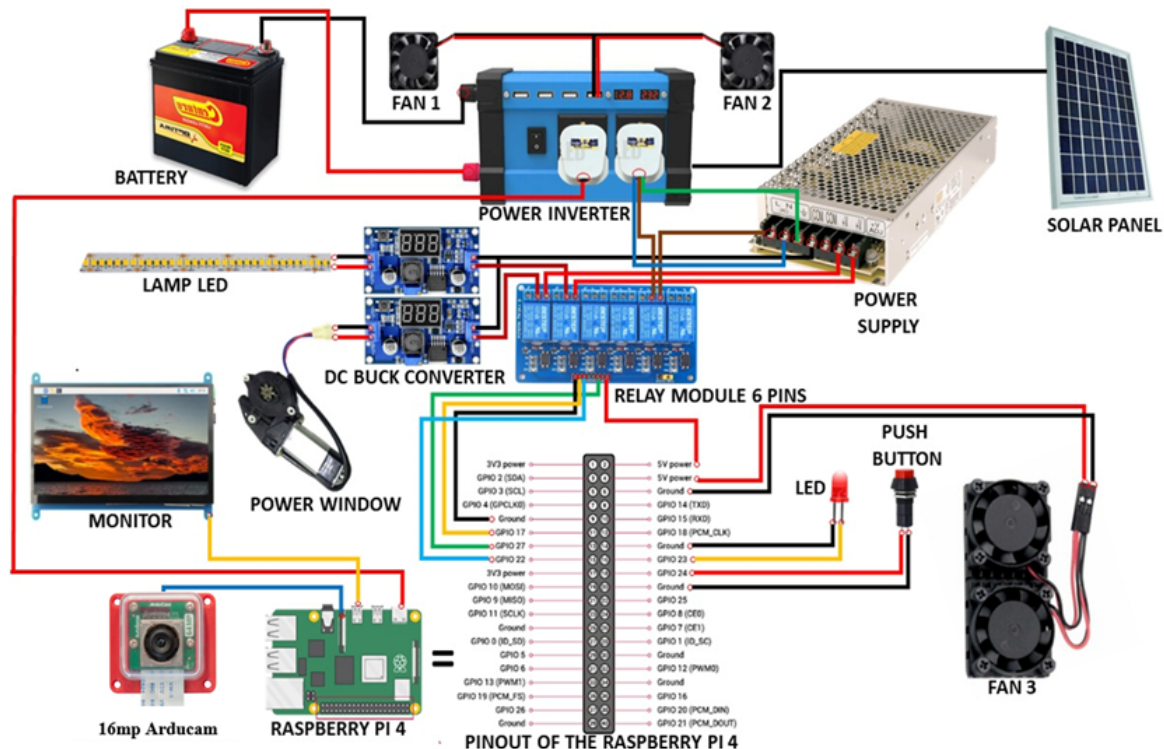


Fig. 6. Hardware diagram of the Whitefly Detection System

The hardware diagram shown in Fig. 6 is the overall prototype design and implementation. The system is made up of different parts, each part has a specific function to ensure the system operates

efficiently and effectively. The main power source for the system is an 18W solar system. The solar system harnesses renewable solar energy, making the system eco-friendly and ideal for outdoor farm environments. The solar system is connected to 3 X 50AH batteries (in parallel), which store solar energy and provide a consistent power supply to the system. The system also includes a solar power inverter that converts the DC power from the solar system and battery into 230V AC power. An additional AC to 24V DC converter is used to transform the AC power into 24V DC which can be used by the system's electronic components. A relay module is used in the system to control the operation of the light and power window. The relay is used as a switch that can be controlled by the system.

Lastly, a 24V to 12V buck converter is included in the system. This DC-to-DC power converter steps down the voltage from its input (24V) to its output (12V), ensuring that the system operates at the correct voltage. Together, these components form a prototype for a Whitefly detection system that can be implemented in real farm environments. The system is designed to provide real-time updates on whitefly infestation levels, aiding in effective pest management.

4. Test and Evaluation

Experiment 3 is designed to test and evaluate the whitefly detection system. The evaluation process is threefold. Firstly, the system's performance is assessed based on the results it detects. Secondly, the system's training and validation results are evaluated to ensure its learning process is effective and accurate. Lastly, a confusion matrix is used to evaluate the system's performance in terms of its true positive, true negative, false positive, and false negative results. This comprehensive evaluation approach ensures a thorough assessment of the whitefly detection system.

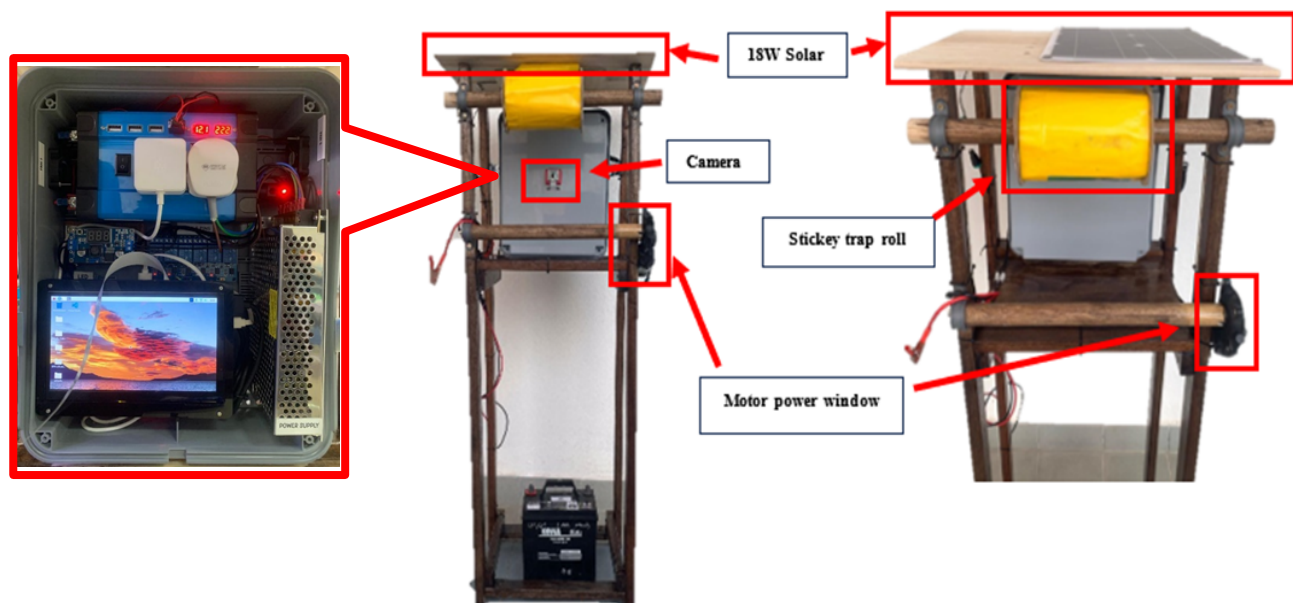


Fig. 7. Whitefly Detection System functional prototype

After analyzing the design prototype shown from earlier experiments and research, we have successfully developed a new prototype for the whitefly detection system. As shown in Fig. 7, the implemented design is both innovative and practical. The design is composed of three main components, which are an 18W solar panel, a camera, and a power window. The solar panel is put at the top of the structure, ensuring a sustainable energy supply. The camera is oriented towards the sticky trap roll, enabling it to capture the image of whitefly on the sticky trap effectively. The sticky

traps are used to monitor the presence of whiteflies for early detection of infestations. The power window, which is designed to roll the sticky trap is added for automation.

Fig. 8 shows the result obtained from the whitefly detection system. The left part is the result that the user receives via telegram. The right side is the previous result that was saved inside Raspberry Pi. Each result captured by the system is saved in the Raspberry Pi and transmitted to the user via Telegram twice daily.



Fig. 8. Whitefly Detection System detection result

Fig. 9 shows a set of graphs representing the training and validation results of a whitefly detection system. The metrics include box loss, classification loss, and different losses for both training and validation sets, as well as precision, recall, and mAP at different IoU thresholds. From the training graphs, it seems that the losses are decreasing over epochs, which is a positive indication of learning. However, the validation graphs show some fluctuations in the losses, which could suggest potential overfitting or instability in the learning process. In terms of rating the results, it's generally good to see the losses decreasing and the precision, recall, and mAP increasing. However, the fluctuations in the validation losses and the non-smooth increase in precision and mAP suggest that there might be room for improvement.

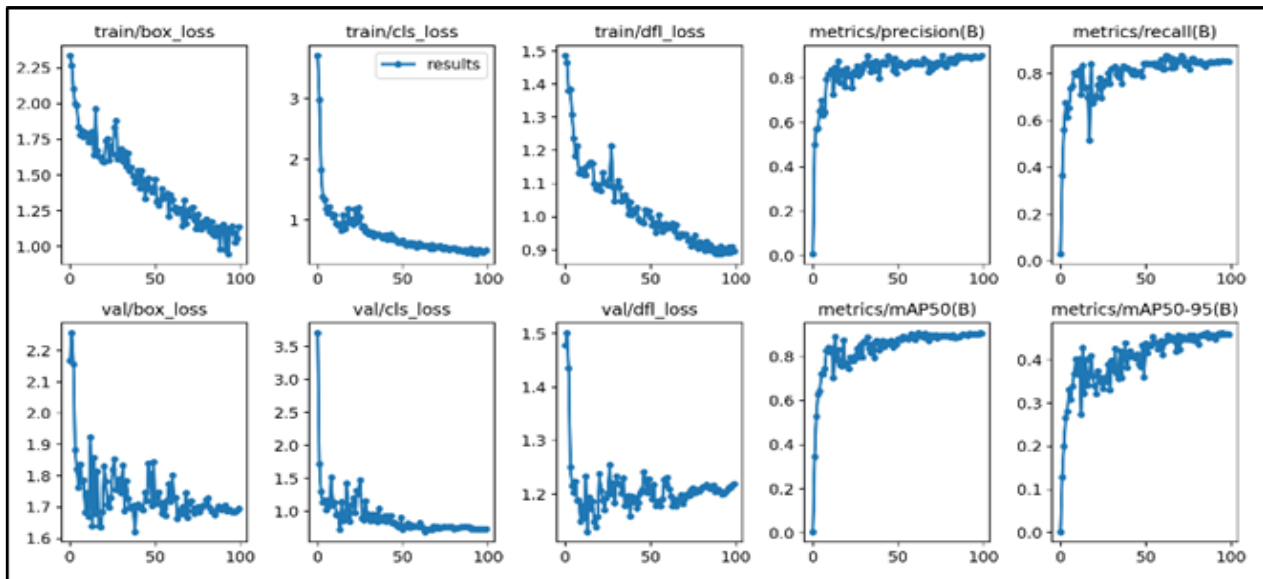


Fig. 9. Result of the Detection.

The model performance can be improved by employing regularization techniques or data augmentation to make the model more robust. It's also important to monitor the model's performance on a separate test set to ensure that it generalizes well to unseen data. Fig. 10 shows a confusion matrix for a whitefly detection system. The matrix is divided into four quadrants representing True Positives (TP), False Negatives (FN), False Positives (FP), and True Negatives (TN). The values are as follows: TP=0.82, FN=0.18, FP=0.28, TN=0.72. This value shows that the system has a fairly good performance with a high true positive rate (0.82) and a high true negative rate (0.72). However, the false positive rate (0.28) and the false negative rate (0.18) suggest that there are still some misclassifications.

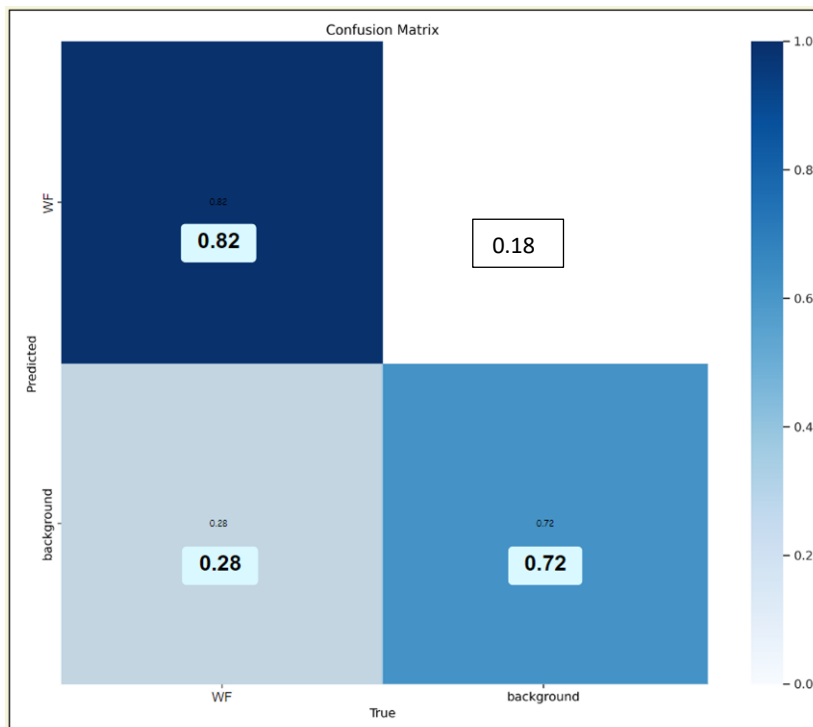


Fig. 10. Confusion Matrix

5. Conclusions

In summary, the whitefly detection system model showed excellent performance in detecting whitefly. To achieve the objectives of this research, three different experiments were carried out, each experiment corresponding to a specific objective. The first experiment focused on the design of the whitefly detection system. The second experiment was to develop a functional prototype for the whitefly detection system. The final experiment was the testing and evaluation of the whitefly detection system to ensure its effectiveness and reliability. The dataset comprises of 1290 images, was trained using Roboflow platform to generate a YAML file for further processing with YOLOv8. The system achieved an average detection rate of 87.5%, facilitating immediate identification of whiteflies.

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REFERENCES

- [1] Statista Research Department, "Agriculture in Malaysia - statistics & facts," Statista, 2023. [Online]. Available: <https://www.statista.com/topics/10680/agriculture-inmalaysia/topicOverview>.
- [2] Statista Research Department, "Contribution of the vegetables industry to the total agriculture sector in Malaysia from 2016 to 2021," Statista, 2023. [Online]. Available: <https://www.statista.com/statistics/956253/malaysiavegetables-share-of-agriculture-sector/>.
- [3] Statista Research Department, "Total consumption of rice in Malaysia from 2019 to 2024," Statista, 2023. [Online]. <https://www.statista.com/statistics/1370840/malaysiaannual-rice-consumption/2023> it was estimated, has been increasing since 2019.
- [4] R. M. Saleem, R. Kazmi, I. S. Bajwa, A. Ashraf, S. Ramzan, and W. Anwar, "IoT-Based Cotton Whitefly Prediction Using Deep Learning," *Sci. Program.*, 2021.
- [5] P. S. Soumia et al., "Whitefly-Transmitted Plant Viruses and Their Management," in *Emerging Trends in Plant Pathology*, 2020.
- [6] D. Naalden et al., "Spotlight on the Roles of Whitefly Effectors in Insect–Plant Interactions," *Front. Plant Sci.*, vol. 12, no. July, 2021.
- [7] K. R. B. Legaspi, N. W. S. Sison, and J. F. Villaverde, "Detection and Classification of Whiteflies and Fruit Flies Using YOLO," in *2021 13th International Conference on Computer and Automation Engineering, ICCAE 2021*, 2021.
- [8] O. Z. Aregbesola et al., "Life history and Temperature dependence of cassava-colonising populations of *Bemisia tabaci*," *J. Pest Sci. (2004).*, 2020.
- [9] W. Zhang, H. Huang, Y. Sun, and X. Wu, "AgriPest-YOLO: A rapid light-trap agricultural pest detection method based on deep learning," *Front. Plant Sci.*, 2022.
- [10] R. S. Chandi, S. K. Kataria, and B. B. Fand, "Effect of temperature on biological parameters of cotton whitefly, *Bemisia tabaci* (Gennadius) (Hemiptera: Aleyrodidae)," *Int. J. Trop. Insect Sci.*, 2021.
- [11] M. Abubakar, B. Koul, K. Chandrashekar, A. Raut, and D. Yadav, "Whitefly (*Bemisia tabaci*) Management (WFM) Strategies for Sustainable Agriculture: A Review," *Agric.*, vol. 12, no. 9, pp. 1–39, 2022.
- [12] W. Li, Z. Yang, J. Lv, T. Zheng, M. Li, and C. Sun, "Detection of Small-Sized Insects in Sticky Trapping Images Using Spectral Residual Model and Machine Learning," *Front. Plant Sci.*, 2022.
- [13] D. Wang, Y. Wang, M. Li, X. Yang, J. Wu, and W. Li, "Using an improved YOLOv4 deep learning network for accurate detection of whitefly and thrips on sticky trap images," *Trans. ASABE*, 2021.
- [14] D. Xia et al., "Insect Detection Research in Natural Environment Based on Faster-R-CNN Model," *Sensors (Switzerland)*, vol. 18, no. 12, pp. 182–186, 2020.
- [15] W. Li, D. Wang, M. Li, Y. Gao, J. Wu, and X. Yang, "Field detection of tiny pests from sticky trap images using deep learning in agricultural greenhouse," *Comput. Electron. Agric.*, 2021.
- [16] C. U. Parab et al., "Comparison of Single-Shot and Two-Shot Deep Neural Network Models for Whitefly Detection in IoT Web Application," *AgriEngineering*, vol. 4, no. 2, pp. 507–522, 2022.

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- [17] Jajja, A.I.; Abbas, A.; Khattak, H.A.; Niedbała, G.; Khalid, A.; Rauf, H.T.; Kujawa, S. Compact Convolutional Transformer (CCT)-Based Approach for Whitefly Attack Detection in Cotton Crops. *Agriculture* 2022, *12*, 1529.
 - [18] S. Rana and M. F. Samad, "End-to-End Jute-Pest Detection By Explainable Lightweight CNN," *2024 6th International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT)*, Dhaka, Bangladesh, pp. 230-235, 2024.
 - [19] H. A and B. S. P, "Paddy Crop Pest Identification and Classification Techniques Using Deep Learning," *2023 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSSES)*, Chennai, India, pp. 1-8, 2023.
 - [20] T. V. Bhandare, S. S. Bendre, V. D. Deshmukh, A. G. Nere and A. B. Patil, "Bug (Insect) Detection using Deep Learning," *2024 MIT Art, Design and Technology School of Computing International Conference (MITADTSociCon)*, Pune, India, pp. 1-5, 2024.