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Original Article

Edge-Based IoT Pest Monitoring System for Chili Farms Using YOLOv8 and Real-Time Alert Notifications

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Abstract *- Infestation by pests is a key issue in growing Chili. It is prone to lead to low yields and increased pesticide needs. Visual inspections are the foundation of conventional monitoring methods, which are labor-intensive and might cause delays along the way. This research suggests a pest detection system utilizing IoT based on image acquisition on sticky traps combined with the YOLOv8 object detection algorithm and Telegram notifications. The model was also trained for whitefly and fruit fly detection. It achieved a maximum mAP@0.5 of 0.45 and mAP@0.5:0.95 of 0.15 to 0.25. While these are modest numbers, they are the first to show the presence of the pests. Notification tests show that the alerts are usually provided within one minute of capturing photos. Variations in detection counts were detected due to changes in light conditions throughout the day and slight position adjustments of the camera frames. These results indicate that the practical use of this pest detection method has the potential to lessen dependence on manual inspection and provide assistive capabilities to manage pests on a timely basis. Areas of improvement have also been identified, such as enhancing dataset diversity, image stability, and system reliability.*

Keywords *- Chili Farming, Edge-Based Pest Monitoring, IoT-Based Pest Detection, Precision Agriculture, Real-Time Alert Notifications, YOLOv8 Object Detection.*

1. Introduction

According to the Food and Agriculture Organization (FAO), insect infestations account for up to 40% of annual global crop losses, representing a major obstacle to sustainable food production [1]. Climate change further exacerbates this issue by accelerating the spread, survival, and reproduction of insect pests, allowing invasive species to colonize new regions and intensify outbreaks [2]. This alarming figure is supported by recent studies showing similar loss patterns across developing agricultural economies [3]. Among tropical crops, red Chili (Capsicum annuum) is particularly affected by these conditions due to its sensitivity to environmental stress, despite its major role in local economies and traditions. Chili is widely used in Asian cuisines and increasingly in global markets; however, its production is frequently hindered by insect infestations, fungal infections, nutrient deficiencies, and weather extremes [4, 5]. Historically, pest detection has relied on manual inspection conducted by agricultural officers or phytosanitary experts. Although widely practiced, manual observation is labor-intensive, subjective, and prone to misidentification, especially when pest populations are small or distributed unevenly [6]. These limitations hinder timely interventions and often result in uncontrolled pest proliferation, ultimately reducing crop productivity. With advances in digital farming tools, pest detection has become more efficient. IoT devices, together with computer vision and machine learning, allow crops to be observed and analyzed remotely, reducing the need for constant field inspection. In many smart farming setups, sensors and cameras connected via IoT collect continuous field data fed to the machine learning systems for high-accuracy pest species detection. It helps reduce the burden on farmers and enables quicker, better-informed choices to protect crop production.

In recent years, there has been an increasing emphasis on environmentally friendly pest management practices. Although chemical pesticides are the best solution for preventing pests, they can pose harm to soil health, biodiversity, and even human safety. Solar-powered sticky traps and other sustainable technologies offer an environmentally friendly alternative for capturing thrips, aphids, and whiteflies [7]. In Malaysia, the use of yellow sticky traps placed under sunlight resulted in an 85% reduction in pesticides used on crops while still maintaining crop yields [8]. Additionally, a few researchers have explored combining sticky traps with artificial intelligence to enhance pest detection, achieving detections with accuracies of nearly 94% through the application of machine learning techniques to analyze trap images. The application of AI presents a promising way to improve the reliability and efficiency of traditional pest monitoring techniques and supports the FAO goal of “Save and Grow” in creating sustainable and productive agricultural practices [9].

Climate change creates an additional burden on pest management efforts. Changes in Earth’s climate, including global temperature and precipitation fluctuations, have made it possible for certain types of pests to establish in new geographical areas, leading to increased crop losses and economic damage [10, 11]. Current initiatives are underway to develop a system that integrates renewable energy sources, IoT sensors, and artificial intelligence to provide sustainable methods for monitoring and controlling pests over time [12]. Recent studies have demonstrated the extent to which IoT and AI-based agriculture platforms can optimize decision-making and improve operational efficiencies, especially for high-value crops such as chilies [13-15].

The current automated pest detection system used for chili cultivation often relies on individual sensing modalities such as vision-based imaging or stand-alone sensor measurements. For instance, one study evaluated edge deployment utilizing performance rubrics that included runtime memory use and connection constraints [16].

Other studies have suggested using UAVs to monitor via Convolutional Neural Networks [17]. However, significant difficulties were experienced in real-time performance when used at the field level. Additionally, Raspberry Pi-based implementations of deep models such as ResNet have also been utilized, but their performance is generally constrained by the computation capability of the embedded hardware solution [18].

Moreover, edge AI and IoT-based solutions rely strongly on cloud computing to process data or make predictions based on the inference model. This dependency on the clouds can create a significant level of latency and bandwidth constraints. Therefore, these devices’ performance may be highly reliant on internet connectivity, which in many cases is extremely unstable in rural agriculture [19].

Even with advanced approaches such as YOLO models to detect small pest targets within pepper crops, these methods typically consume a considerable amount of computational resources and will limit their scalability and real-world implementation [20]. The collective evidence suggests that high computational requirements and cloud dependency are two significant impediments in the development of a durable, stand-alone pest monitoring solution that can operate continuously in field environments.

To resolve these limitations, an IoT-based system was developed that incorporates the use of sticky trap images with an object detection system based on the YOLO V8 model. The images will be analyzed on the Raspberry Pi 4B, and the results will be sent to farmers via Telegram. This configuration enables the detection of pests early to minimize the problems they can create during farming under normal conditions, such as limited power and lighting, and minor camera misalignment.

The system relies exclusively on the edge for processing, in contrast with many existing systems, which makes it more suitable for resource-constrained agricultural environments. The objective of this project is to design and evaluate a complete edge-based IoT pest monitoring system using YOLOv8 object detection on a Raspberry Pi. It also aims to determine if the solution will work consistently for on-farm operations under real-world agricultural conditions.

2. Methodology

The processes to design, develop, and deploy an IoT-based system to identify chili pest infestation are outlined in this section. These include the installation of all relevant hardware components, the collection and preparation of an appropriate image dataset, and the training and deployment of a detection model. Finally, the potential for integrating the various elements listed above to create one fully operational system will be discussed.

The various stages of creating the system and ensuring compatibility between hardware and software for ongoing monitoring of pests via IoT devices and sending real-time alerts to the agricultural community.

2.1. System Architecture and Hardware Design

Figure 1 contains a diagram of the system block featuring a Raspberry Pi 4B as the primary processing and communication hub. An integrated camera captures images from the yellow sticky traps, where each image will be processed locally on the Raspberry Pi and sent to the farmer’s mobile phone via the Telegram application. The entire system is powered by a solar panel that charges the battery through a charger controller and maintains a consistent voltage regulation for powering the Raspberry Pi.

With this configuration, the system could operate continuously in outdoor conditions without depending on an external power source, making it feasible to deploy in rural agricultural areas.

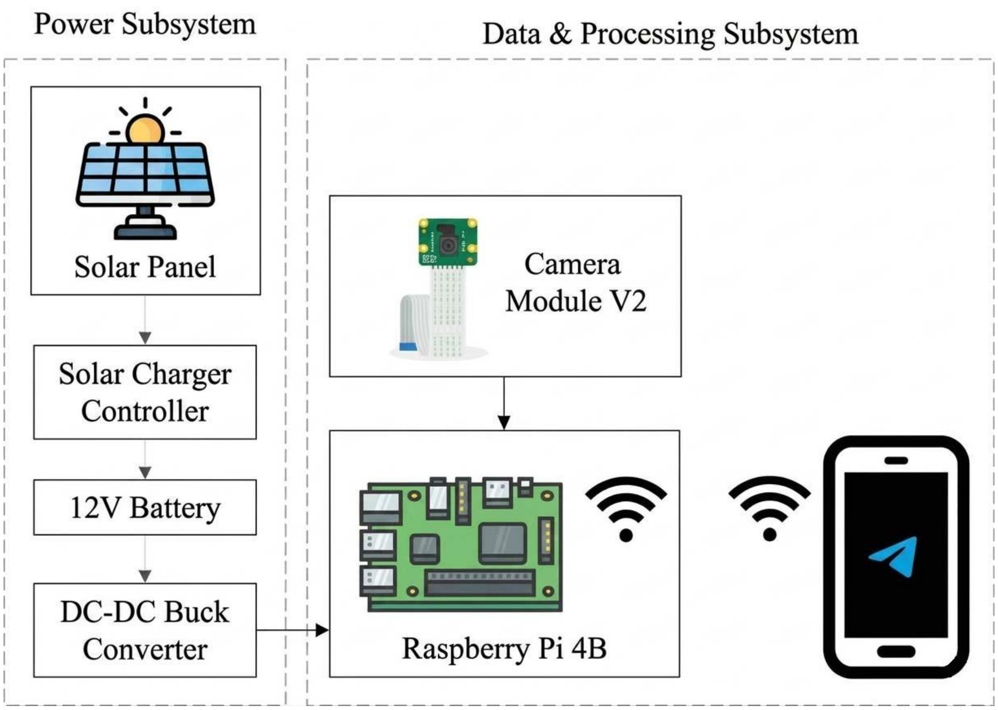


Fig. 1 System block diagram

2.2. Data Collection and Annotation

Dataset construction involves a combination of direct image collection from chili farms and supplemental open-source pest imagery. To trap target pests from the chili plants, mainly whiteflies and fruit flies, yellow sticky traps are used. Approximately one hundred yellow sticky traps were used throughout this study and collected once every other week to limit any over-saturation of traps and keep the cost of operations down. To ensure the dataset is balanced, traps are set at different stages of growth of the chili plants. Traps on mature plants were bound to trap more fruit flies, whereas traps on flower plants trapped mostly whiteflies, which have been found to occur during the flowering stage. Yellow sticky traps were collected every two weeks, with a total of approximately 25 traps used throughout the study.

(a)

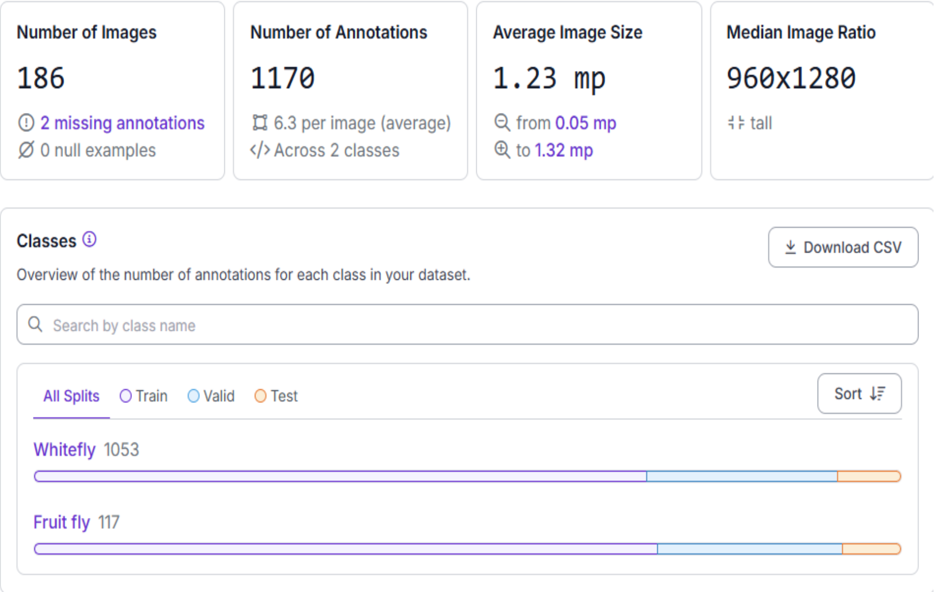
(b)

Fig. 2 Data collection setup: (a) yellow sticky trap placed on a mature chili plant to capture fruit flies, and (b) yellow sticky trap placed on a flowering chili plant to capture whiteflies.

Each trap was photographed using a smartphone, and the images were stored in a dedicated library for subsequent annotation using Roboflow software. The use of a two-week collection period ensured the dataset corresponded to real field conditions, and there was sufficient variation for training the detection model, as illustrated in Figure 2.

The dataset consists of 186 images of yellow sticky traps collected from an agricultural farm under real field conditions. Images were captured using a smartphone camera at a biweekly interval, with an average image resolution of 1.23 megapixels and a median size of 960 × 1280 pixels. A total of

1,170 insect instances were annotated, resulting in an average of approximately 6.3 annotations per image, as can be seen from Figure 3. Whiteflies and fruit flies are two classes of pests studied in this research. One thousand fifty-three (1053) annotations for whiteflies and one hundred seventeen (117) annotations for fruit flies in the dataset indicate an imbalance in class size, which reflects the actual abundance of pests captured on the sticky yellow traps at the site of data collection. Instead of artificially balancing these two classes, maintaining the inherent distribution of species allows the model to more accurately emulate real-world agricultural conditions.



Number of Images
186
2 missing annotations
0 null examples

Number of Annotations
1170
6.3 per image (average)
Across 2 classes

Average Image Size
1.23 mp
from 0.05 mp
to 1.32 mp

Median Image Ratio
960x1280
tall

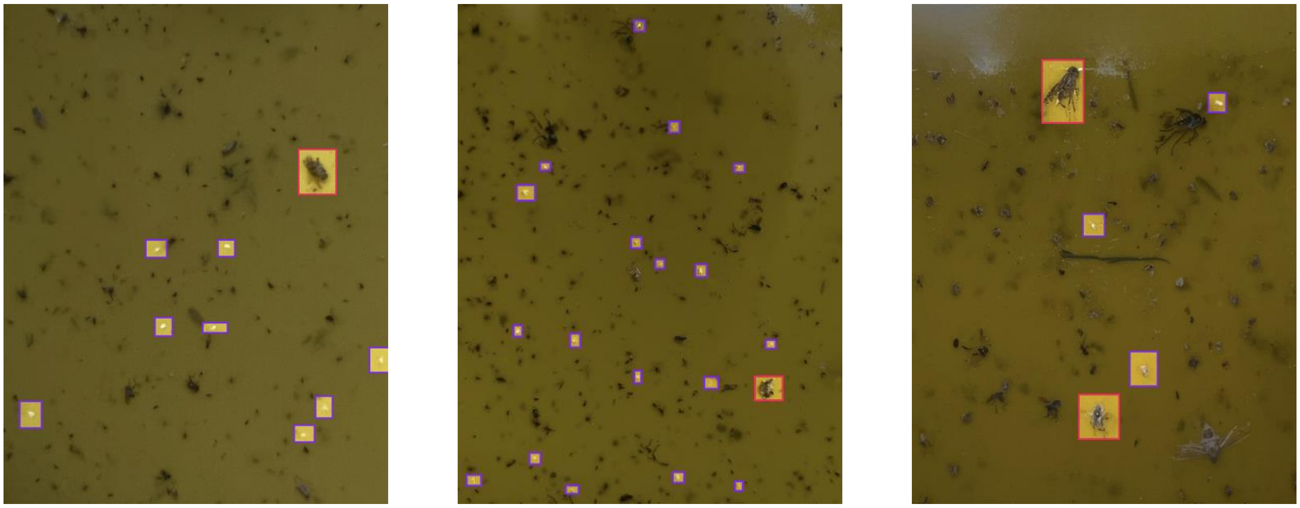
Classes
Overview of the number of annotations for each class in your dataset.

Whitefly 1053
Fruit fly 117

Fig. 3 Dataset statistics and class distribution of whitefly and fruit fly annotations

The images were assigned to an initial labeling phrase by a primary annotator, followed by a second annotator. Consensus-based resolutions are used by the annotators to address any discrepancies in the annotations. For small-object labeling, a bounding box was drawn around the visible insect body to label the image accurately.

Insects that were partially occluded were labeled if 30% or greater of their bodies were visible when the image was captured. Images with severe blur or extreme glare were excluded from training but retained for robustness testing. Figure 4 presents representative annotated images illustrating the whitefly and fruit fly classes.



(a) (b) (c)

Fig. 4 Representative annotated yellow sticky trap images showing mixed whitefly and fruit fly detections under real field conditions: (a–c) different sample images with bounding box annotations

2.3. Data Splitting

The dataset was divided into training, validation, and testing sets at the annotation level using the standard Roboflow partitioning strategy. About 70.8% of the annotations are used for training, 21.9% for validation, and 7.3% for testing. Within the whitefly class, training utilized 744 out of 1,053 total annotations (70.7%), while validation and testing accounted for 231 (21.9%) and 78 (7.4%), respectively. In comparison with the fruit fly class, 84 (71.8%) of the available annotations were allocated as part of training data, 25 (21.4%) were used as validation data, and 8 were used as test data (6.8%). The splits in both classes of data provide an equal comparison when measuring the performance of the model.

2.4. Model Selection and Deployment

Due to its high accuracy, good recall, and reliability in working with overlapping objects, the YOLOv8 was selected as the most appropriate algorithm for pest detection. Its lightweight nature also qualifies it for processing power-limited devices such as the Raspberry Pi 4B. Training using the self-annotated dataset was started first, then validation and testing to comprehend its performance. Figure 5 illustrates an overview of the deployment process. After the training, the YOLOv8 model was integrated within the Raspberry Pi system to conduct real-time image analysis of captured entries. Figure 6 displays the system flow overall with IoT hardware and machine learning for the automatic detection of pests.

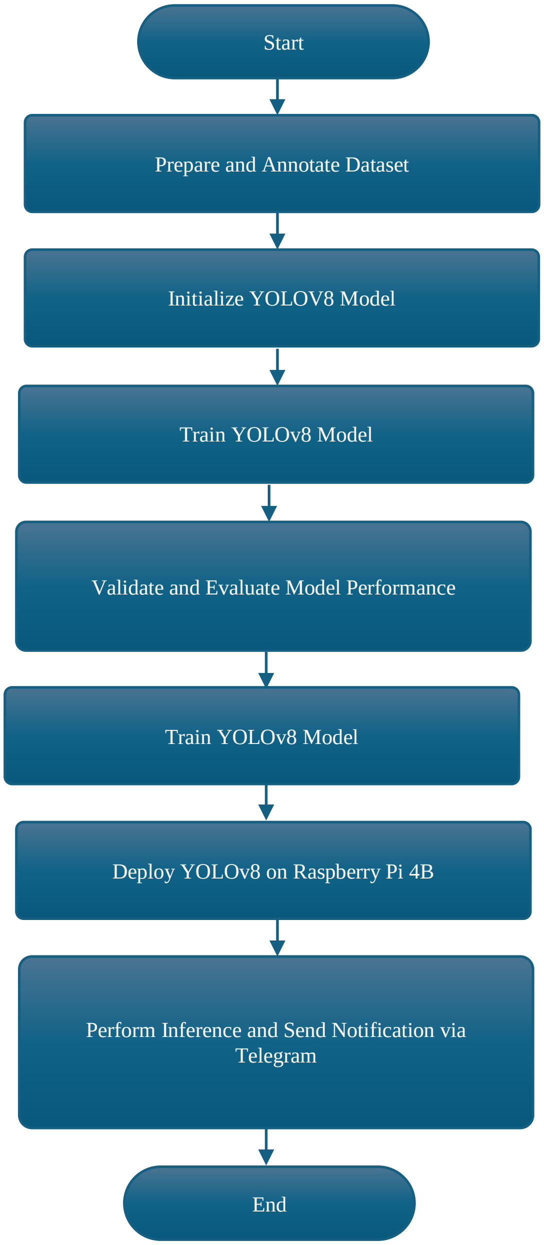


Fig. 5 YOLOv8 model deployment workflow

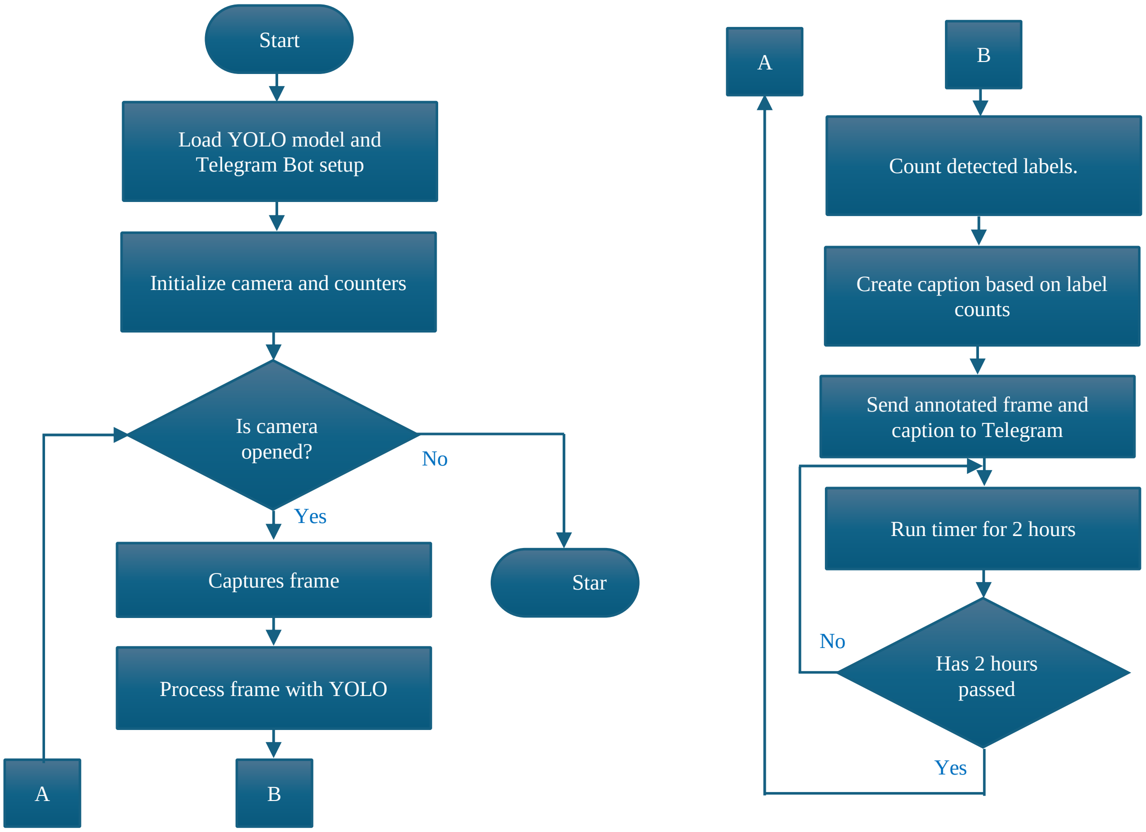


Fig. 6 System process flow integrating image analysis and IoT

2.5. Evaluation Setup

The hardware is designed to operate independently in outdoor agricultural settings. It consists of an 8-megapixel Raspberry Pi camera module connected to a Raspberry Pi 4B microcontroller, powered by a solar panel with a rechargeable 12 V plug-in battery and a charge controller to allow permanent operation, as indicated in Figure 7. The Raspberry Pi 4B works as the main controller of the system. It handles image capture, data processing, and communication between all components.

Fig. 7 Hardware setup for the IoT-based pest detection system

The camera module was oriented toward the yellow sticky traps to be able to capture high-quality pictures of the insects that are on the traps. The system is powered by a solar panel, charged via a charge controller, and has a voltage stabilizer to avoid overcharging and sudden power surges.

Images captured are processed directly on the Raspberry Pi to enable local detection and counting of pest infestations. The output data, including pest types and quantities, reaches farmers via Telegram alerts. This remote monitoring capability supports rapid response and reduces the need for frequent field visits.

2.6. Ethical Consideration

This study was conducted with adherence to strict protocols for data protection, farm consent, and responsible AI use. The dataset consists exclusively of images obtained from a chili farm in Segamat, Johor, following permission from the farm owner for the purpose of research and monitoring. No part of the dataset contains any personal or other identifiable information on any individual. Image processing and pest detection occur locally on the edge device to minimize data transmission and mitigate privacy risks associated with cloud service. The proposed system will provide the farmer with the ability to investigate pests early and support informed decision-making on pest management. The farm will remain in control of all pest management activities.

3. Results and Discussion

The section presents the performance evaluation of the proposed system in an IoT-based pest detection. The findings include the training result for the model, detection accuracy, and system response time. The analysis will show how well the system is able to correctly identify and detect whiteflies and fruit flies in yellow sticky traps and provide alerts to farmers in real-time.

3.1. Training and Validation Performance

Figure 8 shows the evolution of Mean Average Precision (MAP) based on the epochs of training data. It also compares the mAP@0.5 and mAP@0.5:0.95. The mAP@0.5 curves reach a peak around 0.45 when the model completes its training. However, the mAP (0.5:0.95) average precision usually varies between 0.15 and 0.25 across epochs. This gap between MAP measures demonstrates that small pest objects, which generally have a small area within an image and may be partially covered or tightly clustered on sticky traps, are difficult to localize accurately.

Despite these moderate performance levels, each metric exhibits a consistent upward trend before reaching a plateau at approximately 200 epochs, confirming learning behavior. These findings imply that the YOLOv8 model is able to learn relevant features for pest detection on yellow sticky traps at a level of performance that makes them suitable for early warning systems in the chili farming industry.

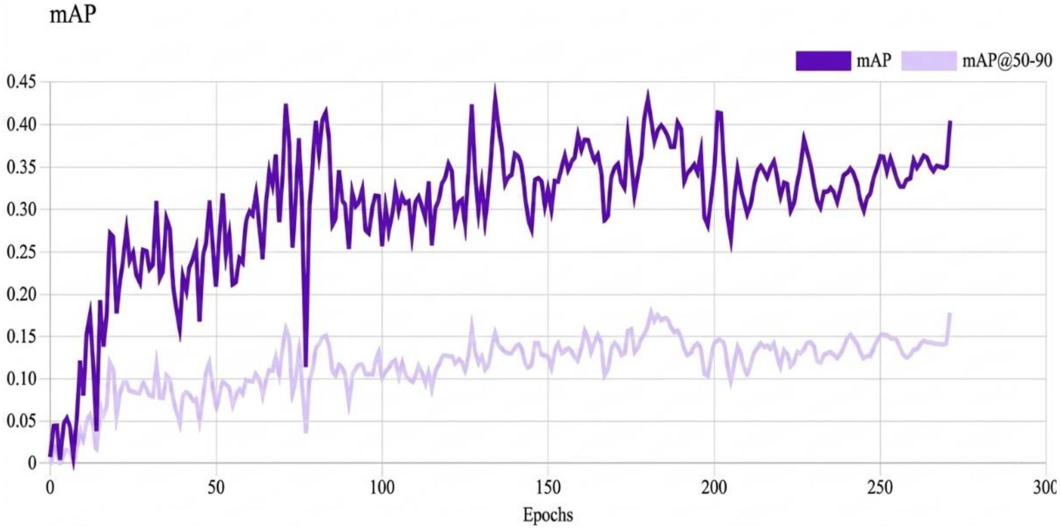


Fig. 8 Training performance of the proposed YOLOv8 model showing the evolution of mAP@0.5 and mAP@0.5:0.95 over training epochs

3.2. Detection Performance

To assess the detection performance of the YOLOv8 model, the precision-recall analysis was carried out over the test dataset. The results of this analysis are displayed in Figure 9, which provides a set of precision-recall curves for both the whitefly and fruit fly categories of detection in relation to the overall Mean Average Precision (MAP) at 0.5 of 0.477. The detection performance for whitefly was slightly better than that of the fruit fly due to the presence of a greater number of training images and easily distinguishable visual features. Detection of fruit fly was more difficult due to its being a significantly smaller number of training images than whitefly, having a greater incidence of being partially occluded, and being found in clusters on sticky traps, especially under variable conditions of field lighting. This accurate localization and classification of fruit flies are made more challenging as a result of these factors. Nevertheless, these results suggest that the proposed pest detection system will be able to reliably detect the presence of pests promptly. This is to assist farmers with potential early warning of imminent threats from pests. The proposed pest detection system was not designed to be perfect at detecting pests but rather to assist in ongoing monitoring of agricultural fields to provide farmers with support in making operational decisions within the realities of commercial agriculture.

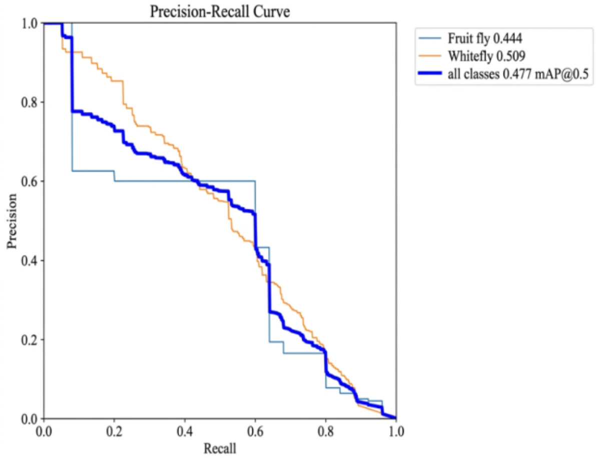


Fig. 9 Precision–recall curves for whitefly and fruit fly detection using the proposed YOLOv8-based model, including the overall performance across all classes

The recall-confidence curves of the whitefly and fruit fly detection system are shown in Figure 10. Each of the confidence thresholds, from the lowest to the highest confidence levels, indicates the model's ability to detect numerous pests. At a lower confidence level, a high number of recalls can be seen.

As confidence level rises, the number of recalls declines, which is an illustration of the trade-off between capturing large numbers of pests and using a more stringent confidence filtering system. It is apparent that for the fruit fly, there is a much steeper slope in the decline in recall than for whiteflies because of the nature of the data set. The fruit flies are small in nature and often partially occluded and are generally present in the dataset at much lower levels than whiteflies. Thus, this behavior is to be expected.

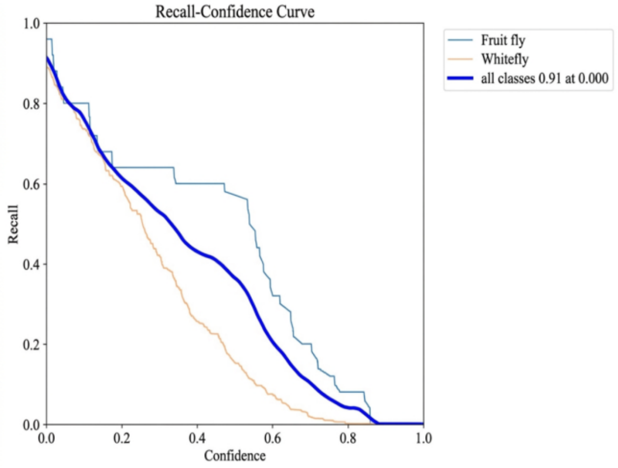


Fig. 10 Recall-confidence curves for whitefly and fruit fly detection, illustrating the effect of confidence threshold selection on detection recall

From a practical deployment standpoint, a lower confidence threshold for detecting early pest warning is more appropriate. Prioritizing the identification of all pest occurrences is essential, as missing pest occurrences can be more detrimental than generating false alerts. This approach is consistent with the expected operational use of the system as a method of continuously monitoring live pest events by edge-based detection methods in real-world agricultural practices.

3.3. Notification and Response Time in Telegram

An added metric for evaluation was the timing of alerting the farmer once a pest was detected in real time. Integration with the Telegram mobile application allowed the Raspberry Pi to send an alert to the farmers when a pest was detected, with details on the image taken, the types of pests, the level of detection confidence, and pest count.

In Figure 11, various images of the sticky trap were captured with little differences in the number of pests, even though the sticky traps were consistently set in the same location. Whiteflies, for example, were detected less between the first and subsequent captures due to slight differences in the position of the camera frame for each of the images captured, causing some part of the sticky trap to be out of the camera view.

Additionally, light conditions at the time of capture affected how well or how poorly each of the image captures performed with respect to the clarity of the image and the alignment of shadows. Despite these environmental constraints, the system maintained reliable detection of pest infestation and provided near real-time alerts suitable for field deployment in chili farms.

The findings indicate that the integration of IoT devices with YOLOv8 into chili farms would facilitate autonomous pest detection. The YOLOv8 model exhibited stable learning performance, achieving a mean average precision of mAP@0.5 to reach about 0.45 and mAP@0.5:0.95 to range from 0.15 to 0.25. Although these estimates are adequate, they are sufficient to initiate early alerts of pest infestation, the main aim of this research.

There can be a significant number of pests present each time the specified traps are displayed. However, there were some fluctuations in the recorded number of pests as detected by the system due to slight changes in camera position or lighting conditions that degrade image quality. Despite these inconsistencies, the system reliably identifies pest presence across all test cases for monitoring purposes. The feature of sending alerts to users via Telegram also added convenience, ensuring alerts reach the user within a minute of image acquisition.

Future studies could improve practical use and field reliability by focusing on addressing issues with camera stabilization, addressing variability in lighting conditions, expanding the dataset, and improving performance under limited connectivity and power constraints.

Whitefly: 9

08:42

(a)

Fruit fly: 1, Whitefly: 6

10:27

(b)

Whitefly: 14

12:20

(c)

Fig. 11 Telegram notification and response time for pest detection: (a) Whitefly detected at 08:42:00 with a response time of 45 seconds, (b) Whitefly and fruit fly detected at 10:27:00 with a response time of 50 seconds, and (c) Whitefly detected at 12:20:00 with a response time of 53 seconds.

4. Conclusion

The studies present an IoT-based chili pest detection system incorporating the utilization of the YOLOv8 model with Telegram alert notifications. Even though the model is lightweight, it would achieve a maximum mAP@0.5 of about 0.45 and an mAP@0.5:0.95 of 0.15 to 0.25. These are sufficient to send out early warnings of pest infestation for the farmer to act accordingly in good time to preserve their produce. Notification experiments confirm that alerts are triggered on average within one minute of the picture being captured. Despite the system performing well in detecting pests and providing timely alerts, some issues remain to be addressed, such as the possibility of increased detection numbers as the camera frames shift.

From a budget perspective, this edge-based pest detection system scales smoothly on budget-friendly hardware. However, expanding into larger agricultural areas requires more than just additional hardware. The integration of multi-camera support and the ability to detect a wider range of pest species are some of the criteria required. In addition, strengthening the imaging stability and diversifying the data set under actual field conditions, while optimizing the communication module for rural environments, must be considered for future improvement. This system marks a practical step towards automated and intelligent pest monitoring for chili farming. Further refinement and extended field validation will drive the adoption of smart monitoring solutions, ultimately boosting the efficiency of farm management. Such progress will enable faster, more informed decision-making and better resource allocation.

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