IoT and YOLOv8-Based Precision Pest Control Instrument for Vertical Farming of Ayesha IPB Chili Pepper

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ABSTRACT

Bird's eye chili (Capsicum frutescens) is a strategic horticultural commodity in Indonesia with high economic value. However, domestic production remains insufficient due to limited agricultural land and severe pest infestations. The Ayesha IPB chili pepper has emerged as a promising alternative for urban agriculture, as it can be cultivated in confined spaces using vertical farming systems. Nevertheless, effective pest control remains a major challenge in such environments. Unlike previous studies that focus mainly on open-field cultivation or standalone pest detection methods, this study proposes an integrated vertical precision pest control system specifically designed for Ayesha IPB chili pepper cultivation. The proposed system combines computer vision-based pest detection using the YOLOv8 algorithm with an Internet of Things (IoT) framework to transmit image data, process detection results, and automatically actuate a mechanized pesticide sprayer. The novelty of this work lies in the application of a zoom-in augmentation strategy to enhance YOLOv8 performance for detecting small-scale pests in vertically cultivated Ayesha IPB chili peppers. Experimental results show that the proposed technique improves the Mean Average Precision (mAP) from 88% to 95%. Moreover, field testing indicates that the implemented system can reduce pest occurrence points by up to 75%. The proposed approach offers a scalable and cost-effective solution for precision pest management and is expected to support sustainable urban agriculture, particularly for vertical farming of Ayesha IPB chili in metropolitan areas.

Keywords-precision agriculture; pest control; vertical farming; Ayesha IPB; IoT; computer vision

I. INTRODUCTION

Precision agriculture is a combination of strategies, methodologies, and technologies aimed at addressing and managing spatial and temporal variability in agricultural fields to improve resource-use efficiency, productivity, quality, profitability, and sustainability of agricultural production. Furthermore, according to [1], precision agriculture involves proximal and remote sensing techniques utilizing Internet of Things (IoT)-based sensors to monitor crop conditions at various growth stages. Currently, precision agriculture is shifting from a macro-scale farming concept toward a micro-scale approach, as evidenced by its development, particularly in urban farming systems [2].

Various agricultural methods have been developed for urban farming, both outdoor and indoor, including crop beds, pots, and hydroponic systems [3]. However, a major constraint in urban agriculture implementation is limited land availability. An effective approach to maximize limited space is vertical farming, which can utilize various growing media, such as soil or water, and can be implemented for vegetable cultivation [4]. This farming method aims to produce fresh and high-quality vegetables for urban communities [5]. In Indonesia, the demand for vegetable consumption is particularly high in urban areas. Bird's Eye chili is a vegetable commodity with high economic value. Based on data from Indonesia's National Food Agency, the average price of Bird's Eye chili in early December 2025 reached IDR 64,335 per kg [6].

In 2017, the Department of Agronomy and Horticulture at IPB University developed a Bird's Eye chili variety suitable for urban cultivation, namely Ayesha IPB chili. This variety differs from other Bird's Eye Chili types in that it has a plant height of approximately 25 cm, whereas other varieties typically range from 50 to 150 cm in height [7]. These morphological characteristics enable Ayesha IPB chili to be cultivated vertically using pot-based growing media.

In addition to its value as a food crop, Ayesha IPB chili also serves as an ornamental plant. In its cultivation, the primary challenge is severe pest infestation during the early generative growth phase. Pests act as vectors of viruses that can cause diseases in chili plants, thereby reducing crop productivity [8]. Pest attacks occur not only in open-field cultivation but also in greenhouse environments. Aphids are one of the pest species that commonly infest greenhouse-grown chili. Aphids are approximately 0.5 to 3 mm in size, allowing them to penetrate insect nets used as greenhouse covers [9]. Currently, pest monitoring in Ayesha IPB chili pepper cultivation is still conducted manually, requiring consistent inspections by farmers to control pest populations. This approach is considered inefficient due to the significant time and labor required, highlighting the need for technological solutions to support this process [10].

The main contributions of this study can be summarized as:

- An IoT-enabled, closed-loop pest control instrument integrates real-time Computer Vision (CV)-based pest detection with targeted pesticide spraying, specifically designed for the vertical cultivation of Ayesha IPB chili.
- System-level integration and real-world validation of a previously developed YOLOv8-based pest detection model with zoom-in augmentation demonstrate its effectiveness in detecting small-object chili pests and support precision pest management in vertical farming.

II. MATERIALS AND METHODS

In this study, several stages were conducted systematically to ensure the precise development of the pest control system for vertical farming. Figure 1 illustrates the overall research methodology. This study began with a review of the literature to identify relevant research and determine potential novelties for further development. In the second stage, pest species commonly affecting the cultivation of Ayesha IPB chili peppers were identified, followed by the collection of pest image data to use as training datasets in the detection process. The third stage involved the development of CV-based image processing software for pest detection. Subsequently, hardware assembly was conducted to construct the pest control system, consisting of sensors, controllers, actuators, and processors integrated through IoT technology. The final stage involved the implementation of the system in chili cultivation and the evaluation of the operational precision of each hardware component.

A. Literature Study

Articles, journals, and books were collected to identify research gaps in relevant prior studies. Several studies were reviewed using methodological approaches aligned with the research keywords, which included "precision agriculture," "pest control," "vertical farming," and "Ayesha IPB chili." Keyword selection followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, which consists of four stages: identification, screening, eligibility, and inclusion. Based on these keywords, relevant studies were identified to generate novel insights for the precise development of a pest control system in vertical farming. Table I shows previous studies that extensively explored the application of intelligent technologies in vertical farming systems. Some studies reviewed the literature on vertical farming to identify key requirements for chili cultivation, while others examined indoor chili farming with a focus on environmental optimization through UV irradiation. These findings highlight a research gap in optimizing chili crop maintenance, particularly in pest control.

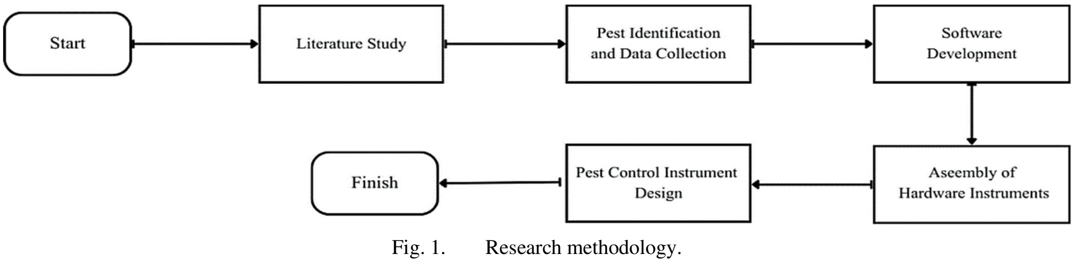

Fig. 1. Research methodology.

TABLE I. RELEVANT WORK

Study	Findings
[11]	Investigated the application of ultraviolet (UV) radiation in indoor vertical farming systems for chili cultivation with a focus on environmental engineering. The findings reveal a research gap related to optimizing chili plant maintenance with an emphasis on pest control.
[12]	Compared the performance of YOLOv8 and YOLOv5 models in detecting grasshopper pests by applying data augmentation techniques to improve model accuracy. This approach can be further developed by proposing object enlargement augmentation to enhance detection precision.
[13]	Evaluates the performance of Faster R-CNN and YOLOv5 in detecting pest objects in trap images, demonstrating that data augmentation techniques significantly improve mean average precision (mAP).
[14]	Described the design and modelling of a linear DC stepper motor based on magnetic flux density analysis to minimize peak thrust force errors. These findings can be adapted to vertical farming mechanization technologies to enable precise positioning of cameras and spraying devices for pest control.
[15]	Presented the development of a CV-based wheeled robotic system for pesticide spraying applications. The platform can be further adapted for Ayesha chili cultivation by redesigning the motion mechanism using DC linear actuators.
[16]	Introduced an intelligent and robust linear control approach to ensure accurate angular position tracking of a DC servo motor. The proposed method is further adaptable to pest detection systems by enabling precise servo-based control for camera alignment and spraying mechanisms.

In the field of computer vision, several studies have developed detection and classification systems using various deep learning models with object segmentation techniques. Some studies compared the performance of recent YOLO models in detecting grasshopper pests using data augmentation, while other studies show that data augmentation significantly improves the mean Average Precision (mAP) of models such as Faster R-CNN and YOLO. These findings indicate a gap in optimizing later YOLO models by integrating image augmentation techniques to enhance mAP in crop pest detection.

Although previous studies have explored intelligent technologies in vertical farming, CV-based pest detection, and precision control mechanisms, these works remain largely fragmented and domain-specific. Existing research on vertical Ayesha IPB cultivation primarily emphasizes environmental optimization, such as UV-based growth enhancement, without integrating a dedicated pest control mechanism tailored to the abaxial leaf area where pests predominantly reside. In parallel, CV studies demonstrate that data augmentation improves detection performance. However, limited work has specifically optimized the YOLOv8 model for chili pest detection within a controlled vertical farming environment. Furthermore, studies on motor control and actuation systems focus mainly on mechanical accuracy without integrating these mechanisms into a unified IoT-enabled pest management framework. Therefore, a clear research gap exists in the development of an integrated system that combines targeted IoT-based spraying, augmentation-enhanced YOLOv8 detection, and precise actuator control specifically designed for Ayesha IPB chili cultivation in vertical farming.

B. Pest Identification and Data Collection

In this stage, pest identification and data collection were conducted on Ayesha IPB chili cultivation using conventional practices under a vertical farming system. The cultivation period spanned from December 2024 to March 2025. During the early generative phase, four major pest species were identified, namely aphids, thrips, whiteflies, and caterpillars. Figure 2 illustrates the vertical farming cultivation of Ayesha IPB chili plants.

Fig. 2. Pest identification in conventional Ayesha chili cultivation.

The pest identification process produced 5,876 primary data samples acquired through direct images captured using a camera. In addition, secondary pest data totaling 8,543 images were collected from several database libraries, including Roboflow [17] and Kaggle [18]. In total, 14,419 pest images were obtained. Figure 3 visualizes the distribution of the collected pest data.

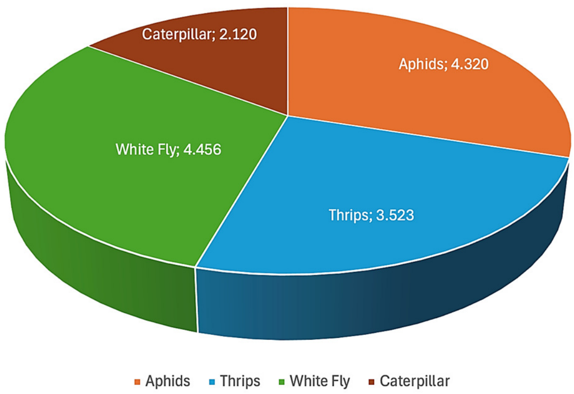

Fig. 3. Pest image dataset.

Following the pest image data collection, the next stage involved training the dataset using the YOLOv8.pt model. The training process focused on precision and recall metrics, as high precision in pest object detection minimizes misclassification errors. The YOLOv8 model was trained on four pest classes, namely aphids, thrips, whiteflies, and caterpillars, with dataset sizes of 4.320, 3.523, 4.456 and 2.120 images, respectively. The dataset was divided into three subsets, consisting of 70% for training, 20% for validation, and 10% for testing. Model training was carried out over 70 epochs, as performance assessment showed that both precision and recall metrics had achieved stable convergence at this stage. The data augmentation process involved 90° rotations, generating four distinct variations from each original image.

The training configuration and YOLOv8 hyperparameter settings were implemented across several object detector variants, the detailed specifications of which are presented in Table II. Training was implemented using the YOLOv8s.pt model variant. A batch size of 16 was employed, with a learning rate set to 0.001. The Adam optimizer was utilized during the training process, considering the available GPU specifications that support large-scale image data processing.

TABLE II. TRAINING SETTINGS AND HYPERPARAMETERS

	Parameters	**Settings**
1	Weights	Yolo8s.pt
2	Class	Aphids, Thrips, Whitefly, Caterpillar
3	DL Framework	Py Torch
4	Language	Python 3.3
5	Neural Network	CNN
6	Optimizer	Adam
7	Batch Size	16
8	Learning Rate	0,001
9	Epochs	70

After the hyperparameter configuration for dataset training, the model was trained to evaluate the data quality and the performance of the YOLOv8 model in detecting pest objects on Ayesha IPB chili pepper. Figure 4 visually represents the model's performance during the training and validation phases. The achieved precision values reflect strong model performance. From the initial training iterations, the model was able to perform pest class classification with an average precision exceeding 80%. Consequently, the trained dataset can be considered a reliable reference for the class testing stage in the Ayesha IPB chili pest control system. The loss values observed during both training and validation exhibit a consistent decreasing trend toward zero, indicating that the model can be regarded as stable with minimal prediction error.

C. Software Development

A web-based software platform was developed, with features for enabling pest detection, periodic pest monitoring, and automated control of pesticide spraying for Ayesha IPB chili pepper cultivation.

D. Hardware Assembly

In this stage, hardware instruments for pest control in vertical farming were assembled. Table III presents a list of hardware components used, classified based on their functions, including sensors, actuators, controllers, and processors. An IP camera was used as the sensor for pest image acquisition, while the actuators included a sprayer, stepper motors, servo motors, DC linear actuators, and a water pump to support motion mechanisms and spraying operations. Motor drivers and power supplies served as system control components. A Raspberry Pi and an Arduino were used as the main processing units to execute detection algorithms and control the hardware in an integrated manner.

Training was conducted within a hardware environment capable of supporting CV implementation. Table IV shows the hardware configuration used during the training process, including an NVIDIA A100 GPU with 32 GB of memory capacity. This hardware significantly accelerated the model training process and enabled efficient handling of large-scale image data.

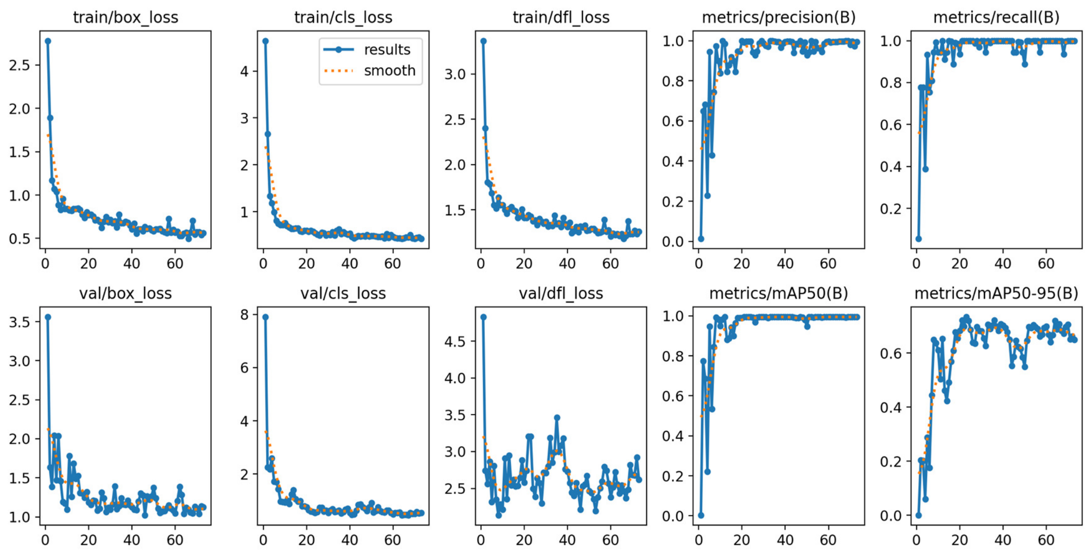

Fig. 4. Results of data training and validation.

TABLE III. LIST OF HARDWARE COMPONENTS

No	Hardware	Type
1	IP Camera	Sensor
2	Sprayer DC	Actuator
3	Stepper motor	Actuator
4	Servo motor	Actuator
5	DC Liner	Actuator
6	Water Pump DC	Actuator
7	Driver motor	Controller
8	Power Supply	Controller
9	Raspberry pi	Processor
10	Arduino	Processor

TABLE IV. TRAINING PARAMETERS

Specification	Details
GPU	NVIDIA A100
RAM	32 GB
Compilers	Google Colab Pro

E. Pest Control Instrument Design

The pest control instrument consists of multiple hardware components interconnected into an integrated IoT-based system. In this vertical farming setup, two rack layers were designed to accommodate Ayesha IPB chili plants. The sample objects comprised six chili plants with an inter-plant spacing of approximately 30 cm, which represents the optimal distance based on plant morphological characteristics. Figure 5 illustrates the instrument design.

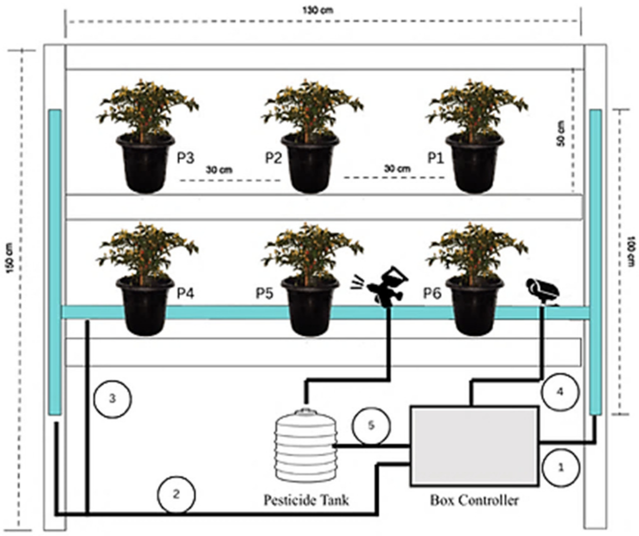

Fig. 5. Design of the pest control instrument.

In Figure 5, the blue regions represent the leadscrew or linear robot mechanisms installed vertically and horizontally according to the rack dimensions. These linear robots function as carriers for the camera and pesticide sprayer and are adapted from the CNC dual-axis concept. The notations are as follows:

- (P) denotes the plant and is used to label each plant pot, indicated as P1 to P6.
- Numbers 1 and 2 represent stepper motors connected to the controller box as the central control unit, with the leadscrew mechanism enabling vertical movement.
- Number 3 denotes a stepper motor responsible for horizontal movement.
- Number 4 represents a servo motor connected to the controller box to determine the camera and sprayer angles during pest image acquisition.
- Number 5 denotes a DC water pump used for pesticide spraying.
- The controller box serves as the power supply and control circuitry unit.

The transport mechanism follows a predefined mechanization path, which constitutes a critical component of the IoT-based pest control instrument. The devices involved in this subsystem include a power supply, stepper motors, motor drivers, and leadscrews. Stepper motors are used to precisely position the camera and sprayer toward each plant pot location. Figure 6 illustrates the mechanization workflow of the stepper motors.

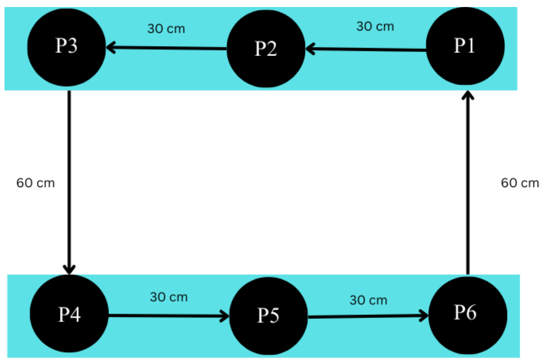

Fig. 6. Stepper motor mechanism flow.

The movement of the stepper motor depends on the predefined travel distance. This study used a NEMA 17 stepper motor that had a step angle of 1.8°. This step angle determines one full revolution, or steps per revolution (N_s). To achieve a full 360° rotation, 200 steps are required [19]. The steps formulation is :

$$N_s = \frac{\theta_{full}}{\theta_{steps}} \tag{1}$$

$$N_s = \frac{360^0}{1{,}8^0} = 200 \text{ steps} \tag{2}$$

where N_s is the number of steps in one full revolution, θ_{full} is the full revolution, and θ_{steps} is the step per revolution.

In addition to the stepper motor, the leadscrew type affects the number of steps required to determine stopping positions. This study used a T8 leadscrew was used, which has a linear travel of 8 mm per full revolution. Equation (3) presents the calculation for determining the linear distance per full rotation of the stepper motor.

$$\Delta x = \frac{L}{N_s} \quad (3)$$

$$\Delta x = \frac{8}{200} = 0{,}04\ mm/step \quad (4)$$

where Δx is the linear displacement per step, L is the linear distance of one full revolution (8 mm), and N_s is the number of steps in one full revolution.

Based on (1), the total stepper motor movement for each position from P1 to P6 can be determined using:

$$steps = \frac{D}{\Delta x} \quad (5)$$

where $steps$ is the number of steps, D is the travel distance, and Δx is the linear displacement per step.

Table V presents the results of the calculation for determining the total number of steps of the leadscrew and stepper motor in the pest control transport mechanism.

TABLE V. STEPPER MOTOR OPERATION

Direction	Distance (mm)	Steps (mm)	Total steps
P6 to P1	600	0,04	15000
P1 to P2	300	0,04	7500
P2 to P3	300	0,04	7500
P3 to P4	600	0,04	15000
P4 to P5	300	0,04	7500
P5 to P6	300	0,04	7500

As shown in Table V, the stepper motor movements along the leadscrew are classified as vertical and horizontal. Vertical motions occur from P6 to P1 and P3 to P4, while horizontal motions occur from P1 to P2, P2 to P3, P4 to P5, and P5 to P6. The vertical travel distance of the transport mechanism is 600 mm, requiring 15,000 steps, whereas the horizontal travel distance is 300 mm per plant pot, requiring 7,500 steps, as calculated using (3).

In the next stage, the angular movement is determined using a Pulse-Width Modulation (PWM) servo motor, which enables precise control of the imaging angle for pest detection and subsequent plant spraying. PWM is employed to adjust the servo angle by varying the pulse width applied to the motor.

Figure 7 depicts the angular movements of the camera and sprayer, both actuated by servo motors connected to the controller box. At each stop from P1 to P6, the devices rotate upward by 45°, allowing effective detection of pests beneath the leaves and enabling precise spraying. The following formulation is applied to determine the camera and sprayer angles.

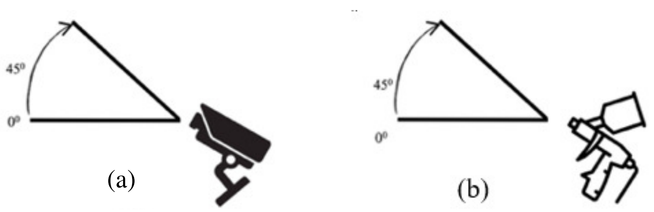

Fig. 7. (a) Camera angular movement, (b) Sprayer angular movement.

$$\theta(t) = \theta_0 + \frac{\theta_f + \theta_0}{T} . t \ \ ,\ 0 \leq t \leq T \quad (6)$$

where θ_t is the angular as a function of time, θ_0 is the initial angle, θ_f is the final angle, T is the duration of motion, and t is the time from 0 to T.

The Pulse Width (PW) required to achieve the desired angular movement is determined using a minimum value of PW_{min} = 1000 µs and a maximum value of PW_{max} = 2000 µs, with the corresponding formulations:

$$PW = PW_{min} + \left(\frac{\theta}{180^0}\right) . (PW_{max} - PW_{min}) \quad (7)$$

$$PW = 1000 + \left(\frac{45}{180}\right) . (2000 - 1000) \quad (8)$$

$$PW = 1000 + 250 = 1250\ \mu s \quad (9)$$

Table VI presents the calculated angular movement requirements for pest image acquisition and pesticide spraying on each plant.

TABLE VI. MOTION OF THE SERVO MOTOR

Plant	Motion Angular (^{0})	Pulse Width (µs)
P1	45	1250
P2	45	1250
P3	45	1250
P4	45	1250
P5	45	1250
P6	45	1250

As shown in Table VI, the required pulse width for the servo motor movement at each plant position is 1250 µs. This pulse value is applied to actuate both the camera and the sprayer at each plant location.

III. RESULTS AND DISCUSSION

A. IoT System Architecture

This study developed a pest control system for Ayesha IPB chili pepper cultivation by integrating two technologies, CV and IoT. The system architecture is adapted from a three-layer IoT model, in which each layer has a specific role, namely the application layer, the network layer, and the perception (or things) layer. Figure 8 provides an overview of the implemented IoT architecture.

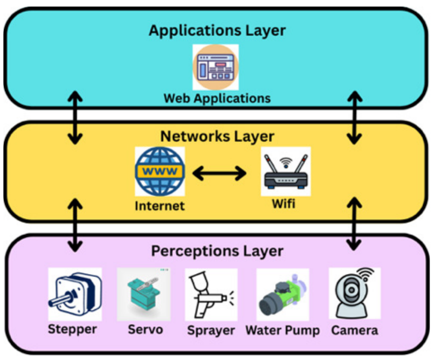

Fig. 8. IoT system architecture.

The application layer consists of a web-based software responsible for pest detection using CV technology. The network layer manages data communication from the processors (Arduino and Raspberry Pi) connected within a local Wi-Fi network and subsequently to the Internet, which serves as a bridge to the web application accessed by users. At the perception layer, actuators such as the stepper and servo motors are controlled by the Arduino microprocessor, while the sprayer, water pump, and camera sensors are connected to the Raspberry Pi. The Arduino and Raspberry Pi function as the processing units of the perception layer, forming an integrated system.

B. Pest Detection Application

Software development was carried out using a web-based platform. The application is designed to facilitate pest detection activities. Specifically, it provides features for image acquisition via a camera, pest classification, presentation of detection results, and control of the pest control device. Figure 9 presents the pest detection application, highlighting the integration of an image augmentation technique in the form of zoom-in during the preprocessing stage of the YOLOv8 model. This approach effectively improves the precision in both pest detection tasks.

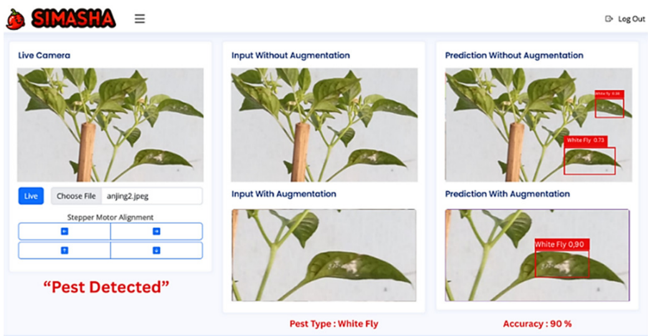

Fig. 9. Pest detection application.

The augmentation technique employed in this study consists of three main stages, namely selection, crop, and zoom. The selection stage is used to determine the pest location to be detected. Subsequently, the crop stage defines the input image dimensions for the YOLOv8 model, which are set to 640×640 pixels. The final stage, zoom, is applied to enlarge the pest objects within the image to enhance their visual representation. This approach aims to improve detection precision, thereby enabling accurate pest classification according to their respective classes. Table VII presents the experimental results obtained directly from the developed software application.

TABLE VII. PRECISION RESULTS

No	Pest class	Precision	
		YOLOV8 with augmentation	YOLOV8
1	Aphids	96.3%	91.3%
2	Thrips	90.3%	75.3%
3	White Fly	95.8%	93.1%
4	Caterpillar	98.5%	95.1%
mAP		**95.2%**	**88.7%**

According to the results in Table VII, the YOLOv8 model achieved an mAP of 88.7% when trained on the original dataset without augmentation. After applying the selection, crop, and zoom augmentation stages, mAP increased to 95.2%, indicating a significant improvement in overall detection performance, particularly for small-scale pest objects. This result confirms the effectiveness of the proposed augmentation strategy in enhancing detection accuracy and reducing false detections. The visualization of these results in Figure 10 demonstrates an improvement in detection values for each pest type. This technique is particularly effective for detecting very small pests, thereby improving the overall pest detection performance in the cultivation of Ayesha IPB chili plants.

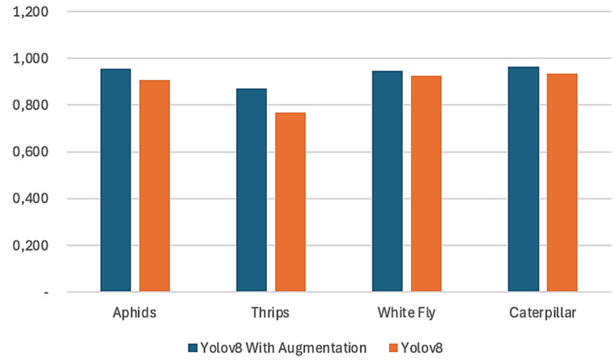

Fig. 10. Pest detection results.

C. Pest Control Instrument

In the pest control instrument, the hardware actuators consist of stepper and servo motors. Both actuators require calibration to ensure precise operation of the pest control system. Stepper motor calibration aims to determine the number of motor steps along the leadscrew corresponding to the designated stop points. The vertical movement of the stepper motor (from P6 to P1 and P3 to P4) spans 600 mm, corresponding to a total of 15,000 steps, while the horizontal movement (from P1 to P2, P2 to P3, P4 to P5, and P5 to P6) between plant pots is 300 mm, corresponding to a total of 7,500 steps. Table VIII summarizes the results of the stepper motor calibration. Experiments 1 through 8 proceeded without issues; however, during the 9th experiment, positioning errors occurred from P4 to P5 and from P5 to P6, showing a deviation of 30 mm from the intended stop positions for pots 5 and 6. Hardware inspection revealed dust accumulation on the leadscrew, which hindered the stepper motor movement. Thus, regular cleaning of the leadscrew threads is necessary to prevent misalignment of the camera and sprayer positions.

In addition to the stepper motor, calibration was performed on the servo motor to control the angular movement of the camera during image acquisition and the sprayer during pesticide application. Calibration applied the appropriate pulse signal to achieve a 45° angle. The required pulse value of 1250 µs, as shown in Table V, allowed the camera and sprayer to operate accurately and precisely. After the stepper and servo motor calibration tests, the next evaluation was conducted directly on the Ayesha chili plant cultivation to assess the overall effectiveness of the pest control system.

TABLE VIII. STEPPER MOTOR CALIBRATION

No	Calibration Testing					
	P6-P1	**P1-P2**	**P2-P3**	**P3-P4**	**P4-P5**	**P5-P6**
1	Passed	Passed	Passed	Passed	Passed	Passed
2	Passed	Passed	Passed	Passed	Passed	Passed
3	Passed	Passed	Passed	Passed	Passed	Passed
4	Passed	Passed	Passed	Passed	Passed	Passed
5	Passed	Passed	Passed	Passed	Passed	Passed
6	Passed	Passed	Passed	Passed	Passed	Passed
7	Passed	Passed	Passed	Passed	Passed	Passed
8	Passed	Passed	Passed	Passed	Passed	Passed
9	Passed	Passed	Passed	Passed	±30mm	±30mm
10	Passed	Passed	Passed	Passed	Passed	Passed

Figure 11 illustrates the experimental trial of Ayesha IPB chili cultivation in a vertical farming setup integrated with IoT and CV technologies. The experiments were conducted during June and July 2025, from the early generative phase to harvest. This trial aimed to evaluate the effectiveness of the pest control system in monitoring and managing pest populations. The results include data on the reduction of pest spots on each plant pot. Figure 12 presents a visualization of pest presence in the IoT- and CV-based Ayesha IPB chili pepper cultivation.

Fig. 11. Experimental trials.

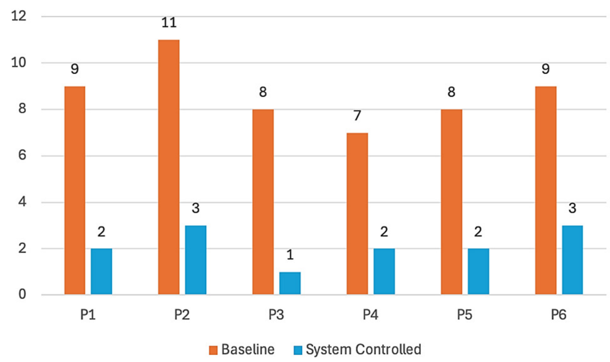

Fig. 12. Pest spots.

In the initial baseline condition, each plant exhibits a relatively high number of pest infestation spots. After the implementation of the proposed pest control system, a significant reduction in pest occurrence was observed across all vertically cultivated Ayesha IPB chili plants, with an average decrease of approximately 75%. These results demonstrate that the proposed system effectively supports optimal plant growth and shows strong potential for implementation in urban farming applications.

IV. CONCLUSION

This study presented an integrated vertical precision pest control system for Ayesha IPB chili cultivation by combining YOLOv8-based computer vision, a zoom-in augmentation strategy, and an IoT-enabled closed-loop control mechanism. Experimental results demonstrate that the proposed augmentation approach significantly improves detection performance, increasing mAP from 88.7% to 95.2%, particularly for small-scale pest objects in vertical farming environments. Moreover, real-world field implementation showed a substantial reduction in pest infestation levels, with an average decrease of approximately 75% across all tested plants. These results confirm that the proposed system is effective, reliable, and suitable for precision pest management in urban vertical agriculture.

Future work will focus on extending the system to support multi-class pest detection, optimizing deployment on edge-computing platforms for real-time and low-power operation, and incorporating adaptive control strategies based on pest density and environmental conditions. Long-term field evaluations under diverse urban farming scenarios are also recommended to further assess system robustness and scalability.

DECLARATION OF COMPETING INTERESTS

The authors declare no competing interests that could have influenced the work reported in this paper.

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DATA AVAILABILITY

The datasets generated and analyzed during this study are available from the corresponding author upon reasonable request.

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