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Revolutionizing tomato pest management: Synergy of Deep Learning, IoT, and Precision Agriculture

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The increasing worldwide demand for agricultural goods, particularly tomatoes, underscores the need for effective pest control. Key pests such as Whiteflies, Fruit Fly, and Helicoverpa Armigera pose significant threats to tomato crops. This research proposes a novel approach by integrating modern technologies such as deep learning and the Internet of Things (IoT) to revolutionize traditional pest management methods. Using a portable Pest Counting Device equipped with the YOLOv8 deep learning model on a Raspberry Pi 4B, coupled with the Firebase IoT platform, facilitates instant surveillance of pheromone traps. This integration enables farmers to make informed decisions and optimize pest control efforts. By leveraging the synergy of advanced technologies, farmers can potentially increase crop yields while reshaping conventional pest management techniques. This holistic approach not only gives farmers more control but also diminishes the environmental repercussions linked with conventional pest control methods, highlighting how technology can advance sustainability in agriculture amid persistent pest issues.

Keywords: *precision agriculture; tomato pests; IoT (Internet of Things); deep learning; pest management; pest detection.*

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1. Introduction

Tomatoes (Solanum lycopersicum) play a pivotal role as a primary horticultural crop cultivated across temperate regions worldwide, with a production exceeding 170 million tons (Mt) globally [1]. Morocco has emerged as a significant player among the nations renowned for tomato production and export. In 2022, there was a notable 7% increase in Moroccan tomato exports, totaling 670 000 tons compared to the previous year's shipment of 629 510 tons [2]. This significant expansion, as documented by the specialized journal East Fruit, resulted in Morocco ascending two ranks in a mere span of one year, achieving the prestigious status of being the world's third-largest exporter of tomatoes [3]. Surpassing Iran and Spain, which occupy the fourth and fifth positions respectively, Morocco stands behind Mexico and the Netherlands. The Souss-Massa region serves as a crucial contributor to this burgeoning productivity, accounting for nearly 90% of the nation's tomato production. The increasing worldwide demand for tomatoes has opened up fresh avenues for both the agricultural and marketing industries. However, the expansion of agricultural production on a global scale has significant implications for the distribution of agricultural pests worldwide [4]. The transformation of the international trade network has sparked a noticeable increase in the introduction of pest species into previously unaffected regions. This phenomenon has led to diminished productivity in vegetable crops and has raised concerns regarding the shelf-life of harvested products [5].

The tomato stands out among agricultural products for its unique status as a vegetable commonly consumed as a fruit, offering significantly higher nutritional value compared to other fruits [6]. With its prolific yield and expanding cultivation areas, especially in greenhouses where acreage rapidly increases [7], tomatoes are highly susceptible to diseases and pests throughout their growth cycle, significantly impacting yield and quality and leading to substantial economic losses for farmers [8]. Notable among these pests are Whiteflies, Fruit Fly, and Helicoverpa Armigera, as depicted in Figure 1. Beyond the threat of widespread infestation and rapid crop destruction, these pests also pose a risk of transmitting viruses, such as the yellow leaf curl virus of tomato (TYLCV), illustrated in Figure 2. TYLCV, a devastating plant pathogen affecting tomato plants, induces yellowing and wrinkling of leaves. Belonging to the Geminiviridae family, TYLCV is primarily disseminated by whiteflies, which transmit the virus while feeding on infected plants [9]. The virus impairs the plant's photosynthetic capacity and overall development, leading to diminished yield and quality. TYLCV represents a significant menace to tomato crops worldwide, necessitating stringent pest management measures.

Fig. 1. Pests Affecting Tomato Crops.

Fig. 2. Symptoms of Yellow Leaf Curl Virus (TYLCV) Infection on Tomato Plants.

Illustratively, in Shandong Province, China, during a single tomato growing season, farmers apply up to five different types of agricultural chemicals. The spraying frequency can escalate to ten instances, resulting in a total usage of around 1000 tons of chemical pesticides aimed at managing diseases and pests [10]. Advanced technological solutions are imperative in agriculture for early pest detection and reducing reliance on harmful pesticides. Traditionally, farmers have relied on personal experience and knowledge to identify pest invasions, often leading to excessive pesticide use [11]. The misuse of pesticides disrupts the ecological balance of agricultural land and exacerbates pest resistance, along with escalating control expenses, resulting in significant adverse consequences for pesticide management [12]. However, mounting concerns regarding environmental and health impacts emphasize the need for reduced pesticide application. A pivotal strategy for achieving this goal involves targeted pesticide application. Traditional methods for pest detection, which rely on manual labor, are laborious and susceptible to errors [13]. Fortunately, recent progress in computer vision technology tailored for precision agriculture has integrated the identification of insect pests and diseases into the monitoring of crop health and growth, offering promising developments [14]. Nonetheless, accurately identifying specific targets like pests poses challenges due to factors such as similar shapes, complex backgrounds, object overlap, fluctuating lighting, and extensive orchard topography [15, 16]. However, technological advancements, particularly in image processing, have made insect pest detection feasible [17]. Precision agriculture has gained significant traction in response to these challenges, aiming to enhance the precision and accuracy of pest identification [18–20]. The adoption of computer vision for acquiring and analyzing visual data has become indispensable for achieving efficient pest detection [21].

In recent years, propelled by rapid advancements in deep learning theories and computational capabilities, deep convolutional networks (CNNs) have achieved remarkable breakthroughs in the field of computer vision. Particularly in object detection, deep learning-driven techniques have demonstrated precision far exceeding that of conventional methods relying on manually engineered features such as HOG and SIFT [22]. Object detection entails identifying various objects of significance within an image, followed by delineating a rectangular bounding box around each item and assigning it a corresponding category label. In the context of insect counting, which can be seen as a specific application of object detection, CNN-based object detectors offer an ideal solution [23–25]. Consequently, numerous researchers are actively exploring image detection methods based on convolutional neural networks (CNNs) [26]. Among these, the YOLO (You Only Look Once) model stands out as the top choice thanks to its ability to respond in real-time with exceptional accuracy. It is worth noting, that there exist eight different versions of the YOLO algorithm: YOLOv1 [27], YOLOv2 [28], YOLOv3 [29], YOLOv4 [30], YOLOv5 [31], YOLOv6 [32], YOLOv7 [33], and YOLOv8 [34].

This research introduces an innovative portable device designed to simplify the process of pest counting within pheromone traps, eliminating the need for an onsite insect expert. Leveraging YOLOv8, the most recent version of YOLO, in conjunction with the Raspberry Pi 4B embedded system, the device offers a powerful solution. In order to facilitate remote monitoring of pheromone traps and provide real-time insights, the system seamlessly integrates with the Firebase IoT platform. Firebase serves as a dependable cloud-based solution that promptly captures, stores, and presents data from pheromone traps. This proposal streamlines intervention procedures, enabling targeted insecticide application solely in affected areas. As a result, the technology encourages responsible pesticide usage, thereby reducing the adverse environmental and human health effects associated with these chemicals. Furthermore, this advanced capability promotes increased yields by minimizing reliance on pesticides, advocating for sustainable and environmentally friendly agricultural practices.

The rest of this paper is organized as follows: Section 2 outlines the approach employed in this study, covering the methodology, materials such as the dataset, object detection models, Firebase IoT platform, and the Pest Counting Device. In Section 3, the obtained experimental results are discussed. Finally, Section 4 presents the conclusions drawn from the research.

2. Methodology

Our proposed approach comprises a series of 7 consecutive stages, as illustrated in Figure 3. Each stage represents::

- **Stage 1 (S1)**: Collecting insect pest images to train and evaluate the deep learning (DL) model.
- **Stage 2 (S2)**: Processing the entire dataset by resizing images to 299x299 dimensions and applying augmentation techniques to expand the sample pool (augmenting images based on specified parameters).
- **Stage 3 (S3)**: Performing image annotation to generate the object detection dataset.
- **Stage 4 (S4)**: Training the YOLOv8 object detection model using the dataset.
- **Stage 5 (S5)**: Validating the detection performance using a subset of the dataset and assessing the results.
- **Stage 6 (S6)**: Selecting the most optimal model for the Pest Counting Device.
- **Stage 7 (S7)**: Transmitting the detection results to the Firebase IoT Dashboard.

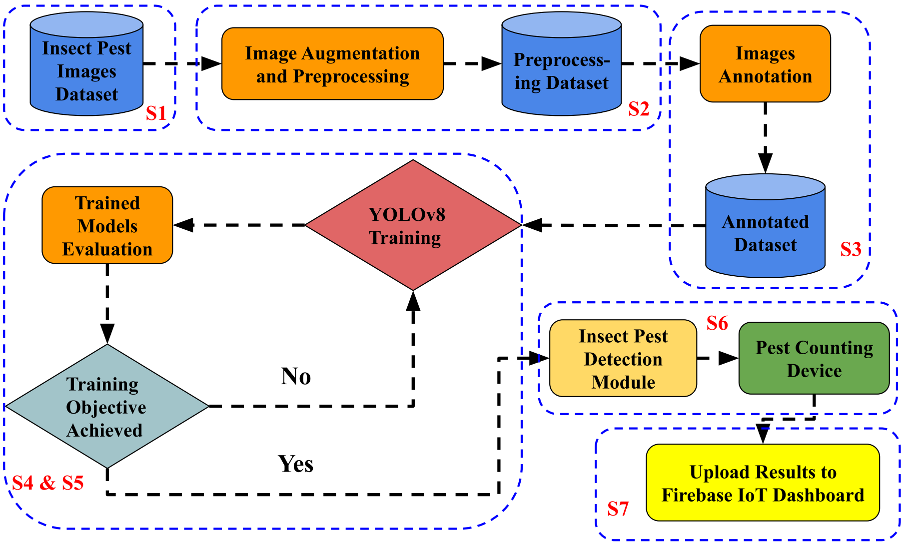


Fig. 3. Flowchart Representation of the Research Methodology.

2.1. Dataset

For the training and validation of the model for detecting insect pests, various sources of data collection were utilized. These include the databases curated by Jeremy Tusubira [35] and Sana Tariq [36], along with one of the projects available on Kaggle [37]. Additionally, images were sourced from the internet through searches across different databases and search engines including IPM Images, iStock, Google, Bing, Lepiforum and Flickr. The dimensions of the images from one of these sources were standardized to 299x299 pixels, and accordingly, all other images were resized to match these dimensions.

The study highlights the challenge of acquiring a substantial dataset essential for the effective performance of deep learning models. Limited data can lead to over-fitting and reduced generalization capabilities. To overcome this challenge, data augmentation techniques such as flipping and shifting were employed. However, managing potential pixel loss at the edges of augmented images was crucial. The research focused on insect pest images and applied geometric transformations, specifically rotation at three angles (90°, 180°, 270°), resulting in three additional images per original one, as depicted in Figure 4. This augmentation process expanded the dataset to 2109 images.

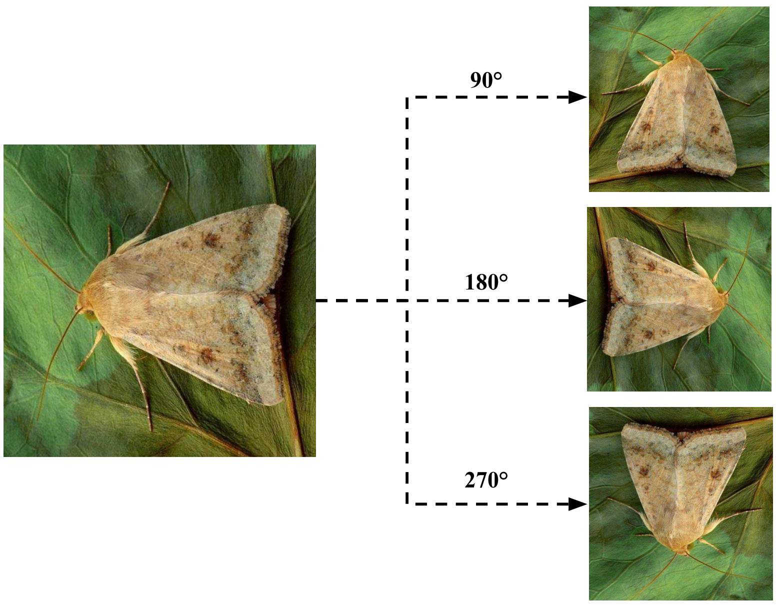
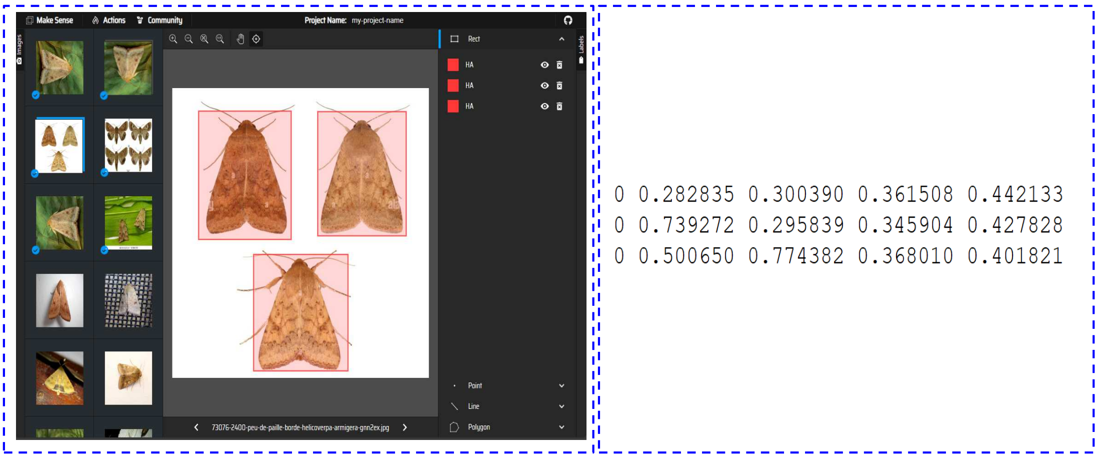


Fig. 4. Data augmentation.

The preprocessing stage of images for training deep learning models was discussed, emphasizing the significance of image annotation. This procedure entails extracting informative features from images and assigning suitable labels based on selected inputs, thereby furnishing labeled data pivotal for supervised learning tasks. In the study, the Makesense online platform [38] was employed for image annotation, as depicted in Figure 5, streamlining the process and augmenting labeling accuracy, thus bolstering the overall quality and effectiveness of the training dataset for the deep learning model. Furthermore, the datasets were partitioned into training and validating sets at an 85:15 ratio, as delineated in Table 1.



(a) The annotated image (b) The TXT document

Fig. 5. Image annotation in the Makesense platform.

Table 1. Pest Dataset.

Pest Dataset	Training Data	Validation Data
Whiteflies (WH)	499	90
Fruit Fly (FF)	574	98
Helicoverpa Armigera (HA)	719	128

2.2. Object detection models

The launch of YOLOv8 by Ultralytics introduced five variants, from nano to extra-large, tailored to various computational needs, with our choice of YOLOv8m offering an ideal balance for our application [34]. Each model varied in terms of network depth and feature map width, providing flexibility in model selection based on specific requirements. To evaluate their performance, these models underwent testing on the COCO dataset, and the results are summarized in Table 2. The table provides significant insights into the complexity of the models, quantified through FLOPs (floating-point operations) and Params (parameters), alongside their detection accuracy, assessed by mAPval 0.5:0.95 (mean Average Precision calculated across a spectrum of intersection-over-union thresholds ranging from 0.5 to 0.95). Furthermore, the response time of each model was assessed under two distinct environmental conditions: GPU A100 TensorRT and CPU ONNX.

The Figure 6 presents a comprehensive depiction of the architecture of YOLOv8. This version shares a similar backbone with YOLOv5 but introduces modifications to the CSPLayer, now known as the C2f module. The C2f module (cross-stage partial bottleneck with two convolutions) combines high-level features with contextual information, thereby improving detection accuracy.

2.3. Firebase IoT platform

The Firebase IoT Platform stands out as a versatile and robust solution designed to seamlessly integrate and oversee Internet of Things (IoT) devices and their associated data. With its intuitive interface, live database capabilities, authentication features, and cloud functions, Firebase equips developers with the tools they need to easily construct and expand IoT applications. Its comprehensive array

Table 2. Detection results for YOLOv8 series models on the COCO dataset.

Model	Size (pixels)	mAPval 50-95	Speed CPU ONNX (ms)	Speed A100 TensorRT (ms)	Params (M)	FLOPs (B)
YOLOv8n	640	37.3	80.4	0.99	3.2	8.7
YOLOv8s	640	44.9	128.4	1.20	11.2	28.6
YOLOv8m	640	50.2	234.7	1.83	25.9	78.9
YOLOv8l	640	52.9	375.2	2.39	43.7	165.2
YOLOv8x	640	53.9	479.1	3.53	68.2	257.8

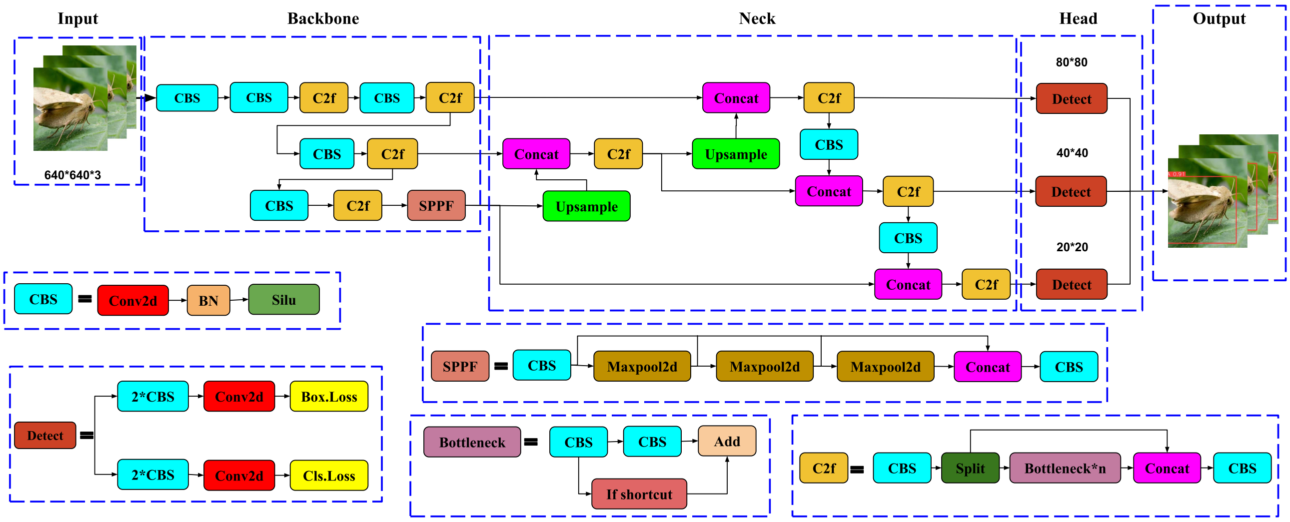


Fig. 6. YOLOv8 Architecture.

of functionalities facilitates secure data transmission, device oversight, and efficient data processing, thereby enhancing the dependability and effectiveness of IoT endeavors. Whether applied in contexts such as home automation or industrial monitoring, Firebase furnishes developers with the requisite resources to streamline their projects and furnish users with exceptional experiences. In our research, we intend to leverage this cloud technology to receive detection outputs generated by the YOLOv8 model from all pheromone traps, effectively enabling remote surveillance of these traps.

2.4. Pest counting device

The pest-counting device represents a groundbreaking tool poised to revolutionize pest management practices for farmers. Engineered to be both portable and efficient, this device offers an innovative solution by enabling farmers to easily detect insects within pheromone traps, eliminating the need for an on-site insect expert. Moreover, this innovation significantly streamlines the process of inspecting multiple traps across the field. Harnessing the capabilities of advanced algorithms, particularly the YOLOv8 model and Embedded System Raspberry Pi 4B, the device swiftly and accurately identifies various insect species and computes their quantities within an impressive 10-second timeframe. Subsequently, the device seamlessly transfers these detection results to the Firebase IoT platform, enabling remote monitoring and facilitating prompt intervention strategies, as depicted in Figure 7. Further details regarding the specifications of Raspberry Pi 4B are provided in Table 3.

3. Results and discussion

Among the YOLOv8 models evaluated, YOLOv8m emerges as the preferred option for pest detection on a Raspberry Pi 4B, thanks to its optimal balance between speed and accuracy. Although YOLOv8n and YOLOv8s yield less precise outcomes and encounter difficulties in effectively identifying small pests, YOLOv8x and YOLOv8l demonstrate superior accuracy. However, they demand increased computational resources and memory, which presents challenges for the Raspberry Pi. As

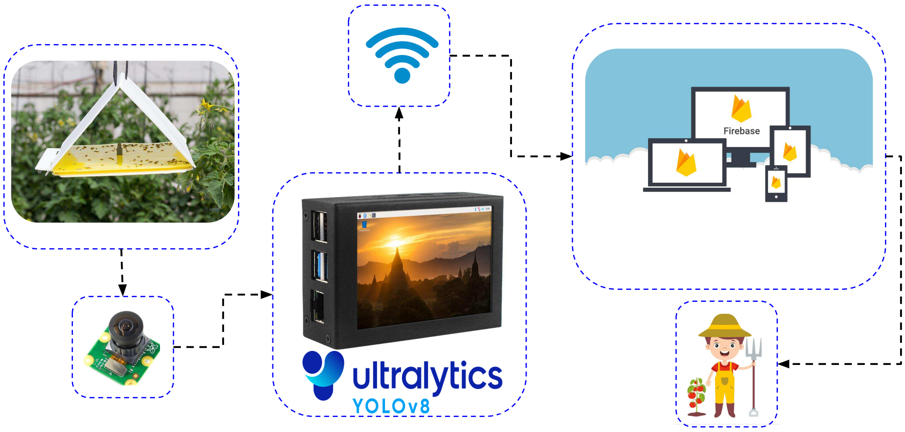


Fig. 7. Structural design of a device for pest counting.

Table 3. Raspberry Pi parameters.

Configuration	Parameter
Raspberry Pi	Raspberry Pi 4B
RAM	2 GB
CPU	Broadcom BCM2711
Wi-Fi	2.4 GHz and 5.0 GHz IEEE 802.11b
Language	Python 3.8
Framework	Torch 1.13, Torchvision 0.14.0
Camera resolution	2592 x 1944
Operating system	Raspberry Pi OS 64 bit

a result, YOLOv8m emerges as a suitable compromise, offering satisfactory accuracy while preserving computational efficiency conducive to Raspberry Pi utilization.

3.1. Experimental setup and metrics

The labeling phase for both the training and validation datasets has been successfully completed, marking a significant milestone in the project. Subsequently, the YOLOv8 model was trained using Google Colab. The training process utilized an NVIDIA Tesla T4 graphics card with 16 GB of memory, running CUDA version 12.2 and driver version 535.104.05. During training, images were resized to dimensions of 299 pixels. Vital data details, including class numbers and names, were stored in the data.yaml file for both the training and validation directories. The dataset was partitioned into 85% for training and 15% for validation purposes. YOLOv8m served as the chosen model for training and underwent training for over 200 epochs.

The effectiveness of the YOLOv8m model is assessed through a range of metrics. These metrics include precision, recall, mean average precision (mAPval) at an intersection over a union (IoU) threshold of 0.5, mAPval across IoU thresholds ranging from 0.5 to 0.95, detection processing time, parameter count, floating point operations (FLOPs), and model size. These metrics collectively provide insights into the model's performance, accuracy, computational efficiency, and resource requirements.

Precision measures the accuracy of positive predictions by evaluating the ratio of correctly predicted positive samples to the total samples predicted as positive. The precision formula is defined as

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}. \tag{1}$$

Recall, also known as sensitivity or true positive rate, measures the proportion of actual positive samples that are correctly identified by the model. It is defined as the ratio of true positive predictions to the total actual positive samples. The recall formula is

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{2}$$

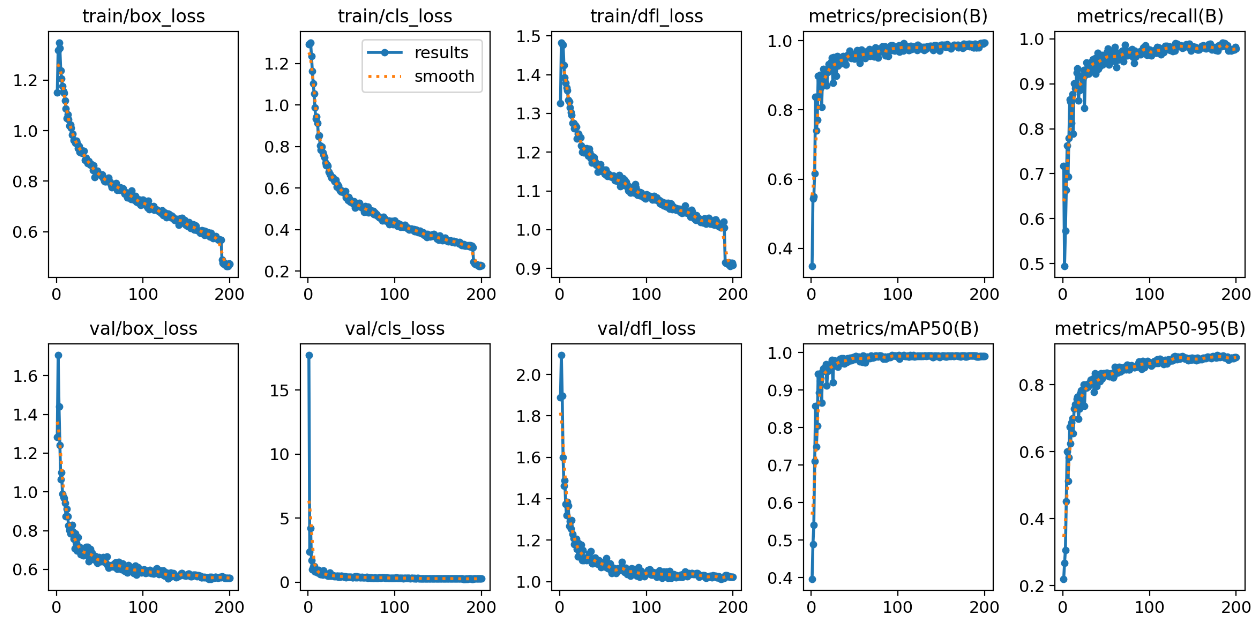


Fig. 8. Training and validation results of YOLOv8m on the tomato pests dataset.

Where TP (True Positives) Instances where the model correctly predicts positive samples; FP (False Positives) Instances where the model incorrectly predicts positive samples; FN (False Negatives) Instances where the model correctly predicts positive samples; TN (True Negatives) Instances where the model incorrectly predicts negative samples (missed detections).

The computation formulas for mAPval 0.5 and mAPval 0.5:0.95 are given below:

$$AP = \int_0^1 P(R)dR, \tag{3}$$

$$mAP = \frac{\sum_{i=1}^{N} AP_i}{\mathrm{N}}. \tag{4}$$

mAPval 0.5 represents the mean Average Precision calculated based on detections with confidence scores exceeding 0.5. This metric evaluates the precision and recall values derived from these detections.

mAPval 0.5:0.95 refers to the mean Average Precision across varying confidence thresholds between 0.5 and 0.95, with increments of 0.05. This comprehensive assessment allows for evaluating the model's performance at different confidence levels.

The model size indicates the saved size upon concluding the final training phase. It reflects the amount of memory required to store the trained model, providing insight into the computational resources needed for deployment.

The results obtained from the training and validation sets in Figure 8 reveal three types of losses: box loss, classification loss, and deformable loss.

Box loss evaluates the model's accuracy in precisely locating an object's center and ensuring that the predicted bounding box effectively encompasses the object. This metric is crucial for ensuring the model's ability to localize objects accurately.

Classification loss measures the algorithm's effectiveness in predicting object classes. It assesses how well the model can correctly classify objects into their respective categories.

The inclusion of deformable convolution layer loss in the YOLOv8 architecture is noteworthy. This loss quantifies errors in deformable convolution layers, which are designed to improve object detection for objects of various scales and aspect ratios. A lower dfl_loss value indicates better handling of object deformations and appearance variations, ultimately leading to improved detection performance.

Moreover, the model demonstrates significant improvements in precision, recall, and mAP (mean Average Precision) metrics after 60 epochs, with stability achieved around 140 epochs. This suggests that the model reaches a point where further training does not yield significant improvements in performance, indicating convergence. This observation underscores the importance of optimizing training duration to balance model performance and computational resources effectively.

3.2. Results of pest counting device

The YOLOv8m model has demonstrated notable proficiency in identifying pests infesting tomato crops, achieving a commendable confidence level of 94%, as illustrated in Figure 9. Furthermore, the model's effectiveness is enhanced by its integration with IoT functionalities via the Firebase IoT platform. This integration enables farmers to monitor field conditions in real-time. Through the Firebase dashboard,

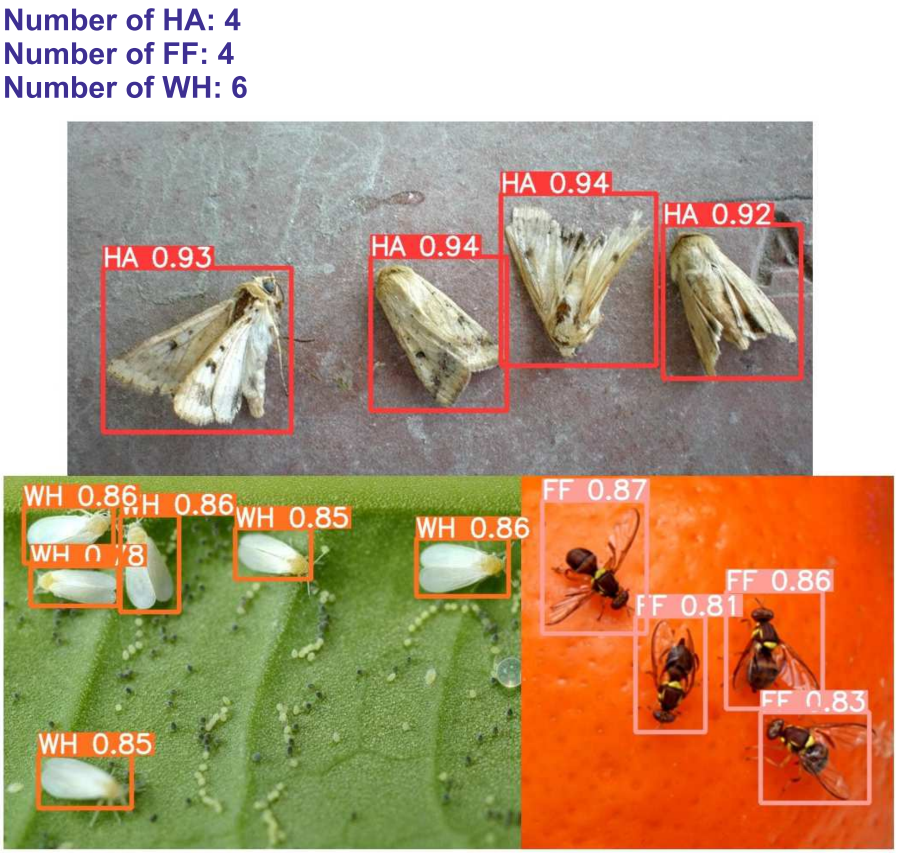


Fig. 9. Experimental Results of Pest Counting Device.

farmers can easily view images of insects captured within traps, along with the corresponding quantities of each pest detected. This streamlined access to data empowers farmers to make informed decisions promptly, enhancing pest management strategies and ultimately contributing to improved crop yields and agricultural sustainability.

Additionally, the portable Pest Counting Device enables rapid identification of areas where insect counts in traps exceed a predefined threshold. This innovative tool streamlines intervention procedures by facilitating targeted application of insecticides exclusively to affected regions. As a result, this technology promotes the optimization of pesticide usage, leading to a reduction in the negative environmental and human health impacts associated with these substances.

Furthermore, this sophisticated functionality plays a crucial role in attaining increased crop yields through cultivation methods that minimize the use of pesticides, consequently fostering sustainable and eco-conscious agricultural practices. By minimizing pesticide usage to only necessary areas, farmers can mitigate potential harm to non-target organisms and ecosystems while maintaining effective pest control measures. This approach aligns with the growing global emphasis on sustainable agricultural practices, supporting long-term food security and environmental conservation efforts.

4. Conclusions

In summary, this research represents a significant advancement in tomato pest management through the integration of deep learning, IoT, and precision agriculture. The introduction of the Pest Counting Device, powered by the YOLOv8 model, revolutionizes how farmers address pest-related challenges, exemplifying the fusion of cutting-edge technology with practical agricultural needs.

This research holds significance across multiple fronts, addressing not only the pressing matter of losses caused by pests but also promoting a more sustainable and effective agricultural methodology. Through the provision of real-time insights and facilitating informed decision-making, the system empowers farmers to enhance their pesticide application practices and protect crop vitality. This ultimately results in better yield and quality while concurrently diminishing the ecological impact of agricultural activities.

Moreover, this study adds to the progression of precision agriculture, heralding a time where data-driven methodologies seamlessly merge with on-field operations. As technology consistently reshapes the agricultural domain, this research highlights the transformative capacity of addressing hurdles with inventive resolutions. By closing the divide between innovation and application, it emphasizes the vital function that advanced technologies can fulfill in securing food supplies, promoting sustainability, and continually advancing the agricultural industry.

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Data availability statement

Data used in this paper are available under requests.

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Революція у боротьбі зі шкідниками томатів: синергія глибокого навчання, Інтернету речей і точного землеробства

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Зростання світового попиту на сільськогосподарську продукцію, зокрема на томати, підкреслює необхідність ефективної боротьби зі шкідниками. Основні шкідники, такі як білокрилка, плодова мушка та Helicoverpa Armigera, становлять значну загрозу для посівів томатів. Це дослідження пропонує новий підхід шляхом інтеграції сучасних технологій, таких як глибинне навчання та Інтернет речей (IoT), щоб революціонізувати традиційні методи боротьби зі шкідниками. Використання портативного пристрою для підрахунку шкідників, оснащеного моделлю глибокого навчання YOLOv8 на Raspberry Pi 4B, у поєднанні з платформою Firebase IoT полегшує миттєве спостереження за феромонними пастками. Ця інтеграція дозволяє фермерам приймати обґрунтовані рішення та оптимізувати зусилля з боротьби зі шкідниками. Використовуючи синергію передових технологій, фермери можуть потенційно підвищити врожайність, змінюючи звичайні методи боротьби зі шкідниками. Цей цілісний підхід не тільки дає фермерам більше контролю, але й зменшує наслідки для навколишнього середовища, пов'язані зі звичайними методами боротьби зі шкідниками, підкреслюючи, як технологія може сприяти стійкості сільського господарства в умовах постійних проблем зі шкідниками.

Ключові слова: *точне землеробство; шкідники томатів; IoT (Інтернет речей); глибоке навчання; боротьба зі шкідниками; виявлення шкідників.*