IoT-Based Pest Detection in Agriculture Using Raspberry Pi and YOLOv10m for Precision Farming

Mohamed Zarboubi[1,*], *Abdelaaziz* Bellout[2,**], *Samira* Chabaa[1,3,***], *Azzedine* Dliou[2,4,****], and *Abdelouhab* Zeroual[3,†]

[1]LISAD Laboratory, National School of Applied Sciences, Ibn Zohr University, Agadir, Morocco.
[2]LISTI Laboratory, National School of Applied Sciences, Ibn Zohr University, Agadir, Morocco.
[3]I2SP Team, Faculty of Sciences Semlalia, Cadi Ayyad University, Marrakech, Morocco.
[4]IMIS Laboratory, Faculty of Applied Sciences, Ibn Zohr University, Agadir, Morocco.

Abstract.
The agricultural sector confronts challenges arising from climate change and evolving global trade, emphasizing the critical need for effective pest management to sustain crop yields. This study introduces an innovative pest detection and monitoring approach, centering on the Codling Moth (Cydia pomonella) as a model insect. The system seamlessly integrates a Raspberry Pi-based trap, the YOLOv10m (You Only Look Once) deep learning model, and the Ubidots IoT platform. The YOLOv10m model, renowned for its real-time object detection capabilities, undergoes training to identify Codling Moths in images captured by the trap. Subsequently, the model-generated data is transmitted to the Ubidots platform, facilitating remote real-time monitoring. The Ubidots dashboard encompasses features like data analysis, historical trends, and notification alerts for elevated pest densities. Results underscore the YOLOv10m model's impressive 89% confidence level in detecting Codling Moths. The Ubidots platform enhances overall system performance, enabling farmers to monitor pest activity and intervene promptly. This integrated system fosters informed decision-making, curtails excessive pesticide use, and advocates sustainable farming practices. Ultimately, this research makes a substantial contribution to precision agriculture by harnessing the synergies of deep learning and IoT technologies, delivering a dependable and cost-effective solution for managing pest populations in agriculture.
keywords: Internet of things (IoT), Pest detection, Cydia pomonella, Precision agriculture, Real-time monitoring, Sustainable farming, YOLOv10.

1 Introduction

Achieving high crop yields is a primary goal for vegetable and fruit growers worldwide. This goal is frequently threatened by insect pests that can cause significant damage, necessitating effective management strategies [1]. The Food and Agricultural Organization (FAO) reports that pests are responsible for roughly 20% to 40% of global crop production losses annually [2, 3]. Moreover, the worldwide economic impact of pest infestations is estimated to be around $220 billion each year, with invasive insect species alone accounting for approximately $70 billion of these losses. One of the most detrimental pests for apple orchards is the codling moth (Cydia pomonella) (Lepidoptera: Tortricidae), a species that has attained near-global distribution due to international trade and tourism [4]. Originally from Central Asia, the codling moth now affects regions including Europe, North America, South Africa, Australia, and China [5].

*Corresponding author: mohamed.zarboubi@edu.uiz.ac.ma
**e-mail: abdelaaziz.bellout@edu.uiz.ac.ma
***e-mail: s.chabaa@uiz.ac.ma
****e-mail: a.dliou@uiz.ac.ma
†e-mail: zeroual@uca.ac.ma

In apple orchards, approximately 70% of insecticide treatments are directed against the codling moth [6]. While traditional management involves scheduled insecticide applications, this method often ignores actual pest population levels, leading to inefficiencies and increased costs [7]. A more sustainable approach would be to apply insecticides only when pest populations exceed the economic threshold, necessitating accurate pest population forecasts [8]. Such forecasts not only reduce the environmental impact by minimizing insecticide use but also provide economic benefits through cost savings and optimized labor use [9].

Pheromone-based traps are a common method for estimating codling moth populations [10, 11]. These traps attract male insects with pheromone substances, causing them to become stuck on sticky paper. This paper is periodically replaced and analyzed by experts who count the captured insects. Despite its widespread use, this manual monitoring method has significant drawbacks, including the need for skilled labor, high costs, and a lack of continuous feedback, which reduces temporal resolution for pest population monitoring.

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To address these challenges, recent advancements have led to the development of automated insect monitoring systems, leveraging technologies such as miniaturized sensors, microcontrollers, and the Internet of Things (IoT) [12]. These systems, often equipped with RGB cameras, provide real-time, enhancing the precision of pest management strategies and supporting Integrated Pest Management (IPM) practices [13–15]. By continuously monitoring pest populations, these smart traps enable timely and precise interventions, reducing the need for unnecessary pesticide applications and their associated costs [16, 17].

Recent advancements in computer vision and machine learning technologies have significantly enhanced precision agriculture, particularly in the detection and identification of insect pests and diseases [18]. Despite challenges such as similar shapes, complex backgrounds, overlapping objects, and varying lighting conditions, modern image processing techniques have made substantial progress in overcoming these obstacles [19, 20]. This has led to a surge in the popularity of precision agriculture, which aims to improve the accuracy and reliability of pest detection [21, 22]. Utilizing computer vision to capture and analyze visual information has become essential for effective pest management.

The development of deep convolutional networks (CNNs) has further propelled the field of object detection, demonstrating remarkable success in various applications, including agriculture [23]. Insect counting is a prime example of object detection, making CNN-based object detectors an optimal solution [24–27]. The YOLO (You Only Look Once) model, known for its real-time performance and high accuracy, stands out for this task. With its ability to detect objects in real-time and handle variations in object size, orientation, and occlusion, the YOLO model has become crucial for timely pest management. Notably, the YOLO algorithms have been developed in ten different versions: YOLOv1 [28], YOLOv2 [29], YOLOv3 [30], YOLOv4 [31], YOLOv5 [32], YOLOv6 [33], YOLOv7 [34], YOLOv8 [35], YOLOv9 [36], and YOLOv10 [37].

This study leverages recent technological advancements by using an innovative Raspberry Pi-based trap design and the latest YOLOV10 model to detect and track Cydia pomonella insect populations in the field. The integration of the Ubidots IoT platform enables remote monitoring and real-time insights, efficiently receiving, storing, and presenting data on a user-friendly platform. The Ubidots dashboard allows users to access and analyze data across various devices, providing real-time insights and thorough monitoring. It also offers historical data analysis and notifications for high pest densities. The primary goal is to determine the optimal timing for insecticide application, contributing to efficient and targeted pest management. Combining Raspberry Pi, YOLOV10, and Ubidots provides a reliable, automated solution for monitoring Cydia pomonella, helping farmers make informed decisions about insecticide usage while minimizing environmental impact.

The remaining sections of the paper are structured as follows: Section 2 provides a comprehensive review of the related work, summarizing previous research efforts in the field of insect identification .Section 3 details the approach taken in this research, covering the methodology and materials used, which encompass the dataset, various object detection models, the Ubidots platform, and the Raspberry Pi trap. Section 4 discusses the experimental results and provides accompanying discussions. Finally, Section 5 presents the conclusions drawn from the research, along with suggestions for future work.

2 Related Work

Previous research on insect identification can be categorized based on various factors. One key factor is image quality. Some researchers have utilized high-quality images captured under controlled laboratory conditions (uniform lighting, well-aligned poses, and minimal noise) [38, 39], while others have relied on images taken in natural field environments [40]. It is not surprising that pest identification algorithms trained on laboratory images tend to perform less accurately when applied to field images [41].

Another important consideration is the number of insects present in an image. In several studies, images taken with mobile devices typically featured only one insect. In a smaller number of cases, multiple insects were present in the images, often in the context of traps [42].

Field images containing multiple insects introduce greater complexity in the segmentation process, as the insects need to be separated before identification can occur. Additionally, these images may include noise and artifacts such as plants, tiny insects, or glue strips.

3 Methodology

Our proposed approach comprises 7 consecutive stages, as illustrated in Fig. 1:

- **Stage N°1**: Collect images of insect pests for training and evaluating the deep learning model.
- **Stage N°2**: Preprocess the entire dataset by adjusting the image size to 640x640 and performing augmentation to increase the sample count (following specific parameters).
- **Stage N°3**: Perform image annotation to construct the object detection dataset.
- **Stage N°4**: Train the YOLOv10 object detection model on the dataset.
- **Stage N°5**: Validate the model's performance with a subset of the dataset and analyze the results.
- **Stage N°6**: Choose the best-performing model for the Raspberry Pi trap.
- **Stage N°7**: Upload the detection results to the Ubidots IoT dashboard.

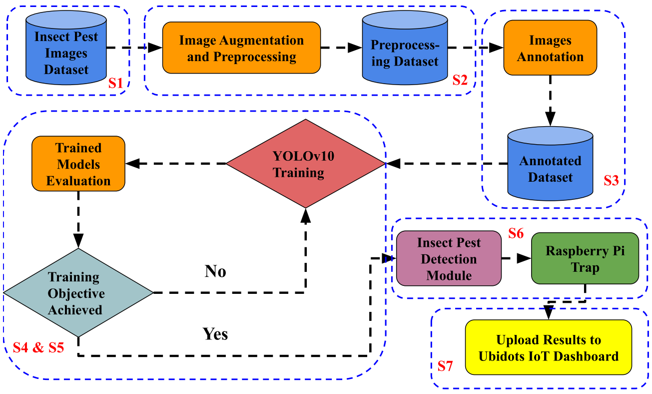

Figure 1. Illustrating the research methodology through a flowchart.

Figure 2. Images of the Cydia pomonella dataset we employed for training and validating the object detection model.

3.1 Dataset

For the purpose of training and validating the system for detecting insect pests, we utilized two main sources for collecting data. The first source was the database used by [38]. The second resource utilized was the internet, where we scoured multiple databases and search engines such as Bing, IPM Images, Google, Lepiforum, iStock, and Flickr in search of images. We standardized the dimensions of all images by resizing them to a consistent size of 640x640, representing an equal width and height. Some illustrative samples from our dataset can be observed in Fig. 2.

Deep learning models generally perform better with larger amounts of data, but collecting a substantial dataset can be challenging. Limited data can lead to overfitting and reduced generalization. Data augmentation techniques, such as flipping and shifting, can help address this problem by introducing diversity and increasing the number of training samples. However, these techniques may cause pixel loss, especially at the edges or corners of augmented images. Careful consideration is needed to ensure accurate and reliable results. In this study, geometric transformation, specifically rotation at three angles (90°, 180°, 270°), was used to augment insect pest images. This technique preserved the same pixels even as the insect's position changed, resulting in 3 additional images for each original image, as shown in Fig. 3. The total number of data images after augmentation was 1011 images.

3.2 Object Detection Models

The YOLOV10 model represents a significant advancement in real-time object detection, building on the robust foundation of its predecessors. The architecture of YOLOV10, depicted in Fig. 4, showcases a meticulously designed network with enhanced backbone, neck, and head components aimed at optimizing detection accuracy and speed. This design integrates several key features such as CSPDarknet, PANet, and a new detection head, which together contribute to its superior performance.

To evaluate the efficacy of YOLOV10, six different versions (YOLOV10n, YOLOV10s, YOLOV10m, YOLOV10b, YOLOV10l, and YOLOV10x) were trained and tested on the COCO dataset. The performance of each model variant was assessed based on parameters such as the number of parameters (Params), FLOPs, Average Precision (AP) on the validation set (APval), and inference latency. The table 1 summarizes the performance metrics for each model.

Each version of YOLOV10 exhibits a trade-off between model size, computational complexity, and detection performance, allowing users to select the most suitable variant based on their specific application requirements. The YOLOV10m variant, for instance, offers a balanced performance with an APval of 51.1% and a la-

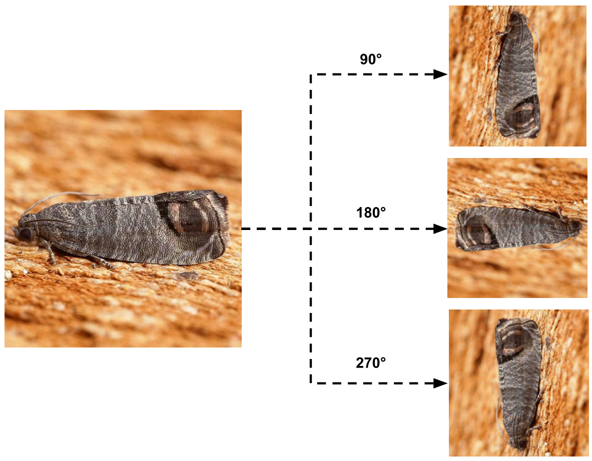

Figure 3. Data augmentation.

Table 1. Performance metrics of YOLOV10 model variants on the COCO dataset.

Model	Test Size	Params	FLOPs	APval	Latency
YOLOv10n	640	2.3M	6.7G	38.5%	1.84ms
YOLOv10s	640	7.2M	21.6G	46.3%	2.49ms
YOLOv10m	640	15.4M	59.1G	51.1%	4.74ms
YOLOv10b	640	19.1M	92.0G	52.5%	5.74ms
YOLOv10l	640	24.4M	120.3G	53.2%	7.28ms
YOLOv10x	640	29.5M	160.4G	54.4%	10.70ms

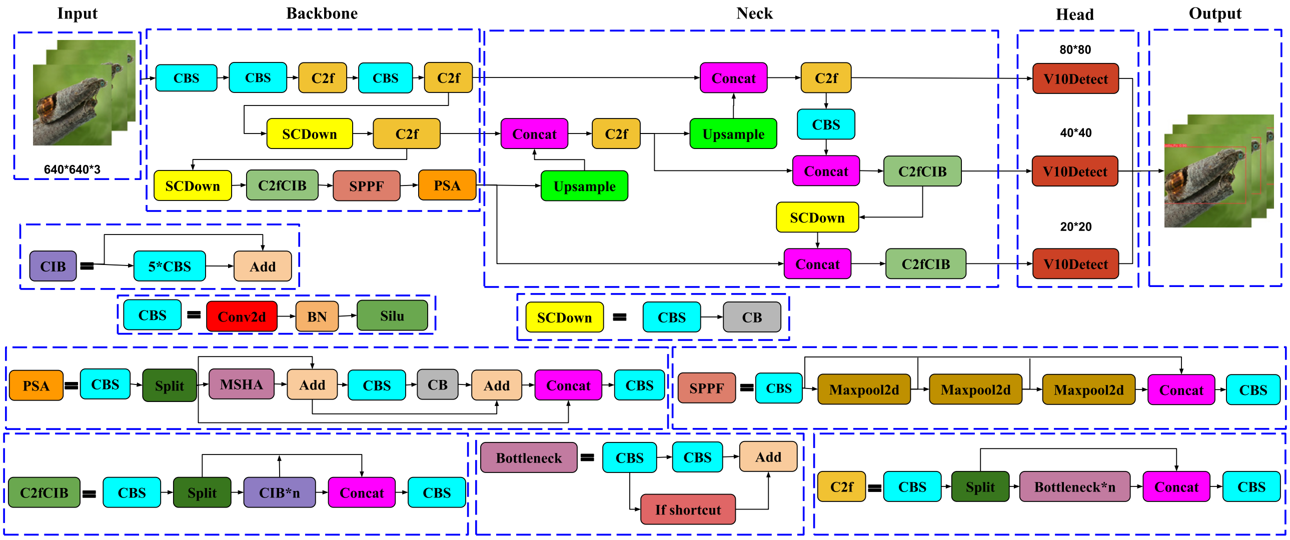

Figure 4. YOLOv10 Architecture.

tency of 4.74ms, making it an excellent choice for applications requiring both accuracy and speed. Overall, the YOLOV10 series demonstrates a substantial improvement in detection accuracy and efficiency, reinforcing its position as a leading solution for object detection tasks in various domains.

3.3 IoT Platform Ubidots

To enable remote monitoring of the trap, we implemented Ubidots as a cloud technology to receive and present the trap's outcomes. Ubidots serves as an IoT platform utilized for showcasing real-time data acquired by the YOLOv8 model. The Ubidots dashboard displays the accumulated data, such as the count of detected pests, across various devices, including computers, tablets, and phones, accessible through both the website and mobile application. Additionally, this platform offers the capability to analyze historical data. Moreover, it facilitates sending notifications, either as messages or emails, to the relevant authorities when the crowd density surpasses a pre-defined threshold.

3.4 Innovative Raspberry Pi-Based Insect Trap for Monitoring Codling Moth Populations

A Raspberry Pi-based insect trap designed for codling moths (Cydia pomonella) presents an innovative solution to assist farmers in monitoring insect populations within their fields. This trap utilizes a camera and the YOLOv8 model to accurately count the number of captured codling moths. Furthermore, the device is equipped with WiFi capabilities, allowing it to transmit data over the internet using the HTTP protocol to the Ubidots IoT Platform. This enables farmers to remotely monitor their fields' conditions, as depicted in Fig. 5. By implementing this innovative solution, farmers can promptly identify changes in insect populations and take immediate measures to protect their crops.

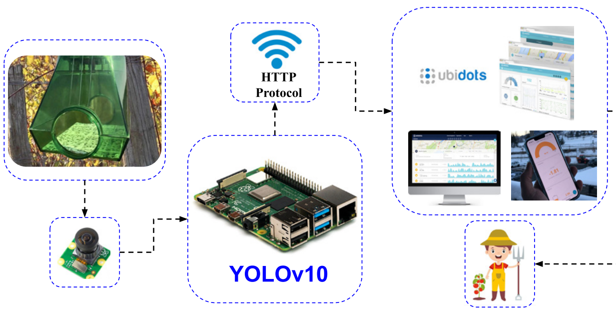

Figure 5. Functional structure of Raspberry Pi trap.

4 Results and discussion

YOLOv10m is the preferable option for pest detection on Raspberry Pi 4B. This model's adeptness at striking a balance between accuracy and speed makes it a prime candidate. YOLOv10n and YOLOv10s exhibit lower accuracy, potentially impacting the efficient detection of small pests, whereas YOLOv10x and YOLOv10l, while offering higher accuracy, pose challenges due to their demanding computational requirements. Consequently, YOLOv10m emerges as an optimal solution, providing a commendable accuracy level while remaining computationally efficient enough to operate effectively on a Raspberry Pi.

4.1 Training environment and evaluation indexes

The labeling process for both training and validation datasets has been completed, marking an important milestone. The subsequent step involved training the YOLOv10 model using the Google Colab platform with an NVIDIA Tesla T4 graphics card. The model operated on CUDA version 11.6 and driver version 510.47.03, resizing images to 640 dimensions. The data.yaml file provided essential information, such as the number of classes

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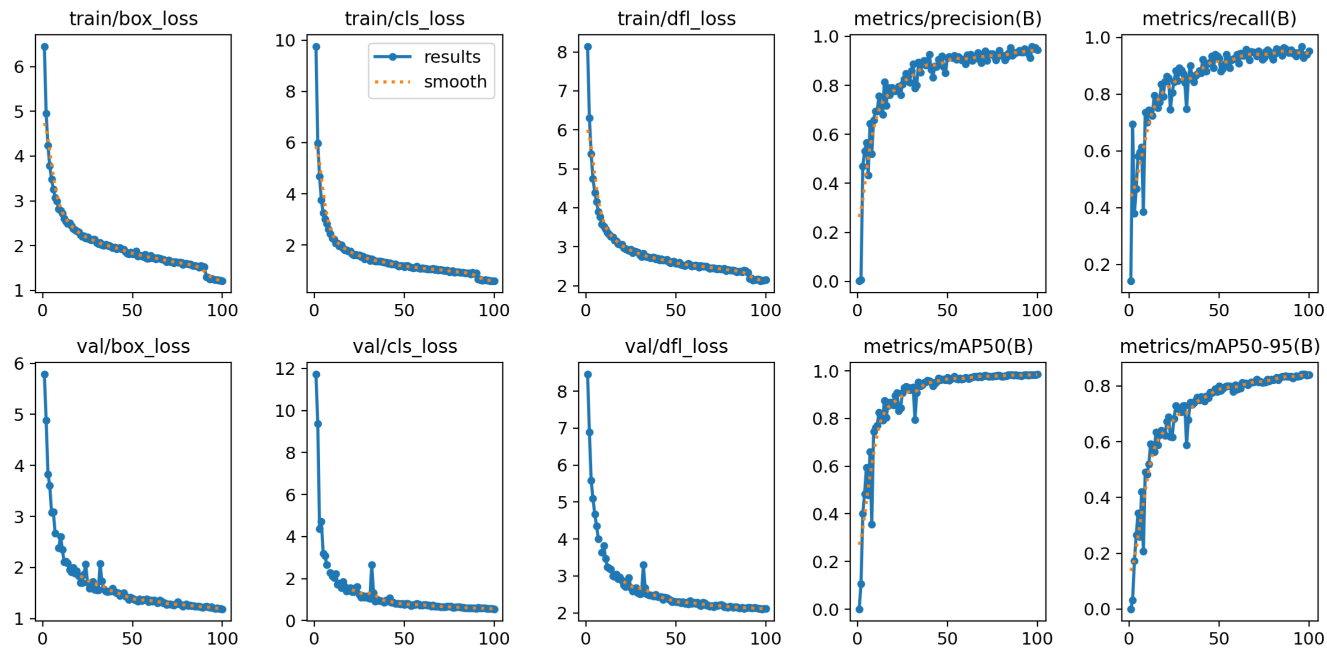

Figure 6. Results of training and validation for YOLOv10m Using the Cydia pomonella dataset.

and their names for both training and validation data directories. The dataset was split into 85% for training and 15% for validation. The YOLOv10m model was trained for 100 epochs.

The performance of the YOLOv10m model was evaluated using various metrics, including precision, recall, mean average precision (mAP) at an IoU threshold of 0.5 (mAPval 0.5), mean average precision at IoU thresholds from 0.5 to 0.95 (mAPval 0.5:0.95), average processing time, number of parameters, FLOPs (Floating Point Operations Per Second), and model size.

Precision, as a metric, assesses the accuracy of positive predictions by calculating the proportion of correctly predicted positive instances among all instances predicted as positive. The formula for precision is as follows:

$$\text{Precision (P)} = \frac{\text{True Positives}}{\text{True Positives + False Positives}} \tag{1}$$

The recall metric is calculated based on the proportion of correctly predicted targets among all targets, and its definition can be elucidated as follows:

$$\text{Recall (R)} = \frac{\text{True Positive}}{\text{True Positive + False Negatives}} \tag{2}$$

Below are the computational formulas for mAPval 0.5 and mAPval 0.5:0.95:

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

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

mAPval 0.5 calculates average precision using detections with a confidence score above 0.5, while mAPval 0.5:0.95 assesses average precision across multiple confidence thresholds from 0.5 to 0.95 in 0.05 increments, providing a comprehensive evaluation of model performance. Model size refers to the saved model size after training.

Training and validation results in Fig. 6 reveal three types of loss: box loss, classification loss, and deformable loss. Box loss measures object localization accuracy, while classification loss assesses the model's ability to predict the correct object class. Deformable loss, introduced in the YOLOv10 architecture, quantifies errors in deformable convolution layers, improving detection of objects with varying scales and aspect ratios. Lower deformable loss indicates better handling of object distortions. The model shows significant improvements in precision, recall, and mAP after 50 epochs, achieving stability after 75 epochs.

4.2 Results of an IoT Platform for Insect Detection

The YOLOv10m model has proven highly successful in detecting the Cydia pomonella insect with an impressive 89% confidence level, as shown in Fig. 7. The model's effectiveness is further enhanced by the IoT feature provided by the Ubidots platform, enabling farmers to monitor their fields in real-time. Through the Ubidots dashboard, farmers can view images of detected insects inside the trap and track the number of insects captured over time. The dashboard compares the total number of insects in the trap to a preset threshold, notifying farmers if this number exceeds the limit. Notifications are sent via SMS or email to prompt timely intervention.

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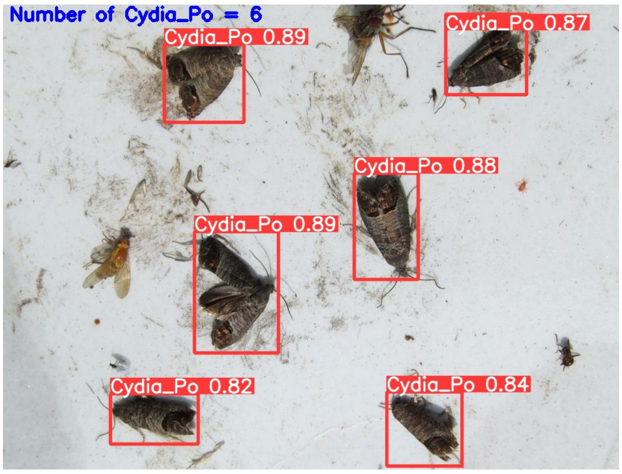

Figure 7. Experimental results of Raspberry Pi trap.

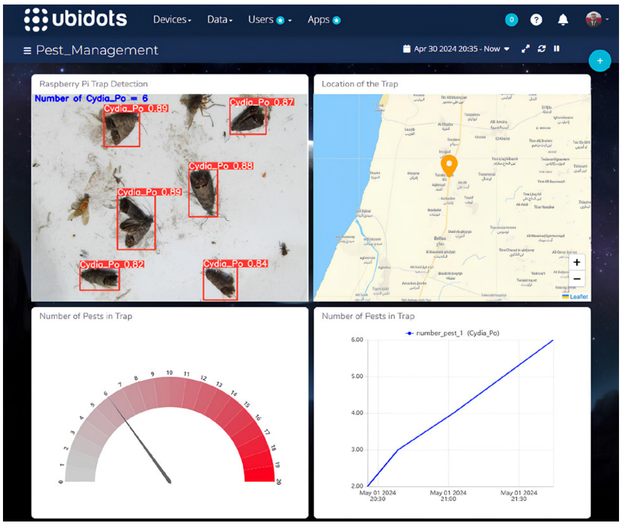

Figure 8. Real-Time pest detection and monitoring using YOLOv10 and IoT integration.

Ubidots also offers a Maps feature, allowing farmers to locate traps and identify areas with high insect activity, facilitating targeted pesticide application. This promotes sustainable farming practices by reducing pesticide usage and minimizing environmental impact. The Ubidots dashboard is accessible across various devices, including computers, tablets, and phones, providing versatile and convenient data management (Fig. 8).

This innovative IoT-based system enables farmers to monitor and track traps in real-time globally, streamlining the intervention process and enhancing efficiency. The integrated mapping and alert mechanisms address limitations found in similar efforts, ensuring precise monitoring and timely notifications, ultimately protecting crops more effectively and at a lower cost.

5 Conclusions and Future Work

The agricultural sector faces new challenges due to climate change, volatile economies, and global trade, which impact insect pest populations and introduce new species. The codling moth (Cydia pomonella) significantly affects apple and pear crops, causing substantial economic losses. This study presents an advanced technology for detecting and tracking Cydia pomonella using a Raspberry Pi-based trap and the YOLOv10 model. By integrating the Ubidots IoT platform, the system provides real-time data and features like data analysis, historical trends, and notification alerts. The YOLOv10m model achieved an 89% confidence level in detecting Cydia pomonella, enhancing pest management efficiency and promoting sustainable farming practices.

The integration of YOLOv10, Raspberry Pi, and Ubidots offers a reliable, automated, and cost-effective solution for managing pest populations, significantly contributing to precision agriculture by empowering farmers to make informed decisions, optimize pesticide usage, and enhance agricultural productivity sustainably.

Future work will focus on further improving the system's capabilities by integrating additional IoT sensors for environmental monitoring. These sensors will track variables like temperature, humidity, and soil moisture, providing a more comprehensive understanding of the factors influencing pest populations. This added functionality will enable even more precise pest control strategies and promote data-driven, sustainable farming practices.

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Data Availability Statement

Data used in this paper are available under requests.

References

[1] Zarboubi, Mohamed, Samira Chabaa, and Azzedine Dliou. "Advancing Precision Agriculture with Deep Learning and IoT Integration for Effective Tomato Pest Management." 2023 IEEE International Conference on Advances in Data-Driven Analytics And Intelligent Systems (ADACIS). IEEE, 2023.

[2] Sarkozi, A. "New standards to curb the global spread of plant pests and diseases." Food and Agriculture Organization of the United Nations: Roma, Italy (2019).

[3] Karar, Mohamed Esmail, et al. "A new mobile application of agricultural pests recognition using deep learning in cloud computing system." Alexandria Engineering Journal 60.5 (2021): 4423-4432.

[4] Son, A-R., S-J. Suh, and Y-M. Park. "Notes on insects captured in codling moth (Lepidoptera: Tortricidae) surveillance traps in South Korea over the last eight years." EPPO Bulletin 48.3 (2018): 578-582.

[5] Jiang, Dong, et al. "Mapping the potential global codling moth (Cydia pomonella L.) distribution based on a machine learning method." Scientific reports 8.1 (2018): 13093.

[6] Čirjak, Dana, et al. "Automatic pest monitoring systems in apple production under changing climatic conditions." Horticulturae 8.6 (2022): 520.

[7] Suto, Jozsef. "Improving the generalization capability of YOLOv5 on remote sensed insect trap images with data augmentation." Multimedia Tools and Applications 83.9 (2024): 27921-27934.

[8] Suto, Jozsef. "Codling moth monitoring with camera-equipped automated traps: A review." Agriculture 12.10 (2022): 1721.

[9] Beers, Elizabeth H., David R. Horton, and Eugene Miliczky. "Pesticides used against Cydia pomonella disrupt biological control of secondary pests of apple." Biological Control 102 (2016): 35-43.

[10] Sun, Yu, et al. "Automatic in-trap pest detection using deep learning for pheromone-based Dendroctonus valens monitoring." Biosystems engineering 176 (2018): 140-150.

[11] Høye, Toke T., et al. "Deep learning and computer vision will transform entomology." Proceedings of the National Academy of Sciences 118.2 (2021): e2002545117.

[12] Zarboubi, Mohamed, et al. "Smart Pest Control in Grain Warehouses: YOLOv8-powered IoT Robot Car for Precision Agriculture." 2024 International Conference on Global Aeronautical Engineering and Satellite Technology (GAST). IEEE, 2024.

[13] Guo, Qingwen, et al. "Automatic monitoring of flying vegetable insect pests using an RGB camera and YOLO-SIP detector." Precision Agriculture 24.2 (2023): 436-457.

[14] Kiobia, Denis O., et al. "A review of successes and impeding challenges of IoT-based insect pest detection systems for estimating agroecosystem health and productivity of cotton." Sensors 23.8 (2023): 4127.

[15] Qing, Jiajun, et al. "Intelligently Counting Agricultural Pests by Integrating SAM with FamNet." Applied Sciences 14.13 (2024): 5520.

[16] Dong, Shifeng, et al. "ESA-Net: An efficient scale-aware network for small crop pest detection." Expert Systems with Applications 236 (2024): 121308.

[17] Gao, Yufan, et al. "Intelligent field monitoring system for cruciferous vegetable pests using yellow sticky trap images and an improved Cascade R-CNN." Journal of Integrative Agriculture (2024).

[18] Karar, Mohamed Esmail, et al. "A new mobile application of agricultural pests recognition using deep learning in cloud computing system." Alexandria Engineering Journal 60.5 (2021): 4423-4432.

[19] Wang, Tiewei, et al. "Recognition and counting of typical apple pests based on deep learning." Ecological Informatics 68 (2022): 101556.

[20] Li, Wenyong, et al. "Classification and detection of insects from field images using deep learning for smart pest management: A systematic review." Ecological Informatics 66 (2021): 101460.

[21] Li, Kangshun, et al. "A fast and lightweight detection algorithm for passion fruit pests based on improved YOLOv5." Computers and Electronics in Agriculture 204 (2023): 107534.

[22] Xu, Weiyue, et al. "A lightweight SSV2-YOLO based model for detection of sugarcane aphids in unstructured natural environments." Computers and Electronics in Agriculture 211 (2023): 107961.

[23] Bellout, Abdelaaziz, et al. "Deep Learning technique for predicting tomato leaf disease." 2023 IEEE International Conference on Advances in Data-Driven Analytics And Intelligent Systems (ADACIS). IEEE, 2023.

[24] Kalfas, Ioannis, et al. "Towards automatic insect monitoring on witloof chicory fields using sticky plate image analysis." Ecological Informatics 75 (2023): 102037.

[25] Chen, Chao, et al. "An automatic inspection system for pest detection in granaries using YOLOv4." Computers and Electronics in Agriculture 201 (2022): 107302.

[26] Zhu, Linqi, et al. "Research on CBF-YOLO detection model for common soybean pests in complex environment." Computers and Electronics in Agriculture 216 (2024): 108515.

[27] Zhao, Chao, et al. "AC-YOLO: Multi-category and high-precision detection model for stored grain pests based on integrated multiple attention mechanisms." Expert Systems with Applications (2024): 124659.

[28] Redmon, Joseph, et al. "You only look once: Unified, real-time object detection." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.

[29] Redmon, Joseph, and Ali Farhadi. "YOLO9000: better, faster, stronger." Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.

[30] Redmon, Joseph, and Ali Farhadi. "Yolov3: An incremental improvement." arXiv preprint arXiv:1804.02767 (2018).

[31] Bochkovskiy, Alexey, Chien-Yao Wang, and Hong-Yuan Mark Liao. "Yolov4: Optimal speed and accuracy of object detection." arXiv preprint arXiv:2004.10934 (2020).

[32] Jocher, Glenn, et al. "ultralytics/yolov5: v3. 0." Zenodo (2020).

[33] Li, Chuyi, et al. "YOLOv6: A single-stage object detection framework for industrial applications." arXiv preprint arXiv:2209.02976 (2022).

[34] Wang, Chien-Yao, Alexey Bochkovskiy, and Hong-Yuan Mark Liao. "YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors." Proceedings of the IEEE/CVF Conference on Com-

puter Vision and Pattern Recognition. 2023.

[35] G. Jocher, A. Chaurasia, and J. Qiu, “YOLO by Ultralytics.” https://github.com/ultralytics/ ultralytics, 2023. Accessed: August 15, 2023.

[36] Wang, Chien-Yao, I-Hau Yeh, and Hong-Yuan Mark Liao. "Yolov9: Learning what you want to learn using programmable gradient information." arXiv preprint arXiv:2402.13616 (2024).

[37] Wang, Ao, et al. "Yolov10: Real-time end-to-end object detection." arXiv preprint arXiv:2405.14458 (2024).

[38] Wang, Jiangning, et al. "A new automatic identification system of insect images at the order level." Knowledge-Based Systems 33 (2012): 102-110.

[39] Yalcin, Hulya. "Vision based automatic inspection of insects in pheromone traps." 2015 Fourth International Conference on Agro-Geoinformatics (Agro-geoinformatics). IEEE, 2015.

[40] Bakkay, Mohamed Chafik, et al. "Automatic detection of individual and touching moths from trap images by combining contour-based and region-based segmentation." IET Computer Vision 12.2 (2018): 138-145.

[41] Wen, Chenglu, and Daniel Guyer. "Image-based orchard insect automated identification and classification method." Computers and electronics in agriculture 89 (2012): 110-115.

[42] Liu, Huajian, Sang-Heon Lee, and Javaan Singh Chahl. "A review of recent sensing technologies to detect invertebrates on crops." Precision Agriculture 18 (2017): 635-666.

[43] Sütő, József. "Embedded system-based sticky paper trap with deep learning-based insect-counting algorithm." Electronics 10.15 (2021): 1754.