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Research Article

Enhancing Pest Management in Precision Agriculture: Integration of Improved YOLOv5 and IoT Technology for Efficient Codling Moth Detection

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Abstract

Effective pest management remains a persistent challenge in precision agriculture, particularly due to the difficulty of accurately detecting small insects in cluttered trap environments under varying lighting and background conditions. Traditional methods often require labor-intensive inspections, while existing deep learning-based object detectors, such as standard YOLO models, face trade-offs between detection accuracy and computational feasibility on edge devices. This study introduces an improved version of the YOLOv5m model tailored for deployment on a Raspberry Pi-based smart insect trap, targeting codling moth (Cydia pomonella) detection. The proposed architecture incorporates a Convolutional Block Attention Module (CBAM) to enhance feature representation and reduce background interference, along with strategic filter reduction to lower computational complexity. As a result, the model achieves a maximum confidence level of 95% and an average of 91.36%, with reduced parameter count and a FLOPs value of 26.88 billion. Integration with the Firebase IoT platform enables real-time monitoring and remote data management. Comparative analysis with YOLOv5–YOLOv12 variants demonstrates that the improved YOLOv5m offers the best balance between accuracy and efficiency for low-power deployment. These findings highlight the potential of combining lightweight deep learning and IoT infrastructure to create scalable, energy-efficient, and sustainable pest detection systems for real-world agricultural applications.

Keywords:

precision agriculture; improved YOLOv5; pest detection; IoT (Internet of Things); sustainable farming; codling moth.

1. Introduction

The global population has experienced a significant surge and is projected to maintain its upward trajectory [1–3]. This upsurge in population has fueled an escalating demand for agricultural products, consequently leading to a notable expansion in cultivated areas, all in an effort to augment the annual crop yield [4,5]. A variety of biotic and abiotic factors affect agricultural productivity around the world. Around 40% of agricultural output is negatively affected by insects, pests, diseases, and weed infes-tations [6]. It is often difficult to achieve the desired level of pest and disease control due to a lack of timely and accurate diagnosis. The improper and excessive use of agro-chemicals can result in financial and environmental problems [7]. According to the Food and Agricultural Organization (FAO), pest damage accounts for approximately 20% to 40% of global production losses each year [8–10]. In addition,the annual economic impact of pest infestations on a global scale is estimated to be approximately $220 billion, while invasive insects alone contribute to economic losses of around $70 billion [8,11]. As a result,

farmers often resort to using various pesticides to improve the productivity and longevity of their crops. However, prolonged pesticide use can lead to environmental contamination and may increase the risk of serious health conditions such as cancer, respiratory diseases, genetic disorders, and adverse pregnancy outcomes [12].

One of these pests is Cydia pomonella, commonly known as the codling moth, which is a major pest that severely affects agricultural crops, particularly apple and pear orchards. The larvae of this moth feed on the fruits, leading to yield loss and quality deterioration. Infestations of codling moths can cause significant economic damage to farmers, with losses estimated to be in the billions of dollars worldwide [13–15].

Sophisticated technological methods are essential in agriculture to detect pests during their initial stages and reduce the extensive dependence on harmful pesticides [16]. Farmers traditionally rely on their expertise and insight to diagnose pest infestations, resulting in excessive pesticide spraying [17]. However, growing environmental and health concerns have emphasized the need for reduced pesticide use. One crucial approach to achieving this is by spraying pesticides only where necessary. Manual pest detection methods are laborious and error-prone, often requiring substantial human effort and susceptible to inaccuracies [18–20]. Fortunately, recent advancements in the Internet of Things (IoT) and computer vision for precision agriculture have made insect pest and disease detection an essential component of monitoring crop growth and health [9,21–24]. This detection holds significant importance in the estimation of future yields, activating intelligent spraying systems, and overseeing autonomous pesticide spraying robots within expansive farms and orchards. However, accurately detecting target objects, such as pests, poses difficulties because of factors like shape similarity, complex backgrounds, overlying of objects, variable lighting, and vast orchard topography [25–27]. Yet, thanks to technological progress, particularly in image processing, identifying insect pests has become achievable [28,29]. Precision agriculture has become increasingly popular as a solution to overcome these challenges, aiming to enhance the precision and accuracy of pest detection [30–38]. Visual information acquisition and processing through computer vision have become indispensable in carrying out effective pest detection.

Recent progress in machine vision and learning technologies has opened up new possibil-ities for addressing object detection challenges. Significantly, the development of deep object detector algorithms has demonstrated remarkable effectiveness in diverse fields, such as agriculture [39–45]. Specifically, Counting insects can be seen as a particular application of object detection, thereby making object detectors based on CNNs an optimal solution [46,47]. Consequently, a considerable number of researchers are currently engaging in rigorous exploration and development of image detection methodologies utilizing convolutional neural networks (CNNs) [48–53]. This surge in activity underscores the significance and potential of CNN-based approaches in advancing image detection capabilities. The CNN-based YOLO (You Only Look Once) model is the ideal solution for this task, providing real-time responsiveness and high accuracy. One of the key advantages of using the YOLO model is its ability to detect objects in real-time, making it particularly suitable for applications that require fast and immediate processing. Additionally, the YOLO model achieves high accuracy by performing object detection and classification in a single pass, resulting in efficient and reliable results. This makes it highly beneficial for tasks such as insect counting in agriculture, where timely and accurate detection is crucial for effective pest management. Furthermore, the YOLO model is known for its robustness against variations in object size, orientation, and occlusion, making it a versatile and reliable choice for object detection tasks in complex environments. Notably, the YOLO algorithms have been developed in twelve different versions: YOLOv1 [54], YOLOv2 [55], YOLOv3 [56], YOLOv4 [57], YOLOv5 [58], YOLOv6 [59], YOLOv7 [60], YOLOv8 [61], YOLOv9 [62], YOLOv10 [63], YOLOv11 [64], and YOLOv12 [65].

This study presents a novel pest monitoring system that integrates an innovative pheromone trap design with a CBAM-enhanced YOLOv5m model, deployed on a low-cost Raspberry Pi platform. Although standard YOLOv5m and other YOLO variants deliver strong detection performance, they face key limitations when deployed on edge devices like the Raspberry Pi. These include large parameter sizes, high FLOPs requirements, and reduced ability to focus on small insect targets within cluttered and variable trap environments. To address these challenges, we modified the YOLOv5m architecture by incorporating the Convolutional Block Attention Module (CBAM) to refine feature representation and suppress irrelevant background information. Additionally, we strategically reduced the number of filters in selected layers to minimize computational complexity without compromising accuracy. The resulting model achieves real-time, energy-efficient detection on lightweight hardware, making it highly suitable for embedded pest detection systems. Coupled with the Firebase IoT platform, our system supports seamless remote monitoring, automated data management, and precision-driven pest control interventions. This enables more informed insecticide deployment, reduces unnecessary pesticide usage, and ultimately pro-

motes sustainable, environmentally responsible farming practices.

The primary objective of this research is to optimize pest management strategies by accurately determining the most effective timing for insecticide application. By harnessing the computational efficiency of the Raspberry Pi, the detection capabilities of the enhanced YOLOv5m model, and the real-time data synchronization features of the Firebase IoT platform, the study proposes a fully automated and cost-effective framework for monitoring the population dynamics of Cydia pomonella. This integrated system empowers farmers with timely and actionable insights, enabling more precise and evidence-based pesticide interventions. In doing so, it supports the reduction of unnecessary chemical usage, lowers environmental impact, and advances the principles of sustainable and intelligent agriculture.

To better contextualize the contribution of this study, it is essential to examine the limitations of current pest monitoring techniques. Conventional methods, such as sticky and pheromone traps, require frequent manual inspections, making them time-consuming, labor-intensive, and impractical for large-scale orchards or remote agricultural sites [66,67]. While automated trapping systems equipped with image sensors and wireless communication technologies have demonstrated potential in reducing field visits and enabling real-time monitoring [68–70], they typically rely on centralized cloud-based infrastructures for data processing and analysis. This dependence introduces challenges such as high energy consumption, increased latency, and elevated operational costs. In parallel, alternative approaches like acoustic traps that detect wingbeat frequencies [71,72] tend to exhibit reduced reliability due to their sensitivity to environmental noise and overlapping frequency patterns among insect species. In contrast, the proposed system provides a lightweight, edge-computing solution that performs real-time image processing locally on a Raspberry Pi, transmitting only essential detection results via the Firebase IoT platform. This architecture significantly reduces data transmission demands and energy consumption while maintaining robust detection accuracy, making it highly adaptable for scalable, sustainable, and cost-effective deployment in precision agriculture.

The remaining sections of this paper are structured as follows: Section 2 outlines the methodology employed in this study, detailing the dataset collection and preparation process, the object detection model utilized, the integration of the Firebase IoT platform, and the innovative trap design. Section 3 discusses the experimental results and provides insights. Section 4 presents the perspectives and future research directions. Finally, Section 5 provides the overall conclusions drawn from this research.

2. Methodology and Performance Enhancements of Improved YOLOv5m Architecture

Our proposed approach unfolds through a sequence of seven distinct phases, illustrated in Figure 1:

- **Stage N°1**: Gather a collection of insect pest images to train and evaluate the deep learning model.
- **Stage N°2**: Prepare the dataset by resizing images to 640x640 and applying data augmentation techniques to expand the number of training samples.
- **Stage N°3**: Label the images to create a dataset suitable for object detection tasks.
- **Stage N°4**: Train the improved YOLOv5 model using the processed dataset.
- **Stage N°5**: Validate the model's performance with a subset of the dataset and analyze the results.
- **Stage N°6**: Select the most accurate model for integration with the Raspberry Pi-based trap.
- **Stage N°7**: Transmit the detection results to the Firebase platform for real-time monitoring.

2.1. Dataset

To develop and validate our insect pest detection system, we compiled a diverse dataset from three main sources. The first source was the team of Akroute et al. [73] at the National Institute of Agricultural Research of Morocco, whose study investigates correlations between apple variety characteristics and codling moth susceptibility to support sustainable pest management. Their research, which involved rearing insects in laboratories and field monitoring using pheromone traps, provided a rich collection of codling moth images for our training data. The second
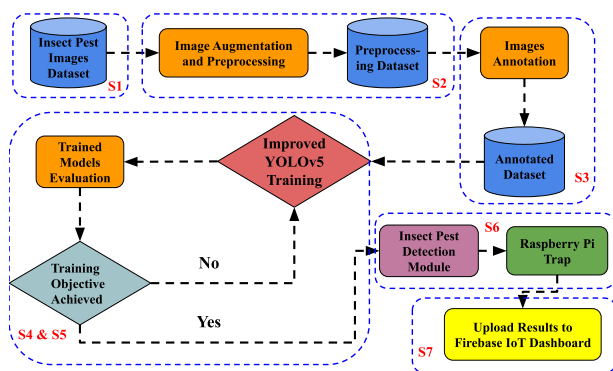
Figure 1: Flowchart illustration of the research methodology [20].

source was the database employed by Sütő [74], further enhancing the dataset's variety. Lastly, we gathered additional images from online platforms, including Google, Bing, Flickr, IPM Images, iStock, and Lepiforum. To ensure uniformity, all images were standardized to 640x640 pixels, and representative samples from the dataset are shown in Figure 2.
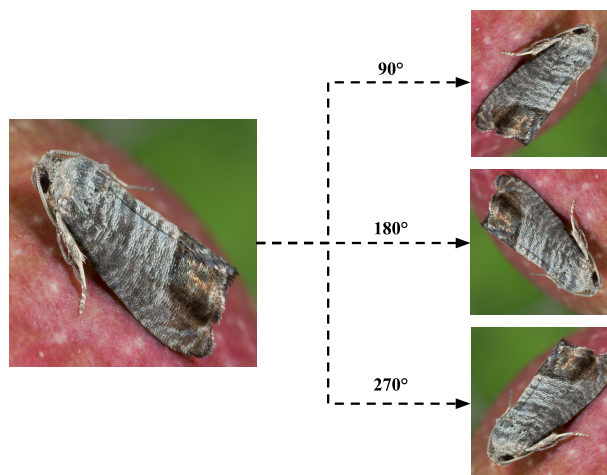
Deep learning models perform better with large datasets, but collecting sufficient data can be challenging. Small datasets can lead to problems like overfitting and reduced accuracy. To address this, techniques like flipping and shifting are often used to create more training data, although they can sometimes cause pixel loss at image edges. In this study, insect pest images were augmented by rotating them at 90°, 180°, and 270°, creating three new images for each original, as shown in Figure 3. This method maintained image quality while varying the insect's position, increasing the dataset to 1,011 images. These additional images help the model generalize better and improve its performance in identifying pests.

During the preprocessing stage of images for DL model training, image annotation assumes a pivotal role. This essential process entails extracting significant features from an image and subsequently assigning appropriate labels to these features based on selected inputs. The significance of image annotation lies in its ability to provide labeled data that serves as the foundation for supervised learning tasks, facilitating the model's understanding of relevant patterns and characteristics in the images.

The dataset used in this study consists of 1,011 images containing a total of 2,551 annotated insect instances. These instances represent different poses, sizes, and lighting conditions of codling moths captured in realistic trap environments, making the dataset both diverse and representative of real-world field conditions.

Figure 3: Data augmentation ((Adopted from online platforms, including Google, Bing, Flickr, IPM Images, iStock, and Lepiforum).

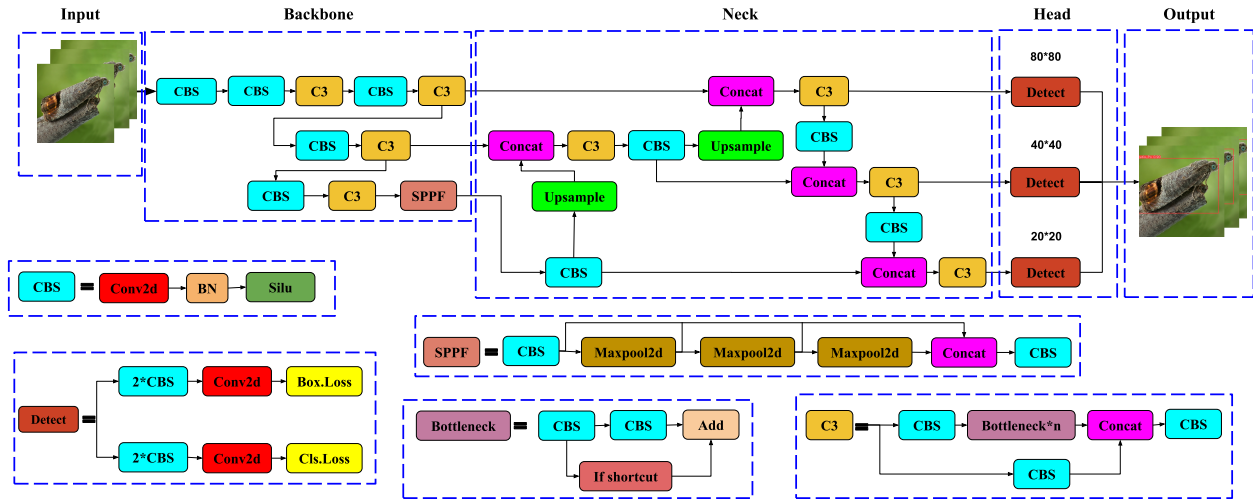(a) The annotated image (b) The TXT document
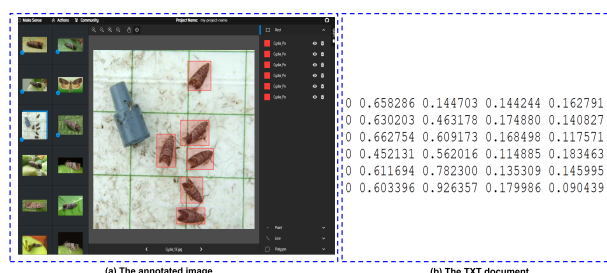
Figure 4: Image annotation in the Makesense platform.

In the context of this study, the process of image annotation is illustrated in Figure 4, where we utilize the Makesense online platform to accomplish this task. This platform streamlines the annotation process, enabling efficient and accurate labeling of the extracted features, thereby enhancing the overall effectiveness and quality of the training dataset for the deep learning model.

2.2. Improvement of YOLOv5m Network Architecture Design

In this study, we present an enhanced YOLOv5m network architecture, integrating the Convolutional Block Attention Module (CBAM) to improve object detection performance. The original YOLOv5m architecture, shown in Figure 5, consists of a backbone for feature extraction, a neck for feature aggregation, and a head for final detection. The backbone utilizes CSPNet-based feature extraction blocks (C3) and a Spatial Pyramid Pooling-Fast (SPPF) module to enhance receptive fields.

In our improved design, depicted in Figure 6, we incorporate CBAM into the YOLOv5m architecture. CBAM, illustrated in Figure 7, consists of a Channel Attention

Figure 2: Images of the Cydia pomonella dataset we employed for training and validation the object detection model.
(Adopted from online platforms, including Google, Bing, Flickr, IPM Images, iStock, and Lepiforum)

Figure 5: YOLOv5 network structure.

Module and a Spatial Attention Module. These modules sequentially refine the input features by focusing on 'what' and 'where' to emphasize, respectively. The Channel Attention Module adaptively recalibrates channel-wise feature responses, while the Spatial Attention Module emphasizes informative regions in the feature map.

We integrate CBAM at multiple strategic points within the backbone and neck of the network. Specifically, CBAM modules are inserted after key convolutional layers and bottleneck structures, allowing the network to focus on more relevant features during the detection process. This integration enhances the model's ability to detect and classify objects, particularly in challenging scenarios involving occlusions or varying object scales.

Additionally, we reduced the number of filters in some areas to optimize computational efficiency. For instance, the number of filters in the last backbone layer was decreased from 1024 to 512 for each of the SPPF, C3, and CBS modules. Similarly, at the beginning of the neck, the filters in the C2f modules were reduced from 512 to 256. These adjustments help balance the model's complexity and performance, ensuring efficient processing without compromising accuracy.

Moreover, we replace the C3 modules with the C2f modules in the improved design to further boost feature learning capacity. The C2f modules, combined with the CBAM, provide a more robust feature extraction process, leading to improved detection accuracy.

Overall, the addition of CBAM to the YOLOv5m architecture, along with strategic reductions in filter counts, results in a more powerful and efficient object detection model, capable of delivering higher accuracy and better generalization across diverse datasets. This improved ar-

chitecture holds significant potential for applications requiring precise and reliable object detection, such as in the context of automated pest monitoring systems.

2.3. Experimental Impact of CBAM on Feature Extraction

Following the architectural enhancements discussed in section 2.2, we conducted experiments to observe how the integration of the Convolutional Block Attention Module (CBAM) improves feature extraction. This section presents a visual analysis of the CBAM's effectiveness in guiding the network to focus on the most relevant regions of an image.

To illustrate the role of CBAM, we applied it at various stages of the network and compared the results with those of standard convolutional layers. The visual outputs in Figure 8 demonstrate how CBAM progressively enhances feature focus as the model processes the image.

- **Original Image (x)**: This is the input image of a moth, which is passed through the model for object detection.
- **CBAM Output on Input (x0)**: Directly applying CBAM on the input results in a darker image with minimal focus. This demonstrates that CBAM alone, without prior feature extraction, lacks enough information to focus effectively.
- **Conv Output (x1)**: After applying a convolution layer, basic image features such as edges and textures become visible. These features serve as the foundation for subsequent layers to build more complex patterns.
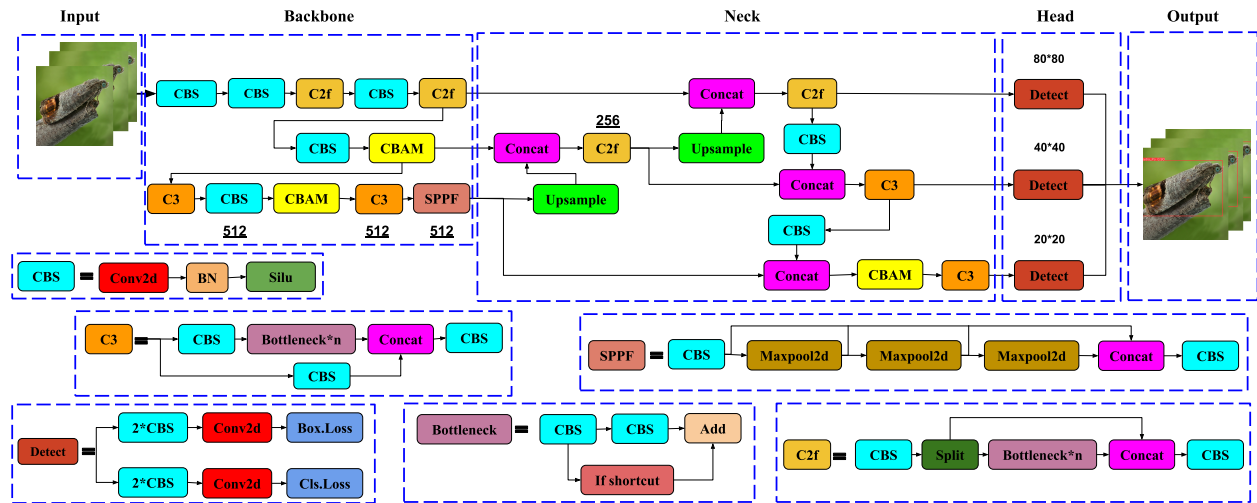
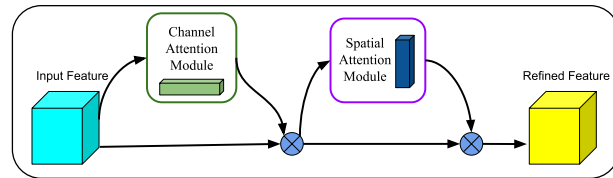**Figure 6**: Improved YOLOv5 network structure.

Figure 7: Convolutional block attention module.

- **CBAM Output on Conv (x2)**: When CBAM is applied after convolution, the attention mechanism improves. CBAM directs the model's focus to key regions of the moth (e.g., wings and body) while suppressing background noise. This indicates that CBAM enhances feature extraction when paired with preliminary convolutional operations.
- **C3 Output on Conv (x3)**: The C3 block further processes the features from the convolution, refining details like texture and structure. The moth's wings and body become more pronounced, showing that C3 captures more complex features than a single convolution layer.
- **C3 Output on CBAM (x4)**: Applying the C3 block after CBAM leads to the clearest and most focused output. The moth's essential features, particularly the wings and body, are highlighted, confirming that the attention-guided feature maps from CBAM significantly enhance the model's ability to extract meaningful information.

The experimental results clearly show that the inclusion of CBAM after convolution improves the network's focus on relevant parts of the image. When combined with the C3 block, CBAM helps extract more complex and ac-

curate features. These findings demonstrate that CBAM plays a crucial role in enhancing the model's ability to focus on important regions, leading to better feature extraction for object detection tasks.

2.4. Firebase IoT Platform

The Firebase IoT Platform provides a flexible and comprehensive infrastructure for connecting and managing IoT devices and their associated data. Its intuitive interface, coupled with real-time database functionality, simplifies the process for developers to create and scale IoT applications efficiently. With secure data transmission via authentication services and cloud functions, Firebase ensures reliable and optimized data handling, enhancing the performance and dependability of IoT solutions. Whether applied in home automation or industrial settings, Firebase equips developers with essential tools to streamline project development and improve the overall user experience. In our project, we utilize Firebase's cloud capabilities to consolidate detection results from the improved YOLOv5 model deployed in various traps, allowing for seamless remote monitoring and data management.

2.5. Raspberry Pi trap

The Raspberry Pi-based insect trap is specifically designed for codling moth (Cydia pomonella) detection, offering an advanced and efficient solution for farmers to monitor pest populations in their fields. The trap uses pheromones to attract the moths, ensuring that targeted pests are effectively drawn for accurate monitoring. Once the moths are attracted, the integrated camera and the improved YOLOv5m model, enhanced with the Convolutional Block
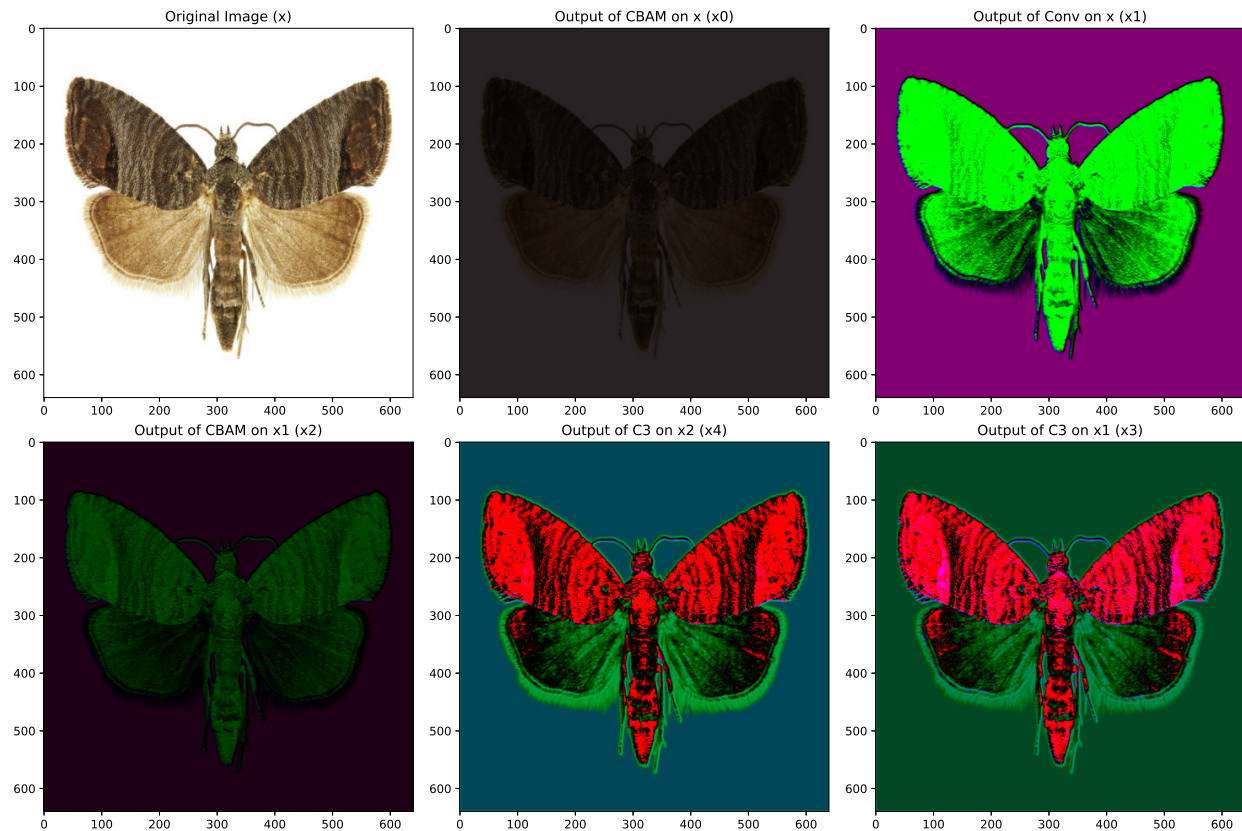
Figure 8: Comparison of outputs at different stages of the network with and without CBAM.

Attention Module (CBAM) to improve feature extraction and focus on relevant image areas, accurately detect and count the number of captured codling moths.

he trap is programmed to capture images at two specific times each day: 08:00 after sunrise and 18:00 just before sunset. This schedule is carefully chosen to coincide with the onset of codling moth activity, as moths typically begin flying and mating shortly before sunset and continue into the night under suitable conditions, avoiding direct sunlight and high temperatures. The Raspberry Pi's activation schedule adjusts throughout the year to align with seasonal variations in moth activity. This setup maximizes energy efficiency, enabling the system to operate autonomously with minimal power consumption.

Locally, the Raspberry Pi processes each image using the improved YOLOv5m model for real-time object detection and classification, identifying and counting codling moths with high precision. The detection pipeline achieves an inference speed of approximately 0.8 frames per second (FPS), with an average energy consumption of around 7 watts during operation. The results are transmitted over the internet via built-in WiFi, using the HTTP protocol

Table 1: Parameters of Raspberry Pi.

Configuration	Parameter
Raspberry Pi	Raspberry Pi 4B
RAM	2 GB
CPU	Broadcom BCM2711
Camera resolution	2592 x 1944
Wi-Fi	2.4 GHz and 5.0 GHz
Language	Python 3.9
Framework	Torch 1.13, Torchvision 0.14.0
Operating system	Raspberry Pi OS 64 bit

to upload data to the Firebase IoT Platform for remote monitoring.

This IoT-enabled setup allows farmers to track pest populations in real time, providing critical insights into field conditions and enabling timely, targeted interventions. By adopting this technology, farmers can swiftly detect fluctuations in pest populations, reducing crop damage and pesticide use. The complete Raspberry Pi parameters used in the trap are listed in Table 1, while an overview of the system is illustrated in Figure 9.
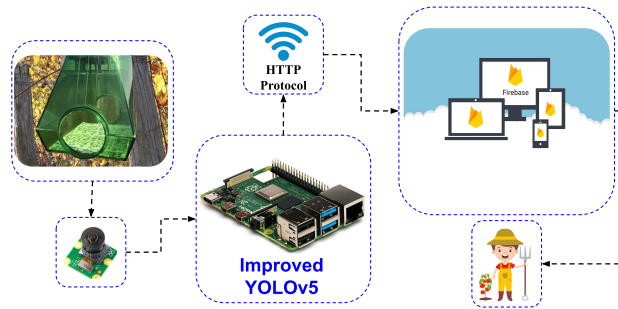
Figure 9: Raspberry Pi-Based insect trap with improved YOLOv5 and Firebase IoT for remote monitoring [3].

3. Results and discussion

The improved YOLOv5m model has been selected for pest detection on a Raspberry Pi 4B because it provides an ideal balance between processing speed and detection accuracy. This model offers the necessary accuracy to effectively detect small pests while maintaining computational efficiency, making it well-suited for use with the Raspberry Pi. Its ability to perform well within the hardware constraints of the Raspberry Pi 4B ensures reliable and efficient pest detection in various agricultural settings.

3.1. Training Environment and Evaluation Metrics

The completion of the data labeling process for both the training and validation sets marks a crucial step in our research. Afterward, we trained the improved YOLOv5m model using Google Colab, utilizing an NVIDIA Tesla T4 GPU with 16 GB of memory, running CUDA version 12.2 and driver 535.104.05. The training images were resized to a resolution of 640 pixels. Key information such as class labels and names was organized in the data.yaml file, applied to both the training and validation datasets. The dataset was partitioned into 85% for training and 15% for validation, and the model was trained for 100 epochs.

The performance of the improved YOLOv5m was measured using several evaluation metrics, including precision, recall, mean average precision (mAP) at an IoU threshold of 0.5, mAP averaged across IoU thresholds from 0.5 to 0.95, and parameter count.

Precision measures the accuracy of positive predictions by determining the ratio of correctly predicted positive samples to the total number of samples identified as positive. The precision calculation is expressed as:

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

Recall measures the rate of correct predictions out of all actual targets, and it is defined as follows:

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

The calculation formulas for mAPval 0.5 and mAPval 0.5:0.95 are provided below:

$$AP = \int_0^1 P(R)dR \quad (3)$$

$$mAP = \frac{\sum_{i=1}^N AP_i}{N} \quad (4)$$

The mAPval 0.5 metric represents the average precision for detections with confidence scores higher than 0.5, which helps calculate precision and recall metrics. Conversely, mAPval 0.5:0.95 evaluates the average precision over a range of confidence thresholds, from 0.5 to 0.95, in increments of 0.05. This provides a more comprehensive view of the model's performance across varying confidence levels. Model size refers to the storage required after the final phase of training is complete. FLOPs (Floating Point Operations Per Second) measure the computational efficiency of a model, indicating the total number of arithmetic operations needed to process a single image. This metric is essential for assessing the feasibility of deploying models in resource-constrained environments.

To better assess the model's performance and training stability, Figure 10 presents the validation curves of mean Average Precision (mAP) over 100 epochs. Subfigure 10 (a) shows the mAPval 0.5 trend, while subfigure 10 (b) displays the more stringent mAPval 0.5:0.95. Both metrics demonstrate a consistent upward trend during the initial training phase, followed by a convergence around epoch 75. This indicates that the model steadily learns to detect insect instances more accurately over time, with minimal oscillation or degradation, reflecting strong generalization capability. The smoothness of the curves suggests that the training process is stable and free from overfitting.

To further investigate model robustness and learning progression, Figure 11 illustrates the evolution of both training and validation loss curves for box loss (a) and objectness loss (b). The box loss, which quantifies the accuracy of predicted bounding box coordinates, exhibits a sharp decline in the early epochs for both training and validation sets before plateauing, indicating rapid spatial learning and consistent localization. Similarly, the objectness loss, which evaluates the model's confidence in identifying objects, shows a smooth and synchronized decrease across both datasets with no divergence or insta-

bility. These trends confirm that the proposed improved YOLOv5m architecture achieves efficient convergence and maintains training stability throughout the learning process.

(a) Validation mAPval 0.5
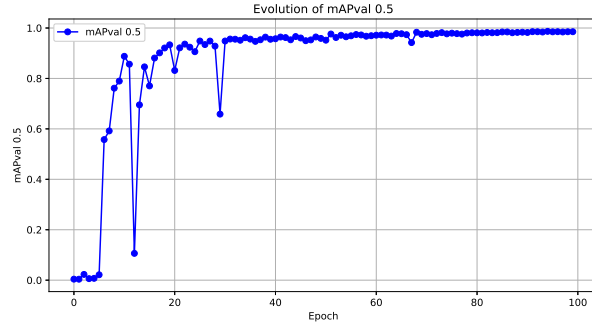

(b) Validation mAPval 0.5:0.95
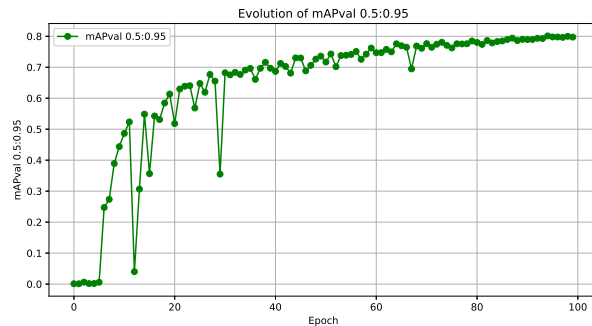
Figure 10: Validation mean Average Precision (mAP) curves over 100 epochs. (a) mAP evaluated at IoU threshold 0.5; (b) mAP evaluated at multiple thresholds from 0.5 to 0.95.

## 3.2. Enhanced Detection Performance with Improved YOLOv5m

In the development of pest monitoring systems, the deployment of the improved YOLOv5m model has significantly advanced pest detection accuracy, computational efficiency, and sustainable computing practices. Demonstrating substantial improvements over previous models, Figure 12 shows the original YOLOv5m model with an average confidence level of 83.36% and a maximum of 88% while using 25.06 million parameters. In contrast:

- **YOLOv6m** (Figure 13) despite having the highest parameter count at 51.99 million, displays slightly lower average and minimum confidence levels of 81% and 67%, respectively, but reaches a higher maximum of 91%.
- **YOLOv8m** (Figure 14) maintains consistent performance with an average confidence level of 84% and a maximum of 88%, similar to the original

(a) Box Loss
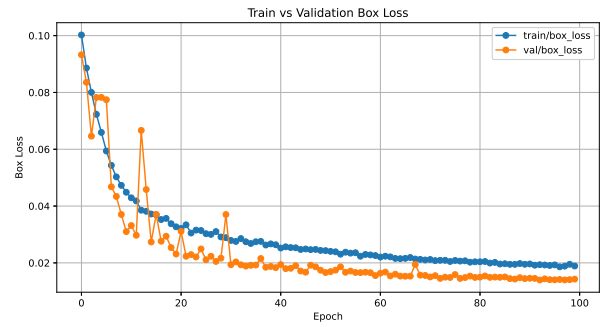
(b) Objectness Loss
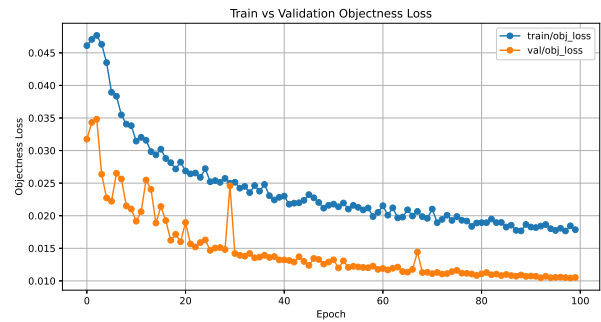
Figure 11: Training and validation loss curves over 100 epochs. (a) Box loss measures the accuracy of bounding box predictions; (b) Objectness loss reflects the model's confidence in detecting objects.

YOLOv5m, but with slightly more efficient parameter usage at 25.85 million.

- **YOLOv9m** (Figure 15) offers a balance with 20.15 million parameters, an average confidence level of 83%, and a maximum of 90%.
- **YOLOv10m** (Figure 16) stands out for achieving the highest maximum confidence level of 94% with the lowest parameter count of 16.4 million, though its minimum confidence level drops to 52%.
- **YOLOv11m** (Figure 17) provides reliable performance with 20.05 million parameters, achieving an average confidence level of 81.2%, a maximum of 88%, and a minimum of 70%.
- **YOLOv12m** (Figure 18) — With 20.10 million parameters, this latest version of the YOLO model achieves a maximum confidence of 89%, a minimum of 57%, and an average confidence of 80.45%.

However, the improved YOLOv5m model, illustrated in Figure 19, elevated the maximum confidence level to 95% and the average to 91.36%, all while significantly reducing the parameter count to 16.98 million. This not only showcases enhanced model efficiency and accuracy but also highlights the model's contribution to sustainable computing by reducing computational demands.
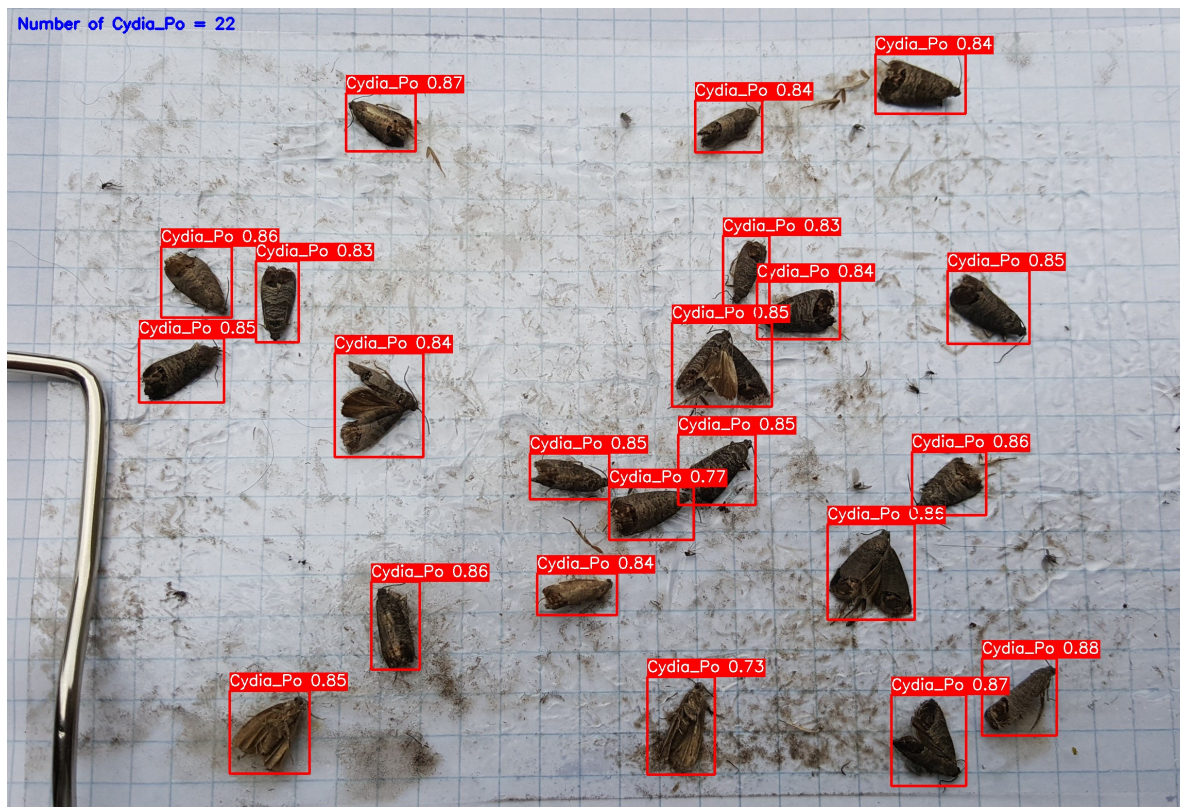
Figure 12: Detection performance of original YOLOv5m model [Adapted from 74].
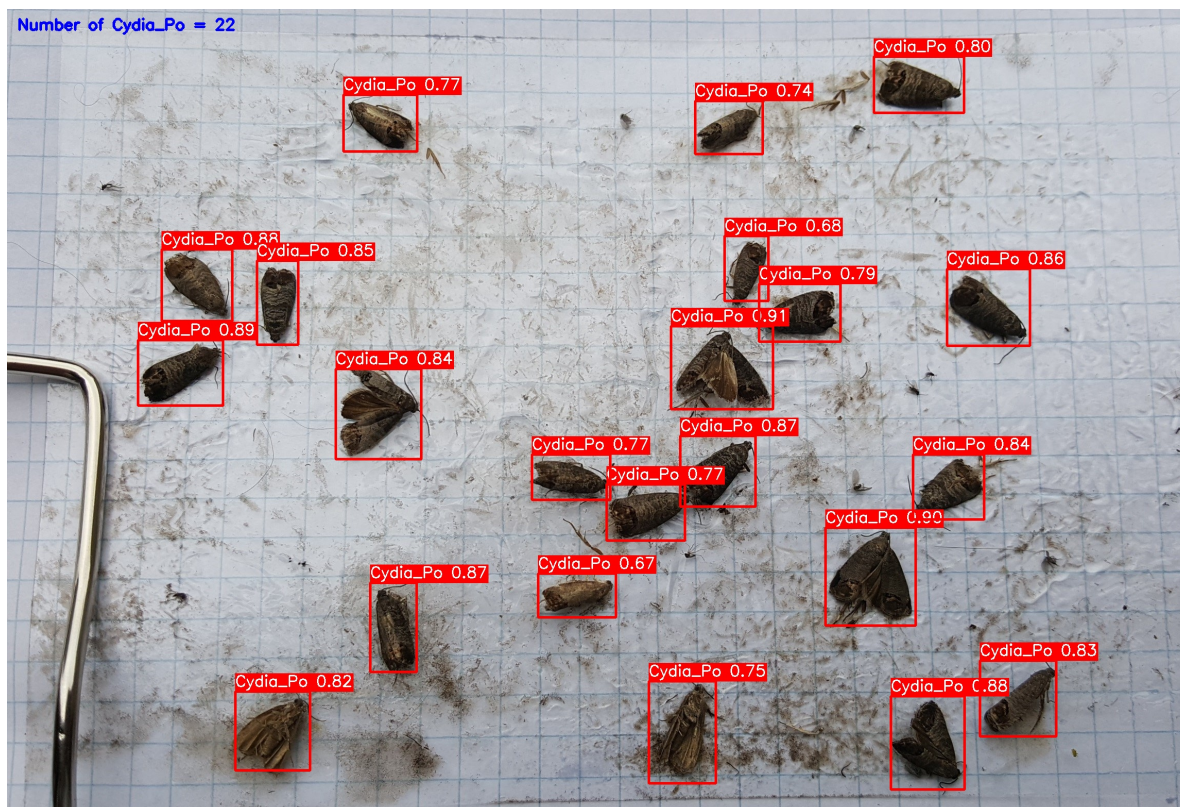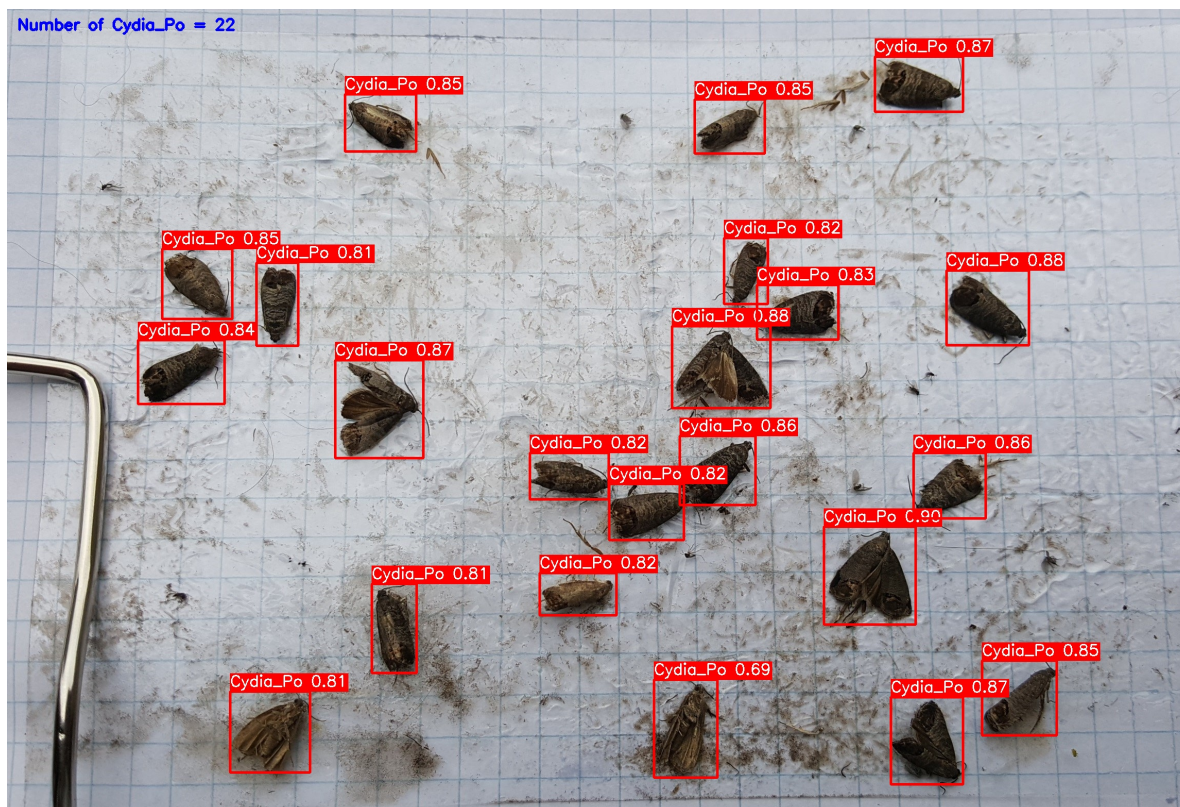

Figure 13: *Performance evaluation of the YOLOv6m model in detecting Cydia pomonella pests [Adapted from 74].*

Figure 14: *Performance evaluation of the YOLOv8m model in detecting Cydia pomonella pests [Adapted from 74].*

Figure 15: *Performance evaluation of the YOLOv9m model in detecting Cydia pomonella pests [Adapted from 74].*

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Figure 16: *Performance evaluation of the YOLOv10m model in detecting Cydia pomonella pests [Adapted from 74].*

Figure 17: *Performance evaluation of the YOLOv11m model in detecting Cydia pomonella pests [Adapted from 74].*
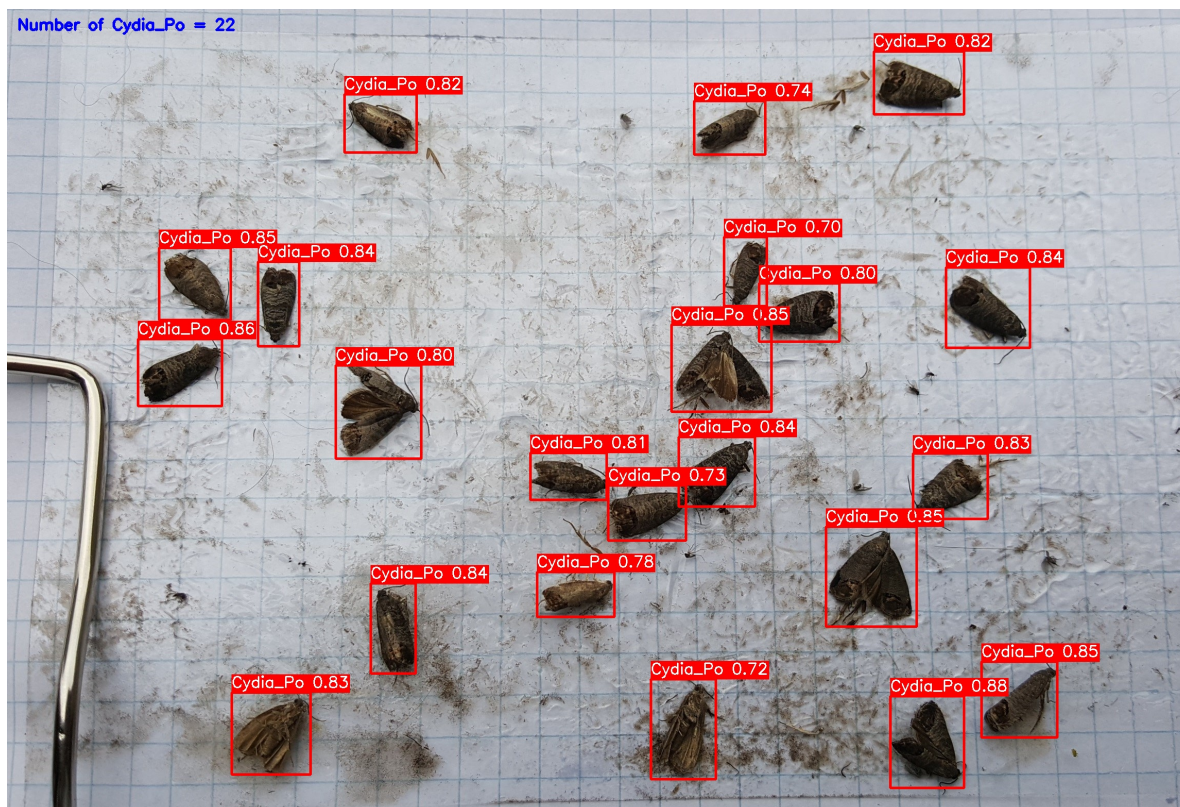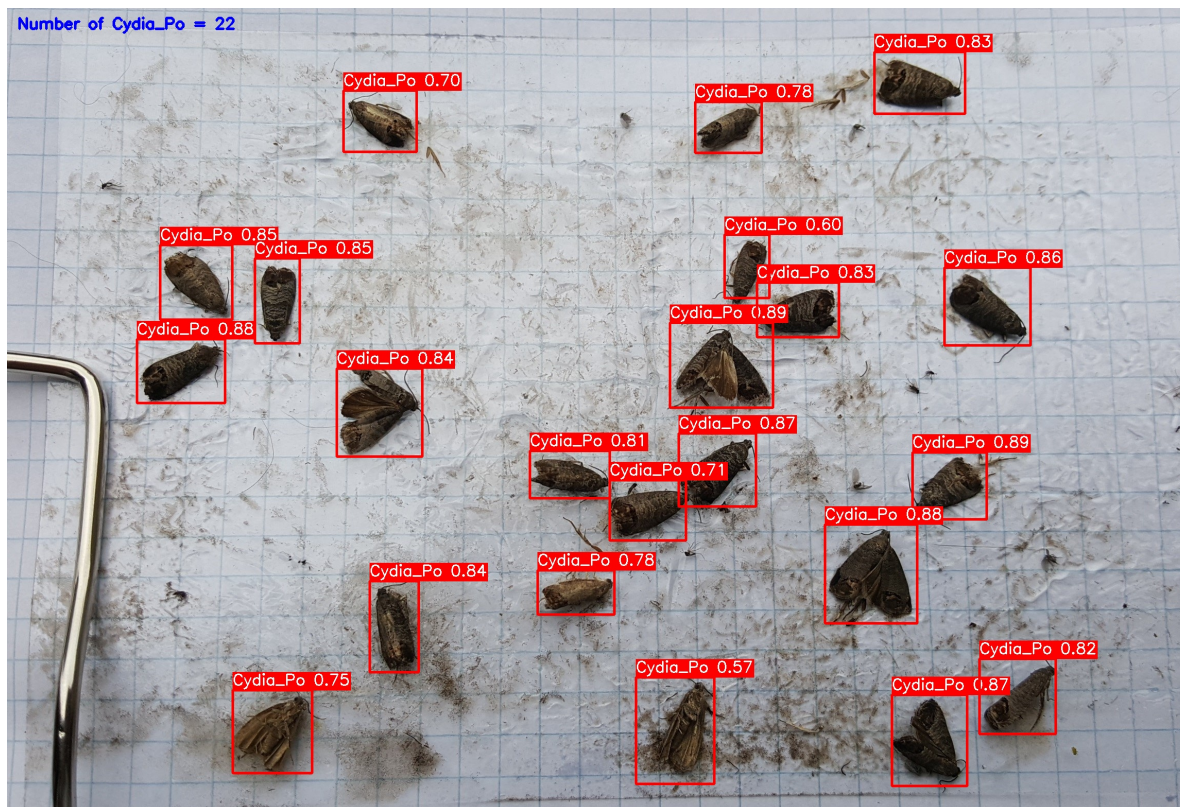
doi:10.x/journal.x.x.x

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Figure 18: *Performance evaluation of the YOLOv12m model in detecting Cydia pomonella pests [Adapted from 74].*

Figure 19: Enhanced detection performance of improved YOLOv5m model [Adapted from 74].

Table 2: Comparative performance metrics of YOLO models.

Models	FLOPs (B)	Number of Parameters (M)	Average Confidence Level (%)	Min Confidence Level (%)	Max Confidence Level (%)
YOLOv5m	32.08	25.06	83.36	77	88
YOLO6m	80.32	51.99	81	67	91
YOLO8m	39.44	25.85	84	73	88
YOLO9m	38.64	20.15	83	69	90
YOLO10m	31.91	16.4	86.5	52	94
YOLO11m	34.02	20.05	81.2	70	88
YOLO12m	35.35	20.10	80.45	57	89
Improved YOLOv5m	**26.88**	**16.98**	**91.36**	**83**	**95**

Table 2 details the comparative performance of the YOLO series, underscoring the superior accuracy and efficiency of the improved YOLOv5m. This model stands out for its high performance coupled with lower energy consumption, with a significant reduction in FLOPs (26.88 billion) compared to other models, aligning with sustainable computing objectives aimed at minimizing the environmental impacts of technology.

The integration of this model into a Raspberry Pi-based trap system has revolutionized pest management strategies. Utilizing the Firebase IoT platform for real-time data transmission, the system enables farmers to remotely monitor pest activity and respond promptly, applying pesticides only where absolutely necessary. This precise and targeted approach drastically cuts down pesticide usage, reducing environmental footprints and promoting sustainable agricultural practices. Additionally, the robust data analytics provided by the system help farmers achieve higher yields by maintaining optimal pest control measures, thus supporting a balance between enhanced productivity and environmental sustainability.

3.3. Firebase IoT Platform Integration for Pest Management

The integration of the Firebase IoT platform is crucial for efficient monitoring of pest detection data collected from the trap. The Firebase storage is organized into two main folders:

- **Database Folder:** This folder systematically stores all images captured by the trap at two specific intervals each day—08:00 after sunrise and 18:00 just before sunset. This ensures targeted data collection during peak codling moth activity periods, which is essential for periodic retraining of the detection model. As new images are consistently added to the dataset, the model can be retrained to maintain its accuracy and effectiveness in identifying pests, adapting to changing environmental conditions and seasonal variations.

- **Trap_Detection Folder:** This folder contains only the most recent image captured and processed by the improved YOLOv5m model. It provides real-time updates on the pest activity within the trap. This feature enables farmers or agricultural professionals to remotely access up-to-date information, supporting timely decision-making for pest management interventions.

The Figure 20 below illustrates the Firebase platform's structure and data organization:

- **Figure 20(a):** Displays the overall folder structure, showing both the Database and Trap_Detection folders within Firebase storage.
- **Figure 20(b):** Depicts the contents of the Database folder, which includes a historical archive of all captured images, forming the dataset for retraining the model with updated data.
- **Figure 20(c):** Shows the most recent image processed by the model, with bounding boxes highlighting detected pests, enabling real-time monitoring.

The proposed Firebase IoT-based system significantly enhances pest detection by integrating intelligent pest recognition models directly within the traps. This localized image processing reduces data transmission loads, minimizes power consumption, and ensures rapid pest identification. Unlike conventional methods, this system enables real-time tracking of insect populations in the field, providing more precise and timely data for decision-making. The combination of embedded processing and cloud-based analytics ensures scalability and accessibility, allowing farmers to optimize pest management strategies efficiently while reducing environmental impact.
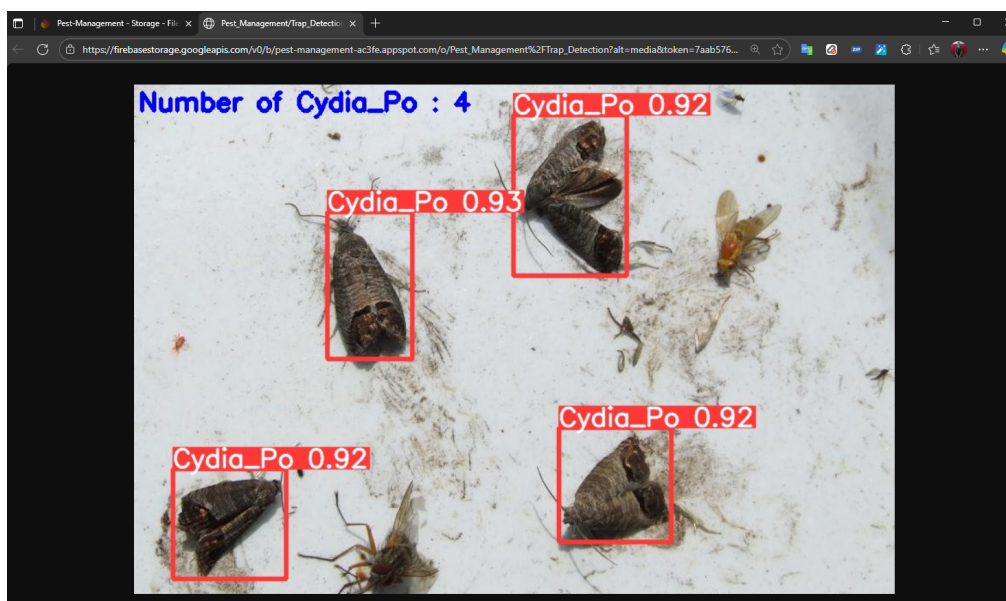
(a)
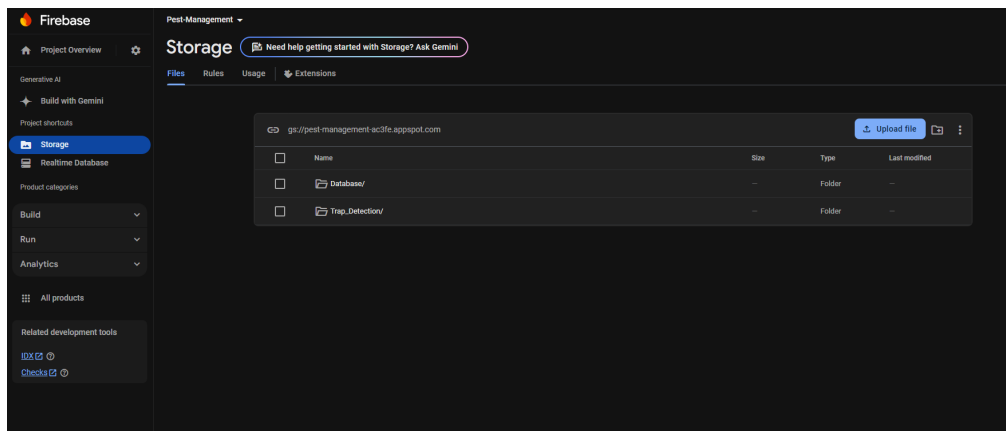
(b)
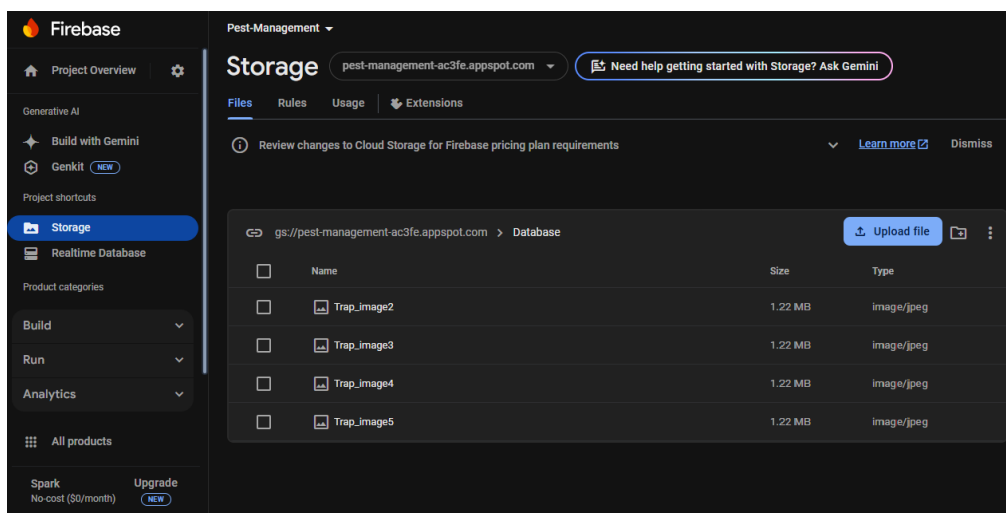
(c)

Figure 20: Firebase IoT platform: (a) folder structure with database and trap detection; (b) database folder showing image archive; (c)recent detection image with bounding boxes[Adapted from 74].

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4. Future Work

This research establishes a foundation for the development of more adaptive, efficient, and intelligent pest monitoring systems within the context of precision agriculture. Future work will focus on enhancing the system's robustness, generalization capabilities, and ecological relevance by addressing practical challenges observed in real-world agricultural deployments.

4.1. Integration of Environmental and Weather Data for Context-Aware Pest Management: To strengthen the system's adaptability and decision-making capabilities, future work will focus on integrating both on-site environmental sensing and regional weather forecasts. IoT-enabled sensors will be deployed to collect real-time data on key variables such as temperature, humidity, and ambient light within the field. In parallel, regional meteorological data-including wind speed, precipitation, and forecasted conditions will be incorporated into the system's notification and control module. This dual-source integration will enable the system to correlate pest population behavior with environmental triggers, support predictive modeling, and recommend optimal timing for pesticide application. Such alignment with favorable conditions will reduce chemical waste, improve treatment efficacy, and promote environmentally sustainable pest control practices.

4.2. Incorporation of Test-Time Adaptation (TTA) for Robustness to Domain Shifts: Given the inherent variability in field conditions-such as changes in lighting, background clutter, trap designs, and crop types-we propose the integration of lightweight Test-Time Adaptation (TTA) techniques. These methods enable the model to adjust its internal representations dynamically at inference time, without requiring access to labeled data or retraining. By adapting to previously unseen distributions during deployment, TTA can significantly improve detection reliability in heterogeneous and evolving agricultural environments [75].

4.3. Exploration of Advanced Data Augmentation Techniques to Enhance Generalization: In addition to biologically realistic rotations, future experiments will incorporate more diverse augmentation strategies to improve model generalization, especially under few-shot or class-imbalanced conditions. Notably, we will evaluate the Random Interpolation Resize (RIR) technique [75], which introduces interpolation variability during resizing to improve robustness to distributional shifts. Furthermore, style-based transformations inspired by content-style disentanglement and contrastive learning [76] will be explored to simulate environmental variability-such as lighting, color tone, and background texture-thereby improving the model's ability to generalize across different agricultural contexts.

5. Conclusions

This study has demonstrated significant advancements in pest detection technology through the optimization of the YOLOv5m model. The improved YOLOv5m, enhanced with the Convolutional Block Attention Module (CBAM) and filter reduction, achieved a maximum confidence level of 95% and an average confidence level of 91.36%, surpassing the performance of the original YOLOv5m. These improvements were attained alongside a reduced parameter count and a lower FLOPs value of 26.88 billion, reinforcing the model's suitability for deployment on low-power edge devices and aligning with the principles of sustainable computing.

The integration of this optimized model into a Raspberry Pi-based trapping system, coupled with real-time data management through the Firebase IoT platform, has proven to be a practical and efficient solution for pest monitoring in the field. This system enables real-time tracking of pest populations and supports precision interventions, ultimately reducing pesticide use, mitigating environmental impact, and improving crop yields.

Additionally, our comparative evaluation of YOLO variants has offered important insights into the trade-offs between accuracy, computational complexity, and generalization capacity. The improved YOLOv5m demonstrated an ideal balance between detection performance and resource efficiency, making it a strong candidate for real-world applications in smart agriculture.

Overall, our findings underscore the transformative potential of combining advanced deep learning techniques with IoT infrastructure in pest management. This approach offers a scalable path toward more sustainable, automated, and intelligent farming systems.

CRediT authorship contribution statement

Mohamed Zarboubi: Writing – review & editing, Writing– original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Abdelaaziz Bellout:** Writing – review & editing, Resources, Validation. **Samira Chabaa:** Supervision, Writing – review & editing, Validation. **Azzedine Dliou:** Supervision, Writing- review & editing, Validation. All authors have read and agreed to the published version of the manuscript.

Abbreviations:

FAO – Food and Agricultural Organization; IoT – Internet of Things; CNN – Convolutional Neural Network; YOLO – You Only Look Once; CBAM – Convolutional Block Attention Module; SPPF – Spatial Pyramid Pooling-Fast; C3 – CSPNet-based feature extraction block; C2f – Modified feature extraction block; GPU – Graphics Processing Unit; FPS – Frames Per Second; mAP – Mean Average Precision; IoU – Intersection over Union

Data Availability Statement

The dataset and source code used in this work will be available on request.

Conflicts of Interest

The authors declare no conflict of interest.

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