### Title
SmartTrap: An On-Field Insect Monitoring System Empowered by Edge Computing Capabilities




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# SmartTrap: An On-Field Insect Monitoring System Empowered by Edge Computing Capabilities

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***Abstract*—Fruit flies pose a significant threat to fruit yields, necessitating immediate detection solutions for effective pest management. In this study, we present our approach using YOLOv7 and the Jetson Nano 4GB for rapid and accurate fruit fly detection. Our method achieves an impressive Average Precision (AP) at Intersection over Union (IoU) of 0.75 score of 0.993, enabling near-instantaneous counting of trapped fruit flies during field deployment. The system sends this data to a designated local or cloud-based server, empowering users to identify areas with high fruit fly populations for targeted pesticide application. This targeted approach has significant implications for sustainable agriculture as it reduces the need for widespread spraying. Moreover, our flexible method can be adapted for the detection of other pests such as aphids or beetles, making it a valuable tool for agricultural scenarios and beyond.**

***Index Terms*—fruit fly, environmental data, smart IoT, edge computing, YOLOv7-tiny, Jetson Nano**

## I. Introduction

Horticultural crops, such as fruits, vegetables, and ornamental plants, play a vital role in agriculture due to their nutritional value and economic importance [1]. However, fruit flies pose a significant challenge worldwide by causing economic losses through the deterioration of mature fruits [2]. These pests are difficult to manage due to their adaptability to different regions and ability to infest various host plants [3]. Effective control measures are crucial to minimize losses and maintain crop quality [3]. Fruit flies, specifically those from the Tephritidae family, are polyphagous pests that target soft-bodied fruits and vegetables like sapodillas, peaches, guava, oranges, bananas, pumpkins, and bitter gourds [4]. Improper pesticide scheduling can result in pesticide residues and environmental damage [5] [6]. Yield losses caused by Tephritidae fruit flies can reach up to 90-100 percent, depending on factors such as population, location, crop variety, and season [7]. To address these challenges, we introduce the SmartTrap, a novel approach to fruit fly management. By utilizing the YOLOv7-tiny model, an advanced object detection algorithm, our solution offers a targeted, efficient, and sustainable method for controlling fruit fly infestations. Equipped with cameras and powered by the Jetson Nano board, the SmartTrap employs machine vision techniques for real-time pest detection and count, reducing the need for manual monitoring. This solution not only minimizes pesticide use but also contributes to environmental preservation and promotes sustainable agriculture. Our research aims to demonstrate the practicality and potential of machine vision techniques in modern pest management by evaluating the efficacy, speed, and power consumption of the YOLOv7-tiny model in the SmartTrap. The SmartTrap represents a significant step towards intelligent, eco-friendly, and efficient pest control methods, ensuring the security and sustainability of global horticultural production.

## II. Related Work

The economic significance of tephritid fruit flies (FF) has led to the widespread adoption of electronic traps (e-traps) as effective monitoring systems. These pests pose challenges to existing control methods, creating a need for efficient and timely monitoring solutions [8].

An e-trap consists of a trap mechanism and an embedded computing device. Its primary function is to attract and capture insects. Additional devices like cameras, meteorological sensors, and wireless modules are often integrated into the trap for image capture, data collection, and transmission to a remote server [9]. Strategic deployment of e-traps allows for comprehensive field data collection and statistical analysis of fruit fly pests [10] [11].

To gather vital information on fruit fly populations and distribution, practical and efficient traps are essential. The McPhail trap [12] [13], a cylindrical plastic device with liquid bait, and the yellow sticky paper [14] [15], designed with adhesive substances on yellow-colored paper, are widely employed for fruit fly monitoring. Both methods effectively capture fruit flies [14] [15].

In their study, G.E. Haniotakis et al. [16] found that the combination of a yellow sticky trap and pheromone was the most effective among various trap types tested, including the McPhail trap, yellow color trap, and pheromone. The Lynfield trap, which utilizes cuelure instead of a protein food lure to attract male fruit flies, outperformed the McPhail trap [17]. Despite the popularity of the yellow trap in our region, glare caused by its mechanical design when exposed to sunlight compromised our model's detection accuracy. Therefore, we chose the Lynfield trap for our project after careful consideration.

However, using a camera inside the trap presents a challenge of condensation on the lens, particularly in the morning, causing a foggy appearance. To address the condensation issue on the camera lens inside the trap, we continued to implement the Lynfield trap while also employing other strategies, such as using moisture-resistant lens covers or cameras. Our main mechanical traps consist of the Lynfield trap, and we utilize pheromones to attract the fruit flies, enabling us to gather crucial information on fruit fly populations and distribution.

Zekai Cheng et al. [18] proposed YOLOLite-CSG, a lightweight crop pest detection method based on convolutional neural networks (CNNs). They optimized the overall structure, introduced k-means++ for generating high-quality prior boxes, and incorporated lightweight sandglass blocks and coordinate attention. Experimental results on the CP15 dataset comprises 3000 crop pests images [18] showed that YOLOLite-CSG achieved a detection precision of 82.9 percent while significantly reducing the number of parameters (8.1 percent of YOLOv3 [19]) and computations (15 percent of YOLOv3 [19]).

Pham et al. [9] studied fruit fly detection using AI object detection methods, evaluating three models: SSD-MobileNetv1, SSD-MobileNetv2, and YOLOv4-tiny, and comparing their performance. YOLOv4-tiny achieved the highest overall performance in accuracy, recall, F1-score, and AP. However, SSD-MobileNetv2 showed comparable performance with faster processing speed. According to Pham et al. [9], YOLOv4-tiny outperforms other models in accuracy, recall, F1-score, AP, and meanIoU, while SSD-MobileNetv2 is the most promising model for real-time fruit fly detection. is the most promising model for real-time fruit fly detection.

In their comprehensive investigation, Salamut et al. [20] evaluated Faster R-CNN, SSD, RetinaNet [21], and YOLOv5 [22] deep learning models for detecting cherry fruit flies on yellow sticky traps. Faster R-CNN achieved the highest performance (AP score of 0.88), followed closely by RetinaNet (0.86) and SSD (0.84). YOLOv5 also showed promising results with an AP score of 0.75. The choice of backbone networks (MobileNet, ResNet, VGG-16) significantly influenced the models' effectiveness. Utilizing pre-trained backbone networks improved the accuracy and efficiency of the models, enhancing their classification ability for cherry fruit flies.

Insect detection models require a balance between performance and processing time, hence the rise in interest in deep learning models. However, high computational models like RCNNs do not fit our research objectives, prompting us to consider single-stage models that balance accuracy and speed. We've chosen the YOLOv7 model for our research due to its promise in improving both accuracy and speed compared to other models [23]. The adoption of YOLOv7 aligns with our goals and opens doors for further progress. Our aim is to enhance the detection system's accuracy and efficiency using YOLOv7, advancing beyond prior research efforts.

The subsequent sections are organized as follows: Section III provides a comprehensive depiction of the trap system, offering detailed insights into its constituent elements. In Section IV, we delve into the conducted experiments and conduct an in-depth analysis of the system's performance. Finally, Section V concludes our research by presenting a comprehensive overview of future prospects and potential advancements that can be explored after implementing the SmartTrap. This section outlines the anticipated outlook and highlights possibilities for further development and enhancements related to the SmartTrap system.

## III. System Overview

SmartTrap comprises two main components: hardware and software. In this section, we will discuss in detail the methods, procedures, and rationale behind their development.

### A. Hardware

In general, the hardware components of SmartTrap include Lynfield trap, Jetson Nano Developer-kit, power supply , and actuators which are illustrated in Figure 1.

- *Lynfield's trap:* The Lynfield trap component of our system is a mechanical trap designed in the shape of a Lynfield trap, comprising a cylindrical plastic box with four holes drilled on the sides. The bottom is covered with a fly adhesive sheet, and a pheromone-soaked cotton ball is placed inside. The trap follows the standard dimensions of 10 cm height and 7 cm diameter specified by the Food and Agriculture Organization of the United Nations, International Atomic Energy Agency, Vienna, 2018 [24]. To ensure consistent detection quality under sunlight exposure, a translucent white box was chosen based on research by Pham et al. [9], which found comparable fly attraction to white and yellow traps after 12 days, and considering potential effects of glossy plastic material used in yellow traps in Vietnam.
- *Jetson Nano:* The Jetson Nano Dev Kit A is equipped with a Quad-core ARM A57 CPU running at 1.43 GHz, providing powerful processing capabilities. The kit also

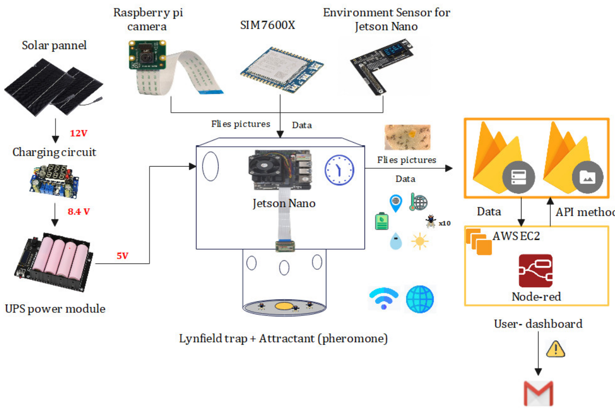


Fig. 1. Overview of the trap system

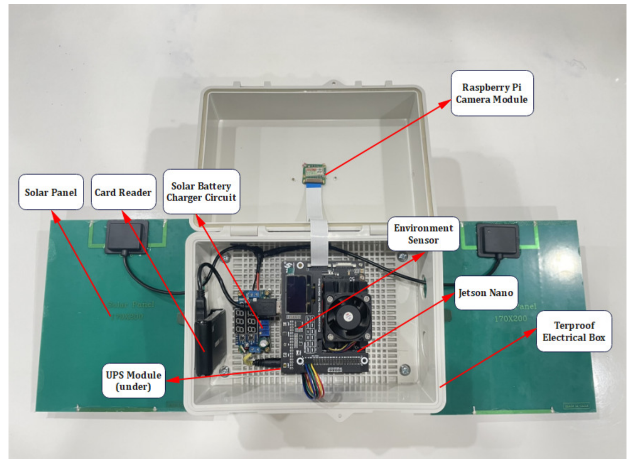


Fig. 2. Hardware system inside the terproof electrical box

includes 4 GB of 64-bit LPDDR4 memory, operating at a speed of 25.6 GB/s, ensuring efficient data handling. Additionally, the NVIDIA Maxwell GPU with 128 CUDA cores enables high-performance AI processing. With two MIPI CSI-2 DPHY lanes supporting high-resolution cameras, the Jetson Nano is well-equipped for capturing detailed imagery. The electrical box is securely suspended from a fruit-bearing tree branch using a specialized wire, ensuring stability and protection while capturing data. Jetson Nano, housed in a waterproof electrical box with sensors and power system, was chosen for its design features, shown in Figure 2.

- *Power Supply:* In terms of energy supply for the trap, we utilized a UPS module specifically designed for the Jetson Nano, along with four 3.7V lithium batteries. Additionally, to facilitate the charging of this system, we employed a setup comprising two 12V-5A solar energy panels accompanied by an adjustable voltage solar charging circuit. Over a duration of three days, we conducted comprehensive testing, and the system exhibited a satisfactory level of stability throughout its operation.
- *Actuators:* The actuator consists of a sensor module system and an object recognition system. The sensor module system measures three parameters: temperature, humidity, and light. We do not require an intermediate microcontroller as the Jetson Nano provides sufficient GPIO pins for seamless data connection and retrieval. Furthermore, the camera system is directly connected to the Jetson Nano, serving the purpose of data acquisition. It provides the necessary input for the Jetson Nano to perform detection and counting of fruit flies, transmitting the results to a web application and issuing alerts when the fly count exceeds a certain threshold.

### B. Software

The software framework plays a crucial role in data acquisition by capturing fly images, performing fly recognition and counting, as well as collecting data from sensor modules. This data is stored in a database and transmitted to a web application. The web application displays the most recent image depicting the status of the fly adhesive, along with information about sensor module data and the count of flies, accompanied by relevant advice. Additionally, email notifications are sent to the user when the fly count exceeds a certain threshold.

- *Yolov7 - tiny:* YOLOv7, as described by Wang et al. [25], is a standout object detection model due to its impressive speed and accuracy, operating between 5 to 160 FPS and reaching a 56.8 percent AP. It outperforms other real-time detectors running at 30 FPS or higher on GPU V100 and outshines models like SWINL Cascade-Mask R-CNN and ConvNeXt-XL Cascade-Mask R-CNN. It also surpasses various detectors, including YOLOR [25], YOLOX [26], Scaled-YOLOv4 [27], YOLOv5 [22], and others like DETR [28], Deformable DETR [29], DINO-5scale-R50 [30], and ViT-Adapter-B [31]. Its excellent performance is due to its exclusive training on the MS COCO dataset without using additional data or pre-trained weights. YOLOv7-Tiny, a reduced version with 1/6 of the parameters, outperforms YOLOv4-Tiny by 7 percent to 14.2 percent across various metrics. This makes it an optimal choice for fine-tuning fruit fly data in our project.
- *User-dashboard:* Our photography system cycles every 20 minutes, capturing images for data collection and concurrent fly quantification. In tandem, our environmental sensor system collects data at one-minute intervals. This gathered information, including images of the fly trap, temperature and humidity sensor readings, light intensity, fly count, and the UPS battery level of Jetson Nano, is consolidated and sent to Firebase Realtime Database and Firebase Cloud Storage. This data is then relayed to a Node-RED server deployed on AWS Cloud, making it accessible to all registered users. If the fly count surpasses 60, an alerting mechanism triggers an email warning to the user, providing timely notifications to mitigate potential risks and safeguard their garden spaces

effectively.

## IV. Experiments and Evaluations

### A. Hardware

In terms of hardware, in addition to using pheromone as bait and following the trap's size and color recommendations from Pham et al.'s research [9], we also incorporated the attractant method proposed by G.E. Haniotakis et al. [16]. Moreover, a solar energy system has been implemented, allowing the device to operate for extended periods of time.

- *Mechanical trap system:* Figure 3 showcases the trap system installed on a sapodilla tree in the garden during the peak activity period for fruit flies (6:00 AM to 6:00 PM). Fruit flies are generally inactive at night and during rainfall [32]. Figure 4 displays consistent patterns in the number of flies captured over a 12-hour interval across two consecutive days. The graph reveals a gradual increase in fly numbers until 1:00 PM, followed by a relatively stable count. These results provide strong evidence of the trap system's effectiveness in a natural environment. Over the course of two days, the trap successfully captured 79 and 62 fruit flies, respectively, demonstrating its ability to attract and capture these pests. These promising results serve as motivation to further develop and enhance the trap system's quality, performance, stability, and reliability in combating fruit fly infestations. We are committed to optimizing the system to achieve even greater effectiveness.
- *Power system:* When not under charge, the battery of the Jetson Nano provides continuous power for up to 6 hours. To overcome this limitation, we have implemented a system where the Jetson Nano restarts every 20 minutes to run the detection process, followed by a shutdown and cycle repetition. Additionally, we have integrated a solar circuit with an 8.4V 2A output, compatible with the uninterruptible power supply (UPS), to facilitate the recharging of the UPS battery. This ensures a consistent and stable power supply for the Jetson Nano throughout its periods of extended operation. Due to the limited trapping time in the garden, we were able to test this system for only 3 consecutive days, and it performed well during that period. We are continuing our research and will provide further updates in the upcoming report.

### B. Software

In our project, we used the AlertTrap dataset with 248 fruit fly images from Pham et al. [20] for training and comparison between Yolov7-tiny and Yolov4-tiny models. We also tested the model's detection speed on the Jetson Nano platform. While the user dashboard has advanced, its final services are still being decided. The model training occurred on Google Colab, with an 80-20 train-test split, a batch size of 16, and ran for 50 epochs, finishing in under 30 minutes. These details were crucial for our model's efficient training and evaluation.

- *Evaluation metrics:* In this experiment, we assess candidate models using key metrics: accuracy, recall, F1 score, and average precision (AP) at IoU thresholds of 0.25, 0.5, and 0.75. We also evaluate processing time to determine real-time viability. Accuracy, recall, and F1 score are computed based on true positives (TP), false negatives (FN), and false positives (FP). Accuracy represents the ratio of correct detections to total detections, while recall signifies the ratio of correct detections to total ground-truth instances. The F1 score offers an overall evaluation of model performance. AP measures the average precision of models using different confidence score criteria. Lastly, we analyze the average processing time across all test sets to assess real-time feasibility.
- *Model Evaluations and Discussion:* The model was trained using the dataset from Pham et al.'s AlertTrap project [9], delivering promising results with AP scores matching those of AlertTrap. The comparison of recall, F1-score, and AP metrics at an IoU threshold of 0.75 between AlertTrap and the SmartTrap models are presented in TABLE 1. Figure 5 demonstrates YOLOv7-tiny's successful fruit fly detection, including those in close proximity, while effectively ignoring a worm, thus proving its high quality and performance. Furthermore, the software was rigorously tested for scenarios with high fruit fly counts and overlaps, with 'numerous' and 'over-

Fig. 3. Trap set up at the sapodilla garden

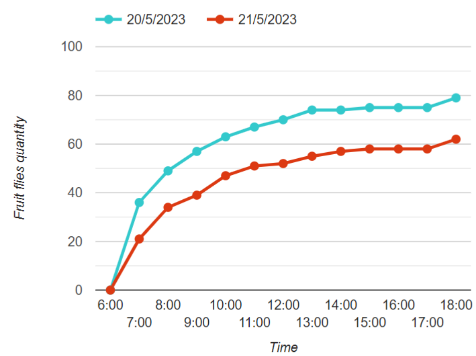


Fig. 4. Fly population fluctuations in the sapodilla garden over 12 hours

lapping' referring to instances of 9 to 24 fruit flies and closely situated or superimposed fruit flies, respectively. Tables II and III display the model's robust performance in these situations using IoU thresholds of 0.25, 0.5, and 0.75. Notably, the model improved the AP score at 0.75 by 18.9 percent compared to AlertTrap [9].

TABLE I
PERFORMANCE COMPARISON BETWEEN YOLOV4-TINY AND YOLOV7-TINY AT AN IOU THRESHOLD OF 0.75 ON THE TEST DATASET.

| Models | Precision | Recall | F1 Score | AP |
|---|---|---|---|---|
| Yolov4-tiny | 0.847 | 0.847 | 0.847 | 0.802 |
| Yolov7-tiny | 0.991 | 0.932 | 0.960 | 0.993 |

TABLE II
YOLOV7-TINY PERFORMANCE ON TEST DATASET WITH NUMEROUS FLIES AT DIFFERENT IOU THRESHOLDS

| IoU Threshold | Precision | Recall | F1 Score | AP |
|---|---|---|---|---|
| 0.25 | 0.952 | 0.925 | 0.938 | 0.930 |
| 0.5 | 0.944 | 0.90 | 0.921 | 0.902 |
| 0.75 | 0.839 | 0.877 | 0.857 | 0.871 |

TABLE III
YOLOV7-TINY PERFORMANCE ON TEST DATASET WITH OVERLAPPING FLIES AT DIFFERENT IOU THRESHOLDS

| IoU Threshold | Precision | Recall | F1 Score | AP |
|---|---|---|---|---|
| 0.25 | 0.950 | 0.845 | 0.894 | 0.831 |
| 0.5 | 0.928 | 0.856 | 0.890 | 0.845 |
| 0.75 | 0.846 | 0.768 | 0.805 | 0.819 |

The model training yielded promising results, with approximate Average Precision (AP) scores of 0.25 and 0.5, comparable to AlertTrap's results. Notably, the AP score at 0.75 reached 0.991, representing an 18.9 percent improvement over AlertTrap [9].

- *Detection Speed:* The software's detection speed was evaluated on a Jetson Nano, achieving real-time speeds of 0.236 FPS with GPU acceleration and 0.02 FPS with CPU utilization. These results highlight the significant improvement in detection speed facilitated by GPU acceleration, enabling more efficient and real-time fruit fly detection within the trap. It should be noted that the detection speed may vary based on hardware configuration and algorithm complexity. Nonetheless, these findings showcase the system's practicality in real-world scenarios, allowing for timely and efficient monitoring of fruit flies in agricultural or research settings.
- *Dashboard for user:* The user features and interface for the dashboard have been nearly completed, and the system is functioning well with smooth performance. Currently, we are utilizing services such as Firebase, Node-red, and AWS for the product demonstration. However, as we scale up the project to accommodate a larger number of traps, we have recognized that the associated costs could become significantly high. Therefore, we are actively exploring alternative services that can provide cost-effective solutions to ensure the project remains financially feasible. Figure 6 illustrates a demonstration of a user-dashboard utilizing a Node-RED server.

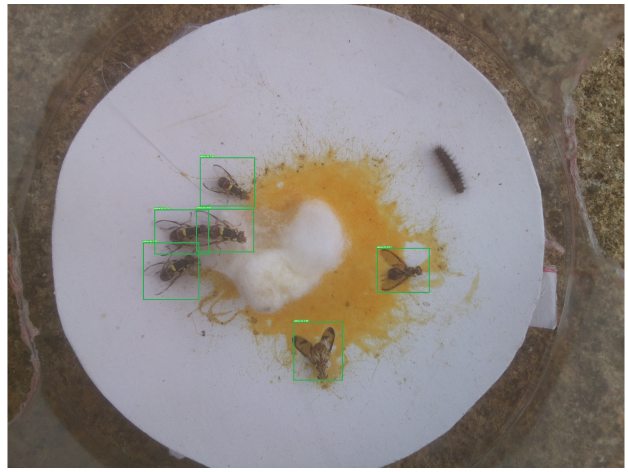

Fig. 5. Detection Example using Yolov7-tiny model

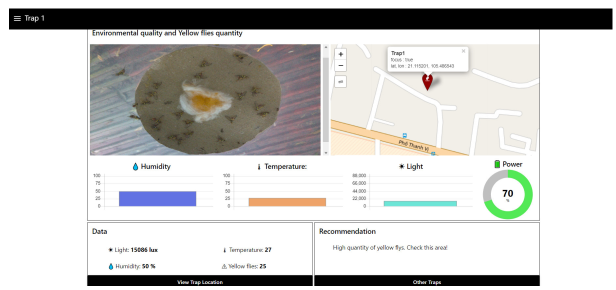


Fig. 6. Demonstration of User-Dashboard using Node-RED Server

Overall, SmartTrap surpasses its predecessor, AlertTrap, in model accuracy, processing speed, orchard testing, and user interface/web application functions. Compared to Zekai Cheng's research, which used a dataset of 200 images per insect species, SmartTrap's model boasts an AP index that's 27 percent higher than their best model, YOLOlite-CSG (82.9 percent).

## V. CONCLUSION AND OUTLOOK

SmartTrap, utilizing the YOLOv7-tiny model, presents an innovative solution for fruit fly detection in horticultural pest control. This innovation sets the stage for sustainable pest management enhancements. For further performance boosts, there's potential in refining training, enlarging datasets, and adding model variations. Effective trapping requires addressing factors like the spread of pheromone doses and the influence of natural elements such as rain and wind on dispersion. Certain areas within fruit tree plots have higher yellow fly attractions, necessitating meticulous placement strategies. By harnessing machine learning and past data, we can create adaptive methods, dynamically adjusting traps and issuing early warnings. A more connected SmartTrap system would provide richer data on fruit fly population trends.

Additionally, transitioning to smaller, cost-efficient models suitable for low-power devices like microcontrollers is a priority. This shift aims to make the system more affordable, especially for farmers with limited resources.

To sum it up, SmartTrap offers an intelligent approach to fruit fly management in horticulture, with avenues for further refinement in system performance, trap placement, and the adoption of cost-effective hardware.

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