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Fruit fly automatic detection and monitoring techniques: A review

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ABSTRACT

Fruit flies affect the production and market of fresh fruits and vegetables worldwide. To minimize their effects, integrated pest management (IPM) strategies are needed. However, the adopted IPM strategies involve human operators who manually monitor and evaluate insect pests and their effects, respectively. The manual methods involved are tedious, labor-intensive, and prone to errors. To avoid the drawbacks, monitoring processes can be made automatic, which involves the detection of the flies without human operator intervention. To achieve automatic detection and monitoring, insect traps are equipped with electronic sensors (i.e., optical, acoustic, or image) for accurate and efficient monitoring. The traps are further linked together over a communication network, allowing the pests to be monitored remotely without requiring frequent field visits, which leads to smart traps. In this work, we summarize automatic techniques that are used to monitor pests in fruit production (such as mangoes, apples, and olives).

1. Introduction

Horticulture sector in the Sub-Saharan Africa is seriously threatened by Tephritid fruit flies, which are regarded as the most commercially significant insect pests [1,2]. The oriental fruit fly (*Bactrocera dorsalis*), the Mediterranean fruit fly (*Ceratitis capitata*), the Olive fruit fly (*Bactrocera oleae*), the Ethiopian fruit fly (*Dacus ciliatus*), and the melon fly (*Bactrocera cucurbitae*) are considered the most pestiferous fruit flies in the region [3,2]. Bactrocera dorsalis, among other fruit fly species, is overabundant and extremely polyphagous [4–6], since its initial discovery in 2003, it has been believed to be the cause of significant economic losses to horticulture crops throughout Africa [7,8,2]. Fruit fly infestation reduces fresh fruit quality and restricts markets vulnerable to quarantine across Africa [4,8]. Other Bactrocera species, including the guava fruit fly (*Bactrocera correcta*) and the peach fruit fly (*Bactrocera zonata*), are among highly polyphagous pests that cause serious damage to banana, guava, and mango fruits [9,10], while the pumpkin fruit fly (*Bactrocera tau*) causes losses in fruits due to high infestation [10].

To mitigate their effects, fruit growers apply chemical pesticides in the control process; however, the overuse of chemicals led the fruit flies to develop resistance to various pesticides [11]. Also, the increased use of pesticides negatively impacts the environment and human health. Furthermore, they negatively affect beneficial pollinating insects and natural enemies of the pests [12,13]. Another approach is the insect pest management (IPM) strategy, which is used to suppress pests and increase fruit yield while minimizing the use of synthetic chemicals. The strategy consists of protein bait spray, male annihilation technique (MAT), and orchard sanitation [14,15].

Monitoring insect pests is necessary to ensure that the right measures are taken at the right time for proper integrated pest management [16]. The approach is regarded as a traditional monitoring method that involves manual inspection from trap to trap, requiring manpower to collect, identify, and count the attracted fruit flies. The traps lure flies using pheromones, color, and light [17], then the trapped insects are counted manually. Manual insect counting is labor intensive, time-consuming, and error-prone [18,19]. Traditional monitoring methods have cost implications because the variables cannot be measured simultaneously at all the monitoring points [16]. To avoid the drawbacks of traditional monitoring, emerging techniques have been adopted that involve the application of computer vision techniques to automatically detect and identify insect pests in trap images [17,20–24]; from insects' wingbeats using acoustic sensors [25,26], optoelectronic sensors [27] and optoacoustic sensors [28], and radar techniques [29]. To avoid frequent field visits, the Internet of Things (IoT) is applied, which

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enables the traps to be monitored anywhere on the globe [30–32].

Performing a basic literature search using *key words*: “automatic fruit fly detection AND monitoring” OR “automatic pest monitoring” OR “electronic trap” OR “automated trap” AND “fruit flies” in a scientific database (Google Scholar) for the last 15 years. About 90% of the searched literature has been published in the last 10 years, from 2013 to 2022, demonstrating the automatic detection and monitoring of fruit flies as a recent discipline. In this work, a comprehensive review of the techniques applied to the automatic detection and monitoring of fruit flies is presented. Also presented are different trap designs and their implementation challenges, the state-of-the-art object detection algorithms for fruit fly detection, and the types of communication technologies used in the transmission of trapped information.

2. Fruit fly traps

A fruit fly trap is a device or container intended to trap and hold flies, often by permitting access but not exit. They are typically low-cost plastic boxes of various shapes that contain a pheromone or food attractant. Early in the 1920s, the first fruit fly traps were introduced [33]; they came in different shapes and were used in various ways for trapping fruit flies. These traps are classified depending on their characteristics, i.e., color, shape, or attractant [33]. The purpose of the trap is to retain insects within a device; a trap that captures target species is referred to as mass trapping [34].

2.1. Traditional fruit fly traps

These were early traps that manually monitored and controlled fruit flies. Navarro-Llopis and Vacas [33] proposed a classification of the traps based on two categories: wet and dry traps. Wet traps were initially invaginated clear glass traps using acetic acid as a lure, molasses, and/or fruit pulp with water. The traps are mostly constructed of plastic, with a few improvements based on the McPhail trap design. They are normally cylindrical and feature a colorful, opaque container with a transparent plastic cover. The bottom of the traps has holes that allow flies to enter, with an invaginated entry as in the McPhail trap, Fig. 1a, or in the cylinder walls, or a mix of both as in the Tephri trap, Fig. 1b. Fig. 1c shows another commonly used trap known as the olipe trap, which is a bottled trap with lateral holes that uses protein or ammonium salt liquids to attract fruit flies.

Unlike wet traps, where flies are trapped by drowning in liquid, dry traps use a knockdown insecticide or a sticky contact surface to trap the flies. Due to the sticky traps’ low cost and disposable nature, they are typically used for detection purposes. However, for mass trapping, sticky traps are not recommended because they lose efficiency due to insects overloading, leaves, or even dust. A dry trap that serves as an alternative to traditional methods was introduced by Tan [35]. This one-way trap, which was later evaluated by Jang [36] and Hiramoto et al. [37], can capture flies without the use of liquid attractants or insecticides. It is designed to enable flies to enter easily, but once inside, they are unable to escape. Several commercial traps available on the market are shown in Fig. 1d, 1e and 1f.

2.2. Electronic traps

In order to automate the monitoring process, the traditional traps in Fig. 1 are integrated with electronic components and perform all the processes. The integration of electrical sensors produces an automatic monitoring system that counts and detects fruit flies. Preti et al. [38] described an automatic trap as a device that consists of software and hardware modules. The hardware module is made up of the trap housing that holds the lure and captured insects, an electronic box with sensors, a communication modem, and a power supply unit. The software consists of a web-based repository where the images from the captured data are saved and accessible, as well as image analysis algorithms that are optional to automatically recognize and count the captures. The automatic monitoring method reduces the expense of monitoring programs while minimizing human error. Electronic traps implemented make use of sensors such as sound, light, and image sensors, as discussed. Unwin and Ellington [39] presented the use of optoelectronics for insect identification. A photoreceptor recorded the fluctuation in ambient light brought on by the insect’s wing beats during flight. The light variation is then processed to determine the insect’s wing beats per second, which is considered the wing beat frequency that can be used to identify a species based on its physiological traits [40]. In the context of the Internet of Things, an electronic trap is referred to as a “thing”, i.e., a typical plastic container with sensors for detecting the presence of an insect as it enters the trap and a wireless communication module for broadcasting the data sensed [27].

Potamitis et al. [41] used a McPhail trap integrated with electronic components to perform insect trapping and detection. Fig. 1 (a) shows a trap with a transparent top and a detached inverted funnel [13]. The trap design allows insects to enter through a hole in an inverted funnel base and be attracted by the lure. Fig. 2 shows an electronic McPhail trap that consists of an array of five (5) photo-transistors (photo receptors) connected in parallel to the infrared-emitting LED (photo emitter). When an insect passes across the emitter-receiver, it causes interruption due to the insect’s wingbeats, which leads to voltage variation (in the analog form). The analog output from phototransistors is then sent to the Arduino microcontroller for counting, and the insect’s wing flaps are recorded on a spectrogram. A well-optimized McPhail e-trap using optoelectronic sensors was able to count and record the wing beats of the olive fruit fly and was capable of sensing the wing beats of several other insects as well. Optoelectronic sensors have the disadvantage of needing to be operated away from artificial light since their phototransistors and diodes are susceptible to interference.

Goldshtein et al. [42] developed an automatic trap to monitor the Mediterranean fly (Medfly: Ceratitis capitata) remotely. The trap was designed with a cylinder-shaped body, as shown in Fig. 3. The body of

(a) (b) (c) (d) (e) (f)

Fig. 1. Traditional traps: (**a**) McPhail trap [13], (**b**) Tephri trap, (**c**) Olipe trap, (**d**) Maxitrap, (**e**) Moskisan trap, and (**f**) Decis-trap [33].

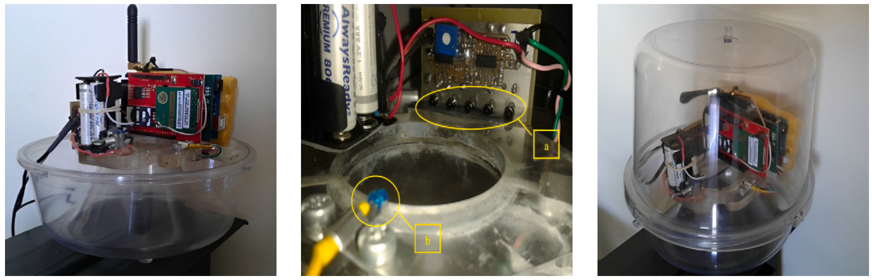


Fig. 2. The Electronic McPhail trap: (**A**) Orientation of optoelectronic sensor, communication module, and microcontroller, (**B**) Electronic components: (a) photoreceptors and (b) photo emitter, and (**C**) Integrated electronics and trap parts [13].

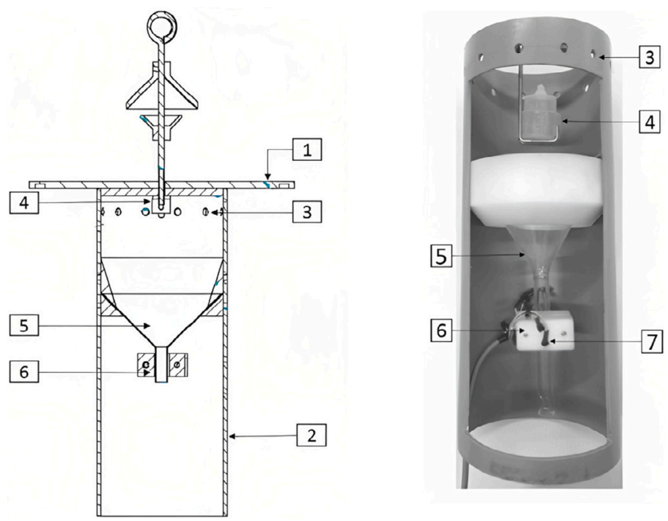


Fig. 3. Automatic Medfly Trap: (**a**) Inner layout construction of the trap and (**b**) Prototype arrangement of the main electronic components: "(1) transparent cover; (2) main body; (3) apertures; (4) a vial with both attractant and toxin; (5) a glass funnel; (6) sensor unit; (7) IR-LED" [42].

the trap was painted gray in order to deter non-target arthropods. The attractant and toxin were mounted inside the funnel. Optical sensors were implemented, forming a sensor unit to detect and count the dead or stunted flies inside the tap. The sensor unit comprised an infrared (IR) LED emitter and a light-sensitive transistor receiver that was attached to the neck of the glass funnel. When the IR-LED emits light, it triggers the positive input on the analog comparator of the sensor unit, thereby activating the receiver. Whenever a fruit fly enters the trap, it blocks the signal between the emitter and the receiver for approximately 2 ms, which turns off the transistor and causes an update of the Medfly count. To prevent counting the same fly again, a 30-second delay mechanism was introduced.

The authors made a slight modification to the proposed system by adding another sensor unit, making the trap a dual-sensor unit trap. A comparison was made between single and dual sensor units; the single sensor unit detected 87% of the trapped flies, while the dual sensor unit detected 90%. The entire system was powered by a 12 V, 38 Ah lead acid battery with a maximum daily usage of 323 mAh.

An infrared (IR) optoelectronic sensor-based trap was created by Sandrini Moraes et al. [43]. The phototransistors in the trap were used to detect the signal resulting from the partial blockage of IR light caused by the fly's wings beating. The trap in Fig. 4 was developed for detecting and classifying two species of fruit flies (*Anastrepha frateculus* and *Ceratitis capitata*) in real time. The fly enters the trap as shown by the

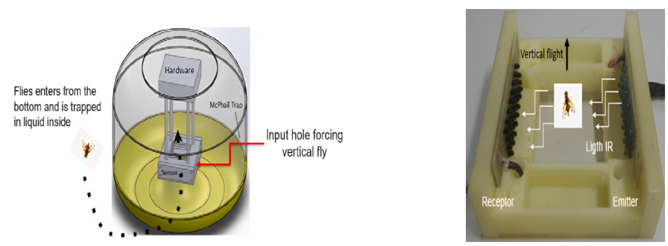


Fig. 4. The overall developed McPhail-based electronic trap: (**a**) The proposed opto-electronic sensor-based intelligent trap and (**b**) Opto-electronic sensor base (showing emitter and receiver unit) [43].

arrow in Fig. 4a, passing through the sensor base, which consists of emitter and receiver circuits that capture signals from the insect's wing beats. The sensor base in Fig. 4b consists of a TIL32 infrared LED used as an emitter and a TIL78 phototransistor used as a receiver. The performance measured from the developed trap indicated that the fundamental frequency of the *Anastrepha fraterculus* wing beat signal was 113.75 $\pm$ 2.04 Hz, while *Ceratitis capitata* generated a fundamental frequency of 160.81 $\pm$ 2.02 Hz. Both experiments yielded a 95% confidence level.

Hermosilla et al. [44] developed a wireless sensor trap for vineyard pest detection (Lobesia botrana). The trap makes use of an acoustic method to identify the sound made by a flying pest. It consists of four main parts: a processing unit, a communication unit, a microphone, and a remote data server. The Ultramic-Um250k microphone [45] is used; the device was selected due to its capability of registering low-frequency sounds (125 kHz). The moth emits a sound that goes as high as 120 kHz, making the Ultramic-um250k a suitable recording device. To attract moths to the trap, a pheromone was used, as shown in Fig. 5. The gathered moths' sound is processed using the Raspberry Pi, which is capable of performing real-time processing of the input signal. For every moth detected, the system creates an audio file, which is then transmitted to the remote server over an access point.

Fig. 5. Wireless acoustic detection trap: (**a**) microphone and pheromone positioning, and (**b**) trap installation in the vine yard [44].

A bimodal optoelectronic sensor-based trap developed by Potamitis et al. [26], is a device used for recording insect wingbeats while in flight inside the trap that is based on Fresnel lenses and a stereo-recording sensor, as shown in Fig. 6a. The trap consists of a single LED emitter and two photodiodes; the emitter associated with the Fresnel lens produces a collimated light beam that is collected at the receiver and focused on the diode. An insect will be detected as it crosses between the emitter and receiver, where the insect's wing-beating lowers the variation of the light intensity and casts a shadow on the black termination cavity, as shown in Fig. 6b. In order to achieve a good signal-to-noise ratio, a high-power 3.4 W LED driven at 0.85 W is chosen to avoid the reception of a small amount of scattered light intensity from the insect's wingbeats.

Shaked et al. [46] developed two versions of fruit fly traps, namely the medlfy and yellow sticky surface (YS). The two traps were used in the field testing of four fruit fly species in Greece, Spain, Italy, and Israel. The fruit flies under surveillance were Bactrocera oleae, Rhagoletis cerasi, Ceratitis capitata, and Dacus ciliatus. Both versions of the traps were based on the wireless transmission of images of the captured insects.

The medfly e-trap is a modification of the "Jackson trap" by Harris et al. [47], composed of three rectangular hard plastic surfaces assembled as a standard "(delta)" trap [46]. As shown in Fig. 7a, the trap consists of two surfaces that form a roof-like structure and another surface coated with adhesive to retain the attracted fly, which serves as the base of the trap. The attractant is either suspended from the "ceiling" of the trap or placed on the base of the trap [46]. When flies are attracted to the trap, they are captured on a 5-megapixel camera embedded into the trap's roof, which is connected to the processor affixed to the pole. The entire system is powered by a DC power supply that includes a rechargeable battery. A solar panel is affixed to the top of the pole, as illustrated in Fig. 7b, while a wireless antenna covers a vast area of approximately 300 m.

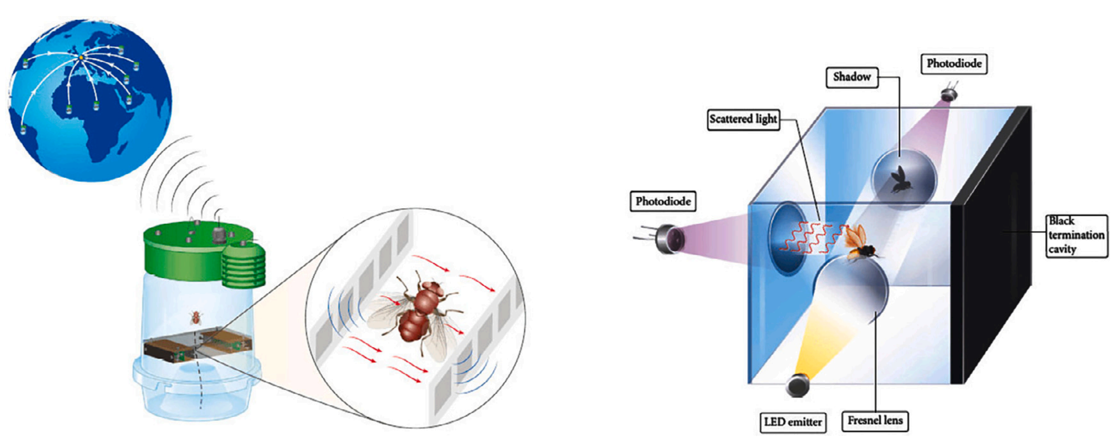
The second trap version, the yellow sticky (YS) e-trap, is made up of a rectangular yellow plastic surface widely used in monitoring pests that do not have specific chemical attractants [46]. These traps are frequently used to monitor adult fruit flies and as mass-trapping devices. The camera was held at an appropriate distance in order to capture the images of the attracted flies, as in Fig. 7c. A 5-megapixel camera was used, and the processor was powered by a rechargeable battery. In both trap versions, the nodes were formed by arranging the traps in the fields, and images were transmitted from the trap nodes to a central node.

Throughout the experiment, it was observed that the Medfly e-trap succeeded in recapturing up to 60% of the flies that were released, whereas the YS trap only recaptured 10%. The traps described in [46] were put into operation for 81 days, with field inspectors manually inspecting the traps for up to 17 days during this time period. The data obtained from the digital images revealed that there was a greater than 88% discrepancy between the number of fruit flies that were counted in the images and the number that the field inspectors reported for the same trap throughout the study.

Pérez-Aparicio et al. [48] developed an electronic insect trap that consisted of two modified 2.8-liter polypropylene food containers, as shown in Fig. 8. One container served as the cover to protect electronic components from varying weather conditions. The inner container box was used to attach electronic components at the top, and through a drilled hole at its center, a camera was positioned to take images of the sticky card lining on the other container. To drain water in case it rained, holes were drilled in each of the four corners of the lid's floor. Two windows were cut into the inner plastic container's two opposite walls, allowing flying insects to enter. The containers were built so that the top box slides over the bottom box. The power supply for powering electronic components was a solar panel, a lead acid battery, and a charge controller. On top of the trap, an extra metal plate was placed that provided further weatherproofing. The Raspberry Pi zero-WiFi board, an infrared camera, and a photoresistor sensor were mounted in the trap, as illustrated in Fig. 9.

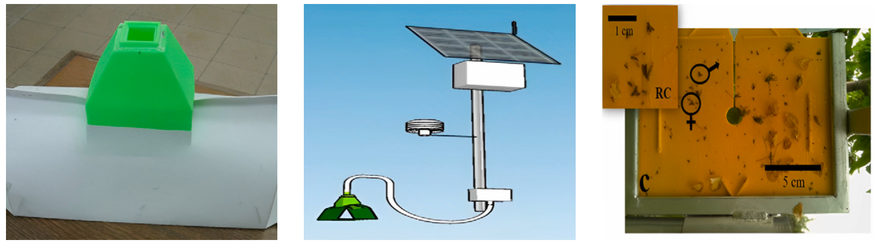
Doitsidis et al. [49] proposed an automated electronic McPhail trap with a custom design capable of capturing field pictures on a real-time basis. The proposed trap was designed for Bactrocera oleae (Gmelin), a fruit fly species that is a pest to olive fruits. The authors used a custom-made McPhail trap (shown in Fig. 10a) to overcome the disadvantages of the classical glass-type McPhail trap. The custom trap is a piece of yellow plastic that is split in order to increase the distance between the camera lens and the attractant for adequate focus, as shown in Fig. 10b. A 16-bit MS430F5436A ultra-low-power microcontroller was used to connect the peripheral. A 2.0-mega pixel camera was used to capture images in the trap; the images were stored locally on an SD card and also transmitted to the web server using the GSM network via the GPRS protocol. The proposed prototype of the automated trap was powered by a 12 V (7000 mAh) battery and operated sufficiently throughout the summer period in 2015. The block diagram in Fig. 10c shows the McPhail trap's embedded system.

Huang et al. [50] developed an automatic-driven electronic trap (e-trap) that is based on yellow sticky paper. The trap consists of an automatic motor-driving system embedded with a computer vision system. Fig. 11 shows a yellow sticky paper with added attractants exposed to capture or trap the insects. The newly captured insects on the paper are omitted by replacing the paper through motor rotation by the auto-control algorithm. The trap was operated in two (2) modes: monitoring mode and paper replacement mode. The monitoring mode involves sampling of images, insect density estimation, insect detection



(a) (b)

Fig. 6. (**a**) Pictorial layout of the wireless acoustic detection trap. (**b**) The bimodal sensor illustration [26].



(a) (b) (c)

Fig. 7. The Medfly e-trap and YS e-trap: (**a**) External construction of the medfly e-trap, (**b**) Mounting of the medfly e-trap, and (**c**) Mass trapping of adult fluit flies by YS e-trap [46].

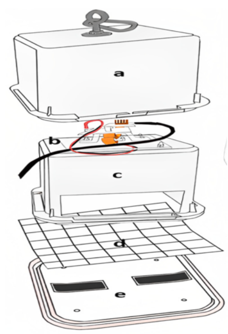


Fig. 8. The trap box [48]: (a) an outer plastic box to protect (b) electronic components board from different weather conditions, that slides through an inner container (c). The sticky card (d) is used to capture insects, and (e) is the lid at the bottom of the inner container.

and recognition, and data transmission to the remote server. While the paper replacement mode involves rolling the paper when the density reaches a limit. The trap begins in monitoring mode and then switches back and forth to paper replacement mode after successfully estimating insect density. Using the concept of a motorized sticky trap, Hadi et al. [51] also developed an automated trap that consisted of two primary components: the controller and the software part. The controller component consists of a control board, sensors, and actuators to regulate vertical and rotating movement. While the software component is responsible for creating and implementing the pest detection algorithm as well as managing the pest sampling detection (PSD) system's input and output.

The motorized sticky paper traps in [50] and [51] offer the following advantages: After making the necessary changes, adjustments, and evaluations, the PSD trap can be easily changed to catch different crop pests. On the other hand, the collection of high-quality images and real-time weather data is hampered by the trap's complicated mechanical structure, which necessitates proper merging when installing the new rolled stick paper [50]. Due to the rapid accumulation of dirt and dust on the sticky region described in [51], the number of insects that can be caught is severely restricted. Also, temperature, humidity, and rain near the trap cause additional curves on the sticky materials that produce noise.

Diller et al. in [52] developed an e-trap based on the McPhail trap to monitor the three major invasive fruit flies (*Bactrocera dorsalis*, *Bactrocera zonata*, and *Ceratitis capitata*). The developed trap consisted of a central cylinder, a cylinder's closing lid, and a battery box (capable of holding six rechargeable and easy-to-replace lithium ion batteries) that attaches to the sideways exterior of the cylinder as shown in Fig. 12a. Internally, the central cylinder is split into multiple lateral chambers that hold the hardware. In the central chamber, fruit flies entering the device are guided onto a yellow sticky board, where they stick and die, as seen in Fig. 12b. Methly Eugenol and Trimedlure were used as attractants for male Bactrocera and Ceratitis fruit flies, respectively, while Biolure was used as an attractant for female fruit flies, as shown in Fig. 12c. The trap sent two images each day and was activated twice daily, running for around 6–7 months without interruption on the power provided by six lithium batteries. The trap was deployed in five different

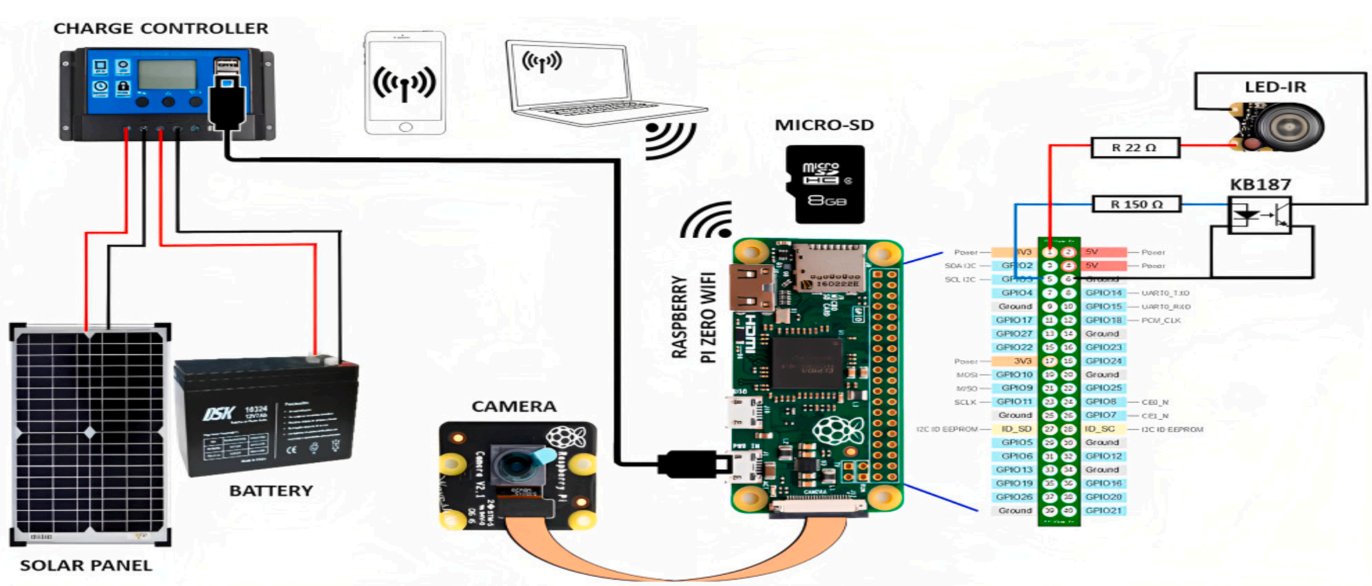
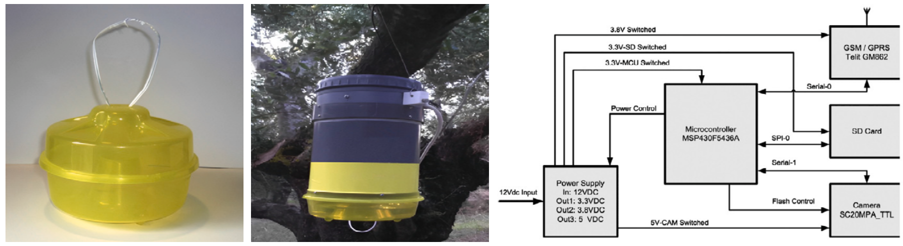


Fig. 9. The schematic representation of electronic components of the automated trap [48].



(a) (b) (c)

Fig. 10. Proposed automated McPhail electronic trap: (**a**) A custom made McPhail trap, (**b**) A modified McPhail electronic trap in the field, and (**c**) Block diagram of the overall McPhail trap's embedded system [49].

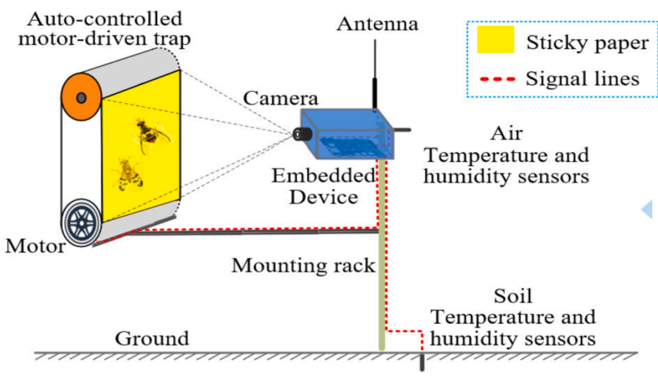


Fig. 11. The basic structure of the developed automatic-driven e-trap [50].

countries: Greece, Israel, South Africa, Italy, and Austria. During the deployment, there were no battery replacements or electronic malfunctions.

The electronic traps identified can therefore be categorized as acoustic-based, opto-electronic-based, and image-based traps. In these traps, sensors are responsible for collecting important insect parameters. Pest overlaps, failure to distinguish the targeted pests from other trapped insects, the attractant used to lure insects, and the replacement mechanism for the trap are the key difficulties with sensor-based trap systems, as identified by Muppala and Guruviah [53]. However, in an acoustic sensor-based trap, Mankin et al. [54] observes a challenge in distinguishing the insect's sound from the background noise.

A summary of the features of the discussed automatic traps is shown in Table 1.

Traditional traps and electronic or automatic traps are both used in the capture of fruit flies, but they differ significantly in their mechanisms and efficacy. Table 2 shows the comparison between the two approaches to the traps.

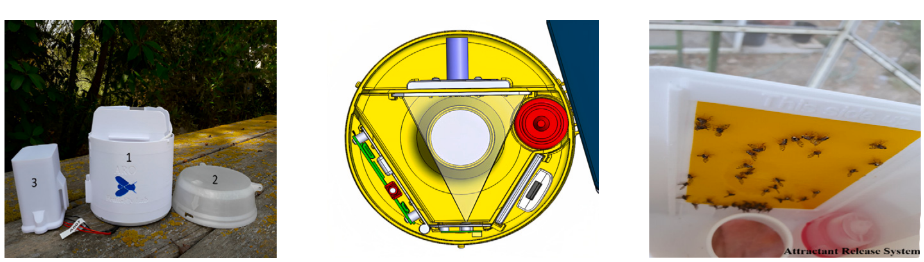
3. Insect detection and data transmission techniques

3.1. Insect detection and counting techniques

For fruit fly counting and detection, different approaches have been employed, from classical to modern methods. With opto-electronic sensor-based traps, insects have been identified through the application of classifiers such as support vector machines with radial basis functions (SVM-RBF) [55] and Bayesian classifiers [56]. The application of deep learning and machine learning models is also regarded as a significant approach in the detection of fruit flies in image sensor-based traps. In this section, the research that has employed models in image recognition is presented. The image recognition system employs software, making it a fully automated system that does not require a human operator [57].

Zhong et al. [21] developed a trapping system for the recognition and counting of flying insects using vision-based methods. The system involved setting up a camera that collected real-time images of insects trapped on a yellow sticky sheet, which were then interpreted using a detection system implemented on a Raspberry Pi computer. The detection method used in this system was YOLO (you only look once)-based object detection, while the classification and counting were based on SVM (support vector machine) using global features. Fig. 13 illustrates the block diagram of the recognition and counting system. The image acquisition block acquires a clear image, which is sent to the YOLO block for detection and course counting. The training set used in this study consisted of 10,000 manually labeled 30×30 pixel images. The feature extraction block uses mathematical tools to quantitatively describe a detected object, and in the final block, the SVM performs insect classification based on the extracted features and fine counting [58,59].

The authors [21] identified that images collected from a yellow sticky trap could be affected by light variations and contaminants such as dead leaves, insect excrement, mud spots, and water droplets. To address this issue, the authors used the YOLO deep learning model by Redmon et al. [60] a single convolutional network, which is capable of adapting to complex environments. In addition to being able to predict class probabilities and multiple bounding boxes simultaneously for



(a) (b) (c)

Fig. 12. The overall design of the McPhail-based electronic trap: (**a**) Three sections of the e-trap: (1) the central body cylinder, (2) the cylinder cover and (3) the batteries-box; (**b**) a 3D model of the top view showing the internal arrangement; and (**c**) the sticky trap board [52].

Table 1
Features of the developed electronic traps.

Trap	Control unit	Power supply	Physical construction	Communication module
Potamitis et al. [41]	Micro controller - MSP430F2132	3.7 V Lithium battery	-	-
Goldshtein et al. [42]	Raspberry Pi	12 V, 38 A Lead acid battery and solar voltaic cells	Cylindrical plastic	USB cellular modem
Hermosilla et al. [44]	Raspberry Pi 2	-	-	TP-Link Access point Router (TL-MR3040)
Shaked et al. [46]	Raspberry Pi, model B+	12 V, 24 Ah Lead acid battery	Jackson trap design (22 cm L×13 cm W×10 cm H)	WiFi/ZigBee
Sandrini Moraes et al. [43]	Computerized system [Intel (R) Core i5-3570M, 3.4 GHz processor]	-	McPhail trap design	-
Pérez-Aparicio et al. [48]	Raspberry Pi Zero	12 V, 7 Ah Lead acid battery	2.8 L Polypropylene box (15 cm×14.5 cm×15 cm)	WiFi
Doitsidis et al. [49]	16-bit ultra-low power Micro controller-MS430F5436A	12 V, 7000 mAh battery	McPhail trap design	GSM module (GM862)
Huang et al. [50]	NVIDIA Jetson Nano developer kit	12 V DC power	-	4 G wireless communication module (SIM 7600 CE-L)
Hadi et al. [51]	Raspberry Pi and Arduino	12 V DC power	Sticky box, Polystyrene plates (20 cm H× 25 cm W× 20 cm L)	-
Diller et al. [52]	Raspberry Pi Zero, v1.3	6-Lithium batteries (NCR 18650PF)	McPhail trap design	4 G USB dongle

object detection and recognition, the model is efficient due to its approach of processing the entire image during both training and testing. This sets it apart from methods such as sliding windows and regional proposals. Fig. 14 depicts the YOLO detection process, which involves (a) dividing the input image into S×S grids and (b) displaying predicted bounding boxes for objects whose centers fall within each grid. The images were labeled using the LabelImg-tool [61], and data augmentation techniques such as contrast adjustment, translation, image rotation, scaling, flipping, and noise addition were applied during deep network training to avoid overfitting. According to the experiment results, the detection and recognition cycle on the Raspberry Pi system took roughly 5 minutes, and the average counting accuracy and the average classifying accuracy were 92.5% and 90.18%, respectively [21].

Ramalingam et al. [30] developed a trap monitoring system based on computer vision. The system's challenge was the detection of smaller objects due to the limited appearance of insects in an image, which could lead to errors in the detection results. Extracting information from the image could lead to the loss of smaller objects when passing through multiple layers of the feature extractor [62]. Therefore, for accurate detection, an ideal feature extractor and detection algorithm are required. To perform the detection and classification of insects, the authors applied the Faster Region-Based Convolutional Neural Network

Table 2
Comparison of the traditional and electronic traps.

Trap	Mechanism	Accuracy and sensitivity	Monitoring
Traditional Traps	The traps typically rely on basic mechanical mechanisms, such as sticky boards, to capture flies lured by pheromones. They require manual setup and placement of bait.	Are not as sensitive or accurate as electronic traps.	They need regular inspections and maintenance. They also require manual checking to see if fruit flies have been captured, which is time-consuming and labor-intensive.
Electronic Traps	Utilize the integration of sensors with pheromones to detect the presence of flies and capture them. They also require a power source for their mechanisms.	Are often equipped with sensors to detect and respond to flies with precision. They are also capable of differentiating between fruit flies and other objects, reducing the chances of false triggers and detection.	They can be linked with additional features, like smartphone connectivity, to notify farmers about fruit flies captured. Which leads to less frequent maintenance and monitoring compared to traditional traps.

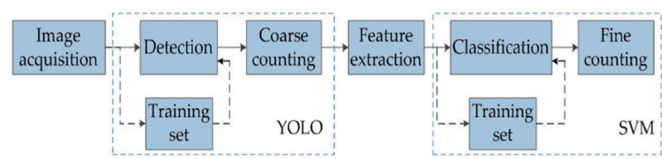


Fig. 13. Detection process using the YOLO-model: (a) an input image divided into grids of equal size; (b) predicted (B) bounding boxes of the grid; (c) class probability, (d) output YOLO object detection [60].

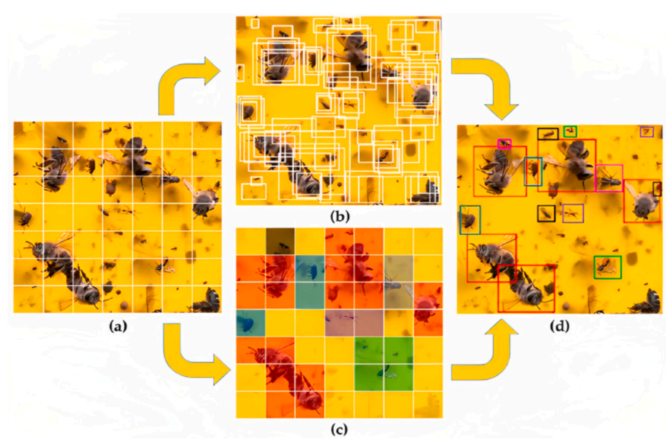


Fig. 14. Block diagram of a counting and recognition system for flying insects [21].

by Ren et al. [63], a two-stage object detector framework. For feature extraction tasks, a pre-trained deep CNN algorithm called ResNet50 by He et al. [64] was applied that generated 1024 feature maps.

Fig. 15 illustrates the feature extraction stage, which involves a 7×7 convolution, rectified linear unit (ReLu), batch normalization (BN), and a maxi-pooling operation, followed by four stages containing residual and identity blocks. The residual block is made up of three convolution layers (i.e., 1×1, 3×3, 1×1) with batch normalization and skip

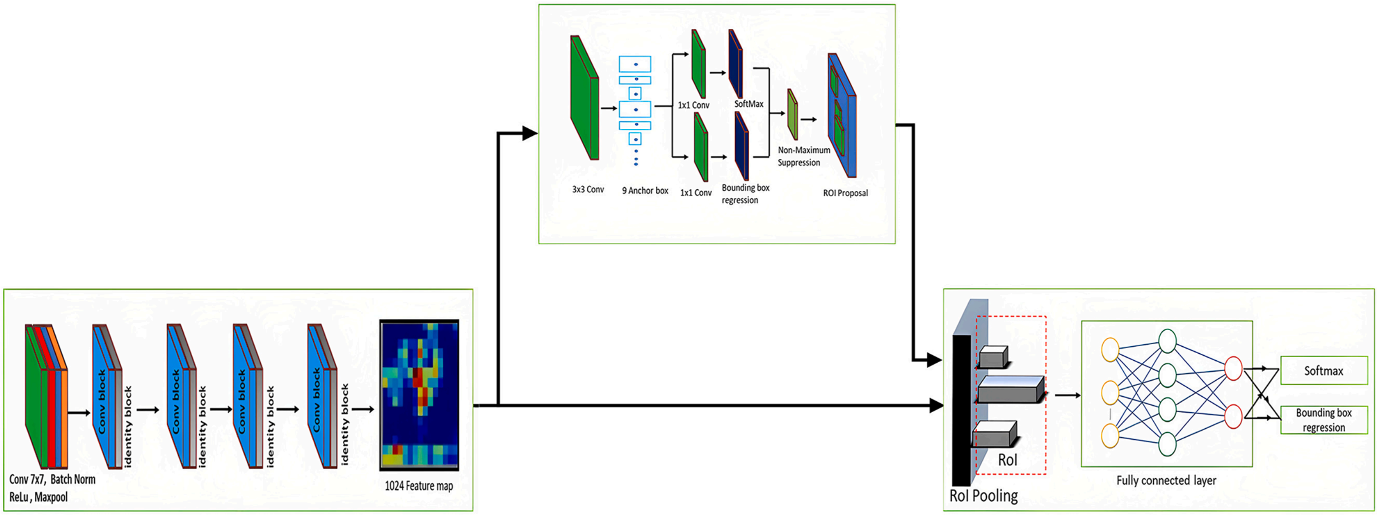


Fig. 15. Faster-RCNN ResNet architecture [30].

connection with 1×1 convolution operation. The fifth stage's output is a feature map of size 1024, which is passed as input to both the Fast RCNN detection network and the region proposal network (RPN) module. The proposal generation process is followed by the use of non-maximum suppression to filter out overlapping boxes. The detection network comprises a region of interest (ROI) pooling layer and a fully connected layer, which takes in the proposals generated by the RPN and shared convolutional features. The ROI pooling layer generates a fixed-size feature map for each RPN-generated proposal. Finally, a second round of non-maximum suppression is performed to eliminate redundant bounding boxes and ensure accurate object localization.

The insect detection model in [30] was developed using TensorFlow 1.9 and trained on a GPU-enabled workstation. In training the Faster-RCNN model, the Stochastic Gradient Descent (SGD) algorithm was used with a batch size of 1, a momentum of 0.9, and an initial learning rate of 0.0002. The model achieved 94% accuracy in detecting insects in farm fields using a Trek AI-ball Wi-Fi-enabled camera and 150 images per class from the insect image database.

Mamdouh and Khattab [23] proposed a model to detect and count olive fruit flies that were captured in smart traps deployed across the olive farm. The proposed model was a deep learning-based algorithm (YOLOv4); however, because fruit flies are small in size, the algorithm could not be applied directly to the problem. Fig. 16 shows the olive fruit fly detection framework designed to be accurate and computationally inexpensive in the detection of only one class, the olive fly. The Dacus Image Recognition Toolkit (DIRT) [65] was utilized as the input dataset, which contains images with a dataset size of 848 images. An entomologist used the LabelImg tool to hand label the photos of fruit flies. Only the floating flies were tagged, leaving the identifiable submerged individuals and clustered flies unlabeled. Because the flies were trapped using liquid pheromone, they were able to float in the liquid. As a result, the acquired images are referred to as "soup images" [23].

The authors used non-target objects (i.e., insects other than the target olive fruit fly) as negative samples to reduce false alarm rates during the training of the deep neural network. The neural network was trained to identify them as the background.

Fig. 17 shows DIRT photos that experience brightness changes due to variations in illumination caused by differences in sunlight intensity and object shadow within the camera and trap. Consequently, bright sections have high pixel values, while dim parts have low pixel values. This large disparity in pixel values may prevent the learning process from reaching the optimal point [65]. The traps are yellow to attract olive fruit flies; however, the values of red and green pixels increase as sunlight intensity increases. To address this issue, the authors proposed a framework that normalizes the input dataset with the yellow mean color in the pre-processing stage before detection. This is done by summing the means of the red and green channels. Following the normalization using the yellow mean color in Equation (1), the authors observed a decrease in pixel values, resulting in more centered values [23].

$$\mu_{Yellow} = \mu_{red} + \mu_{green} \tag{1}$$

Where; μ_{Yellow} is yellow mean color normalization, μ_{red} red mean channel, and μ_{green} green mean channel.

(a) (b)

Fig. 17. Sample images from the DIRT dataset [65].

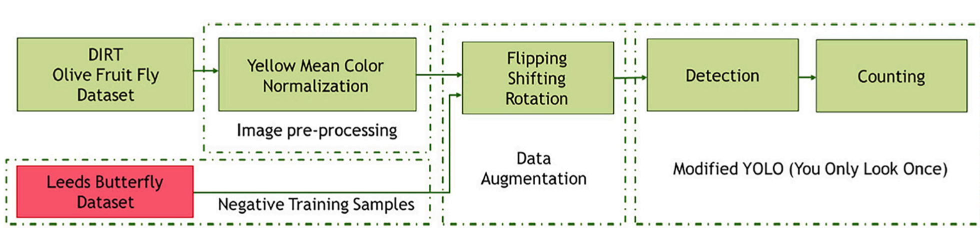


Fig. 16. The proposed olive fruit fly detection framework [23].

To expand the dataset size and prevent over-fitting, data augmentation techniques were employed as described by Xia et al. [22]. These techniques consisted of rotating DIRT dataset images by (90°, 180° and 270°), as well as flipping them along vertical and horizontal axes and shifting them in the horizontal and vertical axes' positive and negative directions. This resulted in a dataset of 11,872 images, a significant increase from the original 848 images in the DIRT dataset. Following the augmentation, the dataset was randomly divided into three sets: 80% for training, 10% for validation, and 10% for testing. In addition, negative samples from the Leeds butterfly dataset were incorporated to further expand the dataset [22].

In the detection stage, the authors used the YOLO-based algorithm YOLOv4 [66] for fast training and accurate detection. The network is composed of three components: the head, which is YOLOv3 [67] responsible for object detection; the other two components are the neck, which is the Path Aggregation Network (PANet) [68], a group of layers that collects feature maps from different stages, and the backbone, which is Darknet-53 [67] a full convolutional neural network responsible for feature extraction. The proposed framework had significant improvements in the performance metrics, such that the mean average precision was 96.68%, recall was 97%, and F1-score was 90%. The framework achieved much better performance compared to the YOLO baseline. The authors acknowledged a limitation of their work in that the file size of their proposed model was relatively large, at 245 MB, which may make it unsuitable for deployment on embedded devices.

In their work, Xia et al. [22] a convolutional neural network (CNN) model was developed for the detection and classification of insects. The model was structured into two stages. In the first stage, a combination of the regional proposal network (RPN) [63] and a very deep neural network (VGG19) [69] was employed. This stage aimed to capture highly abstracted information and learn the insects' locations in the images. In the second stage, feature maps were reshaped to a uniform size and transformed into a one-dimensional vector to enable insect classification. Fig. 18 presents the VGG19 model, an enhanced CNN architecture with a self-learning approach to local image feature progression from low to high level, as described by Simonyan and Zisserman [69]. In order to extract features, the initial 16 convolution layers of this architecture were employed. To make recommendations on the locations of insects based on the feature map and minimize the impact of extraneous backgrounds on classification results, the regional proposal network (RPN) was included in the first 16 layers of the architecture, as proposed by Xia et al. [22]. As described by Ren et al. [63], the regional proposal network (RPN) is a fully convolutional network that can process images of any size as input and generate a series of rectangular object proposals, each with an objectness score. To generate high-quality regional proposals, a small network is slid over the convolutional feature map produced by the last shared convolutional layer by the RPN. The network architecture comprises an $n \times n$ convolutional layer followed by two fully connected layers: the box-classification layer (*cls*) and the bounding box regression layer (*reg*), as depicted in Fig. 19.

Applying the learning rate of 0.001 and 160,000 iterations, the proposed model's performance was compared to the state-of-the-art methods, which include the single-shot multibox detector (SSD) and the fast region-based convolutional neural network (Fast RCNN). As shown in Table 3, the proposed method had a better mean average precision compared to the other methods.

In their study, Ren et al. [70] proposed a straightforward framework for insect pest recognition using a variant of the residual block, referred to as the "feature-reuse residual block." This block merges the features from the input signal of the residual block with the residual signal, resulting in a feature reuse residual network (FR-ResNet) when combined. The researchers assessed the network's effectiveness on the IP102 dataset, which revealed an enhanced capacity for insect pest classification.

The proposed network originates from the original block, whose identity mapping is expressed by Equations (2) and (3):

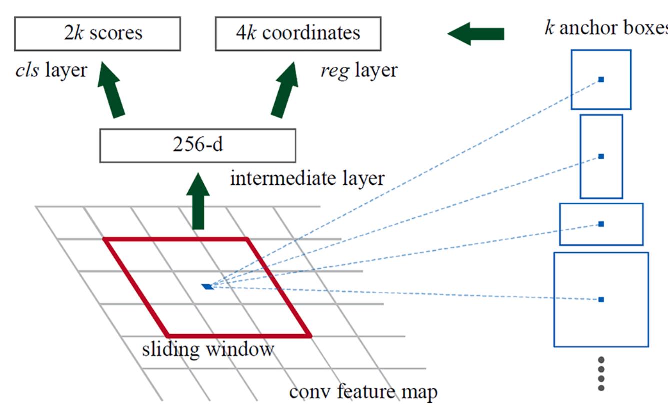


Fig. 19. Regional proposal network (RPN) [22].

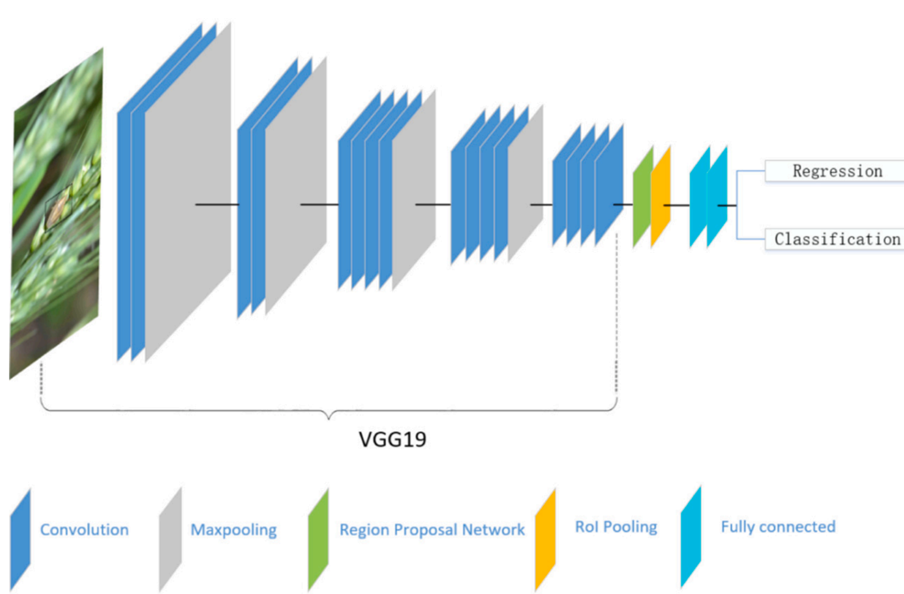


Fig. 18. The proposed schematic structure of the VGG19 detection model [22].

Table 3
Experimental performance metrics comparison [22].

Method	Number of iterations	Training time (h)	Inference time (S)/per image	Mean avg. precision (mAP)
Fast RCNN	60,000	70.1	0.195	0.7964
SSD	30,000	38.4	0.120	0.8534
Proposed method [22]	-	11.2	0.083	0.8922

$$y_l = h(x_l) + F(x_l, w_l) \tag{2}$$

$$x_{l+1} = f(y_l) \tag{3}$$

Where x_l and x_{l+1} are input and output of the l-th residual block in the network, F represents a residual function, and w_l parameters of the l-th residual block. The identity mapping is denoted by the function $h(x_l)$, while f denotes a rectified linear activation unit (ReLU) function. The original residual block in Fig. 20 (a) is constructed as form of two successive 3×3 convolutional layers. Through stacking of the residual blocks, residual networks can be constructed as shown in Fig. 20 (b). The proposed feature reuse residual block is denoted by the Equations (4) and (5):

$$y_l = h(x_l) + F(g(x_l), w_l) o g(x_l) \tag{4}$$

$$x_{l+1} = f(y_l) \tag{5}$$

Where g is the function that transforms the feature map size and dimensions, which is realized by a 1×1 convolutional layer without ReLU.

The proposed algorithm by Ren et al. [70] was tested on the IP102 data set, an insect pest data set that contains over 75,000 images covering 102 species of insect pests. Table 3 shows the F1-score and accuracy of FR-ResNet compared with other state-of-the-art methods: AlexNet, ResNet-50, ResNet-101, Googlenet [71], VGG-16 [69], and DenseNet-121 [72].

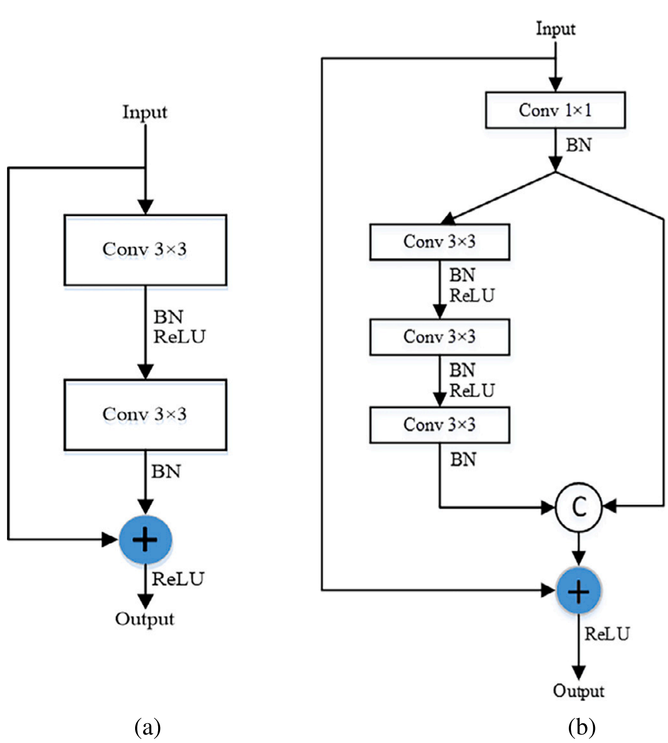


Fig. 20. Structures of the original residual block and feature-reuse residual network: (**a**) The original residual block and (**b**) Feature reuse residual network [65].

From Table 4, the proposed 34-layer FR-ResNet had 54.18% F1-score on the test set and a test accuracy of 55.24% outperforming the rest of the state-of-the-art methods. Despite the better accuracy of the proposed method, the classification performance of the IP102 dataset by FR-ResNet was affected by the color similarity between the objects (pests) and the background of the pest images [70].

Peng et al. [73] addressed the issue of image background complexity by proposing an innovative approach to enhance the performance of convolutional neural network (CNN). The proposed method involved replacing the softmax classifier with an SVM to achieve accurate fruit fly image classification with complex backgrounds. The objective was to eliminate the need for manual feature extraction from these images. By adopting this strategy, the authors demonstrated the effectiveness of their method in improving the classification of fruit fly images with complex backgrounds. The proposed method introduced a combined approach that incorporated CNN and SVM, as illustrated in Fig. 21. The CNN was utilized to automatically extract effective image pixels as features, while the SVM was employed to classify the images. Due to the diverse and complex nature of the backgrounds in images containing fruit flies, feature extraction can be challenging. To overcome this difficulty, the authors proposed increasing the number of CNN layers. Equation (6) shows the function of the convolution layer, wherein the weight of the layer is denoted by W, the activation function is denoted by σ, the preceding convolution layer's output is denoted by X, and a bias is denoted by b.

$$A = \sigma(Z) = \sigma\left(W^T \times X + b\right) \tag{6}$$

The features extracted by the convolution process were sampled using the maximum pooling method in the pooling layer, resulting in reduced computational complexity and overfitting during forward propagation. Equation (7) is used to calculate the loss function.

$$J(W, b) = \frac{1}{m} \sum_{i=1}^{m} L\left(\hat{y}^i, y^i\right) \tag{7}$$

Where, the convolution kernel weight vector is denoted by W, while the offset is represented by b. The final output is represented by $\hat{y}^i$, the real value is represented by y^i, and the loss function is denoted by L.

The support vector machine is a powerful technique for supervised learning that uses a linear function of the form $\omega^T x + b$, similar to logistic regression [74]. The application of SVM to image recognition has yielded impressive results without significantly increasing computational complexity. This method is capable of handling non-linear problems, and by using a kernel function, it can map low-dimensional data to high-dimensional data. In their work, the authors employed the Gaussian kernel function as an SVM classifier, as expressed mathematically in Equation (8).

$$k(x_1, x_2) = \exp\left\{ -\frac{||x_1 - x_2||^2}{2\sigma^2} \right\}, \sigma > 0 \tag{8}$$

Where, the center of the kernel function is denoted by x_2, while the parameter that governs the radial range of the function is represented by σ.

Table 4
Comparison of the test performance on IP102 data set [70].

Method	F1-Score (%)	Accuracy (%)
AlexNet	48.22	49.41
VGG-16	51.20	51.84
Googlenet	51.24	52.17
ResNet-101	52.00	53.07
ResNet-50	52.93	54.19
DenseNet-121	52.97	54.59
Proposed FR-ResNet [70]	54.18	55.24

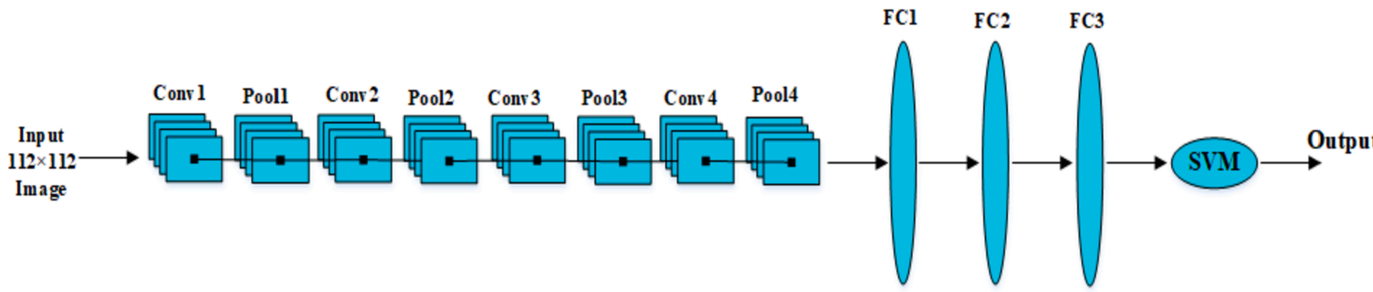


Fig. 21. The proposed fruit fly complex background image classification model structure [73].

The proposed model, illustrated in Fig. 21, comprises an input layer that receives a 112×112 three-channel image, four convolutional layers, four pooled layers, and three fully connected layers. The kernel size for the convolutional layers is 3×3, with 32, 64, 64, and 128 filters, respectively. The fully connected (FC) layers consist of 512, 256, and 4 neurons. The Tensorflow deep learning framework was used to implement the proposed model, which was run on a system with an Intel Core i7-6700 processor, 8 GB of memory, and a 64-bit Windows 7 operating system. Prior to the experiment, the dataset underwent preprocessing to expand its size. This involved adjusting the image rotation, brightness, and darkness to prevent overfitting due to the small size of the training samples. The model was trained to classify images of four fruit fly species with complex backgrounds. A comparison was conducted between the proposed model and other models (CNN, CNN-KNN, CNN-AdaBoost, and CNN-RF), revealing that the proposed method achieved a higher accuracy of 92.04% compared to the other models.

Roosjen et al. [75] developed a trap monitoring system that employs deep learning-based image object detection to identify spotted wing drosophila (SWD) that attack soft-skinned fruits. The proposed model is based on ResNet-18 [64], which generates only a single classification output per image. In order to generate a regular grid prediction for a low-resolution trap image, the final layers of the model were replaced with two 1×1 convolutional layers, rectified linear unit non-linearities, a 50% dropout probability, and a final softmax activation. This transformation allowed the model to convert the 512-dimensional feature vectors of the base ResNet output (which represents the last residual block) into an intermediate tensor with 1024 dimensions. By doing so, the model was converted into a fully convolutional network, which preserved spatial predictions. Using a compact camera with 20 MP resolution, images were captured at a distance of 50–80 cm from a horizontally arranged trap under various illumination conditions. The purpose of this was to develop a robust algorithm that would function not only under laboratory conditions but also in the real world and could detect whether an insect was male or female. In total, 249 images were collected and then randomly divided: for the training set, 70% were allocated, while for the validation set and the test set, 20% and 10% were allocated, respectively. The images of the trapped insects were labeled by an expert using the LabelImg-tool [61], by drawing rectangular bounding boxes as shown in Fig. 22 (b).

To increase the training set, augmentation methods were employed through horizontal and vertical flips and multiples of 90°-stop rotations of the images. For the 300 epochs, the learning rate was tuned to 10^{-5} for the first 50 epochs and 10^{-6} for the remaining 250 epochs. The results obtained when not considering the sex of the insects had a recall of 0.82.

An automatic algorithm for insect detection and recognition using deep learning was proposed by Rustia et al. [76]. The algorithm leveraged CNN object detection to identify insect objects within images and filter out non-insect objects. The monitoring system employed a wireless-based system with multiple Wi-Fi-connected imaging nodes. The goal of the algorithm was to classify objects within images as either insects or non-insects, with a particular focus on identifying four insect pest species that impact greenhouse fruits, including tomato plants. These insect species include thrips, gnats, whiteflies, and flies.


(a) (b)

Fig. 22. Image of attracted insects on a sticky board: (**a**) Training-set images and (**b**) Labeled ground truth bounding boxes [75].

The wireless imaging node shown in Fig. 23 transmits acquired images to a remote server via the internet for batch processing. The detection and recognition algorithm processes each image using an object detector based on YOLOv3 to obtain bounding coordinates. Insect objects are counted, while non-insect objects are ignored. To make the images separable into equal parts [76], the RGB images (3,280×2,464) are resized using cubic interpolation to (3,200×2,400). The resized

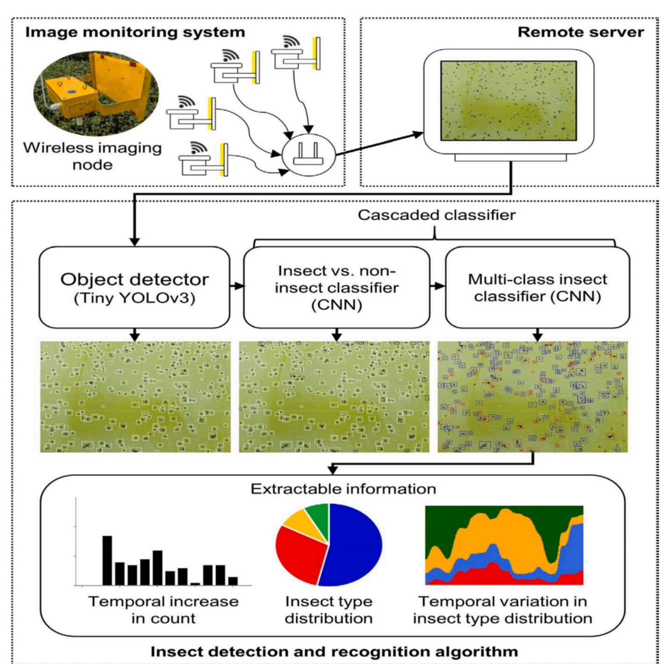


Fig. 23. The proposed system for insect detection and recognition [76].

image is then divided into 12 images of 840×840 resolution to reduce the size of the object detector input image and facilitate detection of small objects. Each of the tiled images is resized into 416×416 images and treated as individual inputs to the object detector model (i.e., tiny YOLOv3). Non-maximum suppression (NMS) is applied to each tiled image to remove candidate bounding boxes. The NMS threshold ranges from 0 to 1, and higher values lead to fewer boxes retained, while lower values result in more retained boxes.

The original image is first cropped using box coordinates obtained from the object detector during the cascaded classifier stage. The resulting cropped images are then resized using cubic interpolation to a size of 128×128. This size was chosen because it is the average size of insects found on sticky paper trap images.

Fig. 24 illustrates the image classifier, which comprises three convolutional layers (CL) and a maximum pooling layer at both ends to extract features from the 128×128 input image's raw RGB pixel values. A fully connected layer (FCL) with rectified linear units (ReLU) is used to obtain deep features from the extracted features, followed by the application of the softmax layer (SL) to determine the prediction probability for each class. The predetermined classification threshold is ultimately used to determine the image's class based on the prediction probabilities.

3.2. IoT communication technologies in fruit fly monitoring

The presence of the internet allows objects and machines to connect and communicate through the Internet of Things. To gather information, various types of sensors are employed, and the collected data is analyzed by a local processor, which then stores relevant data in local storage while discarding unnecessary data. The stored information is then sent to the cloud or remote server through different communication technologies such as Bluetooth, ZigBee, Wi-Fi, and long-range radio (LoRa) for appropriate actions [80]. The application of IoT is vast, encompassing various sectors such as healthcare, transportation, smart homes, industrial automation, and smart agriculture [81,82]. Insect traps are among the systems that can be remotely monitored using wireless communication technology, which allows field trips to be avoided or postponed [38]. Table 5 outlines the essential features of IoT-enabled trapping systems.

Ramalingam et al. [30] proposed a system that utilizes an Internet of Things (IoT) application to monitor insects. The system, illustrated in Fig. 25, was built using a four-layer IoT architecture that includes the perception, transport, processing, and application layers. To capture images of the insects, a camera (an image sensor) was installed in the perception layer. This camera is a small, low-energy device equipped with Wi-Fi that sends the images to the processing layer through the transport layer for remote monitoring and identification. The transport layer connects all the IoT devices (image sensors) from all perception layers, which are then processed using detection and classification algorithms in the processing layer. Finally, the application layer delivers information about the insect trap's status to the user.

Liao et al. [77] developed an autonomous system for monitoring the oriental fruit fly, also known as *B. dorsalis*, using two wireless protocols, namely GSM and ZigBee. The proposed system, depicted in Fig. 26,

Table 5
Features of the remote communication-enabled trapping system.

Author	Communication protocols	Transmitted parameters	Operation mode	Additional features
Ramalingam et al. [30]	WiFi	Insect images	Fully-automated and real-time	-
Liao et al. [77]	ZigBee, GSM	Relative humidity, Temperature, illumination, number of captured fruit flies	Fully-automated real-time early warning system	Capable of providing sensor fault warning message
Potamitis et al. [27]	GPRS	Wingbeat recordings, humidity, temperature, GPS tag	Fully-automated	-
Shaked et al. [46]	WiFi, ZigBee	Images of captured insects	Fully-automated and real-time	-
Rustia and Lin [78]	WiFi / 4G	Insect pest count, temperature, pressure, humidity, light intensity	Fully-automated and real-time	-
Doitsidis et al. [49]	GSM-GPRS	Images	Fully-automated and real-time	The system was able to send out early warnings in the event of suddenly rising pest populations
Ünlü et al. [79]	GPRS	Images	Semi-automated and real-time	-

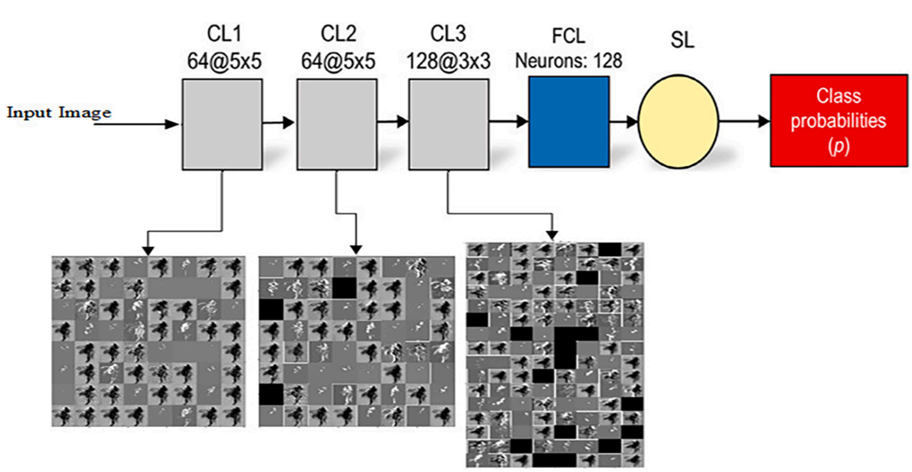


Fig. 24. The proposed image classifier structure [76].

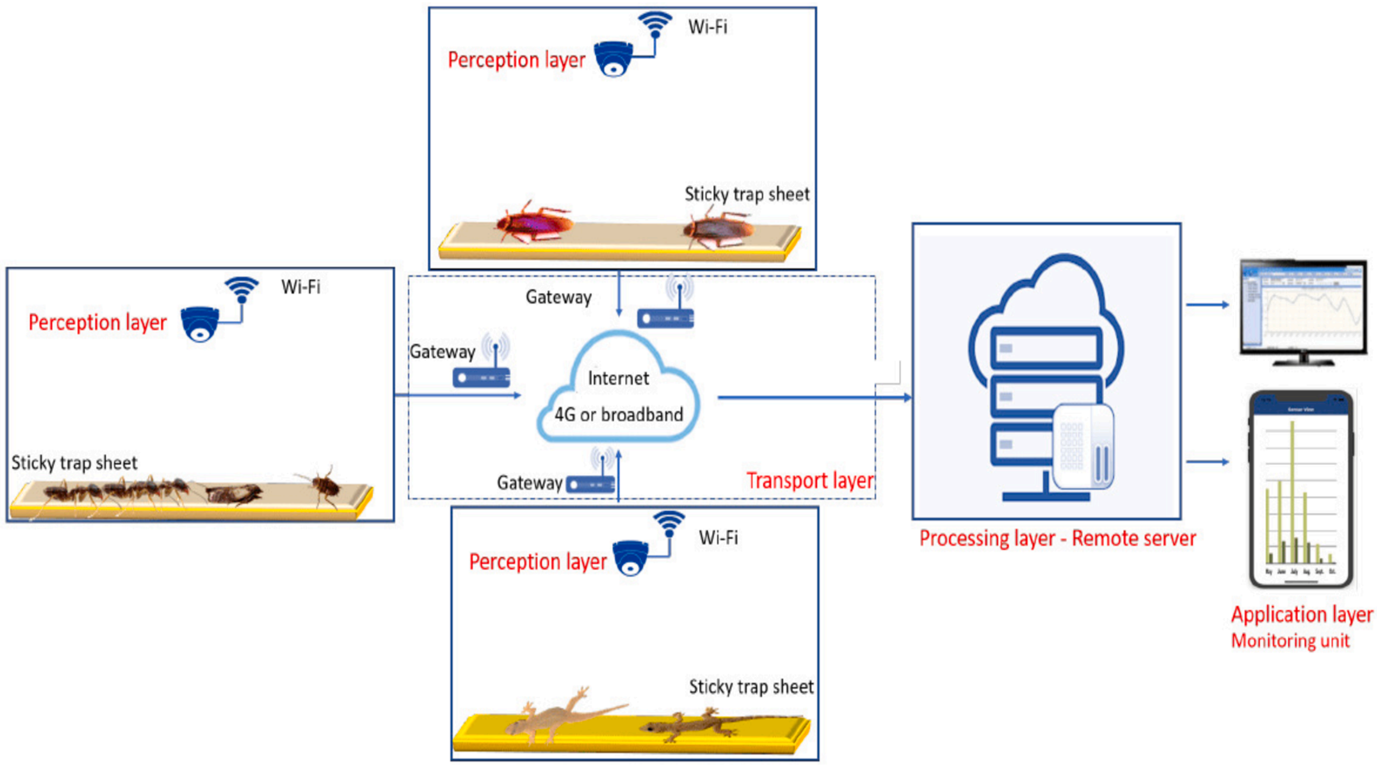


Fig. 25. Overview of Internet of Things (IoT) based insect detection system [30].

comprised three main components, namely remote sensing information gateways (RSIGs), wireless monitoring nodes (WMNs), and host control platforms (HCPs). Ten (10) WMNs were installed in the fruit orchard to collect data on the number of fruit flies counted and meteorological parameters such as temperature and humidity. The data collected by the WMNs was transmitted to the RSIG through ZigBee using the maximum radio power of 1 mW. After every 30 minutes, the information from all WMNs was aggregated and sent to the HCP through GSM. All the data collected by the system was stored in the HCP and made publicly accessible. The proposed system was capable of classifying information in the form of event types, that is, normal status events, pest outbreak events, and fault sensor events. Potamitis et al. in [27] applied IoT in delivering the collected data remotely. The transmitted data included insect counts and time stamps when entering the traps, as well as environmental data (i.e., humidity and temperature). The gathered information was transmitted to the web server using a GPRS modem for internet connectivity.

Shaked et al. in [46] identified the importance of selecting a suitable network topology when deploying traps, depending on the local constraints. In cases where the landscape permitted it, the nodes (i.e., traps) were arranged in a star topology, with the coordinator node (i.e., router) placed at the center. This arrangement allowed the furthest node in the topology to be reached, and communication between the trap nodes and the coordinator node was established using the Wi-Fi protocol based on a star topology and the ZigBee protocol for a mesh topology. To upload the collected images to the server, cellular communication (3G) was used. It was observed that the transmission efficacy of clear images was above 90%, indicating good image transmission and reception quality.

4. Discussion

4.1. Discussion on electronic traps

The impact of technology on the approach to fruit fly monitoring is disruptive, as evident from the development of electronic traps (e-traps) that are capable of continuously monitoring pests in real-time, thereby replacing traditional trapping techniques that rely on manual

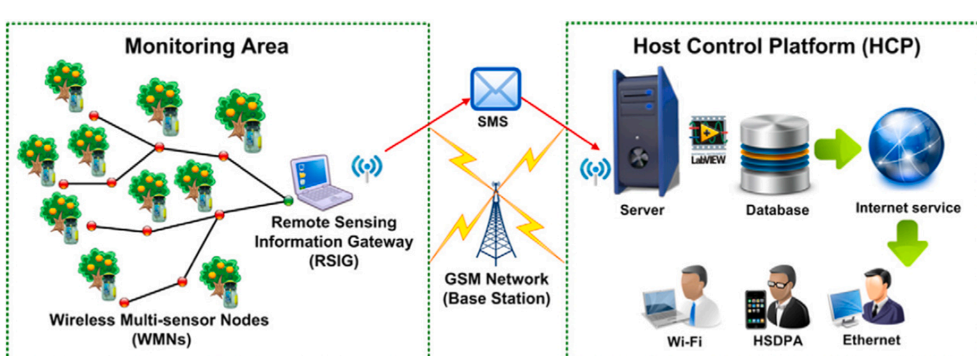


Fig. 26. The proposed autonomous monitoring system for Bactrocera dorsalis (Hendel) [77].

inspections. An electronic trap can be fully or semi-automatic. According to [83], a fully automatic trap involves insect counting inside the trap, while a semi-automatic trap sends the captured data to the remote server via wireless communication, where the counting will be performed by a human expert. These traps are targeted in areas with high insect activity, reducing the need for excessive insecticide use. The difficulties encountered in detecting and monitoring fruit flies using e-traps can be divided into four (4) categories: difficulties related to image acquisition, detection models, field conditions, and insects themselves. Infrared sensors cannot work properly during the day due to sunlight interference, and acoustic sensors may pick up the surrounding sound, leading to false counting of the flies in the trap. In their review, Barbedo [84] identified weaknesses in the state-of-the-art of pest monitoring using image sensor-based techniques. The camera captures images under low illumination conditions, with variation in the background of captured images, overlapping of insects, and visual similarities of insects with other species.

A significant challenge with insect traps is that they become excessively crowded with insects over time, which leads to the overlapping of insects. This affects the performance of detection models; therefore, frequent replacement of the trap is required to ensure the captured data is reliable. However, the task of replacing traps may require time and manpower resources, posing another challenge to monitoring. To address the challenge of insect overlap in captured images, a potential solution could involve automated replacement of the trap as soon as it reaches its maximum insect capacity. The automatic approach can be used by integrating pheromone, insect-triggering sensors, image acquisition (camera), and recognition models into the trap. The pheromone attracts the insect towards the trap; upon entering the trap, insect-triggering sensors will activate the camera using the insect's properties (i.e., wing vibrations). The camera facing the rotating base will be triggered to capture images and videos of the trapped insects (fruit flies). Image acquisition can be specified either by time interval or number of flies trapped. To avoid the accumulation and overlapping of the trapped flies, after every image capture, the rotating base driven by a small servo motor will flip to remove the flies for the next image acquisition. This approach will reduce the number of trapped insects that are closely clustered and provide a more comprehensive method for managing pests. Table 6 shows a summary of the strengths and weaknesses of the identified electronic sensor-based traps.

Table 6
Summary of the strengths and limitation of the traps.

Author	Trap	Strength	Limitation
Potamitis et al. [41]	Opto-electronic sensor-based McPhail trap	The opto-electronic sensor was capable of sensing the wingbeats of several insects.	The trap cannot operate in artificial light since the sensors are prone to picking up interference.
Doitsidis et al. [49]	Image sensor-based trap	Extremely low power consumption, low cost, and fault-tolerant trapping system able to operate for extended periods without human intervention.	Potential electromagnetic interference was caused by various installed electronic components.
Goldshtein et al. [42]	Opto-electronic sensor-based	Excellent at detecting small fruit flies.	Over-counting of insects due to intrusion of unwanted or non-targeted insects.
Potamitis et al. [26]	Bimodal optical sensor-based	Good detection accuracy,with an average of 0.99 for precision, recall, and F1-score.	The LED and photo-diodes require placement at a specific focal point, making the construction of the trap bulkier. Trap placement under bright sunlight results in over-amplification of the photodiodes' current.
Shaked et al. [46]	Image sensor-based trap	Excellent capability in the transmission of real-time images of the trapped flies. High specificity for trapping different fruit fly species.	-
Sandrini Moraes et al. [43]	Opto-electronic sensor-based trap	-	The system had higher power consumption.
Hermosilla et al. [44]	Acoustic sensor-based trap	-	Effective detection and counting in laboratory conditions. The components used are of broad purpose and overdimensioned.
Pérez-Aparicio et al. [48]	Image sensor-based trap	Good resistance to standard weather and a higher time resolution.	The traps had a large power supply unit and were made of non-ultraviolet-resistant plastic containers that degraded after a certain period of time, necessitating a field visit to collect the captured images.
Diller et al. [52]	Image sensor-based trap	In the field, the trap could identify and count three different kinds of adult fruit flies.	Flies can be misclassified due to the way they land on the sticky board. During high fruit fly infestations, the sticky board may become oversaturated, necessitating frequent servicing and replacement.

4.2. Discussion on insect detection and data transmission techniques

The application of deep learning and machine learning models has become increasingly prominent in the detection and counting of fruit flies in image electronic traps. Based on the reviewed articles, it has been observed that object recognition models encounter challenges in the detection and classification of fruit flies. The two commonly used evaluation metrics, accuracy and mean average precision, were applied in assessing the performance of the proposed models. Accuracy measures the proportion of correctly classified instances out of the total number of instances, while mean average precision is the measure of accuracy of the model's performance across all classes.

Table 7 shows the comparison of object detection and counting algorithms that have been implemented in fruit fly recognition.

The YOLO model [60] that has gained significant attention in the field of computer vision since its release in 2016 has shown promising results. The model with its updated versions has been adopted in studies that involve fruit fly monitoring [21,23,76] presenting a better performance in counting and classification with an average accuracy of 90%. While the experimental result of the proposed model Faster RCNN-ResNet50 by Ramalingam et al. [30] had an accuracy of 94% that was applied in the detection of built environment insects and farm field insects.

There were several challenges encountered during the implementation of the proposed models. The model proposed by Ren et al. [70] demonstrated an improved accuracy of 54.73% compared to the tested models. However, the model's performance was affected, leading to errors primarily due to the inherent difficulty in accurately identifying and distinguishing the objects from the image background. This difficulty arises specifically because of the color similarities between the objects and the background. To address this challenge, it is necessary to

Table 7
Comparison of detection and counting algorithms for fruit flies.

Author	Method	Accuracy (%)	mean Average Precision (mAP) (%)
Zhong et al. [21]	YOLO-SVM	Counting - 92.5, Classification- 90.18	-
Ramalingam et al. [30]	Faster RCNN-ResNet 50	94	-
Mamdouh and Khattab [23]	YOLOv4	-	96.68
Xia et al. [22]	VGG19-RPN	-	89.22
Ren et al. [70]	FR-ResNet	54.73	-
Peng et al. [73]	CNN-SVM	92.04	-
Roosjen et al. [75]	ResNet-18	-	-
Rustia et al. [76]	YOLOv3	Counting - 90	-

carefully set up the background to ensure clear visibility of the captured insects' details. Additionally, adding a pre-processing stage could further refine the features of the captured objects (i.e., insects) before proceeding to the recognition stage. The model proposed by Peng et al. [73] had a better accuracy 92.04%, and addressed the issue of complex background. The model was capable of identifying the insects under the complex conditions; however, the color similarity of the image background and fruit fly affected the model's performance. To address this challenge, the authors proposed separating the object (a fruit fly) from the background before further classification. Images captured under background interference, the presence of shadows, and illumination inconsistencies may contribute to the poor performance of the model. These challenges can be reduced by selecting the best time of day to capture images and avoiding the positioning of the traps under trees.

There is a clear demand for the development of models that can address the challenges arising from the limited availability of training datasets specific to fruit flies and the need for optimal detection of small objects, such as small insects. One potential approach to tackling this issue is the utilization of data augmentation methods, which can artificially expand the size and diversity of the training dataset. By employing augmentation techniques, the training dataset becomes more varied, thereby aiding the object detection model in generalizing better to the potential variations it may encounter during inference. This augmentation process has several benefits, including improving the model's robustness, reducing overfitting, and enhancing its ability to handle diverse object appearances, orientations, and backgrounds. When it comes to small-sized insects like fruit flies captured in images, they occupy a specific region with only a few pixels, resulting in a lack of information that accurately represents the insect. This scarcity of pixel information poses a challenge in distinguishing the insect from the background, particularly in scenarios involving multi-class classification, where the model may struggle to differentiate between the classes. The developed models should be capable of effectively identifying small objects like fruit flies while operating with limited datasets, especially in cases where insect-specific datasets are scarce. Also, the proposed models often suffer from large file sizes, rendering them unsuitable for deployment in embedded systems that necessitate compact and lightweight models.

In order to manage fruit fly traps remotely, effective communication infrastructure is required to connect the traps to a centralized system, enabling real-time data collection and analysis. Several key factors were identified for consideration when selecting a communication infrastructure. These factors include the distance between devices (traps) and the gateway, the deployment location (rural or urban), the volume of data to be transmitted or received, the desired transfer rate, and the power source of the device. It is imperative to account for these factors to ensure an optimal communication infrastructure is chosen.

5. Conclusion

In this paper, a survey of automatic detection and monitoring techniques for fruit flies is provided. The flies are notorious pests that cause significant damage to fruits and lead to substantial economic losses. The benefits of automatic techniques could result in the replacement of traditional monitoring strategies that are time-consuming, labor-intensive, and often inefficient, as identified in 2. The integration of electronic components in the traps leads to smart integrated pest management, which reduces the amount of time spent by farmers visiting every trap in the orchard. The traps provide automation in the detection and counting of the flies, providing early information about the infestation level on the farm. This process will allow a farmer to make informed decisions about how to manage the situation to prevent fruit losses.

Our review has highlighted various fruit fly automatic detection and monitoring approaches employing the application of sensor-based systems, machine learning, and IoT. Unlike other sensor-equipped traps, image sensor-based trap mechanisms have been found to offer suitable means for monitoring fruit flies with the integration of state-of-the-art deep learning algorithms, enhancing smooth detection and counting of fruit flies and allowing for the timely implementation of proper measures. With the Internet of Things and the growing trend in technology, researchers are focusing their efforts on using technology to simplify and meet the field's demand. Several different IoT communication technologies for exchanging data between the traps and remote servers were also discussed. Because each technology has its own unique benefits and drawbacks, the selection of technology depends on the specific requirements of the application.

In conclusion, the use of intelligent insect traps in conjunction with data analysis performed on the remote server will be essential to the reduction of labor expenses associated with conventional fruit fly control as well as the production of more optimized pest management strategies that are based on real-time information.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Data availability

No data was used for the research described in the article.

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