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Towards fruit fly automatic counting: Electronic trap design and long-term feature data acquisition

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ABSTRACT

Bactrocera Dorsalis is a major agricultural insect that severely damages many fruit crops in Southeast Asia. Many integrated pest management (IPM) plans have been implemented to minimize its impact. However, these programs often rely on traditional traps to manually capture and count fruit flies, which is time-consuming and laborious. Current electronic traps have many limitations and face various challenges in their practical implementation. The purpose of this study is to take the first step in developing an electronic trap device capable of automatically collecting the characteristic data of fruit flies that enter the trap over an extended period. Two types of sensors, infrared and sound, were integrated into the trap to gather data on the characteristic behaviors of fruit flies, including trap entry behavior and wingbeat sounds. Analysis of the collected data shows that using infrared data to detect the intrusion of fruit flies into traps achieves an accuracy of 90.72%. Additionally, infrared data revealed several unusual behaviors of the flies while entering the trap, such as entering consecutively, moving around the sensor, and remaining stationary. These behaviors significantly affect the accuracy of counting the number of flies entering the trap but have not been thoroughly analyzed in previous studies. The size of the fruit flies also affected the reliability of the collected data. Moreover, the wingbeat sound data of fruit flies contain distinct frequency characteristics in two ranges: 0–2000 Hz and 5000–8000 Hz, differentiating them from other sound sources. When combining both infrared and sound data, the system could simultaneously detect and count flies entering the trap with an accuracy of 88%. These results suggest that integrating infrared and sound sensors can serve as a new approach for designing traps to monitor fruit fly populations over extended periods because dead flies accumulating at the bottom of the trap do not interfere with the sensors. The use of sound data also opens the possibility of embedding artificial intelligence directly into the trap, enabling it to operate independently, consume minimal energy, and reduce bandwidth usage, etc paving the way for a large-scale fruit fly monitoring system.

Keywords: Electronic trap, Embedded system, Data acquisition system, Insect recognition, Automatic monitoring system, Wingbeat frequencies.

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1. INTRODUCTION

The horticulture sector is one of the most vital industries in the world but is threatened by fruit flies (Diptera: Tephritidae). Every year, fruit flies cause direct damage to important export crops, leading to losses of 40% to 80%, depending on locality, variety, and season (Dias et al., 2018), and causing millions of dollars in losses due to lost fruit products (Papadopoulos et al., 2024). There are several fruit fly species, but the oriental fruit fly (Bactrocera Dorsalis) is overabundant and highly polyphagous. They are endemic to Southeast Asia but have rapidly spread throughout Asia and worldwide (Weems et al., 2012). Oriental fruit flies directly attack fruits and vegetables; the female flies lay eggs inside the fruit, which causes the fruit to rot from the inside (Aluja, 1994). In Vietnam, oriental fruit flies attack many fruit crops with high economic value, such as longan, dragon fruit, and mango (Hien et al., 2019; Tran et al., 2019; Oanh and Duc, 2020).

To reduce damage from fruit flies, chemical pesticides were applied in the control process. However, overuse of chemicals can lead to resistance to various pesticides in the control process. However, overuse of chemicals can lead to resistance to various pesticides in fruit flies (Hsu et al., 2004; Vontas et al., 2011). Furthermore, long-term use of pesticides can negatively impact the health of users and the surrounding environment. Moreover, chemical pesticides can negatively affect natural enemies and other beneficial insects (Macharia et al., 2009). In recent years, Integrated Pest Management (IPM) programs have been applied to control pests while reducing the use of synthetic chemicals (He et al., 2023). These methods include the use of natural pesticides as an alternative to chemical pesticides (El-Gendy et al., 2021), biotechnology such as the Sterile Insect Technique (SIT) (Enkerlin, 2021; Mandanayake et al., 2023), Male Insecticide Technology (MAT) (Hussain et al., 2022), biological control (Abeijon et al., 2025), and orchard sanitation (Urbaneja et al., 2020).

Pest monitoring is crucial to ensure the effectiveness of IPM programs (Jiang et al., 2008). The traditional fruit fly monitoring strategy involves manual inspection from trap to trap, requiring labor to collect, identify, and count trapped fruit flies. These traps use pheromones, light, or color to attract insects. After an amount of time, the trap was inspected to identify, classify, and count the number of captured flies. Manual insect counting is labor-intensive, time-consuming, and error-prone (Lello et al., 2023). Automatic identification of invasive insects would significantly speed up the recognition of pests and expedite their removal (Nanni et al., 2022). Therefore, many studies have focused on detecting insects using electronic traps (Cardim Ferreira Lima et al., 2020). In the field of fruit fly detection, electronic traps are often improved versions of traditional traps, enhanced with electronic components to enable the identification and counting of trapped flies (Lello et al., 2023). Electronic traps can be classified based on their insect recognition and counting principles. Commonly used sensors for insect detection include imaging, photoelectric, and acoustic sensors. Each trap type has its advantages and limitations, which affect its effectiveness in managing fruit fly populations.

Electronic traps based on photoelectric sensors typically use infrared sensors to detect fruit fly entry. Pairs of infrared emitter and receiver LEDs were positioned at the entrance of traditional single-entry traps. Jiang et al. (2008) installed two consecutive pairs of infrared emitter and receiver LEDs at the entrance of a bottle trap, a mechanism known as double counting, to track the number of flies entering the trap. Another approach is to use bucket traps with sensors placed on the body of the trap. The attractant and toxin are positioned at the roof of the trap to lure and kill fruit flies. Dead or stunned fruit flies fall to the bottom, triggering sensors on the body of the trap. This method was applied in the studies by Holguin et al. (2010) and in the Medfly Automatic Traps (Medfly-ATs) proposed by Goldshtein et al. (2017). Another design based on the McPhail trap was proposed by Potamitis et al. (2014) and Sandrini Moraes et al. (2019). In this design, infrared sensors were placed at the lower entrance of the McPhail trap to record fruit fly entries. Electronic trap designs using infrared sensors rely on changes in the voltage or current of the infrared receiver LED to detect insect intrusions. When an insect enters the trap, it blocks the signal between the emitter and receiver LEDs, causing a drop in the receiver LED's voltage, which allows the system to count the number of flies entering the trap. Additionally, Potamitis et al. (2014) and Sandrini Moraes et al. (2019) developed a method to distinguish fruit fly species based on their wingbeat frequencies. They sampled the infrared receiver LED signal at high rates, with 4000 samples/s in the study of Potamitis et al. (2014) and 192,000 samples/s in the study by Sandrini Moraes et al. (2019). The signals were then analyzed to identify the frequency characteristics of the fruit fly species. The use of infrared sensors to count fruit flies entering the traps is a simple approach. When combined with microcontrollers (MCUs) to read and analyze sensor signals, this method is cost-effective and energy-efficient, making it well-suited for long-term field applications. However, this solution has some limitations that affect the accuracy of fruit fly counting. First, the voltage-based detection method used by Jiang et al. (2008), Holguin et al. (2010), and Goldstein et al. (2017) cannot distinguish fruit flies from other insects. This can lead to counting errors if other insects enter traps. Second, previous studies have not thoroughly evaluated the impact of erratic insect behavior on counting accuracy, particularly in the wingbeat-based approach of Potamitis et al. (2014) and Sandrini Moraes et al. (2019). For example, if a fruit fly crawls into the trap instead of flying, the sensor may fail to detect wingbeat vibrations, resulting in identification errors. Fruit fly size also affects the amplitude and frequency of the recorded signal. However, this factor has not yet been adequately analyzed. Another issue arises when an insect repeatedly moves in and out of the trap, triggering the sensor multiple times and causing significant counting errors. Therefore, improvements are required to address these limitations of infrared-based fruit fly counting. Additionally, a more detailed analysis of insect behavior over time is essential to enhance the practical effectiveness of traps.

Another widely used method for detecting and counting fruit flies relies on image-based analysis. Studies using this approach typically employ a camera to capture images of the trapped fruit flies. Yellow sticky traps are commonly used to attract and capture fruit flies, as seen in studies (Shaked et al., 2018; Huang et al., 2021; Diller et al., 2023; Molina-Rotger et al., 2023). In this method, a camera is positioned facing the sticky trap to record images of flies stuck inside. The sticky trap and camera setup can be enclosed within a protective cover (Diller et al., 2023) or exposed to the environment (Shaked et al., 2018; Huang et al., 2021; Molina-Rotger et al., 2023). Other types of traditional traps have also been used, such as the McPhail trap in the study by Doitsidis et al. (2017), the Lynfield trap in the study by Le et al. (2021), bottle and funnel traps in the study by Deqin et al. (2016), and plastic bottle traps in the study by Hahn et al. (2023). All of these studies utilized a camera mounted at the top of traditional traps to capture images of fruit flies trapped at the bottom, and image processing algorithms and machine learning techniques were used to count and identify fruit flies. Doitsidis et al. (2017) and Hahn et al. (2023) applied thresholding algorithms to count trapped flies in collected images. Deqin proposed a multi-object tracking algorithm that combines image feature extraction with a Kalman filter to count flies entering the trap (Deqin et al., 2016).

Other studies combined image processing with deep learning for insect classification and counting. Remboski et al. (2018) integrated image processing with machine learning algorithms such as Support Vector Machine (SVM), k-nearest Neighbors (KNN), Decision Tree (DT), and Gaussian Naive Bayes (GNB) to count trapped flies from images (Remboski et al., 2018). Similarly, Molina-Rotger et al. (2023) used a combination of Random Forest (RF) and SVM to identify and count fruit flies on sticky traps. Deep learning models based on CNN and YOLO architectures were widely applied. Variants of ResNet, MobileNet, R-CNN, and YOLO were used for fruit fly classification in studies (Martins et al., 2019; Le et al., 2021; Diller et al., 2023).

Applying deep learning enhances the ability to distinguish between fruit fly species with relatively high accuracy. However, this method also has several limitations. It is difficult to classify insects with shapes similar to fruit flies if relying solely on image processing. Furthermore, deep learning models are often large and require powerful image-processing hardware or remote servers for inference, which affects the feasibility of long-term field deployment. Another major challenge highlighted by Lello et al. (2023) is that the number of trapped flies increases over time, leading to insect overlap and reduced recognition accuracy. This affects the long-term functionality of the trap, which requires regular cleaning or replacement. Most studies have not addressed this issue, except Huang et al. (2021), who proposed an automated sticky trap replacement mechanism using a motor-driven rolling system. These limitations indicate that image-based fruit fly counting is less efficient for long-term trap operations. Alternative sensor-based classification and counting techniques with uncomplicated processing and maintenance requirements should be explored.

In addition to infrared and image sensors, acoustic sensors have been used to detect and identify various insect species (Lello et al., 2023). However, there is a lack of research employing acoustic sensors, specifically for fruit fly identification. Although Potamitis et al. (2014) recorded fruit fly wingbeat vibrations, the data were mainly used for comparison with infrared signals rather than direct species identification. Potamitis's study demonstrated that acoustic sensors can capture more detailed frequency characteristics of fruit fly wingbeats than infrared sensors. Similarly, previous research by Webb et al. (1976) and Mankin et al. (2006) indicated that fruit fly sounds contain unique frequency patterns that can differentiate them from those of other insects. This suggests that acoustic sensors could be viable tools for fruit fly identification.

A promising solution involves the integration of infrared and acoustic sensors within an electronic trap. An infrared sensor at the trap entrance detects and counts insects entering, whereas an acoustic sensor inside the trap identifies fruit flies based on their wingbeat frequency. This approach addresses the limitations of infrared sensors that cannot distinguish insect species by leveraging acoustic data. Unlike cameras, acoustic sensors are not affected by lighting conditions, are cost-effective, and consume less power. Moreover, both infrared and acoustic data can be processed using a microcontroller unit (MCU). Another advantage of this method is that the infrared sensor can trigger the acoustic sensor only when an insect enters, thereby minimizing environmental noise interference. In addition, because the sensors are placed in the upper part of the trap and only record fruit fly movement, they are not affected by dead flies accumulating at the bottom. However, in real-world conditions, acoustic sensors capture various background noises. Further research into fruit fly wingbeat sound characteristics is required to refine the identification accuracy and provide a valuable dataset for future studies.

This study focused on developing an electronic trap designed to continuously collect characteristic data of fruit flies in the Vietnamese Mekong Delta over an extended period. The trap was integrated with sensor systems to analyze the fruit fly entry behavior and assess the species identification accuracy. The fruit fly entry behavior is tracked using infrared emitter/receiver pairs, similar to existing electronic traps. Wingbeat sounds were recorded to evaluate their effectiveness for fruit fly identification, representing a novel aspect of this research. The trap is tested over a long duration to gather environmental noise data, thereby improving the reliability of the analysis and evaluation. Prolonged deployment will also help capture the natural behavior of flies entering the trap. This study aimed to develop an automated system for monitoring fruit fly populations over time and space. The collected data provide valuable insights for farmers and pest control agencies, enabling them to implement effective management strategies.

The remainder of this paper is organized as follows. The Methods section provides details on the research location, hardware and software design of the electronic trap, data analysis, and evaluation methods, and the experimental setup. The Results and Discussion section presents the collected data and in-depth analyses to clarify the characteristics and behavior of fruit flies. Finally, the Conclusion section summarizes the research output and offers recommendations for future research

2. MATERIALS AND METHODS

2.1 Study Area

The study was conducted in a rectangular apple orchard covering approximately 2,000 m² in Can Tho, Vietnam, at coordinates 10°06'55.9"N 105°39'31.3"E, as shown in Fig. 1. The orchard consists of 70 apple trees, each spaced 5 m apart, reaching a height of approximately 3 m. The area is primarily used for rice cultivation and other fruit crops. Pest control methods for fruit flies in the orchard mainly rely on chemical insecticides and fruit bagging.

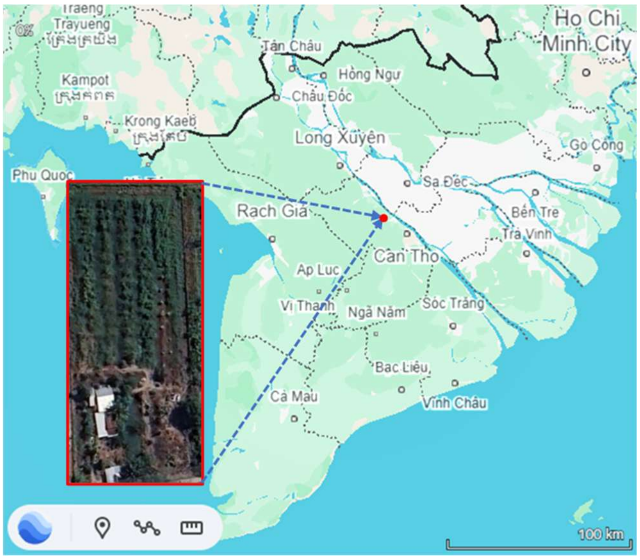

Fig. 1. Study area

2.2 Model Trap Design

The electronic trap is designed to be integrated into traditional traps, allowing the collection of characteristic data from fruit flies as they enter. This study aimed to detect flies using infrared waves and distinguish them from other insect species based on their wingbeat sounds. The trap was specifically designed to overcome the limitations of existing traps, as previously analyzed. The structure and operating principles are shown in Fig. 2. Fig. 2(a) presents the conceptual design of the electronic trap, which features a funnel-shaped entrance integrated with infrared and acoustic sensors (marked in red) and connected to the top and the bottle of a traditional trap. Two pairs of infrared emitter and receiver sensors, IR sensor 1 and IR sensor 2, respectively, were placed at the beginning and end of the narrowed entrance. A microphone was positioned below the funnel near the exit to capture the sound of the flies as they passed through. An attractant solution containing methyl eugenol and a toxic agent was used to lure and eliminate fruit flies at the bottom of the container. An ESP32 microcontroller unit (MCU) collects data from the sensors and records them on an integrated memory card. The system is powered by a battery and a 5 V voltage regulator. A solar charging feature will be integrated for real-world deployment.

When a fruit fly is attracted to the bait and enters the trap, it crawls through the funnel and passes through two infrared sensor pairs (IR sensor 1 and IR sensor 2). Each time the fruit fly crosses a sensor, it blocks the infrared beam sensor pairs (IR sensor 1 and IR sensor 2). Each time the fruit fly from the emitter LED, causing a voltage drop in the receiver LED. Figs. 2(b) and 2(c) illustrate the ideal signal patterns when the fruit fly crosses each infrared sensor pair (IR1 and IR2, respectively). This configuration allows the system to detect whether a fruit fly enters or exits the trap, thereby enabling behavioral analysis. After exiting the funnel, the fruit fly had to fly down to the bottom of the trap to reach the attractant. At this point, the microphone records the wingbeat sound, providing a data source for training embedded AI models for future fruit fly identification.

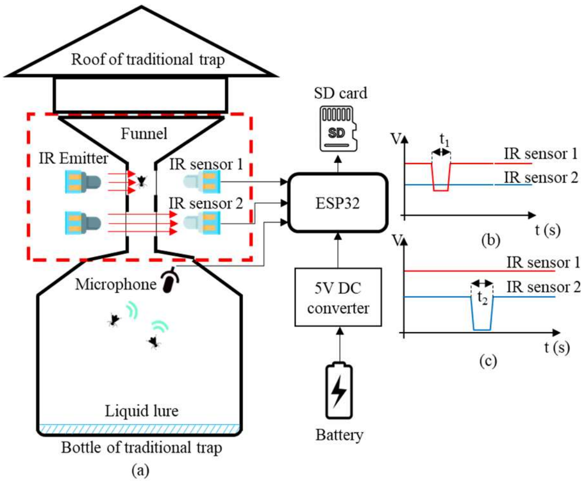

Fig. 2. Operating principle of the electronic trap integrating infrared and acoustic sensors: (a) Block diagram of the trap's operating principle, (b) Signal pattern at the infrared sensor when a fruit fly passes through IR1, (c) Signal pattern at the infrared sensor when a fruit fly passes through IR2.

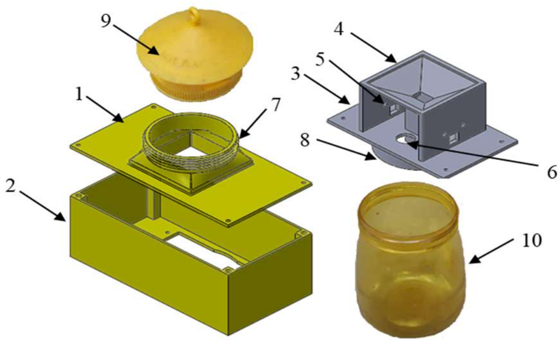

Fig. 3. 3D design of the device casing: (1) Device lid, (2) Outer casing, (3) Sensor mounting frame with entrance, (4) Funnel-shaped entrance, (5) Infrared sensor mounting position, (6) Acoustic sensor mounting position, (7) Thread for connecting to the traditional trap lid, (8) Thread for connecting to the container (9) Traditional trap lid, (10) Traditional trap container).

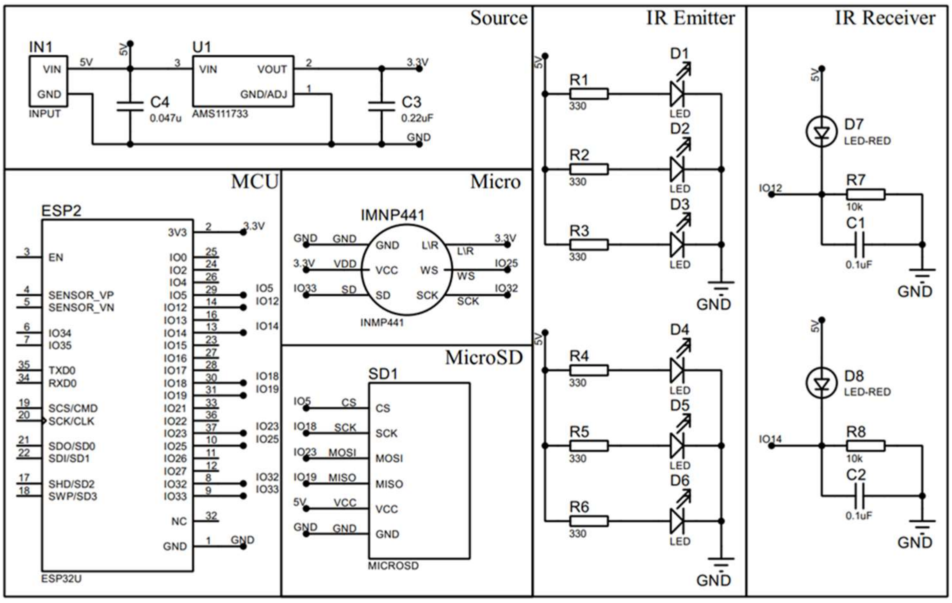

Fig. 4. Schematic diagram of control circuit and other devices

The device casing was designed using SOLIDWORKS 2022 and manufactured using 3D printing technology. Fig. 3 presents the simulated design of the casing, which consists of three main components: the lid (1), outer shell (2), and sensor mounting frame with a funnel-shaped entrance (3). The sensor mounting frame (3) includes several key features: the funnel-shaped entrance (4), infrared sensor mounting position (5), and acoustic sensor mounting position (6). Additionally, the device lid (1) contains an external thread (7), while the sensor mounting frame (3) features an internal thread (8), allowing it to connect seamlessly with the lid (9) and container (10) of the traditional trap.

2.3 Electronic Circuits and Control Programs

The wiring diagram of the electronic trap components is shown in Fig. 4. The circuit was designed using Proteus v8.16. The ESP32 microcontroller served as the central processing unit and continuously collected and stored both infrared and acoustic signals. The circuit is powered by an external 5V power source, which is regulated down to 3.3V using an AMS1117 IC to supply power to the microcontroller and microphone. Each infrared emitter module consisted of three infrared LEDs operating at 5V. The two infrared receiver LEDs were also powered by 5V and were equipped with 0.1 µF capacitors to filter noise. ESP32 reads data from the infrared receiver LEDs via an ADC module at a sampling rate of 500 samples/s. This speed is chosen to optimize memory usage and prioritize storing large volumes of audio data, but it can still capture all fruit fly entry events. The INMP441 microphone was used to capture wingbeat sounds owing to its high-accuracy omnidirectional recording, low power consumption, and support for the I2S protocol, which enables high-speed data transmission (Nguyen et al., 2023; Invensense, 2025), as shown in Table 1. The audio data were sampled at 16,000 samples per second, allowing for a frequency analysis of up to 8,000 Hz. ESP32 has sufficient temporary storage capacity before writing the data to an SD card.

Table 1. Technical specifications of INMP441 microphone

Technical specifications	Value
Operating voltage	1.8 – 3.3 VDC
Connection protocol	I²S Interface 24 bit
Current consumption	1.4 mA
High sensitivity	-26 dBFS
Flat frequency response	60 Hz – 15 kH
High SNR	61 dBA
High PSR	-75 dBFS

To accurately collect characteristic data of fruit flies in real-time and over an extended period, the trap control algorithm must simultaneously acquire and store infrared and acoustic data onto a memory card. Fig. 5 illustrates the control algorithm governing the trap operation. Both cores of the ESP32 microcontroller were used to ensure simultaneous data collection at two different sampling rates. Core 1 is responsible for reading the voltage signals from the two infrared receiver LEDs and writing them to the microSD card. The sampling rate was precisely controlled using a timer interrupt, and a double-counting mechanism was implemented to ensure continuous data acquisition. Variable n is accustomed to storing the number of samples collected in buffer 1. Whenever n reaches or exceeds 500 samples, the program checks whether a microSD card is available for writing. If the card is ready, n samples from buffer 1 are copied to buffer 2 and written to memory, while n is reset to 0, and buffer 1 is refreshed for continued data collection. If the microSD card is busy, data collection continues, and n exceeds 500 until the card becomes available, at which point all the collected samples are stored. To prevent buffer overflow, if n exceeds 3,000 samples, the program resets n to 0, clears the data array, and triggers a buffer full error notification.

Simultaneously, core 0 handles the audio data collection. The data acquisition and storage process by this core follows a principle similar to that of core 1 but with some key differences. First, the Direct Memory Access (DMA) module of ESP32 automatically collects data from the microphone and stores it in its buffer. The program continuously checks the DMA buffer to retrieve k samples from the microphone. Variable m is used to store the total number of collected audio samples. When m reaches 16,000 samples (equivalent to one second of data), the program checks the availability of the microSD card to proceed with data writing. If the microSD card is not ready, the program continues to retrieve data from the DMA buffer while checking the status of the card. Once the card is available, the program writes all *m* samples to memory. To prevent memory overload, if m exceeds 33,000 samples due to extended wait times, the data array is cleared, m is reset to 0, and a buffer full error is triggered.

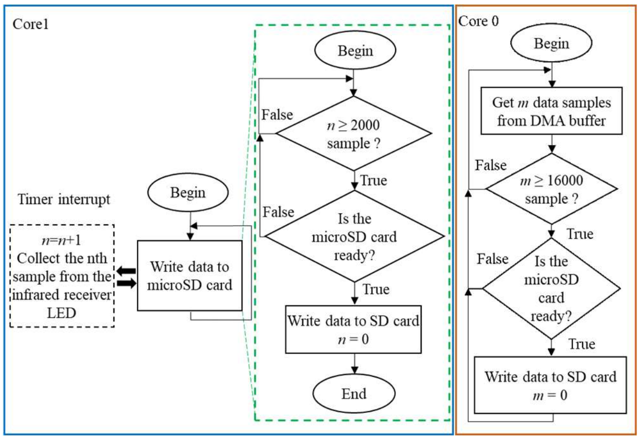

Fig. 5. Algorithm diagram of electronic trap data collection program

2.4 Experimental Setup and Data Processing and Evaluation Methods

The designed trap was firmly installed in an apple orchard at the experimental site, as shown in Fig. 6. Each day, the trap was powered on in the morning and turned off in the evening to extract the collected data from the memory card and to manually count the number of trapped flies. The trap was inoperative at night because the fruit flies were inactive during this period. Data were collected continuously for one month, from January 17, 2025, to February 17, 2025. At the end of each day, data from the infrared sensors and microphone were stored on the microSD card as text files. Each data type was processed separately to extract characteristic information about the fruit flies. Fig. 7 illustrates the data-processing steps. First, the infrared data were filtered using a low-pass filter at 8 Hz to eliminate high-frequency noise that could interfere with the detection of fruit fly signals. Both data types were then manually inspected to identify and extract segments containing fruit fly activity. For infrared data, this involved detecting signal amplitude drops, whereas, for audio data, it involved isolating segments containing fruit fly wingbeat sounds. In addition, environmental noise samples were collected for comparison with fruit fly sounds and future recognition applications. Next, infrared data segments corresponding to flies entering the trap were analyzed to measure parameters such as the signal amplitude and the time interval between the entry of the fruit fly and the appearance of its wingbeat sound. The infrared data were then categorized based on different fruit fly behaviors to facilitate analysis. For audio data, fruit fly wingbeat sounds and other recorded noises were subjected to a frequency analysis to identify distinct frequency characteristics. These characteristics were compared to highlight the differences, helping to determine features suitable for fruit fly detection. After processing and classification, all data was stored as text files for further analysis and application.

Fig. 6. Electronic trap arrangement at the experimental site

3. RESULTS AND DISCUSSION

The complete trap model is illustrated in Fig. 8. The final design consisted of an electronic device integrated with a traditional trap, as illustrated in Figs. 8(a), 8(b) and 8(c) show the arrangement of the key components, including the battery, control circuit, and sensors. Figs. 8(d), 8(e) and 8(f) present the final version of the control circuit, infrared receiver LED, and infrared emitter LED, respectively. The fully assembled trap in Fig. 8(a) is equipped with an attractant solution and deployed at the experimental site to collect infrared and acoustic data from fruit flies under real-world conditions. The collected data were stored on a micro-SD card, which was extracted daily for storage and processing. Additionally, the number of trapped fruit flies was manually counted and recorded daily to evaluate the accuracy of the collected data.

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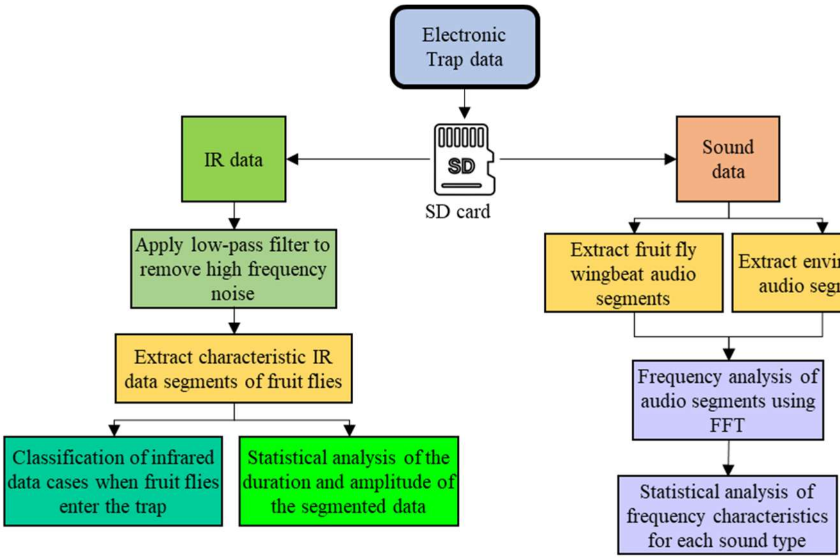

Fig. 7. The processing flowchart of data collected from the electron trap

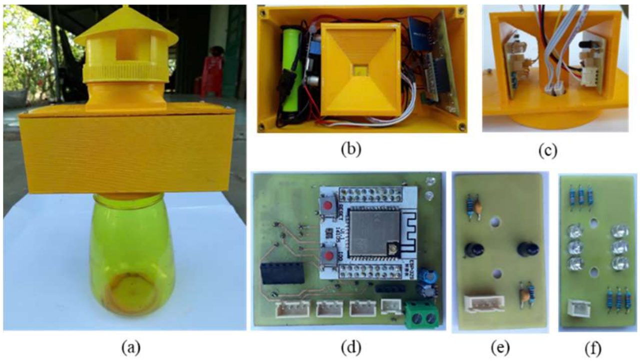

Fig. 8. Completed trap and other components: (a) Completed trap, (b) Component layout inside the trap, (c) Sensor layout, (d) Control circuit, (e) Pair of infrared receiving LEDs, (f) Two clusters of infrared emitting LEDs

3.1 Feature Dataset of Fruit Fly

After processing the collected data, two datasets were obtained: infrared data containing signals of fruit flies entering the trap and audio data capturing fruit fly wingbeat sounds and other environmental noises. The infrared dataset revealed different behaviors of fruit flies as they entered the trap. Fig. 9(a) illustrates the ideal case, in which a single fruit fly moves directly into the trap. Fig. 9(b) presents the corresponding audio signal recorded after the fruit fly entered. As the fruit fly moves through the trap, it sequentially triggers the infrared receiver LEDs (IR sensor 1 and IR sensor 2), causing voltage drops in eachcorresponding LED. These signal drops can be used to detect when a fruit fly enters and exits a funnel. Fig. 9(b) also shows the wingbeat sound signal (highlighted in red), which appears after the fruit fly enters the trap. This signal can be analyzed based on its frequency characteristics to identify fruit flies.

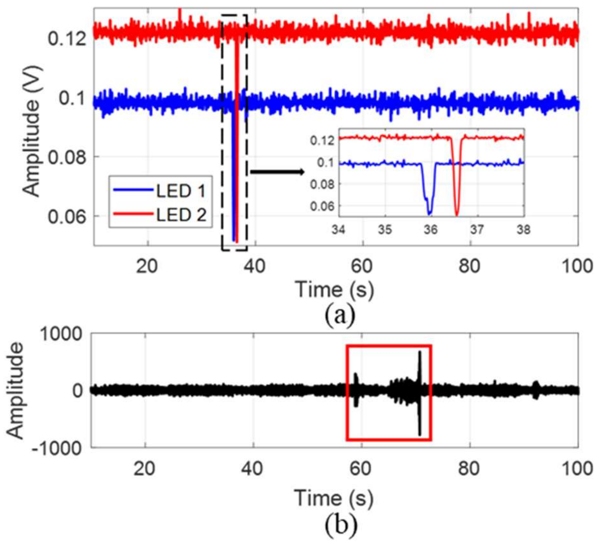

Fig. 9. Fruit fly data after processing: (a) Infrared data, (b) Audio data

In addition to the ideal case, several unusual fruit fly behaviors were recorded, as shown in Fig. 10. These behaviors can be categorized into four main groups. The first group was the sequential entry of two or more flies (Fig. 10(a)). In this scenario, the first fruit fly enters the trappassing LED 1 and reaching LED 2, whereas another fruit fly arrives simultaneously at LED 1. This causes both infrared LEDs to register voltage drops simultaneously, making it difficult to distinguish between individual entries The second group is the fruit fly reversing direction (Fig. 10(b)). Initially, the fruit fly enters the trap, generating a

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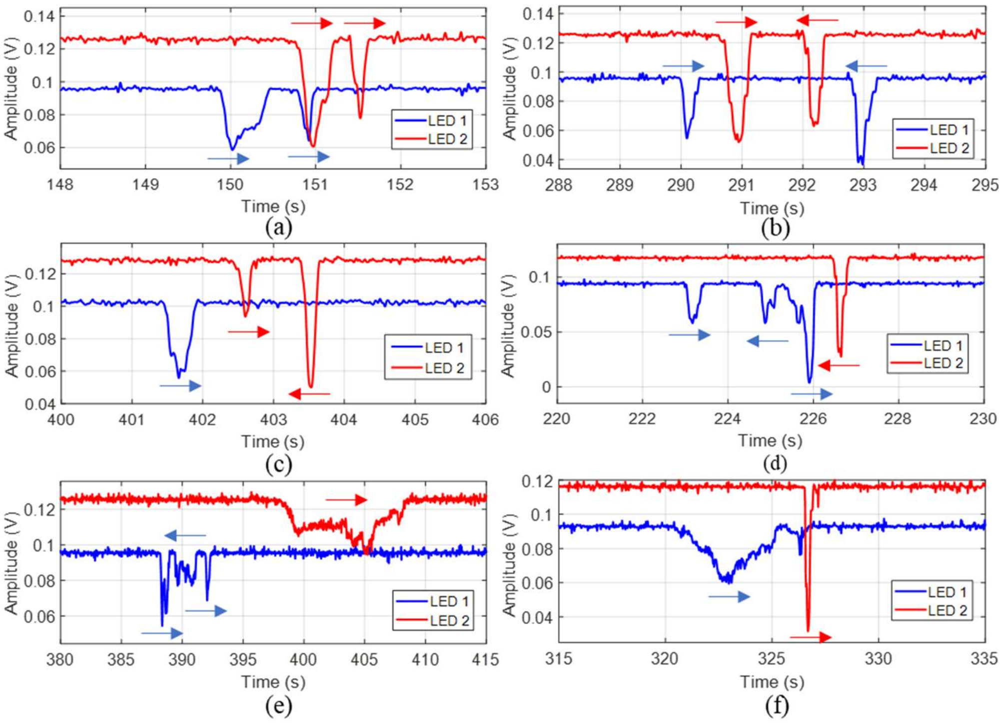

Fig. 10. Cases of erratic behavior of fruit flies entering the trap: (a) Sequential entry of two fruit fly causing overlap of signals (red and blue arrows), (b) Fruit fly reversing direction (red and blue arrows), (c and (d) Fruit flies repeated their movements near a single LED (red and blue arrows), (e) and (f) Fruit flies stopped or moved slowly in an LED (red and blue arrows)

typical entry signal with sequential voltage drops at LEDs 1 and 2. However, instead of continuing downwards, the fruit fly turns around and exits, creating a reverse signal pattern compared with the ideal case.

The next group consisted of repeated movements near a single LED (Figs. 10(c) and 10(d)). In this case, the fruit fly moved back and forth near one of the LEDs, repeatedly triggering multiple infrared signal drops instead of the expected single event.

The last group is prolonged stopping at an LED (Figs. 10(e) and 10(f)). Here, the fly stops or perches in front of the LED for an extended period, producing a long-duration signal pulse instead of a brief drop. While stationary, the fruit fly may exhibit natural behaviors like cleaning its legs or wings and causing small fluctuations in the infrared signal.

The collected audio dataset consisted of 1,125 segments containing fruit fly wingbeat sounds, 500 segments of bird-chirping sounds, 500 segments of glass trimmer noise, and 100 segments of dog barking. Fruit fly wingbeat audio was analyzed to identify the characteristic frequency groups. Fig. 11(a) presents the time-domain waveform of a fruit fly wingbeat signal, whereas Fig. 11(b) displays nine distinct frequency groups found in the wingbeat sound of a single fruit fly. The analysis shows that fruit fly wingbeat sounds contain both low and high-frequency components, with the fundamental frequency having the highest amplitude in the low-frequency range. Fig. 12 presents a statistical analysis of the characteristic wingbeat frequency groups based on the frequency analysis of 105 audio samples. The results revealed nine frequency groups, each consisting of closely spaced frequency peaks within a specific range. Table 2 provides detailed information on the frequency bandwidths, median values, and the number of samples in which each frequency group was detected. Most frequency groups appeared in nearly all tested samples, with six groups (1, 2, 3, 4, 6, and 8) being present in over 95.2% of samples (more than 100 detections). Notably, frequency group 1 was detected in all 105 samples, suggesting that it may represent the fundamental frequency of fruit fly wingbeat signals.

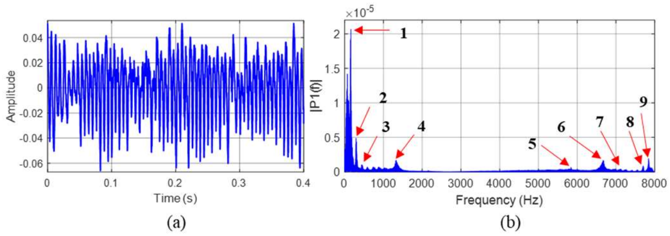

Fig. 11. Wingbeat of fruit fly: (a) Time-domain waveform of the fruit fly wingbeat sound, (b) Key frequency peaks in the wingbeat sound of a single fruit fly

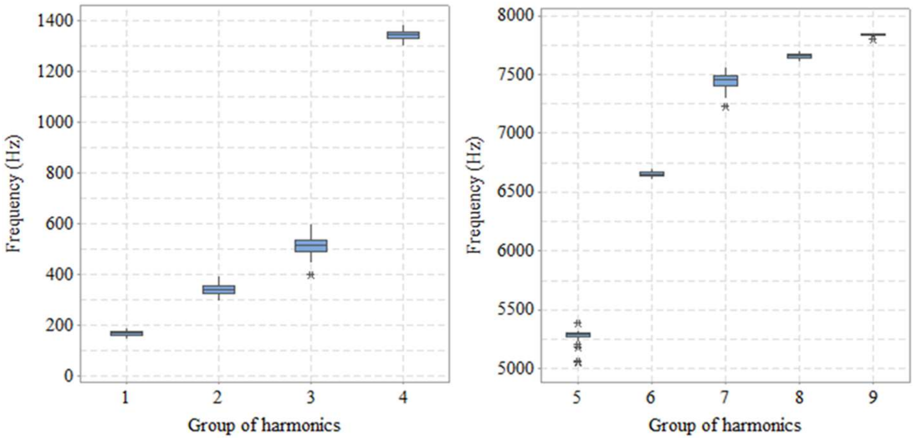

Fig. 12. Frequency group distribution of characteristic fruit fly wingbeat sounds

Table 2. Characteristic frequency groups extracted from fruit fly wingbeat sounds

Group		1	2	3	4	5	6	7	8	9
Range of frequency (Hz)	Min	147	296	400	1300	5051	6605	7229	7601	7801
	Median	168	340	513	1344	5291	6652	7454	7672	7830
	Max	190	393	601	1386	5387	6686	7556	7705	7854
Number of samples		105	102	102	104	89	104	98	100	98

The first three frequency groups listed in Table 2 [147-190] Hz, [296-393] Hz, and [400-601] Hz, were detected in nearly all tested samples. Moreover, these frequency ranges are consistent with those reported in previous studies. Mankin et al. (2006) reported that the fundamental frequency of C. capitata fruit fly wingbeat sounds falls between 150 Hz and 220 Hz, with the following two harmonics at 370 Hz and 555 Hz. Similarly, Webb et al. (1976) found that the fundamental frequency of fruit fly wingbeats was approximately 165 Hz, with subsequent harmonics at 332 and 496 Hz. Thus, the study accurately identified the characteristic frequency components of fruit flies in the sub-1 kHz range.

Beyond the fundamental frequency and the first two harmonics, the 16,000 Hz sampling rate used in this study revealed additional frequency components in the fruit fly wingbeat sounds. These high-frequency groups include [1300-1386] Hz, [5051-5387] Hz, [6605-6686] Hz, [7229-7556] Hz, [7601-7705] Hz, and [7801-7854] Hz, corresponding to frequency groups 4, 5, 6, 7, 8, and 9, respectively.

3.2 Analysis of Fruit Fly Behavior When Entering the Trap

The use of infrared signals to detect fruit flies entering traps has proven effective in previous studies. However, based on the collected results, the accuracy of this method can be affected by unpredictable fruit fly behaviors during entry. As shown in Fig. 10, fruit flies exhibit various irregular behaviors when entering the trap, which can be categorized into four main types: (1) multiple flies entering consecutively, causing overlapping infrared signals; (2) a single fruit fly entering the trap but reversing direction and exiting; (3) fruit fly repeated movements near the LED sensor, and (4) a fruit fly remaining stationary or moving slowly near an infrared receiver LED.

Among these cases, types (1), (3), and (4), along with the ideal case, can be used for fruit fly counting. In a total of 401 recorded infrared signals corresponding to fruit fly entries, the ideal case accounted for 65.34% (262 samples), behavior (3) (back-and-forth movement) accounted for 25.69% (103 samples), behavior (4) (stationary or slow movement) represented 8.23% (33 samples), and behavior (1) (multiple flies entering consecutively) was the least frequent at 0.75% (three samples). Additionally, 14 cases of behavior (2) were recorded. These behaviors indicate that relying solely on voltage-drop detection can lead to miscounting errors in automated fruit fly detection algorithms.

In addition to unusual behaviors, the time interval between a fruit fly entering the trap and its flight toward the bottom of the trap is also a critical factor. Table 3 presents a statistical analysis of the time delay between the infrared detection of a fruit fly entering the trap and the detection of its flight sound. This analysis was conducted manually by simultaneously comparing infrared and audio data and measuring the time from the end of the infrared signal at LED 2 until the wingbeat sound was detected. A total of 442 flies were trapped, and 401 infrared signals were successfully recorded, corresponding to 9 detection accuracy of 90.72 %. The time delays were classified into five categories: less than 1 min, between 1 and 5 min, between 5 and 30 min, more than 30 min, and no wingbeat sound detected.

Table 3. Statistical analysis of time interval between trap entry and wingbeat sound detection

Time	Number of fruit fly	Total trapped fruit fly
Less than 1 min	176	
Between 1 and 5 min	117	
Between 5 and 30 min	87	442
More than 30 min	9	
Sound not found	12	
Total detected fruit fly from IR signal	401	

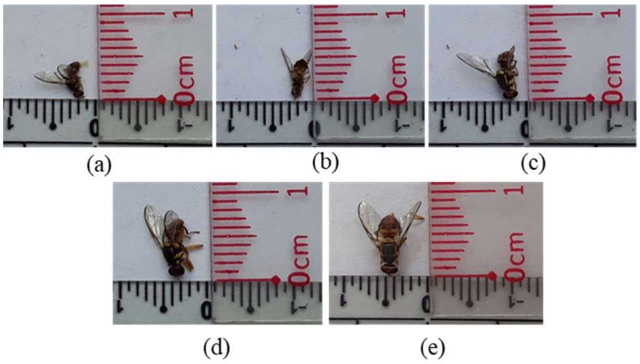

Fig. 13. Different sizes of fruit flies: (a) Small size, (b) and (c) Medium size, (d) and (e) Large size

The results showed that 85.97% of the flies began flying within 30 min of entering the trap. A small proportion (2.04%) remained stationary for more than 30 min, whereas 2.71% of the cases had no detectable wingbeat sounds. The absence of wingbeat sounds in some cases can be explained by the fact that certain fruit flies choose to crawl down to the bottom of the trap instead of flying, making it impossible to detect their wingbeat sounds. Another factor is the size variation among trapped flies, as shown in Fig. 12. Flies can vary in size, with some being small (Fig. 13(a)), medium (Figs. 13(b) and 13(c)), or large (Figs. 13(e) and 13(f)). Smaller flies block less infrared light between the two LEDs, generating weaker signals that are more difficult to distinguish from noise. In addition, smaller flies produce weaker wingbeat sounds, making it more difficult for the acoustic sensor to detect.

By combining infrared and acoustic signals, the fruit fly counting and identification accuracy reached 88%. Although this is slightly lower than using only infrared detection, integrating both sensor types reduces the miscounts caused by non-target insects crawling into the trap. These results highlight that fruit flies exhibit a wide range of unpredictable behaviors that significantly affect the collected data. This aspect could be considered a novel contribution of this study, as most previous studies did not conduct long-term trap deployments to evaluate performance, instead relying on short-term experiments.

3.3 Analysis of Noise Factors in Acoustic Feature Collection

During the extraction of the fruit fly data from the electronic trap, several other frequently occurring environmental sounds were recorded. The three most common noise sources at the experimental site were bird sounds, grass trimmer noises, and dog barking. Table 4 presents the frequency analysis and statistical characteristics of the noise types. Among these, bird sounds primarily contain high-frequency components, whereas grass trimmer noise and dog barking exhibit both low- and high-frequency characteristics. Notably, all three noise sources have fundamental frequencies close to the 168 Hz fundamental frequency of fruit fly wingbeat sounds. This similarity suggests that using only low-frequency components could lead to misclassification between fruit fly sounds and noise sources. Of the three noise types analyzed, grass trimmer noise shared the most similar frequency characteristics with fruit fly wingbeat sounds, making it the most likely source of misclassification. However, the number of distinct frequency components in grass trimmer noise is still lower than that in fruit fly wingbeats. Thus, leveraging the full set of fruit fly wingbeat frequency characteristics enables effective differentiation from background noise, improving classification accuracy.

Figure 14 presents a comparative analysis of the wingbeat sound of the fruit fly and various environmental sound sources, using frequency spectrum representations. The spectrogram of the fruit fly reveals distinct characteristics, including prominent spectral components spanning both low and high frequency ranges with relatively elevated amplitudes. In contrast, other sound sources exhibit narrower spectral distributions confined to specific frequency bands. These findings support the feasibility of employing frequency spectrum analysis as an effective approach for distinguishing fruit fly wingbeat signals from environmental noise.

3.4 Discussion

Table 5 presents a comparison between the tasks carried out in this study and those conducted in previous works. Most earlier studies focused on designing electronic traps that performed either insect detection or identification. In contrast, this study aims to develop an electronic trap capable of both detecting and identifying Bactrocera dorsalis as they enter the trap. The analysis of infrared signals revealed several unusual behavioral patterns exhibited by the fruit flies during the trapping process. These recorded behaviors highlight the complexity of fruit

Table 4. Statistical analysis of frequency characteristics of three environmental noise sources

Audio source		Bird			Grass trimmer							Dog					
Group		1	2	3	1	2	3	4	5	6	7	1	2	3	4	5	6
Range of frequency (kHz)	Min	0.12	5.03	7.82	0.15	0.31	1.28	5.23	6.57	7.38	7.81	0.10	0.60	1.29	6.54	6.90	7.81
	Median	0.15	5.82	7.84	0.17	0.33	1.36	5.29	6.64	7.67	7.83	0.15	0.64	1.35	6.71	7.34	7.85
	Max	0.1	5.40	7.90	0.19	0.38	1.43	5.44	6.75	7.69	7.85	0.18	0.72	1.42	7.90	7.40	7.93
Number of samples		49	39	50	50	50	50	39	50	35	50	47	41	49	49	37	46

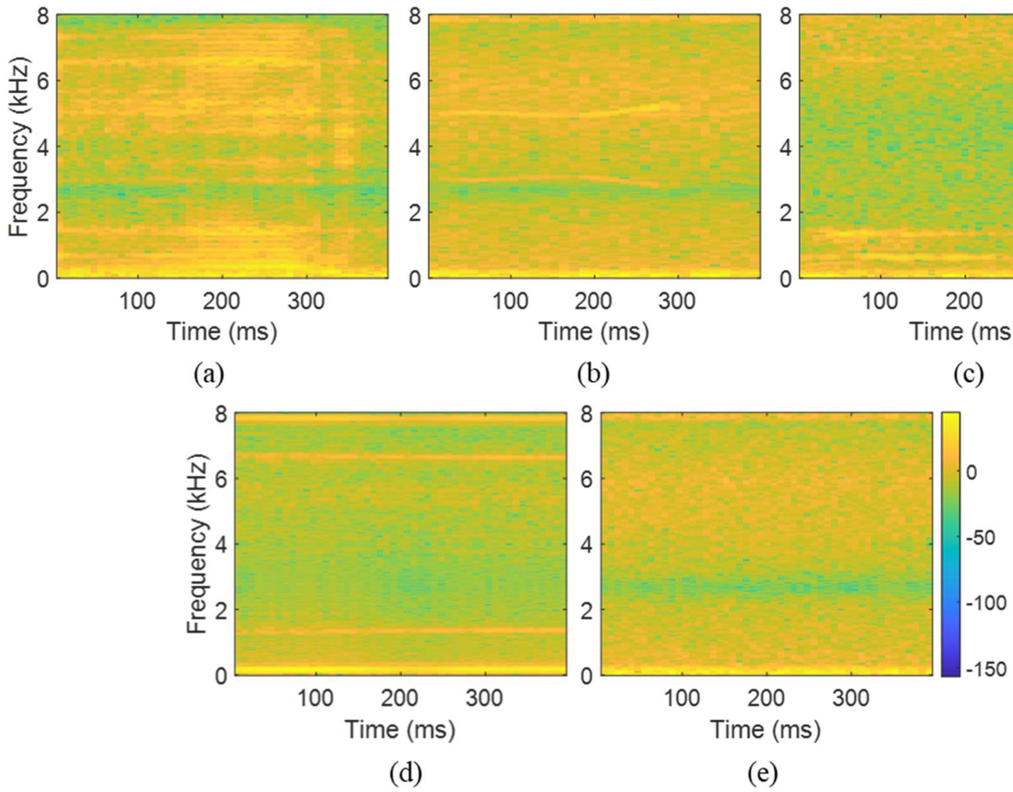

Fig. 14. Frequency spectrum images of the fruit fly wingbeat compared to other sounds: (a) fruit fly wingbeat, (b) Bird, (c) Dog, (d) Glass trimmer, (e) Background noise.

fly movements when entering the trap, which significantly affects the fruit fly-counting solutions based on infrared sensors. Most studies that monitor fruit fly populations using infrared sensors (Goldshtein et al., 2017; Jiang et al., 2008; Potamitis et al., 2014; Potamitis et al., 2017; Potamitis et al., 2018) have not yet carried out assessments to fully evaluate these behaviors. Because these actions align with the natural instincts of insects, they should be considered in the development. Moreas et al. (2018) mentioned cases where fruit flies walked through the sensors instead of flying, and proposed a method to mitigate this issue. However, the authors did not analyze how repeated entries and exits of flies in and out of the trap could affect the accuracy of insect counting.

The analysis of acoustic data also revealed that the wing-beating sounds of Bactrocera dorsalis during flight exhibit multiple frequency characteristics within the ranges of 0–2000 Hz and 5000–8000 Hz. Notably, the use of acoustic sensors has enabled the detection of frequency features in the range of 5000–8000 Hz, which have not been analyzed in previous studies that primarily employed optical sensors. Therefore, these higher-frequency groups could serve as additional distinguishing features, enhancing the accuracy of fruit fly identification and improving their differentiation from other insect species.To evaluate the performance of the trap under real-world conditions, a one-month field experiment was conducted.

4. CONCLUSION

In this study, we developed an electronic trapping device capable of real-time data collection from fruit flies. The proposed system integrates infrared and acoustic sensors with a traditional trap to capture data on Bactrocera Dorsalis flies in real time. The experimental results show and-forth

Table 5. Comparison of trap functions, behavioral and acoustic analyses, and evaluation duration across studies

	Trap function	Analysis of fruit fly behavior when entering the trap	Analysis of the wingbeat frequency		Cost	Power consumption	Long-term evaluation features	Experimental location
			Sound sensor	Optical sensor				
This study	Detection and identification	✓	✓		23$	140 mAh	Conduct data collection for about one month	Field
Holguin et al. (2010)	Detection	-	-	-	-	-	-	Field and lab
Liao et al. (2012)	Detection and count	✓	-	-	-	-	-	Field
Potamitis et al. (2014)	Identification	-	-	✓	40 €	43 mAh	-	Lab
Goldshtein et al. (2017)	Detection and count	-	-	-	-	93 mAh or 323 mAh (with Raspberry Pi)	-	Field
Moreas et al. (2018)	Detection, count, and identification	✓		✓	-	-	-	Lab
Khalid et al. (2025)	Detection and identification	-	✓		-	-	-	Lab

movement in front of an LED, prolonged stopping at an LED and exiting after partial entry. The fruit fly size significantly affected the detection accuracy. Smaller flies generate lower infrared signal amplitudes and weaker wingbeat sounds, making them harder to detect. The infrared detection method achieved an accuracy of 90.72 %. When combined with wingbeat sound data, the accuracy was 88%. The fruit fly wingbeat sound, sampled at 16,000 samples/s, exhibited a fundamental frequency between 147 Hz and 190 Hz. The other frequency components were primarily distributed in two ranges: 0–2000 Hz and 5000 – 8000 Hz. Environmental noises, particularly bird sounds, glass trimmer noise, and dog barking, share some overlapping frequency characteristics with fruit fly wingbeats. However, fruit fly wingbeat sounds contain more distinct frequency features, making them effectively distinguishable from other noises. The infrared sensor is efficient for counting fruit flies entering the trap, whereas the acoustic sensor improves species identification. This combination enables real-time, automated monitoring of fruit fly populations in the field. Future research should focus on developing advanced algorithms that integrate both data types for more precise fruit fly counting and identification, with potential deployment in real-world pest control applications. Furthermore, the classification algorithm's ability to distinguish between the fruit fly wingbeat sounds and other environmental noise should also be considered and further developed

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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