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RESEARCH PAPER

Development of a cost-effective IoT-based smart fruit fly trap with LoRa communication for area-wide pest monitoring

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ABSTRACT

Fruit flies (Diptera: Tephritidae) are among the most destructive pests of horticultural crops, requiring continuous and coordinated surveillance to support effective Area-Wide Pest Management (AWPM). This study developed and evaluated a low-cost IoT-based smart fruit fly trap designed for automated pest monitoring under field conditions. The system was adapted from a conventional fruit fly trap and integrated with automatic infrared counting sensors, environmental sensors, a microcontroller, and LoRa/GSM communication for wireless data transmission Sensor performance was evaluated under laboratory conditions using three fruit fly population densities (10, 30, and 50 individuals). Single- and two-sensor configurations produced relatively low counting accuracy (<35% and 34–58%, respectively), whereas the three-sensor configuration consistently achieved counting accuracies exceeding >84%, demonstrating reliable automated insect detection. Power consumption remained stable during sensing operations, with only brief increases during data transmission, allowing the system to operate for approximately 3.5 days using rechargeable batteries before recharging. Field evaluation showed that LoRa communication maintained stable wireless data transmission over distances of up to 3 km, enabling coordinated monitoring across multiple trapping locations. Monitoring data were transmitted to a web-based platform for real-time visualization, storage, and management, facilitating rapid access to pest population information. The developed smart trapping system provides a practical, affordable, and energy-efficient approach for large-scale fruit fly surveillance and has strong potential to support timely decision-making in AWPM programs and sustainable pest management.

Keywords: Area-wide pest management, fruit fly, IoT, LoRa communication, smart trap

INTRODUCTION

Fruit flies (Diptera: Tephritidae) are among the most destructive insect pests of horticultural crops worldwide, causing substantial economic losses through direct fruit damage, reduced marketability, and quarantine restrictions. The family comprises more than 4000 described species belonging approximately 500 genera (White & Elson-Harris, 1992). Despite decades of research and control efforts, infestations by economically important tephritid species continue to threaten fruit and vegetable production, frequently resulting in severe yield losses and restrictions on domestic and international trade (Qin et al., 2015; Radonjić et al., 2019). Their high reproductive capacity, rapid population growth, long-distance dispersal, and adaptability to diverse agroecosystems make fruit flies particularly difficult to suppress, often leading to recurrent outbreaks and unstable production (Savary et al., 2019; Manurung et al., 2013; Vargas et al., 2016). These biological characteristics limit the effectiveness of isolated farm-level interventions and underscore the need for coordinated management strategies. Consequently, Area-Wide Pest Management (AWPM) has been widely promoted as a sustainable approach for suppressing highly mobile fruit fly

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populations across entire production landscapes (Vargas et al., 2010; Vargas et al., 2016). Although conceptually aligned with Integrated Pest Management (IPM), AWPM differs by integrating multiple control tactics—including host plant resistance, cultural practices, biological control, mechanical control, and judicious pesticide use—across an entire production region rather than individual farms (Klassen, 2005; Vreysen et al., 2007). Central to the success of AWPM is a reliable monitoring system capable of providing continuous information on pest abundance, spatial distribution, and invasion dynamics to support timely and coordinated management decisions while minimizing unnecessary pesticide applications (Cox, 2007; Van Huis, 2007).

Implementing AWPM at operational scales requires extensive monitoring networks capable of covering large agricultural areas while maintaining reliable, timely, and accessible pest information (Cox, 2007; Dara, 2019; Green et al., 2007). Conventional fruit fly monitoring systems, consisting primarily of baited traps equipped with food attractants, methyl eugenol, cue lure, pheromones, or colored sticky surfaces, remain the standard approach for fruit fly surveillance (Jung et al., 2003; López Jr, 1998; Pobozniak et al., 2020; Vargas et al., 2000; Kardinan & Maris, 2022; Saputra & Afriyansyah, 2021). However, these systems depend heavily on manual inspection, requiring frequent field visits to count captured insects and record observations. Such procedures are labor-intensive, time-consuming, and costly, particularly when hundreds of traps are distributed across large production areas. Moreover, manual recording delays data availability and limits integration with environmental information needed for predictive pest management. Consequently, conventional monitoring often fails to provide the real-time information required for precision agriculture and effective area-wide decision-making (Cox, 2007; Talebpour et al., 2015).

Recent advances in digital agriculture have stimulated the development of smart insect trapping systems that integrate automated insect detection with Internet of Things (IoT) technologies for real-time pest surveillance (Cardim Ferreira Lima et al., 2020; Eliopoulos et al., 2018; Sciarretta & Calabrese, 2019). Automated insect counting has been achieved using image processing, machine vision, and wing-beat frequency recognition, enabling continuous pest monitoring and digital data acquisition (López et al., 2012; Potamitis et al., 2015; Thulasi Priya et al., 2013). These technologies allow pest information to be transmitted remotely to cloud-based platforms for near real-time visualization and decision support (Shaked et al., 2018; Shi et al., 2015; Shieh et al., 2011). More recently, Low-Power Wide-Area Network (LPWAN) technologies, particularly LoRa/LoRaWAN, have have emerged as promising communication solutions for smart agricultural monitoring because they provide kilometer-scale wireless transmission while consuming considerably less energy than Wi-Fi or cellular communication systems. These characteristics make LoRa especially suitable for battery-powered devices deployed across extensive agricultural landscapes. Several studies have successfully incorporated LoRa communication into smart traps for monitoring lepidopteran pests and mosquito vectors, demonstrating reliable long-range wireless transmission from sensor-equipped traps to cloud-based decision-support systems (Jiménez-López et al., 2024; Oliveira & Mafra, 2024).

Despite these advances, currently available LoRa-enabled smart trapping systems remain constrained by several important limitations. Most rely on relatively expensive computing platforms such as Raspberry Pi, high-resolution cameras, and image-processing algorithms that substantially increase hardware costs, computational requirements, and energy consumption (Jiménez-López et al., 2024; Miles et al., 2020; Oliveira & Mafra, 2024). Consequently, these systems are generally deployed as pilot-scale prototypes with only a limited number of traps, restricting their practical implementation in dense monitoring networks required for operational AWPM. Furthermore, camera-based recognition systems require considerable processing power and are often affected by varying field illumination, dust, and insect overlap, thereby increasing maintenance complexity. These limitations indicate that a simple, energy-efficient, and affordable smart trapping architecture suitable for large-scale fruit fly monitoring is still lacking.

An alternative approach is the use of infrared interruption sensors for automated insect detection. Compared with camera-based systems, infrared sensors require minimal computational resources, consume substantially less power, and provide rapid detection of insects passing through a sensing chamber, thereby reducing both hardware costs and operational complexity. Coupled with LoRa communication, such sensors offer the potential to develop cost-effective monitoring units that can be deployed at high densities across extensive agricultural areas while maintaining reliable long-range data transmission.

Therefore, this study developed and evaluated a cost-effective IoT-based smart fruit fly trap integrating an infrared automatic counting sensor with LoRa communication technology for area-wide pest monitoring. The developed system combines automated insect detection, environmental sensing, wireless data transmission, and web-based data visualization to provide timely monitoring information for pest management. Unlike previously reported smart traps that rely primarily on image-based recognition, the proposed system emphasizes low hardware cost, low power consumption, operational simplicity, and scalability for deployment across large agricultural areas. Specifically, this study aimed to (i) develop a low-cost infrared-based smart fruit fly trap, (ii) evaluate the accuracy of automated insect counting, (iii) assess the communication performance and power consumption of the LoRa-based system, and (iv) examine its potential application for supporting Area-Wide Pest Management (AWPM) of fruit flies.

MATERIALS AND METHODS

Research Site. The study was conducted at the Applied Entomology Laboratory, Department of Plant Protection, Faculty of Agriculture, Universitas Gadjah Mada, Yogyakarta, Indonesia, during the period of 2021–2022.

The smart trapping system developed in this study was designed to support Area-Wide Pest Management (AWPM) programs by providing a cost-effective, durable, and scalable monitoring tool suitable for large-scale deployment. Rather than emphasizing high-end computing platforms, the system was designed to maximize affordability, energy efficiency, and ease of field maintenance. The study consisted of five components: (1) fruit fly collection and laboratory rearing, (2) evaluation of automatic counting sensors, (3) power consumption analysis, (4) LoRa communication performance testing, and (5) server architecture and web-based data visualization.

Fruit Fly Collection and Mass Rearing. Wild fruit fly adults were initially obtained from naturally infested fruits collected from orchards surrounding the Universitas Gadjah Mada (UGM) campus, Yogyakarta, Indonesia. The collected fruit flies belonged to *Bactrocera* spp. These wild insects served only as initial populations for establishing laboratory colonies and were not directly used in the experiments to minimize variation associated with age, physiological condition, and genetic background.

Infested fruits were maintained inside ventilated plastic containers containing sterilized sawdust as a pupation substrate. Approximately nine days after collection, pupae were separated using a fine sieve and transferred into acrylic emergence cages (0.027 m^3). Adults emerged approximately 13 days later and were maintained at 27 ± 2 ºC, 70–80% RH, under a 12:12 hours (L) photoperiod. Newly emerged fruit flies were supplied with yeast–sugar diet (1:4) or 90% honey solution absorbed in cotton, ensuring consistent nutritional status. Only these standardized, mass-reared adults were used for evaluating the automatic counting sensors and behavioral response assays, ensuring uniformity and repeatability of experimental outcomes.

Evaluation of Automatic Counting Sensors

Smart Trap Configuration. The smart trap was developed by modifying a conventional fruit fly trap to incorporate automatic counting, environmental monitoring, and wireless communication modules. The trap structure allowed adult flies to enter while minimizing escape and was compatible with food lures, methyl eugenol, cue-lure, sticky inserts, or light attractants depending on the target species as commonly applied in fruit fly monitoring programs in Indonesia (Kardinan & Maris, 2022).

The electronic system was controlled using an Arduino Nano microcontroller (ATmega328P), which coordinated sensor acquisition, data storage, and wireless communication. Environmental variables were monitored using a DHT11 temperature-humidity sensor, a rainfall sensor, and a GPS positioning module. Automatic insect counting was performed using an infrared interruption sensor installed inside the entrance tunnel.

Unlike camera-based monitoring systems requiring high computational power, the infrared sensor detects insects by recording interruptions of the infrared beam as individuals pass through the sensing chamber. This approach substantially reduces processing requirements, energy consumption, and hardware costs while maintaining reliable automated counting. Sensor data were recorded every two minutes and stored locally before transmission to the central server every six hours. The hardware specifications of the smart trapping system are summarized in Table 1.

Sensor Accuracy Testing. The performance of two optical sensing technologies, namely infrared and laser-beam sensors, was evaluated under laboratory conditions. Two optical sensor types—infrared and laser beam—were tested, while ultrasonic sensors were excluded due to low performance.

Experiments were conducted using three fruit fly population densities (10, 30, and 50 adults), representing low, moderate, and high infestation levels. Each treatment combination was replicated five times.

The experimental arena consisted of two transparent acrylic chambers (20 × 10 × 10 cm) connected by a V-shaped acrylic tunnel equipped with the optical sensor (Figure 1). Adult flies were deprived of food for one hour before testing to stimulate movement toward a yeast-based attractant placed in chamber B. Each insect passing through the tunnel was automatically detected by the sensors, and the recorded counts were compared with manual observations to determine counting accuracy, which was calculated as: Accuracy (%) = (Number of fruit flies counted by the sensor / Number of fruit flies counted manually) × 100.

Sensor outputs were recorded through the Arduino IDE serial monitor and exported for statistical analysis.

Power Consumption Analysis. Power consumption was evaluated to estimate battery requirements and optimize operational intervals for long-term field deployment.

Each operational cycle consisted of: GPS acquisition, environmental sensor measurements, insect detection, local data storage, and wireless data transmission.

The sensing stage was defined as the "reading operation", whereas communication with the server was defined as the "sending operation". To accommodate rural areas without stable 4G or 5G coverage, data transmission did not rely on high-bandwidth networks. Instead, the system used GSM/GPRS (2G) communication via a SIM800L module, which remains widely available in remote agricultural regions. This low-bandwidth connection was sufficient for transmitting small data packets at scheduled intervals while maintaining energy efficiency. The system operated with six-minute sensing intervals followed by scheduled data transmission. Each experiment was repeated three times, resulting in an average operational cycle of approximately 412 s. The average current consumption during the sensing and communication phases was subsequently used to estimate battery life for continuous field operation.

Power management in the developed system was based on two Li-ion 18650 batteries connected in parallel, each with a capacity of 2600 mAh. The total energy consumption of the system was calculated using the following equation:

$$Wi = \sum_{i=1}^{n} Pi \times ti \ldots\ldots\ldots\ldots (1)$$

Wi = Total energy consumption (Wh);

Pi = Power consumption during the i^{th} operating

Table 1. Technical specifications of the LoRa communication module used in the smart trapping system

Characteristic	Specification
Module power	20 dBm
Antenna gain	2 dBi
Frequency Carrier	923 MHz
Bandwidth	125 kHz
Spreading factor	7
Coding Rate	4/5

Figure 1. Experimental apparatus used to evaluate the accuracy of automatic insect counting sensors under laboratory conditions. The system consisted of two transparent acrylic chambers connected by a V-shaped tunnel equipped with an optical sensor. Adult fruit flies moved from chamber A toward chamber B containing a yeast attractant, allowing automatic counts to be compared with manual observations. A. Overall view; B. Top view; C. Side view.

condition (W);
ti = Operating time during the ith operating condition (h);
n = Number of operating conditions.

Since the system operates in two main modes, namely insect counting and environmental sensing (temperature and relative humidity), and data transmission (insect count and environmental variables), Equation (1) can be simplified as follows:

$$Wt = (Pr.tr) + (Ps.ts) \ldots\ldots\ldots\ldots (2)$$

Wt = Total energy consumption (Wh);
Pr = Power consumption during insect counting and environmental sensing (temperature and relative humidity) (VA);
tr = Operating time for insect counting and environmental sensing (temperature and relative humidity) (h);
Ps = Power consumption during transmission of insect count and environmental data (temperature and relative humidity) (VA);
ts = Operating time for transmitting insect count and environmental data (temperature and relative humidity) (h).

The ratio of the total energy consumption to the available battery capacity was calculated using the following equations:

$$R = \frac{Wt}{Wb} \ldots\ldots\ldots\ldots (3)$$

$$R = \frac{Wt}{Vbat \times AHbat} \ldots\ldots\ldots\ldots (4)$$

R = Energy consumption ratio;
Wt = Total energy consumption (Wh);
Wb = Total battery energy capacity (Wh);
Vbat = Battery voltage (V);
AHbat = Battery capacity (Ah).

LoRa Wireless Communication Performance. To support area-wide pest monitoring, the smart trapping system employed a LoRa-based star network architecture consisting of multiple client nodes and a single gateway (Figure 2). LoRa technology was selected because it provides long-range wireless communication with low power consumption, making it suitable for battery-powered monitoring devices deployed across extensive agricultural areas (Petäjäjärvi et al., 2017).

Each client node represented an individual smart trap equipped with an Arduino Nano microcontroller, an infrared counting sensor, environmental sensors, and a LoRa transceiver. Sensor data collected by each trap were transmitted via LoRa to a centrally located gateway. The gateway subsequently forwarded the aggregated data to the cloud server through a GSM/ GPRS (SIM800L) communication module, enabling synchronized monitoring of multiple traps distributed across the study area (Mikhaylov et al., 2016; Rachmani & Zulkifli, 2018).

The communication performance of the LoRa network was evaluated under open-field

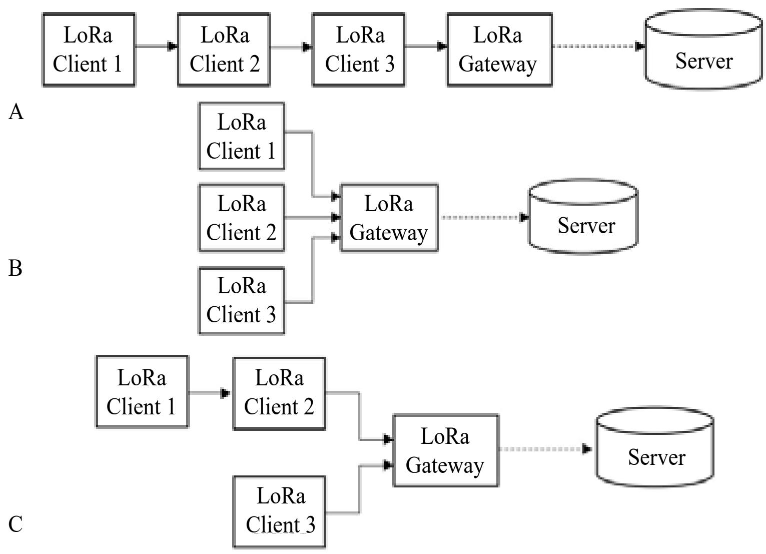

Figure 2. Proposed LoRa communication network topologies for area-wide pest monitoring using smart traps. A. Line topology, in which data are relayed sequentially between nodes; B. Star topology, in which multiple client traps communicate directly with a central gateway; C. Tree topology, in which client nodes communicate through intermediate nodes before reaching the gateway.

conditions. The gateway was installed at a fixed location, whereas client nodes were positioned at progressively increasing distances from the gateway. Communication performance was assessed based on the maximum communication distance, successful packet transmission, Received Signal Strength Indicator (RSSI), and Signal-to-Noise Ratio (SNR). These parameters were used to determine the reliability of wireless data transmission for large-scale field deployment.

Server Architecture and Web-Based Visualization. A cloud-based monitoring platform was developed to receive, store, visualize, and manage sensor data transmitted from all smart traps (Figure 3). Communication between the gateway and server employed a RESTful Application Programming Interface (REST API), with sensor data formatted using JavaScript Object Notation (JSON). REST architecture was selected because it provides efficient HTTP-based communication, reduced bandwidth requirements, and compatibility with multiple software platforms. Incoming data were automatically stored in a MySQL database and displayed through a web-based dashboard that provided real-time visualization of insect captures, environmental conditions, GPS locations, and historical monitoring records. The overall workflow of the smart monitoring system is illustrated in Figure 4.

RESULTS AND DISCUSSION

The IoT-based smart fruit fly trap developed in this study integrates automatic insect counting, environmental sensing, and wireless data transmission into a compact, low-cost monitoring platform suitable for Area-Wide Pest Management (AWPM). The

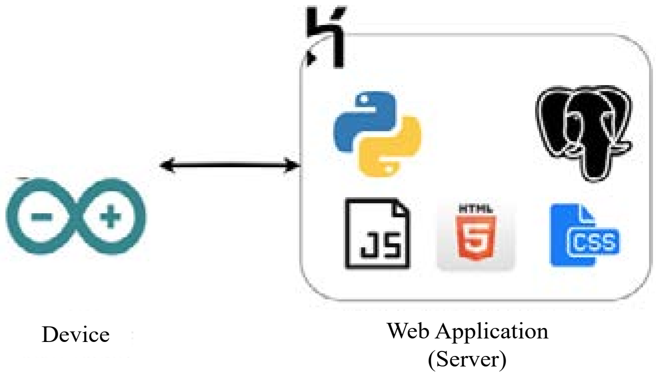

Figure 3. Data transmission architecture of the IoT-based smart fruit fly trapping system. Sensor measurements collected by each smart trap are transmitted to the cloud server through a RESTful API for data storage, processing, and web-based visualization.

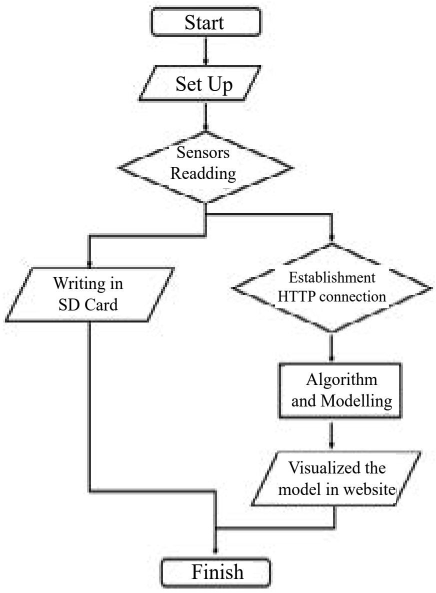

Figure 4. Operational workflow of the IoT-based smart fruit fly trapping system, illustrating sensor data acquisition, local data storage, wireless transmission through the LoRa–GSM network, cloud-based data processing, and web-based visualization for real-time pest monitoring.

system was evaluated based on prototype performance, sensor accuracy, power consumption, wireless communication, and web-based data visualization to determine its suitability for large-scale fruit fly surveillance.

General Trapping Prototype Design and Function. The prototype of the IoT-based smart fruit fly trap is presented in Figure 5. The external structure followed the conventional fruit fly trap design to maintain compatibility with existing monitoring practices while incorporating an internal compartment containing an infrared counting sensor, environmental sensors, an Arduino Nano microcontroller, a LoRa communication module, and methyl eugenol as the attractant (Vargas et al., 2010). This modification enabled automatic insect counting and wireless data transmission without altering the basic trapping mechanism.

Trap design should consider the behavior and bioecology of the target insect because these factors determine both trapping efficiency and monitoring strategy. In fruit fly surveillance, species-specific attractants play a crucial role in increasing trap effectiveness. Studies conducted in Indonesia have demonstrated that methyl eugenol-baited traps effectively monitor the daily activity and population dynamics of *Bactrocera* spp., highlighting the importance of attractant-based trapping in surveillance programs (Kardinan & Maris, 2022; Manurung et al., 2013). Monitoring systems developed for urban pests, such as cockroaches (Blattodea), ants (Hymenoptera: Formicidae), and stored-product beetles (Coleoptera), generally rely on crawling traps integrated with image-processing technologies for automated detection (Eliopoulos et al., 2018). In contrast, monitoring of agricultural insect pests usually requires species-specific attractants, including sex pheromones, food lures, light, or color, to maximize trap efficiency. Sex pheromone traps are widely used for many Lepidoptera and Coleoptera species, whereas light traps are effective for nocturnal insects and colored sticky traps are commonly employed for sap-sucking pests such as *Bemisia tabaci* and other hemipteran insects (Jung et al., 2003; López Jr, 1998; López et al., 2012; Pobozniak et al., 2020; Thulasi Priya et al., 2013; Vargas et al., 2000.

Because attractant efficacy was not the primary objective of this study, trap performance was evaluated based on the accuracy of the automatic insect counting system. The results demonstrated that sensor configuration strongly influenced counting accuracy (Table 2). Single-sensor configurations produced relatively low detection accuracy (<35%), whereas two-sensor configurations improved performance but remained inconsistent (34–58%). In contrast, three-sensor configuration consistently achieved counting accuracies exceeding 84% across all tested fruit fly population densities, indicating that wider sensor coverage substantially reduced undetected insect passages. Similar improvements in automated insect monitoring have been reported for multi-sensor detection systems, in which additional sensing points significantly increased counting reliability (Potamitis et al., 2015; Jiménez-López et al., 2024). Although both sensors showed comparable performance when three sensing units were used, the infrared sensor consistently produced slightly higher counting accuracy than the laser-beam sensor at medium and

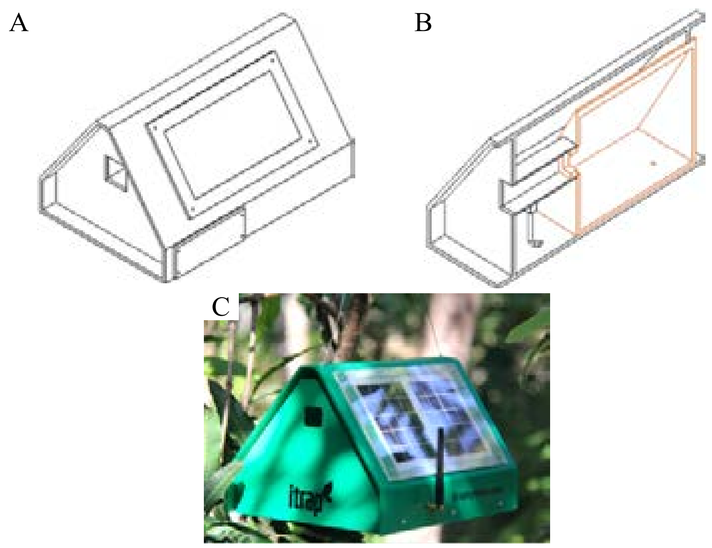

Figure 5. Prototype of the IoT-based smart fruit fly trap. A. External structure; B. Internal configuration of the electronic components; C. Field-ready smart trap prototype.

high fruit fly densities. In addition, infrared sensors are generally simpler, less expensive, and require lower power consumption than laser-based systems, making them more suitable for large-scale deployment in AWPM programs. Therefore, the final smart trap prototype incorporated three infrared sensors operating simultaneously to provide stable and reliable automatic counting suitable for area-wide fruit fly monitoring programs.

Electrical Circuit Design. The electrical circuit of the developed smart trap is presented in Figure 6. The system integrates an Arduino Nano microcontroller with an infrared counting sensor, a DHT11

Table 2. Counting accuracy of infrared and laser-beam sensors at different fruit fly population densities

Number of sensors	Fruit flies population	Counting accuracy (%)*	
		Infrared	Laser beam
1	10	28.00 ± 19.20	34.00 ± 8.90
	30	16.00 ± 5.50	31.30 ± 6.90
	50	20.00 ± 7.50	30.40 ± 4.60
2	10	34.00 ± 16.70	58.00 ± 8.40
	30	48.00 ± 8.70	49.30 ± 2.80
	50	47.20 ± 7.00	52.40 ± 6.20
3	10	84.00 ± 8.90	84.00 ± 8.90
	30	86.70 ± 4.70	84.70 ± 3.80
	50	88.40 ± 4.80	85.60 ± 4.30

Values are expressed as mean ± SD (n = 5).

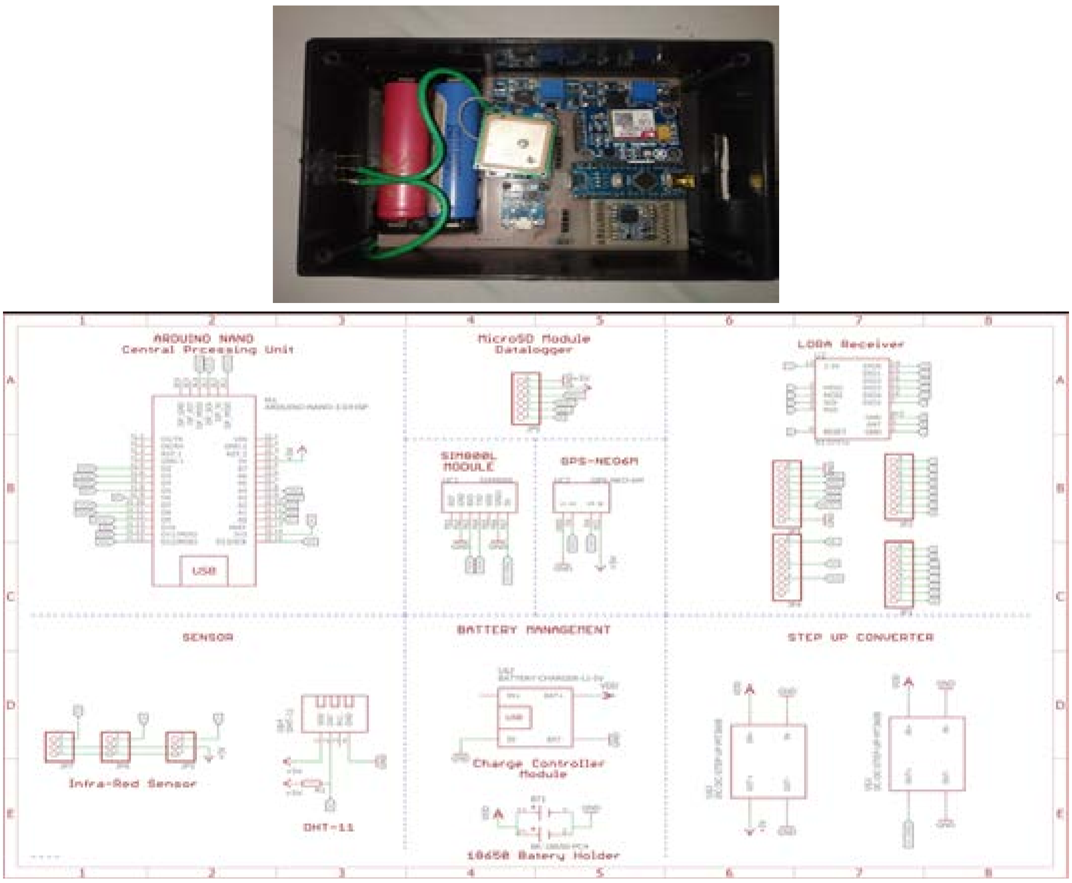

Figure 6. Electrical circuit diagram of the IoT-based smart fruit fly trap showing the integration of the Arduino Nano, MicroSD storage module, LoRa communication module, infrared sensor, DHT11 temperature–humidity sensor, battery management unit, and DC step-up converter. The upper panel shows the actual circuit implementation, whereas the lower panel presents the corresponding schematic diagram.

temperature–humidity sensor, a LoRa communication module, a MicroSD storage module, a battery management unit, and a DC step-up converter. These components function collectively to perform automatic insect detection, environmental monitoring, local data storage, and wireless transmission of monitoring data to the central server.

The simplified circuit architecture was designed to minimize hardware complexity while maintaining reliable monitoring performance. In contrast to image-based smart trapping systems that require cameras, high computational capacity, and machine-learning algorithms for insect recognition, the proposed system combines an infrared interruption sensor with the species-specific attractant methyl eugenol, thereby eliminating the need for electronic species identification. A comparable non-image-based approach based on wing-beat frequency detection has also been reported by Potamitis et al. (2015), although the present system requires substantially simpler hardware and lower computational resources.

The reduced hardware complexity contributes to lower manufacturing costs, lower energy consumption, and easier maintenance under field conditions. These characteristics are particularly advantageous for Area-Wide Pest Management (AWPM), where numerous trapping units must operate simultaneously over large agricultural areas. Moreover, the centralized collection of monitoring data from multiple traps provides a practical basis for pest surveillance, population trend analysis, and timely decision-making within integrated pest management (IPM) programs.

Power Consumption. The power consumption profile of the developed smart trap is presented in Figure 7. During the reading operation (0–357 s), power consumption remained relatively stable at an average of 1.332 VA because only the microcontroller and sensing modules were active. A temporary increase occurred during the sending operation (358–411 s), when the communication module was activated for wireless data transmission. Peak power consumption reached 1.369, 1.643, and 1.813 VA; however, these short-duration increases had only a minor effect on the overall energy requirement of the system.

One operational cycle consisted of two stages: (1) a reading operation, during which environmental variables and insect counts were recorded, and (2) a sending operation, during which the collected data were transmitted to the server. The reading operation consumed an average of 1.332 VA for 360 s, whereas the sending operation consumed 1.378 VA for 56 s, resulting in an average power consumption of 1.338 VA per operational cycle. These results indicate that wireless data transmission contributed only slightly to the total energy demand.

The smart trap was powered by two 3.7-V 18650 lithium-ion batteries connected in parallel, providing a total capacity of 5.2 Ah. Assuming the trap operates for four hours per day (morning, noon, afternoon, and night), the total daily power consumption (Wt) was calculated using the following equation:

$$Wt = P \times t$$

$$Wt = 1.332VA \times 4h + 1338VA \times 0.016h = 5.328VAh + 0.021VAh$$

$$Wt = 5.349VAh = 5.349Wh$$

The battery consumption ratio (R) was estimated as follows:

$$R = \frac{Wt}{Wb}$$

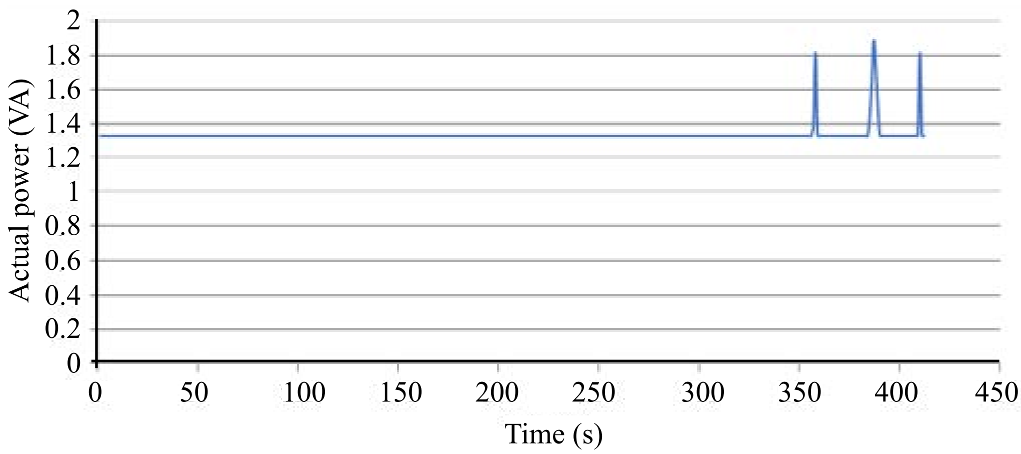

Figure 7. Power consumption (VA) over time during the reading and data transmission phases of one operational cycle.

$$R = \frac{Wt}{V_{battery} \times R = \frac{Wt}{Wb} It_{battery}}$$

$$R = \frac{5.349VAh}{3.7V \times 5.2Ah}$$

$$R = \frac{5.349\ VAh}{19.21\ VAh} = 0.28$$

Based on these calculations, the smart trap consumed approximately 28% of the available battery capacity during four hours of daily operation. Under these operating conditions, the battery could sustain continuous operation for approximately 14 hours 23 min 24 s (approximately 3.5 days) before recharging.

This operating duration demonstrates that the developed system has relatively low energy requirements and is suitable for long-term pest monitoring. For continuous field application, particularly under AWPM programs, integrating the system with a small solar panel would provide a practical solution for extending operational time and minimizing maintenance associated with battery replacement or recharging.

Coverage Test of LoRa Communication Module. The performance of the LoRa communication system was evaluated under field conditions to determine its suitability for area-wide fruit fly monitoring. The developed network consisted of multiple client nodes (smart traps) that transmitted monitoring data to a gateway, which subsequently forwarded the aggregated information to the central server via a GSM module (Figures 2A and 2B). This communication architecture enables synchronized data collection from multiple trapping locations while minimizing manual data retrieval.

Communication performance was assessed by measuring the maximum transmission distance between client nodes and the gateway under different field conditions. Transmission range was influenced by antenna height, transmission power, operating frequency, and environmental conditions, particularly whether communication occurred under line-of-sight (LOS) or non line-of-sight (NLOS) conditions. The communication performance obtained using the hardware specifications listed Table 1 is summarized in Table 3. The developed system maintained stable wireless communication over distances of up to 3 km under suitable field conditions. This coverage is sufficient for establishing monitoring networks in large agricultural areas, allowing multiple traps to transmit data through a single gateway while reducing the need for frequent field inspections. The power consumption of the LoRa communication module is presented in Table 4.

The reliability of data transmission was further evaluated using two client nodes and one gateway over a one-week observation period. In the first configuration, Client 1 transmitted data through Client 2 before forwarding it to the gateway, whereas in the second configuration both clients transmitted directly to the gateway. The average communication performance is presented in Table 5.

The ecorded Received Signal Strength Indicator (RSSI) values ranged from −31 to −42 dBm, indicating strong signal strength throughout the experiment. Signal quality was primarily influenced by transmission distance, antenna configuration, and

Table 3. Maximum communication distance between the client node and gateway under different antenna heights and transmission conditions

Antenna height (m)		Transmission condition	Maximum communication distance (km)
Gateway	Client		
1–2	1–2	None line of sight (NLOS)	0.6–1.0 km
10–15	1–2	Line of sight (LOS)	2.0–3.0 km

Table 4. Current consumption of the LoRa communication module under different operating modes

Operating mode	Current consumption
Transmit power: 20 dBm	120 mA
Transmit power: 14 dBm	93 mA
Transmit power: 5 dBm	55 mA
Active radio listening	40 mA
Sleep mode	300 µA

surrounding environmental conditions. Likewise, the Signal-to-Noise Ratio (SNR) remained within the operational range required for reliable LoRa communication, indicating that data transmission was only minimally affected by background noise. Using a spreading factor of 7 and a bandwidth of 125 kHz, the system maintained stable communication throughout the observation period. These findings demonstrate that the proposed LoRa-based network provides reliable long-range wireless connectivity for real-time fruit fly monitoring and is well suited for large-scale deployment in AWPM programs.

Web-Based Monitoring and Data Visualization. The developed smart trapping system successfully integrated automatic insect detection with a web-based monitoring platform, enabling real-time visualization and management of fruit fly populations. The overall workflow of data transmission and processing is presented in Figure 8. Sensor data collected by each smart trap, including insect counts, temperature, relative humidity, rainfall, light intensity, and geographic coordinates, were transmitted to the server in JSON format, automatically processed through the RESTful API, and stored in the database for subsequent visualization.

The monitoring results were displayed through an interactive web dashboard that allowed users to observe temporal fluctuations in fruit fly populations together with associated environmental conditions and trap locations (Figure 9). This centralized data management enables rapid access to field information

Table 5. Communication performance of the LoRa client nodes during the one-week transmission test

Clients node	SNR (dB)	RSSI (dBm)	Estimated airtime (ms)
Client 1	7.80	-31.62	41.20
Client 2	7.80	-42.90	36.10

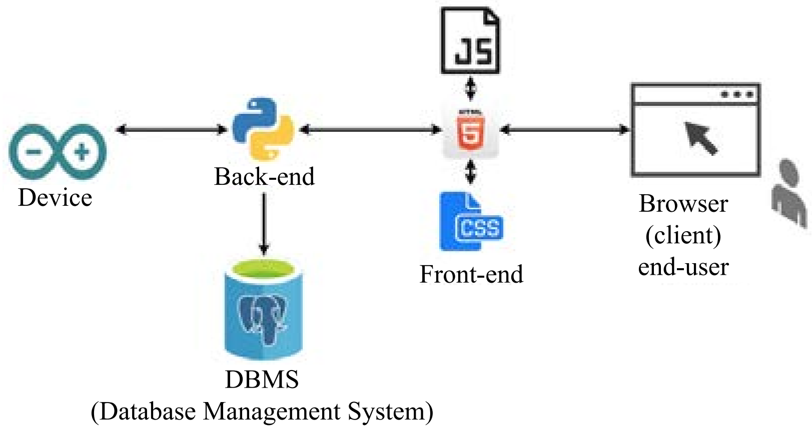

Figure 8. Architecture of the smart trap monitoring system.

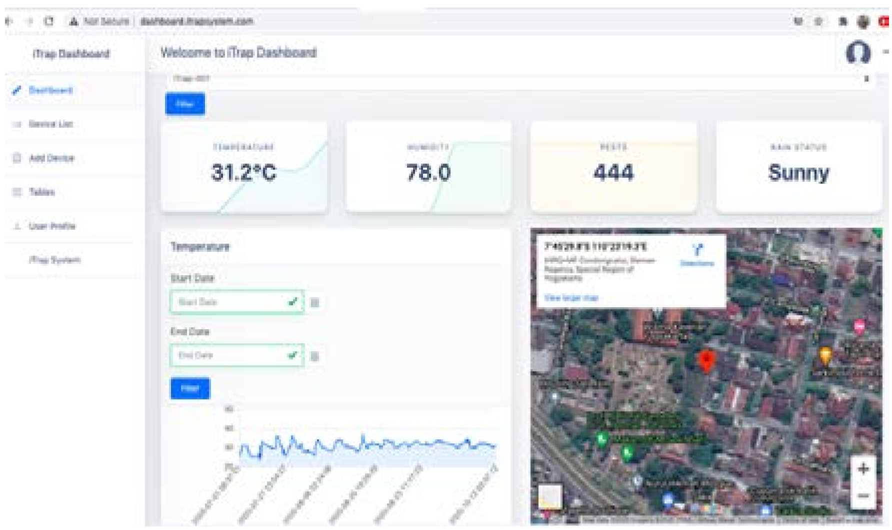

Figure 9. Web-based dashboard for real-time visualization of smart trap monitoring data.

without requiring frequent manual inspection of individual traps, thereby improving the efficiency of pest surveillance across large monitoring areas.

The web application provides several practical functions, including real-time data visualization, summary reporting, date-based data filtering, map-based visualization of trap locations, and data export in CSV and PDF formats. In addition, a user authentication system supports multiple users and multiple trapping locations while maintaining secure access to the monitoring database. These features provide a practical decision-support platform for Area-Wide Pest Management (AWPM), facilitating continuous surveillance, early detection of population increases, and timely implementation of fruit fly management strategies.

The integration of automated monitoring with web-based visualization is expected to strengthen surveillance and early warning programs by facilitating continuous collection of spatially distributed trapping data, complementing conventional fruit fly monitoring approaches used in Indonesia (Junaidi et al., 2026).

CONCLUSION

The developed IoT-based smart fruit fly trap provides a practical, cost-effective, and energy-efficient solution for supporting Area-Wide Pest Management (AWPM). The three-sensor configuration consistently achieved high counting accuracy (>84%) across different fruit fly population densities, demonstrating reliable automated insect detection. LoRa communication enabled stable wireless data transmission over distances of up to 3 km, making the system suitable for deployment across large agricultural areas. Low power consumption allowed continuous operation for several days using rechargeable batteries and can be further extended through solar charging. Integration with a web-based monitoring platform enabled real-time visualization, data storage, and efficient management of pest monitoring information. Overall, the developed system has strong potential to improve fruit fly surveillance by providing timely, reliable, and accessible monitoring data that support more effective pest management decisions.

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AUTHORS' CONTRIBUTIONS

AS contributed to the conceptualization, methodology, validation, investigation, and preparation of the original draft. HBT contributed to the methodology, sensor development, and validation. F contributed to the methodology, LoRa communication testing, validation, and manuscript writing. MFS was responsible for hardware development, methodology, and validation. S contributed to the methodology and manuscript review. IAM developed the web application and server architecture and contributed to manuscript writing. DAD contributed to hardware development, validation, and field testing. FAR contributed to the conceptualization, methodology, and validation. All authors read and approved the final version of the manuscript.

COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this study.

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