Sarjana International Journal of Sustainable Food and Agriculture

Journal homepage:
https://sarjanaintelek.my/index.php/sijsfa/index
ISSN: 3093-7086



Solar-Powered Edge AI Framework for Real-Time Thrips Population Assessment and Automated Biopesticide Spraying Iin Citrus Orchards

Huda Al Ihsan[1], Gilang Maulana Lazuardi[1], Imelda Alya Putri Kusuma[2], Melanie Putih Dwi Cahyani[2], Cintiya Diva Ramadan[2], Dian Nugraheni[2,*]

[1] Department of Engineering Technology, Power Plant Engineering Technology, Faculty of Vocational, State University of Malang, 65145 Malang, Jawa Timur, Indonesia
[2] Department of Science Education, Faculty of Mathematics and Natural Sciences, State University of Malang, 65145 Malang, Jawa Timur, Indonesia

ARTICLE INFO

Article history:
Received 20 August 2026
Received in revised form 30 August 2026
Accepted 30 September 2026
Available online 28 October 2026

Keywords:
Thrips Infestation; Edge Artificial Intelligence; Tiny Machine Learning; Automated Spraying; Solar-Powered Agriculture

ABSTRACT

Thrips *(Thrips sp.)* are significant pests of citrus plants that can reduce crop yield and fruit quality, particularly under warm and dry environmental conditions. Conventional control using synthetic pesticides can lead to pest resistance, pesticide residues, and adverse effects on non-target organisms, creating a need for more sustainable pest management approaches. This research aims to develop SmartAgroTrips, a solar-powered smart agriculture system that integrates Internet of Things (IoT) technology, on-device Edge Artificial Intelligence (AI), and botanical pesticide spraying for the real-time monitoring and automated control of thrips infestations in citrus orchards. The system was developed using an ESP32 microcontroller, a Light Dependent Resistor (LDR) sensor integrated into a yellow sticky trap, temperature and relative humidity sensors, an ultrasonic sensor, and a battery monitoring sensor. A Tiny Machine Learning classification model was developed to categorize environmental conditions into "Safe" and "Danger" statuses based on light intensity, temperature, and relative humidity. The model was optimized using the EON Compiler and deployed directly onto the ESP32. System performance was evaluated through feature space simulation, hardware-in-the-loop testing, classification metrics, and dynamic actuator validation across various battery voltage conditions. The results demonstrated a clear separation between "Safe" and "Danger" conditions, with the deployed model achieving a weighted F1-score of 1.00 and zero classification errors. The model exhibited an inference latency of 1 ms, peak RAM usage of 1.4 KB, and Flash memory usage of 14.4 KB. A deterministic dual-trigger safety mechanism successfully prevented spraying when the battery voltage fell below the operational threshold, even when the predicted probability of danger reached 1.00. These findings demonstrate that SmartAgroTrips is capable of providing an efficient, autonomous, and energy-saving system for monitoring and controlling thrips infestations, while also supporting the use of eco-friendly botanical pesticides in citrus cultivation .

* *Corresponding author.*
E-mail address: nugraheni.fmipa@um.ac.id

1. Introduction

Thrips (*Thrips sp.)* are a major pest of citrus crops, with the severity of infestation influenced by seasonal and climatic conditions. Infestations during the early stages of plant growth can reduce crop yields by as much as 34-38%, and delays in control measures can potentially result in total crop failure for farmers [1]. Thrips infest citrus plants by damaging flowers, leaves, and young fruit, resulting in spots and defects on the fruit's skin. Data from Turkey indicate that thrips can cause up to 28% damage to affected fruit [2]. Thrips infestations also lead to a decline in citrus crop yields, primarily due to flower drop and stunted shoot growth [3].

Thrips populations tend to increase sharply during the dry season when rainfall is low, as these conditions provide favorable conditions for the pests' feeding and reproductive activities [4]. An optimal temperature of around 27°C results in the highest survival and reproduction rates [5]. Conversely, high rainfall and humidity during the rainy season can suppress thrips populations by disrupting the pests' survival [4].

The imprudent use of synthetic pesticides can lead to pest resistance, secondary pest outbreaks, phytotoxicity, and harm to non-target organisms. Pest resistance is the most serious consequence because it reduces the long-term effectiveness of pest control and increases farmers' dependence on chemical pesticides [6]. Improper use of chemical pesticides can leave harmful residues on agricultural products, even exceeding the Maximum Residue Limit (MRL) by up to 3.65 ppm. The WHO reports approximately 1-5 million cases of pesticide poisoning each year, resulting in approximately 220,000 deaths, with 80% of these cases occurring in developing countries despite their use of only 25% of the world's total pesticides [7].

Research over the past five years has demonstrated the effectiveness of botanical pesticides in controlling thrips (Thrips sp.) populations on horticultural crops. Plant extracts such as garlic and soursop leaves have been shown to significantly reduce the intensity of thrips infestations compared to untreated plants, due to their content of bioactive compounds with antifeedant and insecticidal properties [8][9]. This potential is supported by research findings showing that the botanical pesticide derived from neem leaf extract is more effective than srikaya leaf extract in controlling the migratory locust (Locusta migratoria manilensis), with a mortality rate of 95% at concentrations of 25% and 50% and the ability to reduce feeding activity by up to 80%, whereas srikaya leaf extract only showed mortality at a 50% concentration [10].

A pesticide sprayer is a device that dispenses liquid pesticide through a pipe or hose in the form of droplets [11]. One technology currently used to assist farmers in applying liquid fertilizer is a nozzle that propels the liquid fertilizer [12]. The flat-fan nozzle is a type of nozzle characterized by a fan-shaped pressure pattern with a spray height of 0.6 m, a wind speed of 0-6 m/s², and a spray pressure of 0.3 MPa [13].

The era of the Fourth Industrial Revolution is the fourth revolution to sweep the world and has the potential to improve people's working lives by expanding their opportunities. One aspect of the Fourth Industrial Revolution is the development of the Internet or the Internet of Things (IoT) [14]. IoT technology was initially conceived to improve business processes in the manufacturing industry; today, it has spread to various economic sectors, including agriculture. IoT technology is well-suited for use in agriculture because it can address various challenges faced by farmers electronically, such as monitoring plant diseases, pest activity, soil fertility, and weather and climate conditions through sensors and wireless networks [15].

However, a gap remains: most agricultural IoT technologies are not specifically designed to address pest issues in horticultural crops such as thrips infestations in citrus plants nor are current technologies integrated with eco-friendly control methods. To address this, the SmartAgroTrips

innovation was developed; it is an IoT-based thrips monitoring and control system integrated with biopesticides. The system is designed to monitor citrus orchard environmental conditions in real time, utilizes On-Device Edge AI (TinyML) computing on ESP32 units, and employs botanical pesticides derived from papaya leaves and seeds as alternatives to chemical pesticides. TinyML is a variant of Edge AI optimized for microcontrollers with limited memory and computing power. Model quantization techniques, such as those used in TensorFlow Lite for Microcontrollers, enable image classification models to run on devices with less than 4 MB of flash memory [16].

This innovation offers a solution to challenges such as low pest control efficiency, crop damage caused by chemical pesticides, and a lack of eco-friendly agricultural technologies. Beyond supporting SDG 2 (Zero Hunger), the innovation contributes to SDG 12 (Responsible Consumption and Production) by reducing chemical pesticide use and utilizing environmentally friendly natural materials, as well as to SDG 13 (Climate Action) through the use of renewable energy from solar panels.

2. Methodology

The research was carried out to develop a solar-powered Smart Farming innovation enhanced with Edge AI (TinyML) technology to predict thrips populations and automate biopesticide spraying in real time. The testing process was conducted using Edge AI-based simulations to determine the AI system's success rate in processing and accumulating data received from sensors. Data acquisition for the simulations involved the use of manual inputs tailored to specific conditions encountered in the field. These conditions were classified into two categories: safe conditions and danger conditions.

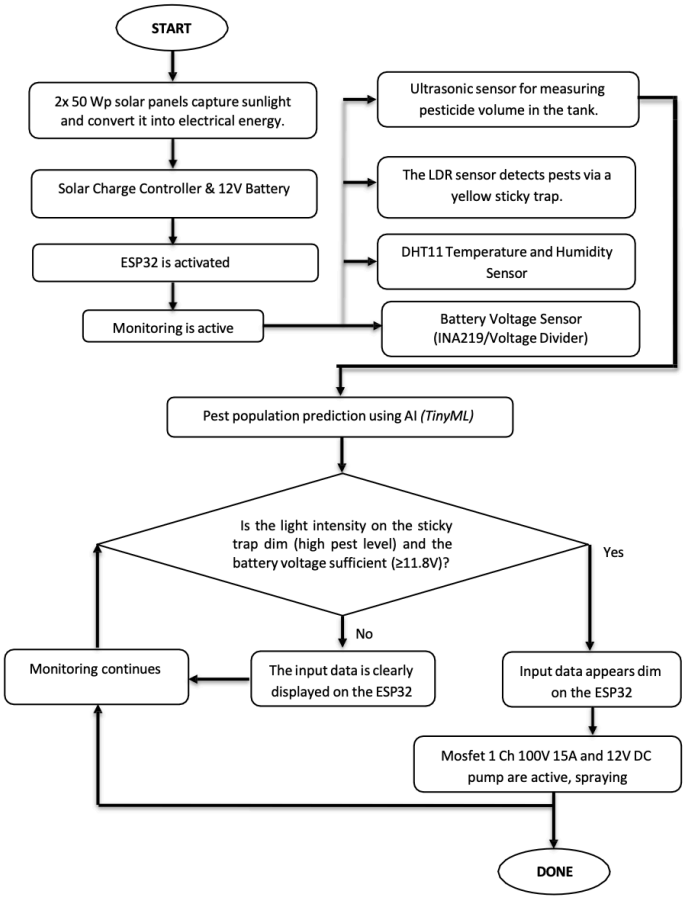


Fig. 1. Research Flow Diagram

Based on Figure 1, the SmartAgroTrips system uses 2 × 50 Wp solar panels as its energy source, which is regulated through a Solar Charge Controller (SCC) to charge a 12V battery in an off-grid configuration. The battery supplies power to the ESP32, which functions as the main controller and Processing & Edge AI Unit for running the TinyML model. The system monitors conditions in real time using the DHT11, ultrasonic sensor, LDR array, and INA219. The sensor data are processed through sensor fusion to identify pest populations, microclimate conditions, and energy availability. When the LDR detects indications of pest accumulation and the battery voltage is ≥11.8 V, the ESP32 activates a 4-channel MOSFET driver to operate four 12V DC pumps and spray Pepaya Mix. If no pest infestation is detected or the battery voltage drops below 11.5V, the spraying command is blocked to prevent deep discharge, and the system returns to the monitoring process.

2.2 SmartAgroTrips Design
2.2.1 Circuit Design

The system circuit design involves configuring the interconnections between components to support automated monitoring and control processes. SmartAgroTrips integrates three main pillars: a 100 Wp off-grid solar power system, an on-device Edge AI (TinyML) computing unit on the ESP32, and an automatic biopesticide spraying unit using Papaya Mix. Figure 2 illustrates the circuit design and the interconnect.

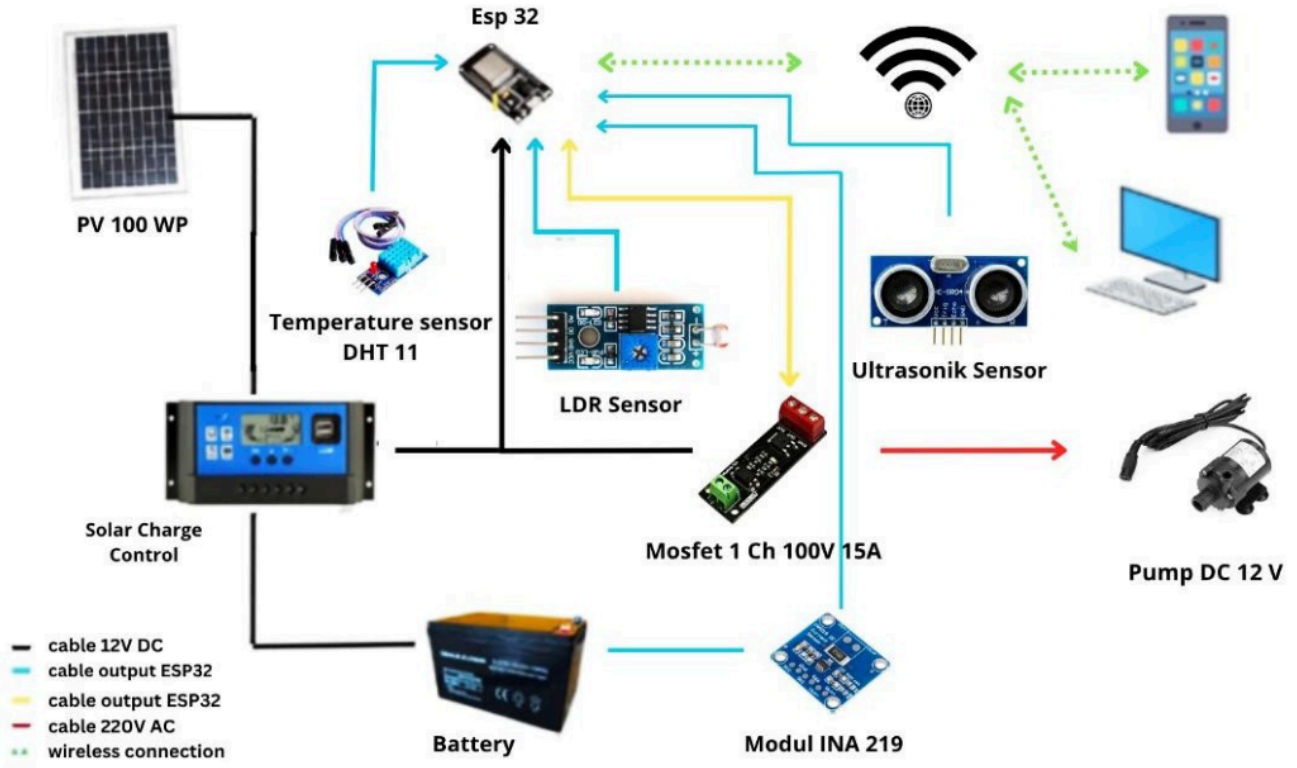


Fig. 2. SmartAgroTrips Circuit

The system of SmartAgroTrips in Figure 2 utilizes a 2 × 50 Wp solar panel array as its primary energy source, which is regulated through a Solar Charge Controller (SCC) to charge a 12V battery in an off-grid configuration. The battery supplies power to the ESP32, which functions both as the main controller and the Processing & Edge AI Unit for running the TinyML model on-device.

The microcontroller processes data from four sensors in real time: the DHT11 microclimate sensor, an ultrasonic sensor for monitoring the pesticide tank, an array of LDR sensors mounted on a yellow sticky trap to detect pest populations through light obstruction, and an INA219 sensor for accurately monitoring battery voltage and current.

The TinyML model performs sensor fusion by integrating pest population indices, weather conditions, and solar energy availability. When the LDR detects reduced light intensity caused by pest accumulation and the INA219 confirms that the battery voltage is within the safe threshold (11.8 V), the ESP32 triggers a 4-channel MOSFET driver module (100V, 15A) to simultaneously activate four 12V DC pumps for pesticide spraying. Conversely, if no pest infestation is detected or the battery voltage drops below 11.5V, the ESP32 blocks the spraying command to protect the battery from deep discharge while maximizing energy replenishment from the solar panels.

2.2.2 SmartAgroTrips Prototype Design

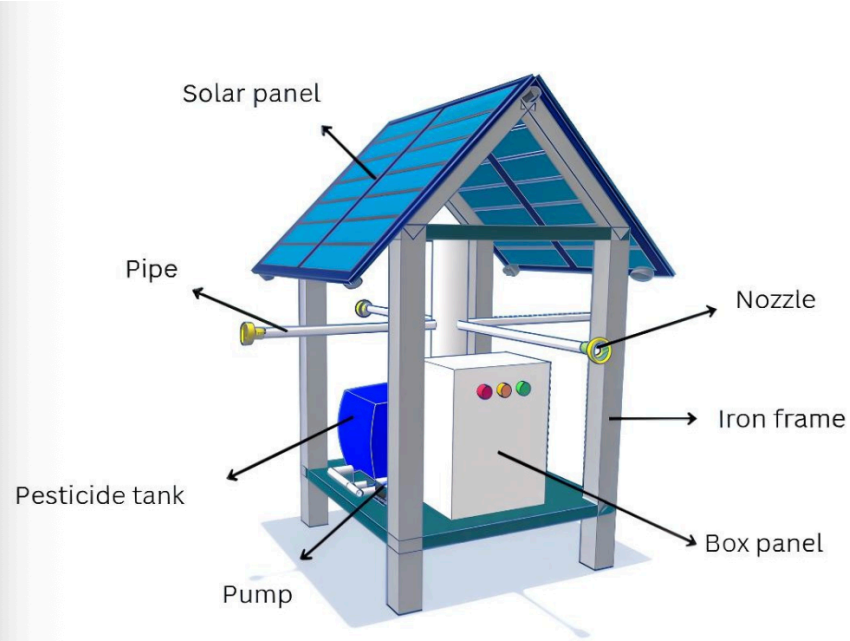
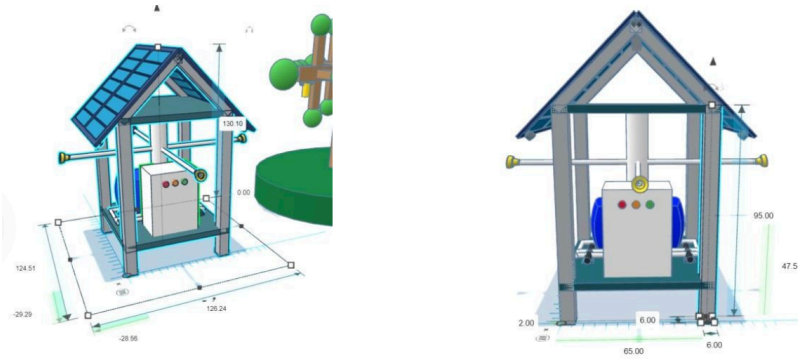


Fig. 3. Component Details

As shown in Figure 3, the device utilizes a solar-powered pesticide spraying system. Energy generated by the solar panels is used directly to operate a pump, which draws the pesticide liquid from the main storage tank. The liquid is then forced through a piping system to the nozzle for the spraying process.

To ensure stable operation, the device features a robust physical structure. All system components are securely supported by an iron frame, which also houses a dedicated panel box. This panel box plays a crucial role by serving as a protective enclosure for the device's control system.



(a) Side view (b) Front view

Fig. 4. Prototype size (a) Side view (b) Front view

The prototype of the SmartAgroTrips system illustrated in Figure 4 consists of a protective housing structure with a base footprint of approximately 126.24cm × 124.51cm and a total height of ±130.10cm. The frame provides an effective height of approximately 95cm above the base. Its structure utilizes four main support posts that hold up the roof and the internal equipment components. The lower section features a width of approximately 65cm, serving as the designated space for the pesticide tank, pump, and control panel box.

2.2.3 Sticky Trap



Fig. 5. System Implementation

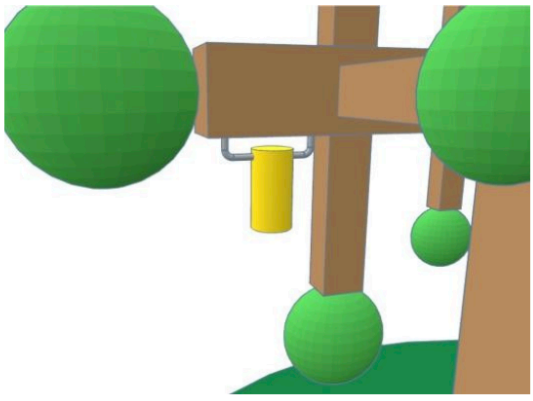


Fig. 6. Sticky trap prototype

Based on Figures 5 and 6, the SmartAgroTrips system and the sticky trap serve to monitor the number of thrips adhering to it. This yellow, cylindrical trap is mounted on the tree; while separate from the spraying components, it remains part of the integrated crop monitoring system. An LDR (Light Dependent Resistor) sensor is installed within the trap to detect changes in light intensity on the trap's surface. As the number of thrips adhering to the trap increases, the surface becomes increasingly covered, reducing the amount of incoming light and causing the sensor to transmit an "ON" (dim) signal. Conversely, when few thrips are present and the surface remains exposed to light, the sensor transmits an "OFF" (bright) signal. These data serve as an indicator of pest prevalence, guiding the spraying operations within the SmartAgroTrips system.

Table 1
Sticky trap composition

Tools and materials	Amount
Pentroganol	2 ml
Fruit fly glue	5 ml
Bottle	300 ml
Rope	60 cm
Plastic packaging	1 sheet

As shown in Table 1, petrogenol contains the active ingredient methyl eugenol, an attractant compound capable of luring insects or pests, which is why it is frequently used in traps [16].

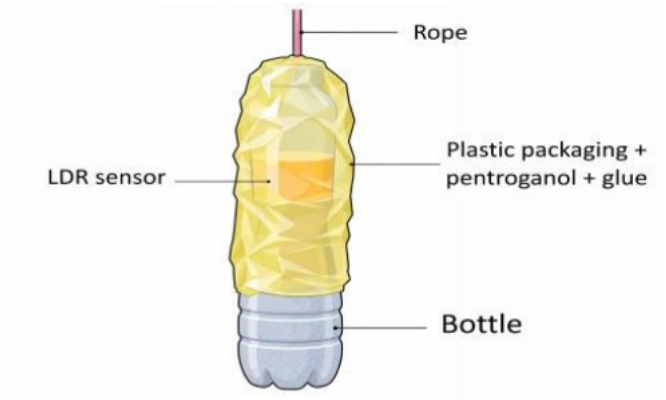


Fig. 7. Sticky trap component details

Figure 7 illustrates the components of the yellow sticky trap, which serves a dual function as a thrips capture medium and as part of the optical detection mechanism. The yellow color was selected based on the visual response of thrips within the 500–550 nm wavelength range [17]. As thrips accumulated on the sticky trap surface, the optical condition detected by the LDR sensor changed, providing an input feature for the Edge AI classification system.

2.3 Biopesticide

From a biochemical perspective, the system's effectiveness is enhanced by the presence of the enzyme papain and the alkaloid carpaine in papaya leaf extract, which can achieve a pest mortality rate of up to 70% by disrupting the pests' nervous and metabolic systems. With an ESP32-based control mechanism, spraying occurs only when a high risk is detected, thereby minimizing organic material waste and ensuring that pesticide droplets are precisely targeted at the leaves and plant growth points.

Table 2
Biopesticide composition for 35 L

Materials	Composition
Papaya leaves	175 leaves
Garlic	53 cloves
Water	35 L
Lemongrass	100 g

The botanical pesticide was prepared by first washing all ingredients listed in Table 2 thoroughly. The ingredients were then cut into smaller pieces and placed in a blender. Clean water was added until the mixture was sufficiently covered, after which the ingredients were blended until homogeneous. The blended mixture was subsequently filtered, and the filtrate was transferred into a clean plastic bottle. The bottle was tightly sealed, and the mixture was fermented for at least 24 hours.

2.4 TinyML Model Development and Pipeline

2.4.1 Data Acquisition and Exponential Moving Average (EMA)

Raw time-series signals acquired from the LDR array and microclimate sensors were filtered to suppress physical disturbance and high-frequency noise using an Exponential Moving Average (EMA) algorithm:

$$\bar{S}_t = \alpha \cdot S_t + (1 - \alpha) \cdot \bar{S}_{t-1} \quad (1)$$

where $\bar{S}_t$ represents the smoothed sensor output at time step t, S_t is the raw sensor measurement, and α = 0.15 is the smoothing coefficient. The initial EMA value was determined from the first available sensor measurement, such that $\bar{S}_o = S_o$. The filtering process was subsequently performed sequentially for every incoming measurement. The resulting smoothed

signals were then used as input features for the TinyML classification pipeline. This approach allowed the system to reduce the influence of transient sensor noise while preserving meaningful changes in LDR intensity, temperature, and relative humidity associated with the transition between Safe and Danger conditions.

2.4.2 Neural Network Architecture and Optimization

A Deep Neural Network (DNN) classifier was designed in TensorFlow Lite for Microcontrollers and trained via Edge Impulse. The input layer accepts three preprocessed environmental parameters (LDR intensity, T, RH). The network consists of fully connected dense layers with ReLU activation functions, ending in a two-class Softmax layer (Safe vs Danger). The model was optimized using the Adam optimizer with a learning rate of 0.001 over 150 epochs. The binary cross-entropy loss function utilized during training is defined as:

$$\mathcal{L} = -(1/N) \sum_{i=1}^{N} [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (2)$$

where $yi \in \{0,1\}$ is the ground truth label $\hat{y}i$ is the predicted class probability, and N is the batch sample size.

2.4.3 Model Quantization and EON Compiler Integration

To deploy the trained neural network onto the ESP32 without exceeding system memory limits, single-precision floating-point weights (float32) were quantized to an 8-bit integer (int8) representation. The linear quantization mapping function is expressed as:

$$q = \text{round}(r/S) + Z \quad (3)$$

where r is the real floating-point value, q is the quantized integer, S is the scale factor, and Z is the zero-point integer offset. The model was compiled using Edge Impulse's EON™ Compiler, generating raw C++ code to eliminate runtime interpreter overhead.

2.4.4 Deterministic Dual-Trigger Actuation Logic

To eliminate improper spraying commands caused by transient sensor errors or low battery conditions, a decoupled dual-trigger safety logic was integrated into the main execution loop. The physical control signal $A(t) \in \{0,1\}$ assigned to the 4-channel MOSFET driver (GPIO 5) is calculated using a logical AND operation between the TinyML class probability output and the INA219 battery telemetry:

$$A(t) = \{ 1, \text{if } P(\text{Danger}) \geq P_{th} \text{ AND } V_{\beta at} \geq V_{th}; 0, \text{otherwise} \} \quad (4)$$

where P (Danger) is the softmax threat probability output, Pth= 0.80 is the AI activation threshold, $Vbat$ is the battery voltage, and Vth= 11.8 V is the low-voltage cutoff limit (11.5V emergency shutdown).

2.4.5 Statistical Analysis and On-Device Metrics

The performance of the classification model was evaluated on validation and testing sets using standard confusion matrix metrics: Precision (P), Recall (R), and F1-Score ($F1$):

$$P = TP / (TP + FP) \quad (5)$$
$$R = TP / (TP + FN) \quad (6)$$
$$F_1 = 2 \cdot (P \cdot R) / (P + R) \quad (7)$$

where TP, FP, and FN represent true positives, false positives, and false negatives, respectively. Statistical Validation between simulated microclimate parameters and physical experimental testbench data was performed using Mean Absolute Percentage Error (MAPE):

$$MAPE = (100\%/k) \sum_{i=1}^{k} |(M_i - E_i)/M_i| \quad (8)$$

where Mi is the measured physical sensor value, Ei is the estimated/simulated value, and k is the total number of evaluation instances.

On-device hardware performance was benchmarked directly on the ESP32 microcontroller by measuring inference execution latency ($tinf$ in milliseconds), peak Static RAM consumption ($MRAM$ in kilobytes), and total Flash memory usage ($MFlash$ in kilobytes).

2.4.6 Microclimate Dataset and Target Class Definition

The dataset for training and validating the TinyML classification model comprises multidimensional time-series environmental telemetry. The input feature space combines three physical parameters, namely LDR light intensity (LDR), ambient temperature (T), and relative humidity (RH). Sensor signals were recorded under field-simulated microclimatic conditions and labeled into two target classes based on thrips infestation risk. The Safe class is characterized by high ambient LDR light intensity due to an unobstructed trap surface, moderate ambient temperature,

and high relative humidity, indicating negligible pest accumulation and safe crop conditions. Conversely, the Danger class is defined by significant LDR light attenuation caused by thrips coverage on the sticky trap surface, elevated ambient temperature, and low relative humidity, signaling an active pest infestation requiring biopesticide actuation. The representative sensor feature ranges and environmental thresholds for each target are presented in Table 3.

Table 3
Representative sensor feature ranges and environmental threshold labeling

Target Label	LDR Intensity (ADC)	Ambient Temperature (°C)	Relative Humidity (%)	Physical System Context
Safe	3,200–4,095	23.0–27.5	65.0–85.0	Unobstructed LDR, optimal microclimate
Danger	500–1,800	28.0–35.0	35.0–55.0	High light attenuation, hot/dry microclimate

3. Results

Research to evaluate the performance of the TinyML-based Edge AI thrips mitigation system (SmartAgroTrips) integrated with a deterministic dual-trigger safety layer on an ESP32 microcontroller has been successfully carried out using 3D feature space simulation validated through hardware-in-the-loop experiments. The research was conducted by decoupling environmental sensing parameters (LDR light intensity, temperature, and relative humidity) from the battery power management system to evaluate its effect on classification accuracy, system latency, and energy consumption efficiency. System performance validation was evaluated using confusion matrix parameters (F1-score, Precision, Recall) alongside dynamic time-step actuation matrix analysis under variable battery voltage conditions (Vbat).

3.1 Microclimate Dynamics and Feature Space Separability

The results of ambient environmental parameter changes for thrips infestation monitoring have been successfully obtained and grouped. From the change in time-step diurnal data across a 24-hour cycle, distinct microclimate thresholds trigger the transition between normal conditions (Safe) and thrips infestation threats (Danger).

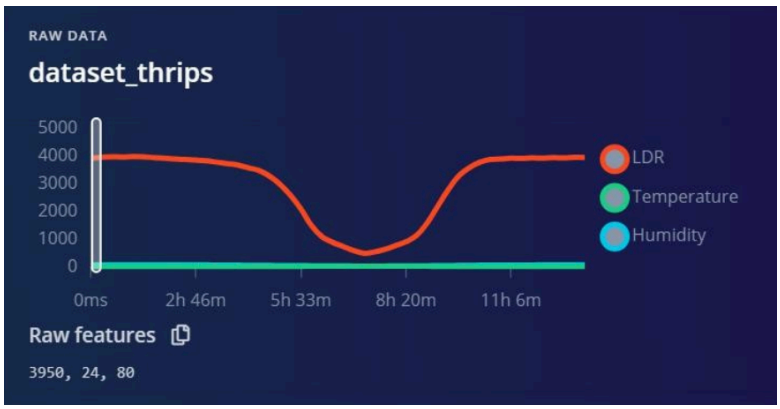


Fig. 8. Diurnal profile of environmental sensor variables across a 24-hour monitoring cycle: (a) LDR light intensity, (b) ambient temperature, and (c) relative humidity

Figure 8 illustrates the diurnal profile of the environmental sensor variables over a 24-hour monitoring cycle. The elevation of ambient temperature above 29.0°C accompanied by a decrease in relative humidity below 50% directly correlates with peak thrips flight activity, consistent with established agricultural entomology literature. The physical accumulation of captured thrips on the yellow sticky trap obscures the LDR surface, causing a sharp decline in light intensity below 1200 ADC.

The spatial distribution of features derived from the Edge Impulse pipeline is illustrated in Figure 9, the 3D feature space contours depict two distinct, highly separated clusters corresponding to Safe (34 samples) and Danger (14 samples). Notably, the absence of overlapping data points between classes confirms that the selected environmental features provide high linear separability without boundary ambiguity.



Fig. 9. 3D feature space visualization of environmental parameters indicating complete cluster separation between "Safe" and "Danger" classification states

3.2 Dynamic Time-Step Analysis and Actuator Decision Logic

The deployment of the trained neural network onto the ESP32 microcontroller utilizing the EON™ Compiler demonstrated superior hardware efficiency compared to uncompiled execution architectures, as summarized in Table 4.

Table 4
Quantitative metrics of TinyML model on-device performance and resource allocation

Performance / Resource Parameter	Measured Value	Operational Impact
Inference Latency	1 ms	Real-time response capability
Peak RAM Usage	1.4 KB	>98% RAM availability retained
Flash Memory Usage	14.4 KB	Minimal storage footprint
Compiler Engine	EON™ Compiler	Optimized C++ code structure
Weighted F1-Score	1.00	Zero misclassification rate

The optimization achieved by the EON™ Compiler reduced the peak RAM consumption to merely 1.4 KB and Flash memory utilization to 14.4 KB. This low memory footprint directly impacts the energy efficiency of the system. By reducing memory bus operations and CPU clock cycles required per inference, the ESP32 maintains an ultra-low inference latency of 1 ms. Consequently, the active processing time of the CPU is drastically minimized, enabling extended deep-sleep power-saving modes between sampling intervals and significantly reducing overall operational power draw.

3.3 Dual-Trigger Actuator Safety Validation

To verify the operational integrity of the dual-trigger mechanism, the TinyML probability outputs were evaluated against the power safety threshold managed by the deterministic safety layer. The actuation response matrix under sequential time-step conditions is presented in Table 5.

Table 5
Dynamic time-step actuation matrix combining Edge AI prediction probabilities and battery safety thresholds

Timestamp (ms)	Simulation Time	Classification Label	AI Probability (Danger)	Battery Voltage (V_bat)	Actuator Output (GPIO 5)	System Status
15,000,000	04:10	Safe	0.00	12.30 V	LOW (0)	Standby Normal
18,000,000	05:00	Safe	0.04	12.25 V	LOW (0)	Standby Normal
19,000,000	05:16	Safe	0.32	12.27 V	LOW (0)	Threat Detection Phase
20,000,000	05:33	Danger	0.92	12.30 V	HIGH (1)	Active Actuation
22,000,000	06:06	Danger	1.00	12.33 V	HIGH (1)	Active Actuation
22,000,000	06:06 (Low-Bat)	Danger	1.00	10.50 V	LOW (0)	Power Override Activated

As detailed in Table 5., the classification system exhibits a smooth probabilistic transition between 18,000,000ms and 20,000,000ms, shifting continuously from 0.04 to 0.92 without erratic signal oscillation.

The deterministic safety layer successfully overrode the AI actuator command during low-power states. Under the test scenario marked with an asterisk (22,000,000ms), despite the TinyML model outputting a maximum threat probability of 1.00, the actuator output remained LOW (0) due to Vbat = 10.50 V falling below the 11.8 V operational limit. This confirms that the decoupled architecture guarantees total battery over-discharge protection without compromising AI classification accuracy.

4. Conclusions

The study was able to develop and validate SmartAgroTrips, an Edge AI system that is powered by solar energy and combines a thrips population assessment based on TinyML with an automatic biopesticide spraying system in citrus orchards. The test results indicate that environmental factors such as LDR light intensity, temperature, and humidity can produce a highly clear separation of the "Safe" and "Danger" states. Additionally, the TinyML model created using the EON™ Compiler had an inference latency of 1 ms, used 1.4 KB of RAM, required 14.4 KB of Flash memory, and achieved a weighted F1-score of 1.00 with no misclassifications.

The fact that the dual-trigger actuator validation shows the deterministic safety layer can prevent the spraying command sent by the AI when the battery voltage falls below 11.8 V is still valid even if the model's predicted threat probability reaches its highest value of 1.00. This result proves that the proposed architecture can protect the battery against over-discharge without affecting the system's classification accuracy or response speed. It therefore follows that SmartAgroTrips is an efficient

method for monitoring and controlling thrips infestations; the system also makes good use of energy and operates autonomously in citrus orchards.

Acknowledgement
The authors sincerely thank the organizing committee of the KI–RBSET 2026 competition for providing the opportunity to present this work. Gratitude is also extended to our supervising lecturer for their invaluable guidance, continuous support, and mentorship throughout this research.

Conflict of Interest Statement
The authors declare that there is no conflict of interest regarding the publication of this paper. No financial support, grants, or other forms of compensation were received that could have influenced the outcomes of this work. The research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author Contributions Statement
Huda Al Ihsan conceived the idea, designed the research and the core system, and implemented the artificial intelligence. Gilang Maulana Lazuardi was responsible for the advanced system design and data acquisition. Imelda Alya Putri Kusuma conducted data analysis and assisted in interpreting the results. Melanie Putih Dwi Cahyani assisted with the literature review and drafted the initial manuscript. Cintiya Diva Ramadan contributed to the development of the methodology and participated in editing the manuscript. All authors assisted in revising the manuscript, reviewed it, and approved the final version.

Data Availability Statement
All data generated or analyzed during this study are included in this published article. Further datasets, such as sensor logs and the training data for the TinyML model, are available from the corresponding author upon reasonable request. Where applicable, publicly available datasets used in the study are cited in the references.

Ethics Statement
This study was conducted in accordance with the ethical standards of the institutional and/or national research committee. Since this study focused on creating and testing an agricultural automation system that didn't involve humans or animals, formal ethical approval was not required. All experiments were conducted carefully, with consideration for environmental protection and safe farming practices.

References
[1] Aditia, A. F., and I. L. I. Putra. “Severity and Incidence of Spodoptera frugiperda Attack on Maize Plants in Sleman District.” Jurnal Ilmu Pertanian Indonesia 30, no. 3 (2025): 581–590. https://doi.org/10.18343/jipi.30.3.581.
[2] Atakan, E. “A New Pest Thrips Species in Citrus in Adana Province: Scirtothrips dorsalis Hood (Thysanoptera: Thripidae).” Cukurova University, Agriculture Faculty 39, no. 2 (2024): 375–381. https://doi.org/10.36846/cjafs.2024.157.
[3] Atakan, E. “Factors Affecting Fruit Damage Caused by Thrips hawaiiensis (Morgan) (Thysanoptera: Thripidae) in Citrus Lemon Groves in Turkey.” Phytoparasitica 52, no. 1 (2024): 1–11. https://doi.org/10.1007/s12600-024-01135-9.
[4] Rakesh, T., N. Chitra, M. Murugan, R. P. Soundararajan, M. Kavitha, and D. Uma. “Relative Abundance and Population Dynamics of Chilli Thrips Scirtothrips dorsalis (Hood) (Thripidae: Thysanoptera) and Its Correlation with Weather Parameters.” Plant Science Today 13, no. 1 (2025): 1–7. https://doi.org/10.14719/pst.7322.

[5] Lin, Tao, Yong You, Zhaohua Zeng, Yixin Chen, Jinfeng Hu, Shuo Lin, Qingling Hu, Fenghua Yang, and Hui Wei. "Temperature-Dependent Demography of Thrips hawaiiensis (Thysanoptera: Thripidae): Implications for Prevention and Control." Environmental Entomology 50, no. 6 (2021): 1455–1465. https://doi.org/10.1093/ee/nvab084.

[6] Hidayah, N., N. Rahma, R. Amelia, R. Kumala, O. Meliandika, and T. Asmadi. "Pemanfaatan Daun Mimba (Azadirachta indica) Sebagai Pestisida Nabati Dalam Mengatasi Masalah Hama di Desa Gondang Kecamatan Gangga Kabupaten Lombok Utara." Jurnal Pengabdian Magister Pendidikan IPA 7, no. 1 (2024): 308–311. https://doi.org/10.29303/jpmpi.v7i1.6527.

[7] Sinambela, B. R. "Dampak Penggunaan Pestisida Dalam Kegiatan Pertanian Terhadap Lingkungan Hidup Dan Kesehatan [The Impact of Pesticide Use in Agricultural Activities on the Environment and Health]." Jurnal Agrotek 8, no. 2 (2024): 178–187. https://doi.org/10.33096/agrotek.v8i2.625.

[8] Gocher, D. K., A. K. Chaudhary, P. Kumar, and J. Goswami. "Efficacy of Different Bio-Pesticide and Botanical against Onion Thrips (Thrips tabaci L.)." Journal of Experimental Agriculture International 46, no. 10 (2024): 381–387. https://doi.org/10.9734/jeai/2024/v46i102960.

[9] Sari, Dian Ekawati, and Sulfiani Ridwan. "Efektivitas Beberapa Pestisida Nabati terhadap Populasi Thrips sp. pada Tanaman Cabai [Effectiveness of Various Botanical Pesticide on Thrips sp. Pest Population in Chili Pepper]." Perbal: Jurnal Pertanian Berkelanjutan 10, no. 2 (2022): 299–304. https://doi.org/10.30605/perbal.v10i2.1856.

[10] Killa, Y. M., A. P. Maranda, and M. R. Hana. "Efektivitas Pestisida Nabati Ekstrak Daun Mimba (Azadirachta indica) dan Srikaya (Annona squamosa Linn) untuk Mengendalikan Hama Belalang Kembara (Locusta migratoria manilensis Meyen)." Agro Wiralodra 6, no. 1 (2023): 9–13. https://doi.org/10.31943/agrowiralodra.v6i1.83.

[11] Annafiyah, S. Anam, and M. Fatah. "Rancang Bangun Sprayer Pestisida Menggunakan Pompa Air DC 12 V dan Panjang Batang Penyemprot 6 Meter." Jurnal Rekayasa Mesin 16, no. 1 (2021): 90–99. https://doi.org/10.32497/jrm.v16i1.2195.

[12] Admin, A. "Rancang Bangun Visualisasi Aliran Air di Dalam Pipa Tubular dengan Vortex Generator untuk Meningkatkan Sifat Turbulensi Fluida." Teknika STTKD: Jurnal Teknik, Elektronik, Engine 7, no. 2 (2021): 205–215. https://doi.org/10.56521/teknika.v7i2.321.

[13] Wang, J., Q. Liang, T. Zeng, X. Zhang, W. Fu, and Y. Lan. "Drift Potential Characteristics of a Flat Fan Nozzle: A Numerical and Experimental Study." Applied Sciences 12, no. 12 (2022). https://doi.org/10.3390/app12126092.

[14] Febrianti, F., S. Adi Wibowo, and N. Vendyansyah. "Implementasi IoT (Internet of Things) Monitoring Kualitas Air dan Sistem Administrasi pada Pengelola Air Bersih Skala Kecil." JATI (Jurnal Mahasiswa Teknik Informatika) 5, no. 1 (2021): 171–178. https://doi.org/10.36040/jati.v5i1.3249.

[15] Istia, Siti Amalia, Fauziah Zahra Ash Shidiq, Rafa Nuzul Qalam, and Salma Salsabilla. "Identifikasi Keanekaragaman Serangga Menggunakan Dua Jenis Perangkap di Lingkungan Universitas Sali Al-Aitaam Kabupaten Bandung." AGRO TATANEN: Jurnal Ilmiah Pertanian 7, no. 2 (2025): 45–51. https://doi.org/10.55222/gp0s3407.

[16] Aulia, M., and B. Styawan. "State-of-the-Art Review: Teknologi Edge-AI dan IoT untuk Keamanan Sistem Smart Parcel Drop Box pada Last-Mile Delivery." TELNECT: Telecommunications, Networks, Electronics and Computer Technologies 6, no. 1 (2026): 2. http://ejournal-purwakarta.upi.edu/telnect/.

[17] Carrillo-Arámbula, Lucia, Francisco Infante, Adriano Cavalleri, Jaime Gómez, José A. Ortiz, Ben G. Fanson, and Francisco J. González. "Colored Sticky Traps for Monitoring Phytophagous Thrips (Thysanoptera) in Mango Agroecosystems, and Their Impact on Beneficial Insects." PLOS ONE 17, no. 11 (2022): 1–20. https://doi.org/10.1371/journal.pone.0276865.