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Enhancing maggot farming with an internet of things-enabled watering and monitoring system

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ABSTRACT

Black soldier fly (BSF) maggot cultivation is a high-efficiency approach to organic waste bioconversion and sustainable protein production; however, productivity is critically sensitive to temperature and humidity, which are poorly regulated under conventional manual practices that are labor-intensive, error-prone, and unresponsive to environmental fluctuations. This study implements an internet of things (IoT)-enabled watering and monitoring system for BSF maggot farming, integrating an SHT20 sensor, ESP32 microcontroller, and three actuators (water pump, heating bulb, and blower fan). The system operates in two modes: manual mode via Telegram Bot API, and automatic mode governed by a Mamdani fuzzy logic inference engine with nine IF–THEN rules. Sensor accuracy was validated across 12 trials (22.5-43.8 °C; 45-89% RH). Mean temperature accuracy of 99.13% (error: 0.87%, SD: 0.58%) and mean humidity accuracy of 99.27% (error: 0.73%, SD: 0.56%) were achieved, both within the ±2% IoT sensing tolerance. Fuzzy logic evaluation confirmed consistent actuator activation with a mean response time of 1.4 s and no conflicting combinations across all trials. The system constitutes reusable knowledge for insect farming automation, combining fuzzy logic actuation, multi-parameter sensing, and Telegram-based monitoring within a low-cost embedded platform, applicable to broader smart agriculture and sustainable waste management domains.

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1. INTRODUCTION

Context black soldier fly (BSF) (*Hermetia illucens*) larval cultivation has emerged as a high-efficiency bioconversion technology capable of reducing organic waste volume by 60–70% while producing protein-rich biomass for animal feed and industrial applications [1]. Within the circular economy and sustainable food system frameworks, BSF farming represents a critical pathway toward reducing food waste, lowering carbon emissions from organic decomposition, and generating high-value protein for aquaculture and poultry feed [2], [3]. BSF larval development is, however, highly sensitive to environmental conditions: optimal temperature ranges between 25 °C and 35 °C, while substrate moisture content should be maintained at 60–80% relative humidity [2], [3]. Deviations from these thresholds result in reduced larval growth rates, elevated larval mortality, ammonia odor generation, and lower bioconversion efficiency [4], [5].

Problem statement despite the sensitivity of BSF cultivation to environmental parameters, the majority of small and medium-scale maggot farming operations continue to rely on manual monitoring and substrate watering. Manual procedures require operators to physically inspect and adjust the farming environment typically one to three times per day, resulting in intervention latency of 3-12 hours as a timeframe far exceeding the environmental response requirements of BSF larvae [4]. This operational limitation leads to inconsistent environmental conditions, suboptimal production yields, and high labor dependency, particularly in resource-constrained settings where automated solutions have not yet been adopted [6], [7].

State of the art internet of things (IoT)-based system integrating sensor networks, microcontrollers, and wireless communication platforms have demonstrated significant improvements in operational efficiency, resource optimization, and environmental stability across smart agriculture [8]-[10], precision irrigation [11]-[13], and livestock housing management [14]-[16]. Recent advances in embedded IoT system, particularly those utilizing low-cost microcontroller such as the ESP32, have further democratized agricultural automation by enabling real-time environmental sensing, automated actuator control, and cloud or mobile-accessible monitoring within single integrated platform [17]-[19]. Within the domain of insect farming specifically, Wibisono *et al*. [20] and Ramadhan *et al*. [21] have implemented IoT-based temperature and humidity monitoring for BSF environments, while Kayonde [5] and Teng and Halim [22] have demonstrated remote monitoring capabilities for BSF farm management.

Gap analysis a critical review of these related works, summarized in Table 1, reveals three measurable gaps. First, all prior BSF IoT systems restrict their scope to data acquisition and notification without implementing closed-loop automated actuator control, a fundamental limitation that prevents autonomous environmental correction. Second, the only existing intelligent control approach for BSF, such as the neuro-fuzzy systems of Sari *et al*. [23], requires substantially greater computational resources (PC-based implementation) and lacks a real-time remote communication interface, making it impractical for deployment on low-cost embedded hardware such as the ESP32. In contrast, the Mamdani fuzzy logic method selected in this study offers comparable interpretability and control precision at a fraction of the computational cost (inference time<5 ms on ESP32), making it substantially more suitable for resource-constrained embedded deployment [24], [25]. Third, no prior system has integrated all three functional layers, such as automated actuator control, fuzzy logic inference, and mobile-accessible real-time monitoring, within a single low-cost embedded platform for BSF cultivation.

Table 1. Comparison of related IoT system for BSF maggot farming

Study	System type	Auto actuator control	Fuzzy logic	Remote monitoring	BSF-specific
Wibisono *et al*. [20]	IoT monitoring	No	No	No	Yes
Ramadhan *et al*. [21]	IoT+hygrometer	No	No	No	Yes
Sari *et al*. [23]	Neuro-fuzzy control	Yes	Yes (NF)	No	Yes
Kayode [5]	IoT monitoring	No	No	Yes	Yes
Teng and Halim [22]	Smart IoT	Partial	No	Yes	Yes
Proposed system	**IoT+fuzzy control**	**Yes**	**Yes (Mamdani)**	**Yes (Telegram)**	Yes

Research contribution to address the identified gaps, this study proposes and implements an IoT-enabled watering and monitoring system for BSF maggot farming with three specific technical contributions: i) a Mamdani fuzzy logic inference engine embedded on ESP32 that provides real-time closed-loop automated control of three actuators (water pump, heating bulb, and blower fan) without reliance on cloud-based processing; ii) the Telegram Bot API as a lightweight, bidirectional remote monitoring, and manual override interface, a practical alternative to proprietary cloud dashboards that eliminates subscription costs, reduces communication latency, and operates reliably over standard mobile internet connections; and iii) a complete, reproducible embedded IoT architecture for insect farming automation that constitutes reusable knowledge applicable to other insect farming species (e.g., mealworm and cricket) and broader smart agriculture microclimate control applications.

Significance, the proposed system contributes to the advancement of AI-driven agriculture automation by demonstrating that lightweight fuzzy logic inference, a classical intelligent systems method, can deliver reliable real-time environment control on resource-constrained hardware at minimal cost. In the broader context of sustainable agriculture, automated BSF farming systems directly support circular economy goals by improving organic waste bioconversion efficiency and reducing the carbon footprint of protein production.

The remainder of this paper is structured as follows. Section 2 describes the system architecture, fuzzy logic controller design, IoT communication implementation, and testing procedure. Section 3 presents

calibration results, system performance analysis, and benchmarking. Section 4 concludes the study with a contributions, limitations, and future research directions.

2. RESEARCH METHOD

The IoT-enabled watering and monitoring system for BSF maggot cultivation is designed to facilitate the automated regulation and supervision of farming environment. The research methodology encompasses hardware and software integration, fuzzy logic controller design, IoT communication implementation and rigorous sensor calibration and system performance testing.

2.1. System architecture

The system architecture follows a four-stage processing pipeline, illustrated in Figure 1: i) sensing: the SHT20 sensor acquires temperature (T,°C) and relative humidity (H,%) via I^2C communication to the ESP32 microcontroller at a 1,000 ms sampling interval; ii) processing: the ESP32 applies the Mamdani fuzzy inference engine (fuzzification to rule evaluation to aggregation to COA defuzzification) to determine binary actuator states (ON/OFF); iii) actuation: the resolved states are transmitted to a relay module and motor driver, which physically activate or deactivate the water pump (irrigation), incandescent heating bulb (heating), and blower fan (ventilation); and iv) communication; sensor readings and actuator states are serialized into a JSON payload and transmitted to the Telegram Bot API via HTTPS for delivery to the registered user. Figure 1 illustrates the complete end-to-end signal flow across all four-stages.

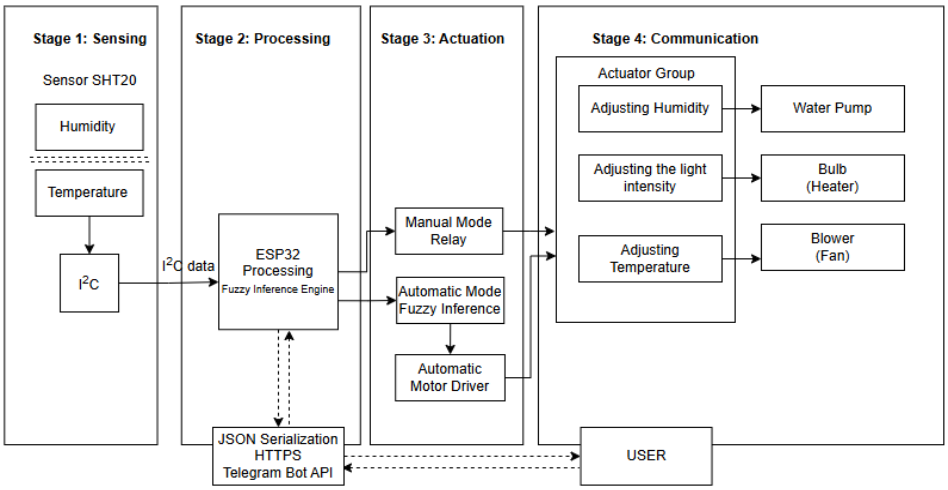


Figure 1. Four-stage architecture of the IoT-enabled watering and monitoring system, illustrating the end-to-end signal flow from SHT20 sensor acquisition through ESP32 fuzzy processing to actuator activation and Telegram Bot API communication

2.2. Fuzzy logic controller design

Two distinct operational modes are implemented: a manual mode, in which actuators are controlled via Telegram commands, and an automatic mode governed by a Mamdani fuzzy logic inference engine. The Mamdani method was selected over alternative approaches, including neuro-fuzzy systems, for three reasons: i) interpretability: Mamdani rules are directly formulated from domain expert knowledge without requiring training data, making the rule base fully transparent and auditable; ii) computational efficiency: Mamdani inference executes in <5 ms per cycle on the ESP32, compared to neuro-fuzzy systems that require dedicated computing hardware [23]; and iii) practical deployability: the complete inference engine is implementable on a single low-cost microcontroller without external processing dependencies. The overall operational flow of the system is illustrated in Figure 2, showing the sequential process from system initialization and sensor data acquisition, through mode selection (manual or automatic), fuzzy processing, and data transmission to Telegram. The operational logic of both modes is detailed in the flowcharts: Figure 3(a) presents the manual mode flowchart, illustrating the request-order sequence for watering pump, bulb (relay 1), and blower (relay 2) control via Telegram commands; Figure 3(b) presents the automatic mode flowchart, showing the fuzzy logic decision process for humidity sensing (RH<60% for water pump activation) and temperature sensing (temp<25 °C for bulb activation; temp>40 °C for blower activation).

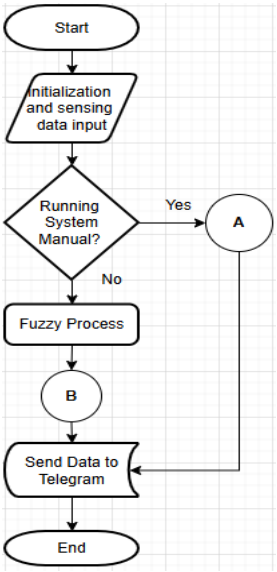
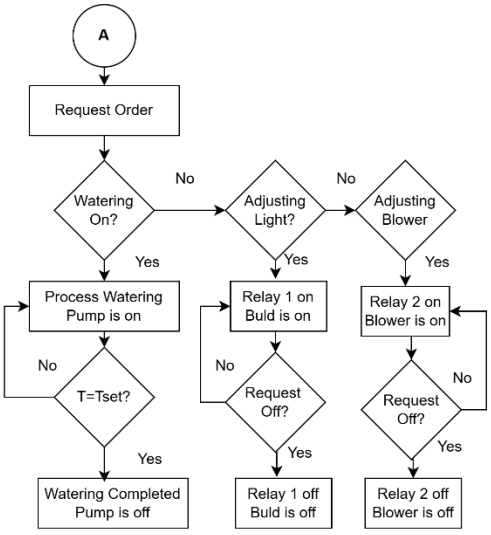
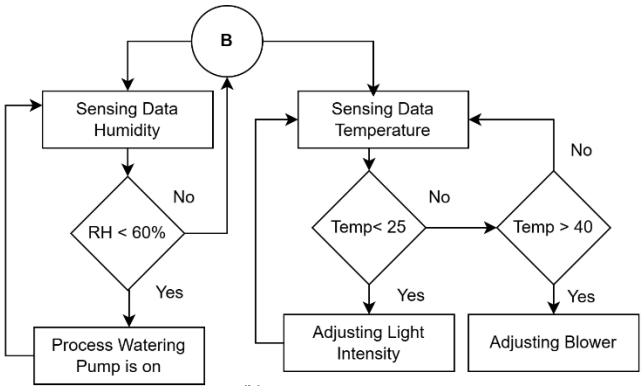


Figure 2. The main flowchart of IoT monitoring system for maggot cultivation



(a)



(b)

Figure 3. Operational flowcharts of both system modes: (a) manual mode as request-order sequence for watering pump, heating bulb, and blower control via Telegram commands and (b) automatic mode as Mamdani fuzzy logic decision process for humidity-based irrigation (RH<60%) and temperature-based actuation (temp<25 °C: bulb ON; temp>40 °C: blower ON)

Fuzzification and membership functions. Two crisp input variables are processed: temperature (T, °C) and relative humidity (H, %). Each input variable is mapped to three triangular membership functions (low, medium, and high). The membership functions thresholds were determined based on published empirical BSF larval development parameters [2], [3]: the medium (optimal) range for temperature (25-40 °C) and humidity (60, 85%) represents the documented range for maximum larval growth rate and bioconversion efficiency; the low and high boundaries represent thresholds at which larval stress and mortality are reported in the literature. Temperature MFs: low (peak: 25 °C, support: [15, 30 °C]); medium (peak: 32 °C, support: [25, 40 °C]); high (peak: 42 °C, support: [35, 50 °C]). Humidity MFs: low (peak: 50%, support: [30, 65%]); medium (peak: 72%, support [60, 85%]; high (peak: 90%, support: [80, 100%]).

Rule base, the rule base comprises nine Mamdani IF–THEN rules derived from BSF agronomic knowledge, presented in Table 2. The rules encode three primary control strategies: i) when temperature is low, activate the heating bulb; ii) when humidity is low and temperature is not high, activate the water pump; and iii) when temperature is high, activate the blower fan. All actuators remain deactivated when both temperature and humidity are within the medium (optimal) range.

Defuzzification, the centroid of area (COA) method converts the aggregated fuzzy output into a crisp actuation signal. Output membership function for OFF (centroid: 0) and ON (centroid: 1) are triangular. If the COA result exceeds 0.5, the actuator is activated. COA was selected for its smooth output response under partial membership conditions and low computational overhead on embedded hardware. Algorithm 1 presents the complete pseudo-code for the ESP32 implementation of the Mamdani fuzzy inference engine, providing sufficient detail for full reproducibility on any compatible microcontroller platform.

Table 2. Mamdani fuzzy logic rule base for bsf maggot farming environmental control

Temperature (input 1)	Humidity (input 2)	Water pump	Bulb (heater)	Blower (fan)
Low (T<25 °C)	Low (H<60%)	ON	ON	OFF
Low (T<25 °C)	Medium (60≤H<80%)	OFF	ON	OFF
Low (T<25 °C)	High (H≥80%)	OFF	ON	OFF
Medium (25 °C≤T<40 °C)	Low (H<60%)	ON	OFF	OFF
Medium (25 °C≤T<40 °C)	Medium (60≤H<80%)	OFF	OFF	OFF
Medium (25 °C≤T<40 °C)	High (H≥80%)	OFF	OFF	OFF
High (T≥40 °C)	Low (H<60%)	ON	OFF	ON
High (T≥40 °C)	Medium (60≤H<80%)	OFF	OFF	ON
High (T≥40 °C)	High (H≥80%)	OFF	OFF	ON

Algorithm 1. Mamdani fuzzy inference engine–ESP32 implementation (pseudo-code)

```
1.  Parameter initialization
Input: T (temperature, °C), H (humidity, %)
Output: O (pump state, bulb state, blower state ∈ {0, 1})
R = Rule base
Begin
State 1: Sensor Acquisition
2.  Read T dan H from SHT20 via I²C
State 2: Fuzzification – compute membership degree using triangular MF
3.  Fuzzification
T-Low = [15, 25, 30]; T-Med = [25, 32, 40]; T-High = [35, 42, 50];
H-Low = [30, 50, 65]; H-Med = [60, 72, 85]; H-High = [80, 90, 100]
State 3: Rule Evaluation
Rule evaluation (9 rules, min operator); N = 9;
For r = r1, … rN do
αr = min (μantecedent1_r, μantecedent2_r)
End For
State 4: Aggregation Apply Max
For each output variable o Do
μagg_o(x) = Max (αr * μconsequent_r(x)), ∀r
End For
State 5: Defuzzification
4.  Defuzzification
For each output variable o Do
crisp_o = Σ x*μagg_o(x) / Σ μagg_o(x)
If crisp_o ≥ 0.5
    state_o = 1
Else
```

$state_o = 0$
End If
End For
State 6: Actuation and Transmission
5. Activate or deactivate actuator according to $pump_{state}$, $bulb_{state}$, $blower_{state}$
6. Serialize sensor readings and actuator states into JSON payload
7. Transmit JSON payload to registered user via Telegram Bot API (HTTPS)
8. **End Begin**

2.3. Internet of things communication and monitoring

The Telegram Bot API serves as the primary communication platform interface [26], selected as a lightweight, cost-free alternative to proprietary cloud-based IoT dashboards (e.g., ThingSpeak, Blynk, and AWS IoT). Unlike cloud platform that require paid subscription, server maintenance, and proprietary SDKs, the Telegram Bot API operate over standard HTTPS with no additional infrastructure cost, supports bidirectional command execution (monitoring and manual override), and is accessible on any mobile device with internet connectivity. This design decision directly reduces deployment cost and increases accessibility for small-scale BSF farming operators.

Sensor data are serialized into a structured JSON payload (field: timestamp, temperature float 1dp, humidity integer, and actuator states Boolean) and transmitted via HTTPS long-polling at 1,000 ms intervals. End-to-end latency ranged from 1.2 to 2.5 seconds under normal Wi-Fi conditions (RSSI>−70 dBm). Three-level error handling ensures robustness under prolonged deployment: i) Wi-Fi reconnection with exponential backoff (500 ms initial, 30 s maximum) prevents permanent disconnection after network interruptions; ii) Telegram API timeout handling (5 s timeout, automatic retry) manages intermittent connectivity; and iii) sensor read failure detection, (3 consecutive failed I²C reads attempts trigger user alert) ensures sensor malfunction is immediately communicated rather than causing silent system failure. These mechanisms have been designed to sustain reliable operation across extended deployment periods without manual intervention.

Figure 4 illustrates the complete Telegram Bot command ordering system, comprising four command categories: i) monitoring order with command/status, /sensor, /ping, and /memory for real-time environmental data retrieval; ii) controlling order with commands /setlow, /sethigh, /relay1 on/off, and /relay2 on/off for threshold configuration and manual relay activation; iii) watering order with commands /waternow, /waterstop, /autowater, and /waterstatus for irrigation management; and iv) system order with commands /restart, /authorize, and /help for system administration. All commands are processed by the ESP32 and responses are returned to the user via Telegram.

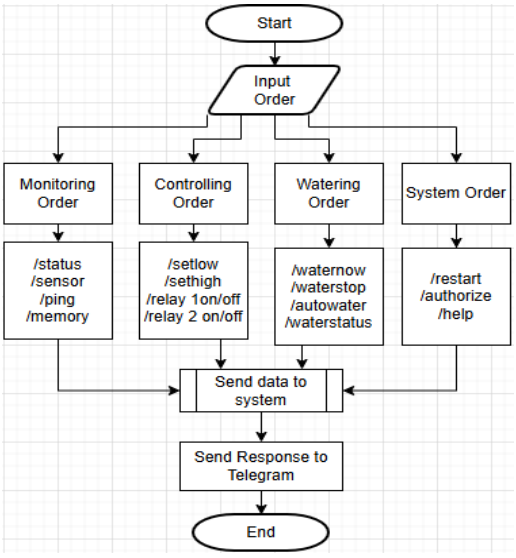


Figure 4. The Telegram bot command ordering system flowchart, showing the four command categories: i) monitoring, ii) controlling order, iii) watering order, and iv) system order

2.4. Testing procedure

System testing encompasses three components: i) sensor accuracy validation, ii) fuzzy logic control response evaluation, and iii) integrated IoT communication testing. Figure 5 presents the complete methodology flowchart illustrating the sequential testing procedure.

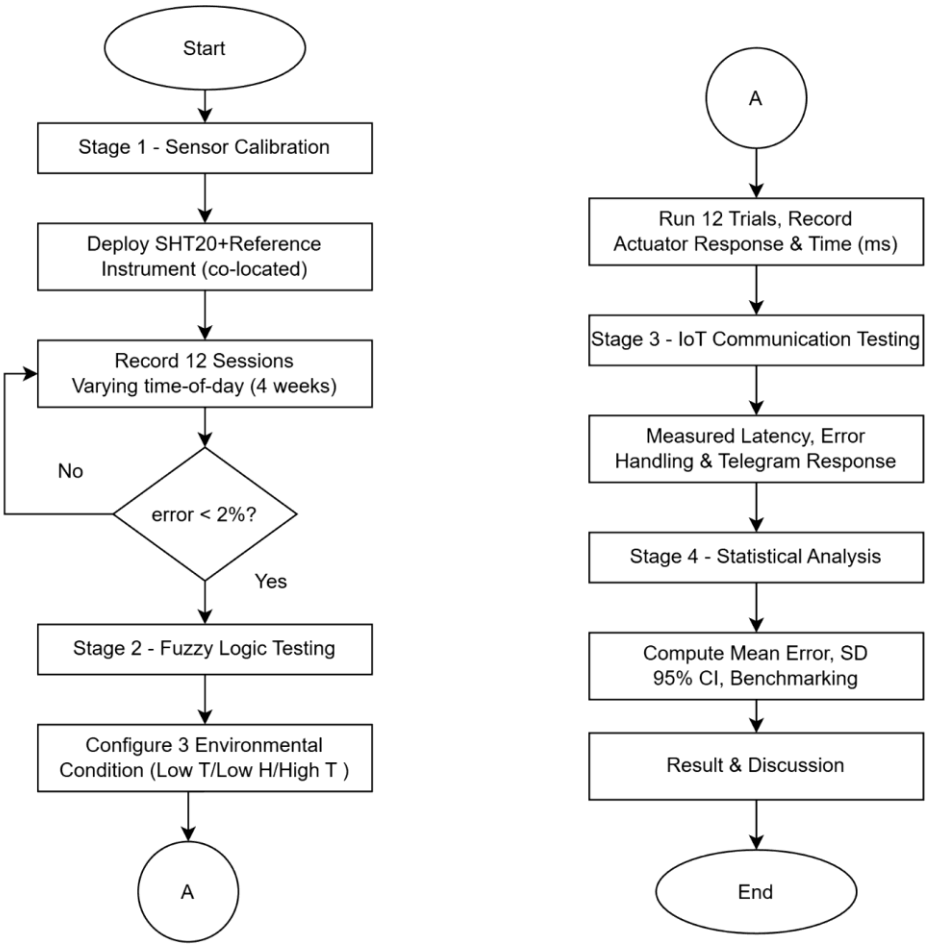


Figure 5. Methodology flowchart of the system testing procedure, showing the sequential stages of sensor calibration, fuzzy logic control evaluation, IoT communication testing, and statistical analysis

Sensor calibration was conducted over a period of four weeks (19 September–15 October 2025/2026) across 12 non-consecutive sessions at varying times of day to capture diurnal environmental variation. Reference instruments: calibrated digital thermometer (resolution: 0.1 °C, accuracy: ±0.3 °C), and digital hygrometer (resolution: 1% RH, accuracy: ±2% RH), both factory-calibrated and within valid calibration period. The SHT20 sensor and reference instruments were co-located within the farming enclosure. Each data point represents the mean of three consecutive SHT20 readings within a 30-second window. Percentage error is calculated as expressed in (1):

$$Error = \frac{|Sensor\ Reading - Reference\ Reading|}{Reference\ Reading} \times 100\% \quad (1)$$

Statistical significance of sensor accuracy was evaluated using 95% confidence interval (CI) for the mean error, calculated as (2):

$$CI = \bar{x} \pm t_{\frac{\alpha}{2}} \times \left(\frac{SD}{\sqrt{n}}\right) \quad (2)$$

Where n is 12 trials, SD is standard deviation of percentage error, and $t_{\frac{\alpha}{2}} = 2.201$ (t-distribution, 11 degrees of freedom, $\alpha = 0.05$). For temperature: $95\%\ \text{CI} = [0.87 \pm 2.201 \times (0.58/\sqrt{12})] = [0.50\%, 1.24\%]$. For humidity: $95\%\ \text{CI} = [0.73 \pm 2.201 \times (0.56/\sqrt{12})] = [0.37\%, 1.09\%]$. Both upper bound remain well below

the ±2% tolerance threshold, confirming statistical significance of sensor accuracy claims at the 95% confidence level.

Fuzzy logic evaluation was performed by configuring the enclosure to represent each of the three principal environmental conditions through controlled ambient adjustment. Each trial was sustained for a minimum of 10 minutes to steady-state sensor confirmation before actuator response recording. Actuator response time was measured using internal ESP32 timestamp with millisecond resolution.

3. RESULTS AND DISCUSSION

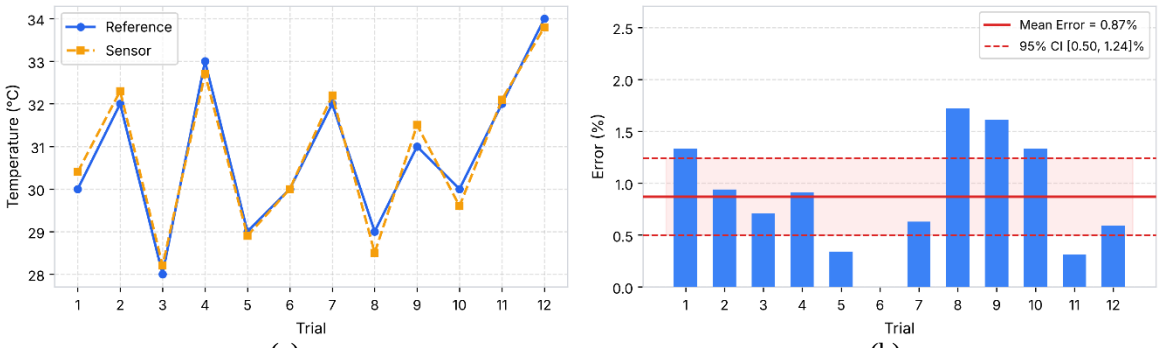
An IoT-enabled watering and monitoring system has been designed and implemented for BSF maggot farming. This section presents sensor calibration results with statistical validation, IoT communication evaluation, fuzzy logic control performance, system benchmarking against related works, and practical implications for sustainable agriculture and waste management.

3.1. Sensor calibration results

The complete IoT-enabled watering and monitoring system was successfully assembled and deployed within the BSF maggot farming enclosure. All hardware components, including the SHT20, ESP32 microcontroller, relay module, motor driver, water pump, incandescent heating bulb, and blower fan, were integrated and mounted within the farming environment as illustrated in Figure 6. The system enclosure housing the ESP32 and relay modules was wall-mounted within the cultivation area to ensure proximity to all actuator connection while maintaining protection from substrate moisture. Following successful deployment, sensor calibration and system performance evaluation were conducted as described in the following subsections. Prior to system evaluation, both sensors were subjected to calibration testing. Figures 7 and 8 present the temperature and humidity calibration results, respectively; Figures 7(a) and 8(a) show sensor versus reference measurements, while Figures 7(b) and 8(b) show the percentage error per trial with 95% CI bounds.



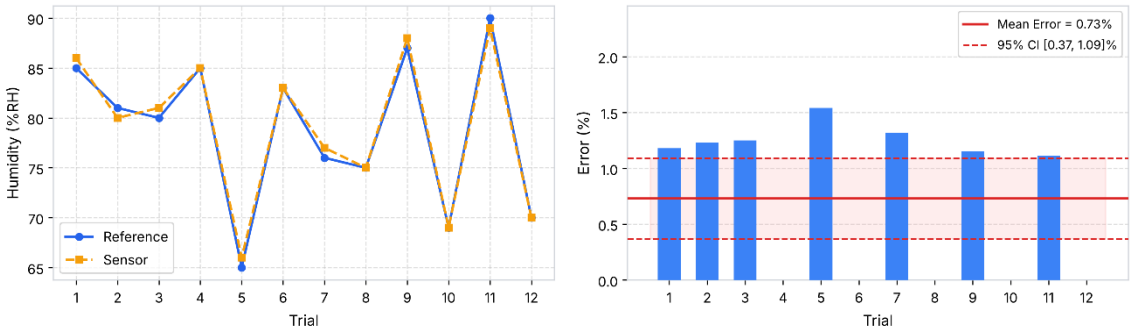
Figure 6. Implementation of IoT-enabled watering and monitoring system in maggot farming



(a) (b)

Figure 7. Temperature sensor calibration results across 12 trials: (a) comparison of SHT20 sensor reading versus reference thermometer measurement and (b) percentage error per trial with mean error reference line (0.87%), upper 95% CI bound (1.24%), and lower 95% CI bound (0.50%)

As shown in Figure 7, the temperature sensor achieved a mean accuracy of 99.13% (mean error: 0.87%, SD: 0.58%, 95% CI: [0.50%, 1.24%]), with a minimum error of 0.00% (Trial 6) and maximum error of 1.72% (Trial 8). The humidity sensor, as in Figure 8, achieved a mean accuracy of 99.27% (mean error: 0.73%, SD: 0.56%, 95% CI: [0.37%, 1.09%]), with four trials recording zero error and a maximum error of 1.54% (Trial 5). Both 95% CI upper bound remain well within the ±2% tolerance threshold for IoT environmental monitoring applications [10], [13], confirming the statistical significance of the accuracy claims. The low SD value (0.58% and 0.56%) indicate consistent measurement performance with limited variability across the full diurnal test range. From a practical perspective, this level of accuracy is sufficient to reliably detect the critical BSF environmental thresholds (T:25 °C and 40 °C; H:60%) that trigger actuator response, ensuring that the fuzzy logic controller operates on trustworthy input data.

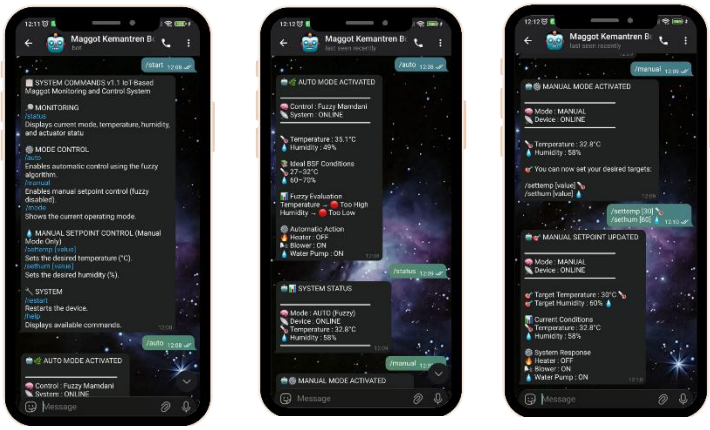


(a) (b)

Figure 8. Humidity sensor calibration results across 12 trials: (a) comparison of SHT20 sensor reading versus reference hygrometer measurement and (b) percentage error per trial with mean error reference line (0.73%), upper 95% CI bound (1.09%), and lower 95% CI bound (0.37%)

3.2. Internet of things communication via Telegram

The system operates under two modes: automatic (fuzzy logic) and manual mode (Telegram commands). Both modes and the monitoring system are interfaced through the Telegram platform. Figure 9 illustrates the Telegram display interface, comprising Figure 9(a) the system monitoring panel displaying real-time temperature, humidity, actuator states, Wi-Fi RSSI, memory utilization, system uptime, and administrator status; Figure 9(b) the control command menu enabling threshold configuration and manual relay activation; and Figure 9(c) the watering management panel for initiating, terminating, and monitoring irrigation operations.



(a) (b) (c)

Figure 9. The monitoring and operational system display at the Telegram platform showing: (a) the system monitoring panel with real-time environmental data and actuator status, (b) the control command menu for manual threshold configuration and relay activation, and (c) the watering management panel for initiating, terminating, and monitoring the irrigation process

The Telegram Bot API achieved end-to-end communication latency of 1.2-2.5 seconds under normal Wi-Fi conditions, providing near-real-time environmental visibility without subscription costs or proprietary operators: compared to cloud-based IoT platforms (which typically require USD 5-25/month and dedicated server maintenance), the Telegram-based interface operates at zero recurring cost while delivering comparable monitoring and control functionality over standard mobile internet connections.

3.3. Fuzzy logic system performance

Table 3 presents the fuzzy logic evaluation results across all 12 trials. Three distinct actuator response patterns were consistently observed: i) heating bulb activation in trials D2 and D8 (T<25 °C), with concurrent water pump activation in D2 where humidity was also below threshold; ii) blower fan activation in trials D4, D6, D9 and D12 (T≥40 °C), with response times of 1.1-1.4 s; and iii) water pump activation in isolation in D4, D7, and D10 (H<60%, T in medium range). Trials D1, D3, and D11, with both parameters in the optimal medium range, resulted in all actuators remaining deactivated. No conflicting actuator combinations were recorded across all 12 trials, confirming the logical integrity of the nine-rule Mamdani inference engine.

Table 3. Running system based on fuzzy logic analysis

Data	Temp (°C)	Humidity (%)	Water pump	Bulb (heater)	Blower (fan)	Response time (s)
D1	30.4	86	Off	Off	Off	-
D2	23.0	50	On	On	Off	1.3
D3	28.2	81	Off	Off	Off	-
D4	43.0	45	On	Off	On	1.1
D5	24.9	66	Off	On	Off	1.6
D6	41.0	83	Off	Off	On	1.2
D7	32.2	55	On	Off	Off	1.5
D8	22.5	75	Off	On	Off	1.8
D9	41.5	88	Off	Off	On	1.4
D10	29.6	53	On	Off	Off	1.3
D11	32.1	89	Off	Off	Off	-
D12	43.8	70	Off	Off	On	1.1
Average	**32.68 °C**	**70.08%**	**ON:4×**	**ON:3×**	**ON:4×**	**1.4 s (mean)**

3.4. System benchmarking against related works

To validate comparative performance, the proposed system is benchmarked against five directly related IoT system for BSF farming automation, as presented in Table 4. The benchmark evaluates six dimensions: platform, sensor accuracy reporting, automated actuation capability, fuzzy logic control, response time, and remote access.

Table 4. Benchmark comparison of proposed system against related IoT BSF farming solutions

Study	Platform	Sensor accuracy	Auto actuation	Fuzzy control	Response time	Remote access
Wibisono *et al*. [20]	ESP8266	Not reported	No	No	N/A	No
Ramadhan *et al*. [21]	Arduino+IoT	Not reported	No	No	N/A	No
Sari *et al*. [23]	PC-based	Not reported	Yes	Neuro-fuzzy	>5 s	No
Kayonde [5]	Raspberry Pi	Not reported	No	No	N/A	Yes (web)
Teng and Halim [22]	ESP32	Partial	Partial	No	N/A	Yes
Proposed System	ESP32	99.13% (T) 99.27% (H)	Yes (3 act.)	Mamdani	1.4 s (mean)	Yes (Telegram)

As shown in Table 4, the proposed system is the only solution that simultaneously achieves automated three-actuator control, Mamdani fuzzy logic inference, sub-2-second actuator response time, and mobile-accessible remote monitoring within a single low-cost embedded platform. Prior systems either lack automated actuation entirely [5], [20], [21], require more computationally demanding approaches [23], or implement only partial actuation without intelligent inference [22]. This benchmark confirms the practical superiority of the proposed system for real-time automated environmental management in BSF cultivation.

3.5. Practical implications for sustainable agriculture and waste management

The proposed system delivers measurable practical benefits across three dimensions relevant to sustainable agriculture and waste management. First, labor cost reduction: by replacing manual monitoring

(1-3 daily inspections requiring 15-30 minutes each) with continuous automated sensing and actuation, the system eliminates approximately 0.5-1.5 person-hours of daily monitoring labor per farming unit. At a conservative labor cost of USD 3/hour in small-scale Indonesian operations, this represents an annual saving of approximately USD 500-800 per cultivation unit, a significant reduction for small and medium-scale BSF farmers. Second, productivity improvement: the reduction of environmental deviation response time from 3-12 hours (manual) to 1.4 seconds (automated) ensures that temperature and humidity remain within the optimal BSF larval development range for a substantially greater proportion of the cultivation cycle. Literature reports indicate that maintaining optimal BSF environmental condition can increase larval biomass yield by 15-25% compared to inconsistently managed environments [4], [7], suggesting meaningful productivity gains achievable through the proposed system. Third, waste management contribution: improved BSF larval survival and bioconversion efficiency directly translates to higher organic waste processing capacity per unit area, supporting municipal organic waste reduction goals and contributing to circular economy targets in urban agricultural setting [1], [2].

Beyond BSF cultivation, the system architecture constitutes reusable knowledge applicable to other insect farming domains. The same ESP32+SHT20+Mamdani fuzzy logic+Telegram architecture can be adapted for mealworm (Tenebrio molitor) cultivation (optimal: 25-30 °C, 50-70% RH), cricket (*Acheta domesticus*) farming (optimal: 28-32 °C, 60-80% RH), and other microclimate-sensitive agricultural applications including mushroom cultivation and seedling germination chambers, with only the fuzzy membership function thresholds requiring adjustment. This architectural generalizability positions the proposed system as transferable intelligent system solution for precision microclimate management across smart agriculture domains [8], [9], [17].

4. CONCLUSION

This study successfully designed, implemented, and evaluated an IoT-enabled watering and monitoring system for BSF maggot cultivation, the first integrated embedded IoT platform for BSF farming combining Mamdani fuzzy logic-driven automated actuation, multi-parameter environmental sensing, and lightweight Telegram-based remote monitoring within a single low-cost system, without reliance on cloud-based processing or proprietary infrastructure.

Sensor calibration confirmed a mean temperature accuracy of 99.13% (error: 0.87%, SD: 0.58%, 95% CI: [0.50%, 1.24%]) and mean humidity accuracy of 99.27% (error: 0.73%, SD: 0.56%, 95% CI: [0.37%, 1.09%]), both statistically significant at 95% confidence level and well within the ±2% IoT sensing tolerance threshold. Fuzzy logic automatic control evaluation across 12 trials confirmed 100% logical consistency across all actuator responses, with a mean response time of 1.4 s (range: 1.1–1.8 s), three to four orders of magnitude faster than manual intervention. Benchmarking against five related BSF IoT systems confirmed that the proposed system is the only solution integrating all three functional layers: closed-loop actuation, intelligent inference, and mobile remote monitoring. The system aligns with intelligent system architectures by demonstrating that classical artificial intelligence (AI) method, specifically Mamdani fuzzy logic, can deliver reliable, real-time environmental control on resource-constrained embedded hardware at minimal cost, constituting a practical contribution to AI-driven agricultural automation. Telegram Bot API implementation demonstrates the viability of lightweight messaging platforms as zero-cost alternatives to proprietary cloud IoT dashboards. The complete system architecture constitutes reusable knowledge directly transferable to other insect farming species and smart agriculture microclimate control applications with minimal modification.

Limitations and future work; four limitations are acknowledged. First, the 12-trial evaluation over a limited duration does not capture long-term performance degradation; future work should conduct multi-lifecycle deployment testing under real commercial conditions. Second, fuzzy membership function thresholds were defined from published BSF parameters rather than empirically optimized from observed larval performance; adaptive or neuro-fuzzy approaches should be explored for dynamic recalibration. Third, only temperature and humidity are monitored; integration of substrate moisture sensors, CO_2 sensors, and larval mass weight sensors would provide more comprehensive environmental control capability. Fourth, system scalability to multi-node commercial farming operations with centralized control has not been evaluated. Future work should additionally investigate integration with machine learning-based predictive models for proactive environmental management, and assess the system's economic feasibility and productivity gains under extended commercial BSF farming deployment.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest

DATA AVAILABILITY

The data that support the findings of this study are available upon request from the corresponding author. The data, which may contain information that could potentially compromise the privacy of research participants, are not publicly accessible due to certain confidentiality restrictions and ethical considerations governing data privacy protection.

REFERENCES

[1] S. Diener, C. Zurbrügg, and K. Tockner, "Bioaccumulation of heavy metals in the black soldier fly, Hermetia illucens and effects on its life cycle," *Journal of Insects as Food and Feed*, vol. 1, no. 4, pp. 261–270, Dec. 2015, doi: 10.3920/jiff2015.0030.

[2] C. H. Lalander, J. Fidjeland, S. Diener, S. Eriksson, and B. Vinneras, "High waste-to-biomass conversion and efficient Salmonella spp. reduction using black soldier fly for waste recycling," *Agronomy for Sustainable Development*, vol. 35, no. 1, pp. 261–271, Jan. 2015, doi: 10.1007/s13593-014-0235-4.

[3] R. Salomone, G. Saija, G. Mondello, A. Giannetto, S. Fasulo, and D. Savastano, "Environmental impact of food waste bioconversion by insects: Application of Life Cycle Assessment to process using Hermetia illucens," *Journal of Cleaner Production*, vol. 140, pp. 890–905, Jan. 2017, doi: 10.1016/j.jclepro.2016.06.154.

[4] P. Madari, C. P. Mallapur, D. N. Kambrekar, and G. Goudar, "Bioconversion of organic wastes using black soldier fly," *Journal of Farm Sciences*, vol. 36, no. 04, pp. 373–376, Dec. 2023, doi: 10.61475/jfs.2023.v36i4.10.

[5] V. Kayonde, "An IoT Based Monitoring and Control System for a Black Soldier Fly (BSF) Farm," B.S. thesis, School of Engineering, Makerere University, Kampala, Uganda, 2023.

[6] D. R. Mulyanti *et al.*, "Utilizing Black Soldier Fly Larvae for Sustainable Organic Waste Management and Urban Farming: Efficiency, Challenges, and Scalability," *Jurnal Teknologi dan Manajemen Industri Terapan*, vol. 4, no. I, pp. 152–161, Feb. 2025, doi: 10.55826/jtmit.v4ii.989.

[7] F. Sankara *et al.*, "Optimization of Production Methods for Black Soldier Fly Larvae (Hermetia illucens L.) in Burkina Faso," *Insects*, vol. 14, no. 9, p. 776, Sep. 2023, doi: 10.3390/insects14090776.

[8] S. F. Fatima, U. B. Shinde, and S. Ali, "IoT Based Smart Agricultural Monitoring System," *International Journal of Innovations in Engineering Research and Technology*, vol. 8, no. 06, pp. 175–179, 2021, doi: 10.17605/OSF.IO/HU2V6.

[9] F. R. de Avila and J. L. V. Barbosa, "Smart environments in digital agriculture: a systematic review and taxonomy," *Computers and Electronics in Agriculture*, vol. 236, p. 110393, Sep. 2025, doi: 10.1016/j.compag.2025.110393.
[10] N. N. Thilakarathne, M. S. A. Bakar, P. E. Abas, and H. Yassin, "Internet of things enabled smart agriculture: Current status, latest advancements, challenges and countermeasures," *Heliyon*, vol. 11, no. 3, p. e42136, Feb. 2025, doi: 10.1016/j.heliyon.2025.e42136.
[11] S. P. Sudha and J. B. S. Loret, "A review on machine learning-based precision agriculture techniques for crop farming monitoring with IOT," *Discover Environment*, vol. 4, no. 1, p. 10, Jan. 2026, doi: 10.1007/s44274-025-00305-8.
[12] M. S. Mekala and P. Viswanathan, "A Survey: Smart agriculture IoT with cloud computing," in *2017 International Conference on Microelectronic Devices, Circuits and Systems, ICMDCS 2017*, Aug. 2017, pp. 1–7, doi: 10.1109/ICMDCS.2017.8211551.
[13] D. Vallejo-Gómez, M. Osorio, and C. A. Hincapié, "Smart Irrigation Systems in Agriculture: A Systematic Review," *Agronomy*, vol. 13, no. 2, p. 342, Jan. 2023, doi: 10.3390/agronomy13020342.
[14] P. P. Ray, "Internet of things for smart agriculture: Technologies, practices and future direction," *Journal of Ambient Intelligence and Smart Environments*, vol. 9, no. 4, pp. 395–420, Jun. 2017, doi: 10.3233/AIS-170440.
[15] S. Wolfert, L. Ge, C. Verdouw, and M. J. Bogaardt, "Big Data in Smart Farming – A review," *Agricultural Systems*, vol. 153, pp. 69–80, May 2017, doi: 10.1016/j.agsy.2017.01.023.
[16] N. Yamsani, K. Muthukumaran, B. S. Kumar, V. Asha, N. Singh, and J. A. Dhanraj, "IoT-Based Livestock Monitoring and Management System Using Machine Learning Algorithms," in *Proceedings of 2024 International Conference on Science, Technology, Engineering and Management, ICSTEM 2024*, Apr. 2024, pp. 1–6, doi: 10.1109/ICSTEM61137.2024.10560908.
[17] A. Tzounis, N. Katsoulas, T. Bartzanas, and C. Kittas, "Internet of Things in agriculture, recent advances and future challenges," *Biosystems Engineering*, vol. 164, pp. 31–48, Dec. 2017, doi: 10.1016/j.biosystemseng.2017.09.007.
[18] A. Abu Sneineh and A. A. Shabaneh, "Design of a smart hydroponics monitoring system using an ESP32 microcontroller and the Internet of Things," *MethodsX*, vol. 11, p. 102401, 2023, doi: 10.1016/j.mex.2023.102401.
[19] A. I. D. Idrissi, A. Abouabdillah, M. Chikhaoui, and R. Bouabid, "Low-cost IoT-based monitoring system for precision agriculture," in *E3S Web of Conferences*, vol. 492, p. 01003, Feb. 2024, doi: 10.1051/e3sconf/202449201003.
[20] F. Ssemakula, B. A. M. Tumwine, M. P. Namugwanya, and S. Mbalire, "A Low-Cost Internet of Things Cloud Based Solution for the Intelligent Rearing of the Black Soldier Fly," in *2023 IEEE AFRICON*, Nairobi, Kenya, 2023, pp. 1-6, doi: 10.1109/AFRICON55910.2023.10293221.
[21] A. R. Ramadhan, T. P. Azzahra, K. Maharani, and D. Rimantho, "The Utilization of Hygrometer and Exhaust with IoT Technology in Temperature Control in Maggot (BSF) Containers: Temperature Control Innovation in BSF Maggot Cultivation through Hygrometer and Exhaust IoT Technology," *MEIN: Journal of Mechanical, Electrical & Industrial Technology*, vol. 2, no. 1, pp. 1–6, 2025, doi: 10.35991/MEIN.V2I1.19.
[22] A. H. Teng and E. Halim, "Smart IoT-Driven Organic Waste Management: A Design-Based Approach Utilizing Black Soldier Fly (BSF) Maggots in Indonesia," in *Lecture Notes in Networks and Systems*, vol. 1785 LNNS, 2026, pp. 372–387, doi: 10.1007/978-3-032-14750-9_31.
[23] Y. S. Sari, Kusrini, E. Utami, and F. W. Wibowo, "VARFIS: A Hybrid Neuro-Fuzzy Model for Intelligent Microclimate Control in Black Soldier Fly Farming Systems," *Jurnal Teknik Informatika*, vol. 18, no. 2, pp. 281–291, Oct. 2025, doi: 10.15408/jti.v18i2.46610.
[24] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Computers and Electronics in Agriculture*, vol. 147, pp. 70–90, Apr. 2018, doi: 10.1016/j.compag.2018.02.016.
[25] S. Karim, K. Hussain, M. B. Alvi, M. A. Rahu, M. A. Kaloi, and H. Haleem, "Artificial Intelligence in Sustainable Smart Agriculture: Concepts, Applications, and Challenges," *VAWKUM Transactions on Computer Sciences*, vol. 13, no. 1, pp. 307–342, Jun. 2025, doi: 10.21015/vtcs.v13i1.2151.
[26] M. I. M. M. Imran, R. Abdullah, S. I. Ismail, and N. N. S. N. Dzulkefli, "IoT-based Emergency Alert System Integrated with Telegram Bot," in *2023 IEEE International Conference on Automatic Control and Intelligent Systems, I2CACIS 2023-Proceedings*, Jun. 2023, pp. 126–131, doi: 10.1109/I2CACIS57635.2023.10193550.

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