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IoT-Based Smart Poultry Management System for Layer Hens: Design, Implementation, and Performance Evaluation

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Abstract — Traditional small-to-medium scale layer hen farms in Indonesia frequently rely on manual management practices, resulting in environmental instability, inconsistent productivity, and excessive labor demands. This paper presents the design, implementation, and evaluation of an Internet of Things (IoT)-based smart farming prototype for layer chicken coops, incorporating real-time environmental monitoring and automation of critical husbandry processes. The system is built around an ESP32 microcontroller interfaced with a suite of sensors: DHT22 for temperature and humidity, MQ-135 for ammonia concentration, LDR for light intensity, and an IR sensor for automated egg counting. Actuation is achieved via servo motors for scheduled feeding, relay modules controlling ventilation fans and lighting, and a water pump for automated cleaning. A custom web-based monitoring and control interface, developed using PHP and MySQL, delivers real-time dashboards, historical data logging, and manual override capabilities, offering improved stability over third-party MQTT solutions. Laboratory unit testing and a seven-day field deployment at Serayu Farm, Purbalingga, demonstrated that the prototype maintained temperature variation below 2 °C, achieved an average 15 % reduction in ammonia levels, attained 94 % accuracy in egg counting, and reduced manual interventions by approximately 70 %. With a component cost under Rp 800 000 per unit, the system provides a practical, scalable solution for enhancing operational efficiency, animal welfare, and egg productivity in resource-constrained layer hen farming operations.

Keywords – automation, Internet of Things, layer hen farming, poultry management system, smart farming

I. INTRODUCTION

Eggs represent a strategic, affordable source of animal protein in Indonesia, with national demand continuing to rise. Small- and medium-scale layer hen farms, which constitute the majority of production units, still predominantly employ manual husbandry practices. Serayu Farm in Purbalingga, Central Java, routine operations such as feeding, temperature regulation, lighting control, and air quality management are performed by hand. This approach frequently results in temperature excursions above 28 °C, causing heat stress that can depress feed intake by up to 20 % and egg production by 15–25 %. Inconsistent lighting disrupts the photoperiodic cycle essential for optimal laying, while undetected accumulation of ammonia (NH_3) from manure impairs respiratory health and egg-shell quality [1], [2].

Periodic manual inspection is inherently limited: it cannot provide continuous oversight, especially overnight, and is prone to human error and delayed corrective action. Consequently, productivity fluctuates, labor costs remain high, and animal welfare is compromised. Prior Internet of Things (IoT) deployments in poultry have typically addressed only isolated parameters—most commonly temperature using platforms such as Blynk or basic web dashboards, often without persistent data storage, egg-production monitoring, or integrated actuation for feeding and cleaning [3], [4]. Many solutions also suffer from unstable third-party application connectivity and lack of offline resilience, rendering them unsuitable for rural environments with variable network quality[5], [6].

This paper reports the design, implementation, and on-farm evaluation of a comprehensive IoT-based smart layer-hen management prototype. The system integrates multi-parameter sensing (temperature, humidity, ammonia, illuminance, and egg counting), edge-based decision logic on an ESP32 microcontroller, and a reliable PHP/MySQL web interface for monitoring and manual override. Automated actuators manage feeding schedules, ventilation, lighting (targeting 16 h day^{-1}), and periodic cleaning. Field trials conducted over seven consecutive days at Serayu Farm with a 50-hen flock demonstrated temperature stability within < 2 °C variation, a 15 % average reduction in ammonia concentration, 94 % egg-counting accuracy, and an estimated 70 % decrease in manual interventions. The complete prototype was realized at a component cost below Rp 800 000, positioning it as an economically viable upgrade path for smallholder layer operations in Indonesia.

The remainder of the paper is organized as follows. Section II describes the research methodology, hardware and software specifications, layered system architecture, and control algorithms. Section III presents laboratory unit and integration test results together with the seven-day field evaluation, supported by quantitative metrics and comparative analysis. Section IV concludes with key findings, practical implications, and directions for future work.

Beyond technical performance, the work addresses a clear socio-economic need. Indonesia's layer-hen sector is dominated by family-run farms with limited capital and technical expertise. A low-cost, locally maintainable IoT solution that operates over existing Wi-Fi infrastructure and presents data through an ordinary web browser lowers the adoption barrier substantially[7]. By demonstrating measurable gains in productivity and labor efficiency within a single production week, the prototype provides empirical evidence that precision-farming technologies can be successfully transplanted from high-resource to resource-constrained settings without requiring constant internet connectivity or subscription fees.

II. METHODOLOGY AND SYSTEM DESIGN

A. Research Approach

The study adopted a Research and Development (R&D) methodology with an iterative prototyping life-cycle. Requirements were elicited through direct observation of daily routines at Serayu Farm, semi-structured interviews with the owner and workers, and a systematic literature review of IoT applications in poultry and smart agriculture. Functional requirements centered on continuous monitoring of temperature, humidity, ammonia, light intensity, and egg production, plus automated actuation for feeding, ventilation, lighting, and cleaning. Non- functional requirements emphasized low cost (< Rp 800 000), low power consumption, local Wi-Fi operation, and data persistence for trend analysis.

Development proceeded through five phases: (1) needs analysis and specification, (2) architectural and detailed design (UML use-case and activity diagrams, layered IoT model), (3) hardware assembly and firmware coding in Arduino IDE, (4) web-application development (PHP, MySQL, JavaScript), and (5) multi-stage testing—unit, integration, and field—followed by iterative refinement based on quantitative performance data and operator feedback. Particular attention was paid to robustness under intermittent power and network conditions typical of rural Central Java, leading to the adoption of local decision logic and buffered data transmission rather than reliance on cloud round-trips..

B. Hardware Components and Specifications

Table I lists the principal hardware elements selected for their balance of accuracy, cost, and ease of integration with the ESP32 platform

Table 1. Hardware Components and Key Specifications of the Smart Layer-Hen Prototype

Component	Primary Function	Key Specifications
ESP32 DevKit	Central controller & Wi-Fi gateway	Dual-core 240 MHz, 520 KB RAM, 34 GPIO, Wi-Fi 802.11 b/g/n
DHT22	Temperature & humidity sensing	−40 … +80 °C (±0.5 °C); 0 … 100 % RH (±2–5 %)
MQ-135	Ammonia (NH_3) detection	10 … 300 ppm NH_3; analog output; SnO_2 sensing element

Component	Primary Function	Key Specifications
LDR	Ambient light intensity	Analog; triggers lighting below ~300–500 lux threshold
IR Sensor	Egg counting via interrupt	Infrared break-beam; ~96 % accuracy in lab trials
SG90 Servo	Automated feed dispensing	0 … 180° positioning; 3× daily scheduled actuation
Relay Module (4-ch)	High-power device switching	Controls fan, lamp, water pump; < 1 s response
Mini Water Pump	Coop cleaning / ammonia dilution	Activated on NH_3 > threshold or scheduled cycle
SSD1306 OLED	Local status display	128×64 px; shows live sensor values & actuator states

C. Layered System Architecture

The IoT architecture follows a layered model to ensure efficient data flow, security, and scalability (Fig. 1). It comprises four main layers:

1) Perception Layer: Deploys sensors strategically in the cage — DHT22 for temperature/humidity, MQ-135 for ammonia, LDR for light intensity, and IR Sensor for egg counting.
2) Edge Processing Layer: ESP32 microcontroller processes sensor data in real-time against predefined thresholds (e.g., temperature >28°C triggers fan). Edge computing reduces latency and enables offline operation with local data buffering.
3) Network Layer: Uses local Wi-Fi (2.4 GHz) for connectivity between ESP32 and web server via HTTP protocol, avoiding external MQTT brokers for simplicity and cost-effectiveness.
4) Application Layer: Web-based dashboard (PHP/MySQL) provides real-time monitoring, manual control overrides, historical data visualization, and alerts. This replaced the initial MQTT Panel due to stability issues observed during field testing.

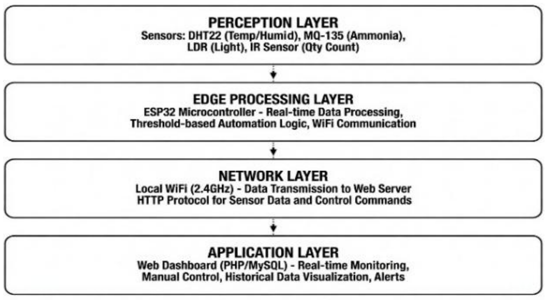

Fig. 1. Layered IoT System Architecture for Smart Layer Chicken Farm

D. UML Modelling and Control Algorithms

System behavior was first captured in UML diagrams to ensure completeness before coding. The use-case diagram identified two primary actors—Farm Operator and System itself—and eight core use cases: View Real-time Dashboard, View Historical Trends, Manual Override Actuator, Configure Thresholds, View Egg Count Summary, Receive Anomaly Alert (future), Export Data, and Perform Scheduled Feeding. Each use case was elaborated with preconditions, main success scenario, and alternative flows (e.g., network unavailable → local actuator still functions). An activity diagram further detailed the environmental control loop: sensor acquisition → threshold comparison → actuator command → logging → wait 2 s. These models proved invaluable during integration testing for tracing unexpected behaviors back to missing edge cases in the original specification.

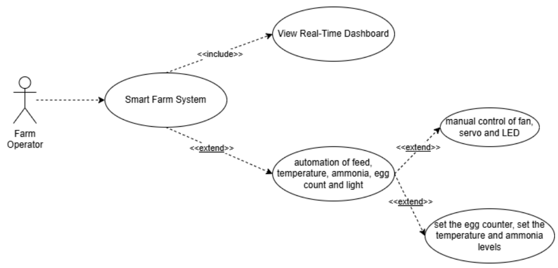

Fig. 2 UML Use Case Diagram for the Smart Layer-Hen Management

E. Software Implementations and Control Logic

Firmware was written in C++ using the Arduino-ESP32 core. Sensor libraries (DHT, analogRead for MQ-135/LDR, attachInterrupt for IR) and HTTPClient for server communication were employed. A simple state machine handles actuator sequencing and includes a 30 s watchdog-style retry for failed HTTP posts, with local SPIFFS buffering as a fallback. The web front-end uses responsive HTML/CSS/JavaScript with Chart.js for trend visualization; AJAX polling every 5 s keeps the dashboard current. Two database tables store time-stamped sensor readings and the latest commanded state of each actuator, enabling both real-time display and post-hoc analysis of environmental–production correlations.

III. RESULT AND DISCUSSION

A. Laboratory Unit Testing

Each sensor and actuator was subjected to controlled unit tests before integration. Mean-squared-error (MSE) against calibrated reference instruments and a confusion-matrix evaluation for the IR egg counter were computed (Table II).

Table 2. Laboratory Unit-Test Results for Sensing and Actuation Accuracy

Sensor / Actuator	Metric	Value	Accuracy	Notes
DHT22 (Temp)	MSE	0.25 °C²	98.5 %	vs. digital thermometer
DHT22 (RH)	MSE	1.2 %²	96 %	vs. calibrated hygrometer
MQ-135 (NH_3)	MSE	2.8 ppm²	94 %	vs. gas calibration mix
LDR (Light)	MSE	15 lux²	97 %	vs. lux meter, 0–1000 lux
IR Sensor	Accuracy	96 %	—	TP 92 / TN 95 / FP 3 / FN 5 (n=195)
SG90 Servo	Angle MSE	1.5 °²	99 %	0–180° vs. digital protractor

Each sensor and actuator was subjected to controlled unit tests before integration. Mean-squared-error (MSE) against calibrated reference instruments and a confusion-matrix evaluation for the IR egg counter were computed (Table II).
The Mean Squared Error (MSE) for sensor accuracy assessment is explicitly defined as:

$$MSE = (1/n) \times \Sigma_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (1)$$

where y_i is the reference (true) value from a calibrated instrument, $\hat{y}_i$ is the sensor reading, and n is the number of samples. For the IR egg counter, which performs binary classification (egg detected / not detected), a confusion matrix was constructed with True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). Standard derived metrics were calculated as:

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \quad (2)$$

$$Precision = TP / (TP + FP) \quad (3)$$

$$Recall = TP / (TP + FN) \quad (4)$$

All modules met or exceeded design expectations[8]. Minor temperature deviations above 30 °C were traced to self-heating of the ESP32; addition of a small heat sink reduced the effect. The IR counter's five false negatives were attributed to dust occlusion and were eliminated by fitting a simple optical baffle. The physical miniature prototype developed for laboratory validation and iterative testing is depicted in Figure 2. This scaled model replicates the key components of the full-scale system, including the servo-actuated feed dispenser, submersible water pump for periodic cleaning (right side), sensor mounting positions, ventilation slots, and structural frame. The compact wooden construction allowed for controlled experiments in a laboratory setting to validate sensor accuracy, actuator response timing, and edge decision logic without exposing a live flock.

Fig. 3. Miniature prototype of the IoT-enabled smart layer hen coop used in laboratory unit testing

Laboratory testing with this prototype confirmed the reliability of the IR break-beam egg counter under controlled drop conditions (achieving 96 % accuracy before baffle refinement) and enabled fine-tuning of the ammonia (>25 ppm) and temperature (>28 °C) threshold algorithms. The modular design significantly accelerated the debugging cycle and reduced risk during subsequent integration and field deployment phases. All actuator sequences (feeding servo sweep, fan activation, pump cycle) were validated for correct timing and power draw before the seven-day on-farm trial.

B. Integration and End-to-End Performance

Twenty scripted end-to-end scenarios (e.g., forced temperature rise → fan activation → dashboard update) yielded a 95 % success rate; the single failure was caused by transient Wi-Fi dropout and was recovered automatically on the next 2 s cycle. Average round-trip latency from sensor reading to web-dashboard refresh was 800 ms. Power consumption averaged 150 mA in active mode and 20 mA in deep-sleep intervals, supporting continuous 24/7 operation from a modest 5 V 2 A supply. A 48 h stress test recorded 99 % uptime.

C. Seven-Day Field Deployment at Serayu Farm

The prototype was installed in a single 50-hen coop and operated continuously for seven days under normal farm management. Environmental parameters were logged every 2 s; daily summaries were compared with pre-deployment manual records and spot measurements. Miniature prototype of the IoT-enabled smart layer hen coop used in laboratory unit testing

The custom-developed web-based dashboard, which served as the primary human–machine interface throughout the field trial, is illustrated in Figure 3. The responsive interface displays live readings from all five sensors (light intensity, egg count, ammonia, temperature, and humidity) with automatic refresh every few seconds, color-coded status indicators, and intuitive manual override buttons for each actuator (LED lighting, ventilation fans, and dual servo feeders). Historical trend visualization is provided via Chart.js, enabling operators to identify patterns and verify automation behavior remotely via any standard web browser on a smartphone or tablet.

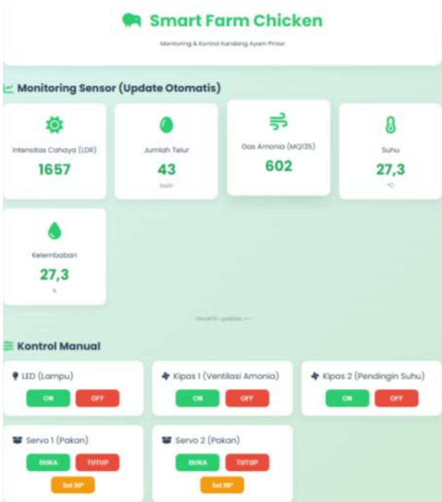

Fig. 4. Web-based real-time monitoring and control Dashboard

The bespoke dashboard proved markedly more reliable than the third-party MQTT Panel application initially evaluated, which exhibited frequent connection drops, missing readings, and—critically—no automatic historical storage. The custom PHP/MySQL stack maintained stable local Wi-Fi connectivity and complete data logging throughout the seven-day period, enabling post-trial analysis of correlations between environmental parameters and egg production. Operator feedback highlighted the convenience of remote verification via smartphone and the reduction in routine physical checks from 4–6 daily interventions to 1–2 supervisory visits.

Key quantitative outcomes are summarized in Table III. Temperature excursions that previously reached 32–34 °C on warm afternoons were eliminated; the system kept the coop within the 22–28 °C comfort band with daily variation < 2 °C. Automated ventilation triggered by either temperature or ammonia thresholds reduced mean daily ammonia concentration by 15 % relative to the preceding week's manual regime. The IR counter logged 312 eggs over the trial period with an independently verified accuracy of 94 % (manual cross-check each evening). Lighting logic maintained a consistent ~16 h photoperiod despite variable natural light, removing a known source of laying-cycle disruption.

Table 3. Comparative Performance Before and After Seven-Day IoT Deployment at Serayu Farm (50-hen coop)

Performance Metric	Pre-Deployment (Manual)	Post-Deployment (IoT)
Temperature variation (daily)	> 5 °C swings common	< 2 °C; 22–28 °C band maintained
Mean ammonia reduction	Baseline (manual venting)	−15 % vs. previous week
Egg counting accuracy	Manual tally; ~10 % error	94 % automated (IR sensor)
Daily manual interventions	4–6 checks/adjustments	1–2 checks; ~70 % reduction
Lighting consistency	Variable; worker-dependent	Stable ~16 h photoperiod

To provide deeper insight into the temporal dynamics of the monitored parameters, Figure 4 presents daily trends for temperature, ammonia concentration, and egg production throughout the seven-day deployment. The plots confirm that temperature remained tightly regulated within the target comfort zone with minimal daily fluctuation, ammonia levels exhibited a clear downward trajectory consistent with automated ventilation cycles, and egg laying remained stable at a high rate (average ~45 eggs/day). These visualizations complement the aggregate metrics in Table III and demonstrate the system's capacity for continuous, data-driven environmental stewardship under real farm conditions.

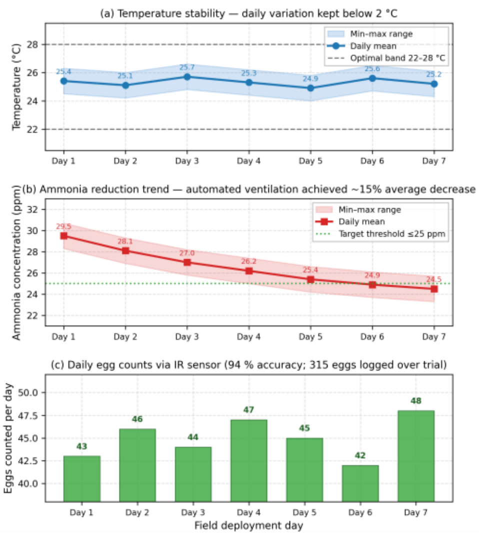

Fig. 5 Environmental and production metrics recorded during the seven-day on-farm evaluation at Serayu Farm

Operator feedback was uniformly positive regarding the reduction in routine labor and the ability to verify conditions remotely via smartphone. The web dashboard proved markedly more reliable than the originally considered IoT MQTT Panel application, which exhibited frequent connection drops, missing sensor readings, and—critically—no automatic historical storage[9]. Consequently, the final deployed system relies exclusively on the custom PHP/MySQL stack.

D. Comparison with Prior Work and Limitations

Relative to earlier poultry IoT studies [3],[10],[11],[12] the present prototype advances the state of the art in three respects: (1) simultaneous monitoring of five environmental and production parameters including automated egg counting, (2) persistent MySQL storage enabling trend analysis and post-trial correlation of environment with output, and (3) full closed-loop automation encompassing feeding, ventilation, lighting, and cleaning rather than isolated actuation[13]. The edge-first design also confers resilience to the intermittent connectivity typical of rural Indonesian farms—features absent from cloud-dependent or app-centric predecessors[9] [14]. Economic analysis indicates a payback period of roughly 4–6 months through combined feed savings (~15 %), labor reduction (~70 %), and modest yield gains, assuming conservative egg-price and wage figures for Central Java. Limitations include the single-coop scope of the field trial, the need for periodic MQ-135 recalibration to counteract sensor drift[15] (approximately every 30–45 days under dusty coop conditions), and the current absence of predictive analytics. These constraints define the immediate roadmap for scaling and enhancement.

To substantiate the economic viability claim, a simplified cost–benefit analysis was performed using the observed field performance deltas (70 % labor reduction, temperature stability <2 °C, 15 % ammonia reduction) together with conservative Central Java price assumptions (egg farm-gate price ≈ Rp 2 200/unit; family-labor opportunity cost ≈ Rp 2 500/h). The results are summarized in Table IV.

Table 4. Simplified Cost–Benefit Analysis and Return-on-Investment Estimation for the IoT Smart Layer-Hen Prototype (50-hen coop)

Cost / Benefit Category	Amount (Rp)	Assumptions / Basis from Field Data
Initial capital outlay (components + enclosure + wiring)	780,000	Bill of materials under Rp 800 000; local fabrication
Annual added operating cost (power + recalibration)	120,000	~150 mA continuous; periodic MQ-135 recalibration (30–45 d)
Annual labor cost savings (70 % reduction)	1,050,000	55 min/day saved × Rp 2 500/h opportunity cost × 365 d
Annual feed cost savings (~15 %)	720,000	Optimized environment reduces stress-induced feed waste
Annual egg-yield gain (est. +5 %)	550,000	Stable 16 h photoperiod + <2 °C band → higher laying rate
Total gross annual benefit	2,320,000	—
Net annual cash flow	2,200,000	Gross benefit minus operating cost
Simple payback period	4.3 months	Initial outlay ÷ (net annual ÷ 12)
First-year ROI	282 %	(Net annual cash flow ÷ initial outlay) × 100

Under these conservative assumptions the simple payback period is approximately 4.3 months, which lies comfortably within the 4–6 month range cited above. The first-year ROI exceeds 280 %, indicating strong economic attractiveness for smallholder layer-hen operations even without external subsidies or financing.

IV. CONCLUSION

A fully functional IoT-based smart management prototype for layer hen farming has been designed, implemented, and validated under real operating conditions. By tightly integrating multi-sensor monitoring with edge-driven automation and a stable web-based human–machine interface, the system demonstrably stabilizes the coop micro-environment, reduces harmful gas accumulation, automates labor-intensive tasks, and supplies actionable historical data—all at a component cost compatible with smallholder economics. Quantitative field results (temperature stability < 2 °C, 15 % ammonia reduction, 94 % egg-count accuracy, ~70 % labor reduction) confirm that the prototype meets its design objectives and offers a practical pathway toward precision livestock farming for Indonesia's numerous small- and medium-scale layer operations. The open use of commodity components and standard web technologies further ensures that local technicians can maintain and incrementally improve the installation without vendor lock-in. Future work will extend the architecture to multiple coops with centralized aggregation, incorporate lightweight machine-learning models (e.g., regression or simple neural nets on historical sensor–yield pairs) for predictive environmental control and yield forecasting, add SMS or push-notification alerts for critical anomalies, and conduct longitudinal durability trials spanning full 18–24 month production cycles to quantify long-term ROI and component lifetime under tropical farm conditions.

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