Journal of Deep Learning, Computer Vision and Digital Image Processing
E-ISSN: 2986-8939 P-ISSN: 2986-8920
Vol. 4 No. 3, September 2026
DOI. https://doi.org/10.61255/decoding.v4i3.1569

Design and Development of an Internet of Things-Based Automatic Chicken Egg Sorting System for Real-Time Sorting and Monitoring

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OPEN ACCESS

ARTICLE HISTORY
Received: June 23, 2026
Revised: July 16, 2026
Accepted: August 27, 2026

KEYWORDS
Egg sorting;
ESP32;
Internet of Things;
Load cell;
Real-time monitoring.

ABSTRACT

Purpose – This study develops and evaluates an IoT-based egg sorter integrating weight grading, gas-response screening, automatic diversion, and monitoring.

Methods – The prototype combined an ESP32, a load cell with HX711, an infrared sensor, an MQ-135 sensor, and a servo actuator. Records were transmitted to a PHP REST API and MySQL database on a local server. Evaluation covered ten calibration masses, ten egg-weight measurements, separate gas-screening sample sets, infrared detection, ten end-to-end routing trials, server communication, and manual-versus-automatic sorting time.

Findings – Mean relative error was 0.33% for calibration masses and approximately 0.24% for egg measurements. The MQ-135 separated the selected good and spoiled sample groups using a threshold of 250 ppm-equivalent sensor-library units. All ten end-to-end trials routed eggs according to the assigned category. Server response averaged 1.17 s (SD 0.09 s). Sorting time decreased from 7.35 to 3.18 s per egg, a reduction of 56.73%.

Research implications – The small samples support preliminary functional feasibility. Routing agreement does not establish independently verified classification accuracy. Gas response was not traceable to a calibrated concentration standard, and several environmental and sensor-preparation conditions were unrecorded. Larger controlled studies are needed to validate quality screening and boundary-case grading.

Originality – The design integrates weight sensing, gas-response screening, mechanical diversion, and local-server records within one low-cost egg-sorting workflow.

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To cite this article : Mahesa, K. A. R., Haq, E. S., Kurniawan, I., Wibowo, G. H., & Fahmi, A. (2026). Design and Development of an Internet of Things-Based Automatic Chicken Egg Sorting System for Real-Time Sorting and Monitoring. *Journal of Deep Learning, Computer Vision and Digital Image Processing*, *4*(3), 244–261. https://doi.org/10.61255/decoding.v4i3.1569

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INTRODUCTION

Chicken eggs remain one of the most important animal-protein commodities in Indonesia because they are widely consumed, nutritionally dense, relatively affordable, and easy to distribute. In practical supply chains, however, the value of eggs is not determined only by quantity. It is also shaped by post-harvest handling, especially sorting and quality screening before packaging and distribution. Eggs with inconsistent size categories reduce packaging uniformity, complicate pricing, and create variability in customer expectations. Eggs of degraded quality or incipient spoilage present an even more serious problem because they affect food safety, product reputation, and overall commercial trust. For that reason, the sorting stage is a strategic point in the poultry value chain rather than a mere administrative activity [1], [2], [3].

In many small and medium poultry farms, egg sorting is still conducted manually. Operators typically collect eggs, inspect them visually, weigh them one by one, and separate them according to experience-based judgment. This process is feasible at very small volumes, but it becomes increasingly inefficient as production grows. Manual work introduces unavoidable variability because operators differ in speed, attentiveness, and fatigue level. When farm activity is intense, repeated tasks may lead to inconsistent classification, delayed handling, and a higher likelihood of human error. Previous studies on agricultural and poultry automation have repeatedly noted that post-harvest manual workflows, while simple to start, become bottlenecks in routine operations once throughput and consistency requirements increase [4], [1], [2].

The challenge does not end with weight grading. Egg quality is equally crucial. Some damaged or deteriorating eggs cannot be identified reliably through casual observation alone, especially during early spoilage stages. As eggs age or undergo microbial decomposition, internal biochemical reactions generate gases such as ammonia (NH3) and hydrogen sulfide (H2S). These gaseous by-products provide a practical signal that quality degradation is occurring. Gas sensing therefore offers an attractive alternative to methods that depend heavily on visual candling conditions. Advances in low-cost gas sensors and electronic nose concepts have opened opportunities for food-quality screening outside laboratory environments, including proof-of-concept applications for meat freshness, egg spoilage detection, and poultry-house gas monitoring [5], [6], [7], [8], [9], [10], [11], [12].

Within this context, Internet of Things technology provides an additional layer of value. IoT systems enable embedded devices to acquire data, process local decisions, transmit results through a network, and display information remotely in near real time. In agriculture and livestock systems, this capability has become increasingly relevant because it allows operators to supervise distributed processes without remaining physically present at one machine or one location. Rather than functioning solely as a data logger, an IoT-enabled sorting system can support traceability, routine performance review, category statistics, and practical decision-making related to production and packaging. Classic and contemporary IoT literature emphasizes the importance of sensing, connectivity, event processing, and server visibility as foundational elements of smart operational systems [13], [14], [15].

Recent egg-sorting studies show meaningful progress but also reveal persistent gaps. Several systems have focused on weight classification through load cells and microcontrollers, while others added image- or light-based methods for internal quality assessment. Some researchers implemented Firebase or other server dashboards for monitoring, and others used Telegram or web-based interfaces for reporting results [3], [16], [1], [17], [2]. Although those studies demonstrate the feasibility of automation, quality screening is still often dependent on candling or light-transmission methods. Such approaches may perform adequately in controlled conditions but remain sensitive to lighting arrangements, positioning consistency, and internal image interpretation. For small and medium farms, simpler robust approaches may be more practical than optical setups that require tighter environmental control.

The present study addresses that gap by combining weight measurement and gas-based spoilage screening in one integrated operational workflow. Instead of relying on a camera or LDR-based

candling process, the proposed system uses an MQ-135 gas sensor to identify quality anomalies associated with decomposition gases. A load cell paired with the HX711 module measures egg weight, an infrared sensor detects egg presence to synchronize the workflow, a servo actuator diverts the egg to the appropriate lane, and an ESP32 microcontroller coordinates sensing, classification, and communication. Processed results are transmitted over Wi-Fi by HTTP to a PHP REST API and stored in a MySQL database on a local server, from which they are displayed on a web dashboard so that the sorting process can be monitored remotely on any device connected to the same network [18], [19], [20].

This design choice is important from both engineering and adoption perspectives. From an engineering standpoint, a multi-sensor embedded system can reduce subjectivity by transforming physical cues into measurable variables. From an adoption standpoint, the selected components are relatively accessible, widely documented, and suitable for prototype-scale implementation in educational and applied settings. The use of ESP32 is particularly attractive because it offers built-in Wi-Fi and sufficient computational capability for practical IoT integration without requiring many external communication modules [19]. Likewise, the load cell and HX711 combination remains one of the most economical and reliable approaches for low-weight precision measurement in embedded systems [18], [21].

The research location also reflects practical relevance. The system concept was motivated by the operational needs of a laying-hen farm where large numbers of eggs are handled routinely and where manual sorting still dominates day-to-day activities. Such a setting is common in Indonesia, where digitalization in small and medium livestock enterprises is growing but remains uneven. Therefore, a prototype that demonstrates not only classification performance but also measurable time efficiency and remote data visibility can serve as a valuable transitional model. It shows how smart-farming principles may be implemented progressively, starting from highly specific post-harvest tasks rather than requiring a full farm-wide digital overhaul from the outset [4], [22], [23].

This study aimed to design, implement, and evaluate an IoT-based automatic egg sorting system that combines weight classification, gas-response screening, mechanical diversion, and local-server monitoring. The prototype integrated an ESP32, an infrared sensor, a load cell with HX711, an MQ-135 sensor, a servo actuator, and a PHP REST API connected to a MySQL database. Evaluation addressed measurement performance, component functionality, data transmission, and sorting time relative to manual operation. The intended contribution is preliminary evidence on the feasibility of integrating these functions in a low-cost prototype.

METHOD

This study used an applied engineering and prototype-development approach. The system was designed and tested in a laboratory-scale setting linked to the operational needs of Mama Home Ayam Wongsorejo, Banyuwangi, Indonesia. Development took place from January to June 2026 and covered assembly, integration, calibration, and performance testing.

The hardware architecture consisted of an ESP32 development board as the main controller; a load cell coupled with an HX711 amplifier module for weight measurement; an infrared sensor for egg-presence detection; an MQ-135 gas sensor for spoilage indication; a servo motor as the sorting actuator; a mechanical frame, hopper, and sorting lane; a regulated power supply with supporting electronic components; and a laptop for programming and testing. The software environment included Arduino IDE, ESP32 and sensor-control libraries, a PHP REST API with a MySQL database on a local server as the data-storage layer, and a web dashboard for real-time data visualization.

The system logic was arranged in three primary stages: input, processing, and output. At the input stage, the infrared sensor detected whether an egg had entered the measurement area and triggered the next sequence. Once an egg was detected, the load cell measured weight while the MQ-135 sensor sampled the surrounding gas response. At the processing stage, the ESP32 read all sensor values, compared them with predefined thresholds and category ranges, and determined the classification result. At the output stage, the servo motor rotated to a target angle so that the egg was directed to

the appropriate path, while the measured values and classification result were transmitted over HTTP to the PHP REST API and stored in the MySQL database for monitoring.

Weight categories were defined according to the classification used in the project proposal: eggs below 55 g were categorized as small, eggs from 55 to 64 g as medium, and eggs equal to or above 65 g as large. This classification was used by the ESP32 as the rule base for automatic sorting after the load-cell measurement stage.

Table 1. Weight classification thresholds used by the system

Category	Weight range (g)
Small	< 55
Medium	55–64
Large	≥ 65

The development procedure began with a literature review and needs analysis. Relevant studies on IoT, embedded measurement, poultry automation, gas sensing, and egg sorting were reviewed to identify suitable sensors, control architecture, and monitoring methods. Next, the hardware and software architecture were designed. The mechanical path was arranged so eggs could move sequentially through detection, measurement, and diversion zones. After assembly, each sensor was calibrated and verified individually before complete integration. The load cell was calibrated against a digital scale, the MQ-135 was exposed to comparative egg conditions to establish a practical threshold, and the infrared sensor was tuned to ensure stable detection at the intended working distance. Integrated testing then covered sensor functionality, weight measurement accuracy, gas-based quality differentiation, servo actuation, end-to-end sorting performance, and time-efficiency comparison. The protocols for each test, including sample sizes and environmental conditions, are specified in the subsections below.

Figure 1 summarizes the research procedure used in this study, from problem identification and prototype development to calibration, testing, and evaluation.

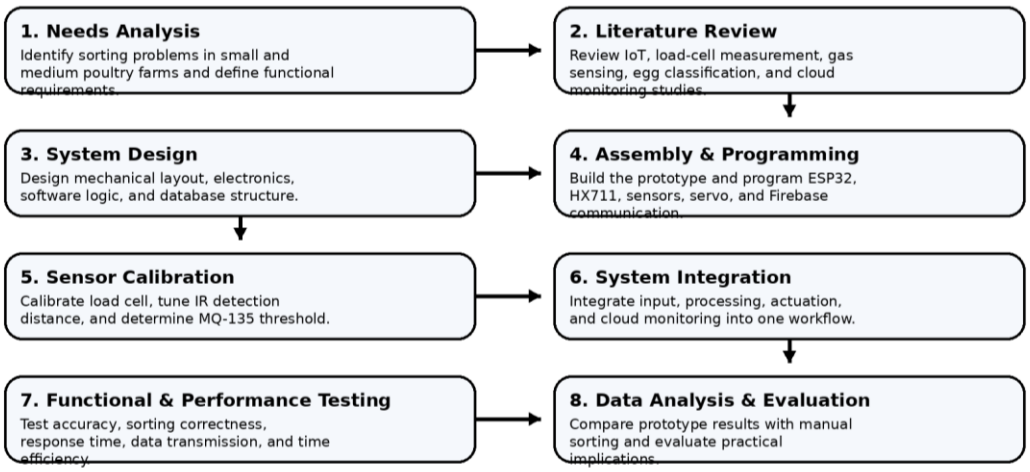


Figure 1. Research procedure of the study

The research procedure was conducted in eight sequential stages: (1) needs analysis at the targeted poultry-farm context; (2) literature review and component selection; (3) mechanical, electronic, and software design; (4) prototype assembly and ESP32 programming; (5) sensor calibration and threshold setting; (6) full-system integration; (7) functional, accuracy, response-time, and efficiency testing; and (8) descriptive and comparative analysis of the collected results.

Research Procedure and System Architecture

Figure 2 presents the relationships among the sensing units, controller, actuator, local-server storage, and dashboard.

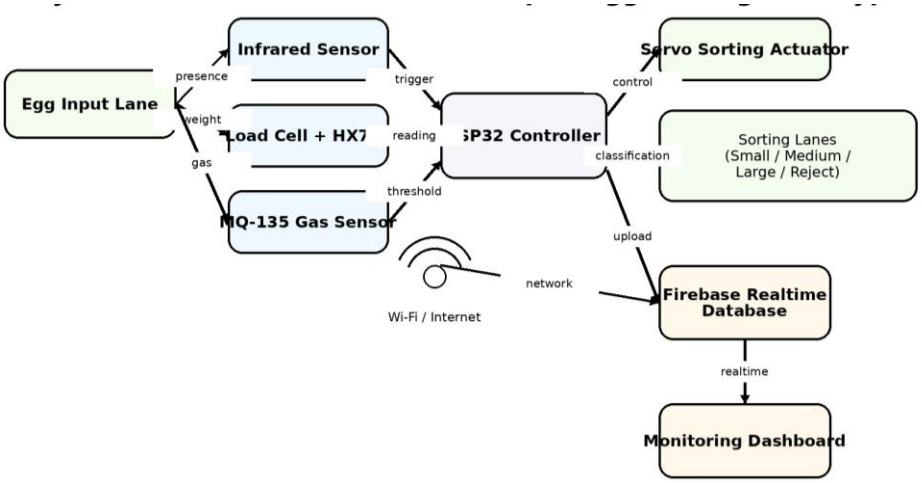


Figure 2. Technical architecture of the developed prototype

The developed tool can be described as five interconnected subsystems: (1) a mechanical egg-guiding lane and hopper, (2) sensing units for egg presence, weight, and gas response, (3) the ESP32 control and decision layer, (4) a servo-based diversion mechanism, and (5) a server-based monitoring layer comprising the PHP REST API, the MySQL database, and the web dashboard. This arrangement enabled the prototype to perform sequential sensing, local decision-making, physical sorting, and real-time data transmission in one integrated workflow.

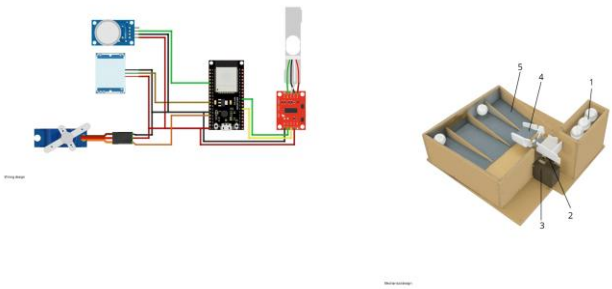


Figure 3. Wiring and mechanical design of the developed egg-sorting tool

As shown in Figure 3, the ESP32 was connected to the infrared sensor, load cell through the HX711 module, MQ-135 sensor, and servo actuator according to the prototype wiring plan. The mechanical arrangement consisted of an egg hopper, a guided lane, sensor-placement points, a servo-controlled diverter, and separate output containers for category-based collection. This visual description clarifies how the developed device translated the sensing-and-classification logic into a working physical tool.

The recorded parameters included egg presence, weight, gas response, assigned quality status, weight category, item count, and server-monitoring data. Table 2 summarizes their operational roles.

Table 2. Measured parameters and outputs used in prototype operation

Measured parameter	Sensor / source	Operational function	System output
Egg presence	Infrared sensor	Triggers the measurement cycle	Egg detected / not detected
Egg weight	Load cell + HX711	Determines size classification	Weight value (g)

Measured parameter	Sensor / source	Operational function	System output
Gas response	MQ-135 sensor	Indicates spoilage-related gas response	Sensor reading
Egg status	ESP32 decision logic	Determines acceptable or spoiled condition	Good / spoiled
Weight category	ESP32 decision logic	Groups eggs by measured mass	Small / medium / large
Egg count	ESP32 counter	Stores total and category-based quantity	Item totals
Server monitoring data	ESP32 + Wi-Fi + PHP API + MySQL	Sends process results to the server over HTTP	Real-time records

Calibration and Testing Protocols

Functional testing was conducted after integration and covered sensor functionality, weight-measurement accuracy, gas-based quality differentiation, servo actuation, end-to-end sorting performance, data transmission to the server, and dashboard responsiveness. The protocol for each test is specified below so that the conditions under which the reported values were obtained are reproducible.

Load cell calibration

The load cell was calibrated against a digital reference scale across the operational egg-weight range. Ten reference masses spanning 50–95 g were applied in ascending order, and for each mass the value displayed by the prototype was compared with the reference reading. For each point, the relative error was computed as $e = |W_{reference} - W_{measured}| / W_{reference} \times 100\%$, and accuracy as $100\% - e$. The calibration factor stored in the ESP32 firmware was adjusted until the mean relative error across the ten calibration points stabilized. A single recorded measurement for each reference mass was retained in the experimental dataset and is reported in Table 4. Repeated readings at each calibration point were not systematically documented; therefore, within-point repeatability could not be evaluated from the available calibration records.

MQ-135 gas-screening protocol

The MQ-135 is a metal-oxide semiconductor sensor whose baseline resistance varies with temperature, humidity, and warm-up state, so its use as a spoilage discriminator required a defined protocol rather than a single ad hoc reading. Screening was carried out in two stages: a calibration stage, in which the response of known good and known spoiled eggs was compared in order to derive a decision threshold, and a validation stage, in which the derived threshold was applied to a separate set of samples whose true condition was known. The parameters applied are summarized in Table 3.

Sample groups. The calibration stage used five eggs in good condition and five eggs that had undergone spoilage. The validation stage used a further ten eggs, again five good and five spoiled, coded T01-T10. Reporting the two stages separately matters because a threshold evaluated on the same samples from which it was derived would overstate the discriminating power of the sensor.

The spoiled egg samples used in this study were selected based on their observable quality degradation during the testing preparation. However, the exact spoilage induction duration and independent laboratory confirmation of spoilage conditions were not systematically recorded. Therefore, the MQ-135 results should be interpreted as a comparative prototype-level observation between the tested good and spoiled egg groups rather than as a quantitative spoilage-age prediction.

Sensor preparation: The MQ-135 was activated according to the module's operating procedure, but the preheating duration and initial burn-in period were not recorded. These omissions limit reproducibility because sensor response may depend on warm-up conditions. Future evaluation should document both procedures [20].

Measurement conditions: Each egg was positioned near the sensing area, and the response was recorded after the reading appeared stable. Egg-to-sensor distance, stabilization time, ventilation interval, ambient temperature, and relative humidity were not recorded. These variables should be standardized in future validation studies.

Repeated measurement. Each egg sample was evaluated during the testing session, but the number of repeated MQ-135 readings per egg was not systematically documented. Consequently, the reported values represent observed sensor responses during the prototype evaluation rather than statistically repeated measurements. Future work should include multiple readings per sample to quantify sensor repeatability.

Threshold setting: Calibration readings ranged from 112 to 126 for good eggs and from 345 to 395 for spoiled eggs. A threshold of 250 was selected as a round value within the observed gap of 219 units. Values below 250 were classified as good and values at or above 250 as spoiled. This threshold was not derived from a formal optimization procedure, and its stability under different conditions was not established. Values are reported as ppm-equivalent sensor-library outputs; they are not traceable measurements of a specific gas concentration.

Table 3. MQ-135 measurement protocol parameters

Protocol parameter	Value applied
Good eggs, calibration stage	5
Spoiled eggs, calibration stage	5
Good eggs, validation stage	5 (T01-T05)
Spoiled eggs, validation stage	5 (T06-T10)
Observed response, good eggs (calibration)	112–126 ppm-equivalent
Observed response, spoiled eggs (calibration)	345–395 ppm-equivalent
Decision threshold	250 ppm-equivalent
Threshold derivation	round value set within the 219 ppm gap between the two groups
Reading units	ppm-equivalent output of the sensor library, not traceable to a gas standard
Spoilage induction method	Not systematically recorded
Independent confirmation of spoilage	Not performed using laboratory analysis
Initial sensor burn-in	Not systematically recorded
Preheating before each session	Not systematically recorded
Egg-to-sensor distance	Not systematically recorded
Ambient temperature and humidity	Not recorded
Repeated readings per egg	Not systematically recorded

Infrared detection, sorting, and timing tests

Infrared detection was tested at 2, 4, 6, 8, and 10 cm, with five trials per distance. End-to-end sorting was tested on ten eggs labeled T01–T10, and each observed output lane was compared with the lane specified by the system's measured-weight and gas-response rules. Servo operation was also checked for the four output lanes. For the timing comparison, the farm operator and the prototype each sorted ten eggs.

Scope of the validation

The end-to-end test involved ten eggs in one session. It demonstrates that the integrated routing workflow operated under the tested conditions but does not establish independently verified classification accuracy. For 10 successes in 10 independent Bernoulli trials, a two-sided exact 95% binomial confidence interval is approximately 69.2%–100%. This calculation illustrates the uncertainty associated with the small sample; it does not address uncertainty in the reference condition or independence of the trials. Larger evaluations across weight categories, spoilage stages, and operating conditions are needed.

Data analysis followed a descriptive and comparative approach. Quantitative results were presented through summary metrics such as average accuracy, percentage error, mean response time, and time-efficiency improvement. Qualitative interpretation was then used to explain how the integrated system behaved in operational terms and how the findings compared with related research. The goal of the analysis was not only to confirm whether each component worked, but also to evaluate whether the complete workflow provided a meaningful practical benefit over manual sorting. This approach was appropriate because the study emphasized prototype feasibility, performance characterization, and applied contribution rather than statistical inference on very large sample populations.

RESULTS AND DISCUSSION

The developed prototype successfully integrated the sensing, control, mechanical diversion, and server-based monitoring functions into a single workflow. During operation the system began with egg detection through the infrared sensor, followed by weight measurement through the load cell and quality screening through the MQ-135. The ESP32 then executed rule-based classification and commanded the servo mechanism to route the egg into the designated lane. In parallel, the measured values and the final category were transmitted over Wi-Fi by HTTP to the PHP REST API and stored in the MySQL database. From a systems perspective, the most important result is that the prototype did not merely perform isolated measurements; it completed the entire operational sequence expected from an automatic sorting device. This integration outcome matters because prototype failure often occurs not in individual components but at the interfaces between sensing, timing, actuation, and communication. The measured device is shown in Figures 4 and 5.

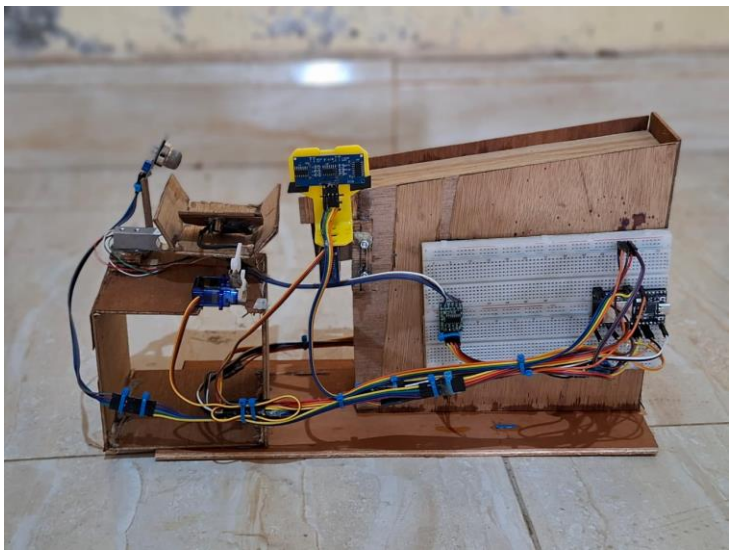


Figure 4. Implemented prototype, side view: MQ-135 sensor and weighing station at the inlet, load cell and HX711, servo-driven diverter, ESP32 and wiring on the vertical panel



Figure 5. Implemented prototype, top view: the guided lane, the servo-actuated gates, and the four output containers for the small, medium, large, and reject categories

Load cell calibration and weight measurement

Table 4 presents ten calibration readings over 50–95 g. Relative errors ranged from 0.13% to 0.55%, with a mean of 0.33% and an SD of 0.13 percentage points. Mean accuracy, defined as 100% minus relative error, was 99.67%. Because each reference mass was measured once in the recorded dataset, these values characterize error across calibration points rather than within-point repeatability.

Table 4. Load cell calibration readings against the digital reference scale (n = 10)

No	Reference mass (g)	Measured mass (g)	Deviation (g)	Error (%)	Accuracy (%)
1	50	49.8	0.2	0.40	99.60
2	55	55.3	0.3	0.55	99.45
3	60	59.7	0.3	0.50	99.50
4	65	65.2	0.2	0.31	99.69
5	70	69.8	0.2	0.29	99.71
6	75	74.9	0.1	0.13	99.87
7	80	80.3	0.3	0.38	99.62
8	85	84.8	0.2	0.24	99.76
9	90	90.2	0.2	0.22	99.78
10	95	94.7	0.3	0.32	99.68
Mean			0.23	0.33	99.67
SD			0.07	0.13	0.13
Min-Max	50-95	-	0.1-0.3	0.13-0.55	99.45-99.87

Table 5 presents measurements for ten egg samples. Relative error ranged from 0.11% to 0.40%, with a mean of approximately 0.24% and an SD of 0.11 percentage points, calculated from the listed reference and measured weights. Mean accuracy was approximately 99.76%. These values describe measurement error on the tested eggs and should be distinguished from the calibration results in Table 4.

Table 5. Weight-measurement accuracy of the integrated system on egg samples (n = 10)

No	Reference weight (g)	System reading (g)	Deviation (g)	Error (%)	Weight category
1	50	49.8	0.2	0.40	Small
2	55	55.2	0.2	0.36	Medium
3	60	59.9	0.1	0.17	Medium
4	65	64.8	0.2	0.31	Medium
5	70	70.1	0.1	0.14	Large
6	75	74.9	0.1	0.13	Large
7	80	80.3	0.3	0.38	Large
8	85	84.8	0.2	0.24	Large
9	90	90.1	0.1	0.11	Large
10	95	95.2	0.2	0.21	Large
Mean			0.17	0.24	-
SD			0.07	0.11	-

The 65 g reference sample was measured as 64.8 g and assigned to the medium category. This illustrates how a small measurement deviation can change the assigned grade near a category boundary. Boundary behavior should therefore be evaluated separately from average measurement error.

Future grading rules should define continuous, non-overlapping intervals and specify how values near each boundary are handled. Repeated boundary measurements would be needed to quantify classification stability.

The observed errors support the feasibility of low-cost weighing over the tested range. They do not by themselves establish more accurate grading than manual operation, because independent category-level accuracy was not evaluated across a representative sample.

MQ-135 quality screening

Table 6 reports the calibration-stage gas responses. Five good eggs produced values of 112–126 ppm-equivalent units (mean 120.0, SD 5.5), and five spoiled eggs produced 345–395 units (mean 370.2, SD 19.7). The threshold of 250 was placed within the observed gap. These results describe the selected sample groups under the recorded prototype conditions.

Table 6. MQ-135 calibration readings used to derive the 250 ppm-equivalent threshold (n = 10)

No	Egg condition	Sensor reading (ppm-equivalent)	Category assigned
1	Good	112	Normal
2	Good	118	Normal
3	Good	120	Normal
4	Good	124	Normal

No	Egg condition	Sensor reading (ppm-equivalent)	Category assigned
5	Good	126	Normal
6	Spoiled	345	Spoiled
7	Spoiled	358	Spoiled
8	Spoiled	371	Spoiled
9	Spoiled	382	Spoiled
10	Spoiled	395	Spoiled
Good eggs: mean / SD / range		120.0 / 5.5 / 112-126	-
Spoiled eggs: mean / SD / range		370.2 / 19.7 / 345-395	-

In the validation set (Table 7), good eggs produced readings of 118–132 ppm-equivalent units (mean 124.4, SD 5.4), and spoiled eggs produced 352–397 units (mean 375.4, SD 18.2). All ten classifications agreed with the assigned sample condition. The highest good-egg reading remained below the threshold, although independent laboratory confirmation of sample condition was not available.

Table 7. MQ-135 quality-detection validation against the 250 ppm-equivalent threshold (n = 10)

No	Egg code	Sensor reading (ppm-equivalent)	True condition	System result	Agreement
1	T01	118	Good	Good	Yes
2	T02	121	Good	Good	Yes
3	T03	124	Good	Good	Yes
4	T04	127	Good	Good	Yes
5	T05	132	Good	Good	Yes
6	T06	352	Spoiled	Spoiled	Yes
7	T07	365	Spoiled	Spoiled	Yes
8	T08	374	Spoiled	Spoiled	Yes
9	T09	389	Spoiled	Spoiled	Yes
10	T10	397	Spoiled	Spoiled	Yes

Because the calibration and validation sets were both small and both drawn from clearly good or clearly spoiled eggs, this result establishes that the sensor separates the two extremes. It does not establish where the threshold falls for eggs in early or borderline spoilage, which is the case that matters most in practice and which was not tested.

The relevance of this result becomes clearer when viewed against the literature on spoilage detection. Gas-based sensing provides a practical proxy for quality degradation because decomposition gases accumulate as spoilage progresses. The results obtained here show that gas-response screening can complement weight grading and extend the function of the device from size-only classification toward quality-aware sorting, without the illumination control that candling or image-based inspection requires.

Infrared detection and servo actuation

The infrared sensor was tested at five distances with five trials each (Table 8). Detection succeeded in every trial from 2 to 8 cm and in four of five trials at 10 cm, so 2-8 cm was adopted as the working

range. Servo actuation was verified for the four output lanes - small, medium, large, and reject - and every commanded diversion reached the intended container, with no misdirection or delay observed during testing.

Table 8. Infrared detection test at five working distances (five trials per distance)

No	Object distance (cm)	Trials	Detected	Success rate (%)
1	2	5	5	100
2	4	5	5	100
3	6	5	5	100
4	8	5	5	100
5	10	5	4	80

End-to-end sorting

Table 9 reports ten end-to-end trials. Each egg reached the lane corresponding to the system's assigned category, and no mechanical routing failure was observed. Eggs assigned to the spoiled class were directed to the reject lane regardless of weight. Agreement between the assigned category and the output lane demonstrates routing consistency; it is not an independent test of the correctness of the assigned category.

Table 9. End-to-end sorting results (n = 10)

No	Egg code	Weight (g)	Quality	Category	Output lane	Status
1	T01	52	Good	Small	Small	Correct
2	T02	57	Good	Medium	Medium	Correct
3	T03	63	Good	Medium	Medium	Correct
4	T04	68	Good	Large	Large	Correct
5	T05	73	Good	Large	Large	Correct
6	T06	81	Good	Large	Large	Correct
7	T07	87	Good	Large	Large	Correct
8	T08	61	Spoiled	Reject	Reject	Correct
9	T09	74	Spoiled	Reject	Reject	Correct
10	T10	89	Spoiled	Reject	Reject	Correct

The 10 successful routing events provide preliminary evidence of integrated operation. Under an independent binomial-trial assumption, the two-sided exact 95% confidence interval for routing success is approximately 69.2%–100%. A larger sample is needed to estimate failure rates more precisely.

Server communication and monitoring

Table 10 reports ten data-transmission events. All records were accepted by the PHP REST API and stored in MySQL. Response times ranged from 1.0 to 1.3 s, with a mean of 1.17 s and a sample SD of 0.09 s. Sorting decisions were made locally by the ESP32 rather than waiting for the server response.

Table 10. Server response time per transmitted record (n = 10)

No	Data transmitted	API status	Database status	Response time (s)
1	Egg weight	Success	Stored	1.2
2	Weight category	Success	Stored	1.1
3	Egg quality	Success	Stored	1.3
4	Egg count	Success	Stored	1.0
5	Sorting status	Success	Stored	1.2
6	Weight data	Success	Stored	1.1
7	Egg category	Success	Stored	1.2
8	Sensor status	Success	Stored	1.3
9	Record history	Success	Stored	1.2
10	Complete record	Success	Stored	1.1
Mean / SD / range				1.17 / 0.09 / 1.0-1.3

The monitoring capability is not a minor add-on. In practical farm management the value of real-time visibility extends beyond curiosity: data on weight categories, reject counts, and throughput can support packaging decisions, quality control, labor allocation, and maintenance review. A farm owner can see whether the machine is operating normally, whether reject rates are rising, or whether output in a given period is dominated by one weight class. Even with a simple dashboard, the move from invisible manual work to traceable digital records changes the managerial quality of the process. For small and medium poultry enterprises this transition can be a first step toward broader digitalization without requiring a high-cost smart-farm ecosystem [4], [24], [22], [25].

Time efficiency

The most directly measurable operational advantage appeared in the timing comparison (Table 11). Manual sorting required a mean of 7.35 s per egg (SD 0.16 s, range 7.1-7.6 s) and the automatic system 3.18 s per egg (SD 0.08 s, range 3.1-3.3 s). The difference of 4.17 s corresponds to an efficiency gain of 56.73%, so the prototype nearly halved the sorting time under the test scenario.

Table 11. Per-egg sorting time and efficiency, manual versus automatic (n = 10 per condition)

Egg	Manual (s)	Automatic (s)
T01	7.4	3.2
T02	7.1	3.1
T03	7.3	3.3
T04	7.5	3.2
T05	7.2	3.1
T06	7.6	3.3
T07	7.4	3.2
T08	7.3	3.1
T09	7.5	3.2
T10	7.2	3.1

Egg	Manual (s)	Automatic (s)
Mean	7.35	3.18
SD	0.16	0.08
Min-Max	7.1-7.6	3.1-3.3
Coefficient of variation	2.15%	2.48%
Mean difference	4.17 s per egg	
Efficiency gain	56.73%	

The SD of sorting time was smaller for automatic operation (0.08 s) than for manual operation (0.16 s). However, their coefficients of variation were similar: 2.48% and 2.15%, respectively. The data therefore demonstrate faster automatic sorting and a smaller absolute timing spread, but not lower relative variation. Longer trials are needed to assess whether performance remains consistent as operating duration increases.

Table 12. Summary of sensor validation and system performance

Subsystem / test	n	Main result
Load cell calibration	10	Mean accuracy 99.67%; mean error 0.33% (SD 0.13 pp) - Table 4
Weight measurement on eggs	10	Mean accuracy 99.76%; mean error 0.24% (SD 0.11 pp) - Table 5
MQ-135 calibration	10	Good 112–126 ppm-equivalent; spoiled 345–395 ppm-equivalent; threshold 250 ppm-equivalent - Table 6
MQ-135 validation	10	10/10 agreement with true condition - Table 7
Infrared detection	25	100% success at 2-8 cm; 80% at 10 cm - Table 8
Servo diversion	4	All four output lanes reached as commanded
End-to-end sorting	10	10/10 routed as classified (preliminary; 95% CI 69.2–100%) - Table 9
Server communication	10	All records stored; response 1.17 s (SD 0.09 s) - Table 10
Timing comparison	10 + 10	Manual 7.35 s vs automatic 3.18 s per egg; 56.73% gain - Table 11

This efficiency result also has implications for consistency. Human-operated sorting performance usually fluctuates over time because fatigue, distraction, and repetition affect judgment and pace. An automatic embedded system, by contrast, executes the same rule set in each cycle so long as the sensors remain calibrated and the mechanical path remains stable. The ten-egg session reported here is too short for that mechanism to show itself, which is why the measured dispersion does not yet demonstrate a consistency advantage; the expectation is reasonable on mechanical grounds, but it remains an expectation rather than a finding of this study.

When compared with earlier research, the contribution of this system lies in its integrated combination of weight grading, gas-based quality screening, automatic mechanical diversion, and real-time IoT monitoring in one coherent workflow. Several previous studies implemented load-cell-based sorting and IoT visibility, but many quality-detection approaches still relied on candling, light transmission, or image-based interpretation [23], [2], [1], [17], [26]. The present study offers an alternative path that is less dependent on illumination setup and potentially simpler to implement in compact hardware. The novelty is therefore not the use of IoT alone, nor the use of a load cell alone, but the way a gas-sensing parameter is added to extend the function of egg sorting from size-only classification toward quality-aware screening.

The findings also suggest that digitalization in poultry operations does not always require expensive or highly complex systems. Using broadly accessible components such as ESP32, HX711, MQ-series sensing, and a PHP/MySQL server stack, the prototype already delivered objective sorting, real-time records, and measurable efficiency gains. This aligns with the broader movement in smart agriculture toward modular, incremental adoption, where specific operational pain points are addressed first before broader automation is pursued [5], [15], [25]. For many small and medium enterprises, this incremental path is more realistic than adopting large integrated industrial platforms from the outset. The present prototype therefore has value as a transitional technology: it demonstrates a manageable entry point into data-aware automation.

At the same time, the results must be interpreted within the constraints of the study, and the most important of these is the scale of the validation. End-to-end sorting was evaluated on ten eggs in one session, and the calibration, gas-screening, and timing tests were of comparable size. A sample of that size is adequate to demonstrate that the integrated workflow functions as designed, but it cannot estimate classification accuracy with useful precision, cannot characterize behavior across weight categories or spoilage stages, and cannot detect infrequent failure modes. The findings are therefore presented as preliminary proof-of-concept evidence and not as a performance specification for the device. Establishing such a specification would require testing on the order of several hundred eggs across multiple sessions, weight categories, operators, and ambient conditions, with confusion-matrix analysis of both weight grading and spoilage classification. The trials were also performed in a controlled prototype setting rather than in a long-duration commercial farm operation. The MQ-135 sensor served as a practical indicator and remains sensitive to ambient conditions, requiring periodic recalibration. The system did not assess shell cracks, shell cleanliness, or external visual defects because no computer-vision module was included. The monitoring stack runs on a local server rather than on a public cloud service, so the results do not speak to internet-scale deployment; dashboard scalability, data security, and network resilience were not investigated. These limitations do not negate the contribution of the work, but they define the boundaries within which the results should be understood. The prototype demonstrates feasibility and practical promise, not the final form of a production-grade industrial machine.

The prototype illustrates how weight sensing, gas-response screening, mechanical diversion, and local-server records can be combined for poultry handling. The timing results suggest a potential operational benefit under the tested conditions. Larger field studies are needed to establish classification reliability, managerial benefits, and suitability for routine farm use. The integrated design may also serve as an applied teaching example for embedded sensing and IoT development.

Future development should expand both technical sophistication and validation scope. Larger sample sizes and longer-duration field trials are necessary to evaluate durability, calibration stability, and real operational throughput. More selective gas sensors or compensated sensing methods could improve spoilage classification robustness. Computer vision could be integrated to detect shell cracks, dirt, or external abnormalities, thereby complementing the gas-based and weight-based subsystems. The server dashboard could also be extended with analytical summaries, historical trends, alerts, and data export features. If such improvements are implemented, the prototype presented in this study may evolve from a laboratory-scale proof of concept into a more mature smart-sorting solution suitable for broader poultry-industry use. The MQ-135 evaluation has several methodological limitations. Although the sensor successfully separated the tested good and spoiled egg groups, the experiment did not control all environmental variables affecting gas sensor response, including temperature, humidity, sensor warm-up duration, and measurement geometry. Therefore, the threshold value obtained in this study should be considered specific to the prototype testing condition and requires further validation under controlled environments.

CONCLUSION

This study developed an IoT-based egg sorter combining weight measurement, gas-response screening, mechanical diversion, and local-server monitoring. Calibration measurements gave a mean relative error of 0.33%, while the ten egg measurements gave approximately 0.24%. All ten

end-to-end trials routed eggs according to the system's assigned category, and the server recorded all ten transmission events with a mean response time of 1.17 s (SD 0.09 s). Mean sorting time decreased from 7.35 s manually to 3.18 s automatically, corresponding to a 56.73% reduction. These results support preliminary functional feasibility under the tested conditions. They do not establish independently validated spoilage detection, general classification accuracy, or long-term reliability; further work should evaluate boundary-case grading and expand calibration and validation under controlled conditions.

ACKNOWLEDGMENT

The authors thank the Diploma IV Program in Applied Computer Engineering Technology at Politeknik Negeri Banyuwangi, the academic supervisors, and Mama Home Ayam Wongsorejo for supporting the design, testing, and data collection.

AUTHOR CONTRIBUTION STATEMENT

Kevin Arya Rizki Mahesa: Conceptualization, Methodology, Software, Data Curation, Formal Analysis, Visualization, Writing - Original Draft. Endi Sailul Haq: Supervision, Methodology, Validation, Writing - Review & Editing. Indra Kurniawan: Validation, Formal Analysis, Writing - Review & Editing. Galih Hendra Wibowo: Supervision, Validation, Writing - Review & Editing. Arif Fahmi: Validation, Writing - Review & Editing.

AI DISCLOSURE STATEMENT

The authors disclose that OpenAI ChatGPT was used only for language polishing, structural reformatting, and editorial assistance during manuscript preparation. All scientific content, data interpretation, analysis, and final decisions remain the full responsibility of the authors. The authors reviewed and revised all AI-assisted outputs before submission.

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