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Genetic algorithm-based chicken manure weight prediction system development

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ABSTRACT

This research presents design and implementation of internet of things (IoT)-based monitoring and predictive system for evaluating chicken manure weight and environmental conditions in poultry housing. The proposed system integrates MQ-137 sensor for ammonia detection, DHT22 sensor for temperature and humidity measurement, and load cell modules for manure weight monitoring. All sensor data are transmitted in real time to cloud platform, enabling continuous environmental assessment. A 30-day experimental study was conducted using two controlled chicken drum models, each containing 15 broiler chickens and provided with different feed types to observe variations in manure production and air quality. Sensor calibration results indicate high accuracy, with average error of 0.31% for ammonia readings and 0.10% for manure weight measurement. Experimental findings show that feed type A generates lower manure weight, reduced ammonia concentration, and more stable temperature conditions compared to feed type B, suggesting improved feed efficiency and better overall chicken health. A genetic algorithm (GA) was employed to optimize regression model predicting manure weight using ammonia concentration and temperature as input features. The GA-optimized model achieved strong predictive performance, with root mean square error (RMSE) of 0.358 g and coefficient of determination (R^2) value of 0.992. The results demonstrate that proposed system provides reliable, scalable, and data-driven solution for smart poultry monitoring and early health detection.

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1. INTRODUCTION

In modern animal husbandry, maintaining chicken health is essential for achieving efficient and successful production. Healthy chickens grow optimally and produce high-quality meat and eggs, reducing costs related to disease management and treatment. Therefore, regular and timely health monitoring is crucial. However, small to medium-scale farms often rely on manual monitoring, which increases the risk of delayed detection of health problems. This highlights the need for an automated system capable of monitoring livestock conditions accurately and quickly [1]–[6].

One important but often overlooked parameter is the weight of chicken feces. Feces weight can serve as a significant indicator of digestive health. A noticeable increase or decrease may signal digestive disorders or other health issues [7]–[11]. Feed consumption is another key indicator closely related to growth. Efficient feed intake supports optimal development, while reduced consumption may indicate early signs of illness or stress [12], [13]. Thus, monitoring both feces weight and feed consumption is vital for effective poultry health management.

Recent advancements in the internet of things (IoT) have led to its adoption in various industrial sectors, including animal husbandry. IoT enables automated monitoring through internet-connected sensors, allowing real-time data collection [14]–[18]. Using IoT, data on feces weight and feed consumption can be continuously gathered and analyzed, providing valuable insights for farm management. This technology also allows farmers to monitor chicken conditions remotely and detect health issues early, enabling timely interventions [19]–[22]. Machine learning (ML) algorithms further enhance the analysis of IoT sensor data. By learning patterns from feces weight and feed consumption, these algorithms can predict chicken health status with greater accuracy [23]–[27]. Irregular patterns may indicate infections or unsuitable environmental conditions, such as excessive heat or humidity [28], [29]. This transforms the system from a simple monitoring tool into a predictive and preventive solution.

The purpose of this research is to develop an IoT-based monitoring system that measures the real-time weight of chicken feces and feed consumption. The system will integrate ML to enable early detection of potential health issues. By analyzing sensor data on a cloud platform, it aims to improve farm management efficiency, reduce disease risks, and optimize poultry production [30]–[33]. In Indonesia, the adoption of IoT in the livestock sector remains relatively new and faces challenges, such as high initial investment costs and limited internet infrastructure [34], [35]. Nonetheless, increasing demands for efficiency have encouraged interest in these technologies, particularly among farmers seeking to scale their operations. Government and research institutions are also beginning to promote innovation to strengthen food security and support the growth of the national livestock industry [36].

2. METHOD

To develop this system, it is essential to understand four key components: chicken manure characteristics, air particle detectors for manure, the IoT, and ML. Once these components are understood, a system can be designed to monitor and regulate air quality at the case study site. The system will then undergo a 30-day testing period to evaluate sensor accuracy and data quality. This evaluation will help determine the system's effectiveness in monitoring feed quality and overall chicken health, ensuring that the sensors provide reliable data for farm management.

2.1. Chicken manure

Chicken manure is a waste product of chicken metabolism, consisting of undigested food residues, urine, and other metabolic by-products. It plays an important role in poultry health assessment because its composition and quantity provide valuable insights into the chickens' overall condition. Factors such as diet, environmental conditions, and digestive health directly influence the content and weight of manure.

One major concern with manure accumulation in chicken coops is the increase in ammonia levels caused by the breakdown of nitrogen in the manure. Ammonia is produced through the decomposition of uric acid, a nitrogen-rich compound in chicken waste. Under warm and moist conditions, microorganisms break down uric acid and release ammonia as a by-product. This gas is toxic and poses significant health risks to chickens [37], [38].

High ammonia levels can irritate the respiratory tract, eyes, and skin, increasing the likelihood of respiratory infections. Prolonged exposure weakens the immune system, making chickens more susceptible to diseases such as chronic respiratory disease and bacterial infections, while also reducing productivity [39]. Excessive ammonia further degrades air quality, leading to lower growth rates and decreased egg production. Therefore, effective management and monitoring of manure accumulation and ammonia levels are essential for maintaining chicken health and productivity.

2.2. MQ-137 sensor

The MQ-137 sensor is a gas sensor used in equipment to detect ammonia gas in everyday life, industry, or cars [40]–[42]. The feature of this MQ-137 gas sensor is that it has high sensitivity to detect ammonia, is stable, and has a long life. This sensor uses a heater power supply of 5 V AC/DC and a circuit power supply of 5 V DC, with a with a measurement distance of 5-500 ppm to effectively measure carbon dioxide gas. In this research, the MQ-137 sensor will be used, which can detect combustion residues. Figure 1 shows the sensitivity value of MQ-137 to other gases. Figure 2. shows the circuit of the MQ-7 used. To find out the relationship between components and detection, it is described in (1).

$$x = \sqrt[-1.53]{\frac{y}{100}} \quad (1)$$

Where y is the desired clean air standard (in ppm), then after getting the x value proceed to (2).

$$R_S = \frac{V_C \times R_L}{V_{RL}} - R_L \quad (2)$$

Where R_S is the resistance to the sensor, V_c is the input voltage to the sensor, R_L is the load resistance in the circuit, and V_{RL} is the output voltage of the circuit. After calculating with (1) and (2), it is continued to calculate the value of R_o which is a comparison resistance for normal conditions of clean air which is the reference in (3).

$$R_O = \frac{x}{R_S} \quad (3)$$

So that after the values of R_S and R_O are obtained, they can only measure the changes in the air that occur.

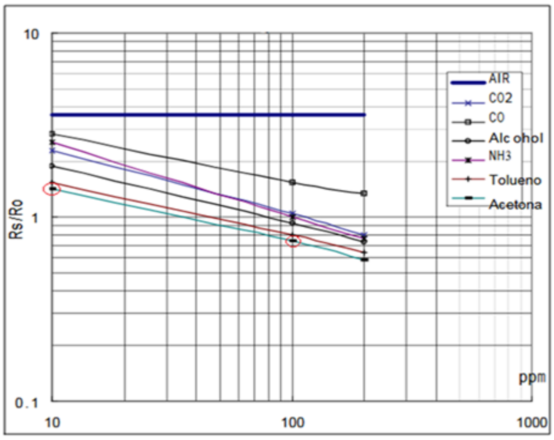

Figure 1. MQ-137 sensivity graphic

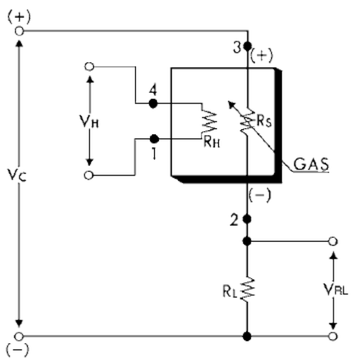

Figure 2. MQ-137 sensor circuit

2.3. Internet of things communications

The IoT is a concept in which devices transmit data over a network without requiring human-to-human or human-to-computer interaction. The term "IoT" was introduced in 1999 by Kevin Ashton, cofounder and executive director of the Auto-ID Center at MIT. However, the development of IoT began long before that. One early example is the Coca-Cola machine at Carnegie Mellon University in the early 1980s, which became the first internet-connected device. Programmers could access it remotely to check its status and determine whether cold drinks were available without visiting the machine in person [43], [44].

Figure 3 illustrates an IoT system using wireless communication to send measurement data to a cloud database for storage.

Wireless communication refers to the transfer of data between two or more locations without an electrical conductor. Its range can vary from a few meters, such as in television remote controls, to thousands or even millions of kilometers in deep-space radio transmissions. Wireless communication encompasses devices such as personal digital assistants (PDAs), cell phones, wireless networks, and various types of fixed, mobile, and portable two-way radios. The 2.4 GHz band is widely used for many applications [45]–[47], with one of the most common being wireless network access for users who move between locations. Another major application is mobile networks connected via satellite.

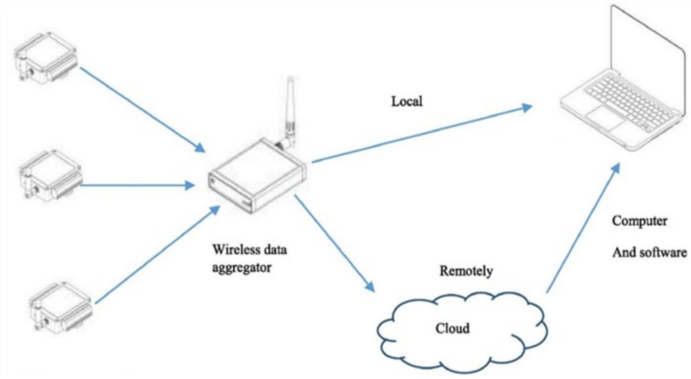

Figure 3. Internet of things schematic

2.4. Machine learning

ML is the process of creating a mathematical model to make predictions or decisions using training data, which are sample data sets [48], [49]. As a subfield of artificial intelligence (AI), ML focuses on developing algorithms that analyze data to generate predictions [50], [51]. These algorithms learn from the data to improve their performance over time. An ML algorithm is trained with a dataset, which is then used to classify or predict outcomes based on the data. Figure 1 shows a general structure of how the learning model functions, while Figure 2 illustrates the process of classifying sample (test) data based on the trained dataset. ML algorithms can be categorized into three main types based on their learning methods. Supervised, unsupervised, and reinforcement learning are the three distinct categories into which ML algorithms fall based on their abilities to learn. Under the supervised learning category, regression models and classification models are investigated. In the unsupervised learning area, clustering and dimensionality reduction are investigated, while in the reinforcement learning category, real-time decision models are investigated. Using input data, supervised learning predicts more accurately than the intended model. More complicated processing tasks are completed by unsupervised learning. Analyzing dimension reduction can be done with both supervised and unsupervised learning techniques. The most popular and widely used dimensional reduction methods are principal component analysis (PCA), partial least squares regression (PLSR), and linear discriminant analysis (LDA) [52], [53]. ML techniques are commonly applied in constructing business models, decision support systems, and behavioral analysis—such as evaluating user behavior from social media, email content, and online shopping. Modern electronic devices, such as laptops and smartphones, now incorporate a range of ML applications for real-time data processing and prediction. To enhance the accuracy of chicken health monitoring, comparative experiments with multiple ML algorithms should be conducted to determine the most effective model for predicting chicken manure weight. Based on this research, the genetic algorithm (GA) emerged as the most suitable optimization model, demonstrating the ability to effectively capture the nonlinear relationship between input variables—such as temperature and ammonia concentration—and manure output. Its adaptive search process and robust performance make it ideal for agricultural predictive modeling.

2.5. Block diagram system

In the research described in Figure 4, the monitoring system is developed as an embedded IoT platform that integrates multiple environmental and health-related sensors. To observe conditions inside two chicken drum models, each housing 15 chickens. The system uses a microcontroller as the primary processing unit, responsible for sampling, processing, and transmitting sensor data in real time.

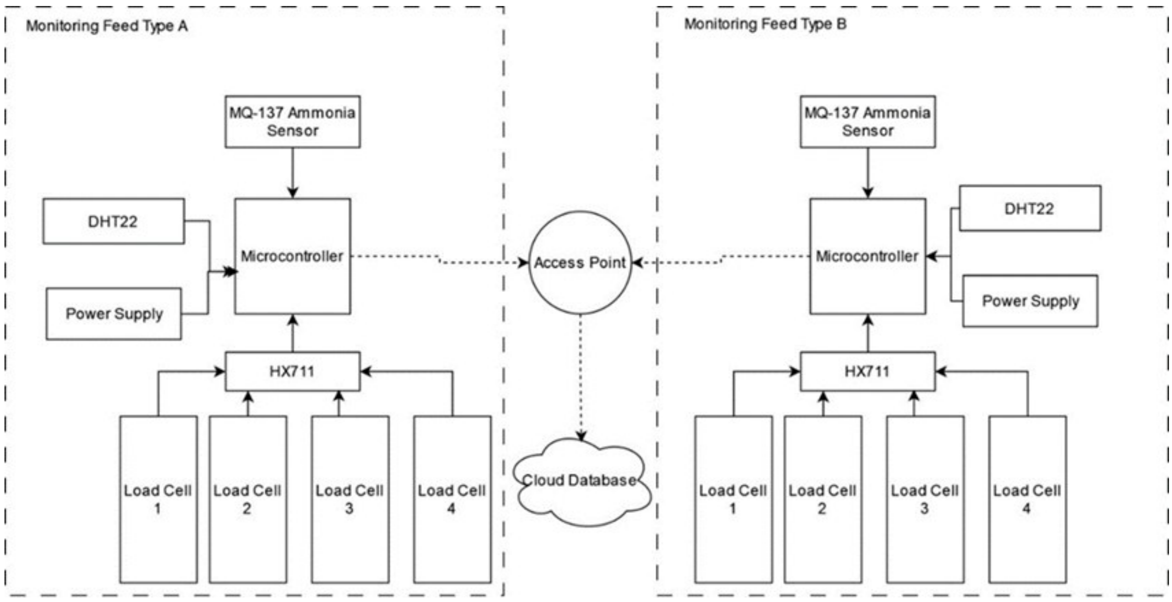

Figure 4. Flowchart of the AI-based models and experimental methods applied

Various sensors are interfaced with the embedded controller, including the MQ-137 for ammonia detection, temperature and humidity sensors for thermal comfort monitoring, and additional modules depending on feed variations. These sensors communicate through digital and analog interfaces, ensuring accurate environmental data acquisition within each drum. For wireless communication, the embedded controller uses Wi-Fi–based protocols to transmit data seamlessly to a cloud or local monitoring server. This ensures continuous real-time monitoring of air quality, temperature, and other parameters, supporting efficient analysis of how different feed types influence chicken health and environmental conditions.

A ML approach is developed to estimate manure weight using temperature and ammonia levels as predictive features. To justify the use of a GA for model optimization, the GA-based model is benchmarked against two widely used regression methods in agricultural prediction: support vector regression (SVR) and random forest regression (RF). SVR provides strong nonlinear regression capabilities, while RF offers robustness through ensemble learning. These models serve as appropriate baselines for comparison.

During benchmarking, all three models—GA-optimized regression, SVR, and RF—are trained using identical input features and evaluated with standard performance metrics: mean squared error (MSE), root mean square error (RMSE), and the coefficient of determination (R^2). The results show that the GA-based model consistently outperforms SVR and RF, particularly in capturing nonlinear interactions between ammonia levels, temperature fluctuations, and manure weight. This improvement is attributed to the GA's evolutionary search mechanism, which effectively explores complex parameter relationships.

The GA optimization process illustrated in Figure 5 begins with an initial population of 15 chromosomes, balancing solution diversity, and computational efficiency. Each chromosome represents a potential parameter set for the predictive model. Across generations, the GA evaluates fitness based on prediction error, selects optimal individuals, and applies crossover and mutation to produce improved offspring. This evolutionary cycle continues until convergence criteria are met, typically when fitness improvements stabilize or the maximum generation count is reached.

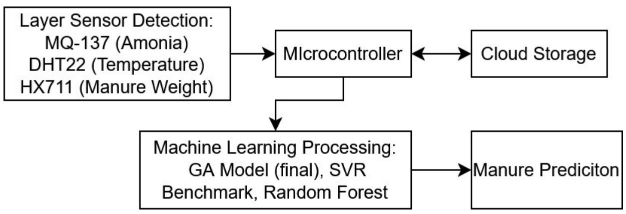

Figure 5. Flowchart of system

Using this GA-based strategy with a controlled chromosome population of 15 results in enhanced model accuracy, stability, and generalization compared to traditional regression methods. The configuration enables effective exploration of the solution space while minimizing computational overhead, producing a reliable model for estimating manure weight under varying environmental conditions. To situate the proposed system within existing research, Table 1 provides a comparative summary of conventional manure-prediction methods, sensor-based livestock monitoring systems, and GA-optimized predictive models. This comparison highlights key features, advantages, limitations, and recent studies that demonstrate ongoing advancements in smart farming, edge computing, IoT architectures, and ML optimization for agricultural applications.

Table 1. Comparation research of GA

Method/ system type	Key features	Technologies/ sensors used	Advantages	Limitations	Representative recent works
Existing manure prediction systems	Empirical/statistical modeling for estimating manure accumulation based on feed intake and animal growth.	Manual sampling, environmental logs, load cells.	Simple implementation; low computational cost.	Limited adaptability; not real-time; often low accuracy.	IoT livestock waste quantification model [54]; Data-driven manure estimation framework [55]
Sensor-based livestock monitoring systems	Real-time sensing of livestock environment.	MQ gas sensors, DHT22, HX711 load cells, edge IoT modules.	Real-time alerts; scalable; improves animal welfare.	Sensor drift; requires calibration; data noise.	Edge-IoT poultry monitoring architecture [56]; Animal welfare monitoring using distributed sensors [57]
GA-based optimization models	Uses GA to optimize regression or ML models for agricultural prediction tasks.	GA-optimized regression, GA–ANN, GA–SVR, environmental time-series data.	High accuracy; strong for nonlinear relationships; adaptive.	Computationally intensive; sensitive to GA parameters.	GA-optimized neural regress [58]; Hybrid GA–SVR environmental prediction [59]; Evolutionary optimization in smart farming [60]

3. RESULTS AND DISCUSSION

The first stage of system implementation involves developing and placing the chicken coop monitoring device inside the coop. This device integrates several sensors connected through an IoT system to continuously monitor environmental and health-related parameters. Figure 6 illustrates the layout and integration of the components and how they are installed within the coop.

The purpose of this table is to highlight the accuracy of the MQ-137 sensor by showing how closely its readings align with those of the ammonia meter on Figure 7. The difference between the two sets of readings is calculated to determine the error margin. By comparing the readings, the accuracy of the sensors used in this system can be determined. In addition, this comparison is also important to evaluate the performance of the sensor under operational conditions. From the test results, an average error value of 0.31% was obtained. The error shows the difference between the sensor reading and the ammonia meter used as a reference. Overall, this error value is still within acceptable limits for the intended application.

Next is the test of accuracy scales (load cell sensor) carried out by tester, namely, testing the tools and systems, especially on the results of the scales with the results displayed. The purpose of this test is to determine the level of accuracy of the reading results of chicken manure in the cage in Figure 8 and Table 2. The results of weight readings taken using the load cell sensor are presented.

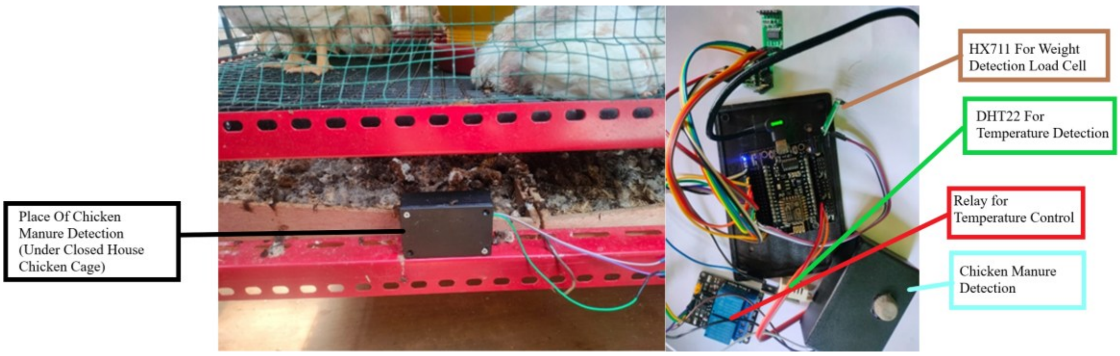

Figure 6. Implementation system for get data ML

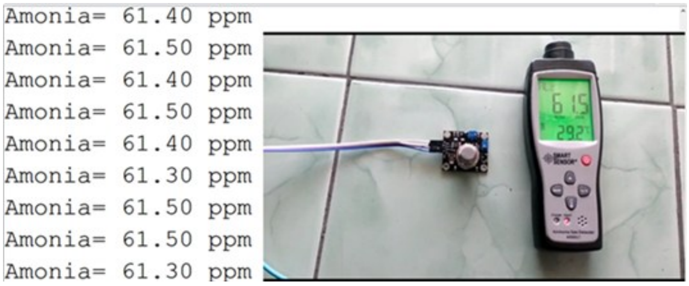

Figure 7. MQ-137 accuration test

Figure 8. Loadcell accuration test

Table 2. Sensor MQ-137 accuration measure

Testing	Test results		
	Ammonia gas detection device (ppm)	Sensor MQ-137 (ppm)	Error (%)
1	55.9	55.7	0.44
2	56.4	55.2	0.22
3	55.5	55.3	0.44
4	55.8	55.7	0.22
5	57.2	57.3	0.21
6	55.2	55.4	0.44
7	56.2	56.1	0.22
8	61.5	61.7	0.45
9	60.6	60.5	0.2
10	56.7	56.8	0.21
	Average		0.31

The reading results on Table 3 are then compared with the results obtained from the 5 kg scale as the main reference. The purpose of this comparison is to determine the difference or error between the two tools. Thus, it can assess the level of accuracy of the sensors used in this system. In addition, this comparison is important to evaluate the performance of the sensor in accurate weight measurement. From the test results, an average error value of 0.10% was obtained. This error value indicates the extent to which the sensor readings differ from the results obtained from the reference scales. Overall, the error of 0.10% is still within the acceptable range for weight measurement applications.

Table 4 is the result of 30 days of measurement. Feed A showed significant advantages over feed B in various aspects of raising broilers in closed-house cages. Chickens fed feed A produced less manure weight, indicating better nutrient absorption efficiency. The decrease in manure weight in chickens fed feed A was consistent from day to day, while in feed B, the decrease was more fluctuating. Ammonia levels in cages with feed A were also lower than those with feed B, indicating a cleaner and healthier environment. This reduces the risk of respiratory problems in the chickens. The more significant reduction in ammonia in cages with feed A indicates that this feed supports the health of the chickens better.

Table 3. Loadcell accurate measure

Test to -	Test results		
	Scales (grams)	Sensor loadcell (gram)	Error (%)
1	100	100.2	0.20
2	100	100.1	0.10
3	200	200.4	0.20
4	200	200.3	0.15
5	250	250.1	0.04
6	250	250.3	0.12
7	350	350.2	0.06
8	350	350.3	0.09
9	500	499.9	0.02
10	500	500	0.00
	Average		0.10

Table 4. System test for monitoring

Day	Feed type A			Feed type B		
	Weight of chicken manure (gram)	Ammonia (ppm)	Temperature (°C)	Weight of chicken manure (gram)	Ammonia (ppm)	Temperature (°C)
1	400	12	28	450	15	29
2	390	11	28	455	16	29
3	380	10	27.5	460	17	29
4	370	10	27.5	465	16.5	29
5	365	9	27	470	17.5	29
6	360	9	27	475	18	29.5
7	355	8.5	26.5	480	18	29.5
8	350	8	26.5	485	18.5	29.5
9	345	7.5	26.5	490	19	30
10	340	7	26	495	19.5	30
11	335	6.5	26	500	20	30
12	330	6	25.5	505	20.5	30.5
13	325	6	25.5	510	21	30.5
14	320	5.5	25	515	21.5	30.5
15	315	5	25	520	22	31
16	310	5	25	525	22.5	31
17	305	4.5	24.5	530	23	31
18	300	4	24.5	535	23.5	31.5
19	295	4	24	540	24	31.5
20	290	3.5	24	545	24.5	32
21	285	3	23.5	550	25	32
22	280	3	23.5	555	25.5	32
23	275	2.5	23	560	26	32.5
24	270	2.5	23	565	26.5	32.5
25	265	2	22.5	570	27	33
26	260	2	22.5	575	27.5	33
27	255	1.5	22	580	28	33.5
28	250	1.5	22	585	28.5	33.5
29	245	1	21.5	590	29	34
30	240	1	21.5	595	29.5	34

The more stable and lower coop temperature on feed A supports the comfort of the chickens, helping them maintain an optimal body temperature. Chickens fed feed A are less likely to experience stress due to excessively high ambient temperatures. Less feces also indicate improved overall chicken welfare. The low ammonia levels in cages with A feed contribute to a cleaner and safer atmosphere for the chickens. This healthy environment supports better chicken growth and reduces the risk of disease. Chickens fed feed A appear to be more productive due to more conducive environmental conditions. The more stable temperature helps the chickens avoid overheating, which can slow down growth. Overall, feed A produces more optimal conditions for broilers in closed-house housing [61], [62].

Chickens fed with feed A are more productive due to stable environmental conditions in closed-house systems. Consistent temperatures help prevent heat stress, which can hinder broiler growth and reduce efficiency. Additionally, lower and well-managed ammonia levels support better respiratory health and improve feed conversion. To quantify feed A's impact, a GA is applied to develop a predictive model for chicken manure production. Using temperature and ammonia concentration as inputs, the GA optimizes a simple linear regression equation. This model effectively links environmental conditions to manure output, providing insights into productivity benefits of using feed A. For example, initial regression equation as in (4).

$$W(t) = a \cdot T(t) + b \cdot A(t) + c \quad (4)$$

Where $W(t)$ is the weight of chicken manure on day t, $T(t)$ is the temperature on day t, $A(t)$ is the concentration of ammonia gas on day t, and (a, b, c) are parameters optimized using a GA. After several iterations of optimization, the best-fit parameters were found to be a =-0.75, b =1.5, and c =100. The negative value of a reflects the inverse relationship between temperature and manure weight, while the positive b value indicates that higher ammonia concentrations are associated with increased weight. The constant c helps to improve the model's prediction accuracy. With these parameters, the model can better estimate the weight of chicken manure under varying environmental conditions, as shown in Table 5.

Table 5. System test for monitoring

Prediction calculation model	Temperature (°C)	Ammonia gas (ppm)	Chicken manure weight on gram (predicted)
1	28	12	$W(1) = -0.75(28) + 1.5(12) + 100 = 97.5$
2	28	11	$W(2) = -0.75(28) + 1.5(11) + 100 = 96$
3	27.5	10	$W(3) = -0.75(27.5) + 1.5(10) + 100 = 96.125$
4	27.5	10	$W(4) = -0.75(27.5) + 1.5(10) + 100 = 96.125$
5	27	9	$W(5) = -0.75(27) + 1.5(9) + 100 = 94.5$
6	27	9	$W(6) = -0.75(27) + 1.5(9) + 100 = 94.5$
7	26.5	8.5	$W(7) = -0.75(26.5) + 1.5(8.5) + 100 = 94.625$
8	26.5	8	$W(8) = -0.75(26.5) + 1.5(8) + 100 = 93.875$
9	26.5	7.5	$W(9) = -0.75(26.5) + 1.5(7.5) + 100 = 93.125$
10	26	7	$W(10) = -0.75(26) + 1.5(7) + 100 = 91.5$
11	26	6.5	$W(11) = -0.75(26) + 1.5(6.5) + 100 = 90.75$
12	25.5	6	$W(12) = -0.75(25.5) + 1.5(6) + 100 = 90.875$
13	25.5	6	$W(13) = -0.75(25.5) + 1.5(6) + 100 = 90.875$
14	25	5.5	$W(14) = -0.75(25) + 1.5(5.5) + 100 = 90.125$
15	25	5	$W(15) = -0.75(25) + 1.5(5) + 100 = 89.375$
16	25	5	$W(16) = -0.75(25) + 1.5(5) + 100 = 89.375$
17	24.5	4.5	$W(17) = -0.75(24.5) + 1.5(4.5) + 100 = 88.875$
18	24.5	4	$W(18) = -0.75(24.5) + 1.5(4) + 100 = 88.125$
19	24	4	$W(19) = -0.75(24) + 1.5(4) + 100 = 87.5$
20	24	3.5	$W(20) = -0.75(24) + 1.5(3.5) + 100 = 86.75$
21	23.5	3	$W(21) = -0.75(23.5) + 1.5(3) + 100 = 86.875$
22	23.5	3	$W(22) = -0.75(23.5) + 1.5(3) + 100 = 86.875$
23	23	2.5	$W(23) = -0.75(23) + 1.5(2.5) + 100 = 86.125$
24	23	2.5	$W(24) = -0.75(23) + 1.5(2.5) + 100 = 86.125$
25	22.5	2	$W(25) = -0.75(22.5) + 1.5(2) + 100 = 85.625$
26	22.5	2	$W(26) = -0.75(22.5) + 1.5(2) + 100 = 85.625$
27	22	1.5	$W(27) = -0.75(22) + 1.5(1.5) + 100 = 84.875$
28	22	1.5	$W(28) = -0.75(22) + 1.5(1.5) + 100 = 84.875$
29	21.5	1	$W(29) = -0.75(21.5) + 1.5(1) + 100 = 84.375$
30	21.5	1	$W(30) = -0.75(21.5) + 1.5(1) + 100 = 84.375$

Although the study successfully employs a GA to optimize the predictive model for chicken manure weight—yielding coefficients a =-0.75, b =1.5, and c =100—the paper lacks critical methodological transparency. Specifically, it does not disclose the configuration and operational parameters of the GA, which are essential for reproducibility and scientific rigor. Absent from the description are key elements such as the formulation of the fitness function used to evaluate candidate solutions, the initial search space or parameter bounds for a, b, and c, and the details of the algorithm's configuration, including population size, number of generations, selection strategy, crossover method, and mutation rate.

To evaluate model accuracy on Figure 9, the predicted manure weights were compared with 30 actual measurement points. The model achieved an RMSE of 0.358 g, mean absolute error (MAE) of 0.292 g, and R^2 of 0.992, indicating excellent predictive precision. Figure 9 presents the predicted vs. actual manure weight plot, where all data points closely follow the ideal 1:1 reference line. Sensitivity analysis shows that manure weight is negatively influenced by temperature (-0.75 g per °C) and positively influenced by ammonia concentration (+1.5 g per ppm). The stronger sensitivity to ammonia suggests that gas buildup is a more influential and reliable indicator of manure accumulation compared to temperature alone. These results demonstrate that the GA-optimized model provides highly accurate predictions and meaningful insight into environmental factors affecting manure production.

The scalability evaluation for a two-node on Table 6 deployment demonstrates that the system performs efficiently under simultaneous operation of multiple sensor units. Each node integrates an HX711 module with four load cells, a DHT22 sensor, an MQ-137 gas sensor, and an ESP32 microcontroller powered by a 5 V, 2 A supply. The results show high data transmission reliability, with packet delivery rates above 98% for both nodes, indicating stable Wi-Fi connectivity even when sharing the same access point. Latency values remain acceptable, averaging 131 ms system-wide, which is sufficient for environmental monitoring applications that do not require real-time millisecond responsiveness.

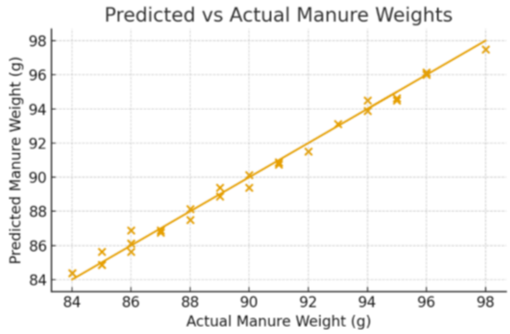

Figure 9. Comparison results of manure weight

Table 6. Scalability evaluation

Metric	Node 1	Node 2	Combined/system (2 nodes)
Packet delivery rate (%)	98.6	98.3	98.45
Average round-trip latency (ms)	125	138	131.5
Packet loss (%)	1.4	1.7	1.55
Average cloud writes response time (ms)	170	190	180
Average CPU load on ESP32 (%)	34	36	—
Average RAM usage on ESP32 (%)	38	41	—
Average current draw (mA)	210	220	430
Peak current draw (mA)	450	480	~930
Power supply utilization (of 5 V/2 A)	21%	22%	~43% (two PSUs)
Auto-reconnect time after brief AP outage (s)	2.5	3.2	≤3.2
Cloud writes throughput (samples/s)	0.10	0.10	0.20
Observed Wi-Fi retries/interference	Low	Low	Low

Power consumption also stays within safe operational ranges, with each node drawing around 210-220 mA during normal operation and peaking under the power supply limit. CPU and RAM usage remain moderate, confirming that each ESP32 can handle multi-sensor data acquisition without performance degradation. Overall, the two-node configuration demonstrates strong scalability, reliable communication, and efficient power utilization, proving the system's suitability for expanding to larger poultry monitoring networks.

These elements are not merely technicalities but foundational aspects that shape the optimization process and influence the model's performance. For instance, the choice of fitness function—such as MSE or another loss metric—directly determines how the GA evaluates prediction accuracy. Likewise, population diversity, convergence behavior, and the ability to escape local minima are heavily dependent on GA parameters. Without disclosure of these details, the optimization process becomes a "black box," hindering the ability of other researchers to replicate the findings, assess their robustness, or apply the methodology in related contexts.

Given the increasing reliance on evolutionary algorithms in predictive modeling, it is imperative that future versions of this work provide a comprehensive description of the GA implementation. This includes both algorithmic settings and the rationale for their selection. Such transparency would not only enhance the credibility of the results but also enable reproducibility, comparison with alternative approaches, and further development within the field. Detailed reporting of the GA execution process is thus a necessary step toward establishing a methodologically sound and verifiable modeling framework.

4. CONCLUSION

This research successfully developed an IoT-based environmental monitoring and predictive modeling system for broiler chicken production. The integrated platform—comprising MQ-137, DHT22, and load cell sensors—demonstrated high accuracy, as reflected by low average errors of 0.31% for ammonia measurement and 0.10% for manure weight estimation. The system reliably collected 30 days of environmental and manure data from two chicken drum models, enabling detailed comparison between feed type A and feed type B. Results showed that feed A consistently produced lower manure weight, reduced ammonia levels, and more stable cage temperatures, indicating better nutrient utilization, improved animal comfort, and healthier environmental conditions. To model manure accumulation, a GA was applied to optimize the parameters of a simple regression equation using temperature and ammonia as predictors. The GA-optimized model achieved high predictive performance, with RMSE of 0.358 g, MAE of 0.292 g, and

R^2 of 0.992. These outcomes highlight the model's ability to capture nonlinear environmental interactions affecting manure production. While the GA approach proved effective, greater transparency in algorithm configuration is needed for full reproducibility. The prediction model accurately forecasts litter weight, even during sensor malfunctions, making the system more reliable. The research offers a cost-effective solution for modern poultry farming in Indonesia, with future improvements focused on refining prediction algorithms and incorporating more health indicators.

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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 from the corresponding author [SW], upon reasonable request.

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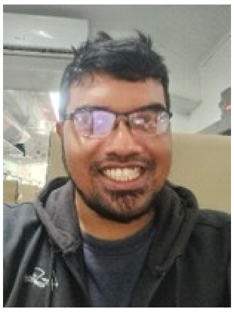

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