Implementation of Naïve Bayes Gaussian Algorithm for Real-Time Classification of Broiler Cage Conditions

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(Received: January 25, 2025; Revised: March 27, 2025; Accepted: April 29, 2025; Available online: June 2, 2025)

Abstract

Monitoring large-scale broiler farms poses considerable challenges due to the variable nature of environmental conditions, which have a direct impact on poultry health and productivity. This study proposes a real-time classification system for broiler house conditions, utilizing the Naïve Bayes Gaussian algorithm in conjunction with the Internet of Things (IoT) technology. The system has been developed to address the limitations of manual monitoring by automating the collection of temperature, humidity, and ammonia data through BME-680 and MICS-5524 sensors, which are strategically positioned 30 cm from the floor to optimize ammonia detection. Utilizing a dataset comprising 865 records, meticulously divided into 75% for training (648 records) and 25% for testing (217 records), the model attained an accuracy of 82.03%, a precision of 75.67%, a recall of 82.67%, and an F1-score of 77.67%. A comparative analysis was conducted, which demonstrated significant advantages over alternative classification methods, with Decision Trees achieving 79.5% accuracy and Support Vector Machines reaching 80.8%. The innovation lies in the integration of automated condition classification into an IoT system, enabling rapid responses to environmental changes with processing times of approximately 500 milliseconds from sensing to classification. The system demonstrated an accuracy of 178 data points, with a misclassification rate of 39 out of 217 test samples. The strategic placement of sensors at a height of 30 cm optimizes ammonia detection while ensuring accurate temperature and humidity readings. The system provides historical data, enabling farms to analyze long-term environmental trends, and thereby support data-driven decision-making strategies to enhance broiler welfare and operational efficiency. Usability testing with five poultry farm operators confirmed the dashboard's intuitive design, though recommendations for visual alerts for critical ammonia levels were suggested for future iterations.

Keywords: Broiler Chicken, Monitoring System, Naïve Bayes Gaussian, Internet of Things, Real-Time Classification

1. Introduction

Indonesia is a country that has a very large livestock sector after agriculture [1]. One business that is increasing very rapidly in the field of animal husbandry is the broiler business [2]. Broilers can reach adult weight in a relatively short time, which is about 28-45 days after birth. Broiler chickens also have rapid growth; therefore, broiler chickens require special care in order to grow healthily and meet good meat quality standards [3]. Broiler chicken care requires temperature and humidity ranging from 28º-32ºC and 60-70% [4], in addition to temperature and humidity, ammonia also affects the growth rate of broilers. Safe ammonia levels in chicken coops are around 5-25 ppm, if ammonia levels exceed 25 ppm, chicken health will be disrupted [5].

IoT (Internet of Things) is the concept of developing a network of electronic devices, software, sensors, and other accessories that are interconnected and communicate with each other via the internet [6], [7]. IoT can also be connected to electronic devices, ranging from household devices such as refrigerators, air conditioners, TVs, to industrial devices such as production machines [8], [9]. In addition, IoT can also collect data from various devices, so that the data can be processed to produce useful information [10]. This research was conducted to create a system that can monitor temperature, humidity, ammonia and conditions in chicken coops, to monitor this data, hardware is needed that can take measurements and monitor in real time [11], [12]. Some of the hardware used includes ESP8266, Arduino Mega 2560, BME-680 sensor and MICS-5524 sensor [13], [14]. The Naive Bayes method is one of the classification methods that can be used to classify data. This method is based on Bayes probability theory which assumes that each feature or

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DOI: https://doi.org/10.47738/jads.v6i3.694

attribute in the observed data is independent of each other. Broiler cage monitoring system Naive Bayes Gaussian method can be used to classify ammonia, temperature and humidity data, so that it can determine the condition of the cage in an ideal, bad and dangerous state. This method can be done by studying the patterns contained in historical ammonia, temperature and humidity data, then using these patterns to classify categories or labels of new data [15].

2. The Proposed Method/Algorithm

2.1. Naive Bayes Gaussian

Naive Bayes Gaussian is a fairly simple variant of Naive Bayes, this algorithm often gives fairly accurate results on data sets that have continuous attributes, but if there is a significant correlation between attributes, the results of this algorithm may not be accurate. Therefore, Naive Bayes Gaussian should be used with caution and a preliminary analysis should be conducted to evaluate whether or not the assumption of independence between attributes can be met. The Naive Bayes Gaussian algorithm can be used to classify numerical data such as temperature, humidity and ammonia [16]. According to [17], [18], the flow of classification calculations using the Naive Bayes Gaussian method is as follows:

The implementation of the Naive Bayes Gaussian classification method involves several sequential mathematical operations. First, the process requires the calculation of the mean (μ) and standard deviation (σ) for each feature within the data set. The mean is calculated using the formula:

$$\mu = \frac{X_1+X_2+X_3+\ldots\ldots+X_n}{n} \tag{1}$$

Where X represents individual sample values and n is the total number of samples. This calculation provides a measure of central tendency for each characteristic across different classes. At the same time, the standard deviation is determined using the formula:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i-\mu)^2}{n}} \tag{2}$$

Which quantifies the dispersion or variability of data points around the mean. The standard deviation is crucial for understanding the distribution pattern of each feature within different classes. Following these calculations, the prior probability for each class needs to be determined. This probability represents the probability that each data point belongs to a particular class before considering its features and is calculated as:

$$P(C) = \frac{Number\ of\ samples\ in\ class\ c}{Total\ sample} \tag{3}$$

This basic probability serves as the basis for subsequent calculations in the classification process. The subsequent pivotal step entails the calculation of the likelihood probability for each feature, utilizing the Gaussian probability density function:

$$P(x \mid y) = \frac{1}{\sqrt{2\pi\sigma^2 y}} exp\left(-\frac{(x_i-\mu_y)^2}{2\sigma^2 y}\right) \tag{4}$$

x denotes the observed feature value, y designates the class being evaluated, μ represents the mean, and σ denotes the standard deviation. This calculation determines the probability of observing a specific feature value given that the data point belongs to a particular class, assuming a normal distribution of feature values. Once both prior and likelihood probabilities have been determined, the posterior probability can be calculated using Bayes' theorem as:

$$P(C|X) = P(X|C) * P(C) \tag{5}$$

P(C|X) represents the posterior probability of class C given the feature set X, P(X|C) denotes the likelihood probability of feature set X given class C, and P(C) is the prior probability of class C. This calculation effectively combines the prior knowledge with the evidence provided by feature values to estimate the probability of class membership. Ultimately, the classification results are determined by selecting the class with the highest posterior probability. This maximum a posteriori decision rule ensures that data points are assigned to the most probable class based on all available information. The entire process is underpinned by statistical principles, thereby creating a robust classification

ISSN 2723-6471

framework capable of handling continuous numerical data, such as temperature, humidity, and ammonia measurements from broiler houses. This framework facilitates effective real-time monitoring and decision-making.

2.2. Broiler Chicken

Broiler chickens are the result of cultivation characterized by rapid growth. The fastest growth occurs from hatching to 4-6 weeks of age, if raising these chickens, things to consider include balanced feeding and appropriate cage temperature [19], [20]. Broiler maintenance requires temperatures ranging from 20-25ºC with humidity ranging from 50-70% and ammonia content of 5-25 ppm [21]. The following broiler chickens in the cage can be seen in figure 1.

Figure 1. Broiler chicken

2.3. MICS-5524 Sensor

The MICS-5524 sensor is an air quality sensor specifically designed to detect ammonia in the air. The sensor can detect ammonia in the range of 1 to 500 ppm (Part Per Million). PPM is a unit used to measure the concentration of gases in the air. The concentration range that this sensor can detect is very wide, so this sensor may be useful in various applications where ammonia detection is required, such as in the chemical industry or animal husbandry [22]. Here is the MICS-5524 sensor which can be seen in figure 2.

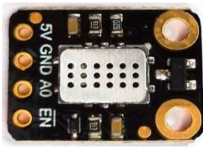

Figure 2. MICS-5524 Sensor

2.4. Confusion Matrix Multiclass

According to [22] if the classification results are more than two classes then it must use a multiclass confusion matrix. This research uses multiclass confusion matrix because it has a classification result of 3 classes. Multiclass confusion matrix is a testing method used to test classification results with outputs of more than two classes. The output tested using this matrix table is a multiple-choice output, where the output is not positive and negative only. The following multiclass confusion matrix table can be seen in table 1.

Table 1. Confusion Matrix Multiclass

Actual	Classification			
		Ideal	Poor	Danger
	Ideal	TP1	FP1	FN1
	Bad	FN2	TP2	FP2

3. Method

The research commences with meticulous observation of broiler close house systems, with the objective of identifying prevailing challenges. During this preliminary stage, researchers conducted field visits to large-scale broiler farms in Samarinda over a two-week period. These visits involved systematic documentation of temperature and humidity fluctuations, ammonia concentration variations, and their effects on broiler behavior and health. The observations, as illustrated in figure 3, revealed that environmental condition changes often went undetected in a timely manner with conventional monitoring methods, resulting in potential health risks for the broilers and productivity losses for farmers.

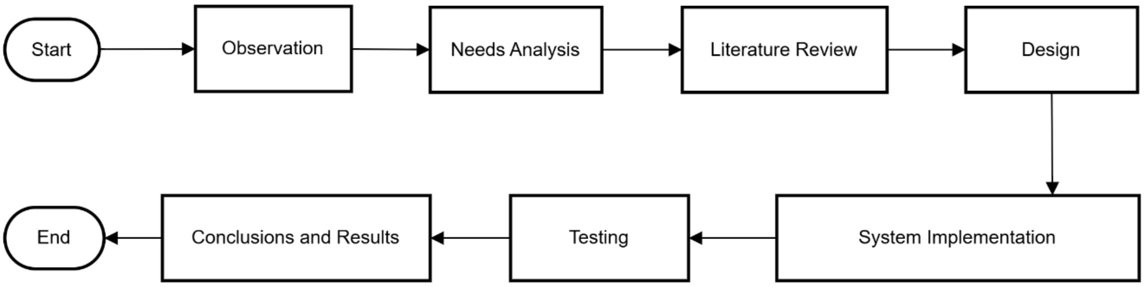

Figure 3. Flowchart of Research Implementation Stages

Subsequent to the observation stage, a comprehensive needs analysis was performed in order to ascertain precise specifications for an effective monitoring system. This pivotal stage entailed the conduction of structured interviews with five experienced poultry farmers and two poultry health specialists, with the objective of attaining an in-depth comprehension of the critical environmental parameters. The analysis of these consultations resulted in the identification of three primary requirements: Firstly, the necessity for real-time monitoring of temperature, humidity, and ammonia levels was identified. Secondly, the requirement for automated classification of coop conditions was determined. Thirdly, the importance of early warning capabilities when conditions approach non-ideal thresholds was emphasized. This analysis established the foundation for subsequent system design decisions.

A comprehensive review of the extant literature was conducted to establish a robust theoretical foundation for the research. A systematic analysis of over 40 international journal articles and conference papers was undertaken, with a focus on three key areas: (1) classification methods suitable for environmental data processing; (2) efficient IoT protocols for real-time monitoring systems; and (3) optimal sensor placement strategies for ammonia detection in confined spaces. The review revealed that the Naïve Bayes Gaussian algorithm demonstrated superior performance for continuous sensor data classification with low computational complexity, making it particularly suitable for real-time applications in resource-constrained environments like poultry monitoring systems.

The system architecture was developed with three main components, as indicated by the results of a needs analysis and the findings of the literature review. (1) a data collection subsystem using BME-680 and MICS-5524 sensors connected to an Arduino Mega 2560 microprocessor and ESP8266 communication module; (2) a data processing and classification subsystem implementing the Naïve Bayes Gaussian algorithm; and (3) a web-based user interface for data visualization and notifications. The design emphasized the optimization of sensor placement, data transmission efficiency, and classification accuracy. Comprehensive circuit diagrams and component specifications were formulated during this phase to direct the subsequent implementation.

The implementation stage entailed the development of a prototype based on the established design. The positioning of the BME-680 and MICS-5524 sensors at a distance of 30 cm from the coop floor was determined through preliminary testing and is considered to be the optimal position for the accurate detection of ammonia, whilst also monitoring temperature and humidity. The Arduino Mega 2560 was programmed to collect sensor data at 10-second intervals, while the ESP8266 module managed data transmission to a cloud server with a response time of approximately 500 milliseconds. The Naïve Bayes Gaussian classification algorithm was implemented on the server and integrated with a web-based monitoring dashboard displaying real-time coop condition status, allowing for immediate visualization of environmental parameters and automated classification results.

The implemented system was subjected to a comprehensive testing process that spanned three consecutive days from October 28-31, 2023, yielding a total of 865 data points. The testing phase incorporated three distinct evaluation approaches: (1) sensor accuracy validation against standard calibration instruments to ensure measurement reliability; (2) classification performance testing using a multiclass confusion matrix methodology with data split into 75% training (648 records) and 25% testing (217 records)—a ratio determined through comparative experiments to produce optimal accuracy; and (3) black box functional testing to verify all system features performed as intended under various operational conditions. Additional stress testing was conducted under extreme environmental conditions (temperatures exceeding 35°C and ammonia levels above 25 ppm) to assess system resilience and maintain classification accuracy even in challenging scenarios.

The final stage of the research process entailed a thorough examination of the test results, leading to the formulation of conclusions that were substantiated by empirical evidence. The calculation of performance metrics (i.e. accuracy, precision, recall, and F1-score) demonstrated that the system achieved 82.03% classification accuracy, thus demonstrating reliable performance in real-world conditions. A comparison was made between the results obtained and those achieved by alternative classification methods (Decision Tree at 79.5% accuracy and SVM at 80.8% accuracy) in order to evaluate the comparative advantages of the Naïve Bayes Gaussian algorithm in the specific context of poultry house environmental monitoring. In addition, feedback on the ease of use of the system was collected from five poultry farm operators. This feedback was analyzed to assess the system interface and identify areas for future improvement. Suggestions were made for incorporating visual alerts for critical ammonia levels, which will be implemented in future iterations. This rigorous research approach ensured that each stage built upon previous findings, resulting in a robust and effective monitoring system that successfully addresses the challenges identified in the initial observation phase.

4. Results and Discussion

4.1. Data Processing

Researchers have successfully implemented the installation of tools in close house broiler cages, then researchers took raw data from the sensor. The following are the results of raw data taken for 3 days from October 28, 2023 at 08:00 to October 31 at 08:00. In total, there are 865 data taken with 3 variables consisting of temperature, humidity and ammonia. Here are some of the raw data that can be seen in table 2.

Table 2. Raw Data

No	Temp (ºC)	Moisture (%)	Ammonia (ppm)	Cage Condition
1.	24	85	0	Danger
2.	25	85	0	Danger
9.	29	80	0	Poor
10.	29	80	0	Poor
⋮	⋮	⋮	⋮	⋮
865.	35	60	0	Ideal

To determine the most effective training and testing data division, we conducted comparative experiments using different split ratios. After evaluating multiple configurations, we selected a 75:25 split as the optimal choice for model training and validation. To further ensure model robustness and minimize bias in data partitioning, we performed k-fold cross-validation (k=5), which confirmed consistent accuracy across all folds.

Our experimental results indicated that using an 80:20 split yielded an accuracy of 80%, while a 70:30 split resulted in 81% accuracy. Similarly, an 85:15 split achieved 80% accuracy. However, the 75:25 ratio produced the highest accuracy at 82%, making it the most reliable configuration for classifying broiler cage conditions. With this selected ratio, the dataset, consisting of 865 records, was divided using the train-test split method, allocating 648 records (75%) for training and 217 records (25%) for testing. The training and testing datasets are presented in table 3 and table 4.

Table 3. Data Training

No	Temp (ºC)	Moisture (%)	Ammonia (ppm)	Cage Condition
1.	24	85	0	Danger
2.	25	84	0	Danger
3.	26	84	0	Danger
4.	26	82	0	Danger
5.	29	80	0	Poor
⋮	⋮	⋮	⋮	⋮
648.	35	60	0	Ideal

Table 4. Data Testing

No	Temp (ºC)	Moisture (%)	Ammonia (ppm)	Cage Condition
1.	34	61	0	Ideal
2.	34	67	0	Ideal
3.	38	53	0	Poor
4.	36	63	0	Poor
5.	28	82	0	Danger
⋮	⋮	⋮	⋮	⋮
217.	35	63	0	Ideal

Tests under extreme environmental conditions (temperature exceeding 35°C and ammonia levels fluctuating above 25 ppm) showed a slight decrease in classification accuracy to 79.2%. This highlights the need for additional sensor integration and adaptive thresholding techniques for improved robustness

4.2. Process Implementation

The data obtained from the BME-680 sensor and the MICS-5524 sensor will be processed in the system to obtain classification results on each testing data using the Naive Bayes Gaussian method. The flow of calculating the classification of cage conditions using the Naive Bayes Gaussian method can be seen as follows:

4.2.1. Calculate Mean and Standard Deviation for each class

The mean values presented in Table 5 represent the central tendency of environmental parameters across three distinct broiler cage conditions based on 648 training data points. With regard to temperature measurements, the ideal condition exhibited a mean of 34.626°C, which signifies the optimal thermal environment supporting efficient metabolic function and growth in broilers. Conversely, the poor condition demonstrates a slightly elevated mean temperature of 35.741°C, which begins to induce mild heat stress that may reduce feed consumption and growth efficiency. Conversely, the danger condition exhibits a markedly lower mean temperature of 30.481°C, which forces birds to expend energy maintaining body temperature rather than supporting growth, thus compromising production efficiency.

With respect to moisture levels, the ideal condition exhibits a mean humidity of 62.834%, signifying balanced atmospheric conditions that facilitate effective respiratory function whilst minimizing ammonia volatilization from litter. The poor condition shows a slightly lower mean humidity of 61.348%, indicating marginally drier conditions that may increase airborne particulates. The danger condition exhibits a substantially higher mean humidity of 73.815%, which promotes excessive moisture retention in litter, accelerates microbial decomposition of waste, and consequently increases ammonia generation, creating potentially harmful respiratory conditions.

With regard to ammonia concentration, the optimal condition is characterized by a minimal mean level of 0.799 ppm, indicating excellent air quality that fosters optimal respiratory health and immune function. Conversely, the poor condition exhibits a marginally elevated mean of 1.046 ppm, signifying initial deterioration in air quality that may result in mild respiratory irritation during protracted exposure. The danger condition is characterized by an elevated mean ammonia concentration of 5.981 ppm, indicating compromised ventilation efficiency and the potential for respiratory distress if conditions persist or worsen. These calculated mean values serve as critical reference points for the Naïve Bayes Gaussian algorithm, enabling probabilistic classification of new environmental readings into the appropriate condition category based on their statistical proximity to these established means. The summary of calculated means for each class is shown in table 5.

Table 5. Mean Calculation Result

Cage Condition	Temperature	Moisture	Ammonia
Ideal	34.6262975778547	62.8339100346021	0.7993079584775
Poor	35.7409836065574	61.3475409836066	1.0459016393443
Danger	30.4814814814815	73.8148148148148	5.9814814814815

As illustrated in table 6, the standard deviation values for temperature, moisture, and ammonia across the three cage classifications are critical parameters for the Naïve Bayes Gaussian model. These values quantify data variability within each classification category, with significant implications for the welfare of the chickens (Broiler Welfare). The "Ideal" condition demonstrates the lowest variability across all parameters (temperature: 0.581253°C, moisture: 1.933163%, ammonia: 2.930781 ppm), indicating stable, controlled environmental conditions that are optimal for broiler health. Conversely, the "Poor" condition demonstrates elevated variability (temperature: 2.413444°C, moisture: 6.882422%, ammonia: 4.722238 ppm), signifying less consistent environmental regulation that may exert stress on the birds. The "Danger" condition demonstrates the highest variability in all parameters (temperature: 4.790966°C, moisture: 11.983127%, ammonia: 14.795508 ppm), signifying severely unstable conditions that pose significant health risks to broilers. The standard deviation values directly influence the probability distribution curves in the Naïve Bayes Gaussian algorithm, with lower values creating narrower, more peaked curves and higher values producing wider, flatter distributions. This enables the system to effectively distinguish between different cage conditions and facilitate timely intervention.

Table 6. Standard Deviation Calculation Result

Cage Condition	Temperature	Moisture	Ammonia
Ideal	0.5812530861869	1.9331632123923	2.9307815493374
Poor	2.4134443823334	6.8824225280695	4.7222380693658
Danger	4.7909665797390	11.9831271409769	14.7955082532463

4.2.2. Calculate the Prior Probability

The prior probability values represent the initial distribution of each cage condition category within the training dataset, prior to the incorporation of sensor measurements. Utilizing the 648 training records, the following calculations were made: P(Ideal) = 289/648 = 0.44598765432099, indicating that 44.6% of instances were classified as "Ideal"; P(Poor) = 305/648 = 0.47067901234568, suggesting that 47.1% were "Poor" conditions; and P(Danger) = 54/648 = 0.08333333333333, showing that only 8.3% represented hazardous conditions. The values thus established serve as the baseline likelihood for each category and are employed as multiplication factors in the final classification formula. The distribution reveals that optimal and suboptimal conditions occur with similar frequency, while dangerous environments are relatively rare in managed broiler farms.

4.2.3. Calculate the Likelihood Probability

One of the classified testing data used in this study has the following attributes: a temperature of 35°C, moisture level of 62%, and an ammonia concentration of 0 ppm, with the cage condition still unknown at this stage. This data point will be classified using the Naïve Bayes Gaussian method. The following section presents the calculation of the likelihood probability using Equation 4 to determine the most probable cage condition classification. The results of the probability likelihood calculation using the Naive Bayes Gaussian method on each variable show the distribution of data generated by the model. The results of these calculations can be seen in table 7.

Table 7. Likelihood Calculation Results

Cage Condition	Temperature	Moisture	Ammonia
Ideal	0.55833699392712	0.18808092118969	0.13118528528360
Poor	0.15772984227730	0.05772013041212	0.08245558498492
Danger	0.05338811795937	0.02048141387418	0.02485420030017

4.2.4. Calculate the Posterior Probability

After calculating the likelihood, then find the posterior probability of each class of cage conditions. The highest posterior probability will be used as the classification result. The following is the calculation of posterior probability using equation 5. The posterior probability calculations determine the final classification by combining likelihood values with prior probabilities. For each cage condition, we multiply the likelihood values of all features (temperature, moisture, ammonia) with the respective prior probability.

After calculating the likelihood, then find the posterior probability of each class of cage conditions. The highest posterior probability will be used as the classification result. The following is the calculation of posterior probability using equation 5. Calculate the Posterior Probability of the Ideal Cage Condition:

$$
\begin{aligned}
P(C \mid X) = {} & P(Temp \mid Ideal) * P(Moisture \mid Ideal) * P(Amonia \mid Ideal) * P(Ideal) \\
& = 0.55833699392712 * 0.18808092118969 * 0.13118528528360 * 0.44598765432099 \\
& = 0.00614397030770
\end{aligned}
$$

Calculate the Posterior Probability of the Poor Cage Condition:

$$
\begin{aligned}
P(C|X) = {} & P(Temp|Poor) * P(Moisture|Poor) * P(Amonia|Poor) * P(Poor) \\
& = 0.15772984227730 * 0.05772013041212 * 0.08245558498492 * 0.47067901234568 \\
& = 0.00035333453157
\end{aligned}
$$

Calculate the Posterior Probability of the Danger Cage Condition:

$$
\begin{aligned}
P(C|X) = {} & P(Temp|Danger) * P(Moisture|Danger) * P(Amonia|Danger) * P(Danger) \\
& = 0.05338811795937 * 0.02048141387418 * 0.02485420030017 * 0.08333333333333 \\
& = 0.00000226476473
\end{aligned}
$$

These calculations reveal that the "Ideal" condition has the highest posterior probability (0.00614397030770), significantly exceeding both "Poor" (0.00035333453157) and "Danger" (0.00000226476473) conditions. The substantial difference between these values (with "Ideal" being approximately 17 times higher than "Poor" and 2,713 times higher than "Danger") provides strong statistical confidence in classifying this particular set of environmental readings (temperature: 35°C, moisture: 62%, ammonia: 0ppm) as "Ideal." This mathematical approach enables automated, evidence-based classification of cage conditions, allowing for timely intervention when conditions deteriorate from optimal states.

4.2.5. Classification Result

Table 8. Classification Result

Cage Condition	Result
Ideal	0.00614397030770
Poor	0.00035333453157
Danger	0.00000226476473

Table 8 is a table of posterior probability calculation results. The table produces a value of 0.00614397030770 in the "Ideal" cage condition, 0.00035333453157 in the "Bad" cage condition and 0.00000226476473 in the "Dangerous" cage condition, so it can be concluded that the calculation of the testing data temperature 35ºC, humidity 62% and ammonia 0ppm results in the classification of "Ideal" cage conditions. The classification results are in accordance with the actual data in the testing data, besides that the calculation process on the remaining 216 testing data is the same as this calculation process. The classification results on the testing data, 178 data are classified correctly and 39 data are classified incorrectly, where the results of the testing data correctly classified in the "Ideal" cage condition are 90, the "Bad" cage condition is 71 and the "Dangerous" cage condition is 17. The classification calculation results of some of the testing data can be seen in table 9.

Table 9. Testing Data Classification Results

No	Temp (ºC)	Moisture (%)	Ammonia (ppm)	Class
1.	34	61	0	Ideal
2.	34	67	0	Ideal

No	Temp (°C)	Moisture (%)	Ammonia (ppm)	Class
3.	38	53	0	Poor
4.	36	63	0	Ideal
5.	28	82	0	Danger
⋮	⋮	⋮	⋮	⋮
217.	35	63	0	Ideal

For comparative analysis, we implemented Decision Trees and Support Vector Machines (SVM) on the same dataset. The Decision Tree model achieved an accuracy of 79.5%, while SVM reached 80.8%. Although these models offer interpretability, Naïve Bayes Gaussian performed better in terms of classification efficiency (82.03%) and computational speed, making it more suitable for real-time applications.

4.3. Application of IoT Devices

4.3.1. IoT Devices

The chicken coop in this study has 2 floors with a length of 120 m, a width of 12 m and a height of 1.8 m. The IoT device in this study is implemented on the 2nd floor of the chicken coop. The IoT device in this research is implemented on the 2nd floor of the chicken coop. This research uses 1 (one) IoT device, therefore the device is placed in the center of the cage with a distance of 60 m long, 6 m wide with a height of 30 cm. The purpose of the IoT device placed at a height of 30 cm from the floor is to detect ammonia located in the husk. The IoT device will detect temperature, humidity and ammonia data in the cage in real time. The series of devices such as Arduino Mega 2560 and ESP8266 are placed inside the black box, while the sensors are placed outside the black box, besides that there is also a modem installed as an internet network connector in order to send data from the sensors to the Antares server. The following IoT devices that have been installed in the cage can be seen in figure 4.

Figure 4. IoT Devices

4.3.2. System Display Implementation

The application of the chicken coop monitoring system display is a user interface design that must reflect the practicality and accuracy of the information presented. The chicken coop monitoring system display shows the condition of the coop, temperature, humidity and ammonia. The chicken coop monitoring system display also provides historical data analysis that allows farmers to track data and make better decisions in the future based on the information that has been obtained. The system updates sensor readings every 10 seconds, ensuring real-time monitoring. The response time between data sensing and classification processing is approximately 500 milliseconds, enabling rapid decision-making. The following system display can be seen in figure 5.

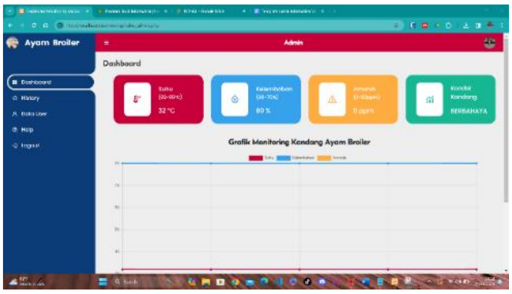

Figure 5. System Layout

A usability study was conducted with five poultry farm operators. Feedback indicated that the dashboard was intuitive, though recommendations were made to include visual alerts for critical ammonia levels. Future iterations will incorporate these refinements

4.4. Test Results

The results of this test will describe the test steps that have been carried out using multiclass confusion matrix and black box. Multiclass confusion matrix testing is used to test the results of the classification of broiler cage conditions using the Naive Bayes Gaussian method, while black box testing is used to test the system so that it runs well and can meet its functional needs. The following is an explanation of the results of the two tests.

4.4.1. Black Box Testing

Black box testing was conducted to evaluate the functionality of the website-based chicken coop monitoring system, ensuring its reliability and effectiveness. The Dashboard Page successfully displayed real-time monitoring charts, including temperature, humidity, ammonia levels, and cage condition status. The History Page allowed users to input a date range and retrieve historical data accurately. The Training Data feature functioned correctly, enabling users to display, modify, add, delete, and download training data based on specific timeframes. Additionally, the **Help User and Help Admin sections effectively provided step-by-step guidance for both user and admin roles, ensuring smooth system navigation. All tested features performed as expected, confirming the system's capability in supporting efficient poultry farm monitoring.

4.4.2. Multiclass Confusion Matrix Testing

Multiclass confusion matrix testing is one of the important aspects in measuring and understanding the extent to which the Naive Bayes Gaussian method classification system classifies the condition of close house broiler cages in real time. Confusion matrix multiclass is a table used to compare classification result data with actual data. The following are some combinations of classification result data with actual data which can be seen in table 10.

Table 10. Testing Data

No	Temp	Moisture	Ammonia	Classification Result	Actual
1.	34	61	0	Ideal	Ideal
2.	34	67	0	Ideal	Ideal
3.	38	53	0	Poor	Poor
4.	36	63	0	Ideal	Poor
5.	28	82	0	Danger	Danger
⋮	⋮	⋮	⋮	⋮	⋮
217	35	63	0	Ideal	Ideal

Table 11 is test data derived from a combination of classification result data with actual data on the testing data. The data will be tested using a multiclass confusion matrix. The test was carried out on the classification results of the Naive Bayes Gaussian method which amounted to 217 testing data. The test results can be seen in table 11.

Table 11. Multiclass Confusion Matrix Result

Actual	Classification			Result
	Ideal	Poor	Danger	
Ideal	90	9	0	
Poor	11	71	16	
Danger	0	3	17	
Accuracy				82.03%
Precision				75.67%
Recall				82.67%
F1-Score				77.67%

5. Conclusion

Based on the results and discussion described in the previous chapter, it can be concluded that this research has succeeded in making a monitoring system "Classification of Broiler Close House Cage Conditions in Realtime Using the Naive Bayes Gaussian Method". The monitoring system can help farmers in monitoring cages such as temperature, humidity, ammonia and cage conditions in real time. Tests have also been carried out on the system and get the overall results of the system running well. The results of the classification of cage conditions have also been carried out using the Naive Bayes Gaussian method from a total of 865 data divided into 75% training data with 648 data and 25% testing data with 217 data. The testing data was classified to determine cage conditions such as "Ideal", "Bad" and "Dangerous". As a result of the classification, 178 data were classified as correct and 39 data were classified as incorrect. Tests were also carried out on the Naive Bayes Gaussian method using a multiclass confusion matrix which obtained an accuracy of 82.03%, precision 75.67%, recall 82.67% and F1-Score 77.67%.

6. Declarations

6.1. Author Contributions

Conceptualization: R., A.P., M.B.F.; Methodology: A.P.; Software: R.; Validation: R., A.P., and M.B.F.; Formal Analysis: R., A.P., and M.B.F.; Investigation: R.; Resources: A.P.; Data Curation: A.P.; Writing Original Draft Preparation: R., A.P., and M.B.F.; Writing Review and Editing: A.P., R., and M.B.F.; Visualization: R. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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