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Application of the XGBoost Algorithm for Predicting the Target Effective Temperature in Closed Broiler Chicken Cage

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Abstract. Broiler chickens are a breed known for their rapid growth, typically reaching maturity in just 4-5 weeks. This growth is influenced by various factors, with cage management playing a significant role. One key factor in cage management is maintaining an optimal target temperature, which is determined by combining measurements of ambient temperature, humidity, and wind speed. This article examines how the XGBoost algorithm can be used to predict the target effective temperature in closed-house broiler chicken systems. The goal is to develop a predictive network model with high accuracy, enabling the regulation of cage conditions to ensure the chickens' comfort. The study findings demonstrate that the proposed algorithm effectively models target temperatures, aiding in the management of cage conditions.

1 Introduction

The livestock sector plays a vital role in meeting the nutritional needs of the Indonesian population. This sector provides high-protein food products such as meat, milk, and eggs commonly consumed. Specifically, the production and consumption of broiler chicken meat in Indonesia have shown significant growth year after year, according to a survey by the Indonesian Central Bureau of Statistics [1].

Broiler chickens are more widely cultivated due to their high productivity. In just 4 – 5 weeks, broiler chicks can grow into mature broiler chickens weighing around 2 kg and ready for harvest, offering promising profits for farmers. In general, there are two main broiler chicken farming systems: open housing and closed housing. The closed housing system (Figure 1) is considered by many farmers because it is less affected by weather conditions and environmental stress. Additionally, in terms of number of chickens per square meter, broiler chickens raised in closed housing can be higher [2].

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Fig. 1. Chicken farming in closed cages taken from [2].

1.1 Background

Several important factors influencing housing comfort must be controlled to ensure optimal broiler chicken growth. These factors include the actual enclosure temperature, air humidity, and wind speed. Housing with low temperatures causes chickens to huddle together and reduce their activity. Conversely, housing with relatively high temperatures makes chickens feel thirsty more easily, leading to higher water consumption compared to food consumption. This can ultimately affect the chickens' growth, resulting in lower weights at harvest.

Therefore, in managing poultry housing, it is crucial to regulate the enclosure temperature to ensure the chickens grow comfortably. Such a temperature is referred to as the target effective temperature, which varies depending on the chickens' age. Older chickens require a lower target effective temperature because their body temperature becomes higher as they age. Additionally, air humidity in the enclosure greatly influences the perceived temperature, as higher humidity makes the chickens feel warmer. To address this, closed housing is usually equipped with fans that can lower the actual enclosure temperature to achieve the target effective temperature (Figure 2).

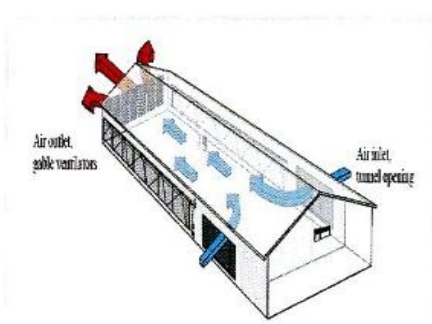


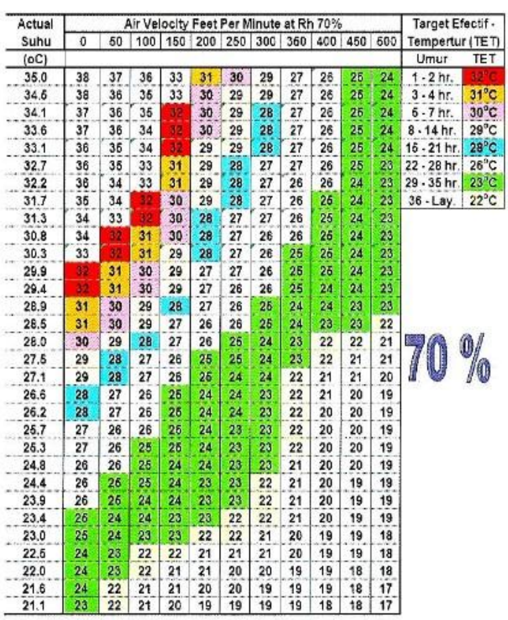
Fig. 2. Closed cages are equipped with fans to lower the temperature taken from [3].

Table 1 provides the target effective temperature in closed housing for chickens of various ages, ranging from 1 – 2-day-old chicks to mature chickens over 36 days old. The target effective temperature ranges from 21°C to 32°C. For 1 – 2-day-old chicks, the closed housing temperature must be set to around 32°C. This temperature is necessary for optimal growth. The table also shows a trend indicating that older chickens require lower housing temperatures for optimal growth.

Table 1. Target Effective Temperature in closed cage taken from [3].

Chicken age (in days)	Target Effective Temperature (in degrees Celcius)
1 – 2 days	32
3 – 4 days	31
5 – 7 days	30
8 – 14 days	29
15 – 21 days	27
22 – 28 days	25
29 – 35 days	22
More than 36 days	21

Additionally, data on predictor variables—such as actual temperature, air humidity, and wind speed (generated by fans)—and the response variable, the target effective temperature, are available for various humidity levels, as shown in Figure 3. In this table, the variables include: housing temperature in degrees Celsius (°C), humidity in the housing as relative humidity (%rH), and wind speed in the housing in feet per minute (fpm). These variables—temperature, humidity, and wind speed—are used as indicators in calculating the estimated target effective temperature such that the comfort of the chickens in the enclosure is maintained. The calculated target effective temperature is then used as an evaluation for adjusting the wind speed settings based on the chickens' needs and comfort during their care.



Actual Suhu (oC)	Air Velocity Feet Per Minute at Rh 70%: 0	50	100	150	200	250	300	360	400	450	600
35.0	38	37	36	33	31	30	29	27	26	25	24
34.6	38	36	35	33	30	29	29	27	26	25	24
34.1	37	36	35	32	30	29	28	27	26	25	24
33.6	37	36	34	32	30	29	28	27	26	25	24
33.1	36	35	34	32	29	29	28	27	26	25	24
32.7	36	35	33	31	29	28	27	27	26	25	23
32.2	36	34	33	31	29	28	27	26	26	24	23
31.7	35	34	32	30	29	28	27	26	25	24	23
31.3	34	33	32	30	28	27	27	26	25	24	23
30.8	34	32	31	30	28	27	26	26	25	24	23
30.3	33	32	31	29	28	27	26	25	25	24	23
29.9	32	31	30	29	27	27	26	25	25	24	23
29.4	32	31	30	29	27	26	26	25	24	24	23
28.9	31	30	29	28	27	26	25	24	24	23	23
28.5	31	30	29	27	26	26	25	24	23	23	22
28.0	30	29	28	27	26	25	24	23	22	22	21
27.5	29	28	27	26	25	25	24	23	22	21	21
27.1	29	28	27	26	25	24	24	22	21	21	20
26.6	28	27	26	25	24	24	23	22	21	20	19
26.2	28	27	26	25	24	24	23	22	20	20	19
25.7	27	26	26	25	24	23	23	22	20	20	19
25.3	27	26	25	25	24	23	23	22	20	20	19
24.8	26	26	25	24	24	23	23	21	20	20	19
24.4	26	26	25	24	23	23	22	21	20	19	19
23.9	26	25	24	24	23	23	22	21	20	19	19
23.4	25	24	24	23	23	22	22	21	20	19	19
23.0	25	24	23	23	22	22	21	20	19	19	18
22.5	24	23	22	22	21	21	21	20	19	19	18
22.0	24	23	22	21	21	20	20	19	19	18	18
21.6	24	22	21	21	20	20	19	19	19	18	17
21.1	23	22	21	20	19	19	19	19	18	18	17

Target Efectif - Tempertur (TET): Umur	TET
1 - 2 hr.	32°C
3 - 4 hr.	31°C
5 - 7 hr.	30°C
8 - 14 hr.	29°C
15 - 21 hr.	28°C
22 - 28 hr.	26°C
29 - 35 hr.	23°C
36 - Lay.	22°C

Fig. 3. Relationship between actual temperature, wind speed and target effective temperature at 70% humidity taken from [3].

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In practice, broiler chicken farmers using closed housing adjust the wind speed (with fans) and humidity (with an evaporator) to achieve the desired target effective temperature in the enclosure, doing so manually based on the data in Figure 2. For example, at a humidity level of 70%, for 1 – 2-day-old chicks in an enclosure with an actual temperature of 34.1°C, the fans must be set to a speed of 150 fpm to bring the enclosure temperature down to 32°C.

1.2 Problem Statement

However, the available tables are quite limited, covering only humidity levels of 50%, 70%, 80%, and 90% for a cage measuring 110 m x 10 m with a capacity of 20,000 chickens.

This study aims to design a mathematical model based on the XGBoost algorithm to formulate the relationship between humidity, wind speed, actual temperature, and the target effective temperature of the cage. As a result, standard tables for other humidity variations can be generated. If this is successfully implemented, the automation of closed-cage management can be achieved. This will further simplify the process for broiler chicken farmers in regulating the target effective temperature of their cages.

2 Method

In this part, we discuss the method outlining the approach and technique used to develop a mathematical model to achieve the objectives of this study. It provides a detailed description of the proposed model and the method of the hyperparameter tuning.

2.1 XGBoost

XGBoost, short for Extreme Gradient Boosting, is a fast, scalable, powerful and efficient algorithm which is used widely for supervised learning tasks, i.e. regression and classification. It is so popular because its superior performance in machine learning competitions and many real applications. The method proposed by Tianqi Chen in 2014 [4], belongs to gradient boosting algorithms which build many decision tree models sequentially and each new model corrects the errors resulted from the previous ones. Furthermore, the XGBoost outperforms the existing gradient boosting implementations in the speed and accuracy, handling missing values, reducing overfitting with regularization, and supporting parallel and distributed computing [5].

The objective function $\mathcal{L}$ of XGBoost algorithm has two key important components to be minimized, i.e. loss function ℓ and Ω regularization term.

$$\mathcal{L} = \sum_{i=1}^{n} \ell(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega\,(f_k) \qquad (1)$$

The loss function ℓ will measure how well the model's output $\hat{y}_i$ predicts the true label y_i, i.e. mean square error for regression and log loss for classification. The regularization term Ω will reduce the complexity of the model to avoid overfitting. For a tree f_k, the regularization is defined as

$$\Omega(f_k) = \gamma\, T + \frac{1}{2}\,\lambda \sum_{j=1}^{T} w_j^2 \qquad (2)$$

where T the number leaves in the tree, w_j weight of the j-th leaf, γ regularization parameter for the number of leaves and λ regularization parameter for leaf weights. The prediction $\hat{y}_i$ for a datum x_i is the sum of the outputs from all K trees, i.e.

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$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i) \quad (3)$$

where $f_k \in \mathcal{F}$ the space of decision trees. XGBoost will minimize $\mathcal{L}$ by adding trees sequentially, where each new tree f_k minimizes the following approximate objective

$$\mathcal{L}^{(t)} \approx \sum_{i=1}^{n} \left[g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t) \quad (4)$$

where $g_i = \frac{\partial \ell\left(y_i, \hat{y}_i^{(t-1)}\right)}{\partial \hat{y}^{(t-1)}}$ is the gradient of the loss function and $h_i = \frac{\partial^2 \ell\left(y_i, \hat{y}_i^{(t-1)}\right)}{\partial \hat{y}^{(t-1)}}$ is the Hessian of the loss function. Here t refers to the index of the current iteration or tree being optimized and the predicted value for an instance i at iteration t is

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i) \quad (5)$$

where $\hat{y}_i^{(t-1)}$ is the prediction from the previous $(t-1)$ iterations and $f_t(x_i)$ is the contribution of the current tree t to correct the residual errors.

2.2 Hyperparameter Tuning

As it is known, XGBoost usually ensembles multiple weak different decision trees in a sequential and additive manner using gradient boosting. Each tree focuses on correcting the errors of the previous ones and the ensemble as a whole becomes a strong predictive model. Like a standard decision tree, the XGBoost model has also several hyperparameters that need to be tuned to optimize prediction accuracy [6,7,8]. The following table lists the most important hyperparameters of the XGBoost model along with their functions and effects.

Table 2. Several important hyperparameters of the XGBoost.

Name of hyparameters	Common abbreviations	Function	Effect
learning rate	eta	control the contribution of each tree to the final model	decreasing prevents overfitting
number of trees	n_estimators	specify the total number of boosting iterations (tree)	increasing may improve scores with large data
maximum tree depth	max_depth	determine the maximum depth of each tree	decreasing prevents overfitting
minimum child weight	min_child_weight	minimum sum of instance weights (hessian) needed to create a child node	increasing prevents overfitting
subsampling	subsample	fraction of training data used for growing each tree to reduce overfitting	decreasing prevents overfitting
column subsampling	colsample_bytree	fraction of features used to grow each tree to reduce overfitting	decreasing prevents overfitting

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L2 regularization constant	lambda	penalizes large leaf weights to prevent overfitting by shrinking weights but retain all features	increasing prevents overfitting
L1 regularization constant	alpha	penalizes large leaf weights to prevent overfitting by introducing sparsity (zero weights for some features)	increasing prevents overfitting

To select the optimal set of the above hyperparameters, we used a method called randomized search [9] that randomly samples combinations of hyperparameter values from predefined ranges. Comparing to grid search method which evaluates all possible combinations of predefined distribution of hyperparameter values, it is more efficient due to its ability to save computational time and identify near-optimal hyperparameter settings.

3 Results and Discussion

This section begins by outlining the key results derived from the analyses, supported by relevant statistical and graphical representations. Emphasis is placed on finding patterns, relationships, or trends that align with or diverge from the initial hypotheses.

3.1 Data Analysis

The data used in this article consists of 1,227 entries, which represent the target effective temperature data for various actual temperature conditions in the cage, air humidity, and wind speed, as available in the literature [3]. Thus, there are three predictor variables: x_1 (air humidity), x_2 (wind speed), x_3 (actual cage temperature), and one response variable y (target effective temperature). Out of the total data points used, around 90% are used as training data to build the model, and the remaining 10% are used as test data.

Before building the model, preliminary data processing will be conducted to get the general description of the data and the relationships between the predictor variables and the response variable. Figure 3 shows the distribution of the data used in this analysis. Using a specific device, the humidity in cage can be adjusted to only a few values, namely 50%, 70%, 80%, and 90%. Wind speed can also be controlled by adjusting a number of fans, resulting in values of 0, 50, 100, ..., 500 feet per minute. The actual cage temperature, measured with a thermometer, ranges from 21.1℃ to 35℃. The target effective temperature, as the response variable resulting from the interaction of the three predictor variables (humidity, wind speed, and actual cage temperature), is distributed as shown in the histogram in the bottom-right corner.

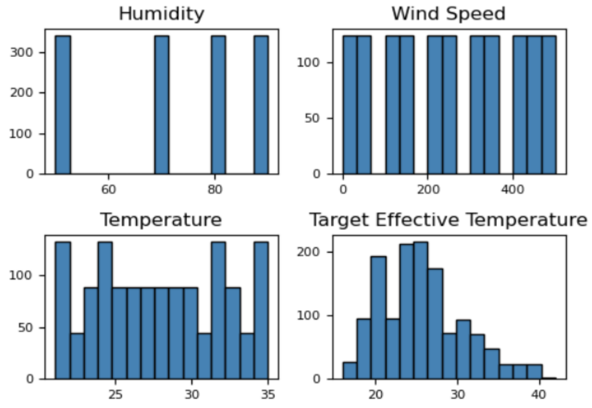

Fig. 4. Histogram of the data distribution.

Figure 5 shows the Pearson correlation coefficient between variable pairs. From the simple correlation between two variables, it can be concluded that the actual cage temperature variable is the most strongly (positively) correlated with the target effective temperature response variable, with a coefficient of 0.67. The wind speed variable has a negative correlation with the target effective temperature, while the humidity variable shows the weakest (positive) correlation. It means that the higher the humidity and temperature, the greater the target effective temperature. Conversely, the higher the wind speed, the lower the target effective temperature.

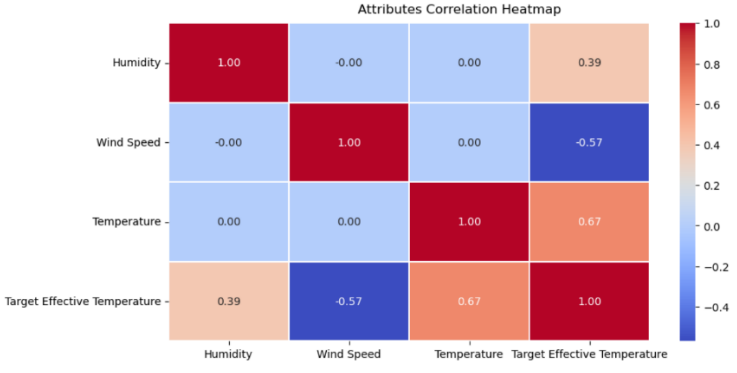

Fig. 5. Correlation coefficient between variables.

Using Python programming language, the XGBoost algorithm [10] is applied to the training data to identify the functional relationship between the predictor variables and the response variable. In this process, hyperparameter tuning is done to find the optimal hyparameters minimizing mean square error (mse). The optimal model obtained will then be tested using the test data, providing an estimate of the actual mse of the model.

3.2 XGBoost Model

The XGBoost regression model for this problem is built on the following hyperparameter setting. The first model using default values for hyperparameter (see third column of Table 3) gives mean square error around 0.1537. The second model using values resulting from randomized search (see fourth column of Table 3) produces a smaller mean square error, i.e. 0.146. Both models demonstrate strong predictive performance in estimating the target effective temperature.

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Table 3. Default value hyperparameter in the XGBoost package.

name of hyparameters	common abbreviations	default values	optimal values
learning rate	eta	0.3	0.05
number of trees	n_estimators	100	1200
maximum tree depth	max_depth	6	3
minimum child weight	min_child_weight	1	6
subsampling	subsample	1	1
column subsampling	colsample_bytree	1	1
L2 regularization constant	lambda	1	0.05
L1 regularization constant	alpha	0	0.05

Furthermore, as shown in Figure 6, the feature importance analysis revealed that actual cage temperature contributed the most to the predictions, accounting for 42% of the total importance. Air humidity and wind speed also showed moderate contributions at 35% and 23%, respectively.

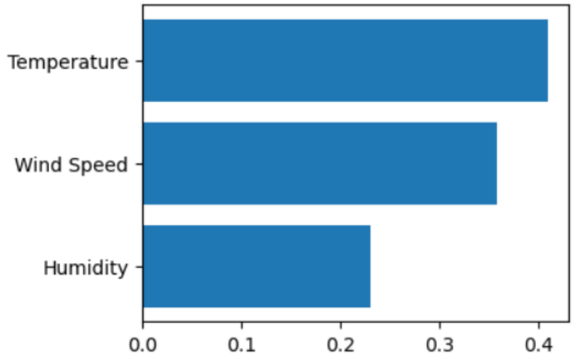

Fig. 6. Feature importance.

Overall, the results indicate that the XGBoost model can effectively predict the target effective temperature with minimal error, making it a robust tool for environmental management in broiler chicken farming.

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4 Conclusion

This study demonstrates the effective application of the XGBoost algorithm for predicting the target effective temperature in closed broiler chicken cages. By utilizing key environmental variables such as actual cage temperature, wind speed, and humidity, the model achieved high accuracy and reliability in forecasting the target effective temperature. The results reveal that the actual cage temperature is the most influential predictor, showing a strong positive correlation with the target effective temperature, while wind speed and humidity contribute less significantly. The findings highlight the potential of XGBoost as a robust predictive tool for optimizing environmental control in closed broiler chicken cages, promoting animal welfare and operational efficiency. Future research could explore integrating additional variables and testing the model under diverse conditions to further enhance its adaptability and precision.

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