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Applying Precision Agriculture to Artificial Waterfowl Hatching, Using the Black Muscovy Duck as an Example

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Abstract: (1) Background: agriculture practices adopt homogenization-farming processes to enhance product characteristics, with lower costs, standardization, mass production, and production efficiency. **(2) Problem**: conventional agriculture practices eliminate products when these products are slightly different from the expected status in each phase of the lifecycle due to the changing natural environment and climate. However, this elimination of products can be avoided when they receive customized care to the expected developing path via a universal prediction model, for the quantitative description of biomass changing with time and the environment, and the corresponding automatic environmental controls. **(3) Methods**: in this study, we built a prediction model to quantitatively predict the hatching rate of each egg by observing the biomass development path along the waterfowl-like production lifecycle and the corresponding environment settings. **(4) Results**: two experiments using black Muscovy duck hatching as a case study were executed. The first experiment involved finding out the key characteristics, out of 25 characteristics, and building a prediction model to quantitatively predict the survivability of the black Muscovy duck egg. The second experiment was adopted to validate the effectiveness of our prediction mode; the hatching rate rose from 47% in the first experiment to 62% in the second experiment without any human interference from experienced farmers. **(5) Contributions**: this research builds on an AI-based precision agriculture system prototype as the reference for waterfowl research. The results show that our proposed model is capable of decreasing the training costs and enhancing the product qualification rate for individual agricultural products.

Keywords: Muscovy duck; waterfowl; thermal imager; artificial intelligence; precision agriculture

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1. Introduction

Conventional agriculture practices adopt homogenization-farming processes to enhance production, with lower costs, standardization, mass production, and production efficiency. For example, waterfowl egg hatching management keeps all waterfowl eggs in the same nature by controlling temperature and humidity in the incubator, periodically inspecting waterfowl egg characteristics, and waterfowl egg status in the hatcher. However, due to agricultural knowledge and the advancement of science and technology, it is found that the above-mentioned practices eliminate the waterfowl eggs—slightly different from the expected status in each phase of the lifecycle due to the changing natural environment and climate. However, the individual variations of waterfowl eggs is tolerable if we provide customized care, i.e., doing the right thing, in the right place, in the right way, and at the right time. That is—this elimination of waterfowl eggs can be avoided when farmers provide customized care to bring these waterfowl eggs back to the expected developing path by a universal prediction model, for the quantitative description of biomass changing with time and environment, and the corresponding automatic environment control.

The previous studies mainly explore the relationship between the environmental factors and the hatching rate of fertilized eggs. Lourens et al. [1,2] studied the effects of eggshell temperature and oxygen concentration on embryo development. Joseph et al. [3] indicate the impact of the incubation environment on broiler chick development. In studies [4–6], the authors investigate the relationship between humidity/eggshell temperature and incubation. However, most waterfowl farms in Taiwan control temperature and humidity based on experience and do not adopt a scientific hatching model. In order to dissipate the heat generated by embryo development and promote the embrittlement of the eggshell to help the young birds to peck the eggshells, it is necessary to cool the egg and spray water during the incubation process. Taiwan is humid and has high temperatures. Therefore, it is necessary to rely on human experiences to control the egg cooling of waterfowl breeding eggs and the time, frequency, and microenvironment of water spraying during the hatching process. The operation and management during the incubation process of waterfowl eggs has a significant impact on the hatching results, so it is necessary to find out customized parameters suitable for the local environment.

This study therefore applies artificial intelligence (AI) technology to build a prediction model to quantitatively describe the biomass development path along with each phase of the waterfowl-like production lifecycle and the corresponding environment settings. First, we use the concept of precision agriculture to cut into the field of waterfowl hatching and find major hatching condition parameters out of the parameters explored by the previous works. In Taiwan, the industry's requirements for the hatching environment of waterfowl are still in the traditional agricultural stage, pursuing the uniformity of the hatching environment, and relying heavily on human experience to make parameter corrections for the individual differences of waterfowl. We intended to carry out precise sensing of each waterfowl egg, which could provide customized parameter adjustments for waterfowl eggs with large individual differences.

A thermal imager was used in our experiment to measure the hatching environment and the eggshell temperature of each fertilized duck egg. The eggshell temperature data were collected to identify the suitable parameter settings for the incubation of fertilized duck eggs. Accordingly, we employed air quality sensors to gather O_2, CO_2, RH, and temperature inside the incubator.

In the second step, we built a sufficient hatching prediction model to predict the hatching rate of fertilized eggs based on the explored major parameters in the first step. This model is expected to help the duck farmer, to provide customized care of each egg with minimized parameters instead of all parameters, which incurs high observation costs and, thus, it can reduce unnecessary elimination of eggs and increase hatchability.

In order to build the prediction model, this study uses the black Muscovy duck hatching as a case study (Figure 1); we explored key characteristics to quantitatively predict the survivability of the black Muscovy duck egg. Data from the experiment were remotely collected by thermal imaging cameras and air sensors to lower the labor costs and build automatic environment control. The black Muscovy duck was used as a case study to build the prediction model [7]. These ducks have been bred in Taiwan for more than 300 years. Their feather colors could be white, blue, black, a white–blue combination, a white–black combination, black with white rings, blue with white rings, or chocolate brown [8]. Initially, people in Taiwan mainly bred black Muscovy ducks. Male Muscovy ducks were a source of food (ginger duck stew) for people to consume during the winter to warm their bodies [9]. In 1962, large-sized, white Muscovy ducks were introduced to Taiwan from Australia, the United States, and the Netherlands. From 1975, they were widely used due to their economic value; thus the number of original black Muscovy ducks in Taiwan reduced.

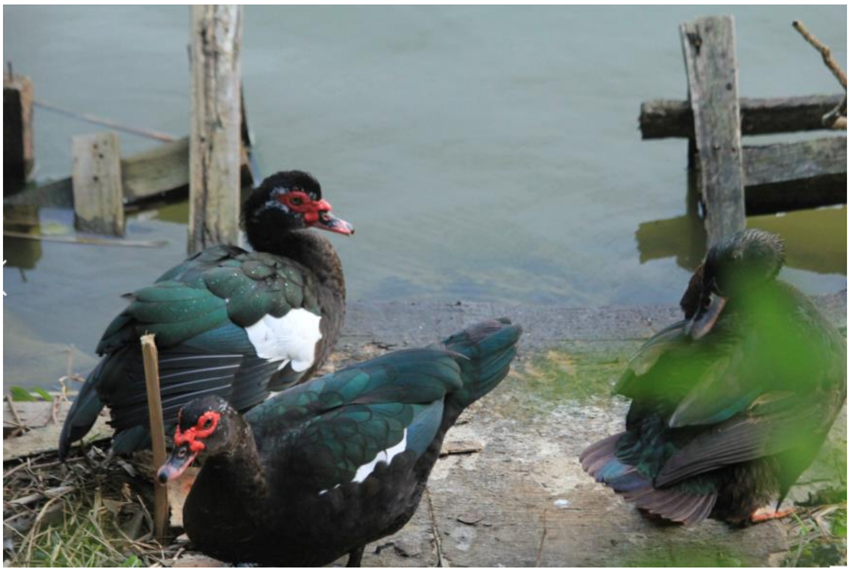


Figure 1. Black Muscovy duck (captured by this study).

In summary, this study provides a prediction model to quantitatively predict the hatching rate of each egg by observing parameters and the waterfowl-like production lifecycle. Two experiments, without any human interference from experienced farmers, were conducted: in the first one, we built the prediction model; the second one was to validate the effectiveness of the prediction model. The proposed prediction model will contribute to the duck industry by minimizing the training costs in the duck industry and maximizing the product qualification rate for individual agricultural products.

2. Literature Review

Many studies have focused on enhancing the hatching rate of fertilized eggs, including exploring the factors that affect the hatching rate and how to inspect the egg effectively by thermal imaging technology.

First, regarding temperature, Lourens et al. [1] attempted to control machine temperature to maintain the eggshell temperature during incubation; they found that the eggshell temperature could vary independently from the machine temperature. Joseph et al. [2] further studied the effects of different eggshell temperature settings in one incubation (e.g., the low eggshell temperature at the start of incubation, and high eggshell temperature at the end of incubation) on hatchability. Joseph also suggested that maintaining the eggshell temperature at 37.8 °C from days 0 to 10 leads to the best hatchability. Ipek [6] noted that embryo development is affected by small changes in the eggshell temperature.

Many scholars have attempted to explore other possible factors on hatchability, i.e., other than temperature. Lourens et al. [3] suggested that oxygen determines the embryo development (via heat production in the egg) rather than eggshell temperature. Molenaar and van der Pol [4,5] found that low relative humidity or low O_2 concentration leads to the highest embryo mortality. In [10–13], the researchers designed an automatic sprinkler cooling egg system to maintain a specific temperature, humidity, and concentration of CO_2 settings. In [14], the authors discuss the possibility of controlling the velocity and temperature of the airflow field in an incubator to increase hatchability.

Many studies apply thermal imaging as a non-invasive and non-contact method of measuring the surface temperature of eggshells in order to eliminate the effect of human factors on egg incubation. McCafferty [15] demonstrated several ways to use thermal imagers in poultry science, including physiological status monitoring, behavior research, and field survey on poultry. Lin et al. [16] employed thermal imagery technology to filter fertilized chicken eggs. Sunardi et al. [17] used thermal imaging to label the eggs and trace their development cycle.

The works discussed above provide valuable knowledge on how to evaluate the egg, with what tools or technology, and explore factors that may affect the hatching rate. However, they do not provide a sufficient hatching prediction model to demonstrate what key factors affect the hatching rate and how to apply these factors to predict the hatching rate of fertilized eggs.

3. The Proposed Method and Environmental Settings of the Experiment

3.1. Proposed Method

This study attempts to build a model based on Extreme Gradient Boosting to quantitatively predict the survivability of the black Muscovy duck egg. Extreme gradient boosting (XGBoost), a type of gradient boosted tree developed by Chen and Guestrin [18], was used for optimization based on tree ensemble models.

$$\hat{y}_i = \theta(X_i) = \sum_{k=1}^{K} f_k(X_i),\ f_k \in \mathcal{F} \tag{1}$$

Tree boosting is used to integrate multiple weak learners to form a strong learner, whereas a tree ensemble model considers the parameter optimization problems of multiple trees. In tree ensemble models, the original model is retained through additive training, and a new function is added to the model. Training is conducted according to the previous tree; it involves the addition of a new tree to the model to mitigate the deficiencies of the previous tree and further optimize the model.

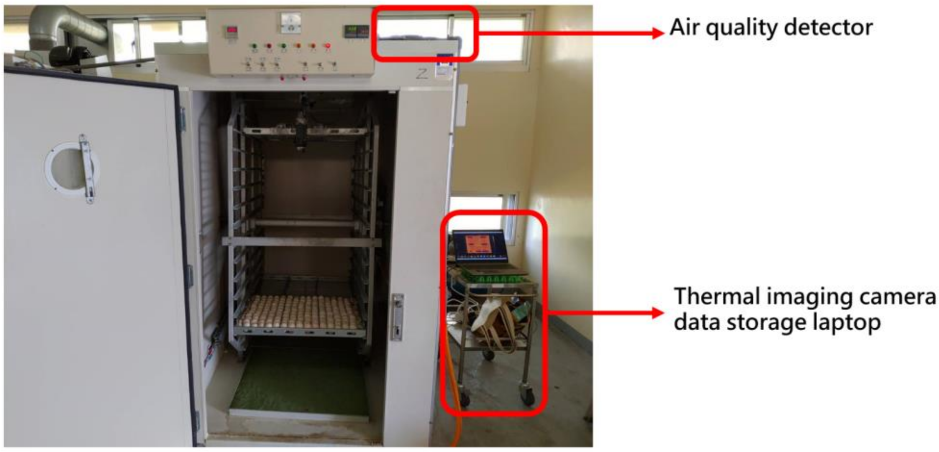
$$\mathcal{L}(\theta) = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k),\ \text{where } \Omega(f) = \gamma T + \frac{1}{2}\lambda|\omega|^2 \tag{2}$$

where l is a loss function. The penalty term at the back prevents model overfitting and ensures a more satisfactory model.

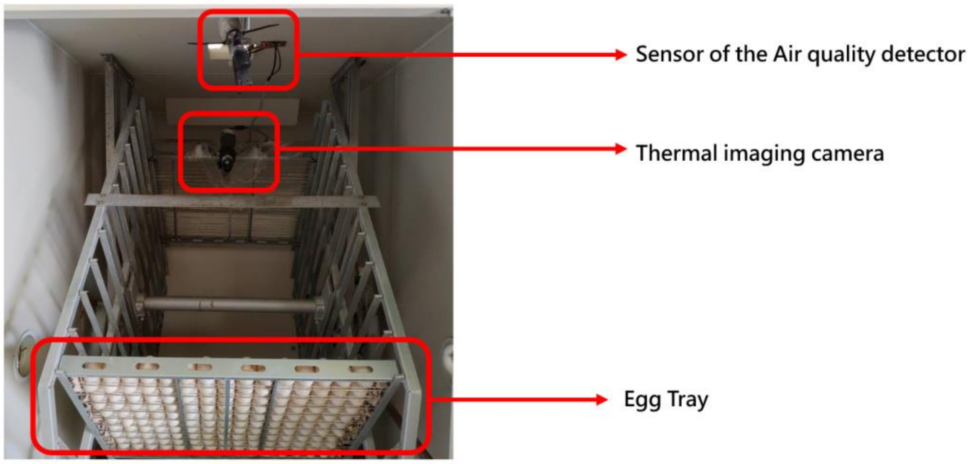
XGBoost, mainly used to explain supervised learning, can be applied for classification and to solve regression problems. In this study, we employed XGBoost to identify the successfully hatched fertilized eggs and those that stopped developing. XGBoost—a decision-tree-based, efficient, and expandable machine learning system—is widely used in various fields and has been frequently adopted by top winners at Kaggle competitions [19–21].

3.2. Environmental Settings of the Experiment

The environmental settings of the experiment was as follows. First, the air quality detector was built outside the incubator (as shown on the right side of Figure 2a) and its sensor was placed inside the incubator (as shown on the top side of Figure 2b). All of the data are stored in the laptop placed outside the incubator, as shown in the right side of Figure 2a. The thermal camera was placed inside the incubator (as shown in the center of Figure 2b) to collect the thermal image of the egg tray (as shown at the bottom side of Figure 2c); the sample of the thermal image is shown in Figure 2d. The thermal imager was covered and protected by plastic wrap, according to the manufacturer's instructions, in order to avoid unnecessary damage from the incubator and hatcher. There were 66 eggs randomly placed in the egg tray; the hatching period was from 11 September to 15 October, 2020, as shown in Figure 2c–e. The hatched ducks in this experiment are shown in Figure 2e. Climatic data of the experimental site are shown in Table 1.



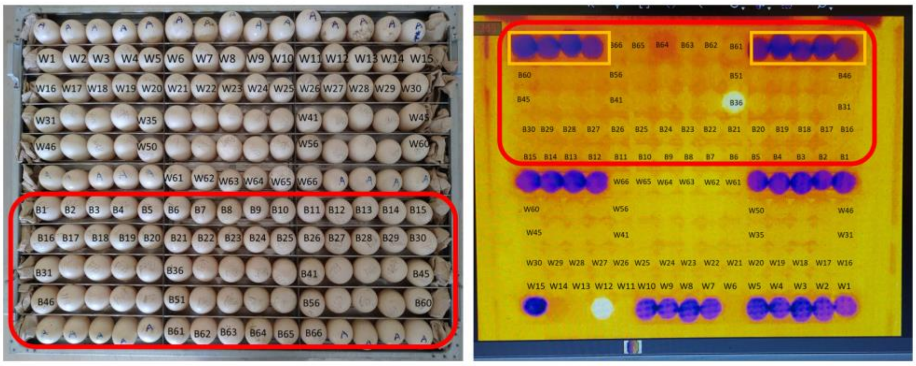
(**a**)



(**b**)

(**c**)

Figure 2. *Cont*.



(**d**)

(**e**)

Figure 2. (**a**) Outside of the incubator; (**b**) inside the incubator; (**c**) 66 eggs tray; (**d**) thermal image of egg tray; (**e**) hatched ducklings.

Two experiments were conducted for this study. The first experiment was applied to (1) explore the major parameters out of all the parameters to affect the hatching rate; and (2) to build a prediction model. Furthermore, the first experiment was executed in the unfamiliar environment to avoid human interference from experienced farmers. Based on the experience, the hatching rate was around 50% in the first experiment. The second experiment validated the prediction model by controlling parameters explored in the first experiment, without any human interference from experienced farmers.

The thermal imager manufacture periodically calibrated the imager based on the contract, and the accuracy was ±2% of the detected temperature value. The precisions of the O_2 and CO_2 sensors were:

1. O_2
   - ±(1% reading + 0.2% O_2).
2. CO_2:
   - ≤1000 ppm: ±40 ppm.
   - 1000 ppm ≤ 3000 ppm: ±5% of reading.
   - 3000 ppm reference only: ±250 ppm typically.

Table 1. Climatic data of the experimental site (Yilan, Taiwan).

Month	Monthly Average Temperature	Highest Temperature	Lowest Temperature	Relative Humidity	Number of Rainy Days	Sunshine-Hour	Altitude	Atmospheric Pressure
September	27 °C	35.3 °C	20.8 °C	76%	13	128.3	7.38 M	1009.2 hpa
October	23.7 °C	31.6 °C	18.1 °C	80%	21	41.4	7.38 M	1014.4 hpa

3.3. Data Collection and Preprocessing Procedure

The sample consisted of 66 Muscovy duck fertilized eggs. We conducted analyses according to the data obtained from the hatching experiment by the candling procedure. Egg candling was implemented on day 6 (E6), day 13 (E13), and day 31 (E31). Unfertilized duck eggs and those with terminated development were removed from the egg tray to prevent the healthy duck eggs from spoiling or rupturing. The egg placement on the egg tray and status of the fertilized eggs are displayed, collected in E13. in Figure 3.

E0 E6 E13 E31

Data collected in E13

B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	~~B15~~
B16	B17	**B18**	B19	B20	B21	B22	B23	B24	B25	B26	B27	B28	B29	B30
B31	~~B32~~	B33	B34	B35	~~B36~~	**B37**	B38	B39	B40	B41	B42	B43	B44	B45
B46	B47	B48	B49	B50	B52	B52	B53	B54	B55	B56	B57	B58	**B59**	~~B60~~
A	A	A	A	A	B61	B62	B63	~~B64~~	**B65**	B66	A	A	A	A

Figure 3. Egg tray of the second experiment: the fertilized egg status on E13. Area A, random duck eggs placed to fill the remaining spaces. Area B, 66 Muscovy duck fertilized eggs; strikethrough, data error; baseline, unfertilized eggs; grayed out boxes, eggs that have stopped developing.

In addition to the thermal imagers, we installed O_2 and CO_2 sensors as well as temperature and humidity sensors on both the interior and exterior of the incubator, to more precisely control the influence of weather on the hatching result. The data gathered during the incubation process were continuously transmitted to the Taiwan Waterfowl Hatching Database. After the completion of the incubation, we marked the successful hatches among all incubation data and imported the results to machine learning for classification training (Figure 4).

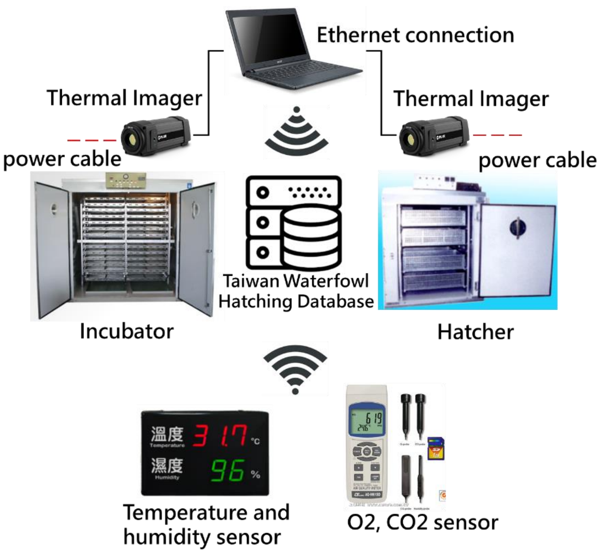


Figure 4. Waterfowl incubation data collection system.

Before the experiment, we recorded the weight, the long and short diameters, and the shape coefficient of each fertilized egg. The eggshell temperatures of the fertilized eggs were automatically obtained by the thermal images captured (per minute, every day) in the incubator. The experiment recorded the mean, min, and max temperature of each egg of each day. During candling, the eggs were weighted and weight loss of the eggs were calculated. Surface temperatures (eggshell temperatures) were recorded using the highest temperature, the lowest temperature, the maximum temperature difference, and the average temperature. We employed the average eggshell temperature rather than the median temperature to compensate for human error in the manual selection of the surface temperature range. This study's objective was to determine the key characteristics and build a model to quantitatively describe the biomass development path, along with each phase of the waterfowl production lifecycle. Therefore, we interviewed duck farmers with numerous site visits and collected features that they observed based on long time experience, as shown in Figure 5b. The interview procedure was conducted and regulated by the "Duck Production System Manual" [22] of the Council of Agriculture (CoA), Executive Yuan in Taiwan. One of the research team members and authors, Chih-Hsiang Cheng, was the coordinator and representative of CoA, project ID 109M000001, project name "Development of sensing modules suitable for waterfowl hatching equipment". The incubation features used in the machine learning classification models are displayed in Figure 5a.

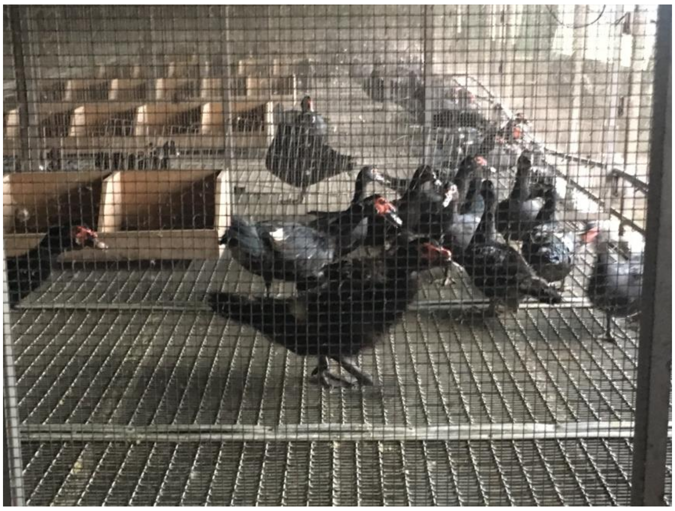
The lifecycle of an egg consists of two phases: (1) incubation and (2) hatching. Each phase has its own model based on XGBoost. We determined how incubation features in various stages affected egg development termination and the final hatching result. Hence, we established two machine learning classification models based on the data gathered during the incubation. Data collected before the third candling examination were used to construct Model 1, and those after the third examination, Model 2.

A FLIR A300 thermal imager was employed and the accuracy is ±2 °C with ±2% of accuracy periodically calibrated by the manufacturer. Figure 6a is a thermal image of an egg tray with a 6 × 5 space arrangement. The thermal imager detected the changes in the surface temperature as well as the highest, lowest, and average eggshell temperatures of the fertilized eggs. Figure 6b demonstrates the heating information of the no. EL1 fertilized egg in the incubator and a chart of temperature changes over a course of 25 min). Each fertilized egg had a distinct maximum temperature difference. We recorded the hatching result of each fertilized egg after the incubation ended. The detailed temperature data were then adopted for machine learning for establishing hatching prediction models. After the models were calibrated and optimized, the temperature parameters could serve as references for improving incubators.

Model list	Incubation features applied in the machine learning classification models	
Model 1:	Day 0	
		Weight on Day 0 Long diameter Short diameter Shape coefficient
	Day 7	
		Weight on Day 7 Weight loss on Day 7 Weight loss ratio on Day 7 Surface eggshell temperature on Days 0–7: maximum temperature difference Surface eggshell temperature on Days 0–7: highest temperature Surface eggshell temperature on Days 0–7: lowest temperature Surface eggshell temperature on Days 0–7: average temperature
	Day 14	
		Weight on Day 14 Weight loss on Day 14 Weight loss ratio on Day 14 Surface eggshell temperature on Days 8–14: maximum temperature difference Surface eggshell temperature on Days 8–14: highest temperature Surface eggshell temperature on Days 8–14: lowest temperature Surface eggshell temperature on Days 8–14: average temperature
Model 2:	Day 31	
		Weight on Day 31 Weight loss on Day 31 Weight loss ratio on Day 31 Surface eggshell temperature on Days 15–31: maximum temperature difference Surface eggshell temperature on Days 15–31: highest temperature Surface eggshell temperature on Days 15–31: lowest temperature Surface eggshell temperature on Days 15–31: average temperature

(**a**)

Figure 5. *Cont.*



(**b**)

Figure 5. (**a**) Features based on the Duck Production System Manual; (**b**) Duck farm of the site visits of this study (captured by this study).

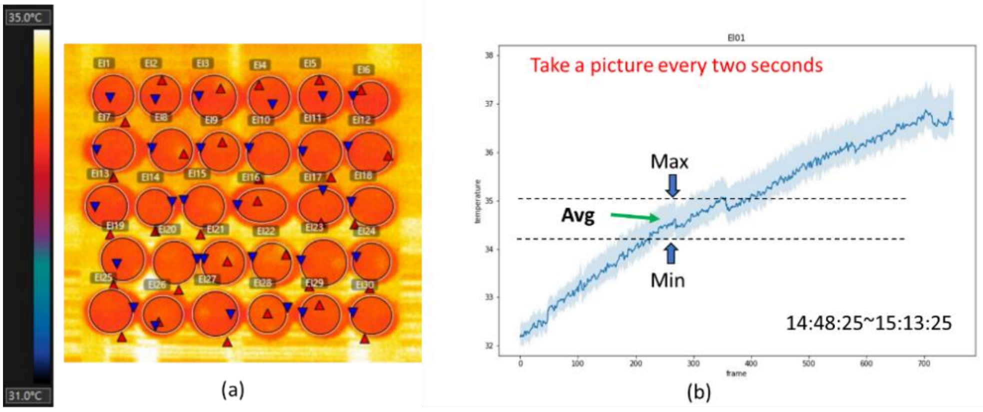


Figure 6. (**a**) Thermal image of the eggs; (**b**) a chart of temperature change.

4. Results and Discussion

The target of this study was to build a prediction model to quantitatively describe the biomass development path along with each phase of the waterfowl-like production lifecycle. That is, we attempted to build a prediction function:

$$\mathrm{Y} = \mathrm{F}(x_i),\ \text{where } x_i \in key\ characteristics\ of\ hatching\ rate$$

where Y is the predicted hatching rate. The duck farmer could use this function to quantitatively describe the biomass development path, i.e., the hatching rate, and provide sufficient customized care along with each phase of the waterfowl-like production lifecycle and the corresponding environment settings.

Figure 7 is the classification tree of Model 1. We applied 18 features to construct this model, including the egg size, weight, surface temperature at different stages, and weight loss. In the first stage of the incubation, and with the temperature, humidity, and air quality held constant, three conditions were discovered to have key influences on the hatching results: a long diameter less than 6.65 cm, a weight loss less than 1.45 g between days 0 and 7, and an average eggshell temperature higher than 41.36 °C between days 7 and 14.

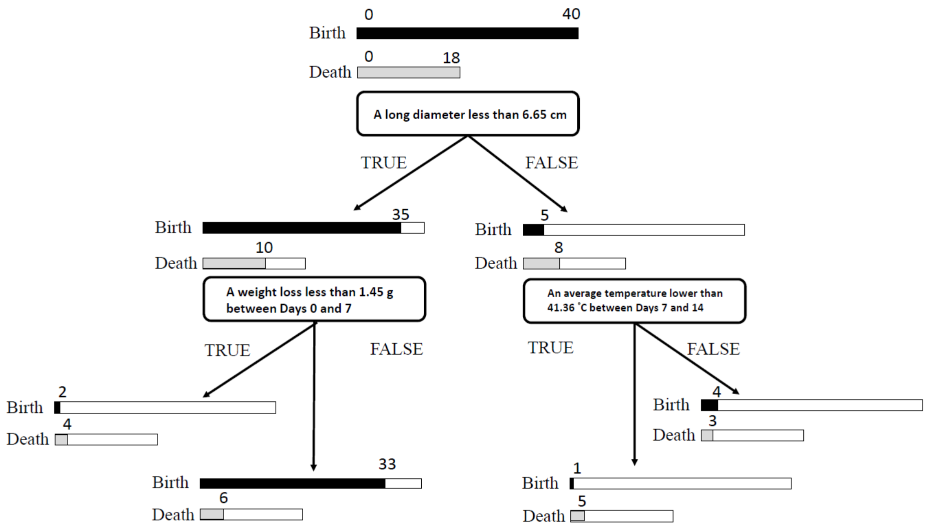


Figure 7. Classification tree result of Model 1.

Figure 8 is the classification tree result of Model 2. We applied 11 features to establish this model, including the egg size, weight, surface temperature at different stages, and weight loss. In the second stage of the incubation, and with the temperature, humidity, and air quality held constant, two conditions were found to influence the hatching result: a shape coefficient greater than 0.6715 and an average eggshell temperature higher than 41.07 °C between days 14 and 31.

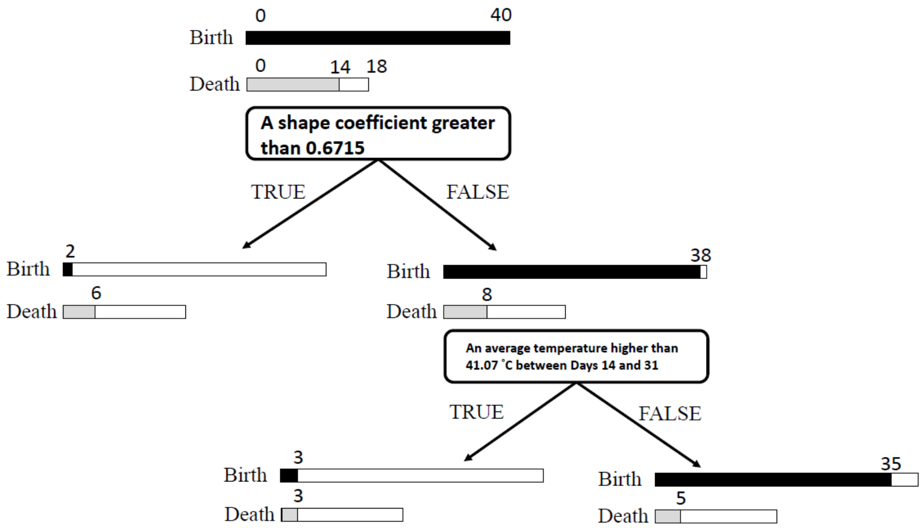
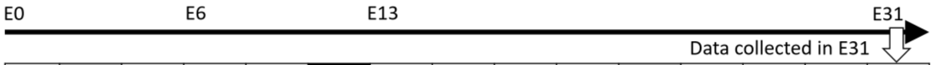


Figure 8. Classification tree result of Model 2.

In addition to the analysis results of the classification trees, some crucial data were obtained from the final state of the egg tray (Figure 9). Nine of the eighteen eggs stopped developing during the last 3 days of the incubation. Judging from the positional relationship of these eggs, some mutual influences might exist among them. The strikethroughs in Figure 8 indicate abnormal data during the three egg candling examinations, which we regarded as manual marking errors. Hence, the data of B15, B32, B36, B60, and B64 were excluded.



B1	**B2**	B3	B4	B5	**B6**	B7	B8	B9	<u>B10</u>	**B11**	B12	B13	B14	~~B15~~
B16	**B17**	**B18**	**B19**	**B20**	B21	B22	B23	B24	B25	**B26**	B27	**B28**	B29	B30
B31	~~B32~~	B33	B34	**B35**	~~B36~~	**B37**	B38	B39	B40	B41	B42	B43	B44	B45
B46	B47	**B48**	B49	B50	**B52**	**B52**	**B53**	<u>B54</u>	<u>B55</u>	B56	B57	B58	**B59**	~~B60~~
A	A	A	A	A	B61	B62	B63	~~B64~~	**B65**	**B66**	A	A	A	A

Figure 9. Egg tray of the second experiment: the fertilized egg status on E31.

Area A, random duck eggs placed to fill the remaining spaces; area B, 66 Muscovy duck fertilized eggs; strikethrough, data error; baseline, unfertilized duck eggs; grayed out boxes, duck eggs that have stopped growing; blacked out boxes, duck eggs that died in the tray.

Based on the above results, we explored four characteristics out of 25 characteristics and built a model to quantitatively predict the survivability of black Muscovy duck egg. The key characteristics include the weight loss percent of an egg, the average eggshell temperature in different phases of the product lifecycle, and the shape coefficient of an egg. Therefore, the prediction function based on the XGBoost algorithm is:

$$\mathrm{Y} = \mathrm{F}(x_1, x_2, x_3, x_4)$$

where Y is the predicted hatching rate, x_1 is the weight loss percent of an egg, x_2 is the average eggshell temperature in different phases of the product lifecycle, x_3 is the shape coefficient of an egg, x_4 is the long diameter of an egg. The duck farmer can use the thermal camera to automatically measure the four characteristics to quantitatively describe the biomass development path, i.e., the hatching rate, and provide sufficient customized care along with each phase of the waterfowl-like production lifecycle and the corresponding environment settings.

To validate the prediction model that we built in the first experiment, we applied this prediction model and conducted the second experiment by controlling parameters explored in the first experiment, without any human interference from experienced farmers. Figure 10 shows the hatching rate rose from 47% in the first experiment to 62% in the second experiment, and this result validates the effectiveness of our prediction model.

In addition, we furthermore evaluated the effects of O_2 and CO_2 values inside the incubator and hatcher toward the survivability of the black Muscovy duck egg between two experiments. Figure 10 illustrates the four types of air quality values inside the incubator. The data from the first and second experiments are displayed using blue and red lines, respectively. The first experiment shows a 47% hatchability, and the second experiment demonstrates a 62% hatchability. The different 'hatchability' between the two experiments is highly related to the difference in CO_2 values in the two experiments. This means that more eggs survived in the second experiment than the first experiment; therefore, the oxygen consumption and CO_2 value of the second experiment were higher than that of the first experiment. However, the CO_2 and O_2 values are the results of the survivability of the black Muscovy duck egg rather than the cause of the survivability of the black Muscovy duck egg. Therefore, our model automatically excludes the CO_2 and O_2 values as being the key characteristics that predict survivability.

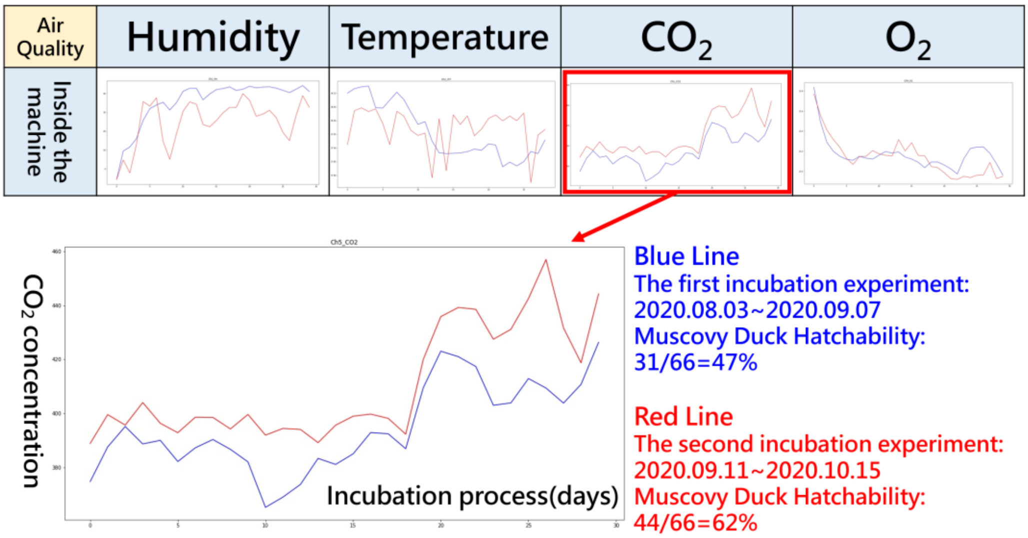


Figure 10. Four types of air quality values measured inside the incubator.

5. Conclusions

In this study, we employed XGBoost to determine four essential incubation features out of 25 features and to build a prediction model. The effectiveness of our prediction model is validated by the experiment results, i.e., the hatching rate rose from 47% to 62% without any human interference from experienced farmers. The results show that our proposed prediction model is capable of decreasing the training costs and enhancing the product qualification rate for individual agricultural products.

This study has several implications for precision agriculture researchers and practitioners. First, this study offers a new system development path in order for farmers to adopt AI technology to predict the hatching rate. This study demonstrates how the prediction model is built and how to use this function to enhance agriculture production.

Second, farmers could apply the proposed model to develop a hatching and business strategy, rather than merely rely on experience. For example, farmers could adjust their future hatching equipment investments by this model, according to the breed of the eggshell and the corresponding nature characteristics.

Third, agriculture wholesalers could use this model to understand the productivity of the breed of the duck egg and predict the business strategy of the farmer, including the pros and cons of their short-/long-term production strategies.

In the future, we will extend our proposed model and explore the possible ensemble learning architecture to minimize false positives and false negatives on classification performance.

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