Using an artificial neural network to predict the probability of oviposition events of precision-fed broiler breeder hens

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ABSTRACT Identifying daily oviposition events for individual broiler breeders is important for bird management. Identifying non-laying birds in a flock that might be caused by improper nutrition or diseases can guide diet changes or disease treatments for these individuals. Oviposition depends on follicle maturation and egg formation, and follicle maturation can be variable. As such, the day and time of oviposition events of individual birds in a free-run flock can be hard to predict. Based on a precision feeding (**PF**) system that can record the feeding activity of individual birds, a recent study reported a machine learning model to predict daily egg-laying events of broiler breeders. However, there were 2 limitations in that study: 1) It could only be used to identify daily egg-laying events on a subsequent day; 2) The prediction outputs that were binary labels were unable to indicate more details among the outputs with the same label. To improve the previous approach, the current study aimed to predict and output the probability of daily oviposition events occurring using a specific time point in 1 day. In the current study, 706 egg-laying events recorded by nest boxes with radio frequency identification of hens and 706 randomly selected no-egg-laying events were used. The anchor point was newly defined in the current study as a specific time point in 1 day, and 26 features around the anchor point were created for all events (706 egg-laying events and 706 no-egg-laying events). A feed-forward artificial neural network (**ANN**) model was built for prediction. The area under the receiver operating characteristic (**ROC**) curve was 0.9409, indicating that the model had an outstanding classification performance. The ANN model could predict oviposition events on the current day, and the output was a probability that could be informative to indicate the likelihood of an oviposition event for an individual breeder. In situations where total egg production was known for a group, the ANN model could predict the probability of daily oviposition events occurring of all individual birds and then rank them to choose those most likely to have laid an egg.

Key words: oviposition, probability, feature, neural network, artificial intelligence

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INTRODUCTION

Egg production of broiler breeders and laying hens is a major contributor to sustainability. At flock-level, egg production over the laying period can be presented by a production curve that consists of a rapid increase phase, a peak production phase, and a gradual decrease phase (Savegnago et al., 2012). At the individual level, oviposition is the egg-laying event that occurs on a specific day. Oviposition occurs in sequences of one or more eggs, separated by one or more pause days, when no oviposition occurs (Robinson et al., 1991). Sequences and pauses are determined by follicle maturation and egg formation, and follicle maturation can be variable due to hormone and environmental factors (van der Klein et al., 2020). As a result, there is a lot of uncertainty in the day and time of oviposition of individual hens. Although previous studies investigated ovulatory cycle (Etches and Schoch, 1984; Johnston and Gous, 2003), oviposition interval (Yoo et al., 1986), sequence length (Lillpers and Wilhelmson, 1993), it is challenging to determine oviposition events of cage-free individual hens.

Identifying daily oviposition events for individual broiler breeders is important to improve bird management. In the laying period, breeders might stop laying due to reasons like nutrition, disease, or facility (Long and Wilcox, 2011). Identifying breeders that have not laid an egg can inform targeted management of those individuals, such as changing the diet or treating a

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disease. It is difficult to identify oviposition events for free-run breeders without a trap nest system. Thus, a system to identify non-laying birds in a group housing system would be desirable.

A recent study (You et al., 2020) predicted daily oviposition events of individual broiler breeders using a random forest classifier. It was the first study to identify daily oviposition events at an individual level in a precision feeding (**PF**) system (Zuidhof et al., 2019) that automatically feeds individual birds and records vast amounts of data regarding the feeding activity of the birds. The study by You et al. (2020) established a relationship between daily oviposition events of individual breeders and the feeding activity and BW change of individual breeders recorded by the PF system. The system feeds birds according to BW measured in real time. Body weight increases following feed and water intake events, and decreases after defecation and oviposition events. Because feed intake is driven by BW in the PF system, feed intake is expected to increase after oviposition. However, there were 2 limitations in the study:

i) It was based on the feeding activity and BW change of breeders in the whole day (from 00:00 to 23:59) to predict the egg-laying events. As a result, identifying egg-laying events for a day by the model could only be applied on the subsequent day.
ii) The prediction outputs were binary labels (0 and 1) representing no oviposition and oviposition, respectively. However, for predicted outputs with the same label, it was not possible to determine which birds were more likely to have laid an egg.

Artificial neural network (**ANN**) is a supervised learning approach, which can be used for regression and classification. It consists of several processing units with characteristics like self-adapting, self-organizing, and real-time learning (Ding et al., 2013). ANN has been widely used in poultry production, including estimation of broiler BW (Amraei et al., 2017), total egg production of quails (Felipe et al., 2015), and detecting drops in egg production of laying hens (Ramírez-Morales et al., 2017). The objective of the current study was to improve the previous approach in 2 aspects: 1) To apply the model on the current day; 2) To output more informative results. To accomplish this, an ANN model was built to predict the probability of oviposition events occurring. Our objective was to use the ANN model not only to predict whether a hen laid an egg, but to rank oviposition probabilities to reconcile the number of hens with the highest oviposition probability with daily flock-level egg production records.

MATERIALS AND METHODS

The animal protocol for the study was approved by the University of Alberta Animal Care and Use Committee for Livestock and followed principles established by the Canadian Council on Animal Care Guidelines and Policies (CCAC, 2009).

Experimental Design

In the current study, data were obtained from a flock of broiler breeders (n = 95) raised in 2 environmentally controlled chambers. Each chamber was equipped with 2 PF stations (Figure 1). There were 76 hens in total. All birds were trained to use the PF station from 0 to 14 d of age, which was described by Zukiwsky et al., (2020). From 15 d to the end of the trial (306 d), breeders were fed by the PF system that could identify individual birds by reading the unique radio frequency identification (**RFID**) tag on their right wing. The PF system determined whether a bird would receive a meal by comparing its real-time BW with a pre-assigned target BW. If the real-time BW was greater than or equal to the target BW of that bird, it would not be fed and was gently ejected. If the real-time BW was less than the target BW, the bird would have a meal in a feeding bout of up to 60 s in the station and then be gently ejected. Throughout the trial, water was provided ad libitum. The RFID, time, date, real-time BW, target BW, and feed intake (**FI**) for each visit were recorded by the PF system.

Data Collection

After photo-stimulation at 22 wk of age, the egg production of individual hens was recorded on a daily basis. From 155 to 306 d, the temperature for chamber 1 and chamber 2 were 22.67 ± 0.95°C (mean ± standard deviation) and 22.86 ± 1.01°C, respectively. In the current study, if a hen laid an egg in 1 day, it was considered as an egg-laying event; if a hen did not lay an egg in 1 day, it was considered as a no-egg-laying event. A traditional trap nest box with 8 nesting sites was placed in each pen, and it was checked every hour from 07:30 to 17:30 every day. After an egg was laid in the trap nest box, it would be set free from the box by researchers. The exact time of egg-laying events that occurred in the trap nest box was not recorded. In addition to the traditional trap nest box, an RFID nest box with 8 nesting sites was also used to determine the exact time of each egg-laying

Figure 1. Picture of precision feeding stations in the trial for the current study.

event for individual hens. When a breeder entered an RFID nesting site, its RFID was read. Inside the nesting site, the floor was sloped. Once a breeder laid an egg, the egg would roll down through a channel into an egg-collection box beneath the nesting site. When the egg-collection box received an egg, the time of receiving the egg would be recorded. Since an egg would be received immediately once being laid, the time of receiving the egg could be considered as the time of oviposition. During the study, 706 egg-laying events occurred in the RFID nest box, while the remaining egg-laying events occurred in the trap nest box. The total number of no-egg-laying events was 3,559.

Data Preprocessing

The current study used Python 3.7.0 to facilitate data preprocessing, feature engineering, and model construction. All 706 egg-laying events recorded by the RFID nest box from 171 to 306 d were used. The number of egg-laying events during each hour was counted, and the distribution of egg-laying events during each hour is shown in Figure 2. All egg-laying events occurred between 05:00 and 18:00. The same number ($n = 706$) of no-egg-laying events was randomly selected from all recorded no-egg-laying events. In the current study, the anchor point was newly defined as a specific time point, corresponding to oviposition time (known for 706 egg-laying events), around which features were created. Anchor points for 706 no-egg-laying events were randomly assigned to correspond to the oviposition times of the 706 known oviposition events. As a result, the time distribution was identical for egg-laying and no-egg-laying event anchor points.

Features were created to describe each observation (egg-laying event or no-egg-laying event). Three periods, including 24 h before the anchor point (ended at the anchor point), 6 h before the anchor point (ended at the anchor point), and 6 h after the anchor point (started at anchor point), were used to create features. Since all breeders were fed by the PF system, BW gain (**BWG**)

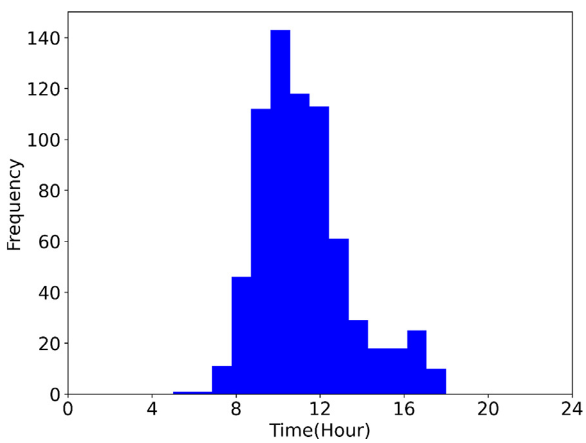

Figure 2. The distribution of egg-laying events during each hour over a 24 h period. The total number of egg-laying events from 171 to 306 d was 706.

for a period of time could be calculated by the equation below:

$$\mathrm{BWG} \;=\; \mathrm{BW}_n - \mathrm{BW}_1 \tag{1}$$

where $\mathrm{BW_n}$ represented the $\mathrm{n^{th}}$ real-time BW in the period that was recorded by the PF system, and $\mathrm{BW_1}$ represented the first real-time BW in the period that was recorded by the PF system. The equation could be expanded to:

$$= (\mathrm{BW}_n - \mathrm{BW}_{n-1}) + (\mathrm{BW}_{n-1} - \mathrm{BW}_{n-2}) + \ldots + (\mathrm{BW}_2 - \mathrm{BW}_1) \tag{2}$$

$$= \Delta\mathrm{BW}_{n-(n-1)} + \Delta\mathrm{BW}_{(n-1)-(n-2)} + \ldots + \Delta\mathrm{BW}_{2-1} \tag{3}$$

where $\mathrm{BW_n}$ represented the $\mathrm{n^{th}}$ real-time BW in the period recorded by the PF system. $\Delta\mathrm{BW_{n\text{-}(n\text{-}1)}}$ represented the BW change between two consecutive ($\mathrm{n^{th}}$ and $\mathrm{n\text{-}1^{th}}$) real-time BW in the period recorded by the PF system. These BW changes could be classified into two groups: BW increase and BW decrease, so the equation could be transformed to:

$$\mathrm{BWG} \;=\; \sum \mathrm{BW\ increase} + \sum \mathrm{BW\ decrease} \tag{4}$$

Generally, any BW change between 2 consecutive real-time BW records could be caused by 4 activities, including FI, water intake (**WI**), excretion and metabolic loss (**EM**), and oviposition. Oviposition occurred at the anchor point that was not included in these three periods (24 h before the anchor time, 6 h before the anchor time, and 6 h after the anchor time). Thus, only FI, WI, and EM contributed to BW change. FI and WI could result in BW increase, and EM could result in BW decrease. The equation for these three periods could be transformed to:

$$\mathrm{BWG} \;=\; \mathrm{FI} + \mathrm{WI} + \mathrm{EM} \tag{5}$$

FI referred to the total amount of feed eaten by an individual in each period. According to the equations above, WI could be estimated by subtracting FI from the sum of BW increases, and EM could be estimated by the sum of BW decreases. There were 8 features for each period. BWG, FI, the estimated WI, and the estimated EM were 4 features for each period. For each period, the mean and standard deviation of the difference between target BW and real-time BW were used as two features. The number of meals and the number of no-meal visits were used as two features. Thus, there were 24 features for these 3 periods. Apart from the 24 features, another 2 features regarding the anchor point were created: the period between 2 consecutive visits over the anchor point and the BW change of 2 consecutive visits over the anchor point. All 26 features are shown in Table 1.

Algorithm

The ANN model was implemented by the deep learning framework Keras package (Chollet, 2015). The ANN

Table 1. Features created for each event (egg-laying event or no-egg-laying event).

No.	Feature	Description
1	FI_24	Feed intake recorded by the precision feeding system in the 24 h before the anchor point [1].
2	WI_24	Estimated water intake[2] in the 24 h before the anchor point
3	EM_24	Estimated excretion and metabolic loss[3] in the 24 h before the anchor point.
4	ΔBW_Mean_24	Mean of differences of DecisionBW[4] and TargetBW in the 24 h before the anchor point.
5	ΔBW_STD_24	Standard deviation of differences of DecisionBW and TargetBW in the 24 h before the anchor point.
6	BWG_24	Difference of the last DecisionBW and the first DecisionBW in the 24 h before the anchor point.
7	Meals_24	The number of meals in the 24 h before the anchor point.
8	No_meals_24	The number of no-meal visits in the 24 h before the anchor point.
9	FI_Pre_6	Feed intake recorded by the precision feeding system in the 6 h before the anchor point.
10	WI_Pre_6	Estimated water intake in the 6 h before the anchor point.
11	EM_Pre_6	Estimated excretion and metabolic loss in the 6 h before the anchor point.
12	ΔBW_Mean_Pre_6	Mean of differences of DecisionBW and TargetBW in the 6 h before the anchor point.
13	ΔBW_STD_Pre_6	Standard deviation of differences of DecisionBW and TargetBW in the 6 h before the anchor point.
14	BWG_Pre_6	Difference of the last DecisionBW and the first DecisionBW in the 6 h before the anchor point.
15	Meals_Pre_6	The number of meals in the 6 h before the anchor point.
16	No_meals_Pre_6	The number of no-meal visits in the 6 h before the anchor point.
17	FI_Post_6	Feed intake recorded by the precision feeding system in the 6 h after egg-laying.
18	WI_Post_6	Estimated water intake in the 6 h after the anchor point.
19	EM_Post_6	Estimated excretion and metabolic loss in the 6 h after the anchor point.
20	ΔBW_Mean_Post_6	Mean of differences of DecisionBW and TargetBW in the 6 h after the anchor point.
21	ΔBW_STD_Post_6	Standard deviation of differences of DecisionBW and TargetBW in the 6 h after the anchor point.
22	BWG_Post_6	Difference of the last DecisionBW and the first DecisionBW in the 6 h after the anchor point.
23	Meals_Post_6	The number of meals in the 6 h after the anchor point.
24	No_meals_Post_6	The number of no-meal visits in the 6 h after the anchor point.
25	Time_gap	The period of two consecutive visits over the anchor point.
26	BW_drop	The BW change of two consecutive visits over the anchor point.

[1]Anchor point was newly defined as a specific time point in one day for predicting oviposition events, and features around the anchor point were created. For 706 egg-laying events, the anchor point referred to the time of oviposition recorded by the RFID nest box. For 706 no-egg-laying events, the anchor point was randomly selected in the assigned hour.

[2]Estimated water intake in a period was calculated by subtracting the feed intake from the sum of all BW increases between two consecutive visits in the period.

[3]Estimated excretion and metabolic loss in a period was the sum of all BW decreases between two consecutive visits in the period.

[4]DecisionBW: the real-time BW recorded by the precision feeding system for making decisions on whether birds would be fed.

structure was based on a feed-forward network shown in Figure 3, and a multilayer perceptron including 1 input layer, 1 hidden layer, and 1 output layer was constructed. Each layer could contain several neurons that were computational units. When training the ANN model, the input data were the 26 created features

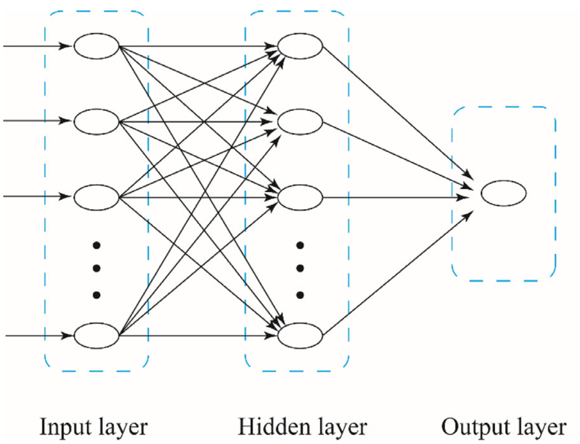

Figure 3. The structure of the feed-forward neural network in the current study. Ovals represented neurons. Arrows represented connections. Rounded rectangles represented layers. The neural network consisted of a group of neurons at each layer. Each neuron was fully connected to all neurons in the next layer. Neurons could forward pass the information to the neuron along the arrow. There were 3 layers in the neural network: an input layer, a hidden layer, and an output layer. The input layer accepted input data. The hidden layer processed input data. The output layer generated output results.

and the output data were binary labels (1 representing egg-laying and 0 representing no-egg-laying). A dropout layer that randomly ignores neurons connected to the prior layer was added between the hidden layer and the output layer to prevent overfitting. Hyper-parameters of ANN were optimized by the grid search method with sklearn.model_selection.GridSearchCV function (Buitinck et al., 2013). The overall accuracy was used as the metric to evaluate the prediction, and a 5-fold cross-validation approach was used in optimization. The optimized hyperparameters were used to build the final ANN model. The processed data were randomly split into 3 parts: 60% (846 observations) for training, 20% (283 observations) for validation, and 20% (283 observations) for testing.

Model Evaluation

The ANN model was evaluated by the receiver operating characteristic (**ROC**) curve and the area under the ROC curve (**AUC**). The ROC curve was able to show the trade-off between the recall (Y-axis) and false positive rate (**FPR**; X-axis) across a variety of thresholds (Hajian-Tilaki, 2013). The recall and FPR were calculated by the equations below:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{6}$$

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}} \tag{7}$$

where TP (true positive) represented predicted egg-laying events for actual egg-laying events; FP (false positive) represented predicted egg-laying events for actual no-egg-laying events; FN (false negative) represented predicted no-egg-laying events for actual egg-laying events; TN (true negative) represented predicted no-egg-laying events for actual no-egg-laying events. The upper left corner (coordinate [x = 0, y = 1]) where the FPR and recall were 0% and 100%, respectively, represented a perfect classification performance. AUC, which summarized the information of the ROC curve, was a measure of the discriminatory capacity of a diagnostic test (Kumar and Indrayan, 2011). The maximum value of AUC was 1, which indicated a perfect test. If the AUC value was 0.5, it indicated no discriminative test. As a result, a higher AUC value represented a larger area beneath the ROC curve, which meant a better classification performance. Eventually, the probability of all testing samples was predicted by the ANN model.

RESULTS AND DISCUSSION

The optimized hyperparameters are shown in Table 2. With these hyperparameters, the loss of the model on both the training dataset and the validation dataset decreased to about 0.2 with 80 epochs (the number of epochs meant the times that the ANN model worked through the entire training dataset), and the accuracy of both concurrently increased to about 0.9 (Figure 4). Figure 5 shows the ROC curve and the AUC of the model. The ROC curve was far away from the diagonal line extending from the lower left corner to the upper right corner, and it was close to the upper left corner where the recall was 100% and the FPR was 0%, indicating an almost perfect test result. The closer the ROC curve approached to the upper left corner, the better the test result was (Marzban, 2004). AUC was 0.9409, which meant a 94.09% chance to correctly distinguish an egg-laying event from a no-egg-laying event. If the AUC value was greater than 0.9, it indicated an outstanding test (Mandrekar, 2010). Thus, the classification performance of the ANN model was outstanding.

Table 2. The optimized hyperparameters for ANN.[1]

Hyperparameter	Value
Number of neurons in the input layer	64
Activation function in the input layer	"relu"[2]
Number of neurons in the hidden layer	32
Activation function in the hidden layer	"relu"
Dropout rate	0.25
Optimizer	"Adam"[3]
Learning rate of optimizer	0.0001
Batch size	50
Epoch	80
Loss function	"binary_crossentropy"[4]

[1]ANN: artificial neural network implemented by the deep learning framework Keras package in Python, and hyper-parameters of ANN were optimized by the grid search method with sklearn.model_selection.GridSearchCV function.

[2]"relu": rectified linear unit that was one of the most commonly used activation functions in artificial neural network.

[3]"Adam": adaptive moment estimation that was a method for efficient stochastic optimization.

[4]"binary_crossentrophy": the loss function for binary classification problems.

To date, one other published study has reported predicting daily egg-laying events of individual birds by a random forest classifier (You et al., 2020). In that study, features regarding the feeding activity and BW change of individual birds were extracted from a dataset collected by a PF system. However, a limitation in the study was that prediction outputs could just be known on the subsequent day because the features in the 24 h (from 00:00 to 23:59) were needed as input variables for the prediction model. The current study aimed to build a prediction model that could be applied before the end of the current day. In the current study, features were also created based on the feeding activity and BW change recorded by a PF system. However, features were created from different periods unlike the previous study. Three periods around a specific time point (anchor point) in the day were used to create features, including 24 h before the anchor point, 6 h before the anchor point, and 6 h after the anchor point. Since it took about 24 h to form an egg, the feeding activity and BW change in the period of 24 h before the anchor point of egg-laying events might be different from that of no-egg-laying events. A target BW was preassigned in the PF system, and a breeder could have a meal if its real-time BW was lower than its target BW. In the 6 h period before oviposition, a breeder that would lay an egg might be less likely to access the feeder in the PF station than a breeder that would not lay. In contrast, in the 6 h period after oviposition, a breeder that laid an egg was more likely to receive feed due to BW loss resulting from having laid an egg compared to a breeder that did not lay. Thus, these three periods were important to create features. There were 8 features in each of the 3 periods. In each period, BWG over the period consisted of several BW changes between 2 consecutive real-time BW. BWG could be partitioned into 2 parts: the sum of BW changes greater than 0 and the sum of BW changes less than 0. The sum of BW changes greater than 0 could be caused by FI and WI, and the sum of BW changes less than 0 could just be caused by EM as oviposition did not occur in the period. Since the FI was recorded by the PF system, WI could be estimated by subtracting FI from the sum of BW changes greater than 0. The sum of BW changes less than 0 could be considered as the estimated EM. Since BWG, FI, estimated WI, and estimated EM over the period might be associated with oviposition, they were used as 4 features. The more frequently hens visited the PF station, the more accurate estimated WI and estimated EM would be. Thus, the number of meals and the number of no-meal visits were used as 2 features. Considering the birds were fed according to the target BW curves, the difference between real-time BW and target BW could indicate the change of BW and substantial BW changes might be associated with oviposition. Thus, the mean and the standard deviation of the

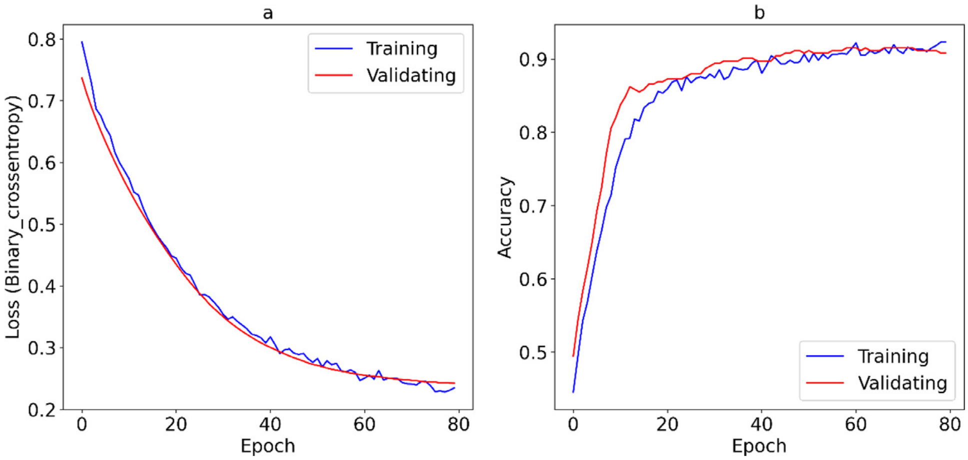

Figure 4. Loss (a) and accuracy (b) of the trained artificial neural network (ANN) model with 80 epochs in the current study. The loss function for the ANN model was binary_cross_entropy that was for binary classification problems. Accuracy was calculated according to the equation: , where TP, TN, FP, and FN meant true positive, true negative, false positive, and false negative, respectively.

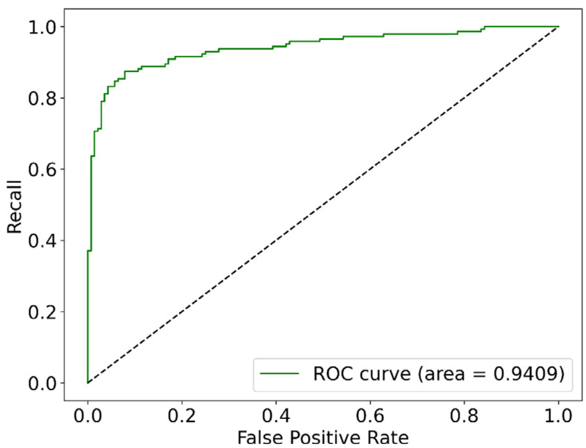

Figure 5. Receiver operating characteristic (ROC) curve and area under the curve of the artificial neural network model. In the figure, the recall was calculated by the equation: , where TP meant true positive and FN meant false negative. False positive rate (FPR) in the figure was calculated by the equation: , where FP meant false positive and TN meant true negative.

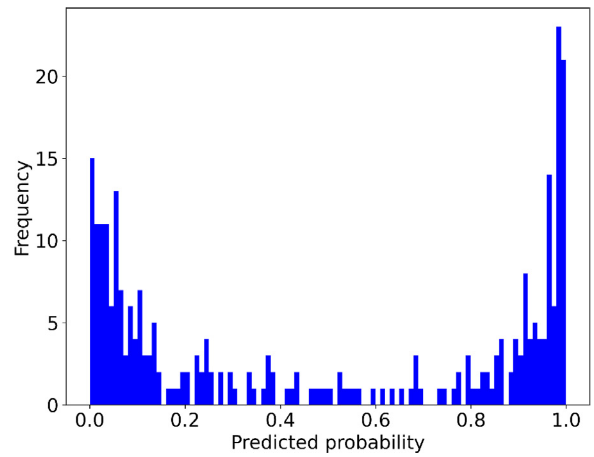

Figure 6. The distribution of predicted probability for testing samples by the artificial neural network. The total number of testing samples was 283.

difference were used as 2 features. Apart from the 24 features, another 2 features regarding the anchor point were created. The time interval between 2 consecutive visits across the anchor point was created because a long-time interval might occur if a breeder laid an egg between the 2 visits. Similarly, the BW change between two consecutive visits across the anchor point was created because a substantial BW change might occur if a breeder laid an egg between the 2 visits. Since all features were around the anchor point in one day, prediction outputs could be achieved in advance before the day was over.

For binary classification, machine learning algorithms could generate a probability between 0 and 1, and then a default decision threshold (0.5) for the probability was used to further generate a label as an output (Freeman and Moisen, 2008). If the probability was higher than or equal to 0.5, it was recognized as 1 (egg-laying); otherwise, it was 0 (no-egg-laying). In the current study, when training the ANN model, outputs were binary labels; when using the ANN model, prediction outputs were a probability between 0 and 1, rather than a binary label. ANN was a nonlinear model that provided a direct estimation of the posterior probabilities for classification problems without prior probabilities and other underlying assumptions (Zhang, 2000). Input variables were received by the input layer, and then computation on these input variables was performed by the hidden layer. A single hidden layer was used in the ANN model in the current study since the dataset was relatively small. The sigmoid function (a smooth nonlinear function) was used as the activation function in the output layer. Since the output of the sigmoid function was between 0 and 1, the ANN model finally generated a value between 0 and 1 as the probability of daily oviposition events occurring. You et al. (2020) used a random forest classifier that was a highly robust and accurate machine learning approach for binary classification. However, the random forest classifier was not a good

Table 3. Evaluation results[1] of the artificial neural network model on the testing set (283 samples included) presented by confusion matrix.[2]

		Predicted oviposition event[3] (d)		Precision[4]	Recall[5]	Overall accuracy[6]
		Egg-laying	No-egg-laying			
Actual oviposition event (d)	Egg-laying	125	18	0.9191	0.8741	0.8975
	No-egg-laying	11	129	0.8776	0.9214	

[1]The original results generated by the artificial neural network model were probability. The binary results presented in the confusion matrix was based on a probability threshold of 0.5 that classified probabilities into two groups: egg-laying group and no-egg-laying group.

[2]True positive (TP) represented predicted egg-laying events for actual egg-laying events; False positive (FP) represented predicted egg-laying events for actual no-egg-laying events; False negative (FN) represented predicted no-egg-laying events for actual egg-laying events; True negative (TN) represented predicted no-egg-laying events for actual no-egg-laying events.

[3]Oviposition event indicated whether a bird laid an egg or not in one day. Predicted oviposition event was predicted by the artificial neural network model.

[4]Precision (egg-laying) = TP / (TP + FP); precision (no-egg-laying) = TN / (TN + FN), based on the testing set.

[5]Recall (egg-laying) = TP / (TP + FN); recall (no-egg-laying) = TN / (TN + FP), based on the testing set.

[6]Overall accuracy = (TP + TN) / (TP + TN + FP + FN), based on the testing set.

choice for generating the probability of classes. Since the probability estimated by the random forest classifier was the average proportion of a class observations in the leaf nodes of all the trees (Khan et al., 2016), abnormal probability might be estimated when the growth of trees was not limited so that there was only one class in the leaf nodes. The probability could indicate confidence in classification and evaluate the possibility of misclassification (Li et al., 2017). In the current study, the probability of daily oviposition events occurring was predicted by the ANN model. Compared with binary labels used in the previous study, the probability of daily oviposition events occurring would be informative because it could indicate how likely oviposition of an individual breeder occurred in the day. A higher probability value indicated that oviposition was more likely to occur. The distribution of the probability of all 283 testing samples showed 2 heavy tails in Figure 6. For most samples, the probability of daily oviposition events occurring was in the range from 0.0 to 0.1 or in the range from 0.9 to 1.0, which indicated that the ANN model could reliably distinguish egg-laying events from no-egg-laying events. Table 3 shows the evaluation results of 283 testing samples presented by confusion matrix and the binary labels of these testing samples were generated based on a probability threshold of 0.5. Overall accuracy of the ANN model was 0.8975, which was higher than that of the random forest classification model (0.8482) in the previous study (You et al., 2020).

Previous studies reported using machine learning models to detect drops in flock-level egg production curves (Morales et al., 2016; Ramírez-Morales et al., 2017). Compared with these studies, the current study could identify non-laying birds and facilitate monitoring of health and other issues at an individual bird level. It would be more beneficial than previous studies because the ANN model in the current study could help to find the individual birds with problems, rather than just to detect flock-level issues. A possible application scenario of using the ANN model was to identify the breeders that have laid an egg in the pen. If the number of collected eggs was n, there were n breeders that have laid an egg in the pen. All breeders in the pen could be ranked by the predicted probability of oviposition events occurring from high to low and then the top n breeders in the rank could be considered as the breeders that have laid an egg. To apply the ANN model, anchor points should be randomly selected between 05:00 and 18:00 because the ANN model was built based on the dataset in which anchor points were between 05:00 and 18:00. Additional analysis showed that using noon as an anchor point yielded the best oviposition prediction accuracy (data not shown).

CONCLUSION

The current study aimed to improve a previous approach that could only be used to identify daily egg-laying events on the subsequent day and the prediction outputs were binary labels. An ANN model was proposed to predict the probability of daily oviposition events based on 26 features around a specific anchor time point corresponding to oviposition time. The AUC value of the ANN model was 0.9409, indicating the ANN model had an outstanding classification performance. The ANN model could be used to predict oviposition events before the end of each day, and the prediction outputs were informative probabilities that indicated the likelihood of oviposition by individual hens within each day. In situations where the total egg production for a flock of breeders in one day was known, the probability of daily oviposition events occurring of all individual birds could be predicted and then ranked to choose those most likely to have laid an egg.

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DISCLOSURES

The authors declare no conflicts of interest.

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