Application of Machine Learning in the Big Data for Broiler Breeders Recorded by a Precision Feeding System

by

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Abstract

A precision feeding (**PF**) system developed at the University of Alberta is an innovation in precise nutrition and management for broiler breeders. The PF system can automatically feed individual broiler breeders and record vast amounts of real-time data regarding the feeding activity of individual broiler breeders that provides a valuable data source. Machine learning (**ML**) is an effective tool for big data analytics, because it can be helpful in revealing hidden patterns and correlations in data. The current thesis aimed to apply ML approaches to extract information from the data collected by a PF system and make predictions based on the information. The first study investigated predicting daily oviposition events of individual broiler breeders by a random forest (**RF**) classification model. The raw dataset from the PF system was processed for 34 features in relation to the feeding activity and body weight (**BW**) change of individual breeders in one day. Important features were selected using the RF-recursive feature elimination method, and 28 features were selected to build the classification model. Overall accuracy of the model was 0.8482, and the out-of-bag score was 0.8510. Precision of no egg-laying and egg-laying, recall of no egg-laying and egg-laying were 0.8814, 0.8090, 0.8520 and 0.8453, respectively. The Kappa coefficient of the model was 0.6931, indicating substantial agreement. This model was able to identify whether a free-run broiler breeder laid an egg or not on a certain day during the laying period with around 85% accuracy. The second study investigated detecting anomalous real-time BW data of individual broiler breeders that are sometimes recorded by a PF system. A supervised learning approach was developed to detect anomalies by considering the data distribution and features regarding the feeding activity of individual birds recorded by the PF system. Based on a manually labelled dataset, 4

supervised learning algorithms were applied, including RF, support vector machine, k-nearest neighbor, and artificial neural network (**ANN**). It showed that RF was the best algorithm because it had the highest F1 score (0.9712) and area under the precision-recall curve (0.9948). Compared with common anomaly detection approaches including Z-scores, interquartile range (**IQR**), density-based spatial clustering of applications with noise (**DBSCAN**), and local outlier factor (**LOF**), RF had a higher average F1 score (0.9448), which indicated that RF was an effective solution to clean anomalous real-time BW data of individual broiler breeders fed by the PF system. The third study investigated improving the prediction for daily oviposition events of individual broiler breeders in the first study. In the first study, the model could only be used to identify daily oviposition events on the subsequent day and the prediction outputs were binary labels. An ANN model was used to predict and output the probability of daily oviposition events occurring using a specific time point in one day. The anchor point was newly defined as a specific time point in one day, and 26 features around the anchor point were created. 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 how likely oviposition of an individual breeder occurred in the day. 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. We concluded that ML approaches could extract meaningful information from the data recorded by a PF system for making predictions.

Preface

Chapter 3 of this thesis has been published as J. You, S. A. S. van der Klein, E. Lou, and M. J. Zuidhof (2020) "Application of random forest classification to predict daily oviposition events in broiler breeders fed by precision feeding system" in Computers and Electronics in Agriculture, 175: 105526. I analyzed the data and drafted the manuscript. S. A. S. van der Klein assisted with data collection and participated in manuscript revisions. E. Lou participated in manuscript revisions. M. J. Zuidhof conceived the study and contributed to the editing of the manuscript. All co-authors read and approved the manuscript.

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Dedication

I would like to dedicate the current thesis to my parents and my wife because I would not complete my Master program without your encouragement and support.

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1. Chapter 1. General Introduction

1.1. Summary

The current thesis used machine learning (**ML**) approaches to extract information from the data recorded by a precision feeding (**PF**) system and make predictions based on the information. The PF system can not only feed the birds automatically but also record vast amounts of real-time data regarding the feeding activity of individual birds. Analyzing the data by ML approaches can be helpful in revealing hidden patterns and correlations in the data and make data-based decisions to further improve the PF system for feeding broiler breeders.

1.2. Introduction

With computer technology, animal agriculture is entering into an era of precision livestock farming (**PLF**). Implementation of a range of hardware and software helps precisely, continuously and automatically monitor individual animals within a herd or a flock in real-time, which can keep farmers informed about animal health, welfare, productivity, and environmental impact (Berckmans, 2017). PLF also makes it possible to apply big data analytics in animal agriculture since vast amounts of real-time data such as image and sound that reflect animal responses can be generated. By extracting meaningful information from the data, it is possible for farmers to improve management and make data-driven decisions to better meet their animal's needs (Norton and Berckmans, 2018).

The PF system developed at the University of Alberta is an innovation designed for broiler breeders (Zuidhof et al., 2019), and it is an excellent example of PLF application in poultry nutrition and management. It aimed to increase the flock uniformity of broiler breeders by allocating the right amounts of feed to each individual, which is critical for maximizing egg production and profit. Since every breeder has a radio frequency identification tag that can be read by PF stations, the PF system can identify each bird once it visits a station and then determine whether the bird needs to be fed by comparing its real-time body weight (**BW**) with its target BW that can be pre-assigned. A benefit of using the PF system is that it can record vast amounts of data with a high-speed data flow regarding the feeding activity of each bird 24 hours in a day, such as the amount of feed, the number of visits, the real-time BW of the bird, and the bird's ID. A previous study (Zuidhof, 2018) reported when feeding 40 broiler breeder pullets in a pen by a PF station from 2 to 22 weeks of age, the average number of visits and meals were 61 and 10 per day, respectively. The data collected by the PF system is a valuable source of big data in poultry science.

There are many analytical techniques to investigate the intricate patterns and correlations hidden in big data. Among these techniques, ML, which is a subfield of artificial intelligence, is an effective tool for exploring big data since it can glean important information from big data. Compared with standard statistical methods, ML can deal with a large number of correlated variables, and is less influenced by assumptions such as data distribution or homogeneity of variances. There are two main types of learning based on the nature of the available data: supervised learning explores the relationship between input variables and corresponding output results; unsupervised learning explores the underlying pattern in input data without any information from output data (L'Heureux et al., 2017). In supervised learning, regression aims to build a model to predict continuous output variables from input features, and classification can be applied to handle categorical output variables as it predicts a label. Many studies have reported using regression or classification in poultry science to predict egg production (Felipe et al., 2015), detect egg freshness (Soltani and

Omid, 2015), estimate the weight of broilers (Mortensen et al., 2016; Amraei et al., 2017; Johansen et al., 2019), analyze behaviours of broilers (Li et al., 2019), and the like. The main objective of the current thesis was to apply ML approaches to extract information from the data recorded by a PF system and make predictions based on the information.

In the current thesis, a literature review discussed the concept and application of PLF, PF system, big data, and ML (Chapter 2). There were three sub-projects in the current project: In Chapter 3, an ML model was built to predict daily egg-laying events of individual broiler breeders fed by a PF system; In Chapter 4, a supervised learning approach was developed to detect anomalies in real-time body weight of broiler breeders recorded by a PF system; In Chapter 5, an ML model was built to predict the probability of daily oviposition events occurring of individual broiler breeders fed by a PF system. In the end, innovation, limitation, implication, future research, and conclusion of the current project were discussed in Chapter 6.

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2. Chapter 2. Literature review

2.1. Precision livestock farming

2.1.1. Concepts

The incorporation of technological advances is beneficial to agriculture. Application of new technologies in agriculture helps to make efficient use of intensive data and information from a variety of networked sensors with the goal of improving crop production and environmental quality, which is called precision agriculture (Mulla, 2013). Precision livestock farming (**PLF**) refers to application of precision agriculture in animal production, which continuously and automatically monitors animal behaviours and environment, and manages animal production (Tullo et al., 2017; Berckmans, 2017a; Berckmans and Guarino, 2017). PLF is developed for the farmers who want to know more details of their animals like health and welfare, to make quick and evidence-based decisions on animals' needs (Norton and Berckmans, 2018). PLF relies on a range of information and computer technologies on the farm. Among them, sensor technology that measures different factors such as temperature, vision, and sound is crucial for PLF (Neethirajan, 2020). Other technologies that are responsible for generating, processing, storing, sharing, and visualizing data are essential as well (Van Hertem et al., 2017; Perakis et al., 2020; Astill et al., 2020). Implementation of these technologies enables farmers to monitor animal health and welfare and detect changes in animal behaviours that might negatively impact production, which increases animal production and economic efficiency. Since PLF can optimize livestock performance, the management supported by PLF might also reduce the environmental impact of livestock farming due to early warnings of PLF that can detect unwanted emissions when animals face health or welfare problems (Tullo et al., 2019).

Another benefit is that less physical contact between people and animals occurs when using PLF, which can reduce the risk of infections or diseases and the risk of influencing animal's response (Berckmans, 2017a). In conclusion, PLF can make livestock farming economically, environmentally, and socially sustainable.

2.1.2. Application of PLF in animal production

Europe is the birthplace of PLF, and it has been about 30 years since research on PLF started there (Norton and Berckmans, 2018). Many studies have reported application of automated and continuous techniques aiming at the goal of PLF. A recent Europe PLF (**EU-PLF**) project from 2012 to 2016 set a great example for the PLF application. This project was immense and comprehensive because several PLF systems involving health, welfare, production, and environment were implemented and explored in broiler, pig, and dairy farms in the project (Berckmans and Norton, 2017; Berckmans and Guarino, 2017; Guarino et al., 2017; Berckmans, 2017b). In the EU-PLF project, PLF systems were installed in 20 farms (10 fattening pig farms, 5 broiler farms, and 5 dairy cattle farms) selected in 8 different countries in Europe. Many parameters were monitored in real-time, including animal activity and distribution, sound, feed intake, climate, water intake, weight (broiler), and location (cow). It showed that these PLF systems had a lot of potential in commercial farms. In broiler farms, most general problems could be detected by continuous analysis of animal behaviour using a camera-based system. In pig farms, health problems in pigs were detected much faster by a sound-based continuous monitoring system than by farmers who were able to monitor only a few hours in a day. In dairy cattle farms, activities of dairy cattle like eating, resting, walking, or standing were monitored at individual-level for health and welfare. These applications indicated that the PLF systems could increase the production and efficiency of livestock and improve the health and welfare of animals.

2.2. Precision feeding system

2.2.1. Concepts

Precision feeding (**PF**) refers to any feeding strategy that provides the right amount of feed to the right animal at the right time. A PF system was developed for broiler breeders at the University of Alberta (Zuidhof et al., 2019). The PF system is an innovation in precise nutrition and management, as it can meet the requirements of each individual by providing precisely measured amounts of feed and record the feeding activity of each individual. The PF system can be considered as a PLF application in poultry nutrition and management because they both rely on information and computer technologies to continuously, precisely, and automatically monitor animals and record data.

The feeding process of the PF system for broiler breeders is based on a precision feeding algorithm (Zuidhof et al., 2017). The PF stations can be installed in pens to feed broiler breeders, and they are connected to computers. Each bird has a radio frequency identification tag on its wing that can be read by PF stations. As a result, a bird can be recognized when it goes into a PF station. The PF station has two chambers: a sorting stage and a feeding stage, and both stages have one entry door allowing birds to go into the stage and two exit doors where birds can leave the stage. Green LEDs are mounted above entry doors and in the feeder, which can not only help birds to find their way through the PF station at night when light is off but also prevent the birds from being photo stimulated. Each bird that goes into a station needs to wait in the sorting stage where a built-in platform scale can weigh it. Since body weight (**BW**) of broiler breeders needs to be controlled to improve BW uniformity, a BW curve for individual birds is pre-assigned in the PF system before using the PF system to feed birds. The real-time BW of an individual bird is compared with its pre-assigned BW to determine whether an individual bird needs to be fed. If the real-time BW is greater than or equal to the pre-assigned BW, the bird would be gently ejected from the sorting stage. If the real-time BW is less than the pre-assigned BW, the bird would be allowed to walk into the feeding stage where it can have access to the feeder. A bird can eat for 45 seconds called a feeding bout, and then it is gently ejected from the feeding stage. The feeding bout can also end early if the bird leaves the feeding stage. Each time only one bird is allowed to go into the sorting stage in the PF station. The next bird can go into the sorting stage once the first bird is ejected from the sorting stage or goes into the feeding stage.

The PF system can record a lot of real-time information regarding the feeding activity of individual birds in a flock 24 hours a day. Zuidhof et al., (2018) reported that when feeding 40 broiler breeder pullets in a pen by a PF station from 2 to 22 weeks of age, the average number of visits and meals were 61 and 10 per day, respectively. In addition to the number of visits and meals, feed weight before and after the feeding bout can be recorded, respectively, which can be used to calculate the feed intake for each bird for each visit. Other information can also be recorded, including the real-time BW, the pre-assigned BW, the time at the start of each visit, the time at the end of each visit, and the bird's ID. The data collected by the PF system makes it possible to analyze the feeding behaviour of birds.

2.2.2. Background

The development of the PF system aimed to increase BW uniformity of broiler breeders by controlling feed intake. Broiler breeders are parents of broiler chicken and lay fertilized eggs for incubation. BW uniformity that measures variation in a flock is important for broiler breeders, because it impacts the reproductive performance of broiler breeders (Abbas et al., 2010). Generally, a high uniform flock that means few underweight and overweight birds in a flock is expected, because too many underweight or overweight birds in a flock have a negative impact on egg production (Hudson et al., 2001). Since sexual maturity is affected by BW, the heavier hens start egg production early while the onset of egg production of lighter hens can be delayed. If underweight or overweight birds account for a large proportion in a flock, the flock would reach the peak egg production later than a normal flock and its peak production would be lower than a normal flock. Besides, the overweight birds tend to produce more double-yolk eggs due to the simultaneous development of two or more follicles, and the size of eggs laid by underweight birds are likely to be variable (Robinson and Wilson, 1996). There is an economic loss in a low uniform flock, not only because of the late and low peak egg production and useless double-yolk eggs or uneven-size eggs that can hardly be incubated, but also because of overconsumption of feed by overweight birds. Thus, increasing the flock uniformity of broiler breeders can maximize egg production and profit in the poultry industry.

Increasing flock uniformity relies on controlling the BW of individual birds. To control the BW of each individual in a flock, restricting feed intake of broiler breeders is important (Richards et al., 2010). The amount of restriction, timing, and duration are three factors for feed restriction programs (Bruggeman et al., 1999). Skip-a-day (birds are fed every other day), or 5-2 programs (in a week, birds are fed 3 days and then 1 non-feed day follows; then the birds are fed 2 days followed by 1 non-feed day) are preferred to use for improving flock uniformity in modern breeder production (de Beer and Coon, 2007). Attempts have been made to increase flock uniformity. The highest uniformity was a CV of 6.2% at 22 weeks of age reported by Zuidhof et al., (2015), which required a labour-intensive grading process. Moreover, feed restriction programs bring about a concern regarding animal welfare as feed restriction programs can result in abnormal behaviours like overdrinking and stereotypic pecking that delays social stability within a flock (Shea et al., 1990; Savory and Maros, 1993; Savory and Kostal, 1996; Tolkamp et al., 2005).

The PF system is an effective solution for increasing flock uniformity. Zuidhof et al., (2017) reported an unprecedented high BW uniformity (CV = 2%) of broiler breeder pullets at 20 weeks of age achieved by using the PF system that allocated feed to individual birds based on their real-time BW, which was much better than the best uniformity (CV= 6.2%) in a previous study (Zuidhof et al., 2015). Moreover, compared with the skip-a-day feed restriction program, the PF system kept a more stable social order despite higher overall levels of aggression and decreased feeding motivation in feed-restricted broiler breeder pullets to some extent (Girard et al., 2017a; b).

2.3. Big data

2.3.1. Concepts

Big data typically refers to vast amounts of data with complex structure and variation, and it can also refer to a field of processing and analyzing vast amounts of data. Big data can be defined as 3 "V"s in three dimensions: 1. volume: a big size of collected data; 2 variety: different forms of data (text, audio, image, *etc*.); 3. velocity: data are generated at high speed (Sagiroglu and Sinanc, 2013). The other definition has five dimensions, including not only volume, variety, and velocity, but also veracity that addresses to confidentiality, integrity, and availability of the data (Kepner et al., 2014) and value that refers to the capacity of turning data into something useful (Demchenko et al., 2014). Morota et al., (2018) concluded the characteristics of big data: 1. In big data, there are a large number of columns (variables) and rows (observations); 2. There might be some missing data, outliers, and confounding data in big data, so the data need to be cleaned before using; 3. Big data requires high computational costs.

Three keywords can help people understand big data: collection, methodology, and application (Chi et al., 2016). Generally, big data can be collected based on a high-performance data processing platform, including hardware and software, to capture, manage, process, store, share, and visualize a high-speed data flow in different forms (Singh and Reddy, 2014). Big data can be analyzed by several approaches, like statistical approaches, machine learning, and data mining (Wu et al., 2014). Big data can be applied to make better data-based decisions, predictions, and strategies because there is often a lot of meaningful information hidden in the data.

2.3.2. Application of big data in animal production

Big data has been applied in areas like marketing, banking, and manufacturing. In animal production, deployment of PLF makes it possible to analyze big data, as it can record vast amounts of data regarding the health, welfare, production, and environmental impact of animals. A great example was the EU-PLF project (Berckmans and Norton, 2017; Berckmans, 2017a; Norton and Berckmans, 2018). In this project, a massive number of sensors such as cameras and microphones were installed in 5 broiler farms, 10 pig farms, and 5 dairy cattle farms in 8 different countries in Europe. Field data were recorded efficiently: 25 images, 20,000 sound samples, and 250 sensor samples were generated per second, respectively. During 3 years of monitoring over 90 fattening periods (5,475 measuring days in total) for pigs, more than 120 terabytes of image data and 4.9 million files of sound data were generated. One potential application of the collected data was to detect respiratory problems by counting the number of coughs in the sound data. Notably, collecting data in a conventional way in animal production (e.g. recording BW and feed intake manually every two weeks in one trial) can not meet the requirements of big data analytics which typically require thousands to millions of records for training models. Compared with PLF, the conventional way for data collection can not provide real-time monitoring for animal production, which can just generate limited information. In other words, a small amount of data involving a limited number of variables is collected at a low speed. Only if the data are accumulated from a large number of trials for different herds or flocks at different locations over a long period of time, can it be used for big data analytics. Johansen et al., (2017a) reported gathering data regarding environmental variables and broiler behavior indicators over a period of 19 months including 12 batches of broilers (each batch contains about 40,000 broilers) for big data analytics.

2.4. Machine learning

2.4.1. Concepts

Machine learning is a subfield of artificial intelligence that is a branch of computing science. It has been widely used in many areas including biochemistry, robotics, medicine, bioinformatics, climatology, and the like. ML can be defined as educating computers to perform specific tasks without explicitly programming to do so (Samuel, 1959). It can also be broadly defined as computational methods to improve performance and make accurate predictions based on experience (Mohri et al., 2018). It is an interdisciplinary field that involves statistics, probability theory, cognitive science, information theory, and the like (Qiu et al., 2016). ML models are data-driven models for making predictions or clustering data, and it is suitable for exploring big data and learning important information from big data. The more data provided, the better results obtained by ML. ML has a lot of potential for big data analytics. Compared with statistical models that are commonly used in research, ML has a couple of characteristics (Bzdok et al., 2018): 1. Unlike statistical models, ML is less influenced by assumptions such as data distribution or homogeneity of variance; 2. Statistical models are used for description, while ML is used for prediction.

Machine learning algorithms include supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, transduction, and learning to learn (Information Resources Management Association, 2020). Supervised learning and unsupervised learning are most commonly used. Supervised learning aims to investigate the relationship between input variables and output variables. Based on the nature of output variables, supervised learning can be separated into two parts: classification and regression. Regression can be applied for continuous output variables as it predicts a quantity, whereas classification including binary and multiclass classification can be applied to handle categorical output variables as it predicts a label. On the other hand, unsupervised learning aims to investigate the underlying pattern in input data without any information from output data. Unsupervised learning consists of clustering and dimensionality reduction. Clustering is to separate data into several groups so that the points are similar to each other in the same group and are different in the other groups (Saxena et al., 2017). Dimensional reduction refers to the techniques that reduce the number of input variables (Huang et al., 2019). Some ML algorithms are introduced as follows:

2.4.1.1. k-nearest neighbor (KNN)

KNN is a simple, efficient, and effective supervised learning method for classification and regression. When training data and a test sample point are given, distance from all training data points to the test sample point can be evaluated. Nearest neighbors refer to the points from training data within the lowest distance that can be measured by metrics like Euclidean distance, Hamming distance, Manhattan distance, and Minkowski distance, and k refers to the number of nearest neighbors (Wu et al., 2002). A test sample point would be assigned to the class that is the most similar to the majority of its nearest neighbors. KNN performs better when there are fewer variables because it requires high computational costs. Several techniques such as ball tree, k-d tree, and tunable metric can be implemented for improving over limitation of KNN (Dhanabal and Chandramathi, 2011).

2.4.1.2. Support Vector Machine (SVM)

SVM was first introduced by Cortes and Vapnik (1995), and it is a robust and efficient method for classification and regression, even for clustering. SVM was initially developed to classify objects that are linearly separable (Raghavendra. N and Deka, 2014). Support vectors refer to objects that determine hyperplanes that are decision boundaries to separate two classes of objects. There can be many hyperplanes. The dimension of the hyperplane depends on the number of input variables, in which the dimension of hyperplane is n-1 if the number of variables is n (Noble, 2006). For example, if the number of variables is 2, the dimension of hyperplane is 1 indicating the hyperplane is a line; if the number of variables is 3, the dimension of hyperplane is 2 indicating the hyperplane is a plane. SVM aims to find the optimal hyperplane that can maximize the margin between support vectors. The margin is associated with training error, and the trade-off between maximizing the margin and minimizing the training error can be controlled. By using kernel trick that can be more efficient and less computationally expensive to transform data into higher dimensions, SVM can also be applied for non-linearly separable data.

2.4.1.3. Decision Trees

Decision trees are supervised learning models with an upside-down tree-like structure to show the decision-making process and final decisions (Stiglic et al., 2012). A decision tree grows from a root node that is a selected variable and breaks the training dataset into smaller subsets. Iteratively, each of the smaller subsets is split into much smaller subsets by a new variable called decision node until end criteria (e.g. the number of depth and the number of samples at a node) are met. Terminal nodes refer to nodes without splitting, and they represent final decisions that place data observations into cagtegories (Alsagheer et al., 2017). Decision tree algorithms determine split values at nodes, and ID3 and CART (Classification and Regression Tree) are two common ones (Che et al., 2011). The predictive performance of decisions trees can be overfitting if a decision tree is big or underfitting if a decision tree is small, so the end criteria that can control the growth of decision trees are crucial to set up properly.

2.4.1.4. Ensemble learning

Ensemble learning refers to models constructed by combining multiple base learners like several decision trees (Sagi and Rokach, 2018). Such a strategy makes it possible to improve the predictive performance of ensemble learning because it reduces the likelihood of relying on a poor base learner. Two techniques are used in ensemble learning: boosting and bagging. Boosting is sequential ensemble learning that can decrease the bias error and the variance, and it builds strong predictive models by sequentially learning from individual base learners. Bagging is parallel ensemble learning that can mainly decrease the variance by averaging the responses of the learners trained by bootstrapping samples (Zhou, 2009). Several ensemble learning algorithms have been proposed, such as random forest, AdaBoost, and Gradient Tree Boosting.

2.4.1.5. Artificial Neural Network (ANN)

ANN refers to an adaptive nonlinear algorithm consisting of numerous processing units characterized by self-adapting, self-organizing and real-time learning (Ding et al., 2013). It can be used for implementing various complex functions, including pattern generation, cognition, learning, and decision making. A multiple-perceptron neural network structure includes three layers: one input layer for receiving data, one or more hidden layers for learning, and one output layer for prediction. ANN is a supervised learning approach, so it can be used for regression and classification. ANN is a big family of analytical approaches including the back-propagation neural networks, general regression neural networks, extreme learning machines, and the like (Li et al., 2017). Compared with traditional ANN, deep neural networks (DNN), also known as deep learning, have more hidden layers and connections, enabling the model to learn complex data representations from meaningful abstractions of input data (LeCun et al., 2015). One of the typical DNN is the convolutional neural networks (CNN) that are mainly used for image processing (Jin et al., 2017). Another one is generative adversarial networks (GAN) that can tackle problems of unsupervised learning (Goodfellow et al., 2014).

2.4.2. ML workflow

A typical workflow for using ML includes three steps: data preprocessing, learning, and evaluation (Raschka and Mirjalili, 2017). In the data preprocessing step, the original dataset can be cleaned, and feature engineering approaches can be used to create features based on the cleaned dataset. In the learning step, machine learning algorithms can be chosen to build models using the preprocessed dataset. In the evaluation step, metrics can be chosen to evaluate the performance of the models. If the evaluation results are poor or not as good as we expect, it might be due to two reasons: 1. Features created in the data preprocessing step make little contribution to model prediction; 2. The algorithm used in the learning step is not appropriate. As a result, we can improve model performance by repeating the data preprocessing step to create more valuable features or the learning step to use other machine learning algorithms.

2.4.2.1. Data preprocessing

Since raw data are usually not in good format and shape, it is necessary to preprocess the raw data before training models. There are mainly two steps in data preprocessing: data cleaning and feature engineering. The purpose of data cleaning is to improve the quality of data. Since missing values, duplicated values, and inconsistent values are likely to appear in the collected raw data, the data need to be examined and corrected in terms of accuracy, consistency, completeness, and validity (Rahm and Do, 2000). Feature engineering is a critical task in data preprocessing. In machine learning, a feature refers to a variable or an attribute that can describe some aspects of individual data objects (Dong and Liu, 2018), and it can be continuous or categorical. Feature engineering aims to improve predictive performance by creating suitable features from given features (Nargesian et al., 2017).

Feature engineering involves several approaches like feature transformation, feature generation, feature selection, and feature extraction.

2.4.2.2. Learning

A model can be trained after data preprocessing. The preprocessed data are separated into two sets: the training set used for training models and the testing set used for testing the models. The ratio of the training set and the testing set is usually set to 60:40, 70:30, or 80:20 depending on the amount of available data (Anifowose et al., 2011). The best model can be selected by training different algorithms. As a popular strategy for model selection, cross-validation trains several models on subsets of input data to achieve the average performance of these models (Arlot and Celisse, 2010). Although cross-validation is computationally expensive, the risk of overfitting can be reduced. There are different strategies for cross-validation such as k-fold and leave-one-out. In k-fold cross-validation, the dataset is split into k subsets, and then each subset is used once as a validation while the k-1 remaining subsets are used for training. As a result, k models are fitted to calculate the average performance (Meijer and Goeman, 2013). Leave-one-out cross-validation is a special case of k-fold cross-validation, when the number of samples is equal to the number of folds (Wong, 2015). Compared with k-fold cross-validation, leave-one-out can provide an almost unbiased estimation of generalization performance but require high computational costs. Thus, leave-one-out is appropriate for the models that are less computational. Hyper-parameters refer to parameters in machine learning algorithms that control the learning process and can not be estimated from data. Since the predictive performance of some algorithms relies on the hyper-parameters, an appropriate combination of the hyper-parameters is crucial. The hyper-parameters can be optimized by using techniques including grid search, random search, and Bayesian optimization (Nishio et al., 2018).

2.4.2.3. Evaluation

An appropriate metric is needed to evaluate the performance of a trained model. In supervised learning, classification and regression are evaluated by different metrics. The confusion matrix is a fundamental tool for binary classification and multi-label classification (Tripathy et al., 2016). Based on the confusion matrix, a series of metrics can be generated to evaluate how well a model predicts a label, including overall accuracy, precision, recall, and the like. For regression models that predict a quantity, MSE (mean squared error), RMSE (root mean squared error), MAE (mean absolute error), and R square are usually used as the metrics. Compared with supervised learning, unsupervised learning like k-means and DBSCAN (Density-based spatial clustering of applications with noise) can not be immediately evaluated by output results since the output results are not available. Silhouette coefficient that considers both the intra-cluster metric and the inter-cluster metric for each sample is the most common metric for evaluating unsupervised learning (Palacio-Niño and Berzal, 2019).

2.4.3. Application of ML in poultry production

Egg production of laying hens and growth performance of broilers are big concerns in poultry production, and ML has a lot of potential to deal with them. Felipe et al., (2015) reported using an artificial neural network for predicting total egg production of quail from 35 to 260 days of age at flock-level. Weight, weight gain, egg production, egg quality measurements at the early age, and the like were used as input variables. In addition to egg production, machine learning can also be used to detect drops in the egg production curve in commercial laying hens. Morales et al., (2016) reported using an SVM approach to detect the problematic days and achieved an accuracy of 0.9854. Ramírez-Morales et al. (2017) reported a similar study that used neural networks with an accuracy of 0.9896. These two studies are helpful for commercial farms to monitor the health of hens and the production of eggs. For broilers, growth performance can be affected by many factors that could be used as input variables for BW prediction. Some studies reported using dynamic neural networks to capture the relationships (Johansen et al., 2017b, 2019a; b). One of the studies aimed to forecast BW, feed consumption, and water consumption using environmental conditions such as heating, light, ventilation, humidity, and temperature as input variables. With the application of image capture techniques, images can be used as input data for supervised learning algorithms to predict the weight and drinking and feeding behaviour of broilers (Mortensen et al., 2016; Li et al., 2019). Using sensor technology and big data for monitoring animal behaviours and the environment, ML can be applied for welfare improvement. Lee et al., (2015) reported using an SVM model with an accuracy of about 96% for analyzing sounds of laying hens, which could detect and classify the stress from changes in the sounds, such as physical stress from changes in temperature and mental stress from fear. A similar study (Du et al., 2020) reported a vocalization detection method based on an SVM model to assess thermal comfort conditions for laying hens, and the sensitivity and precision of the SVM classifier were around 95% and 97%, respectively. These applications can be used to indicate the state of animal welfare that helps people to manage the welfare of the flock. ML can also be applied in other aspects in the poultry industry, such as egg freshness detection, poultry catching, and environment control (Jaiswal et al., 2005; Soltani and Omid, 2015; Debauche et al., 2019).

2.5. Conclusion

Application of PLF, big data, and ML is beneficial for animal agriculture. PLF that monitors animal behaviours and the environment by different kinds of sensors can record a lot of information for big data analytics. To deal with big data, ML is a useful tool because it can take into account a large number of variables in the presence of complicated interactions and capture complex relationships among these variables. By using ML, the hidden patterns and correlations in data can be revealed to make better data-based decisions, predictions, and strategies. Similar to PLF, the PF system is an innovation in precise nutrition and management developed for broiler breeders. It can continuously, precisely, and automatically feed birds and record vast amounts of real-time data regarding the feeding activity of birds. The vast amounts of data recorded by the PF system can provide a valuable source of big data. However, it is challenging to extract meaningful information from the data recorded by the PF system and make predictions based on the information. Thus, it would be worth dealing with the data using ML approaches, which could help to understand the information in the data and make data-based predictions for knowing behaviour of breeders fed by the PF system.

2.6. Objectives

The main objective of the current thesis was to apply ML approaches to extract information from data recorded by a PF system and make predictions based on the information. There were three subprojects in the current project, and the objective of each sub-project was shown below:

1. The objective of the first subproject was to build an ML model to identify daily egg-laying events of individual broiler breeders fed by a PF system based on the data that recorded their feeding activity (Chapter 3).

2. Anomalous real-time BW data are sometimes recorded by a PF system, which have negative impacts on BW estimation. Although common anomaly detection methods were used to clean these anomalous real-time BW data, these methods were not very effective. Before further investigating prediction of oviposition events, the second subproject aimed to develop a supervised learning approach to detect anomalies in real-time BW of individual broiler breeders recorded by a PF system (Chapter 4).

3. Since the ML model in Chapter 3 had two limitations: i) It could only be used to identify a daily egg-laying event on a subsequent day; ii) The prediction outputs were binary labels, the objective of third subproject was to improve it. An ML model was built to predict the probability of oviposition events occurring of individual broiler breeders in one day using features around a specific time in the day (Chapter 5).

2.7. Hypotheses

1. Features regarding the feeding activity of individual birds in one day developed from a dataset recorded by a PF system could predict oviposition events of individual birds (Chapter 3).

2. Features regarding the feeding activity of individual birds recorded by a PF system could detect anomalous real-time BW observations recorded by the PF system (Chapter 4).

3. Features regarding the feeding activity of individual birds around a specific time in one day developed from a dataset recorded by a PF system could predict oviposition events of individual birds (Chapter 5).

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3. Chapter 3. Application of random forest classification to predict daily oviposition events in broiler breeders fed by a precision feeding system

3.1. Abstract

In group-housed poultry, hormone and environment modulated variability in the processes of follicle maturation and egg formation make it difficult to predict a daily egg-laying event (oviposition). Recording daily egg laying events has required individual cages or expensive technology such as RFID equipped nests or labor intensive trap nests. The current study implemented the random forest classification algorithm to predict oviposition events of 202 free run Ross 708 broiler breeder hens fed by a precision feeding system from week 21 to 55, based on a dataset recording information of all visits to the station. The raw dataset from the precision feeding system was processed for 6 classes of features (34 features in total) in relation to feeding activity and real-time body weight of birds. The dataset of the features was then combined with a corresponding daily individual oviposition record. The processed data were shuffled and separated into 2 subsets: 90% for training, and 10% for testing. Important features were selected using random forest-recursive feature elimination with 5-fold cross-validation. A total of 28 features were selected to build the classification model. Overall accuracy of the model using the testing samples was 0.8482, and out-of-bag score was 0.8510. Precision (a measure of purity in retrieving) of no egg-laying and egg-laying, recall (a measure of completeness in retrieving) of no egg-laying and egg-laying were 0.8814, 0.8090, 0.8520 and 0.8453, respectively. The Kappa coefficient of the model was 0.6931, indicating substantial agreement (substantial agreement range: 0.61-0.80). This model was able to identify whether a free run broiler breeder laid an egg or not on a certain day during the laying period with around 85%

accuracy.

Key words: binary classification; egg-laying event; machine learning; variable selection.

3.2. Introduction

Domestic hens lay eggs in sequences of one or more eggs, separated by one or more non-laying days called a pause (Robinson et al., 1991; Zakaria et al., 2005). Sequence length and pause length depend on the timing of ovulation and oviposition, which are further determined by follicle maturation and egg formation processes (van der Klein et al., 2020). Because of variability in the maturation process modulated by hormone and environmental factors, the exact day and time of oviposition events during the laying period is highly variable. Given that oviposition contributes to nutrient requirement, identifying oviposition events might be helpful in future precision feeding applications aimed at increasing feed efficiency and reducing excretion of N, P, and CO_2 to the environment. The daily oviposition event of a caged bird can be readily recorded upon the onset of egg laying. In a flock of free run birds, however, it is difficult to determine the daily oviposition event of each individual bird unless a trap nesting system is provided. There might be some clues to indicate the oviposition in broiler breeders, like a decreased body weight (**BW**) after oviposition because of the expulsion of the egg mass (e.g. about 60 g). However, these subtle performances are not easily noticed, due to a series of complex daily activities of the broiler breeder and no effective machine to monitor the bird's status and behavior over the whole laying period.

A precision feeding system was developed at the University of Alberta (Zuidhof et al., 2017; Zuidhof et al., 2019). The system was designed to increase BW uniformity in the flock by making decisions in real-time on whether or not to feed the individual bird after weighing it and feeding it (or not) based on its BW relative to the target BW. In contrast with conventional feeding management, the individual precision-fed bird is able to get free access to the station 24 h per day. Vast amounts of real-time feed intake, time of visiting, and BW data can be recorded, being helpful to analyze each bird's behavior.

Random forest is an ensemble learning algorithm in machine learning proposed by Breiman (1999), and it is a widely used machine learning method with high prediction accuracy. It consists of a large number of decision trees with randomly selected features, which are used to construct a deterministic forest by averaging their predictions (Breiman, 2001). Moreover, it is suitable to deal with data of high dimensionality and multi-collinearity (Evans et al., 2011), because the most relevant variables can be selected from a large number of variables (Genuer et al., 2010). Since there were many features regarding feeding activity and real-time BW of birds in this study, random forest algorithm was used to handle these features.

The objective of the current research was to develop a random forest classification model to predict oviposition events of free run broiler breeders fed by a precision feeding system, based on observations recorded by the system.

3.3. Materials and methods

3.3.1. Data Collection

The data used in this study was obtained from previous studies in our laboratory (van der Klein et al., 2018a; van der Klein et al., 2018b). The animal protocol for the study was approved by the University of Alberta Animal Care and Use Committee for Livestock (AUP00000121).

3.3.1.1. Precision Feeding System Dataset

A total of 202 Ross 708 free run broiler breeder pullets were randomly allocated to 8 environmentally controlled rooms so that temperature and humidity of 8 rooms were as similar as possible. Each room was equipped with a precision feeding station (Figure 3-1). Birds were trained to use the precision feeding station with ad libitum feed intake from d 0 to d 16 of age. From d 17 to week 55, birds were allowed to access to the feeder in the precision feeding station for a duration of no more than 45 seconds (a feeding bout). The precision feeding system was developed to increase BW uniformity in a flock. Thus, if a bird's BW was lower than the target BW, the bird could have a meal and then ejected. Birds were immediately ejected by the precision feeding station without any provision of feed if their BW were greater than target BW. During the entire experiment, water was provided *ad libitum* with nipple drinkers. Water intake was not recorded. Each bird was given a radio frequency identification tag on the wing so that information about each bird upon each visit to the station could be recorded in a database. From week 21 to 55, 2,378,920 visiting events for 202 birds recorded by precision feeding system were considered as observations. The relevant information from the database are shown in Table 3-1.

3.3.1.2. Egg Production Dataset

Daily oviposition events were confirmed by palpation every morning at 7:00 AM. Since it takes about 20 hours to synthesize egg shell in shell gland, it indicates the egg shell has almost or completely formed and the egg would be laid in the following hours if the egg shell can be palpated by finger. Thus, hens with a hard-shelled egg in the shell gland at 7:00 AM were assumed to have laid an egg later that day. From week 21 to 36, cloacae of all hens were palpated every day; from week 37 to 55, daily palpation was performed for 7 consecutive days followed by 7 days without palpation. As a result, egg-laying events were not counted in even week 38, 40, 42…54. Once a bird was dead or a sick bird was culled, palpation was stopped and its oviposition events were not counted. A detailed explanation of the materials and methods can be found in the previous studies (van der Klein et al., 2018a; van der Klein et al., 2018b).

3.3.2. Data Processing

3.3.2.1. Feature Engineering

Since the precision feeding stations were sometimes visited by more than one bird at a time, the raw dataset was cleaned by using Z-scores method (Shiffler, 1988) (deleting observations where daily BW were not within the range of mean ± 3 × standard deviation (**SD**) of daily BW of each individual bird). Among 2,378,920 observations, 14,159 observations were identified as outliers and were removed. After cleaning the data, 2,364,761 observations in the station dataset were processed to extract 6 classes of features (34 features; Table 3-2):

1. Age: The age (d) of each bird was recorded by precision feeding system.
2. BW: Mean and SD of BW (g) for each bird in a given day was calculated according to RealtimeBW recorded by the precision feeding system. μ_{BW} and σ_{BW} were the mean and SD of BW for each bird in one day, respectively.
3. FI: For each bird, feed intake (**FI**) (g) in every hour (from 00:00 h to 24:00 h) in each day was calculated, and there were twenty four features in total (e.g. FI_0h represented 00:00 h to 01:00 h feed intake from to in one day).
4. TI: Time interval (**TI**) (s) between 2 successive meals was calculated according to the equation:

$$\text{TI} = \text{BoutStartTime}_{(m+1)} - \text{BoutEndTime}_{(m)} \quad (1)$$

where BoutStartTime $_{(m+1)}$: BoutStartTime corresponding to the m+1th meal in one day; BoutEndTime $_{(m)}$: BoutEndTime corresponding to the mth meal in one day. μ_{TI} and σ_{TI} were the mean and SD of TI for each bird in one day, respectively.

5. ΔBW: BW (g) change between 2 successive meals was calculated according to the equation:

$$\Delta\text{BW} = \text{RealtimeBW}_{(m+1)} - \text{RealtimeBW}_{(m)} \quad (2)$$

where RealtimeBW$_{(m)}$: RealtimeBW recorded by a precision feeding system corresponding to the mth meal in one day. $\mu_{\Delta BW}$ and $\sigma_{\Delta BW}$ were the mean and SD of ΔBW for each bird in one day, respectively.

6. Daily: FI, Meals, and Visits represented feed intake (g), number of meals, and number of visits to a precision feeding station in one day, respectively.

3.3.2.2. Data Combination

The 34 features were combined with ID and daily oviposition result of each bird to form the processed dataset (Figure 3-2). Eventually, the data with 35,443 rows (daily oviposition events from week 21 to 55, and week 38, 40, 42…54 were not included) × 36 columns (34 features, "ID" of the birds, and oviposition results) was acquired. Following machine learning methodology, the processed data were shuffled and randomly divided into training samples and testing samples, with 90% (31,898 samples) and 10% (3,545 samples), respectively (Table 3-3). Although a split ratio of 70:30 or 80:20 of training samples and testing samples are usually used, 10% processed data was used for testing in this study because it included 1,541 egg-laying events and 2,004 no egg-laying events and it was large enough.

3.3.3. Random Forest Classification

Random forest classification was implemented by using Python 3.7.0 and sklearn.ensemble.RandomForestClassifier (**RFC**) in scikit-learn library 0.21.0 (Pedregosa et al., 2011). Graphviz 2.3.8 (Ellson et al., 2001) was used to draw the decision trees in random forest algorithm. In RFC, three hyper-parameters n_estimators, random_state and oob_score were "500", "0" and "True", respectively. Among them, n-estimators referred to the number of trees in random forest, and a large number of trees can improve model accuracy because of limited generalization error (Prasad et al., 2006). In this study, 500 trees were grown in the model for higher accuracy than the default value (10 trees). It can also partially reduce the negative impact of the problem that one of the correlated features might become more important when it was randomly selected at a node (Alsahaf et al., 2018). Random_state = 0 was for randomness of the bootstrapping of samples and the sampling of features. Oob_score = True meant out-of-bag samples were considered as another data set of testing samples to validate the random forest model. The other hyper-parameters were default values, including min_samples_leaf = "1", min_samples_split = "2", max_depth = "None", and max_features = "auto". It meant the nodes would not stop splitting until only one class of samples was at the node or at least 2 samples at the node, and each node should contain at least 1 sample. There was no restriction for maximum depth of growth, and the size of the random subsets of features to split a node was the square root of the number of features. The default value of bootstrap which was "True" was used, indicating subsets of samples were used to grow a tree by drawing samples randomly with replacement (Strobl et al., 2007). The default value of class_weight which was "None" was used, because there was no need to adjust weights of egg-laying events and no egg-laying events. Importance is the decrease of Gini impurity in random forest classification (Louppe et al., 2013), which reflects how well the samples at a parent node which is a selected feature are separated into 2 child nodes (Menze et al., 2009). In scikit-learn library, the default value of measuring importance was Gini, which measures the impurity of the samples at child nodes resulted from a parent node split by a feature (Qi, 2012). In each split, the sum of Gini value of child nodes must be less than that of their parent node. Based on the reduction of Gini value from the parent node to child nodes for a feature, the average of the reduction among all the trees was calculated, which was the importance of the feature.

In this study, random forest-recursive feature elimination (**RF-RFE**) was used to select important features. At each iteration, it ranks the features based on measured importance of features and then eliminates the least relevant feature till the most informative features are retained (Granitto et al., 2006; Pang et al., 2012; Diao et al., 2020). RF-RFE was implemented by using scikit-learn library 0.21.0 sklearn.feature_selection.RFECV (Pedregosa et al., 2011). All parameters were all default values, except that estimator, cv, and scoring were RFC, 5, and "accuracy", respectively. Among them, estimator = RFC referred to the random forest classification model. Cv = 5 meant that 5-fold cross-validation was applied for feature selection using training samples, based on the importance of the features measured by random forest. Score = "accuracy" indicated accuracy was used to evaluate the model during feature selection.

Testing samples were used to evaluate the performance of the classification model built on the selected features, and out-of-bag samples were used to validate the model. True positive (**TP**), true negative (**TN**), false positive (**FP**), and false negative (**FN**), respectively, were presented in a confusion matrix (Tripathy et al., 2016), and they were then used to calculate overall accuracy, precision, recall (Lu et al., 2004), as well as Kappa coefficient (Cohen, 1960):

$$\text{Overall Accuracy } (P_0) = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

$$\text{Precision (egg-laying)} = \frac{TP}{TP+FP} \tag{4}$$

$$\text{Precision (no egg-laying)} = \frac{TN}{TN+FN} \tag{5}$$

$$\text{Recall (egg-laying)} = \frac{TP}{TP+FN} \tag{6}$$

$$\text{Recall (no egg-laying)} = \frac{TN}{TN+FP} \tag{7}$$

$$\text{Kappa coefficient} = \frac{Po - Pe}{1 - Pe} \tag{8}$$

where Po is the proportion of observed level of agreement (Overall Accuracy), and Pe is the proportion of agreements expected by chance:

$$Pe = \frac{(TP + FP) * (TP + FN) + (TN + FP) * (TN + FN)}{(TP+TN+FP+FN)^2} \tag{9}$$

3.4. Results

3.4.1. Feature importance and selection

To build the classification model, important features were selected from original 34 features and the number of the selected features was determined using RF-RFE with 5-fold cross validation. Figure 3-3 showed the highest accuracy was 0.8522 with 28 features selected. Figure 3-4 showed the ranked importance score of the 28 selected features which were used to build the model. Among the 28 features, FI was the most important one, followed by μ_{TI}, Age (d), σ_{BW}, etc. FI _0h, FI _1h, FI _2h, FI _3h, FI _22h, and FI _23h were not selected.

3.4.2. Model Evaluation

Testing samples were used to evaluate the classification model. In Table 3-4, the performance of the model was described in a confusion matrix. Based on the values (TP, TN, FP, FN) in the confusion matrix, a series of rates for the binary classifier were computed. The overall accuracy of the model was 0.8482, and out-of-bag score was 0.8510. Precision of no egg-laying and egg-laying, recall of no egg-laying and egg-laying were 0.8814, 0.8090, 0.8520 and 0.8453, respectively. The Kappa coefficient of this classification model was 0.6931.

3.5. Discussion

There have been some studies regarding prediction of egg production using mathematical or artificial intelligence models (Grossman and Koops, 2001; Ahmad, 2011; Omomule et al., 2020). These studies stimulated egg production curve for a flock or an individual over a period of time, and they used hen-day egg production (percentage) or number of eggs to measure the prediction results. Compared with these previous studies, this study is the first time to identify oviposition events that if a hen lays in one day, and the result was binary classification which were " yes" and "no". Previous studies have also reported prediction of oviposition times which was based on a mathematical model of ovulatory cycle (Etches and Schoch, 1984; Johnston and Gous, 2007). In this study, feeding activity and body weight were used for prediction. Another innovation of this study was using vast amounts of real-time data for prediction due to application of precision feeding system.

As data-driven models, machine learning methods are able to solve a large number of features and produce accurate predictions (Ellis et al., 2020). Felipe et al. (2015) reported artificial neutral network was the best predictive model for total egg production in meat type quail, based on 30 input variables including weekly body weight, body weight gain, egg weight and the like. In this study, machine learning method was used to predict oviposition based on the visit information recorded by a precision feeding system. The precision feeding system is capable of capturing a lot of details throughout 24 hours as long as birds visit the station. Zuidhof (2018) reported the average visit frequency and average meal frequency of the bird fed by precision feeding system were 61 and 10 per d, respectively, which indicated 61 observations regarding a bird's feed intake, real-time BW, and time were recorded per day, on average. Such frequent visits lay a foundation for analyzing bird's behavior. A series of features were used to describe a bird's age, fluctuation of BW, distribution of feed intake, time interval between the successive meals, and BW change between the successive meals. However, no features performed very well in prediction because they were all weak classifiers. As an ensemble machine learning algorithm, random forest algorithm can combine several weak classifiers together so that a strong classifier was built to achieve better performance with low bias and low variance (Diaz-Uriarte and Alvarez de Andres, 2006). On the basis of decision trees, random forest classifier can make an accurate prediction by the majority votes of many trees. Overfitting is no longer an issue for random forest because of its ensemble and bootstrapping schemes (Qi, 2012).

Although random forest was regarded as a "black-box", it can be explicable to some extent. To construct a single tree, 20,195 samples were randomly drawn from 31,898 training samples with replacement. In each decision tree, binary splits were determined by choosing the optimal threshold value to minimize the impurity if the attribute is numeric

(Berzal et al., 2004). In this study, 34 features were all numeric attributes. For example, the optimal threshold of FI_12h was <=13.359 (Figure 3-5) leading to the highest information gain, which was selected from the range of FI_12h. This was a conditional statement at the node for 167 samples (bootstrapping samples) to make a split. By answering True or False, 166 samples and 1 sample were separated into two child nodes, respectively, with a Gini value of 0.26. At this node, 226 samples (training samples) indicating no oviposition events and 41 samples (training samples) indicating oviposition events would be classified by the conditional statement that FI_12h was no more than 13.359.

By using the RF-RFE, the least important features can be pruned from the set of features, which recursively repeated several times until the desired number was reached. In this study, 28 features were selected to build the model, suggesting that the highest accuracy of the model appeared when the first 28 features were selected. The importance score of FI was the highest among the 28 features, which indicated that the daily feed intake in one day made the greatest contributions to the prediction. Feed intake increased in the egg forming day (Morris and Taylor, 1967), because more nutrients and energy were needed for egg formation. In this study, however, the prediction benefited from feed intake mainly due to a decrease of BW. Target BW was preset in precision feeding system before the experiment, and a breeder was allowed to have a meal only if its real-time BW was lower than target BW. Body weight drop can be caused by oviposition, excretion, and metabolic losses (CO_2 and water), and a dramatic body weight drop is most likely to follow oviposition. As a result, a dramatic BW drop caused by oviposition can help the bird to meet the criterion for receiving a meal, which would increase the daily feed intake or number of meals in a short time on an egg-laying day. Given that the same amount of feed was distributed by the precision feeding system every meal, more feed intake resulted in more meals in one day. Thus, there might be differences in the number of meals on egg-laying and no egg-laying days. As a result, Meals was an important feature for prediction. In relation to Meals, μ_{TI} and σ_{TI} were selected as important features, because more meals in one day meant a shorter time interval between two successive meals. On the other hand, the BW drop caused by egg-laying might decrease the average of BW in one day and increase the standard deviation of BW in one day, which explained why μ_{BW} and σ_{BW} were selected as important features for prediction. Similarly, considering the BW drop was associated with the change of BW between two successive meals, $\mu_{\Delta BW}$ and $\sigma_{\Delta BW}$ were selected as well. The features of feed intake from 22:00 h to 03:00 h were pruned, whereas the features of feed intake from 04:00 h to 21:00 h were retained. Although the features of feed intake at 04:00 h, 05:00 h and 21:00 h were selected as important features, they were less important than the other selected features. According to Campo et al. (2007), eggs are normally laid from 7:00 am to 16:00 pm. Since oviposition events are more likely to occur in the daytime, features of feed intake in the evening were less important for prediction. Age (d) was a selected feature because there might be a threshold day of age from week 21 to 55 as a potential binary split.

The classification model aimed to classify the oviposition events into 2 groups: no egg-laying and egg-laying. This study focused on prediction of when an egg-laying event occurs, as well as when a no egg-laying event occurs. In the confusion matrix, TN and FN represented the correct and wrong prediction of the event of no egg-laying, respectively. Similarly, TP and FP represented the correct and wrong prediction of the event of egg-laying, respectively. Precision and recall were used to measure the effectiveness in retrieving of the model: precision was for excluding non-relevant items from the retrieved set, and recall was for including relevant items in the retrieved set (Buckland and Gey, 1994). The results showed that the precision of no egg-laying event (0.8830) was higher than that of egg-laying event (0.8080), indicating the model was more effective to exclude egg-laying events when predicting no egg-laying event than to exclude no egg-laying events when predicting egg-laying event. The recall of both no egg-laying and egg-laying were around 0.85, indicating the effectiveness of predicting no egg-laying events in including no egg-laying events was almost the same as that of predicting egg-laying events in including egg-laying events. By bootstrapping samples, around 37% of samples called out-of-bag samples were randomly excluded to build the random forest model (Breiman, 1996). The out-of-bag accuracy (0.8510) was in line with overall accuracy (0.8482), indicating the model was not overfitting and can generalize to new data. The Kappa coefficient of the model was in the substantial agreement range (0.61-0.80) (Viera and Garrett, 2005), indicating a robust measure of the difference between observed agreement (0.8482) and expected agreement (0.5055; the expected agreement was not shown in Table 3-4).

The improvement in accuracy of predicting oviposition in the study should be further explored by considering biological characteristics of broiler breeders and strategies of machine learning. On the one hand, features for prediction in this study were associated with each visit of breeders to the precision feeding station. There might be some features regarding nutrition (e.g. energy requirement) which can make a contribution to the prediction. On the other hand, since the objective of this study was just to propose a prediction method using random forest classification, there was no comparisons with other machine learning methods like SVM and ANN. Thus, the improvement of prediction might be achieved by using other machine learning methods.

3.6. Conclusion

To our knowledge, this is the first time the random forest algorithm was applied to predict daily oviposition events in broiler breeders. The dataset was from a precision feeding system which can automatically feed the broiler breeders and precisely record data in relation to each visit of the bird. Built on the selected 28 features extracted from the raw dataset, the strong classifier (classification model) was able to predict the daily oviposition event of free run broiler breeders with an overall accuracy of 0.8482. Since oviposition is a contributor to nutrient requirements, identifying egg-laying events of free run broiler breeders would be beneficial for providing the birds with precise amounts of feeds appropriate for individual egg production levels. This approach would increase feed efficiency, reduce production costs, and reduce excretion of N, P, and CO_2 into the environment. To improve the prediction accuracy of the model, the biological characteristics of broiler breeders and other machine learning methods might be considered.

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3.9. Tables

Table 3-1. Crucial information regarding each visit of breeders to the station in database recorded by precision feeding system.

Variable	Units	Description
ID	-	The unique number identifying an individual bird.
Day	d	The age of the bird.
DateTime	s	Unix time at the start and end of every visit to a precision feeding station.
RealtimeBW	g	The BW recorded by the precision feeding system to make the feed or no feed decision when a bird visited the station.
FI	g	Feed intake.
Hour	h	Hour of the day.
BoutStartTime	s	Unix time at the start of a feeding bout.
BoutEndTime	s	Unix time at the end of a feeding bout.

Table 3-2. Six classes of features extracted from the precision feeding system dataset.

Class[1]	Features	Number
Age[2]	Age (d)	1
BW[3]	μ_{BW}, σ_{BW}	2
FI[4]	FI _0h, FI _1h, FI _2h, FI _3h, FI _4h, FI _5h, FI _6h, FI _7h, FI _8h, FI _8h, FI _9h, FI _10h, FI _11h, FI _12h, FI _13h, FI _14h, FI _15h, FI _16h, FI_17h, FI _18h, FI _19h, FI _20h, FI _21h, FI _22h, FI_23h	24
TI[5]	μ_{TI}, σ_{TI}	2
ΔBW[6]	$\mu_{\Delta BW}$, $\sigma_{\Delta BW}$	2
Daily[7]	FI, Meals, Visits	3
Total		34

[1] Class refers to a category of features describing certain aspect of broiler breeders.
[2] Age: a class in relation to age of a broiler breeder (Age (d)).
[3] BW: a class in relation to BW of a broiler breeder in one day. μ_{BW} indicates mean of BW, and σ_{BW} indicates SD of BW.
[4] FI: a class in relation to feed intake in a specific hour of the day. E.g. FI _0h indicates feed intake from 00:00 h to 01:00 h.
[5] TI: a class in relation to time interval between two successive meals. μ_{TI} indicates mean of TI, and σ_{TI} indicates SD of TI.
[6] ΔBW: a class in relation to change of BW between two successive meals in one day. $\mu_{\Delta BW}$ indicates mean of ΔBW, and $\sigma_{\Delta BW}$ indicates SD of ΔBW.
[7] Daily: a class in relation to feed intake in one day (FI), number of meals in one day (Meals), and number of visits to a precision feeding station in one day (Visits).

Table 3-3. The number of no egg-laying events and egg-laying events in processed dataset.

Oviposition events	Processed dataset	Training samples	Testing samples
No egg-laying event	20,530	18,526	2,004
Egg-laying event	14,913	13,372	1,541
Total	35,443	31,898	3,545

Table 3-4. Evaluation results of random forest classification model by using the 10% testing data (3,545 samples included).

		Predicted oviposition event [2] (d)		Precision [3]	Recall [4]
		Egg-laying	No egg-laying		
Actual oviposition event (d)	Egg-laying	1,313	228	0.8090	0.8520
	No egg-laying	310	1,694	0.8814	0.8453
Overall accuracy [5]		Out-of-bag score [6]		Kappa coefficient [7]	
0.8482		0.8510		0.6931	

[1] True positive (**TP**): predicted and actual oviposition event was an egg-laying event; true negative (**TN**): predicted and actual oviposition event was no egg-laying event; false positive (**FP**): predicted oviposition event was an egg-laying event but actual oviposition event was no egg-laying event; false negative (**FN**): predicted oviposition event was no egg-laying event but actual oviposition event was an egg-laying event.

[2] Oviposition event indicated whether a bird laid an egg or not in one day. Predicted oviposition event was estimated by the random forest classification model.

[3] Precision (egg-laying) = TP / (TP + FP); precision (no egg-laying) = TN / (TN + FN), based on 10% testing samples.

[4] Recall (egg-laying) = TP / (TP + FN); recall (no egg-laying) = TN / (TN + FP), based on 10% testing samples.

[5] Overall accuracy = (TP + TN) / (TP + TN + FP + FN), based on 10% testing samples.

[6] Out-of-bag score was the validation result of the random forest model by using the out-of-bag samples which were randomly excluded samples from 90% training samples.

[7] Kappa coefficient = (Po - Pe) / (1 - Pe), where Po is overall accuracy, Pe = ((TP + FP) * (TP + FN) + (TN + FP) * (TN + FN)) / $(TP + TN + FP + FN)^2$, based on 10% testing samples.

3.10. Figures

Figure 3-1. Photo of a precision feeding system which was used to feed broiler breeders in the trial.

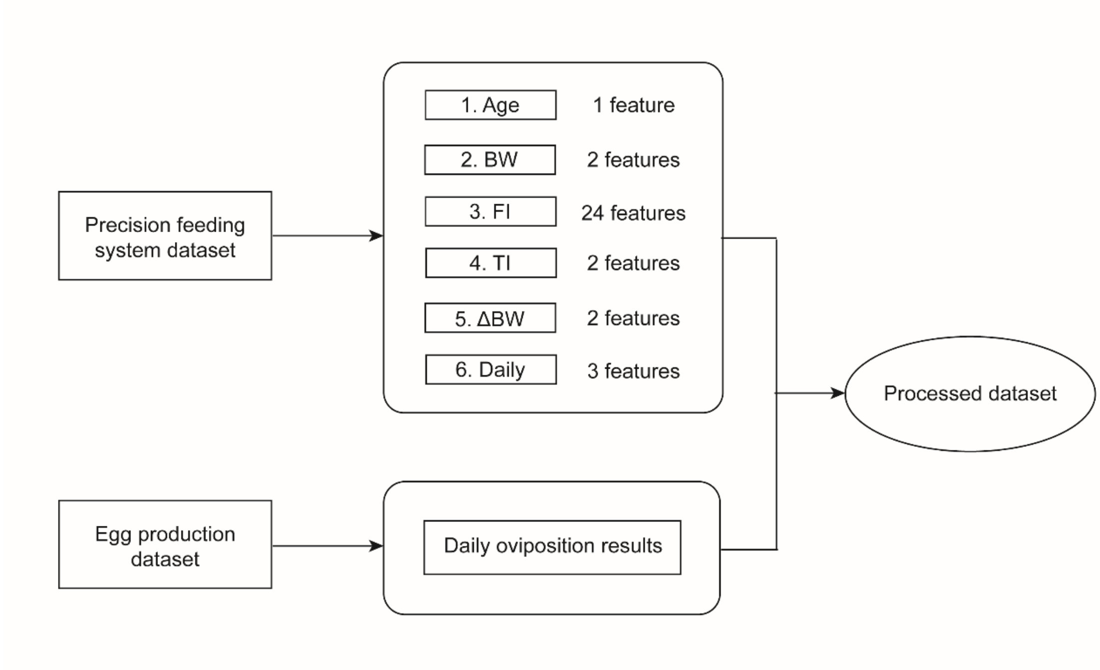

Figure 3-2. Graphical illustration of data processing. Six classes of features were extracted from a precision feeding system dataset (1.Age: a class in relation to the age of hens, including 1 feature; 2. BW: a class in relation to BW of hens in one day, including 2 features; 3. FI: a class in relation to feed intake in a specific hour of the day, including 24 features; 4. TI: a class in relation to time interval between two successive meals, including 2 features; 5. ΔBW: a class in relation to change of BW between two successive meals, including 2 features; 6. Daily: a class in relation to the sum of certain feature, including 3 features). Then, they were combined with the daily oviposition events recorded in egg production dataset to form the processed dataset.

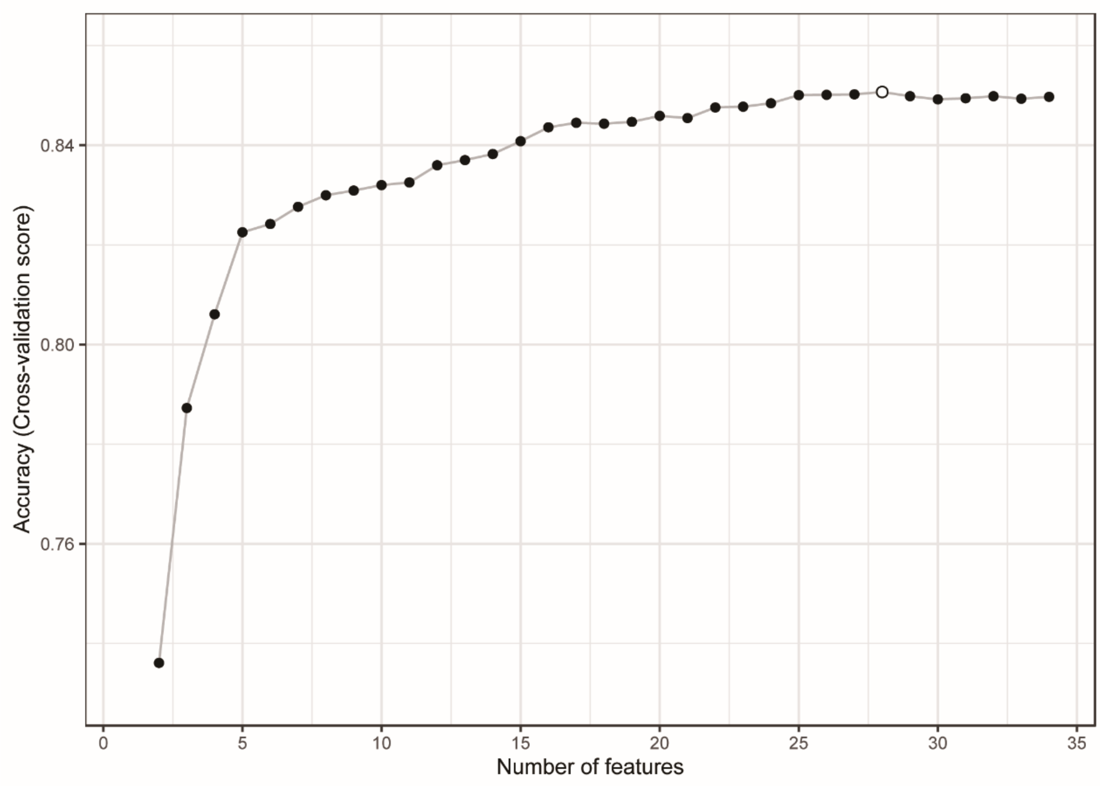

Figure 3-3. Feature selection by using random forest-recursive feature elimination with 5-fold cross validation and 90% training samples. The curve represented the classification accuracy and the dots represent the number of features which were used to build the model. The circle marked in the figure showed the highest accuracy of the classification where the first 28 features were selected.

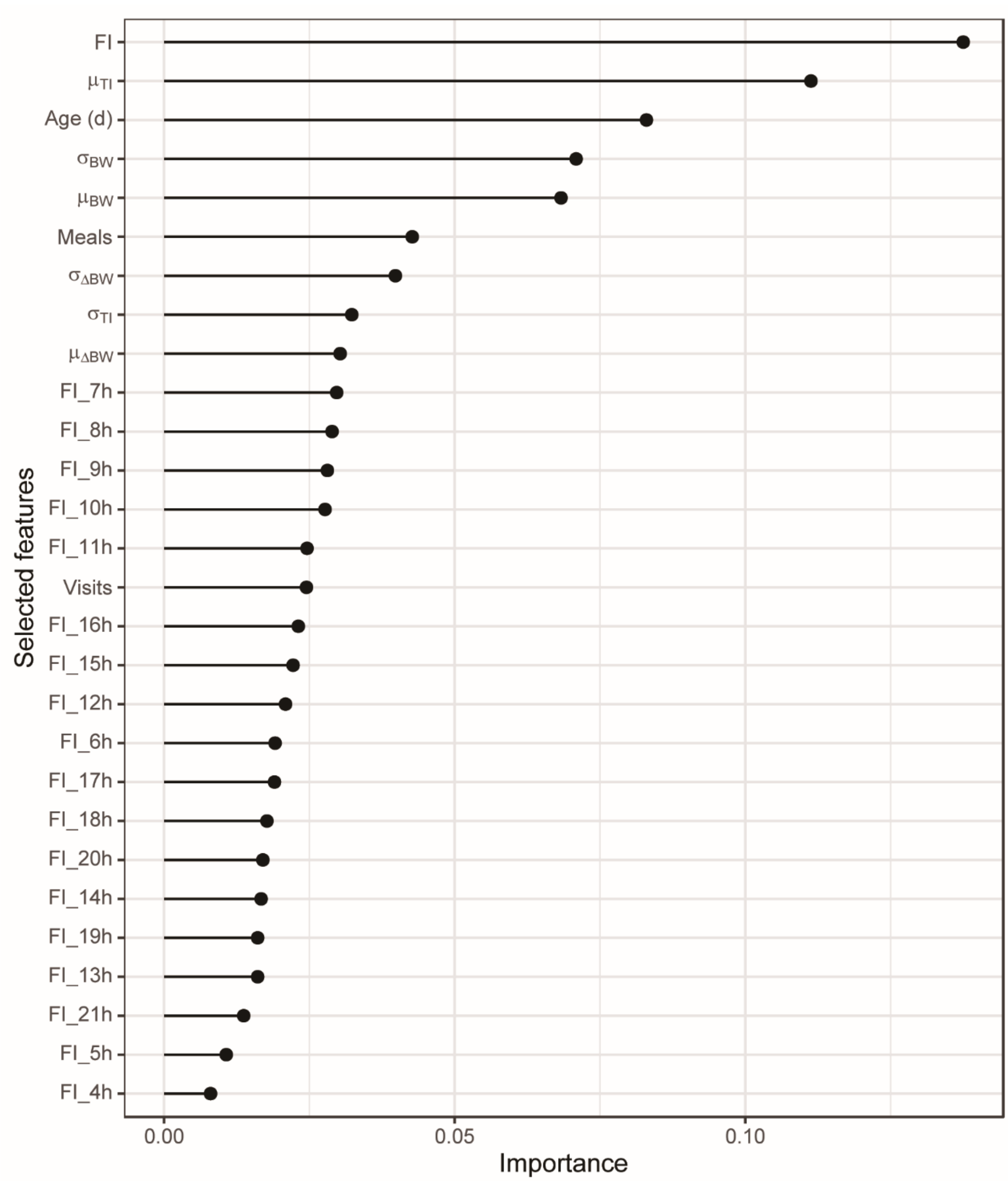

Figure 3-4. The ranked importance scores of the 28 selected features estimated by the random forest classification model and 90% training samples. FI: feed intake in one day; μ_{TI}: mean of TI (time interval between two successive meals) in one day; σ_{BW}: SD of BW of a broiler breeder in one day; μ_{BW}: mean of BW of a broiler breeder in one day; Meals: number of meal in one day; $\sigma_{\Delta BW}$: SD of ΔBW (change of BW between two successive meals) in one day; σ_{TI}: SD of TI in one day; $\mu_{\Delta BW}$: SD of ΔBW (change of BW between two successive meals) in one day; FI_7h: feed intake from 07:00 h to 08:00 h; Visits: number of visits to a precision feeding station in one day.

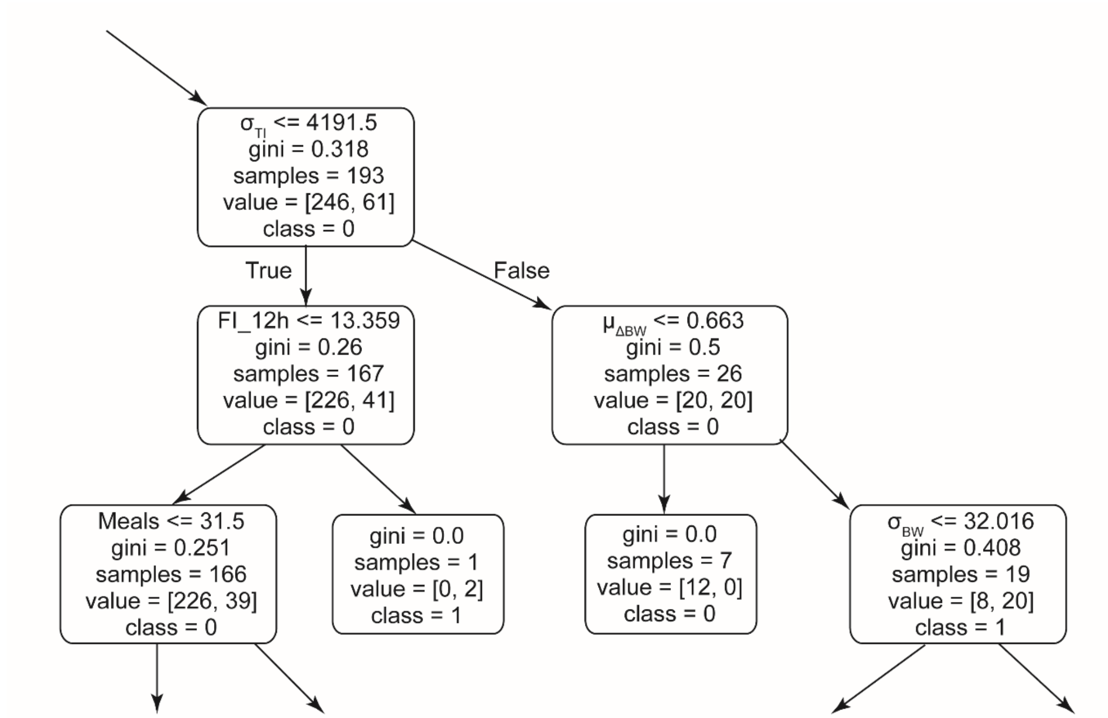

Figure 3-5. Part of a decision tree in random forest classification model. σ_{TI}: SD of TI which was the time interval between two successive meals in one day; FI_12h: feed intake from 12:00 h to 13:00 h in one day; $\mu_{\Delta BW}$: mean of ΔBW which was the change of BW between two successive meals in one day; Meals: number of meals in one day; σ_{BW}: SD of real-time BW in one day. A cell in the figure represented an impure node in a decision tree if the first line was a conditional statement that a feature was not greater than a certain value (e.g. fi_12h <= 13.359). A cell represented a leaf node (or a pure node) in a decision tree if the first line was not the conditional statement. By following the true or false path, an impure node can split into two nodes or a node and a leaf or two leaves. "gini" represented a metric that quantifies the purity of the node or leaf. If gini > 0.0 (e.g. gini = 0.26), samples belonged to different classes. If gini = 0.0, only one class of samples existed in the leaf. "samples" referred to the number of drawn samples (20,195 drawn samples by bootstrapping from 31,898 training samples) in the data set at the node or leaf (e.g. samples = 167 meant there were 167 samples in the data set at the node). "value" represented how many training samples (31,898 training samples) fell into each class. The first value was the class of no egg-laying and the second value was the class of egg-laying (e.g. value = [226, 41] meant that 226 samples belonged to no egg-laying class and 41 samples belonged to egg-laying). If the first value was greater than or equal to the second value, "class" showed "0" which meant the prediction result of a given node or leaf node was no egg-laying; if the first value was less than the second value, "class" showed "1" which meant the prediction result was egg-laying.

4. Chapter 4. A supervised machine learning method to detect anomalous real-time broiler breeder body weight data recorded by a precision feeding system

4.1. Abstract

A precision feeding (PF) system is an intelligent computer-controlled feeding system that can be used to feed individual broilers, breeders or layers automatically based on measuring real-time body weight (BW). Vast amounts of real-time BW data can be generated every day when birds visit a PF station. However, anomalous observations occurred in real-time BW observations, which were caused by multiple birds entering the station at the same time, upward or downward variation in scale measurement in the recorded data due to the movement of the bird, or a misread for radio frequency identification tag. Known anomalous data should be removed because they have a negative impact on the interpretation of the data. Manually cleaning the anomalies is accurate, but time-consuming and labor-intensive. Statistical methods and unsupervised machine learning methods are effective in detecting anomalies to some extent because they just check data distribution. The current study reported a supervised machine learning method to detect anomalies in real-time BW recorded by the PF system. Real-time BW data of 5 broiler breeders from day 15 to day 306 were checked and the anomalies were manually labeled. Variables regarding the statistical distribution of data and features regarding the feeding activity recorded by the PF system in each day were extracted from the dataset. Four machine learning algorithms were used to identify anomalies including k-nearest neighbor (KNN), random forest classifier (RF), support vector machine (SVM), and artificial neural network (ANN). RF produced the highest F1 score (0.9712) and area under the precision-recall curve (0.9948). Compared with 4 other common anomaly detection

methods including Z-scores, interquartile range (IQR), density-based spatial clustering of applications with noise (DBSCAN), and local outlier factor (LOF), RF had the highest average F1 score (0.9448), which indicated that RF was the most effective anomaly detection algorithm for this type of data.

Key words: outlier detection; machine learning; model selection; imbalanced classification.

4.2. Introduction

Applying computer technology has proved to be beneficial to animal agriculture. Hardware and software can be used to automatically monitor animal's performance (Banhazi et al., 2012; Berckmans, 2014), making research and production less labor-intensive, while at the same time collecting big data that is helpful to interpret and improve animal performance. A current example is a precision feeding (**PF**) system for poultry, which was developed at the University of Alberta (Zuidhof et al., 2017; Zuidhof et al., 2019). It is a sequential feeding system that aims to increase the body weight (**BW**) uniformity in a flock of birds by allocating the right amount of feed over several small meals each day to birds on an individual basis. Birds are individually weighed in the PF station, and then a decision is made within the system on whether or not to feed the bird based on comparing its real-time BW to the target BW. Birds frequently visit the PF station to gain access to feed, and BW and feed intake data are recorded upon each visit and meal, respectively (Figure 4-1). Visit frequency of breeder pullets from 2 to 22 weeks of age varied from 28 to 138 visits per day (Zuidhof, 2018). These data are likely to be contaminated by occasional anomalous observations, which can be caused by multiple birds entering the station at the same time, upward or downward variation in scale measurement in the recorded data due to the movement of the bird, or a misread for radio frequency identification (**RFID**) tag.

These anomalous observations would cause incorrect estimations of daily BW and daily BW gain. Although statistical methods and unsupervised learning methods might be used to detect the anomalies in real-time BW, these methods were only somewhat effective because they focused on checking data distribution alone, and were incapable of distinguishing reasonable variations of BW caused by the feeding activity from unreasonable variations of BW that can not be explained by the feeding activity. Removing the anomalies in the data manually is assumed to be more accurate but time-consuming and labor-intensive. In the current study, a supervised machine learning method was developed to detect anomalies in real-time BW of individual birds recorded by a PF system, based on manually labeled data. Variables regarding not only statistical distribution but also features associated with the feeding activity of individual birds recorded by the PF system were extracted from a dataset recorded by a PF system. Based on the labeled data, various machine learning algorithms were applied, and then the algorithm with the highest F1 score and area under the precision-recall curve (**AUCPR**) was selected to compare with 4 other common anomaly detection methods.

4.3. Methods

Figure 4-2 illustrates the key steps for developing supervised learning methods to detect anomalies. In the current study, Python 3.7.0 was used to facilitate all the data analysis work including data preprocessing, feature engineering, algorithm selection, and comparison with other common anomaly detection methods. Scikit-learn library 0.21.0 (Pedregosa et al., 2011) and the deep learning framework Keras (Kumar and Manjula, 2019) were used to implemented machine learning algorithm.

4.3.1. Data Collection

The data were obtained from a study that used broiler breeders with an approved animal care and use protocol. The breeders were fed with the PF stations from day 15 to the end of the trial (day 306). As shown in Figure 4-3, a PF station consisted of two stages: a sorting stage and a feeding stage. Each breeder was required to walk into the sorting stage where the bird was identified by reading a unique RFID tag on its right wing, then recorded its real-time BW. The real-time BW was compared with its target BW, which was pre-assigned prior to the beginning of the trial. If the real-time BW was lower than the target BW, the bird was allowed to progress to the feeding stage where it could access a feeder for a duration of no more than 60 seconds (a feeding bout) before being gently ejected from the exit door of the feeding stage. If the real-time BW was higher than or equal to the target BW, the bird was immediately ejected from the exit door of the sorting stage without being given access to feed. The date and time, real-time BW, target BW, and feed intake for each visit were recorded in the PF system database.

To manually label anomalous real-time BW of broiler breeders, 5 breeders from day 15 to day 306 were randomly selected from the flock and their real-time BW data were checked. If the real-time BW value of an observation deviated a lot from that of other observations in one day and the deviation could not be explained by the feeding activities of a bird, the observation was defined as an anomaly or an anomalous observation. On the other hand, if the real-time BW value of an observation did not deviate too much from that of other observations in one day, or the real-time BW value of an observation deviated a lot from that of other observations in one day but the deviation could be explained by the feeding activities of a bird, the observation was defined as a normal observation. The labeled results of 5 breeders are shown in Table 4-1.

4.3.2. Feature Engineering

In the current study, the whole period of the trial (day 15 to day 306) was segmented into days, and each observation in one day was described by variables extracted from the dataset based on the following terms. To check data distribution of real-time BW in one day, Fisher's skewness and kurtosis (Cain et al., 2017) were calculated using the equation below (Kokoska and Zwillinger, 2000):

$$\text{Skewness} = \frac{\sqrt{n(n-1)}}{n-2} \cdot \frac{m_1^2}{m_2^{3/2}} \tag{1}$$

$$\text{Kurtosis} = \frac{n-1}{(n-2)(n-3)} \cdot \left[(n+1)\left(\frac{m_4}{m_2^2} - 3\right) + 6\right] \tag{2}$$

where n was the number of the observations (real-time BW) in one day, and m was calculated as the equation below:

$$m_r = \sum_{i=1}^{n} \frac{(x_i - \bar{x})^r}{n} \tag{3}$$

where n was the number of the real-time BW observations in one day; $\bar{x}$ was the mean of real-time BW in one day; x_i was the real-time BW of the i^{th} observation in one day; r was the subscript of m, and r could be 1, 2, and 4, as shown in equation (1) and (2).

In the current study, original skewness and original kurtosis were newly defined to calculate the skewness of all real-time BW observations of a bird in one day and the kurtosis of all real-time BW observations of a bird in one day, respectively. Variable 3, 4, 5, and 6 were newly defined based on original skewness and original kurtosis (Table 4-2).

In the current study, average distance to neighbor observations (**ADNO**) was newly defined to describe how far an observation deviated from its neighbors, and the equation used is shown below:

$$\mathrm{ADNO}_n = \frac{|Realtime\ BW_{n+1} - Realtime\ BW_n| + |Realtime\ BW_n - Realtime\ BW_{n-1}|}{2} \quad (4)$$

As shown in Table 4-2, variable 7, 8 and 9 were based on ADNO.

Number of station visits, the age of bird, and the difference between target BW and real-time BW were also included as variables. The descriptions of all variables are shown in detail in Table 4-2.

4.3.3. Algorithm selection

Four supervised learning classification algorithms were applied to distinguish anomalies from normal observations. K-nearest neighbor (**KNN**; Coomans and Massart, 1982), random forest classifier (**RF**; Breiman, 2001), and support vector machine (**SVM**; Cortes and Vapnik, 1995) were implemented by sklearn.neighbors.KNeighborsClassifier function, sklearn.ensemble.RandomForestClassifier function, and sklearn.svm.SVC function , respectively. Artificial neural network (**ANN**; Jain et al., 1996) was implemented by Keras package, and a 4-layer perceptron including 1 input layer, 2 hidden layers, and 1 output layer was constructed. For KNN, RF, and SVM, observations of the 5 labeled birds were randomly split into 2 parts: 80% (48,120 observations) for training and 20% (12,030 observations) for testing. For ANN, the data were randomly split into 3 parts: 60% (36,090 observations) for training, 20% (12,030 observations) for validating, and 20% (12,030 observations) for testing. The grid search method (Buitinck et al., 2013), implemented by sklearn.model_selection.GridSearchCV function, was used to optimize hyper-parameters of KNN, RF, SVM, and ANN. F1 score (Jeni et al., 2013) that took both precision and recall into account was used as the metric for evaluation, and 5-fold cross validation was used in optimization. To select the best algorithm, the result of each machine learning algorithm with optimized hyper-parameters was presented in terms of the confusion matrix (Tripathy et al., 2016). True positive (**TP**), false positive (**FP**), false negative (**FN**) and true negative (**TN**) were used to calculate precision, recall, and F1 score, using the equations below (Kumar et al., 2011):

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{5}$$

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

$$\text{F1 score} = \frac{2\times\text{Recall}\times\text{Precision}}{\text{Recall+Precision}} \tag{7}$$

The precision-recall (**PR**) curve was used to displays the trade-off between precision (Y axis) and recall (X axis) for different threshold values (Ozenne et al., 2015). Compared with the receiver operating characteristic curve that was appropriate for the balanced dataset, the PR curve can be informative for the imbalanced dataset (Davis and Goadrich, 2006). The precision and recall in the PR curve both captured the minority class (anomalies), and they were not concerned with the majority class (normal observations). If the PR curve was close to the top right corner where the precision and recall were both 100%, the model had an almost perfect classification performance. The AUCPR was a metric that used a float number between 0 and 1 to summarize the information of the PR curve (Boyd et al., 2013). A higher AUCPR value represented a larger area beneath the PR curve that meant a better classification performance. In the current study, AUCPR was applied to evaluate 4 algorithms. The algorithm with the highest F1 score and AUCPR was selected.

4.3.4. Comparison with common methods

The selected machine learning algorithm was compared with common anomaly detection methods including two statistical methods: Z-scores (Shiffler, 1988) and interquartile range (**IQR**; Tukey, 1977), and two machine learning methods: Density-based spatial clustering of applications with noise (**DBSCAN**; Ester et al., 1996) and local outlier factor (**LOF**; Breunig et al., 2000). To compare performance of these methods, the detection results of each labeled bird was presented. For the machine learning method presented in the current study, data of each labeled bird were tested by a model built on the data of the other 4 birds, which was similar to 5-fold cross-validation. Since Z-scores, IQR, DBSCAN, and LOF were not model-based methods, they were implemented on each bird without using the data of other birds for training a model. The Z-scores and IQR methods were used to detect anomalies day by day in each bird. Z-scores of +3 and -3 were used in the current study, which meant the mean of real-time BW ± 3 standard deviations of real-time BW within each day. A point was recognized as an anomaly if it was not within this range. In the IQR method, IQR referred to the difference between third quartile (Q_3) of data and first quartile (Q_1) of data. The upper limit was calculated as $Q_3 + 1.5 \times IQR$ and the lower limit was calculated as $Q_1 - 1.5 \times IQR$, and a point was considered as an anomaly if it was beyond either limit (Barbato et al., 2011). As a clustering algorithm, DBSCAN created a clustering area by finding a center that had a dense neighborhood and then connecting the center with its neighborhood (Sukmasetya and Sitanggang, 2016). Based on the cluster, all points in a dataset can be classified as: 1. Core point that was inside a cluster; 2. Border point that was on the edge of the cluster; 3. Noise point (Anomaly) that was neither a core point nor a border point. In contrast to DBSCAN, LOF detected anomalies by searching local density of points with respect to local density of its neighbors rather than whole data (Behera and Rani, 2016). It considered observations that had lower density than their neighbors as outlier samples. In the current study, DBSCAN and LOF were implemented by sklearn.cluster.DBSCAN function and sklearn.neighbors.LocalOutlierFactor function. Hyper-parameters of DBSCAN algorithm were “eps” = 15 and “min_samples” = 20 in the current study, which meant the radius of the neighborhood area of center and minimum number of samples in the neighborhood area (Karami, 2013). Hyper-parameters of LOF were "n_neighbors" = 50 and "contamination" = 0.12 in the current study, which meant the number of neighbors that were used to calculate the local density and the percentage of anomalous values in the dataset. "eps" and "min_samples" of DBSCAN and "n_neighbors" and "contamination" of LOF were optimized based on the manually labeled dataset. Other hyper-parameters were all default values. Anomalies were detected in each bird from day 15 to day 306 using the same hyper-parameters.

4.4. Results

Table 4-3 shows the evaluation of 4 machine learning algorithms with optimized hyper-parameters. KNN had the highest precision (0.9746) and SVM had the highest recall (0.9917); however, RF had the highest F1 score (0.9712) that was the harmonic mean of precision and recall. In addition, Figure 4-4 shows AUCPR of RF (0.9948) was higher than all other algorithms, indicating that RF was a more effective model for this imbalanced binary classification problem. Thus, RF was selected as the best algorithm for anomaly detection.

As the best selected machine learning algorithm in this application, RF was compared with other common anomaly detection methods (Table 4-4). RF had a higher precision, recall, and F1 score (over 90%) than other 3 methods including Z-scores, LOF, and DBSCAN. Although the recall of IQR was higher than RF, its precision and F1 score were much lower than RF. As shown in Figure 4-5, Z-scores, LOF and DBSCAN were able to identify anomalies that deviated from normal observations, but were not able to detect anomalies that were close to normal observations. On the other hand, there were many normal observations that were incorrectly recognized as anomalies. RF detected almost all anomalous observations without identifying many normal observations as anomalies.

4.5. Discussion

The PF system recorded real-time broiler breeder BW in two dimensions: real-time BW and time. There were two characteristics for the recorded data: regularly shaped over a long period of time and irregularly scattered in one day (Figure 1). Since the PF system fed each individual birds following a target BW curve that was a sigmoidal shape, real-time BW data of an individual bird throughout the trial (from day 15 to day 306) that were temporally sequenced can be described by a triphasic Gompertz model (Zuidhof, 2020). However, there was no pattern for the real-time BW data in a short period of time (e.g. within 24 hours). The real-time BW of an individual bird could fluctuate drastically or slightly due to BW variations resulted from one or several activities of the bird including feed intake, water intake, excretion, and oviposition that commenced at 22 weeks of the age. The fluctuation of the real-time BW should be in a reasonable range determined by these activities, and normal real-time BW observations could be explained by these activities. Anomalous real-time BW observations could not be explained by the activities of birds, and they might be caused by three reasons. First, there were multiple birds in the station. Second, there was a substantial upward or downward variation in scale measurement caused by the movement of a bird when it was weighed in the station. Third, there was a misread for the RFID tag. The RFID antenna generated electromagnetic (**EM**) fields to energize the RFID tag, and then the RFID tag sent the data to the RFID reader. There were complex EM fields inside the PF station, but small EM fields were likely to leak outside the PF station. In most cases, the RFID tag can be read successfully because the RFID tag of a bird was in alignment with the EM fields when the bird was in the sorting stage. However, a misread might occur if the RFID tag of a bird in the sorting stage was insufficiently aligned with the EM field and the RFID tag of a nearby bird outside the sorting stage was aligned with the leaky EM field. Such a misread would cause an anomalous real-time BW record if the two birds had different BW.

The anomalies were temporally occasional and quantitatively random, which meant that extremely higher or lower real-time BW were likely to appear at any time of a day during the period of the trial once birds walked into the station where they were weighed. Manually labeling the anomalies was accurate but time consuming and labor-intensive. People first tried to find the extreme values that deviated a lot from other observations as suspected anomalies. Then the anomalies were confirmed by considering the activities of the bird that could cause BW variation: If a suspected anomaly can be explained by the activities, it would be a normal observation. Otherwise, it would be a real anomaly. In the current study, the PF system that was used to feed the birds recorded the feeding activity of each individual birds, which made it possible to mimic the process of manually labeling the anomalies. Variables were extracted to describe observations in terms of data distribution and features regarding the feeding activity of individual bird recorded by the PF system in each day. Variable 1 through 6 indicated the impact of each observation on the data distribution in one day in terms of skewness and kurtosis. Skewness was a measure of asymmetry of a distribution around its mean, and kurtosis was a measure of flatness of the distribution compared with normal distribution (Čisar and Čisar, 2010). If an anomalous real-time BW occurred, the data distribution might be severely affected and reflected by skewness or kurtosis. The variable OS and OK represented the distribution of all observations in one day, whereas ES, EK, ΔS, and ΔK were used to evaluate the impact of eliminating a certain observation on the distribution of all observations. Variable 7 through 12 were used to describe features associated with the feeding activity of an individual bird recorded by the PF system for each observation. ADNO was a measure of how far an observation deviated from the previous and subsequent observations. The variable A/F represented the proportion of ADNO to feed intake in one day, and the two variables A/S and A/R represented the proportion of ADNO to variation of BW (range and standard deviation of real-time BW, respectively) in one day. These variables were included because feed intake and variation of BW in one day might determine a reasonable range for the ADNO of each observation in the day. Other information of each bird including the number of visits, age, and ΔBW was additionally taken into account for anomaly detection. The number of visits might be associated with feed intake and standard deviation of real-time BW in one day. Age was associated with the activities of a bird. For example, once a bird has begun to lay eggs (after photo-stimulation at 22 weeks of age) oviposition can result in a BW decrease of about 60 g, but such a BW change was very likely to indicate an anomaly at the age of day 50. In the current study, each individual birds was fed based on the preset target BW. Although the target BW was a sigmoid curve throughout the trial, it changed very slightly within a day. The real-time BW could be higher or lower than the target BW, or equal to the target BW, but the real-time BW should not deviate a lot from the target BW. ΔBW represented the difference between each target BW and the corresponding real-time BW, and a substantial ΔBW might be related to an anomaly.

In the current study, 4 supervised learning classification algorithms were applied, and F1 score and AUCPR were used to select the best algorithm on the dataset that was heavily imbalanced. A similarity between F1 score and AUCPR was that they were both associated with precision and recall. F1 score represented the balance between precision and recall, and AUCPR was the area beneath the PR curve. The difference between F1 score and AUCPR was regarding the classification threshold. The machine learning classification algorithms were usually not able to predict labels immediately, and they calculated probabilities and then classified the labels based on a threshold. F1 score showed the classification performance of the algorithm based on a single threshold, but AUCPR was based on the PR curve that provided an overview of different performance with multi-thresholds (Saito and Rehmsmeier, 2015). In the current study, when using F1 score to compare 4 algorithms, it aimed to select the best algorithm that identified anomalies from normal observations by the threshold of 0.5; when using AUCPR, the best algorithm was selected by considering its classification performance at different thresholds.

As the best algorithm selected from the 4 different machine learning algorithms, RF was compared with 4 common anomaly detection methods. When detecting anomalous real-time BW data with statistical methods, anomalies were checked just in the dimension of real-time BW. In the current study, the recall and precision of the Z-scores method were lower than other methods, because the assumption of the Z-scores method was that data should be normally distributed. When real-time BW data did not follow normal distribution, some real-time BW observations that were not anomalies could be identified as anomalies. This would decrease precision of the Z-scores method, which was what we observed. Although recall of the IQR method was much higher than other methods, precision of IQR was the lowest. This indicated that the IQR method recognized a large number of normal observations as anomalies regardless of detecting almost all real anomalies. The IQR method was ineffective to deal with asymmetric data distribution, since it checked absolute deviation from the center (Jones, 2019). In the current study, the high recall and low precision of IQR might be due to the asymmetry in data. As a result, these two statistical methods were ineffective to detect anomalous observations. Unlike the Z-score and IQR methods, DBSCAN and LOF were implemented simultaneously in two dimensions (real-time BW and time). In the pre-trial of the current study, hyper-parameters of these two unsupervised learning methods had been optimized based on the manually labelled dataset. The basic idea of DBSCAN was to identify the observations in low density region as anomalies. As an unsupervised machine learning algorithm, anomaly detection of DBSCAN relied on its hyper-parameters: “eps” and “min_samples” which determined the area of and the density of a cluster. Samples in the cluster with high density were normal while samples in clusters with low density were detected as anomalies (Emadi and Mazinani, 2018). However, the density of observations was different among birds since some birds had more visits than others. For example, the bird whose ID was 1902 visited PF station 15,596 times but the bird whose ID was 1811 only visited 9,380 times during the trial. In addition, frequency of visits for each bird would change during the trial even during one day, which resulted in variation of density of observations for each bird. Like DBSACN, LOF was over-sensitive to its hyper-parameters: “n-neighbors” and “contamination”. It was difficult to determine a proper value for “n-neighbors” which meant the number of surrounding neighbors which was used to estimate the local density, due to variation of number of visits among birds. It was also difficult to estimate “contamination” which meant percentage of anomalous values in the dataset, because the percentage of anomalies ranged from 0.73 to 1.32 in the 5 labeled birds in the current study and a higher or lower estimation of “contamination” would have a negative impact on anomaly detection. Thus, the disadvantage of LOF and DBSCAN was the difficulty in determining an appropriate combination of hyper-parameters for each bird before detection. In the current study, “eps” and “min_samples” of DBSCAN and “n_neighbors” and “contamination” of LOF were optimized based on the manually labeled dataset. However, when DBSCAN and LOF were implemented to a new dataset, an appropriate combination of hyper-parameters of DBSCAN and LOF would be difficult to determine without the manually labeled results. Statistical methods and unsupervised learning methods detected anomalies by investigating input data (distribution or density of observations), whereas RF as a supervised learning method detected anomalies by building a relationship between input data (12 features) and output data (anomalies). Compared with Z-score, IQR, LOF, and DBSCAN, RF had better performances (higher precision, recall, and F1 score) on detecting anomalies in real-time BW data of each bird recorded by the PF system.

4.6. Conclusion

The current study was the first to propose a supervised machine learning method to detect anomalies in real-time BW data of broiler breeders collected by a PF system. Real-time BW data of 5 randomly selected broiler breeders were used in the current study. To detect the anomalous observations over the period of trial (from day 15 to day 306), 12 variables considering statistical distribution of data and features regarding the feeding activity recorded by the PF system for each day were created, and then supervised learning algorithms were used to identify anomalies from normal observations. RF was selected as the best algorithm among 4 different supervised learning algorithms because it had the highest F1 score (0.9712) and AUCPR (0.9948). Comparing with common anomaly detection methods (Z-scores, IQR, DBSCAN, and LOF) that just checked data distribution, the RF method in the current study had a higher average F1 score (0.9448). The current study provided an effective solution to clean anomalous observations of real-time BW of broiler breeders fed by the PF system.

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4.9. Tables

Table 4-1. Anomalous observations and normal observations of 5 breeders that were manually labeled.

ID	Number of total observations	Number of anomalous observations	Number of normal observations	Percentage of anomalous observations (%)
1811	9,380	101	9,279	1.08
1887	11,695	85	11,610	0.73
1902	15,596	165	15,431	1.06
1961	13,923	103	13,820	0.74
1987	9,556	126	9,430	1.32
Total	60,150	580	59,570	0.96

Table 4-2. Variables created for describing a real-time BW observation of one bird in one day.

No.	Variable	Description
1	OS	The skewness[1] of all observations of real-time BW of a breeder in one day.
2	OK	The kurtosis[2] of all observations of real-time BW of a breeder in one day.
3	ES	The eliminated skewness for an observation that was the skewness all real-time BW of a breeder in one day without the observation.
4	EK	The eliminated kurtosis for an observation that was the kurtosis of all real-time BW of a breeder in one day without the observation.
5	ΔS	The difference of skewness for an observation that was the difference between original skewness and eliminated skewness.
6	ΔK	The delta difference of kurtosis for an observation that was the difference between original kurtosis and eliminated kurtosis.
7	A/S	The ratio of ADNO[3] of an observation and standard deviation of real-time BW in one day.
8	A/R	The ratio of ADNO of an observation and range of real-time BW in one day.
9	A/F	The ratio of ADNO of an observation and sum of feed intake in one day.
10	Number	Number of observations (visits) in one day.
11	Day	The age (d) of each bird recorded by precision feeding system.
12	ΔBW	Target BW minus Real-time BW

1.

$$\text{Skewness} = \frac{\sqrt{n(n-1)}}{n-2} \cdot \frac{m^3}{m_2^{3/2}}$$

$$\text{where } m_r = \sum_{i=1}^{n} \frac{(x_i - \bar{x})^r}{n}$$

2.

$$\text{Kurtosis} = \frac{n-1}{(n-2)(n-3)} \cdot \left[(n+1)\left(\frac{m_4}{m_2^2} - 3\right) + 6\right]$$

$$\text{where } m_r = \sum_{i=1}^{n} \frac{(x_i - \bar{x})^r}{n}$$

3. Average distance to neighbor observations, newly defined in the current study as:

$$\text{ADNO}_n = \frac{|Realtime\ \text{BW}_{n+1} - Realtime\ \text{BW}_n| + |Realtime\ \text{BW}_n - Realtime\ \text{BW}_{n-1}|}{2}$$

Table 4-3. Comparison of evaluation of different machine learning algorithms using testing samples.

	KNN [2]	RF [3]	SVM [4]	ANN [5]
TP [6]	115	118	119	115
FP [7]	3	5	33	7
FN [8]	5	2	1	5
TN [9]	11,907	11,905	11,877	11,903
Precision [10]	0.9746	0.9593	0.7829	0.9426
Recall [11]	0.9583	0.9833	0.9917	0.9583
F1 score [12]	0.9664	0.9712	0.8750	0.9504

1. The hyper-parameters of these machine learning algorithms has been optimized by using grid search method implemented by sklearn.model_selection.GridSearchCV.
2. KNN: k-nearest neighbor implemented by sklearn.neighbors.KNeighborsClassifier. Hyper-parameters were optimized as follows: n_neighbors = 3; weights = "distance"; algorithm = "ball_tree"; other hyper-parameters were all default value.
3. RF: random forest classifier implemented by sklearn.ensemble.RandomForestClassifier. Hyper-parameters were optimized as follows: n_estimators = 190; min_samples_leaf = 6; max_depth = 9; class_weight = "balanced"; other hyper-parameters were all default value.
4. SVM: support vector machine implemented by sklearn.svm.SVC. Hyper-parameters were optimized as follows: gamma = 0.075; C =1.22; class_weight = "balanced"; other hyper-parameters were all default value.
5. ANN: artificial neural network implemented by Keras. A 4-layer perceptron was constructed and hyper-parameters of each layer were optimized as follows:
   a. Input layer: units= 64; activation = "relu".
   b. First hidden layer: units = 64; activation = "relu".
   c. Second hidden layer: dropout = 0.5.
   d. Output layer: units = 1.

The model was compiled with following hyper-parameters: loss ="binary_crossentropy"; optimizer= "rmsprop". The batch size was 6000 and the number of epochs was 500. Other hyper-parameters were all default value.

6. TP: true positive. It meant actual anomalies and the model predicts them as anomalies.
7. FP: false positive. It meant actual normal observations but the model predicts them as anomalies.
8. FN: false negative. It meant actual anomalies but the model predicts them as normal observations.
9. TN: true negative. It meant actual normal observations and the model predicts them as normal observations.
10. Precision = TP / (TP + FP).
11. Recall = TP / (TP + FN).
12. F1 score = 2 x Precision x Recall/ (Precision + Recall).

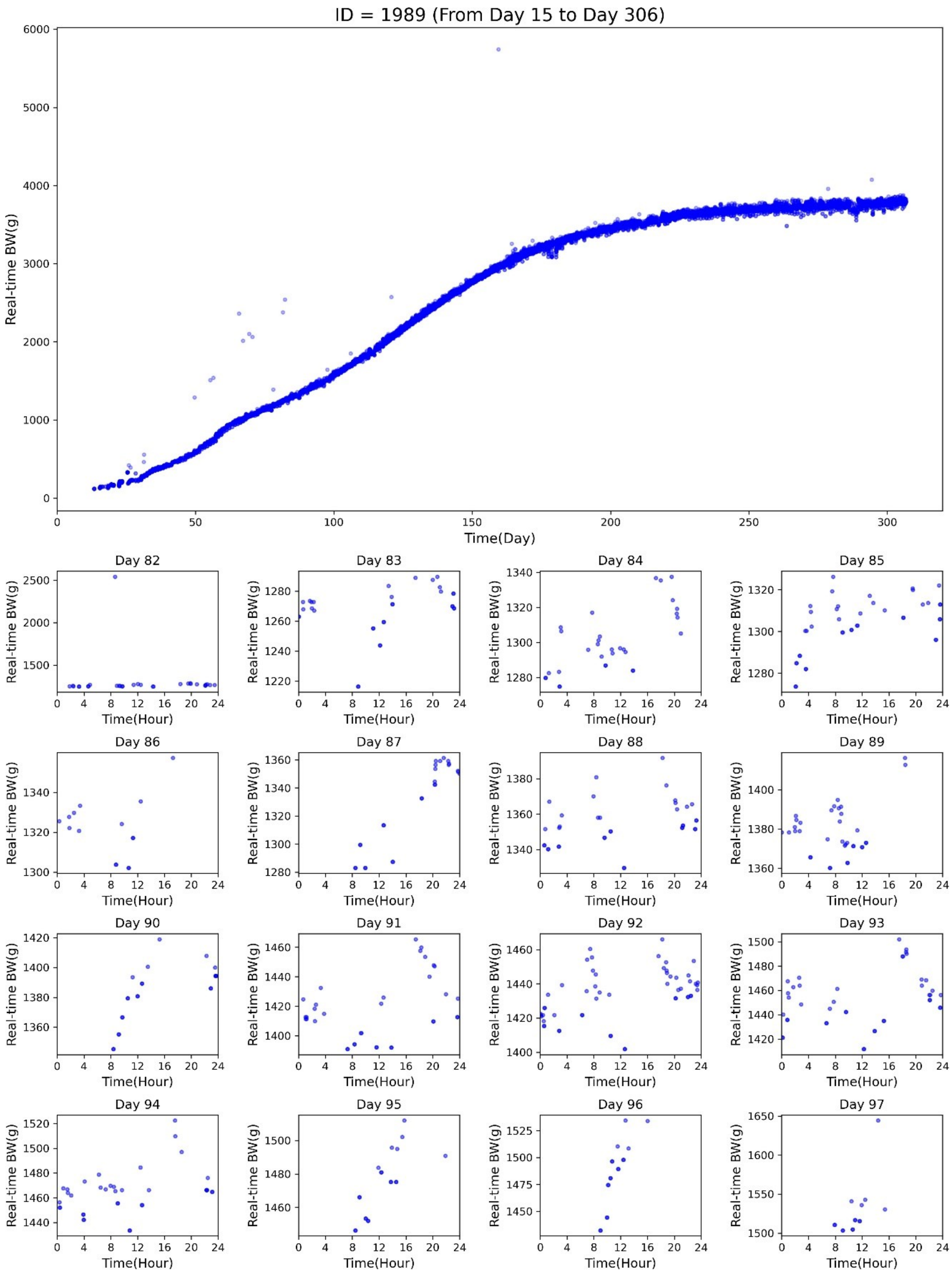
Table 4-4. Comparison of anomalies detection by machine learning method (selected algorithm) presented by the current study with other common methods (Z-scores, IQR, LOF, and DBSCAN).

Methods		ID 1811	1887	1902	1961	1987	Average [13]
	TP [6]	100	80	154	95	124	
	FP [7]	1	5	10	5	18	
	FN [8]	2	5	11	8	2	
RF[1]	TN [9]	9,277	11,605	15,421	13,815	9,412	
	Precision [10]	0.9804	0.9412	0.9390	0.9500	0.8732	0.9368
	Recall [11]	0.9901	0.9412	0.9333	0.9223	0.9841	0.9542
	F1 score [12]	0.9852	0.9412	0.9362	0.9360	0.9254	0.9448
	TP	58	76	129	85	88	
	FP	35	36	53	67	28	
	FN	43	9	36	18	38	
Z-scores [2]	TN	9,244	11,574	15,378	13,753	9,402	
	Precision	0.6237	0.6786	0.7088	0.5592	0.7586	0.6658
	Recall	0.5743	0.8941	0.7818	0.8252	0.6984	0.7548
	F1 score	0.5980	0.7716	0.7435	0.6666	0.7273	0.7014
	TP	100	83	156	98	126	
	FP	267	289	419	377	288	
	FN	1	2	9	5	0	
IQR [3]	TN	9,012	11,321	15,012	13,443	9,142	
	Precision	0.2725	0.2231	0.2713	0.2063	0.3043	0.2555
	Recall	0.9901	0.9765	0.9455	0.9515	1.0000	0.9727
	F1 score	0.4274	0.3632	0.4216	0.3391	0.4666	0.4036
	TP	84	70	138	71	111	
	FP	29	71	50	97	4	
	FN	17	15	27	32	15	
LOF [4]	TN	9,250	11,539	15,381	13,723	9,426	
	Precision	0.7434	0.4965	0.7340	0.4226	0.9652	0.6723
	Recall	0.8317	0.8235	0.8364	0.6893	0.8810	0.8124
	F1 score	0.7851	0.6195	0.7819	0.5240	0.9212	0.7263
	TP	90	65	136	70	116	
	FP	12	47	46	47	101	
	FN	11	20	29	33	10	
DBSCAN [5]	TN	9,267	11,563	15,385	13,773	9,329	
	Precision	0.8824	0.5804	0.7473	0.5983	0.5346	0.6686
	Recall	0.8911	0.7647	0.8242	0.6796	0.9206	0.8160
	F1 score	0.8867	0.6599	0.7839	0.6364	0.6764	0.7287

1. RF: the random forest classifier that was the best algorithm selected from 4 different machine learning algorithms. Hyper-parameters of RF had been optimized and were the same as in Table 4-3. Each time, four birds were used as training samples and the rest one was used as testing samples.
2. In the Z-scores method, Z-scores of +3 and -3 were used and anomalies were detected in each day of each bird.

3. IQR: interquartile range. In the IQR method, anomalies were detected in each day of each bird.
4. LOF: local outlier factor. Hyper-parameters were optimized as follows: "n_neighbors"=50 and "contamination"=0.12. Other hyper-parameters were all default value. Anomalies were detected in each bird from day 15 to day 306 using the same hyper-parameters.
5. DBSCAN: density-based spatial clustering of applications with noise. Hyper-parameters were optimized as follows: "eps"=15 and "min_samples"=20. Other hyper-parameters were all default value. Anomalies were detected in each bird from day 15 to day 306 using the same hyper-parameters.
6. TP: true positive. It meant actual anomalies and the model predicts them as anomalies.
7. FP: false positive. It meant actual normal observations but the model predicts them as anomalies.
8. FN: false negative. It meant actual anomalies but the model predicts them as normal observations.
9. TN: true negative. It meant actual normal observations and the model predicts them as normal observations.
10. Precision = TP / (TP + FP).
11. Recall = TP / (TP + FN).
12. F1 score = 2 x Precision x Recall/ (Precision + Recall).
13. Average: the arithmetic mean of 5 birds.

4.10. Figures



ID = 1989 (From Day 15 to Day 306)
Real-time BW(g)
Time(Day)
Day 82
Day 83
Day 84
Day 85
Day 86
Day 87
Day 88
Day 89
Day 90
Day 91
Day 92
Day 93
Day 94
Day 95
Day 96
Day 97
Time(Hour)

Figure 4-1. An example of real-time BW of a broiler breeder (ID=1989) recorded by the precision feeding system over the period of the trial (day 15 to day 306). To show the daily recorded real-time BW, day 82 to day 97 of the breeder were presented.

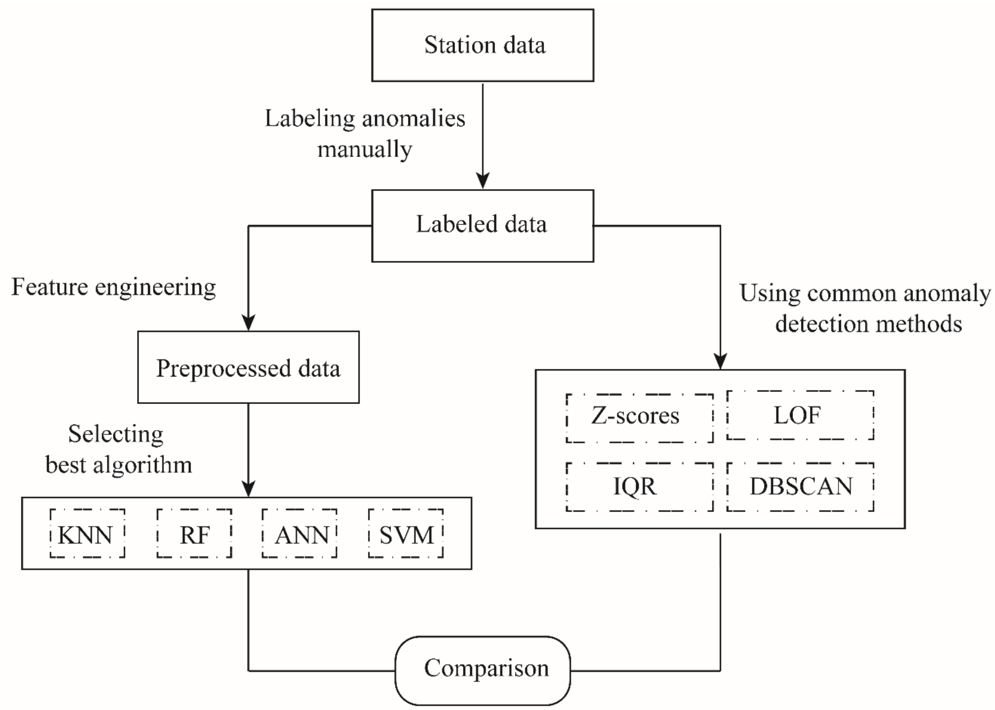


Figure 4-2. Flow chart of the current study. KNN: k-nearest neighbor; RF: random forest classifier; ANN: artificial neural network; SVM: support vector machine; LOF: local outlier factor; IQR: interquartile range method; DBSCAN: Density-based spatial clustering of applications with noise.

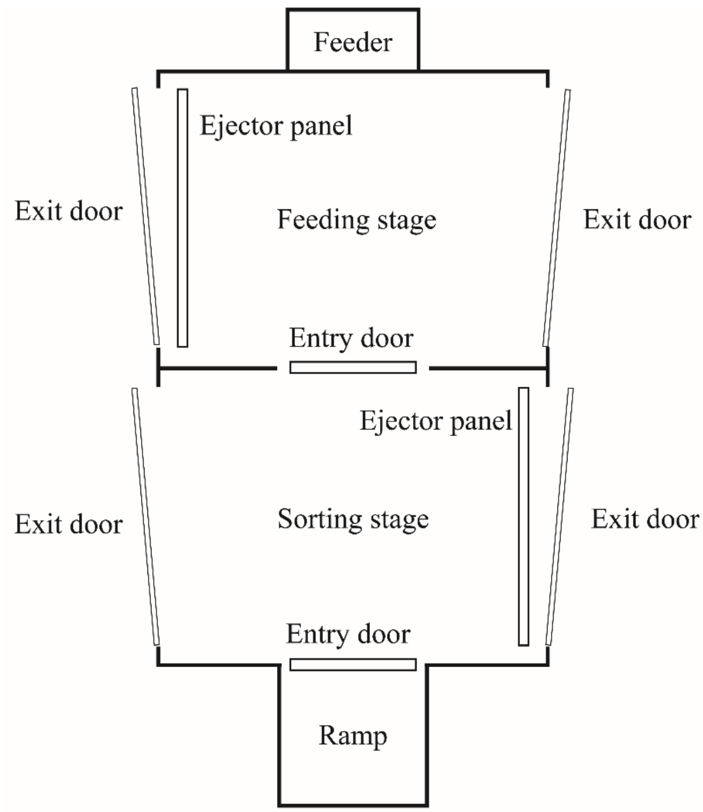


Figure 4-3. Section view of a precision feeding station.

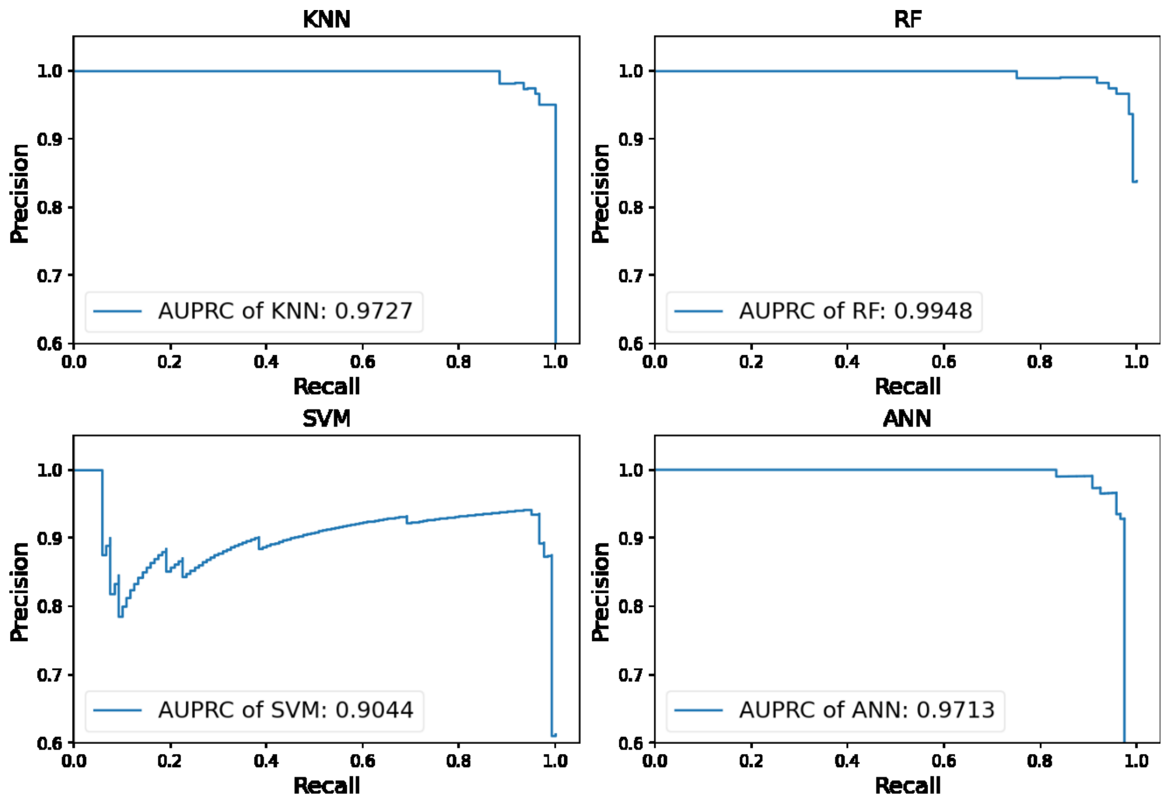


Figure 4-4. Precision-recall curve performance of different machine learning algorithms. AUCPR: area under precision-recall curve; KNN: k-nearest neighbor; RF: random forest classifier; SVM: support vector machine; ANN: artificial neural network.

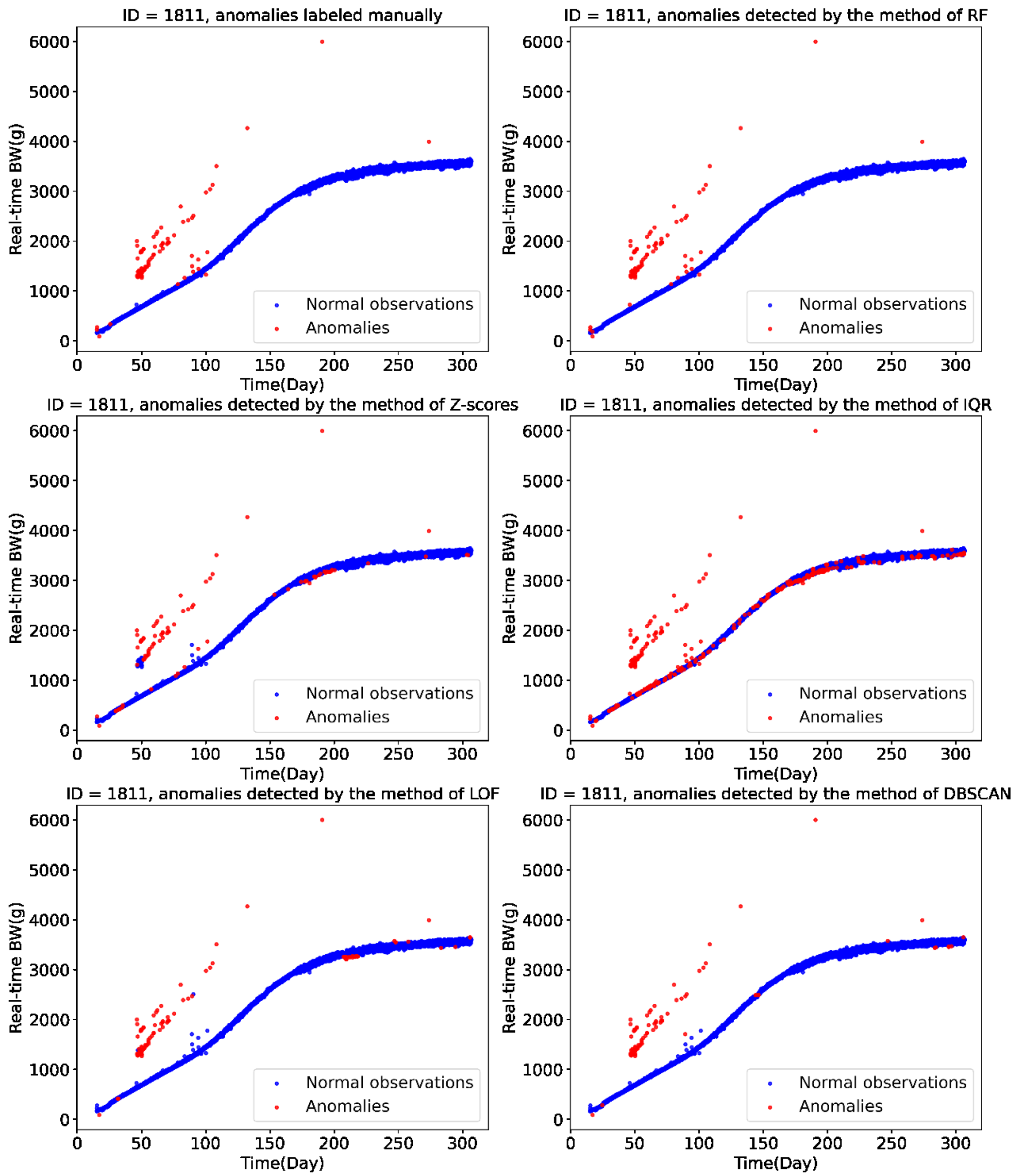


Figure 4-5. An example (ID = 1811) of comparison of the method proposed in the current study with other common anomaly detection methods. Blue points indicate normal observations and red points indicate anomalies.

5. Chapter 5. Using an artificial neural network to predict the probability of daily oviposition events occurring of precision-fed broiler breeders

5.1. Abstract

Identifying daily oviposition events for individual broiler breeders is important for bird management. Knowing non-laying individual birds in a flock that might be caused by improper nutrition or diseases can be helpful to manage these birds by changing the diets or treating the diseases for these birds. 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 two limitations in that study: i) It could only be used to identify daily egg-laying events on a subsequent day; ii) 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 one 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 one 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 how likely oviposition of an individual breeder occurred in the day. In situations where total egg production was known for a group, the ANN model could predict the probability of daily oviposition events occurring for all individual birds and then rank them to choose those most likely to have laid an egg.

Key words: oviposition; probability; feature; neural network.

5.2. Introduction

Identifying daily oviposition events for individual broiler breeders is important to improve bird management. In the laying period, individual breeders in a flock might stop laying due to the reasons like improper nutrition or diseases. Knowing which breeders laid an egg in a flock is helpful to manage the non-laying individual birds by changing the diets or treating the diseases. Oviposition occurs in sequences of one or more eggs, separated by one or more non-laying days called a pause (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 the 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 an individual hen. The oviposition of individually caged birds can be easily noticed. For free-run birds, it is challenging to determine oviposition events of individual hens without a trap nest system.

A recent study (You et al., 2020) reported predicting daily oviposition events of individual broiler breeders using a random forest classifier. It was the first study to identify daily oviposition events at individual-level, by using a precision feeding (**PF**) system (Zuidhof et al., 2019) that can automatically feed individual birds and record vast amounts of data regarding the feeding activity of the birds. This study built a relationship between daily oviposition events of individual breeders and the feeding activity and body weight (**BW**) change of individual breeders recorded by the PF system. 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 including 1 representing egg-laying and 0 representing no egg-laying. However, for predicted outputs with the same label, it is difficult to indicate which one is more likely to occur than others.

Improving on the previous approach, the current study aimed to develop an artificial neural network (**ANN**) model to predict the probability of daily oviposition events occurring using a specific time point in one day. It was hypothesized that the probability for the time point in one day predicted by the ANN model would be used for representing how likely egg-laying events occur in the day.

5.3. 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).

5.3.1. 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. 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 a 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 seconds 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.

5.3.2. Data Collection

After photo-stimulation at 22 wk of age, the egg production of individual hens was recorded on a daily basis. In the current study, if a hen laid an egg in one day, it was considered as an egg-laying event; if a hen did not lay an egg in one 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, the bird inside the box would be set free 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 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 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.

5.3.3. 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 5-1. 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. No egg-laying events during each hour were randomly selected from 706 no egg-laying events, based on the number of egg-laying events during the corresponding hour. As a result, the distribution of egg-laying events during each hour was identical to that of no egg-laying events during each hour. In the current study, the anchor point was newly defined as a specific time point in one day for predicting egg-laying 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. For example, for a no egg-laying event during 7 h, the anchor point was randomly selected between 07:00 and 08:00, such as 07:07, 07:19, or 07:36.

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

$$\mathrm{BWG} = \mathrm{BW}_n - \mathrm{BW}_1 \quad (1)$$

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

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

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

where BW_n represented the n^{th} real-time BW in the period recorded by the PF system. $\Delta BW_{n-(n-1)}$ represented the BW change between two consecutive (n^{th} and $n\text{-}1^{th}$) 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:

$$\mathrm{BWG} = \sum \mathrm{BW\ increase} + \sum \mathrm{BW\ decrease} \quad (4)$$

Generally, any BW change between two consecutive real-time BW 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:

$$\mathrm{BWG} = \mathrm{FI} + \mathrm{WI} + \mathrm{EM} \quad (5)$$

FI referred to the total amount of feed eaten by an individual for 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. In addition to the 24 features, another 2 features regarding the anchor point were created: the period between two consecutive visits over the anchor point and the BW change of two consecutive visits over the anchor point. All 26 features are shown in Table 5-1.

5.3.4. Algorithm

The ANN model was implemented by the deep learning framework Keras package in Python (Kumar and Manjula, 2019). The ANN structure was based on a feed-forward network shown in Figure 5-2, and a multi-layer perceptron including 1 input layer, 1 hidden layer, and 1 output layer was constructed. Each layer could contain several neurons that were computational units. 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 for optimization. The optimized hyper-parameters 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.

5.3.5. 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:

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

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

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 that 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.

5.4. Results and Discussion

The optimized hyper-parameters are shown in Table 5-2. With these hyper-parameters, 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 5-3). Figure 5-4 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.

Although previous machine learning approaches to predict egg production at flock-level have been reported (Ahmad, 2011; Felipe et al., 2015), few studies focused on the prediction at individual-level. 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 the 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 on 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 pre-assigned in the PF system, and a breeder could have a meal if its real-time BW was lower than its target BW. In the period of 6 h before the oviposition, a breeder that would lay an egg might be less likely to access to the feeder in the PF station than a breeder that would not lay due to heavier BW resulted from forming an egg. In contrast, in the period of 6 h after the oviposition, a breeder that laid an egg might be more likely to access to the feeder in the PF station than a breeder that did not lay due to lighter BW resulted from dropping an egg. 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 two 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 difference were used as 2 features. In addition to the 24 features, another 2 features regarding the anchor point were created. The time interval between two consecutive visits across the anchor point was created because a long time interval might occur if a breeder laid an egg between the two 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 two 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 representing egg-laying. Otherwise, it was 0 representing no egg-laying. The ANN model was used in the current study, and 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 that was 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 choice for generating the probability of classes. Since the probability estimated by the random forest classifier was the average proportion of a class of 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 two heavy tails in Figure 5-5. 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 distinguish the events that oviposition was more likely to occur from the events that oviposition was less likely to occur.

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.

5.5. Conclusion

The current study aimed to improve a previous approach that could only be used to identify daily oviposition 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 occurring in one day based on 26 features around a specific time in the day (anchor 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 that occurred on the current day, and the prediction outputs were the probability that could be informative to indicate how likely oviposition of an individual breeder occurred in the day. In the 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.

5.6. Acknowledgements

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5.8. Tables

Table 5-1. 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.

Table 5-2. The optimized hyper-parameters for ANN.

Hyper-parameter	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.

5.9. Figures

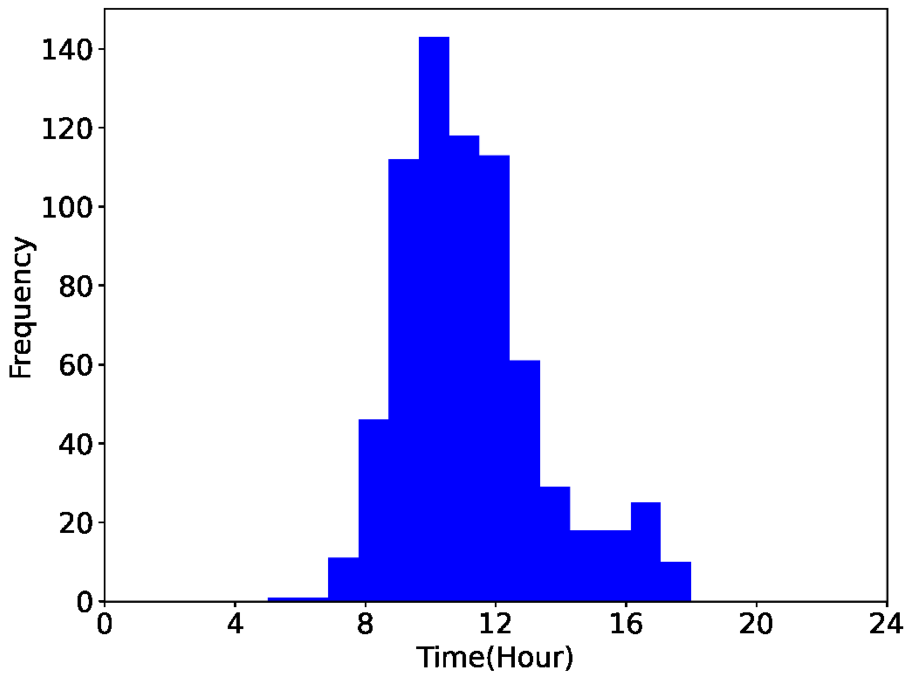

Figure 5-1. The distribution of egg-laying events during each hour over a 24 h period. The total number of egg-laying events from 171 to 306 d was 706.

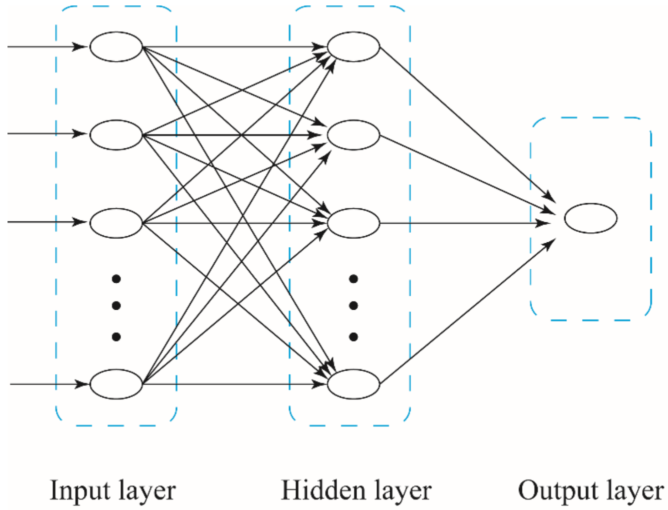

Figure 5-2. The structure of the feed-forward neural network in the current study. Ovals represented neurons. Arrows represented connections. Rounded rectangles represented layers. The neural network consisted of a group of neurons at each layer. Each neuron was fully connected to all neurons in the 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.

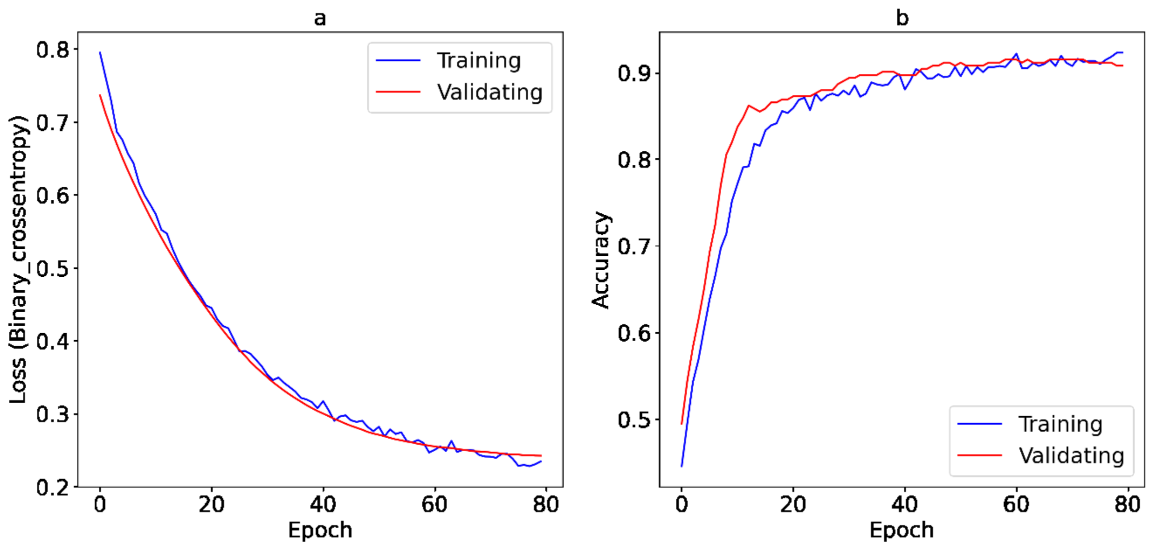

Figure 5-3. Loss (a) and accuracy (b) of the trained artificial neural netwrok (ANN) model with 80 epochs in the current study. The loss function for the ANN model was binary_cross_entropy that was for binary classification problems. Accuracy was calculated according to the equation: $Accuracy = (TP + TN)/(TP + FP + TN + FN)$, where TP, TN, FP, and FN meant true positive, true negative, false positive, and false negative, respectively.

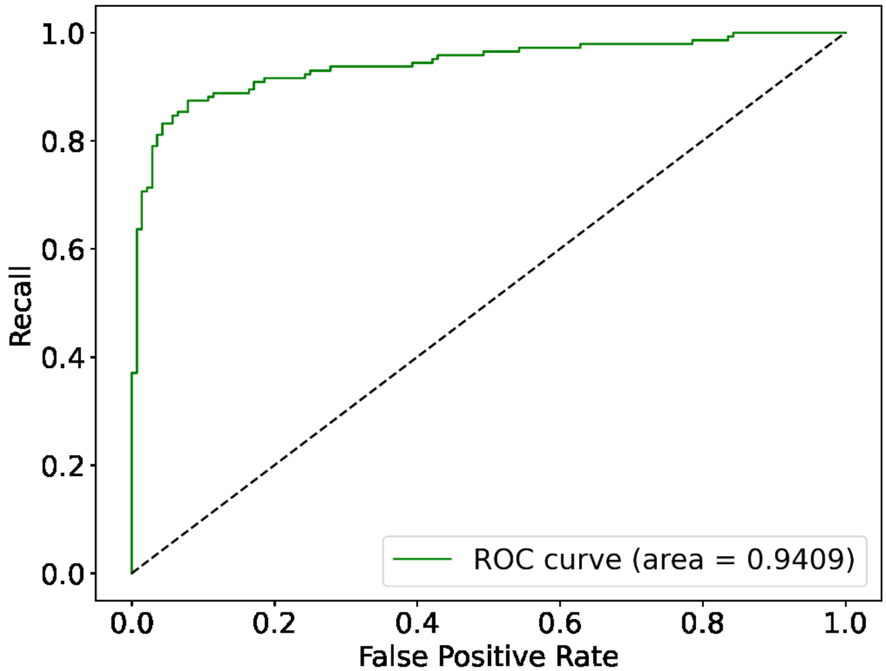

Figure 5-4. ROC curve and the area under the ROC curve of the artificial neural network model. In the figure, the recall was calculated by the equation: $Recall = TP/(TP + FN)$, where TP meant true positive and FN meant false negative. False positive rate (FPR) in the figure was calculated by the equation: $FPR = FP/(FP + TN)$, where FP meant false positive and TN meant true negative.

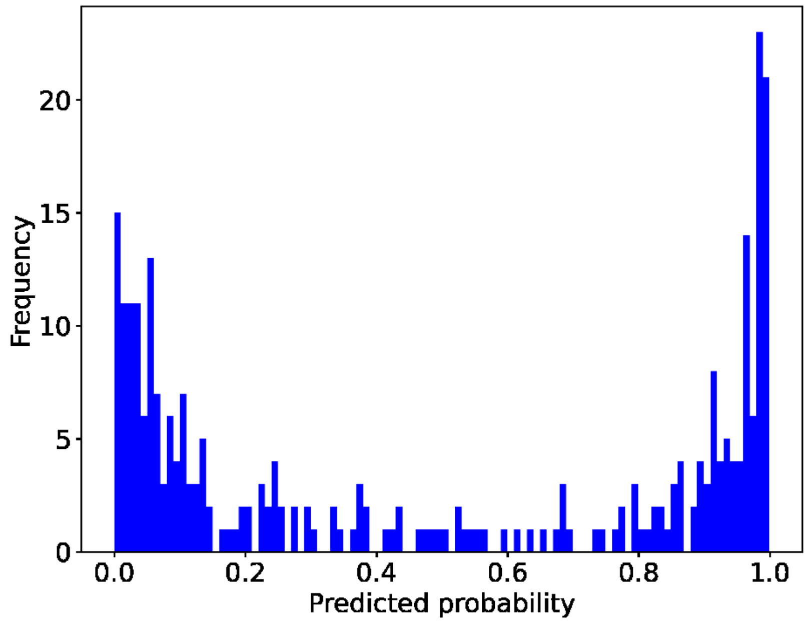

Figure 5-5. The distribution of predicted probability for testing samples by the artificial neural network model. The total number of testing samples was 283.

6. Chapter 6. Synthesis

6.1. General discussion

6.1.1. Background

Information and computer technologies have been applied in animal production to monitor animal behaviours and environment and manage animal production. A great example of applying these technologies in poultry nutrition and management was a precision feeding (**PF**) system that aimed to increase body weight (**BW**) uniformity of broiler breeders (Zuidhof et al., 2019). The PF system can automatically feed individual breeders and record real-time data regarding the feeding activity of the individual breeders. As a result, vast amounts of data can be collected by the PF system, which provides a valuable source of big data. However, it is challenging to extract meaningful information from data recorded by the PF system and make predictions based on the information. Machine learning (**ML**) is an appropriate tool for big data analytics, which is effective to reveal hidden patterns and correlations in big data. Thus, ML would be helpful in dealing with the data recorded by the PF system.

6.1.2. Objectives

The current thesis aimed to make predictions based on the real-time data recorded by a PF system, using ML approaches. There were three sub-projects in the current thesis, which focused on two subjects: predicting daily oviposition events of individual birds and detecting anomalous real-time BW data.

Chapter 3 and Chapter 5 aimed to predict daily egg-laying events of individual birds. The daily egg-laying events referred to whether oviposition of an individual bird occurred in one day or not. The day and time of oviposition during the laying period are highly variable, due to variability in follicle maturation modulated by hormone and environmental factors (van der Klein et al., 2020). Individual birds in a flock might stop laying because of improper nutrition or diseases, and identifying those non-laying birds would be helpful to improve bird management such as changing the diets or treating the diseases. In Chapter 3 and Chapter 5, ML models were built to predict whether an individual bird laid an egg in one day. Chapter 3 aimed to generate binary labels (1: laid an egg; 0: no egg was laid) for individual birds in a flock, and Chapter 5 aimed to generate a probability of daily oviposition events occurring for individual birds in a flock. Compared with Chapter 3, the model in Chapter 5 would be more useful in production for two reasons: 1) It could be used to predict oviposition events that occurred on the current day; 2) The prediction outputs were the probability that could be informative to indicate how likely oviposition of an individual breeder occurred in the day.

Chapter 4 aimed to detect anomalous real-time BW data recorded by a PF system. When feeding individual broiler breeders, the PF system can record real-time BW data of individual breeders. However, anomalous real-time BW data are sometimes recorded by the PF system. These anomalous observations should be cleaned because they would cause incorrect estimations of daily BW and BW gain. For example, several features regarding BW change were created for building ML models in Chapter 3 and Chapter 5. Anomalous real-time BW data would have negative impacts on these features, resulting in poor predictive performance of ML models. Although statistical methods and unsupervised machine learning methods can be used, they are effective in detecting anomalies to some extent because they just check data distribution. Manually labeling anomalies is accurate but time-consuming and labor-intensive. In Chapter 4, ML models were built to detect anomalous real-time BW data of individual broiler breeders, considering the statistical distribution of data and features regarding the feeding activity recorded by the PF system.

6.1.3. Other investigations attempted but not shown in thesis

For Chapter 3, egg-laying events in the previous day were used as an input feature for the RF model. When using the 29 features (28 selected features + 1 new feature) to train the RF model, overall accuracy of the model increased to around 88%. It indicated egg-laying events in the previous day would make a contribution to prediction. Although this feature could improve prediction, it was not included in the final model. Compared with feeding activity data recorded by a PF system, recording oviposition events for individual birds in a flock is labor-intensive and time-consuming. If this feature was not included in the RF model, only feeding activity data recorded by a PF system was needed. Otherwise, more work was needed for prediction. In addition, I tried logistic regression, which is the most commonly used ML classification algorithm. Overall accuracy of logistic regression was only around 78%, which was lower than the RF model (about 85%). Logistic regression was a linear classification algorithm whereas RF was a non-linear classification algorithm. The non-linear classification algorithm was a better choice for the data in Chapter 3.

In Chapter 4, Z-scores of ±3 were used as one of common anomaly detection methods, which referred to a range of the mean of real-time BW ± 3 standard deviations of real-time BW within each day. A point was recognized as an anomaly if it was not within this range. In fact, different Z-scores including ±2, ±2.5, and ±3 were tried. Eventually, Z-scores of ±3 were used in Chapter 4 because less normal observations were identified as anomalous observations.

In Chapter 5, anchor points that referred to a specific time point in one day were used. Features were created around the anchor point. When the anchor point was an input feature added to the 26 features (there were 27 features in total), the AUC value of the

ANN model was around 0.94. When the anchor point was not included (there were 26 features in total), the AUC value of the ANN model was still around 0.94. As a result, the anchor point was excluded in the final model because it made little contribution to prediction performance. In addition, the ANN model was compared with the RF model in Chapter 3. The RF model predicted binary labels whereas the ANN model predicted probabilities. A probability threshold of 0.5 was used to generate binary labels for the results predicted by the ANN model. Overall accuracy of the ANN model was about 90%, which was higher than the RF model (about 85%).

6.1.4. Application of the models

The ML models that were developed in Chapters 3, 4, and 5 could be applied as follows:

Figure 6-1 shows a workflow diagram of applying the RF model to identify daily oviposition events in Chapter 3. To know which breeders in a pen laid in one day, data regarding feeding activity for each bird recorded by a PF system for the day are needed. The data need to be cleaned to remove anomalous real-time BW observations, based on the anomaly detection approach that was developed in Chapter 4. Then the 28 features as shown in Chapter 3 need to be created from the cleaned data. Based on 28 features (input), the RF model that was built in Chapter 3 can be used to predict a label (output) for the bird for the day: 1 representing that a bird laid an egg in the day or 0 representing that a bird did not lay an egg in the day. The predicted results can be included as a new variable in the dataset generated by the PF system. A built-in function can be developed in the PF system to monitor this variable for each bird in a flock. For an individual breeder during the laying period, if several no egg-laying events consecutively occur, the PF system can trap the bird when it goes into the station and report to researchers or farmers for further management.

Figure 6-2 shows a workflow diagram of applying the RF model to detect anomalies in Chapter 4. To detect anomalies in real-time BW observations, the 12 features as shown in Chapter 4 for each observation need to be created from a dataset of individual broiler breeders recorded by a PF system. Based on 12 features (input), the RF model that was built in Chapter 4 can be used to predict a label (output) for each real-time BW observation: 1 representing an anomalous observation or 0 representing a normal observation. The predicted results can be included as a new variable in the dataset generated by the PF system. When researchers process data, the real-time observations that are identified as anomalies can be excluded to form a cleaned dataset.

Figure 6-3 shows a workflow diagram of applying the ANN model to generate a probability of daily oviposition events occurring in Chapter 5. To apply the model for generating a probability of oviposition events occurring for a breeder for a day, data regarding feeding activity for the bird recorded by a PF system for the day are needed. The data need to be cleaned to remove anomalous real-time BW observations, based on the anomaly detection approach that was developed in Chapter 4. A specific time point called an anchor point needs to be selected between 05:00 and 18:00, and then the 26 features as shown in Chapter 5 need to be created around the anchor point from the cleaned data. Based on 26 features (input), the ANN model that was built in Chapter 5 can be used to generate a probability of oviposition event occurring (output) for the bird for the day. The predicted results can be included as a new variable in the dataset generated by the PF system. As shown in Chapter 5, a higher probability value indicated that oviposition was more likely to occur. As a result, a built-in function can be developed to monitor the maximum probability for each bird in a flock and to rank all birds based on the maximum probability. The rank that can be updated every a few minutes can present those most likely to have laid an egg.

6.2. Novelty of research

This thesis was the first investigation into the application of ML in dealing with real-time data of individual broiler breeders collected by a PF system. There were three sub-projects in this thesis, and the objective of these sub-projects was to extract information from the data recorded by a PF system and make predictions based on the information. Chapter 3 and Chapter 5 focused on predicting individual oviposition events using ML approaches, which was the first study to predict daily oviposition events at individual-level. Previous studies reported using ML for prediction at flock-level (Ahmad, 2011; Felipe et al., 2015). Compared with these previous studies, Chapter 3 and Chapter 5 were able to explore individual egg-laying events because the PF system can monitor and record a lot of information regarding the feeding activity of individuals in a flock. Chapter 4 was a study of developing a supervised learning approach to detect anomalous real-time BW data of individual broiler breeders recorded by a PF system. Statistical methods and unsupervised learning methods might be only somewhat effective for detecting anomalies because they just checked data distribution. The most effective approach was manually labeling anomalies, but it was time-consuming and labour-intensive, which was not suitable for vast amounts of data. In Chapter 4, a supervised learning approach was developed considering data distribution and features regarding the feeding activity of individual birds recorded by the PF system.

6.3. Study limitation

In the current thesis, ML approaches were used to analyze the data collected by a PF system in two previous trials: the data for Chapter 3 were from one trial, and the data for Chapter 4 and Chapter 5 were from another trial. For the data of Chapter 4 and Chapter 5, I partially participated in the trial conducted in 2019. For the data of Chapter 3, however, I was not able to participate in the trial because it was conducted in 2017. Thus, in Chapter 3, there might be some details in the trial that I did not know. For example, some birds might experience diseases for a few days during the trial, which could affect egg production. In addition, there were some other limitations for Chapters 3, 4, and 5.

In Chapter 3, the original dataset that recorded feed intake, BW, time, and the like for each visit was processed to create input variables that might be associated with egg-laying events. As a result, 34 features were extracted in relation to the feeding activity and BW change of individual birds. There might be some other features that could contribute to the prediction. Another limitation was the RF classifier used all default hyper-parameters except the number of trees. The performance of the RF classifier can be manipulated by several hyper-parameters such as the maximum depth of the tree, the minimum number of samples required to split an internal node, and the minimum number of samples required to be at a leaf node. A better overall accuracy, precision, and recall might be achieved if these hyper-parameters were optimized. In Chapter 3, the hyper-parameters were not optimized because it required high computational costs and no high performance computers were available at that time. In addition to RF classifier (non-linear ML classification algorithm), logistic regression that was a linear ML classification was tried but not reported in Chapter 3 due to lower overall accuracy. There could be a comparison of RF classifier with other non-linear ML classification algorithms like ANN and SVM.

These non-linear classification algorithms might have a better performance than the RF model. Another limitation was the RF model was not tested by a dataset from another trial. The dataset for Chapter 5 could be used as another testing set for the RF model.

In Chapter 4, supervised learning models were developed to detect anomalous real-time BW data points. The data for building the models were 5 breeders that were randomly selected from all breeders fed by a PF system from day 15 to day 306. Since supervised learning algorithms investigated relationship between input data and output data, manually labelled anomalies were important because they were used as output for building supervised learning models. There were 60,150 observations in the dataset in total, and I manually labelled 580 observations in 60,150 observations as anomalies. However, manually labelled results might be different among people. Thus, it would be better to manually label the data by a few people and then combine the different manually labelled results as the output for building the models. It would also be valuable to investigate quantitative criteria to systematically label anomalous real-time BW observations. In addition, when building supervised learning models, training set and testing set were both from the data of 5 breeders. Another breeder could be randomly selected and then all observations of the bird could be manually labelled as a new testing set to evaluate the models.

In Chapter 5, the training, validation, and testing sets for building an ANN model were relatively small because of the limited number of samples. Although a large number of egg-laying events and no egg-laying events occurred in the trial, only 706 egg-laying events could be used because they were recorded by RFID nest boxes that can record the exact time of egg-laying events. As a result, there were only 1,412 samples in total. It would be better to build the ANN model from a larger dataset. In addition, the ANN model was not tested by a dataset from another trial. The dataset for Chapter 3 could be used as another testing set for the ANN model.

6.4. Future research

Future research for the current thesis should focus on three objectives:

1. To improve performance of the models. Future research should explore new features and different ML algorithms to improve the prediction performance. For Chapter 3, future research should investigate using other ML algorithms. For example, feed intake during each hour in one day were used as 24 features, which could be considered a sequence in time order. Thus, it might be helpful to use recurrent neural network that was well-suited to time series data. Since different supervised learning algorithms were compared in Chapter 4, future research for Chapter 4 should investigate creating new features. There might be some other features that would be helpful for anomaly detection. For example, real-time BW observations of a bird in a few consecutive days (e.g. 3 days) could fit a linear model, due to growth of the bird. How far an observation deviated from the line might be helpful to detect anomalous observations. As a result, the distance from the observation to the line and the slope and intercept of the linear model might be used as features. In Chapter 5, features were mainly from 24 hours before the anchor point, 6 hours before the anchor point, and 6 hours after anchor point. Real-time data for a period of 30 hours (24 hours before the anchor point and 6 hours after anchor points) were needed to build the ANN model. To use less real-time data from a shorter period, other periods could be investigated to create features like 18 hours before the anchor point, 2 hours before the anchor point, and 2 hours after the anchor point. In addition, other ML algorithms such as SVM and RF should also be further investigated for Chapter 5.

2. To generalize the models. Generalization refers to the ability of models to adapt well to new data. In the current thesis, the model in each chapter was built based on one dataset. The RF model in Chapter 3 was built based on the dataset of a trial conducted in 2017. The RF model in Chapter 4 and the ANN model in Chapter 5 were built based on the dataset of a trial conducted in 2019. The dataset was randomly split into a training set and a testing set, and the model was trained and tested by the subsets from the same dataset. However, new datasets were not used to evaluate these models. The prediction performance of these models on other datasets from different trials might not be as good as in the current thesis. Thus, these models should be tested by a new dataset about whether these models are general. To further generalize these models, future research for Chapter 3 and Chapter 5 should collect data from different trials to build models. For Chapter 4, future research should generalize the RF model by using data from more birds with a longer period from different trials, and anomalous observations should be manually labelled by different people.

3. To validate and use the models on commercial farms. Future research should investigate validating and using the models developed in the current thesis on commercial farms. These models were developed based on data from the trials that were conducted in environmental chambers in Poultry Research Center at the University of Alberta. These models need to be validated by data from commercial farms before using them on the farms. To validate the models in Chapter 3 and Chapter 5, a few birds can be randomly selected in a flock on a farm, and then they can be labelled. Each of labelled birds should be palpated every morning to know if it is going to lay in the day, which can be used as the actual oviposition events. The models can predict oviposition events for each labelled bird, based on its feeding activity data recorded by a PF system. Based on the actual oviposition events

and the predicted oviposition events, overall accuracy of the models can be calculated. If overall accuracy of the models on the validation data is as good as that on the testing data (shown in Chapter 3 and Chapter 5), it indicates the models can predict oviposition events of birds on the farm very well and the models can be further used to predict oviposition events of other birds on the farm. Similarly, data from the randomly selected birds can be manually labelled to validate the model in Chapter 4. If the performance of the model on the validation data is as good as that on the testing data, the model can be further used to detect anomalous real-time BW data of other birds on the farm.

6.5. Overall implications

The PF system was capable of recording vast amounts of real-time data regarding the feeding activity of birds. To analyze the data, ML was used in the current thesis because it can deal with hidden patterns and correlations in data for making better data-based decisions, predictions, and strategies.

In Chapter 3 and Chapter 5, daily oviposition events of individual broiler breeders were predicted by ML classification models, based on the feeding activity and BW change recorded by a PF system. The models both had outstanding binary classification performance: Chapter 3 showed that the overall accuracy and Kappa coefficient were 0.8482 and 0.6931, respectively, and Chapter 5 showed that the AUC value was 0.9409. This was the first time ML models were built to identify daily oviposition events of individual broiler breeders. The approach in Chapter 3 could be used to generate binary labels of oviposition events for breeders, which helped to directly distinguish the breeders that laid an egg from the breeders that did not lay an egg in a flock. The approach in Chapter 5 could be used to generate a probability of daily oviposition events occurring of individual birds in a flock, and these probabilities could be ranked to choose those most likely to have laid an egg. For these two models, research is required to improve prediction performance by exploring new features and using other ML algorithms. Research is also required to generalize the models and apply the models to commercial farms.

In Chapter 4, a supervised learning classification model was developed to detect anomalous real-time BW data of individual broiler breeders. Compared with common anomaly detection methods that just checked data distribution, a supervised learning approach was developed for anomaly detection based on data distribution and features regarding the feeding activity of individual birds recorded by the PF system. The RF model selected from 4 different supervised learning models had a higher average F1 score (0.9448) than other common anomaly detection approaches, indicating that the RF model was an effective solution to clean anomalous observations for this type of data. This approach could be used to clean anomalous real-time BW data recorded by the PF system, which could help to correctly record real-time BW of individual birds and provide correct estimations of BW such as daily BW and BW gain in one day. However, research is required to improve model performance by investigating new features and generalize the model by collecting more data and using anomalies labelled by different people.

6.6. Conclusion

In the current thesis, ML approaches were applied to make predictions based on big data recorded by a PF system. The PF system not only feeds birds automatically but also records vast amounts of real-time data regarding the feeding activity of individual birds. ML approaches can be helpful in revealing hidden patterns and correlations and make predictions based on the data. In the current thesis, the recorded data were analyzed by ML approaches to predict daily oviposition events of individual breeders (Chapter 3 and Chapter 5), and an innovative ML approach was developed to detect anomalies in real-time

BW data of individual breeders (Chapter 4). The current thesis indicated that ML approaches had a lot of potential to deal with the data recorded by the PF system.

6.7. References

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6.8. Figures

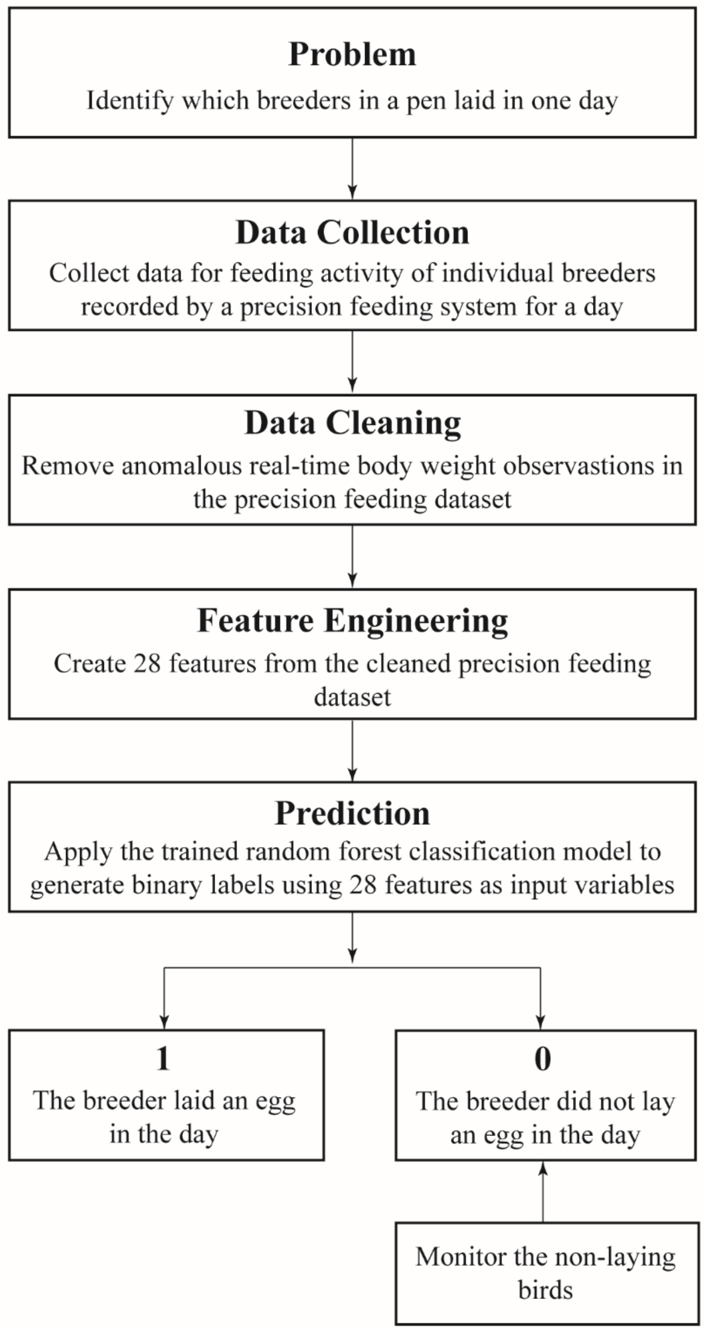

Figure 6-1. Workflow diagram of applying the random forest model to identify daily oviposition events in Chapter 3. In the step of data cleaning, anomalous real-time body weight observations were cleaned by the approach in Chapter 4. In the step of feature engineering, 28 features referred to the selected 28 features in Chapter 3. In the step of prediction, the trained random forest classification model referred the random forest model in Chapter 3.

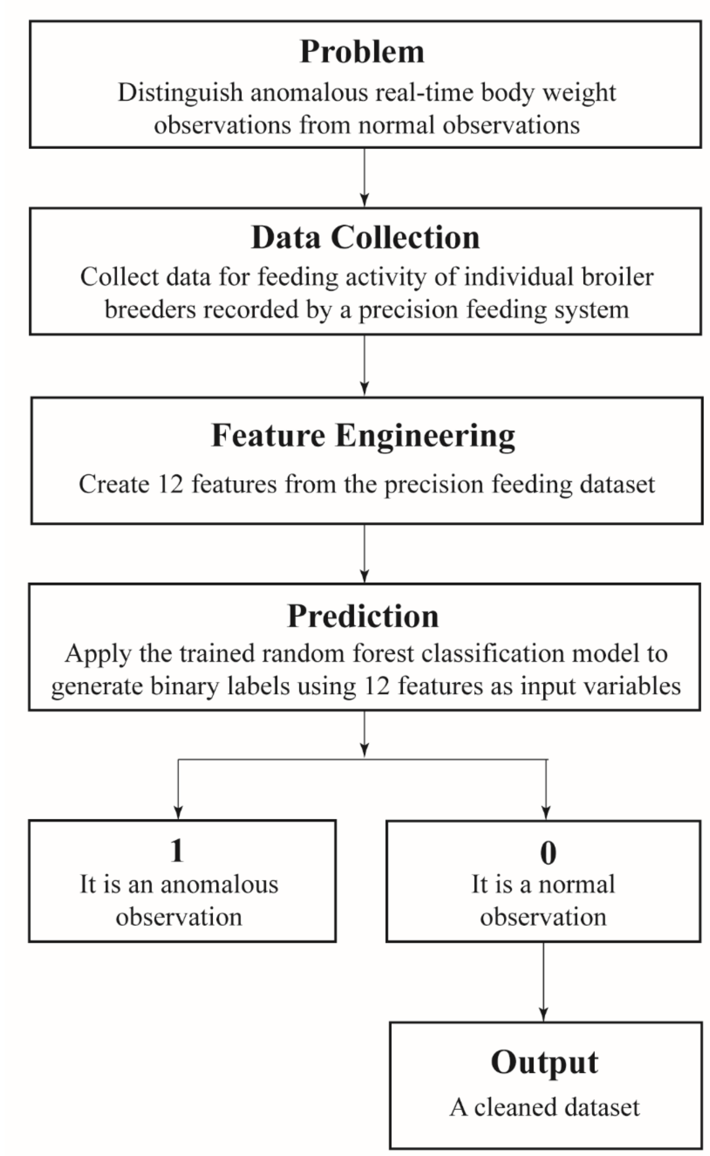

Figure 6-2. Workflow diagram of applying the random forest model to detect anomalies in Chapter 4. In the step of feature engineering, 12 features referred to the 12 features created in Chapter 4. In the step of prediction, the trained random forest classification model referred the random forest model in Chapter 4.

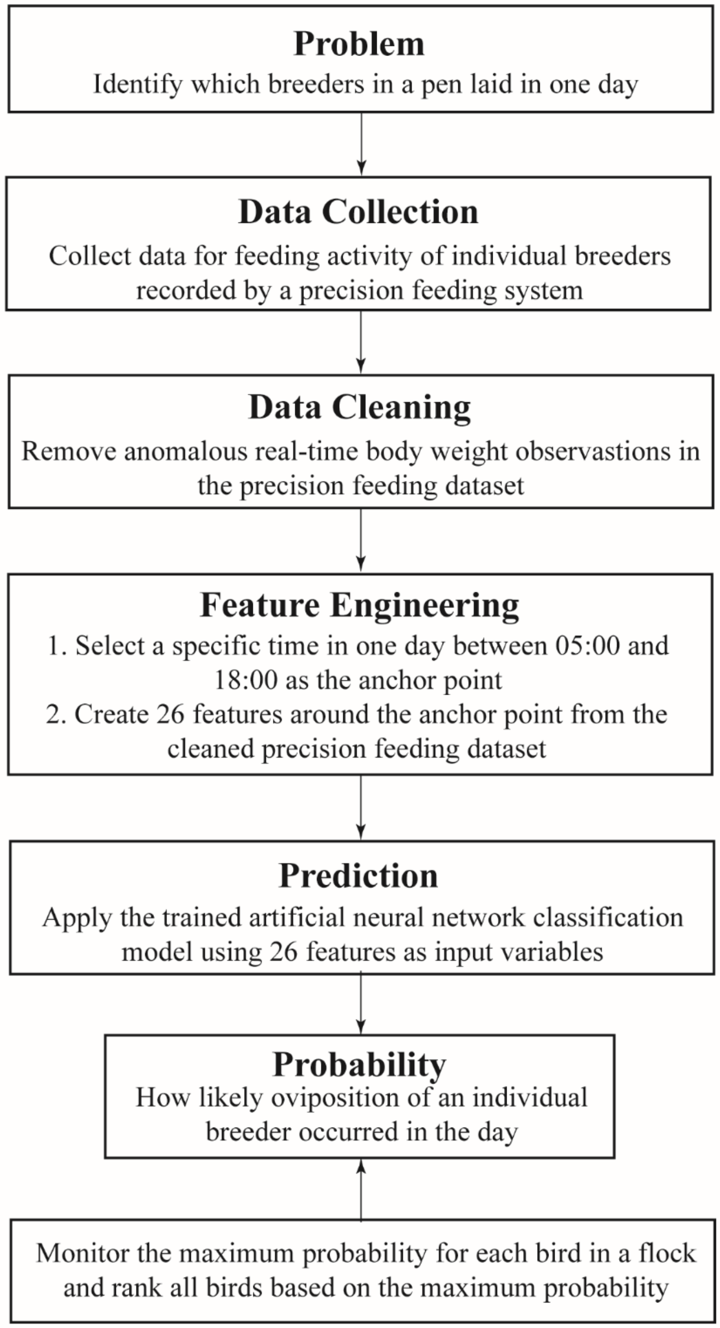

Figure 6-3. Workflow diagram of applying the artificial neural network to generate a probability of daily oviposition events occurring in Chapter 5. In the step of data cleaning, anomalous real-time body weight observations were cleaned by the approach in Chapter 4. In the step of feature engineering, 26 features referred to the 26 features created in Chapter 5. In the step of prediction, the trained artificial neural network classification model referred the artificial neural network model in Chapter 5.

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