In vivo prediction of abdominal fat and breast muscle in broiler chicken using live body measurements based on machine learning

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ABSTRACT The purpose of this study was to predict the carcass characteristics of broilers using support vector regression (**SVR**) and artificial neural network (**ANN**) model methods. Data were obtained from 176 yellow feather broilers aged 100-day-old (90 males and 86 females). The input variables were live body measurements, including external measurements and B-ultrasound measurements. The predictors of the model were the weight of abdominal fat and breast muscle in male and female broilers, respectively. After descriptive statistics and correlation analysis, the datasets were randomly divided into train set and test set according to the ratio of 7:3 to establish the model. The results of this study demonstrated that it is feasible to use machine learning methods to predict carcass characteristics of broilers based on live body measurements. Compared with the ANN method, the SVR method achieved better prediction results, for predicting breast muscle (male: $R^2 = 0.950$; female: $R^2 = 0.955$) and abdominal fat (male: $R^2 = 0.802$; female: $R^2 = 0.944$) in the test set. Consequently, the SVR method can be considered to predict breast muscle and abdominal fat of broiler chickens, except for abdominal fat in male broilers. However, further revaluation of the SVR method is suggested.

Key words: carcass characteristics, noninvasive method, support vector regression, artificial neural network

2023 Poultry Science 102:102239
https://doi.org/10.1016/j.psj.2022.102239

INTRODUCTION

With the rapid growth of population, broiler chicken has become the main source of meat for human consumption with its advantages of high feed conversion rate and low production cost. Breast is the most valuable part of the broiler carcass. In recent years, the poultry industry's preference for high-yield and high-breast muscle has increased the production rate of broiler by more than 300%, resulting in problems such as metabolic disorders, skeletal diseases and abdominal fat accumulation (Knowles et al., 2008). Excessive accumulation of fat will lead to a decrease in feed efficiency, as compared with the same amount of muscle, the accumulation of the same amount of fat takes 3 to 5 times the feed costs (Melot et al., 2003), which greatly increased the cost. Therefore, the carcass characteristics with high breast muscle and low abdominal fat can effectively increase the output of the poultry industry. To achieve this goal, it is very important to understand the carcass composition and quality during the breeding process. The traditional way to determine carcass composition is detailed dissection (with slaughter), which provides accurate carcass composition data, but is often time-consuming and costly. Therefore, relevant scholars have carried out a series of studies on the prediction of carcass characteristics by live body measurements, in order to simplify the breeding work. For example, some researchers used ultrasound scan to predict weight of breast muscle in broilers (Koenig et al., 1997; Remignon et al., 2000; Silva et al., 2006), some researchers predicted abdominal fat through live body measurements and ultrasound scan data (Melot et al., 2003; Souza et al., 2017). In addition, the indirect detection methods and the live body measurements are also widely used for predicting the carcass characteristics of other animals, including the Muscovy ducks (Kleczek et al., 2006), Japanese Black steers (Maeno et al., 2014), guinea pigs (Barba et al., 2018), Peking duck (Lin et al., 2018), and sheep (Barcelos et al., 2020). Overall, B-ultrasound measurements and live body measurements have been

Received July 17, 2022.
Accepted October 5, 2022.

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widely used in carcass characteristics prediction in poultry.

These studies all established mathematical models to predict the carcass composition of poultry by multiple linear regression. However, for the multiple linear analysis, the data need to meet the assumptions of linearity, normality, and non-multicollinearity, and can also cause biased estimates due to the high correlation among input variables (Ali et al., 2015). With the continuous development of machine learning in recent years, methods such as Support Vector Machines (**SVM**) and Artificial Neural Networks (**ANN**) have been widely used in various fields, which may improve the prediction accuracy of poultry carcasses. ANN is a computing mechanism which simulates biological neural networks with advantage lies in that it can find the complex relationship between input variables and output variables, solve nonlinear fitting problems and improve the fitting accuracy of complex problems (Felipe et al., 2015). Nevertheless, there are also problems such as sophisticated hyperparameter optimization, easily falling into local optimal value and overfitting (Tay and Cao, 2001). SVM was first proposed by Vapnik in 1997 as a new method of data mining based on structural risk minimization principle (Vapnik et al., 1997), widely used in computer learning, pattern recognition, prediction fitting, and other fields. SVM can find nonlinear relationship between input and output variables in a certain precision range, get global optimal solution and strong generalization capability, which makes SVM widely used in engineering, science, economy, military and many other fields. However, machine learning has been not well applied in predicting poultry carcass characteristics using live body measurements. Hence the purposes of this study were 1) to established Support Vector Regression (SVR) and Artificial Neural Network (ANN) mathematical models to predict abdominal fat and breast muscle in broilers by live body measurements to guide breeding works, 2) and compare the performance of established SVR and ANN models.

MATERIALS AND METHODS

Animals

All procedures of this experiment were performed under the guidance of the Care and Use of Animals of the Zhejiang University (Hangzhou, China). The Committee on the Ethics of Animal Experiments of Zhejiang University approved the protocol. A total of 200 yellow-feather broilers (Sanhuang, male:100, female:100)were housed in deep litter pens in Huzhou Nanxun Wens Animal Husbandry Co., Ltd. This strain, which has been recorded in National Breed List of Livestock and Poultry Genetic Resources by the Chinese Agricultural Ministry, was chosen because of its popularity in China and genetic stability (Yang et al., 2018). The room temperature was maintained at 31°C for the first 4 days, and then reduced by 1°C every 2 d until it reached 21°C on d 25, which was maintained until the end of the experiment. The mean RH was around 60% and was kept constant within this value throughout the experiment. Follow the immunization schedule for vaccinations. All broilers had ad libitum access to food and water. Their diets were formulated according to the Agricultural industry standard of China (Ministry of Agriculture, PRC, 2004a), initial phase feed (0−3 wk) with 12.54 MJ/kg of metabolic energy (**ME**) and 21.51% crude protein (**CP**); growth phase feed (4−6 wk) with 12.96 MJ/kg of metabolic energy (ME) and 20.00% crude protein (CP), fattening phase feed (7−14 wk) with 13.17 MJ/kg of metabolic energy (ME) and 18.00% crude protein (CP).

Live Body Measurements and Carcass Characteristics

The live body weight (X_1, g) was measured after were fasting for 12 h in broilers aged 100 d. Subsequently, live body measurements were performed before slaughter according to the Agricultural industry standard of China (Ministry of Agriculture, PRC, 2004b) and Kleczek et al. (2006), as follows:

1. Body slope length (X_2, mm): Distance from shoulder joint to ossa sedentarium on the same side by a tape measure;
2. Neck length (X_3, mm): Distance from the first cervical vertebra to the end of the neck by a tape measure;
3. Fossil bone length (X_4, mm): Distance from the anterior border of the fossil bone to the posterior of the fossil bone by a tape measure;
4. Breast circumference (X_5, mm): Behind the wing, through the anterior border of the fossil bone and the first thoracic vertebra by a tape measure;
5. Shank circumference (X_6, mm): Girth of the central of shank by a tape measure;
6. Humerus length (X_7, mm): Distance from the shoulder joint to the elbow joint by tape measure;
7. Drumstick length (X_8, mm): Distance from knee joint to ankle joint by a tape measure;
8. Breast depth (X_9, mm): Distance from the first thoracic vertebra to the anterior of the fossil bone by a caliper;
9. Breast width (X_{10}, mm): Distance between the two shoulder joints by a caliper;
10. Pelvis width (X_{11}, mm): Distance between the two hip joints by a caliper;
11. Shank length (X_{12}, mm): Distance from the ankle to the third and four toe by a caliper;
12. Breast muscle thickness (X_{13}, mm): The measurement position is one-third of the fossil bone length and 1.5 cm from the right of border of the fossil bone;
13. Skin fat thickness (X_{14}, mm): Measured at the same position as breast muscle thickness measurement, including the skin and subcutaneous fat.
14. Mass index (%): Mass index = Live body weight (kg) / Body slope length (cm) × 100%.

15. Leg index (%): Leg index = Drumstick length (cm) / Body slope length (cm) × 100%.
16. Brevity index (%): Brevity index = Breast circumference (cm) / Body slope length (cm) × 100%.

When live body measurements are performed, each animal was measured by 2 trained operators who assist each other. In lying position, the selected broilers were held on their backs and gently restrained by hand, the other operator took measurements. In standing position, an operator took the right leg of the broilers between the thumb and index finger of his left hand, the left between the ring and little fingers, and places the abdomen of the selected broilers in the palm of his left hand and controlled the wings with his right hand, the other operator took measurements (Yang, 2002). In live body measurements, except for fossil bone length, breast muscle thickness and skin fat thickness, which were measured in lying position, the other measurements were all in standing position.

The $X_{2\text{-}8}$ live body measurements were measured by a tape measure with a precision of 1 mm; $X_{9\text{-}12}$ measurements were measured by a caliper with a precision of 0.1 mm; Breast muscle thickness and skin fat thickness were measured by a portable B-ultrasound apparatus (Mindray DP-10VET, www. mindray. com) with the precision of 0.1 mm. Furthermore, defeathering and oil application have been processed at the measurement position before breast muscle thickness and fat skin thickness measurements to ensure adequate contact between the probe and broiler skin. About 14−16 indexes were calculated from other live body measurements. These indexes can provide initial information on the fat and muscle of broilers, which is of great significance and application value for massive broiler production. In the study, descriptive statistics and correlation analysis were carried out to test the correlation between these indexes and carcass characteristics of broilers, in order to provide preliminary carcass characteristics information for massive broiler production (difficult to make detailed live body measurements). However, since these indexes were calculated from other live body measurements, it is not necessary to use them as input variables to establish the broiler carcass characteristics prediction model, otherwise multicollinearity will occur, resulting in unstable model prediction.

The broilers were killed by severing the carotid arteries and jugular veins of the neck with a sharp knife. Following slaughter, the broilers were bled for about 5 min, and then scalded in hot water about 60℃ for 2 min to facilitate plucking. The broilers were de-feathered manually. Next, the carcasses were eviscerated and abdominal fat (Y_1, g) was isolated and weighed accurate to 0.01 g. Then the eviscerated carcasses were placed in separate plastic bags and chilled for 24 h at +4℃ for detailed dissection. Breast muscles (Y_2, g) were dissected from the breast quarter by cutting along the fossil bone crest, clavicle and coracoids, and along the line of the attachment of these muscles to the ribs. The tissue components were weighed accurate to 0.01 g. Finally, 176 yellow-feather broilers (90 males and 86 females) were used in the following analyses after removing broilers with missing records during rearing and slaughter.

Statistical Analysis

Descriptive statistics (mean, standard deviation, variance, minimum, and maximum) of live body measurements and carcass characteristics of broilers were performed using SPSS Statistics 25.0. ANOVA was then performed to test the significance of the influence of gender on live body measurements and carcass characteristics. In order to unify the dimensions of different variables and accelerate the training speed of the prediction model, it is necessary to normalize each column of variables. The normalization of variables is as follows:

$$x_{ij} = \frac{\left(X_{ij} - \overline{X}_j\right)}{\max\left(X_j\right) - \min\left(X_j\right)} \tag{1}$$

$X_{ij}$is the i_{th} observed value of the j_{th} variable, X_j is the set of the j_{th} variable, $\overline{X}_j$ is the mean of the j_{th} variable, $\max(X_j)$ represents the maximum value of the j_{th} variable, $\min(X_j)$ represents the minimum value of the j_{th} variable.

Then, Pearson correlation analysis was conducted on the normalized variables to determine the coefficient of correlations between live body measurements and carcass characteristics. The coefficient of correlation between variable A and variable B is calculated as follows:

$$coeff_{AB} = \frac{\sum_{i=1}^{n}\left(A_i - \overline{A}\right)\left(B_i - \overline{B}\right)}{\sqrt{\sum_{i=1}^{n}\left(A_i - \overline{A}\right)^2}\sqrt{\sum_{i=1}^{n}\left(B_i - \overline{B}\right)^2}} \tag{2}$$

A_i is the i_{th} observed value of the variable A, $\overline{A}$ is the mean of the variable A, B_i is the i_{th} observed value of the variable B, $\overline{B}$ is the mean of the variable B.

Prediction Models

After data preprocessing, a total of 90 data lines for male broilers and 86 data lines for female broilers were used to predict weight of breast muscle and abdominal fat in broilers. Live body measurements were used as input variables, and output variables were weight of breast muscle and abdominal fat in broilers after slaughter and detailed dissection. To enhance the generalization ability of the SVR and ANN models, the datasets were randomly divided into the train set and the test set, with 70% and 30%, respectively. The SVM model was first proposed by Vapnik in 1997 and designed based on the structural minimum risk principle (Vapnik et al., 1997), originally used to solve complex nonlinear classification problems, which has been widely applied in the nonlinear classification problems of small sample because of the advantage of simple model structure, convenient hyperparameter optimization, global optimal solution, and avoiding overfitting. The basic principle of

SVM classification is to find an optimal hyperplane, segment the 2 classes of data, and ensure that the maximum spacing between the nearest data points to the hyperplane (Rodrigues et al., 2015). The SVM was then applied to the regression problem, namely support vector regression (SVR), and the basic principle is to find an optimal hyperplane that makes the minimum spacing between the furthest data points to the hyperplane. Among the various types of SVR, the most commonly used one is ε-SVR, which is designed to find a function that make the maximum error between the predicted value and the observed value not more than ε. For traditional SVR model, the training data points are all inside the ε-insensitive band (ε-tube). However, when solving nonlinear practical problems, if the data points are strictly in the ε-tube, it will cause problems such as increased model complexity and reduced generalization ability of model. Therefore, the slack variables ξ are introduced, which makes some data points can be on the ε-tube margin or even slightly out of the ε-tube margin (analogously to the soft margin in SVM for classification), without having to be strictly inside ε-tube, see Figure 1 (Alonso et al., 2013). Its objective function and constraints are as follows:

$$min\frac{1}{2}\parallel \omega \parallel ^2 + C\sum_{i=1}^{n}\left(\xi_i + \hat{\xi}_i\right) \quad (3)$$

$$s.t.(\langle w, \phi(x_i)\rangle + b) - y_i \le \varepsilon + \xi_i,$$

$$y_i - (\langle w, \phi(x_i)\rangle + b) \le \varepsilon + \hat{\xi}_i$$

$$\xi_i \ge 0, \hat{\xi}_i \ge 0, i = 1, 2, \cdots n,$$

C, ε are the hyperparameter, C is the regularization parameter, which represents the tolerance of model

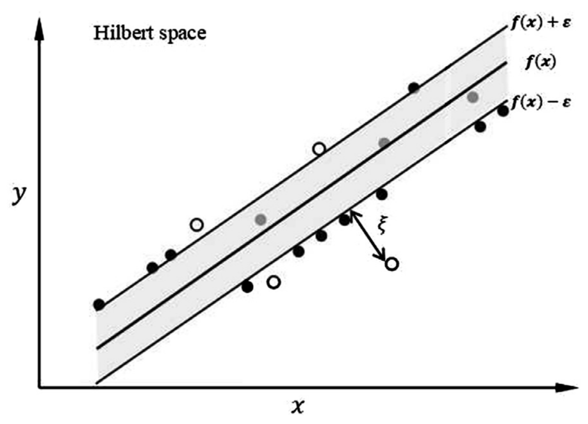

Figure 1. Geometrical interpretation of ε-SVR in Hibert space. ε-SVR is designed to find a function that make the maximum error between the predicted value and the actual value not more than ε. But allow the data points on the basis of deviation from ε stray out ξ slightly again, in order to enhance the ε-SVR model generalization ability. The gray part of the figure is ε-tube, which represents the tolerance of the model prediction error. $f(x)$ is the objective function. namely the ideal prediction model; ξ is slack variable, is the distance between data points that distributed outside the ε-tube beyond the ε-tube, that's the soft margin.

prediction error, used to trade off the model complexity and prediction accuracy. The larger C, the smaller $\sum_{i=1}^{n}(\xi_i + \hat{\xi}_i)$, the greater the structural risk, easily to overfit. Conversely, the opposite; ε also indicates the tolerance of the model prediction error. Slack variables ξ_i and $\hat{\xi}_i$ represent more than ε above the observed value and more than ε below the observed value, respectively. The smaller the sum of slack variables is, the higher the fitting accuracy of the regression will be.

However, when dealing with practical problems, the relationship between input variables and output variables is often complex and nonlinear. Therefore, the input space needs to be mapping to the Hilbert space through the kernel function $\phi(x_i)$, so as to transform the nonlinear relationship to the linear relationship and reduce the difficulty of model training. The types of kernel functions include linear, polynomial, radial basis function (**RBF**), and radial base kernels. The most widely used kernel function is the radial basis function (RBF), which is optimized by tuning the kernel parameter γ. According to the above elaboration, before training the SVR model, the three hyperparameters C, ε, γ need to optimize to get the best prediction model. In this study, we adopted the ε-SVR model invoking the RBF kernel to predict the weight of breast muscle and abdominal fat in female and male broilers, respectively. The grid search method within 10-fold cross-validation framework was used to optimize hyperparameters of ε-SVR model (increasing the generalization ability of the model and avoiding overfitting problem). This paper evaluated the predictive ability of the SVR model through R^2, MAE, RMSE.

ANN has attracted the attention of scholars in many fields due to its automatic learning, automatic organization, and excellent nonlinear approximation ability (Dongre et al., 2012). ANN was originally proposed by Rosenblatt in 1958 and called a perceptron (Rosenblatt, 1958), but it did not attract much attention because it could not solve nonlinear problems. Until the 1980s, the feed forward multilayer perceptron proposed by Rumelhart et al. (1986) overcame this shortcoming well, making Artificial neural network rapidly develop and applied in the various field of data mining. The structure of the feed forward multilayer perceptron (**MLP**) consists of an input layer, one or more hidden layers and an output layer. The data is input by the input layer and reaches the hidden layer after the weighted summation and activation function. Next the data in the hidden layer is also processed by weighted summation and activation function to reach the next layer, and finally reaches the output layer after multiple layer calculations (Dongre et al., 2012). In this study, the input and output variables of the ANN model were the same as those in the SVR model for comparison. The hidden layer of ANN model had only one layer to ensure the generalization ability of the model, and the number of hidden neurons was determined by trialing and error method. The activation function between each layer was selected among Log-Sigmoid, Tan-Sigmoid, and Purelin. Finally, the weights and offsets in the weighted summation process were determined by the back propagation learning algorithm in MLP in order to find the nonlinear relationship between input variables and output variables (Fernández et al., 2007). ANN model had the same evaluation criteria as SVR model.

RESULTS AND DISCUSSION

Descriptive Statistics of Live Body Measurements and Carcass Characteristics

Table 1 shows the means, standard deviations, coefficients of variation and ranges (minimum-maximum value) for the live body measurements in male and female broilers. It could be observed that the average live body weight of male and female broilers were 2,108.68 g and 1,768.47 g, respectively, while the coefficients of variation were 11.80 and 12.05%. Sweeney et al. (2022) studying on Ross708 broilers, found that the average live body weight of broilers was 1,948.1 g and the coefficient of variation was 11.2%, which was consistent with the data of this study. For all live body measurements except for the live body weight, it could be seen that the coefficients of variation of each live body measurement ranged from 4.62 to 12.99% in this study. Zhang et al. (2010) found that the coefficients of variation for these measurements ranged from 4.38% to 15.95%, which agreed with this study. In addition, Lin et al. (2018) found that the coefficients of variation for these measurements ranged from 3.93 to 17.55% in Peking ducks. Live body measurements except for breast muscle thickness were significant difference in male broilers and females ($P < 0.01$), suggesting that gender was able to statistically significantly influence the live body measurements in broilers.

Table 2 shows the means, standard deviations, coefficients of variation, and ranges (minimum-maximum values) for the carcass characteristics in male and female broilers. It could be observed that the weights of breast muscle in male and female broilers were 178.32 g and 163.27 g, the percentages of breast muscle were 8.47 and 9.26%, respectively, while the coefficients of variation ranged from 11.82 to 16.00%. Silva et al. (2006) found the range of breast muscle percentages in broilers were 14.3 to 24.6% in male broilers. For the fat traits, the weights of abdominal fat in male and female broilers were 32.48 g and 64.65 g, the percentages of breast muscle were 1.51 and 3.57%, respectively, while the coefficients of variation ranged from 33.12 to 53.67%. Male broilers had the highest coefficient of variation in weight of abdominal fat, up to 53.67%. In broiler, Melot et al. (2003) reported that the coefficient of variation for the weight of abdominal fat was 30.43%. For the sexual dimorphism, the weight of breast muscle was significantly higher in males than in females ($P < 0.01$), while the weight and percentage of abdominal fat were

Table 1. Means, standard deviations (SD), coefficients of variation (CV) and ranges (Min = minimum; Max = maximum) for live body measurements in broiler.

	Male					Female					
Variable	Mean	SD	CV (%)	Min	Max	Mean	SD	CV (%)	Min	Max	P value
Live body weight (X_1, g)	2,108.68	248.92	11.80	1,530.00	2,783.00	1,768.47	213.08	12.05	1343.00	2325.00	<0.001
Body slope length (X_2, mm)	204.78	15.53	7.58	171.00	245.00	184.59	16.53	8.95	154.00	252.00	<0.001
Neck length (X_3, mm)	158.28	17.75	11.21	119.00	206.00	135.85	16.35	12.04	105.00	191.00	<0.001
Fossil bone length (X_4, mm)	116.57	9.45	8.11	94.00	140.00	106.06	8.18	7.72	91.00	128.00	<0.001
Breast circumference (X_5, mm)	284.61	13.14	4.62	251.00	320.00	264.08	13.56	5.14	235.00	299.00	<0.001
Shank circumference (X_6, mm)	39.07	2.34	5.98	34.00	48.00	33.70	2.38	7.07	29.00	39.00	<0.001
Humerus length (X_7, mm)	105.93	8.76	8.27	80.00	129.00	95.17	6.07	6.38	83.00	118.00	<0.001
Drumstick length (X_8, mm)	150.41	15.97	10.62	113.00	245.00	128.91	12.30	9.54	102.00	162.00	<0.001
Breast depth (X_9, mm)	108.98	6.86	6.30	93.80	125.80	98.14	6.70	6.82	70.20	111.90	<0.001
Breast width (X_{10}, mm)	76.56	7.48	9.77	58.80	96.00	70.01	7.96	11.38	54.80	107.70	<0.001
Pelvis width (X_{11}, mm)	82.68	5.35	6.47	68.60	97.30	77.81	7.38	9.48	65.10	121.30	<0.001
Shank length (X_{12}, mm)	102.26	6.26	6.12	83.90	121.20	88.93	6.82	7.67	75.20	123.95	<0.001
Breast muscle thickness (X_{13}, mm)	10.72	1.28	11.92	6.90	14.40	10.40	1.16	11.18	7.50	13.30	0.082
Skin fat thickness (X_{14}, mm)	4.84	0.63	12.99	3.80	6.80	4.37	0.54	12.26	3.20	5.50	<0.001
Mass index (%)	10.27	1.05	10.27	6.47	13.49	9.61	1.10	11.40	7.29	12.64	<0.001
Leg index (%)	73.04	6.01	8.23	51.83	84.97	70.11	6.58	9.39	43.65	84.86	0.002
Brevity index (%)	139.13	10.21	7.34	107.35	164.91	143.94	12.19	8.47	110.32	170.59	0.005

Table 2. Means, standard deviation (SD), coefficient of variation (CV) and ranges (Min = minimum; Max = maximum) for carcass characteristics in broiler.

	Male					Female					
Variable	Mean	SD	CV (%)	Min	Max	Mean	SD	CV (%)	Min	Max	P value
Weight of abdominal fat (Y_1)	32.48	17.43	53.67	4.54	76.08	64.65	26.61	41.15	14.40	132.39	<0.001
Percentage of abdominal fat (%)	1.51	0.74	49.09	0.29	3.42	3.57	1.18	33.12	0.99	6.50	<0.001
Weight of breast muscle (Y_2)	178.32	28.53	16.00	118.86	249.62	163.27	24.99	15.31	99.78	231.44	<0.001
Percentage of breast muscle (%)	8.47	1.07	12.63	5.95	11.50	9.26	1.09	11.82	6.35	11.62	<0.001

significantly higher in females than in males ($P < 0.01$). It was consistent with the conclusion of Zuidhof et al. (2014).

Correlation Coefficients Between Live Body Measurements and Carcass Characteristics

Table 3 shows the correlation coefficients between carcass characteristics (the weight of breast muscle and abdominal fat) and live body measurements. In males and females, the variables that significantly correlated to abdominal fat weight included live body weight (r ♂ = 0.50, r ♀ = 0.77), mass index (r♂ = 0.56, r♀ = 0.70), pelvis width (r ♂ = 0.32, r ♀ = 0.46), breast circumference (r ♂ =0.29, r ♀ = 0.47), breast muscle thickness (r ♂ = 0.29, r ♀ = 0.32; $P < 0.01$). Furthermore, the skin fat thickness was also significantly correlated to abdominal fat in females (r ♀ = 0.32; $P < 0.01$). According to the above results, it could be concluded that the correlation coefficients between the live body measurements and abdominal fat weight in females are higher than that in males. On the other hand, body slope length, neck length, fossil bone length, humerus length, leg index, brevity index, and shank length were not significantly correlated with abdominal fat weight in both male and female broilers. In broiler, Melot et al. (2003) showed that live body weight was significantly correlated with abdominal fat weight (r = 0.82). Moreover, Latshaw and Bishop (2001) found that pelvis width was significantly correlated ($P < 0.01$), which was consistent with the conclusion of this study. Since the phenotypic correlations were weighted the sums of both genetic and environmental components, it is easy to explain that genetic correlations can influence phenotypic correlation coefficients (Liu et al., 2021). Live body weight and pelvis width were significantly positively correlated with the weight of abdominal fat because live body weight and pelvis width had significant genetic correlations with the weight of abdominal fat ($P < 0.01$; Zerehdaran et al., 2004). And after recent years of breeding for fast-growing broilers, modern broilers have been able to eat more food than they require for muscle growth and maintenance, so that the excessive energy intake is converted into fat and the higher the body weight, the more abdominal fat (Zerehdaran et al., 2004). This indicated that live body weight and pelvis width are excellent predictors of the weight of abdominal fat in broiler, and may help breed the broilers with less abdominal fat. In addition, abdominal fat can be regulated in combination with food restriction during rearing (Arafa et al., 1983). However, Erensoy et al. (2020) found that fossil bone length and breast width had no significant correlation with abdominal fat weight in the study of broilers. In this study, there was no significant correlation between fossil bone length and abdominal fat weight, but there was significant correlation between breast width and abdominal fat weight (r ♂ = 0.26, r ♀ = 0.23; $P < 0.05$). In duck, Lin et al. (2018) showed that only live body weight and skin fat thickness were significantly correlated with abdominal fat weight ($P < 0.01$), and there was no significant correlation between live body weight and abdominal fat weight in females. Nevertheless, live body weight, breast muscle thickness, and breast circumference had also significant correlation with the abdominal fat weight in this study ($P < 0.01$).

The weight of breast muscle was positively correlated with all live body measurements except for leg index and brevity index. For males, except for drumstick length, leg index ,and brevity index, other live body measurements were significantly correlated to the weight of breast muscle ($P < 0.05$). However, the correlation coefficients of neck length, fossil bone length, and breast depth did not reach a significant level in females. For males and females, the variables that significantly

Table 3. Correlation coefficients (r) between carcass characteristics[1] (Y) and live body measurements (X) in broiler.

	Male				Female			
	Y_1		Y_2		Y_1		Y_2	
Variable	R	P value	r	P value	r	P value	r	P value
Live body weight (X_1)	0.50**	<0.001	0.65**	<0.001	0.77**	<0.001	0.65**	<0.001
Body slope length (X_2)	0.08	0.459	0.32**	0.003	0.17	0.116	0.35**	0.001
Neck length (X_3)	−0.19	0.078	0.21*	0.047	−0.16	0.155	0.17	0.126
Fossil bone length (X_4)	−0.02	0.887	0.40**	<0.001	−0.02	0.829	0.21	0.056
Breast circumference (X_5)	0.29**	0.006	0.47**	<0.001	0.47**	<0.001	0.56**	<0.001
Shank circumference (X_6)	0.25*	0.016	0.36**	<0.001	0.13	0.247	0.43**	<0.001
Humerus length (X_7)	0.02	0.844	0.34**	0.001	0.12	0.256	0.22*	0.045
Drumstick length (X_8)	−0.22*	0.037	0.09	0.427	0.05	0.675	0.35**	0.001
Breast depth (X_9)	0.25*	0.018	0.26*	0.015	0.14	0.211	0.18	0.092
Breast width (X_{10})	0.26*	0.012	0.36**	<0.001	0.23*	0.037	0.35**	0.001
Pelvis width (X_{11})	0.32**	0.002	0.52**	<0.001	0.46**	<0.001	0.45**	<0.001
Shank length (X_{12})	0.12	0.248	0.30**	0.005	0.20	0.072	0.47**	<0.001
Breast muscle thickness (X_{13})	0.29**	0.006	0.56**	<0.001	0.32**	0.003	0.38**	<0.001
Skin fat thickness (X_{14})	0.18	0.079	0.44**	<0.001	0.33**	0.002	0.25*	0.019
Mass index	0.56**	<0.001	0.55**	<0.001	0.70**	<0.001	0.41**	<0.001
Leg index	−0.19	0.073	−0.048	0.655	−0.097	0.374	0.033	0.762
Brevity index	0.164	0.123	0.012	0.908	0.122	0.263	−0.019	0.861

[1]carcass characteristics: Y_1 = weight of abdominal fat (g); Y_2= weight of breast muscle (g).
**Significance of the correlation coefficient (r) at $\alpha = 0.01$;
*$\alpha = 0.05$.

correlated to breast muscle weight included live body weight (r♂ = 0.65, r♀ = 0.65), breast muscle thickness (r♂ = 0.56, r♀ = 0.38), mass index (r♂ = 0.55, r♀ = 0.41), breast circumference (r♂ = 0.47, r♀ = 0.56), pelvis width (r♂ = 0.52, r♀ = 0.45), and so on ($P < 0.01$). Raji et al. (2010), studying on broilers, found that the weight of breast muscle was significantly correlated with live body weight and breast circumference ($P < 0.01$), while breast depth did not reach a significant level. It was consistent with the data in this study. And some scholars all came to the conclusion that the weight of breast muscle was significantly correlated with live body weight and breast muscle thickness ($P < 0.01$) (Remignon et al., 2000; Silva et al., 2006; Oviedo-Rondón et al., 2007). Kleczek et al. (2006) also got a similar conclusion in study of Muscovy ducks. This was because live body weight and breast muscle thickness were significantly genetic positively correlated with the weight of breast muscle ($P < 0.01$; Zerehdaran et al., 2004). In addition, breast muscle accounts for more than half of the torso muscles of poultry, and the growth of breast muscle was proportional to weight gain in broilers (Zuidhof, 2005), which could also explain these significant correlations. It indicated that live body weight and breast muscle thickness could be excellent predictors for the weight of breast muscle during selective breeding. In addition to a significant genetic correlation between breast muscle thickness and the weight of breast muscle (Scheuermann et al., 2003; Case et al., 2012), there was also a significant genetic correlation between breast muscle thickness and meat quality in broilers (Gaya et al., 2011). This indicated that breast muscle thickness could not only be used as an important indicator to predict the weight of breast muscle, improve the efficiency of breeding work, but also help selection breeding to improve broiler meat quality.

From the correlation analysis of mass index, leg index, brevity index, and carcass characteristics, it could be seen that mass index was significantly correlated with the weight of abdominal fat and breast muscle in broilers ($P < 0.01$), respectively. It indicated that when the scale of commercial broiler production is too large to carry out detailed live body measurements of broilers, the preliminary information of broiler fat and muscle can be obtained through mass index so as to adjust the management measures. This is similar to the preliminary information about human body fat obtained by BMI (body mass index).

Predictive Ability

This study attempted to establish the SVR and ANN models through live body measurements to predict the weight of breast muscle and abdominal fat in broilers. With the continuous development of poultry industry, carcass characteristic with high breast muscle and low abdominal fat proportions have become breeding targets, and the high heritability of breast muscle weight and abdominal fat weight indicated that these two carcass characteristics were important breeding traits (Rance et al., 2002; Gaya et al., 2006). Therefore, it is of great significance for poultry farmers and breeders to predict the carcass characteristics in broilers with non-destructive and cheap mathematical models, which can provide slaughtering lot standardization, carcass characteristics for the poultry farmer to make management decisions; selection criteria for the breeder to assist breeding work. In this study, coefficient of determination (**R^2**), mean absolute error (**MAE**), root mean square error (**RMSE**) were used to evaluate the predictive ability of SVR model and ANN model. Tables 4 and 5 summarized the predictive ability of SVR and ANN models on the weight of abdominal fat and breast muscle, respectively.

In terms of abdominal fat, it could be seen from Table 4 that SVR model also had better R^2 value and lower MAE and RMSE, which was similar to the results of breast muscle in broilers. However, for male broilers, neither SVR model nor ANN model achieved good prediction effect, which might be due to the low correlation between live body measurements and abdominal fat weight in males, and the large coefficient of variation of abdominal fat weight in males affecting the predictive ability of the mathematical model. For female broilers, the R^2, MAE, and RMSE of the abdominal fat prediction with the SVR model were 0.944, 4.65, and 6.18 for the test set; 0.952, 4.74, and 6.13 for train set, respectively. It indicated that the SVR model is accurate, reliable, and feasible for the prediction of abdominal fat in

Table 4. Comparison of the support vector regression (SVR) and Artificial neural networks (ANN) developed to predict weight of abdominal fat in terms of coefficient of determination (R^2), mean absolute error (MAE), root mean square error (RMSE).

Items		SVR		ANN	
		♂	♀	♂	♀
data lines (no.)	train	63	61	63	61
	test	27	25	27	25
R^2	train	0.804	0.952	0.758	0.924
	test	0.802	0.944	0.751	0.915
MAE	train	7.77	4.74	6.89	5.61
	test	4.08	4.65	7.59	7.75
RMSE	train	9.07	6.13	9.46	7.79
	test	5.42	6.18	9.07	9.46

Table 5. Comparison of the support vector regression (SVR) and Artificial neural networks (ANN) developed to predict weight of breast muscle in terms of coefficient of determination (R^2), mean absolute error (MAE), root mean square error (RMSE).

Items		SVR		ANN	
		♂	♀	♂	♀
data set (no.)	train	63	61	63	61
	test	27	25	27	25
R^2	train	0.960	0.968	0.936	0.918
	test	0.950	0.955	0.904	0.908
MAE	train	5.43	4.60	5.61	5.33
	test	3.92	3.66	6.47	5.68
RMSE	train	5.61	4.69	7.23	7.33
	test	5.67	4.87	7.88	6.92

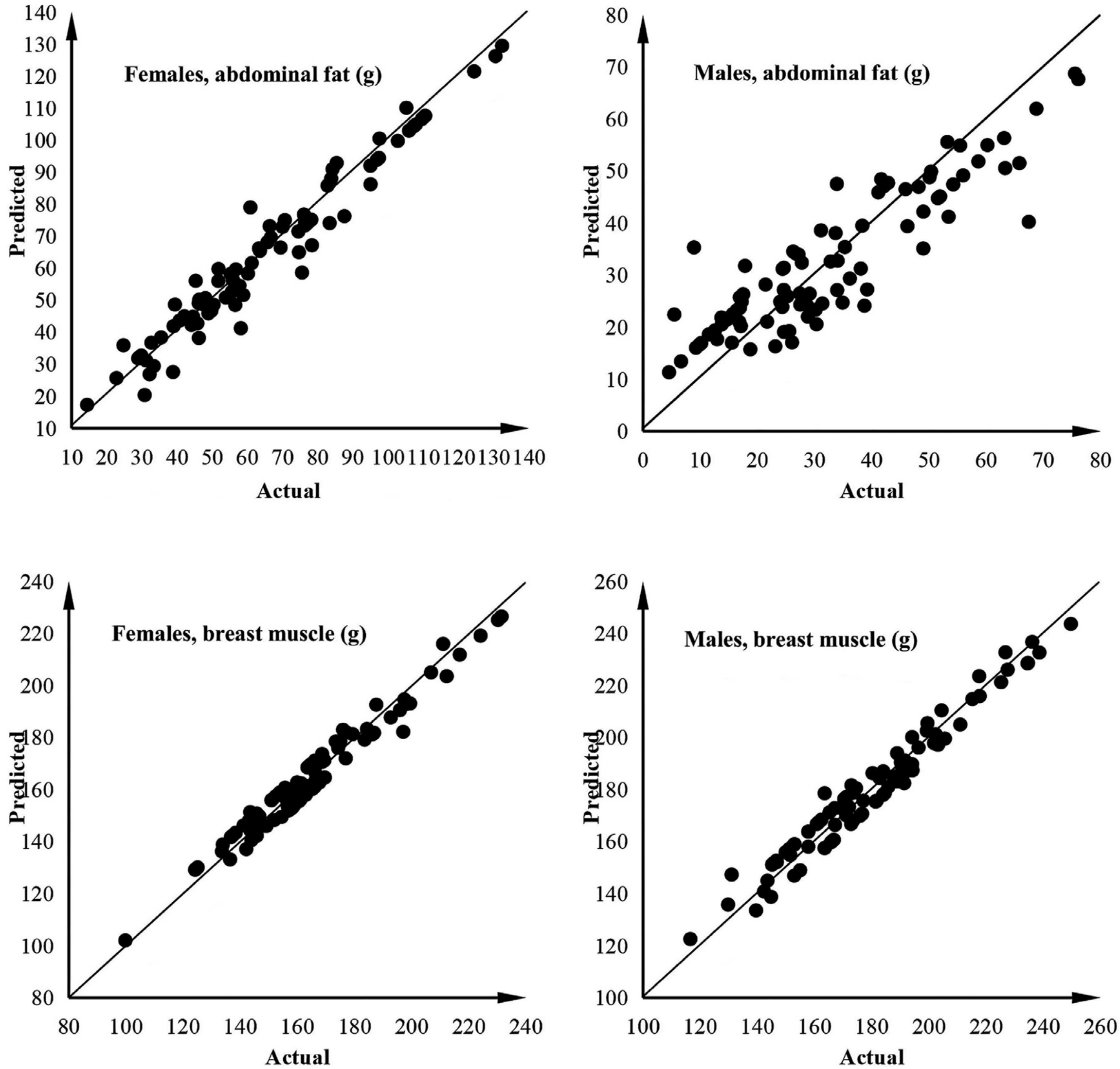

Figure 2. Scatter plot of actual and predicted carcass characteristics by SVR for male and female broilers. In the figure, the abscissa value and ordinate value of the data point are the actual value and the predicted value respectively. If the data point falls on the line with slope 1, it means that the predicted value and the actual value are equal.

female broilers. It indicated that the prediction results were reliable and the model had no overfitting problem. To sum up, SVR model had better predictive ability than ANN model for predicting carcass characteristics in broilers, but the predictive ability of model is also affected by the dataset quality, hyperparameter optimization, evaluation criteria, and other factors.

In terms of breast muscle, it could be seen from Table 5 that SVR model yielded higher R^2 and lower MAE, RMSE than ANN model. Taking male broilers as an example, the R^2, MAE, and RMSE of the breast muscle prediction with the SVR model were 0.950, 3.92, and 5.67 for the test set; 0.960, 5.43, and 5.61 for train set, respectively. It suggested that the prediction results of the model are accurate and reliable, there was no overfitting problem, and it had application potential. Female breast muscle predictions had similar results. The reason why ANN model was inferior to SVR may be that the dataset is small, and the division of the dataset to train set and test set further reduce the amount of data, which might bring limitations to the analysis of ANN model (Ekiz et al., 2020). Moreover, ANN model had the problem of overfitting (R^2 in train set: 0.936, R^2 in test set: 0.904). This is because ANN model is prone to fall into local minima in the process of model training, which increases the error on a novel dataset and reduces the model generalization capability (Kim, 2003; Javed et al., 2007). Faridi et al. (2012) predicted the carcass characteristics of Ross and Cobb broilers based on nutritional information, and also found that SVR model had better predictive and generalization ability than ANN model, which was consistent with this study.

The scatter plots of observed and predicted values for carcass characteristics by SVR model are shown in Figure 2 for males and females, respectively. If all data points lie on the straight line through the origin, the acquired model makes accurate prediction results. As seen in Figure 2, the results of this study suggested that machine learning (SVR) models are effective in predicting carcass characteristics based on live body measurements. Using mathematical model to predict the weight of breast muscle and abdominal fat is nondestructive and low cost, so this method has the potential of popularization.

CONCLUSIONS

The study aimed to predict the weight of breast muscle and abdominal fat in broiler through live body measurements using machine learning methods. For this purpose, this study compared the performance of 2 widely used machine learning methods (artificial neural networks and support vector machines) in predicting broiler carcass characteristics through live body measurements. Compared with the ANN method, the SVR method achieved better prediction results, for predicting breast muscle (male: $R^2 = 0.950$; female: $R^2 = 0.955$) and abdominal fat (male: $R^2 = 0.802$; female: $R^2 = 0.944$) in the test set. It indicated that it is feasible to achieve accurately predict the weight of breast muscle and abdominal fat in broilers weight using SVR model. This method does not require detailed dissection, saves time and costs, and greatly improves the efficiency of breeding work and management decisions in the poultry industry. However, the small size of data set is the limiting factor of the study. Therefore, it is expected that in future studies, deep learning methods can be adopted to improve the prediction accuracy and generalization ability of the model by using large data sets.

ACKNOWLEDGMENTS

This work was supported by the National Natural Science Foundation of China (32102597), the Key R&D Program of Zhejiang Province, China (2021C02026), and the Agriculture Research System of China (CARS-40)

DISCLOSURES

The authors declare no conflicts of interest.

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