Prediction of Peking duck intramuscle fat content by near-infrared spectroscopy

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ABSTRACT Peking duck is the most representative of the meat-type duck breed, and it is also one of the most popular meats in Asia. Few studies were reported on the fast assessment of duck meat quality. This study aimed to develop a fast measuring of duck fat content by using the near-infrared spectroscopy (**NIRS**) method. We measured 273 duck breast muscle intramuscle fat (**IMF**) content and spectra. Partial least-squares regression (**PLSR**) was used to model the fat content prediction by using the spectra in the wavelengths between 950 and 1650 nm. The best predictive abilities were obtained after the first derivative pretreatment, with coefficient of calibration ($\mathbf{R^2_C}$) of 0.92, with coefficient of prediction ($\mathbf{R^2_P}$) of 0.90, ratio performance to deviation (**RPD**) of 2.72, and ratio of error range (**RER**) of 15.45, for samples of 30 g duck. Results demonstrated that the near-infrared spectroscopy is a useful tool for fat content assessment of Peking duck meat.

Key words: fat content, meat quality, near-infrared spectroscopy, partial least-squares regression

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INTRODUCTION

Poultry meat is considered to be an important component in healthy diets and has reached high levels of consumption worldwide (Alexandrakis et al., 2012). Among the poultry meat market, duck meat is the second largest consumed meat, especially in Asia. Peking duck is the most representative of the meat-type duck breed. With the development of society, the demand and requirements for meat quality assessment and control of poultry continue to increase. The fat content is an important factor affecting the quality of meat, which is closely related to flavor, tenderness, moisture content of meat (Li et al., 2016). Fast meat quality assessment is critical to commercial production and breeding program (Huang et al., 2016, 2017).

Traditional analytical methods are often destructive and require complex sample preparation procedures. Therefore, traditional analytical methods are not suitable for the fast-growing rapid industrial meat sector. Recently, new techniques for rapid, reliable, and reagent-free meat quality assessment have been well applied in production. Near-infrared spectrometers have become a useful tool for providing information on the physical and chemical properties of complex organic matrices. The application of NIRS analysis for monitoring, quality control, and analytical purposes is increasing in agricultural industries and food (Alexandrakis et al., 2012; Barbin et al., 2015). NIRS can provide an objective, rapid, repeatable, nondestructive and accurate method for evaluating meat to predict the chemical composition and qualitative attributes in meat and meat products (Grau et al., 2011; Jia et al., 2017; Jiang et al., 2018). NIRS has been applied in the prediction and evaluation of pork, beef, and chicken meat quality, and the prediction accuracy can match the requirements in the field (Wu et al., 2014; Khulal et al., 2016; Qiao et al., 2017a,b; Wu et al., 2017). However, few studies were performed on the fast assessment of duck meat quality. At the same time, large-scale spectrometers are generally, and portable spectrometers are less used (Perez et al., 2018). In general, duck meat has the higher fat content compared with chicken (https://fdc.nal.usda.gov/). We didn't find PSE, DF, and wooden muscle meat in ducks. So, the intramuscle fat (**IMF**) is one of the major issues in ducks. The amount of input meat for predicting IMF is lacking of investigation in practice.

This study aimed to identify the critical wavelengths linked to IMF content in ducks, evaluate the effect of the different total amount of measuring samples, and

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then build the prediction model to evaluate the IMF content in duck meat.

MATERIALS AND METHODS

Ducks and Phenotypes

The Peking ducks used in the experiment were provided by the Beijing Golden Star Duck Breeding Center. Processing methods were the same as our previous study (Deng et al., 2019). The left breast muscle was stored at 4°C which used to measure IMF and NIRS. The IMF content and near-infrared spectroscopy data were measured in time. In total, 273 duck breast samples were used in this study. The fascia was removed from the muscle. Then, the muscle was minced using a kitchen chopper for 20 s.

Near-Infrared Spectra

Spectral scanning of duck meat was performed using a Micro NIR Pro spectrometer (VIAVI Solutions Inc., Scottsdale, AZ). Before the measurement, the instrument was preheated firstly, and the test temperature was set to 51 ± 1°C. The wavelength range was set to range from 900 to 1,700 nm at 6-nm intervals. We use the 99% diffuse reflectance standard included with the MicroNIR to collect the 100% background measurement and collect the 0% dark measurement with the lamps on and warmed up. The 100% background measurement and the 0% dark measurement are reset every 1 h. The prepared duck breast muscle samples were taken in a sample cup by taking 5 g and 30 g of meat emulsion, respectively. The sample cup was a cylinder with an external diameter of 5.1 cm and a height of 8 cm. A heavy stainless stopper was placed on each sample. It was spun in two circles so that the sample became a uniform tablet under the action of the gravity and rotation of the stopper. Each sample was repeatedly scanned 3 times, and each sample was rotated 3 times. The average spectrum was used as an effective spectrum for each sample.

IMF Determination

According to previous methods, the fat content was measured (Zerehdaran et al., 2004; Ding et al., 2020). The steps for determining the fat content of duck breast are:

(1) Take the sample from 0.95 to 1.1 g of the minced duck breast muscle into a filter bag and weight the fresh sample m (not including the filter bag).
(2) Dry the fresh sample at 105°C for 3 h to constant weight, and weigh the dry sample weight m1 (not including the filter bag).
(3) The dried sample was placed in a fat extracting apparatus and determined by the Soxhlet extraction method, extracted with anhydrous ether for 3 h, and the other was recovered for 30 min.
(4) After the extraction, the filter bag was taken out, and dried in an oven at 105°C for 2 h to constant weight, and the final weight m2 (not including the filter bag) was weighed.

$$\text{Fat content} = (m2 - m1)/m \times 100\%.$$

All steps described for spectral analysis were carried out in multivariate analysis software (Unscrambler version 10.4, CAMO, Trondheim, Norway).

Spectral Data Preprocessing and Modeling

Spectral data preprocessing and partial least-squares regression (**PLSR**) method was performed by using Unscrambler X software (v10.4). In NIRS measurements, sample physical characteristics and inconsistency in instrument response may be responsible for perturbations in spectra (shifts, slope changes, baseline, etc.) (Windham et al., 2003; Huang et al., 2017). Scattering effects can be attenuated by some mathematical treatments, such as derivation, standard normal variate (**SNV**), and multiplicative scatter correction (**MSC**), as the wavelength dependency of light scatter is different from that of chemically-based light absorption (Balage et al., 2015; Yang et al., 2018). There is still no standard procedure to decide which spectral preprocessing method to apply. Usually, the only approach is trial and error. So, we explored multiple pretreatment methods to deal with spectral data. The spectral preprocessing methods used in this study were listed as follows:

S-G5: 5-point Savitzky-Golay Smoothing; S-G7: 7-point Savitzky-Golay Smoothing; S-G9: 9-point Savitzky-Golay Smoothing; 1D1: 1-point first derivative; 1D3: 3-point first derivative; 2D3: 3-point second derivative; SNV: Standard Normal Variate; DT: detrending; MSC: Multiplicative Scatter Correction; SNV-1D1: Standard Normal Variate and 1-point first derivative; SNV-2D3: Standard Normal Variate and 3-point second derivative; S-G5-1D1: 5-point Savitzky-Golay Smoothing and 1-point first derivative.

The functionality of the preprocessing technique was compared by the prediction ability of the regression model relating IMF content of Peking duck to the preprocessing spectra. The best model was selected based on the highest R^2 (multiple correlation coefficient in calibration) and the lowest RMSE of calibration and cross-validation (RMSEC and RMSEP, respectively).

PLSR method was used to model Y by means of X. The values of the IMF content of Peking duck were stored in matrix Y. Matrix X collected spectral data of the Peking duck Samples. In total, 275 samples were randomly selected as a calibration set and a prediction set in a 3:1 ratio. Mean center data, cross-validation, and kernel PLS algorithm was chosen.

RESULTS AND DISCUSSION

IMF Content of Peking Duck Breasts

The basic summary statistics are shown in Table 1. The changes in IMF content in the 5 g and 30 g breast

Table 1. Experimental results for IMF content of Peking duck samples.

Group	Weight (g)	Number	Min	Max	Mean	SD	CV%
Calibration	5	205	0.62	2.20	1.09	0.26	24.24
	30	200	0.63	2.31	1.08	0.26	24.14
Prediction	5	68	0.64	1.85	1.05	0.24	23.02
	30	65	0.67	2.20	1.08	0.30	27.77

There are almost no differences between the calibration and prediction group for IMF content.

muscle, respectively. The results suggested the presence of a wide range of variation in Peking duck IMF content, with a large CV%. IMF did not show any significant differences between 2 randomly divided groups. The prediction results of the model are affected by the range of the IMF content in the sample. The more full the range, the more accurate the result. The breast IMF content of Peking duck is roughly between 0.62 and 2.31%, which covers the distribution range of the existing Peking duck breast fat content. At the same time, the average IMF content of the calibration set and the prediction set are close to 1; the standard deviation is about 0.3 (Table 1). The data distribution is following a normal distribution with a considerable variation range, indicating that the sample selected in this experiment has strong representativeness. The calibration set range covers the range of prediction-set, which can improve the reliability of the established model and increase the applicability of the model in the field.

Near-Infrared Average Spectrum

The spectral range between 950 and 1650 nm was selected for processing, and the original average spectrum of the 5 g and 30 g group of duck breast samples is shown in Figure 1. Although the extracted spectral information has a similar spectral pattern, it shows different absorbance values for each sample. Therefore, the relationship between the near-infrared spectral information difference and the IMF content could be used to establish a model to predict the IMF content of the duck breast.

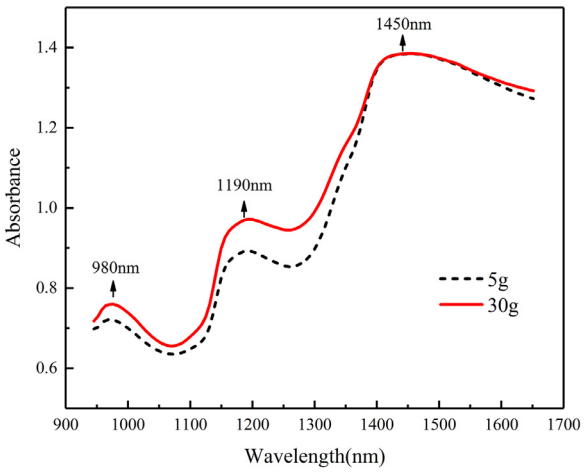

Figure 2. Average spectrum of all samples of duck breast samples 5 g and 30 g.

The difference in absorbance among samples could be ascribed as sample composition in the NIR electromagnetic range (Dixit et al., 2017). A few broad local absorption maxima are noticeable around 980, 1,190 and 1,450 nm (Berzaghi et al., 2005; Huang et al., 2015). The characteristic bands of 980 nm and 1,450 nm are related to second and first overtone O-H stretching of water (Xiong et al., 2015; Perez et al., 2018) and 1,190 nm is related to the second overtone of CH_3 stretching (Nolasco-Perez et al., 2019) while the combination bands could be attributed to water absorption and fat structure changes. In-depth scrutiny of absorbance related to each chemical vibration bond could also help in a better understanding of how each quality parameter affects spectral fingerprints of duck samples.

Figure 2 shows the average spectrum of all samples of 5 g and 30 g groups. The trend of the two spectral curves is the same. However, the absorbance of the 30 g group is stronger than 5 g group and has different performance in different wavelength ranges. In the range of 950 to 1,400 nm, the absorbance of the 30 g group is significantly improved compared to the 5 g group. The major reason is that the 30 g sample is larger in mass and higher in thickness, allowing the sample to absorb more

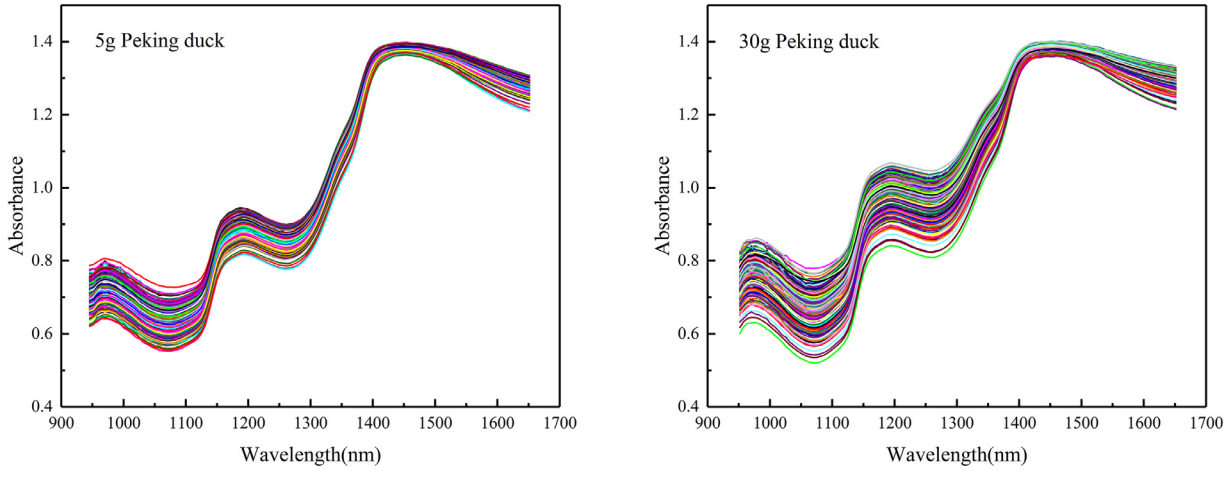

Figure 1. Raw average spectra of 5 g (left) group and 30 g (right) group duck samples.

light. The curves of the two groups are almost similar in the range of 1,400 to 1,650 nm, indicating the thickness and mass of the sample have little effect on the spectral absorption of the duck breast samples.

PLSR Model

The effects of different preprocessing methods on the PLSR model of 5 g and 30 g groups were presented (Tables 2 and 3). According to previous research (Nolasco-Perez et al., 2019), R^2 between 0.66 with 0.81 would make the general quantitative prediction, while R^2 from 0.82 to 0.90 would allow a better prediction and R^2 over 0.91 would provide a superior model. Furthermore, duo to verify the capacity and ability the models were evaluated based on RPD and RER. RPD from 1.8 to 2.0 indicated that the model was good; from 2.0 to 2.5 indicated that the model was better, and higher than 2.5 indicated that the model was excellent (Kamruzzaman et al., 2016). RER less than 3 indicated that practical utility was little, from 3 to 10 indicated that the model was good practical utility, and RER more than 10 indicated excellent accuracy (Jia et al., 2017).

Using the raw spectral data to establish the PLSR model directly, the calibration set model in the 5 g group (R^2_C = 0.90, RMSEC = 0.081, R^2_P = 0.87, RMSEC = 0.090, Table 2) is very similar to the 30 g group (R^2_C = 0.90, RMSEC = 0.082, R^2_P = 0.89, RMSEC = 0.100, Table 3). The second derivative, SNV, detrending correction (**DT**), and MSC pretreatment methods were used to reduce the principal components and improve accuracy of the model (Qiao et al., 2017a). However, the correlation coefficients of these models are also reduced, which did not improve the prediction accuracy. Among 12 different correction methods, the coefficients range from 0.78 (DT) to 0.93 (1D1) in the correction set for 5g group, while the coefficients range from 0.70 (2D3) to 0.87 (SG9) in the prediction

Table 2. Effect of different preprocessing methods on PLSR model of 5 g Peking duck samples.

		Calibration		Prediction			
Pretreatment method	Factors	R^2_C	RMSEC	R^2_P	RMSEP	RPD	RER
None	**11**	**0.90**	**0.081**	**0.87**	**0.090**	2.69	13.44
S-G5	10	0.89	0.086	0.86	0.090	2.67	13.44
S-G7	10	0.89	0.087	0.86	0.090	2.66	13.44
S-G9	11	0.90	0.085	**0.87**	**0.089**	2.71	13.60
1D1	**11**	**0.93**	**0.069**	0.81	0.110	2.32	11.00
1D3	11	0.92	0.072	0.84	0.100	2.52	12.10
2D3	9	0.87	0.095	0.70	0.144	1.83	8.40
SNV	9	0.90	0.084	0.85	0.096	2.52	12.60
DT	8	0.78	0.123	0.74	0.127	1.95	9.53
MSC	9	0.90	0.084	0.86	0.093	2.61	13.01
S-G5-1D1	9	0.90	0.083	0.86	0.093	2.61	13.01
SNV-1D1	10	0.92	0.072	0.82	0.108	2.36	11.20
SNV-2D3	8	0.84	0.104	0.69	0.144	1.74	8.40

Factors: The optimal number of factors used in the PLSR model; S-G5: 5-point Savitzky-Golay Smoothing; S-G7: 7-point Savitzky-Golay Smoothing; S-G9: 9-point Savitzky-Golay Smoothing; 1D1: 1-point first derivative; 1D3: 3-point first derivative; 2D3: 3-point second derivative; SNV: Standard Normal Variate; DT: detrending; MSC: Multiplicative Scatter Correction; SNV-1D1: Standard Normal Variate and 1-point first derivative; SNV-2D3: Standard Normal Variate and 3-point second derivative; S-G5-1D1: 5-point Savitzky-Golay Smoothing and 1-point first derivative.

Bold letters mean the highest value in the same row.

Table 3. Effect of different preprocessing methods on PLSR model of 30 g Peking duck samples.

		Calibration		Prediction			
Pretreatment method	Factors	R^2_C	RMSEC	R^2_P	RMSEP	RPD	RER
None	**12**	**0.90**	**0.082**	**0.89**	**0.100**	2.70	15.30
S-G5	12	0.88	0.089	0.88	0.105	2.62	14.57
S-G7	11	0.87	0.095	0.86	0.114	2.34	13.42
S-G9	11	0.87	0.095	0.86	0.113	2.38	13.54
1D1	**12**	**0.92**	**0.075**	**0.90**	**0.099**	2.72	15.45
1D3	10	0.89	0.087	0.88	0.103	2.63	14.85
2D3	8	0.82	0.111	0.79	0.141	1.84	10.85
SNV	9	0.84	0.106	0.82	0.132	1.84	11.59
DT	12	0.86	0.096	0.84	0.119	2.25	12.86
MSC	9	0.84	0.106	0.83	0.129	1.86	11.86
S-G5-1D1	11	0.88	0.090	0.89	0.100	2.64	15.30
SNV-1D1	11	0.90	0.084	0.86	0.115	2.24	13.30
SNV-2D3	7	0.82	0.109	0.76	0.148	1.72	10.34

Factors: The optimal number of factors used in the PLSR model; S-G5: 5-point Savitzky-Golay Smoothing; S-G7: 7-point Savitzky-Golay Smoothing; S-G9: 9-point Savitzky-Golay Smoothing; 1D1: 1-point first derivative; 1D3: 3-point first derivative; 2D3: 3-point second derivative; SNV: Standard Normal Variate; DT: detrending; MSC: Multiplicative Scatter Correction; SNV-1D1: Standard Normal Variate and 1-point first derivative; SNV-2D3: Standard Normal Variate and 3-point second derivative; S-G5-1D1: 5-point Savitzky-Golay Smoothing and 1-point first derivative.

Bold letters mean the highest value in the same row.

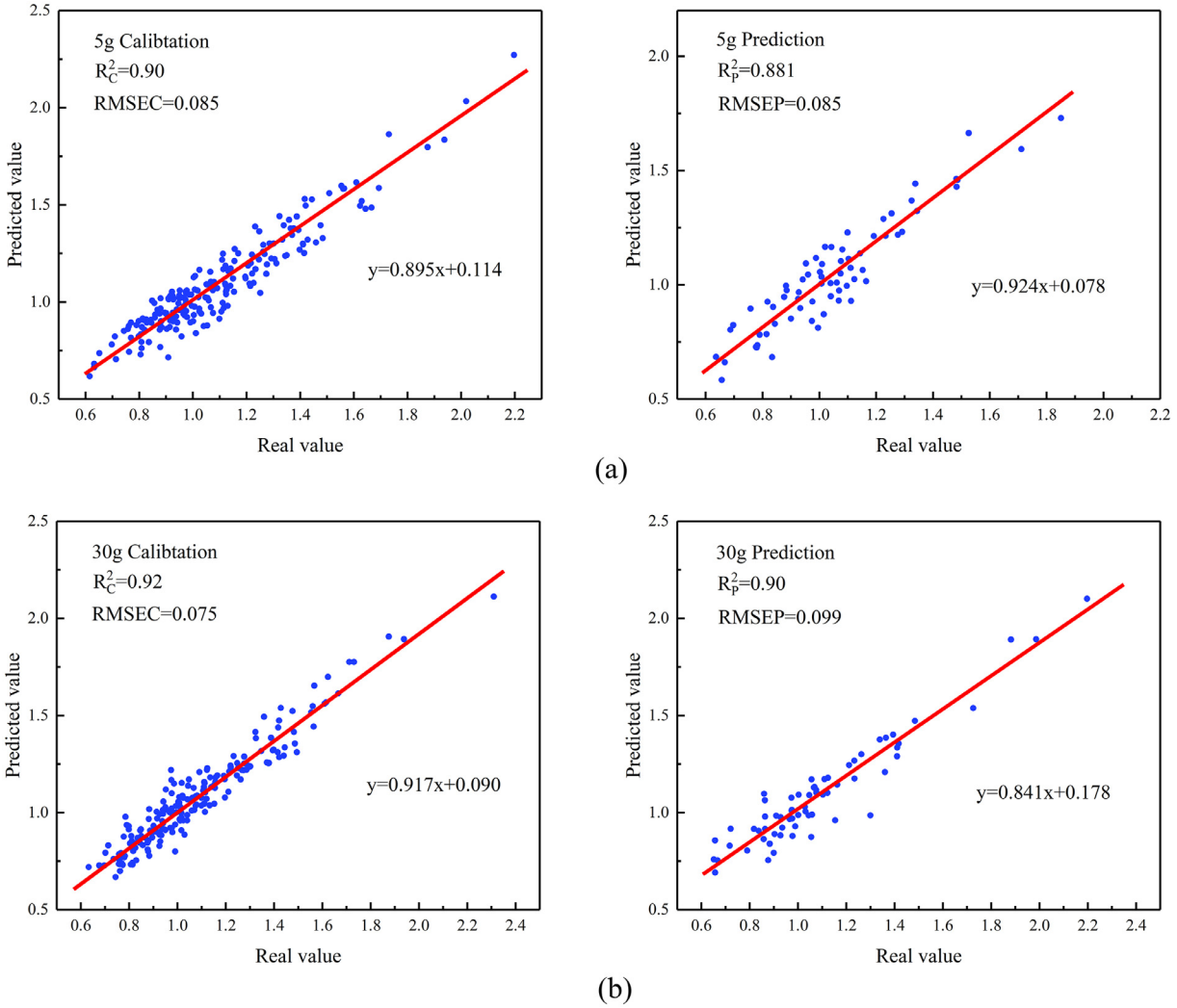

Figure 3. Distribution of actual and predicted values of IMF. (A) 5 g Peking duck S-G5 pretreatment PLSR model; (B) 30 g Peking duck 1D1 pretreatment PLSR model.

set for 5 g group. The coefficients range from 0.82 (2D3) to 0.91 (1D1) in the correction set for 30 g group, while the coefficients range from 0.76 (SNV-2D3) to 0.90 (1D1) group in the prediction set for 30 g group. On the basis of RPD and RER, most of the models were higher than 2 and 10, respectively, thus being reliable and high accuracy.

In general, the best model is the SG9 for 5 g group and 1D1 for 30 g group (Tables 2 and 3). Figure 3 shows the distribution of the real and predicted values of the 5 g group (Figure 3A), 30 g group (Figure 3B) of the PLSR model correction set and validation set. Therefore, the best PLSR model was obtained with the first derivative pretreatment, with R^2_C of 0.92, R^2_P of 0.90, RMSEC of 0.075, RMSEP of 0.099, with RPD of 2.72, RER of 15.45, for samples of 30 g duck (Table 4). It can be concluded that most of the samples were near the predicted line and were close to the predicted line so that the model can predict the fat content of Peking duck.

It was interesting to know that the accuracy of the best prediction model for both 5 g and 30 g group is almost the same as using the raw spectral data (Table 4). For example, the coefficients of the raw spectral group are 0.87, 0.89 for 5 g group and 30 g group, respectively. It was the same as the best prediction model in the two groups. In further, we also noticed that

Table 4. Comparison of the best PLSR model of Peking duck samples.

			Calibration		Prediction			
Group	Pretreatment method	Factors	R^2_C	RMSEC	R^2_P	RMSEP	RPD	RER
5 g	None	11	0.90	0.081	0.87	0.090	2.69	13.44
	S-G9	11	0.90	0.085	0.87	0.089	2.71	13.60
30 g	None	12	0.90	0.082	0.89	0.100	2.70	15.30
	1D1	12	0.92	0.075	0.90	0.099	2.72	15.45

the prediction accuracy was also the same in the prediction set for both 5 g and 30 g group. It would be important in the application. Some commercial instruments need very high input meat samples when using NIRS to predict fat content (Alexandrakis et al., 2012; Yang et al., 2018). The results showed that the 5 g group could achieve the same prediction performance as the 30 g group.

CONCLUSIONS

This research compared the quantitative prediction of the IMF of Peking ducks under different quality samples and different processing methods by near-infrared spectroscopy. The results showed that the 5 g group and the 30 g group can obtain almost the same prediction results. The raw spectral data can obtain the highly similar accuracy as the best correction method. The NIRS can predict IMF in ducks relatively accurate and can match the fast measurement requirement in the field.

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DISCLOSURES

The authors declare that they have no conflict of interest.

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