Meat Research
Vol 2, Issue 6 Article 37
ISSN: 2790-1971
https://doi.org/10.55002/mr.2.6.37
http://www.bmsa.info/meatresearch

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Keywords:
NIR Spectroscopy
Calibration
Multivariate analysis
Partial Least Square Regression
Chevon-Goat meat

Article Info
Received: 17th September, 2022
Accepted: 21st November, 2022
Published online: 30th December, 2022

Research Article

Prediction of chevon quality through near infrared spectroscopy and multivariate analyses

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Abstract

The aim of this study was to test the ability of near-infrared (NIR) reflectance spectroscopy to predictdry matter, crude protein, ether extract, ash, moisture, cooking loss, and drip loss of chevon. In total, 114 samples were collected from 38 young (two teeth aged) castrated goat carcasses from a local market in Mymensingh district of Bangladesh. For conducting the studyExperimental longissimus dorsi (LD) muscle were sampled from 9th to 13th ribs in the early morning hours. A total of 342 NIRs spectra were collected using the DLP NIRscan Nano Software and average spectrum was 114. Partial least square regression analysis for the calibration and validation models were developed using the Unscrambler X software. Prediction models were satisfactory for dry matter (R^2 = 0.75), crude protein (R^2 = 0.82), moisture (R^2 = 0.75), and drip loss (R^2 = 0.83). The most promising model found for ash (R^2 = 0.85), and Root Mean Square Errors (RMSE) also very low (0.15). Lowest R^2 was found for cooking loss at 0.57. Based on these results, the NIR spectroscopy and multivariate analysis method were reasonably efficient for the rapid assessment of physicochemical traits of ash, drip loss, crude protein, moisture, and dry matter content of chevon.

Introduction

The meats we eat contain skeletal muscle, adipose, and connective tissue. Skeletal muscles contain approximately 75% water, 20% protein, 1-10% fat and 1% glycogen (Listrat et al., 2016). Meat and meat products are important sources for human to obtain protein, vitamins, and minerals Current trends show that there has been a significant increase in global meat consumption over time (Akter et al., 2009; Sadakuzzaman et al., 2021; Salter 2017). Due to the development of living standards, better quality meat products are in high demand by consumers, and meat quality differentiation is considered a key factor for success in market space (Hashem et al, 2022 and 2021; Sun et al., 2020) .

Different techniques such as sensory analysis, chemical procedures and instrumentation methods have been employed to provide information on meat quality. Sensory analysis is often implemented by a highly trained panelist. However, it is subjective, laborious, time-consuming and inconsistent. Chemical analyses methods have been used in detecting quality attributes for a long time, which are more convenient, precise and effective than sensory analysis. For chemical methods, the standard protein analysis method is the Kjeldahl method, and the method of choice for fat analyses is a solvent-based method for measuring the total fat content in meat, both of which are time consuming and destructive. In instrumental methods, pH is traditionally measured by pH meter by inserting it into the muscle directly after an incision on the muscle, and colorimeters are commonly utilized for meat color evaluation. Most of the above-mentioned techniques are destructive, tedious, time consuming and require lengthy sample preparation. In contrast to conventional methods, many novel and automatic technologies based on mechanical, optical, dielectrics, X-rays, spectroscopy, imaging, and nuclear magnetic resonance have emerged for detecting these quality and safety attributes. Near-infrared spectroscopy (NIRS) is an analytical technique that uses a source producing light of known wavelength pattern (usually 800–2500 nm) to scan food materials to obtain complete information of the organic composition of the analyzed substance/material (Van Kempen 2001). The main disadvantages of the method are its dependence on reference method, weak sensitivity to minor constituents, limited transfer of calibration between different instruments and complicated spectral data interpretation. In published studies, a lot of attention has been paid to investigating the capability of NIRS to predict meats' chemical composition and their quality traits in different domestic species e.g., beef, mutton, chicken and pork. But there is a lack of information on the use of NIRS technique to predict and classify chevon's (goat meat) major quality attributes.

Modern NIRS software offers different statistical (regression) methods to prepare calibrations (equations), multiple linear regression, partial and modified partial least square (PLS), principal component regression (PCR) and a host of other non-linear regression analysis like artificial neural networks (Hashem et al., 2021 & 2022; Li et al., 2007). The predictive ability of NIRS is generally judged by statistical parameters such as coefficient of determination (R^2), root means square error (RMSE) and standard error (SE) of calibration and/or prediction. According to the literature, NIRS

is considered as one of the most promising techniques for evaluating meat quality. NIRS has shown enormous potential to predict food quality attributes such as protein, fat, moisture, ash, myoglobin, pH value, water-holding capacity (WHC), color, marbling, tenderness, and safety attributes (Bertram et al, 2005; Prieto et al., 2017; Prieto et al., 2009). Near-infrared is non-destructive, rapid, real-time, non-chemical and low-cost for online prediction of meat and meat products (Prieto et al., 2017). The existing researches indicate that NIR spectroscopy has been successfully applied to quantitatively determine these attributes in meat with high accuracy and the coefficients of determination (R^2) of some indicators were up to 0.90 between predicted and reference values.

In Bangladesh, the production of meat and meat products is increasing consistently. According to the Department of Livestock Services, Bangladesh (DLS, 2019), the annual meat production in Bangladesh is 7.51 million metric ton and demand is 7.29 million metric ton and surplus 0.22 million metric ton. Traditional techniques are widely used here for raw and processed meat quality measurements. This method of quality and safety assessment involves human visual inspection, in addition to chemical or biological determination experiments that are not cost-effective aside, from being laborious and destructive. To meet the increasing demand for meat, there is a need to develop a quick assessment method for their quality attributes. The meat processing companies and suppliers need accurate, fast, real-time, non-destructive, low-cost, and non-chemical detection technologies, to optimize quality and assure the safety of meat to enable them to satisfy different market needs. Recent developments in microfabrication and miniaturization of optical systems have allowed the creation of "palm-sized" spectrophotometers which are compact, mobile and can be carried in a pocket. To our knowledge, only one study has been conducted by Dixit et al. (2020) by mini NIR spectroscopy for predicting intramascular fat in lamb and another study was conducted by Teixeira et al (2015) in goat meat through NIRS. In the current study, a "palm-sized" mini NIR spectrophotometer has been used for predicting seven physicochemical traits of chevon combined with Chemometrics. Therefore, the objective of the present study was to evaluate the feasibility of mini NIRS to predict drip loss, cooking loss and proximate components in chevon.

Materials and methods

Experimental site

This experiment was conducted at Meat Science Laboratory under the Department of Animal Science, Bangladesh Agricultural University, Mymensingh.

Meat samples preparation

In total, 114 samples of longissimus dorsi muscle (between the 9^{th} and 13^{th} ribs) were collected from 38 carcasses of indigenous goat from a local market in the Mymensingh district of Bangladesh at 7.00 am. The meat samples were immediately transferred to the Animal Science Meat Laboratory, Bangladesh Agricultural University, Mymensingh in an icebox. The collected meat samples were weighed and stored in a refrigerator for 24 hours at 4°C for further analysis. After 24 hours, the samples were removed from the refrigerator and then kept on a tray for about 10-12 minutes to release absorbed moisture and then used for NIR spectra collection.

NIR spectra acquisition

NIR reflectance spectra were collected using mini NIR (DLP NIRscan Nano EVM, Texas Instruments Inc., Texas, USA). Mini NIR works in the wavelength range of 900-1700 nm with an optical resolution of 10 nm. A scan configuration specifies the following parameters of a scan:

Wavelength range: Start and End wavelengths (in nm) or spectral range of interest for the scan. The minimum wavelength is 900 nm and the maximum wavelength is 1700 nm.

Width in nm: This number must be greater than 8 nm and corresponds to the desired smallest wavelength content that needed to resolve in a scan. The DLP NIRscan Nano optical resolution is 10 nm, so values less than 10 nm result in lower signal intensity.

Number of patterns: This number defines how many wavelength points are captured across the defined spectral range. Depending on the previous setting, the GUI computes the maximum number of patterns and indicates them as the "Max Limit."

Number of scans to average: This is the repeated back-to-back scans that are averaged together. Refrigerated chevon samples were thawed and subjected to spectroscopic analysis while packed in ziplock plastic bags. For NIR analysis, the sample window of mini NIR was placed over the meat samples (114) surface and the spectra were collected at 3 different locations and average to make total 114 spectra. Each spectrum was recorded at room temperature in the NIR region of 900 to 1700 nm with a spectral increment of about 3.90 nm between the contiguous bands, thus producing a total of 228 bands.

Chemical and physical attributes analyses

Proximate components such as dry matter (DM), Ether Extract (EE), crude protein (CP) and ash were carried out according to the methods (AOAC 1995). All analyses were done in triplicate and the mean value was reported. The differences in weight between the fresh and dried samples represent the water content. An oven (GALLENKAMP Hot Box Oven with Fan - Size 2 CHF097 XX2.5) was used for determining dry matter kept for 24 hrs at 105°C. Crude Protein (CP) was determined using total nitrogen content of each sample by using Kjeldahl apparatus. Ether extract content was determined by Soxhlet apparatus using diethyl ether. Total Ash content was measured using muffle furnace where porcelain crucibles with samples were heated at 550°C for 6 hours, then cooled inside desiccators and weighed. Cooking loss was measured by using a hot water bath and food-grade thermometer at 71˚C internal temperature of meat sample. Cooking loss was determined following the methods of Haque et al. (2017). Drip loss was determined following the methods of Arain et al. (2010).

Model development and spectral data analysis

Calibrations and predictions of goat meat samples based on full spectra (228 variables) were established using partial least-squares regression (PLSR). The calibration models were strictly built using the calibration dataset and validated with cross-validation technique using The UNSCRAMBLER program (version 9.7.0, Camo, Trondheim, Norway). In this study, leave-one-

out (i.e. full) cross-validation method was employed to validate the PLSR models. This was done by removing one sample (test sample) from the data set and PLSR model was then established for the remaining samples (training sample). Finally, the model was used to predict the sample left out. This procedure was repeated for every sample in the data set, giving a more realistic measure of the predictive errors of the model. The precision and the predictive capabilities of the models were evaluated by the coefficients of determination (R^2), root-mean-square error of calibration (RMSEC) and the root-mean-square error estimated by cross-validation (RMSECV). The best model was selected for each attribute on the basis of the highest determination coefficient (R^2) and lowest standard error of calibration (RMSEC) and validation (RMSECV). The R^2 and RMSEC or RMSECV are defined as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{N}(\hat{y}_i - \bar{y}_i)^2} \quad (1)$$

$$RMSEC \text{ or } RMSECV = \sqrt{\frac{\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}{N}} \quad (2)$$

Where $\hat{y}_i$ = predicted value of the i^{th} sample, y_i= measured value of the i^{th} sample, N = number of samples.

Moreover, to assess the practical utility of the prediction models the ratio performance deviation (RPD) and the range error ratio (RER) were calculated. The RPD was calculated as the ratio of the standard deviation (SD) to the SEcv of a given trait and the RER was calculated as the ratio between the range and the SECV of the trait (Edney et al.1994). Ratio performance deviation values higher than 10 are considered equivalent to reference method (Williams and Sobering 1993) and values above 2.5 are considered adequate for analytical purposes (Sinnaeve et al. 1994). The RER is a method of standardizing the SECV by relating it to the range of the reference data. For example, RER values of less than 6 indicate very poor classification and are not recommended for any application; RER values between 7 and 20 classify the model as poor to fair and indicate the model could be used for screening purposes, and RER values between 21 and 30 indicate a good classification suggesting the model would be suitable for a role in quality control systems (Williams and Norris 2001).

Results and discussion

Reference values for physicochemical attributes of longissimus dorsi muscle of chevon

To provide an overview of the physicochemical attributes of the samples used in the investigation, the mean, range, standard deviation, and coefficient of variation for drip loss (DL %), cooking loss (CL %), moisture (%), dry matter (DM %), crude protein (CP %), ether extract (EE %) and ash (%) for all muscles determined by laboratory reference methods are summarized in Table 1. Average moisture, dry matter, protein, ether extract and ash contents of goat meat from longissimus dorsi muscle were found as 74.11%, 25.84%, 21.49%, 2.55% and 1.15%, respectively in this study. Regarding proximate composition, Dhanda (2001) reported that goat meat on average consists of 72.3% moisture, 21.0% protein, 4.7% fat and 1.1% ash per 100 g of fresh meat. Drip loss was found 8.30% which is higher than Arain at al., 2010. They found drip loss 4.93%. but cooking loss within the range of other findings . These values may vary considerably with the factors such as breed, age, sex, weight, and nutritional history. There are different opinions regarding the reasons behind the increase in drip loss, namely protein degeneration, sarcomere shortening and myosin degeneration resulting in shrinkage of myosin, drawing the thick and thin filaments more closely together (Nagaraj et al. 2005). Among the proximate components, the highest variability was observed in ash content (CV of 33.11%) and the lowest variable traits were moisture and cooking loss (CV of 7.45% and 7.76%). This is in agreement with the findings of De Marchi et al. (2007). They found that CV of cooking loss was 4%.

Table 1. Descriptive statistics for moisture, dry matter , crude protein, ether extract , ash (%), drip loss and cooking loss of chevon longissimus dorsi muscle determined by the conventional method

Parameters (%)	Mean ± SD	CV (%)	Min.	Max.
Moisture	74.11±5.52	7.45	60.35	82.73
Dry Matter	25.84±5.45	21.10	17.27	39.65
Crude Protein	21.49±4.79	22.30	7.03	38.48
Ether Extract	2.55±0.44	17.41	1.90	3.23
Ash	1.15±0.38	33.11	0.85	2.89
Drip loss	8.30±1.59	19.14	5.78	13.10
Cooking Loss	33.72±2.62	7.76	28.98	39.87

SD= Standard deviation, CV= Co-efficient of variation

Development of calibration model based on NIR spectra

NIRS calibration and prediction statistics for drip loss (DL %), cooking loss (CL %), dry matter (DM %), moisture (%), crude protein (CP %), ether extract (EE %) and ash (%) of chevon longissimus dorsi muscle are presented in Table 2. Spectral data at full wavelength range (900-1700 nm) with 228 variables were modeled using linear multivariate method of PLSR. The performance of the calibration models was optimized by leave-one-out cross-validation. The detailed results of PLSR are listed in Table 2, where for PLS model, R^2_c, R^2_{cv}, R_p, RMSEC, and RMSECV reported. In this study, the calibration results were highly correlated to cross-validation results. The similarity in model performance implied that the models did not over-fit data, and the majority of the variance presented in the measured values was reproduced in the prediction model. Based on model

performance in terms of R^2_c, R^2_{cv}, RMSEC and RMSECV, it seems that the PLSR model was reasonably appropriate for predicting the physicochemical attributes of chevon.

Table 2. NIRS calibration and prediction statistics for physicochemical attributes of chevon

Attributes	Calibration		Cross-validation		SD	RPD	RER
	R^2c	$RMSE_c$	R^2cv	$RMSE_{cv}$			
Moisture	0.75	2.73	0.68	3.10	5.52	1.78	7.21
Dry Matter	0.75	2.70	0.67	3.11	5.45	1.75	7.20
Crude Protein	0.82	2.05	0.77	2.28	4.79	2.10	13.80
Ether Extract	0.59	0.28	0.48	0.32	0.44	1.36	4.12
Ash	0.85	0.15	0.79	0.18	0.38	2.13	11.46
Drip loss	0.83	0.65	0.75	0.79	1.59	2.01	9.27
Cooking Loss	0.57	1.71	0.48	1.87	2.62	1.40	5.81

R^2c = calibration coefficient; R^2cv = cross-validation coefficient; SD = standard deviation; $RMSE_c$ = standard error of calibration; $RMSE_{cv}$ = standard error of cross-validation; RPD = residual standard deviation; RER = range error ratio.

Table 2 shows that R^2_c value for moisture and dry matter is 0.75. The models for the prediction by NIRS of water content or dry matter content of meat present widely ranging results [R^2 from 0.07 (Cozzolino and Murray 2002) to 0.96 (De Marchi et al. 2007)] according to the study, although most of the publications consulted found $R^2 > 0.90$ (Cozzolino et al. 2000; Leroy et al. 2003). But in our study it was less than 0.90. In another study of Alomar et al. (2003) found R^2_c value for dry matter is 0.77 in beef which is little higher to the present findings but he found similar R^2_c value for protein which is 0.82.

R^2_c value for fat in our study is 0.59. On the contrary Cozzolino et al. (2003) found R^2_c value for fat 0.71 in beef which is higher than the present findings. The causes of it may be due to differences in sample size and a wide and even distribution in composition, along with precise reference analysis techniques are recognized as important characteristics of the calibration set of samples, in order to obtain a successful equation.

R^2_{cv} value for drip loss and cooking loss in our study is 0.75 and 0.48, respectively. Leroy et al. (2003) reported these values as 0.38–0.54 and 0.25–0.47 in beef. R^2_{cv} value for drip loss was higher in our findings but similar with the maximum reported values. The variability of the results obtained for all the determinations of chemical composition can be explained mainly by the characteristics of the meat, its preparation, and how the samples are presented. Calibrations from Serrana breed meat for prediction chemical composition by Teixeira et al. (2015) have produced results with better accuracy for moisture, protein, and fat as the calibrations obtained this study. However, ash prediction was much better predicted in our study than in Serrana breed goat meat.

The predictive ability of the PLS model is assessed by the coefficient of determination of cross-validation (R^2_{cv}) and root mean square error of cross-validation ($RMSE_{cv}$). The best model for each trait is selected based on the highest coefficient of determination of cross-validation (R^2_{cv}) and the lowest root mean square error of cross-validation ($RMSE_{cv}$) (Edney et al., 1994). To assess the practical utility of the prediction models the ratio performance deviation (RPD) and the range error ratio (RER) was calculated. It indicates that crude protein, drip loss, and ash values are adequate for analytical purposes as values above 2.0 are adequate for analytical purposes (Williams and Sobering, 1993). The range of the reference data, RER value between 7-20 classify the model as poor to fair and indicate it could be used for screening purposes and RER values between 21 and 30 indicate a good classification suggesting the model could be suitable for application in quality control. So for the above RER values the model is fair to good except cooking loss (5.81) and ether extract (4.12).

To visualize graphically the performance of the PLS calibration models, the measured value and its predicted values resulting from the optimal PLS models are plotted and displayed in Figures 1, 2, 3 and 4.

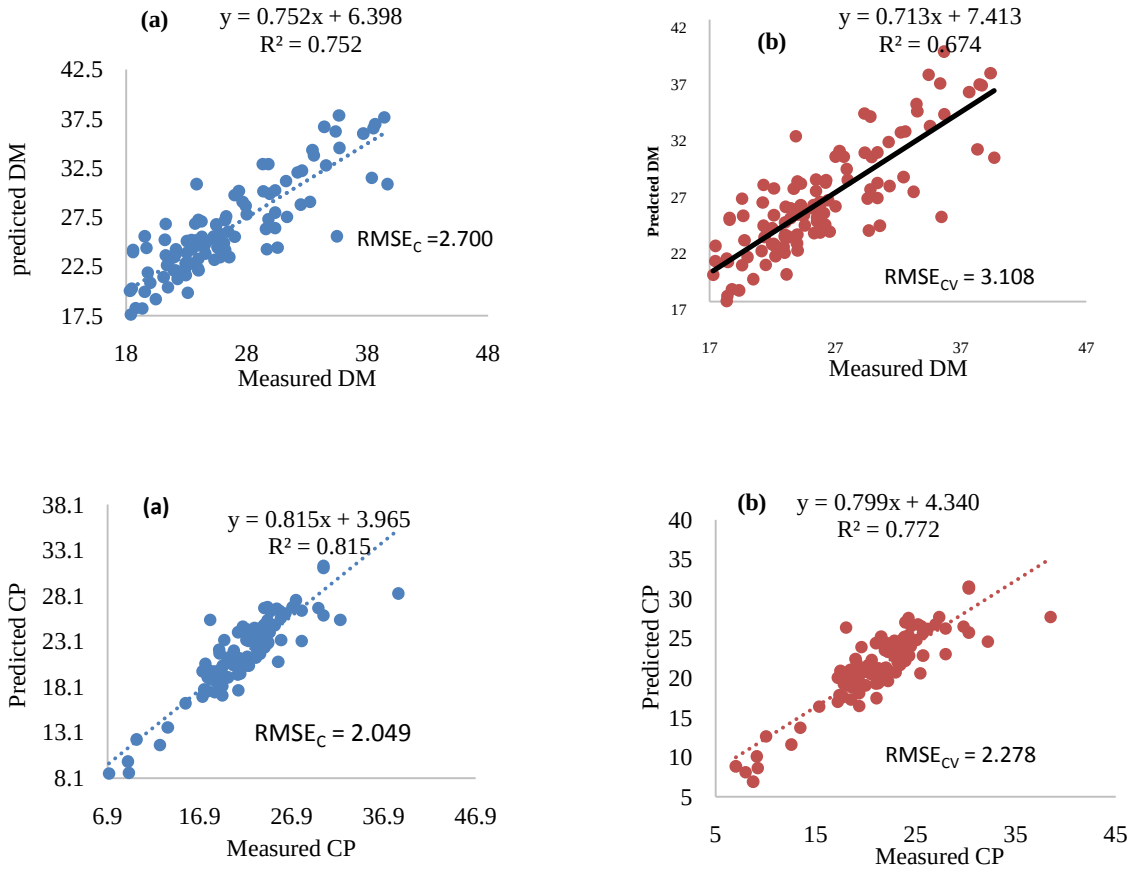

Figure 1: Prediction of DM and CP using PLSR (a) Calibration (b) Cross validation.

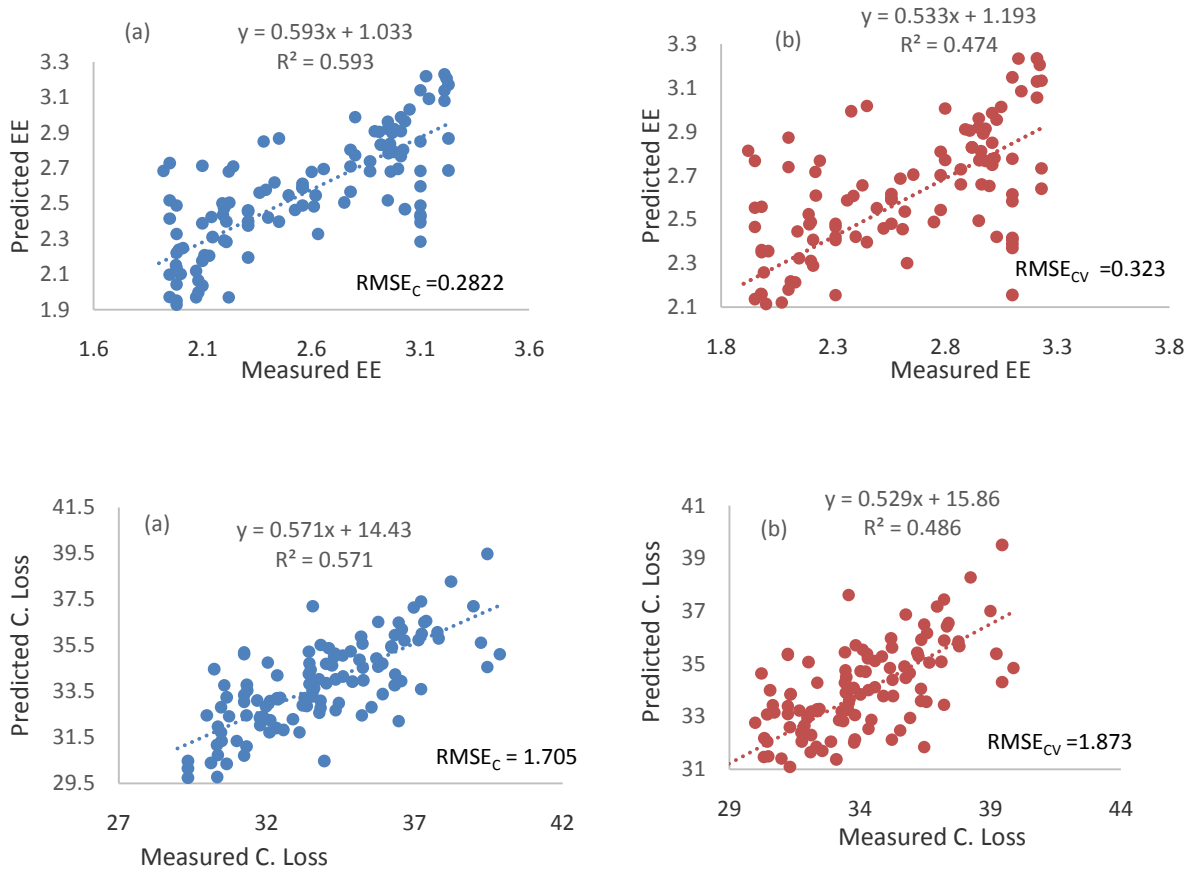

Figure 2: Prediction of EE and Cooking Loss using PLSR (a) Calibration (b) Cross validation.

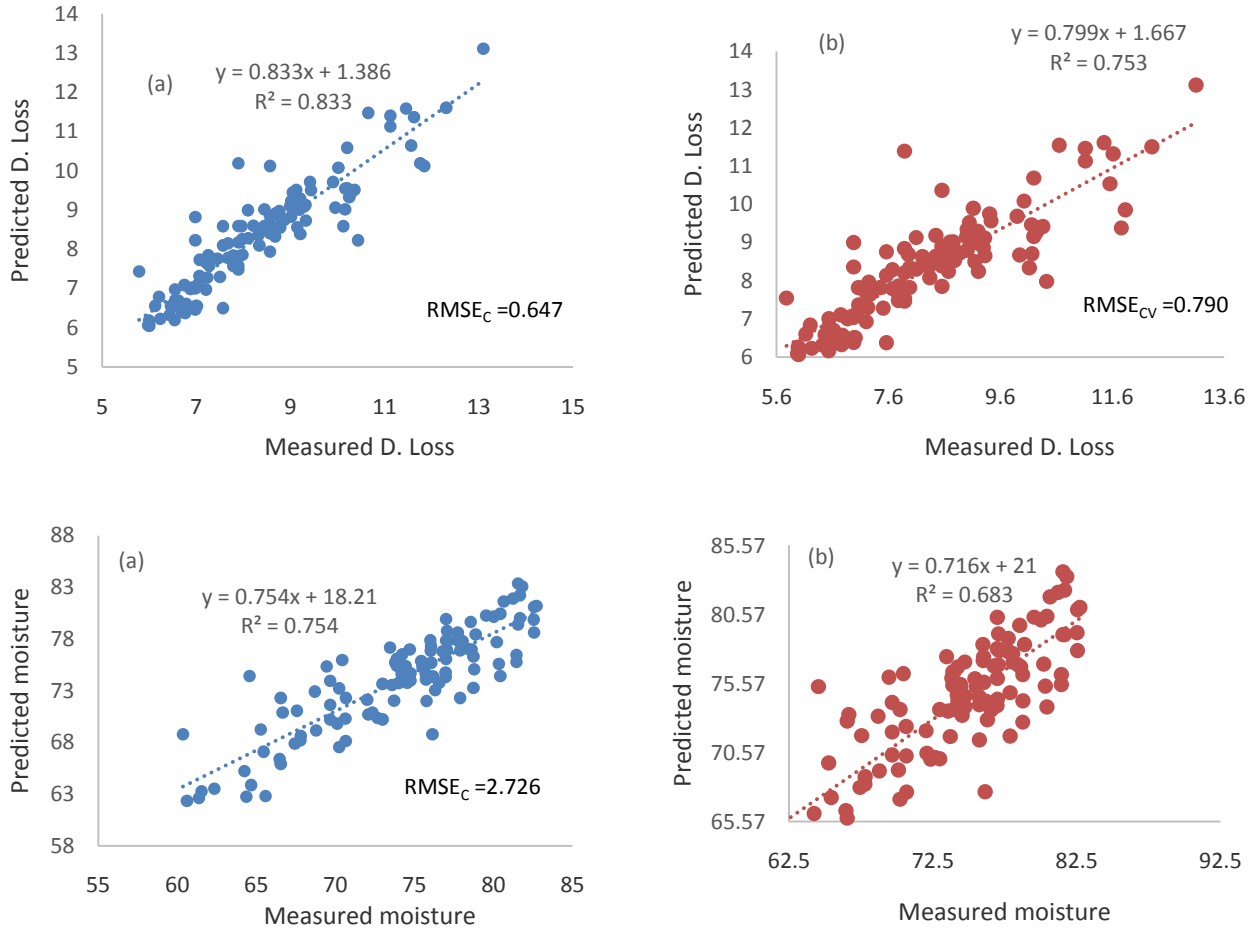

Figure 3: Prediction of drip loss and moisture using PLSR (a) Calibration (b) Cross validation.

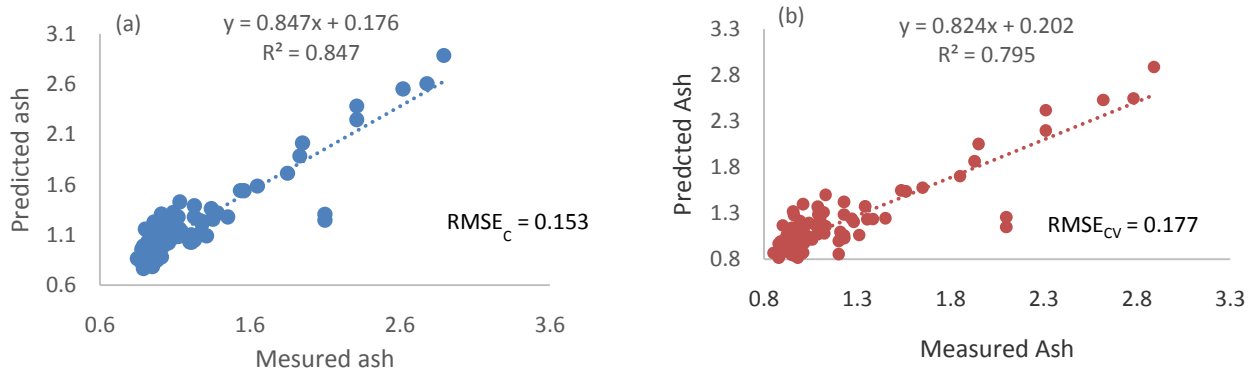

Figure 4: Prediction of Ash using PLSR (a) Calibration (b) Cross validation.

The above graphs show the values of regression models. The higher the value of R^2 (near to 1.00) indicates the higher the accuracy of the models. In this research highest R^2_c was found for ash (0.85), drip loss (0.83), crude protein (0.82), moisture (0.75) and dry matter (0.75). Therefore, those models could be used for prediction purposes.

Conclusion

The results of this study suggest that NIRS is a feasible technique for the assessment of several quality traits of chevon. And it could potentially replace the conventional methods used for meat analysis as the laboratory scales are laborious and time-consuming. NIRS showed good predictive potential for meat qualities like drip loss, crude protein, moisture, dry matter, and ash. Further research with larger samples and different experimental conditions would improve the model quality.

Acknowledgements

We are grateful to BAURES, Bangladesh Agricultural University, Mymensingh, Bangladesh for funding this research.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors. Meat samples were collected from the slaughterhouse.

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