Application of Visible and Shortwave Near Infrared Spectroscopy Combined with PCA-LDA and PLS-DA to Distinguish Sirloin and Shank Beef

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Abstract. Beef is a worldwide commonly consumed meat, and the physicochemical properties of meat differ depending on meat cuts. A method that detects beef cut types is necessary to protect the customer's rights and prevent fraud in processing and distribution. This study used Vis-NIR and SW-NIR spectroscopy to determine and predict the sliced, minced beef shank and sirloin cut integrated with PLS-DA and PCA-LDA. For both PCA-LDA and PLS-DA, the calibration accuracy and reliability of the Vis-NIR and SW-NIR models were 100%. The result shows that Vis-NIR and SW-NIR spectroscopy can distinguish beef cuts rapidly and accurately.

Keywords: beef cuts · Vis-NIR · SW-NIR · spectroscopy · PCA-LDA · PLS-DA

1 Introduction

Beef is a commonly consumed meat in both developed and developing countries which serves as a source of protein, amino acids, and trace elements [1]. After pork and poultry, beef is the third most popular meat consumed globally, making up about 21.8% of total meat consumption [2]. In 2020, over 71 million tons of beef were produced globally [3]. Population growth has been accelerated recently, which will impact beef consumption. For the consumer, the meat's physicochemical characteristics, such as softness, juiciness, flavour, and meat quality, are crucial [4]. The physicochemical properties of meat differ depending on meat cuts [5].

According to [4], based on the USDA Agricultural Marketing Service's data, beef shank cuts have a low value in the United States. Therefore, most beef shank meat produced in the US is converted into minced beef. In Brazil, sliced beef sirloin cuts have the highest average price of all beef cuts [3]. The appearance of different beef cuts is similar, making it challenging to distinguish between the various beef cuts, both sliced

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and minced. The adulteration of minced and sliced beef is potentially in the beef cuts. Typical adulteration substitutes cheap meat for expensive meat [6]. So, identifying beef cuts is essential to protect the customer's rights and the quality of the meat and stop fraud in the processing and sale of beef cuts.

Several analytical techniques have recently been used to detect and identify meat quality. However, the commercial methods are costly, require the expertise of a skilled specialist, have expensive tools, considerable processing time, and are destructive and unsuitable for modern industrial processing [7]. Therefore, it is necessary to design a detection approach that is efficient, accurate, and non-destructive.

Spectroscopy-based methods are one of the most popular analytical techniques for food classification [8] and authentication [9]. Spectroscopy is an attractive technology that provides a rapid, simple, non-destructive process. There are numerous varieties of spectrometers dependent on the wavelength range used. Vis-NIR spectroscopy is one of those technologies that can accurately identify food in solid, liquid, or powder form and has low instrument prices [10]. A Vis-NIR spectrometer can detect food quality based on visible light pigments and chemical interactions at NIR wavelengths [11]. However, limited research has been conducted to identify various beef cuts using Vis-NIR spectroscopy.

Portable and modular visible near-infrared (Vis-NIR) and shortwave near infrared (SW-NIR) spectrometers that work in the wavelength range of 350–1000 nm and 1000 – 1600 nm provide alternatives for identification or classification. This study used both Vis-NIR and SW-NIR spectroscopy to identify sliced and minced beef shank and sirloin cuts. Principal component analysis - discriminant analysis (PCA-DA) and partial least square-discriminant analysis (PLS-DA) were used as multivariate chemometric analysis.

2 Material and Methods

2.1 Beef Samples

Beef cuts were purchased from local markets. Sirloin and shank beef cuts were separately sliced and minced using a grinder (Turbo EHM 8330). Before measuring the spectra, a 10 ± 1 g sample of minced and sliced beef cuts was weighed and placed in an aluminum cup (6.5 cm diameter, 1 cm thin) to retain the uniform shape and solidity of the samples. During sampling, samples were stored at a temperature of $\pm$ 18°C.

2.2 Measurement of Vis-NIR and SW-NIR Reflectance Spectra

The spectra of beef cuts were collected using a Flame-T-VIS-NIR (Ocean Optics, USA) spectrometer working at 400 – 1000 nm as Vis-NIR spectra and a Flame NIR (Ocean Optics, USA) spectrometers working at 1000 – 1600 nm as SW-NIR spectra. The spectrometers were equipped with a tungsten halogen lamp (HL-2000-HP-FHSA Ocean Optics, USA), and a reflection sensor (QR400–7-VIS-NIR Ocean Optics, USA) was arranged as shown in Fig. 1. The sample was put 0.5 cm distance below the probe on a sample holder. Each sample was scanned ten times on different sides with an integration duration of 100 ms, a scan average of 100, and a boxcar width of 1.

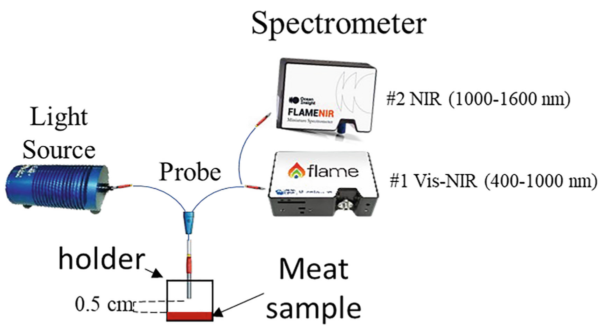

Fig. 1. Visible near-infrared and near-infrared spectrometer set-up

2.3 Chemometrics and Data Analysis

For multivariate analysis, all acquired spectra were compiled using Microsoft Excel and imported into The Unscrambler® X version (10.5.1, CAMO, OLSO, Norway) software. A total of 100 spectra were acquired from both Vis-NIR and SW-NIR spectroscopy. Before the multivariate analysis, all data were separated into calibration sets comprised of 60 spectra and prediction sets comprised of 40 spectra. PLS-DA and PCA-DA were chosen as the chemometric methods used to classify beef cuts. PLS-DA and PCA-DA models were built separately for Vis-NIR spectroscopy and SW-NIR spectroscopy for each minced and sliced meat. Model performances were rated by the Accuracy and Reliability values. Accuracy is the ratio of the number of correct predictions with the total samples calculated using Eq. 1. Reliability shows the model's ability to predict the class correctly by considering each class independently and is calculated using Eq. 2. The higher the value of accuracy and reliability, the better the model performance [12, 13].

$$Accuracy = \frac{n_{Shank}^{Correct} + n_{Sirloin}^{Correct}}{n_{Shank}^{Total} + n_{Sirloin}^{Total}} \times 100\% \tag{1}$$

$$Reliabilty = \left(\frac{n_{Shank}^{Correct}}{n_{Shank}^{Total}} + \frac{n_{Sirloin}^{Correct}}{n_{Sirloin}^{Total}} - 1 \right) \times 100\% \tag{2}$$

3 Results and Discussion

3.1 Vis-NIR and SW-NIR Spectra of Sliced and Minced Beef Cuts

Figure 2 shows the Vis-NIR spectra of minced beef shank, minced beef sirloin, sliced beef shank, and sliced beef sirloin. All spectra' overall trends are similar in that noticeable peaks are recorded at the visible region around 400–600 nm due to the absorbance of meat pigments [14]. The color of meat is determined by myoglobin (a pigment-protein presence in muscle), the muscle structure morphology and ability to absorb or scatter the incident light [15], and heme proteins in the form of hemoglobin and cytochrome

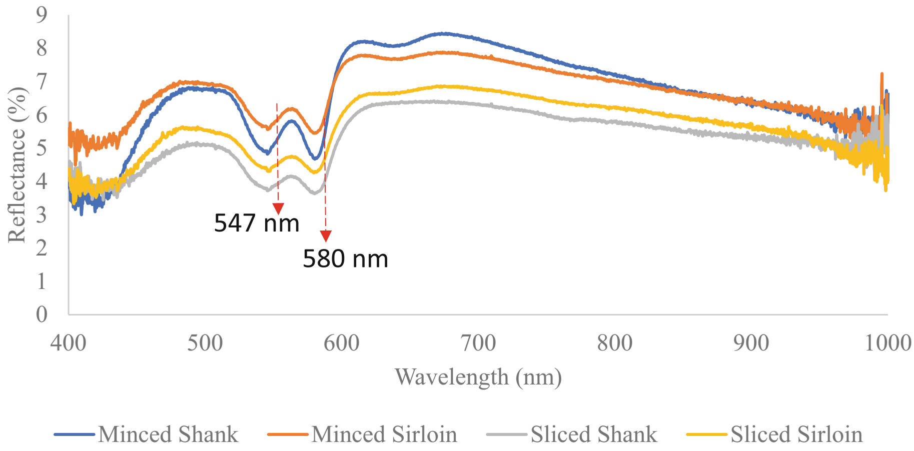

Fig. 2. Vis-NIR spectra of beef cuts

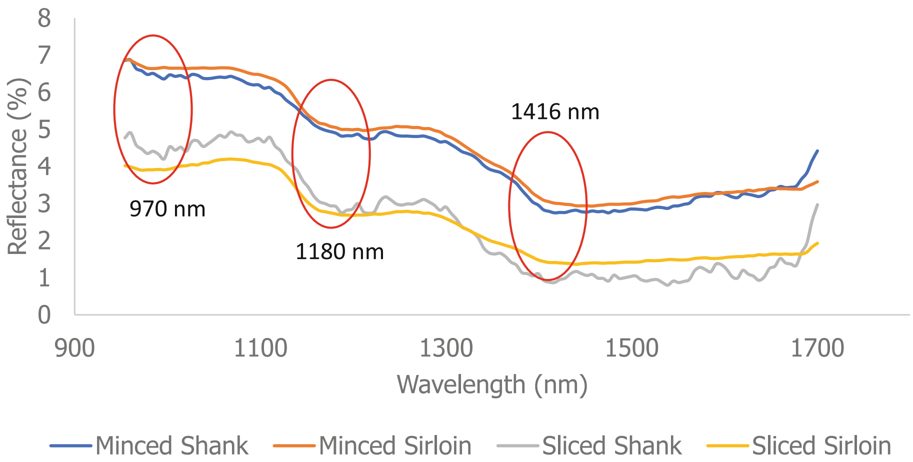

Fig. 3. SW-NIR spectra of beef cuts

C. The result showed that two distinct absorptions were observed at 547 and 580 nm. The absorption peak at 547 nm corresponds to respiratory pigments, i.e., myoglobin or deoxy myoglobin [1], and at 580 nm corresponds to oxymyoglobin. At 720–900 nm, relatively low and stable absorbances of water molecules were observed [16].

Figure 3 shows the SW-NIR spectra of minced beef shank, minced beef sirloin, sliced beef shank, and sliced beef sirloin. The spectra have a relatively low reflectance ($<10\%$) due to the high moisture content in meat. Two absorbance peaks of water can be noticed at around 970 and 1416 nm [17] Another absorbance peak, a broad reflectance valley at around 1180 nm, which extends up to 1200 nm, is affected by protein as well as the second overtone of C-H stretching in lipids [14, 17, 18].

Table 1. PCA-LDA and PLS-DA performances of Vis-NIR spectroscopy to distinguish shank and sirloin meat (datasets for calibration (Cal) = 60, prediction (Pred) = 40)

True Class	Predicted	PCA-LDA				PLS-DA			
		Minced		Sliced		Minced		Sliced	
		Cal	Pred	Cal	Pred	Cal	Pred	Cal	Pred
Shank	Shank	28	21	29	19	28	21	29	19
Shank	Sirloin	0	0	0	0	0	0	0	0
Sirloin	Shank	0	0	0	0	0	0	0	0
Sirloin	Sirloin	32	19	31	21	32	19	31	21
	Accuracy	100%	100%	100%	100%	100%	100%	100%	100%
	Reliability	100%	100%	100%	100%	100%	100%	100%	100%

3.2 Result of PCA-LDA and PLS-DA from Vis NIR Spectra

The performance of the PCA-LDA and PLS-DA models using Vis-NIR Spectra to identify the beef cut type is displayed in Table 1. Perfect calibration models of PCA-LDA and PLS-DA were obtained using raw spectra for beef cut classification. The results show that beef cuts minced and sliced were perfectly classified using a Vis-NIR spectrometer using both PCA-LDA and PLS-DA methods. A perfect model with complete accuracy (100%) and calibration (100%) reliability were obtained across all models. The model's prediction performance also shows that it can accurately classify beef cuts into each categorize.

3.3 Result of PCA-LDA and PLS-DA from SW-NIR Spectra

The performance of the PCA-LDA and PLS-DA models using SW-NIR Spectra to identify the beef cut type is displayed in Table 2. The outcomes showed the calibration model accuracy using PCA-LDA and PLS-DA for beef cuts classification. Beef cuts can be perfectly classified using raw spectra. The results show that beef cuts minced and sliced were accurately classified using a Vis-NIR spectrometer using both PCA-LDA and PLS-DA methods. A perfect model with full accuracy (100%) and calibration (100%) reliability were obtained across all models. The model's ability to accurately categorize beef cuts is further demonstrated by its strong prediction performance.

Table 2. PCA-LDA and PLS-DA performances of SW-NIR spectroscopy to distinguish shank and sirloin meat (datasets for calibration (Cal) = 60, prediction (Pred) = 40)

True Class	Predicted	PCA-LDA				PLS-DA			
		Minced		Sliced		Minced		Sliced	
		Cal	Pred	Cal	Pred	Cal	Pred	Cal	Pred
Shank	Shank	30	21	28	18	30	21	28	18
Shank	Sirloin	0	0	0	0	0	0	0	0
Sirloin	Shank	0	0	0	0	0	0	0	0
Sirloin	Sirloin	30	19	32	22	30	19	32	22
	Accuracy	100%	100%	100%	100%	100%	100%	100%	100%
	Reliability	100%	100%	100%	100%	100%	100%	100%	100%

4 Conclusion

The result shows the availability of Vis-NIR and SW-NIR spectroscopy to classify sliced and minced sirloin and shank beef cuts. The classification and prediction models had perfect calibration performances of 100% accuracy and 100% reliability for both the PLS-DA and PCA-LDA models. Overall, the model built using both Vis-NIR and SW-NIR spectroscopy combined with either PCA-LDA or PLS-DA could accurately discriminate sliced and minced sirloin and shank beef cuts. Therefore, it can be concluded that Vis-NIR and SW-NIR spectroscopy are promising methods for classifying beef cutsthem if possible.

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