

EVALUATION OF NEAR-INFRARED (NIR) SPECTROSCOPY FOR RAPID DETERMINATION OF PHYSICOCHEMICAL CHARACTERISTICS OF BEEF

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Abstract

Rapid and reliable assessment of beef quality is essential for ensuring product consistency and consumer satisfaction. Conventional laboratory methods used to determine physicochemical characteristics are accurate but are destructive, labour-intensive, and time-consuming. This study evaluated the potential of Near-Infrared (NIR) spectroscopy as a rapid and non-destructive alternative for determining the physicochemical characteristics of beef. Sixty beef samples were analysed using both conventional proximate analysis and NIR spectroscopy. Physicochemical properties, including moisture, crude protein, crude fat, ash content, pH, water-holding capacity, shear force, and instrumental colour, were determined using standard laboratory procedures. The results obtained from NIR spectroscopy were compared with those from conventional proximate analysis to assess their agreement. Moisture content showed no significant difference ($P > 0.05$) between the two methods, indicating good agreement, whereas significant differences ($P \leq 0.05$) were observed for crude protein, crude fat, and ash content. The measured physical quality attributes also demonstrated normal variation among beef samples. Overall, the findings indicate that NIR spectroscopy provides a rapid, non-destructive, and practical approach for routine evaluation of beef quality, with particularly promising performance for moisture determination. Further studies using larger datasets and improved analytical approaches are recommended to enhance prediction accuracy and support the wider application of NIR spectroscopy in the meat industry.

1. Introduction

Beef is one of the most widely consumed sources of animal protein and provides essential nutrients, including high-quality proteins, vitamins, minerals, and micronutrients that support human growth and overall health (FAO, 2019). Owing to its high nutritional value and versatility, beef is extensively utilized in a variety of food products and culinary preparations. In recent years, growing

consumer awareness of food quality and safety, together with several reported incidents of meat adulteration, has increased the demand for reliable methods to assess meat quality and authenticity (Lohumi et al., 2015). Consequently, the meat industry is under increasing pressure to implement rapid, accurate, and reliable quality assessment techniques that ensure product consistency and maintain consumer confidence.

The physicochemical composition of beef plays a crucial role in determining its nutritional value, processing characteristics, sensory attributes, and overall consumer acceptability. Major components, including moisture, protein, fat, and ash, vary according to factors such as animal breed, age, sex, feeding regime, and muscle location (Gill, 2014). Beef typically contains approximately 75% water, 20% protein, 2.5% fat, 1.2% carbohydrates, and 1.65% nitrogen-containing compounds (Pereira and Vicente, 2013). Variations in these constituents directly influence important quality characteristics, including tenderness, juiciness, flavour, texture, and shelf life.

Among these constituents, intramuscular fat (IMF) is recognized as one of the most important determinants of beef eating quality because it enhances tenderness, juiciness, flavour, and overall consumer satisfaction (Troy et al., 2016; Zhang et al., 2022). Beef proteins also provide all nine essential amino acids required for human nutrition, making protein content another key quality indicator (Geiker et al., 2021). Conventional laboratory methods recommended by the Association of Official Analytical Chemists (AOAC), such as oven drying for moisture determination, solvent extraction for fat analysis, Kjeldahl digestion for protein estimation, and muffle furnace ashing, are widely used to quantify these physicochemical properties. Although these methods provide accurate and reliable measurements, they are destructive, labour-intensive, time-consuming, and unsuitable for rapid or real-time quality monitoring during industrial processing.

To address these limitations, Near-Infrared Spectroscopy (NIRS) has emerged as a promising non-destructive analytical technique for food quality evaluation. NIRS enables rapid analysis with minimal or no sample preparation and has been successfully applied to predict various physicochemical properties of meat and other food products (Beć et al., 2021). Compared with conventional analytical methods, NIRS offers several advantages, including rapid data acquisition, non-destructive measurement, lower operating costs, and suitability for laboratory, at-

line, and on-line quality assessment (Osborne et al., 1993; Bajwa et al., 2009). Furthermore, multipoint NIRS systems improve prediction accuracy by reducing the influence of sample heterogeneity and providing additional spatial information compared with conventional single-point spectrometers (Dixit et al., 2016).

The predictive performance of NIRS depends not only on spectral acquisition but also on appropriate data processing and calibration modelling. Raw NIR spectra are often affected by light scattering, particle size variation, and baseline shifts, requiring suitable preprocessing techniques before model development. Multivariate calibration methods, including Partial Least Squares Regression (PLSR), have been widely used to establish relationships between spectral information and reference physicochemical measurements. More recently, machine learning algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest (RF) have demonstrated considerable potential for modelling complex nonlinear relationships and improving prediction accuracy beyond conventional linear calibration approaches (Li et al., 2012; Vasconcelos et al., 2023).

Despite the growing application of NIRS in meat quality evaluation, developing robust calibration models capable of accurately predicting multiple physicochemical characteristics under varying sample conditions remains a significant challenge. The predictive performance of different machine learning algorithms may vary depending on sample variability, spectral characteristics, and the quality attributes being analysed. Therefore, systematic comparison of calibration models is essential to identify the most reliable and accurate approach for rapid, non-destructive assessment of beef quality.

Accordingly, the objective of this study was to evaluate the potential of Near-Infrared Spectroscopy (NIRS) as a rapid and non-destructive technique for determining the physicochemical characteristics of beef by comparing its measurements with those obtained from conventional proximate analysis.

2. Materials and Methods

2.1 Experimental Site

The study was conducted at the Meat Processing Laboratory, University of Veterinary and Animal Sciences (UVAS), Lahore, Pakistan, and the Animal Nutrition Laboratory, Central Laboratory Complex (CLC), Ravi Campus, Pattoki.

2.2 Sample Collection and Preparation

Fresh beef samples were collected from crossbred cattle slaughtered at the Punjab Agriculture and Meat Company (PAMCO) slaughterhouse, Shahpur Kanjran, Lahore. The average carcass weight was 140 ± 10 kg. Immediately after slaughter, the samples were transported to the Meat Science Laboratory, UVAS Ravi Campus, in insulated ice boxes.

Approximately 800 g of the Trapezius muscle from the shoulder region was collected from each carcass. Each sample was divided into two equal portions: one 400 g portion was used for proximate (wet chemistry) analysis, while the remaining 400 g portion was used for Near-Infrared (NIR) spectroscopic analysis.

2.3 Experimental Design

Sixty beef samples were analyzed for both physical and chemical quality characteristics. Physical properties included pH, colour, water-holding capacity (WHC), cooking loss, and texture profile analysis. Chemical composition, including moisture, crude protein, crude fat, and ash content, was determined using both conventional proximate analysis and NIR spectroscopy. All laboratory analyses were performed in triplicate.

Table 1. Experimental design for the analysis of physical and chemical properties of beef meat.

Conditions	Physical properties		Beef Meat Samples
Parameters	Ph., Color, WHC, Cooking loss, Texture profile Analysis		60
Conditions	Chemical properties	Replicate	Total no of samples
Proximate Analysis	Moisture	3	10×3=30
	Crude Protein		
	Crude Fat		
	Ash content		
NIR	Moisture		10×3=30
	Crude Protein		
	Crude Fat		
	Ash content		

2.4 Proximate Analysis

The chemical composition of beef samples was determined according to the Association of Official Analytical Chemists (AOAC) standard methods.

Moisture Content

Moisture content was determined using the oven-drying method (AOAC 930.15). Approximately 3 g of each sample was dried at 105°C for 3 h until constant weight. Moisture percentage was calculated as:

$$\text{Moisture\%} = (W_1 - W_2)/W$$

Where W_1 the initial sample is weight and W_2 is the dried sample weight.

Crude Protein

Crude protein was determined using the Kjeldahl method (AOAC 2001.11). Samples (0.5–1.0 g) were digested with concentrated sulfuric acid in the presence of a Kjeldahl catalyst, followed by steam distillation and titration with standardized hydrochloric acid. Nitrogen content was converted to crude protein using a conversion factor of 6.25.

$$\text{Protein\%} = (A - B) N 1.4007 6.25 / W$$

Where A = HCl used for the sample, B = HCl used for the blank, N = normality of HCl, and W = sample weight (g).

Ash Content

Ash content was determined using the dry ashing method (AOAC 942.05). Approximately 5 g of each sample was incinerated in a muffle furnace at 550°C until complete combustion. After cooling in a desiccator, the ash residue was weighed.

$$\text{Ash\%} = \frac{\text{Ash weight}}{\text{Sample weight multiplied by 100}}$$

Crude Fat

Crude fat was determined using Soxhlet extraction (AOAC 2003.05). Approximately 3–5 g of each sample was extracted with petroleum ether for 14 h. After solvent evaporation, the extracted fat was weighed.

$$\text{Fat \%} = \frac{\text{fat weight}}{\text{sample weight}} * 100$$

2.5 Physical Quality Measurements

pH

Muscle pH was measured using a portable puncture-type pH meter (Model 3110, Germany). The instrument was calibrated using pH 4.01 and 7.00 standard buffer solutions before measurement (Colle et al., 2015).

Colour Measurement

Surface colour was measured using a Konica Minolta CR-410 Chroma Meter. The instrument was calibrated using a standard white calibration tile supplied by the manufacturer. Three readings were obtained from different locations on each sample, and the average value was used for statistical analysis (Calnan et al., 2016).

Cooking Loss

Samples were weighed before cooking and cooked in a Memmert WNB-45 water bath until the internal temperature reached 72°C. After cooling and surface drying, samples were reweighed.

$$\text{Cooking Loss (\%)} =$$

$$\frac{\text{Weigh before cooking (kg)} - \text{Weigh after cooking (kg)}}{\text{Weigh before cooking (kg)}} \times 100$$

Water-Holding Capacity (WHC)

Water-holding capacity was determined using the compression method (YYW-2, Nanjing Soil Instrument). Approximately 2 g of fresh beef was compressed between two filter papers, and WHC was calculated from the amount of released water (Li et al., 2012).

Texture Profile Analysis (TPA)

Texture profile analysis was performed using a TA.XT Plus Texture Analyzer (Stable Micro Systems, UK) fitted with a 35-mm cylindrical probe. Samples were compressed twice to 50% deformation using a trigger force of 20 g, and texture parameters were recorded (Mittal et al., 1992).

2.6 Near-Infrared Spectroscopy (NIRS)

Spectral Acquisition

Prior to scanning, beef samples were stored at 4°C and equilibrated to room temperature (approximately 20°C). NIR reflectance spectra were collected using a Fabry–Perot interferometer-based spectrophotometer (VTT, Finland) equipped with four fibre-optic reflectance probes. Spectra were recorded over the wavelength range of 1515–2100 nm at 5 nm intervals, generating 118 spectral variables per sample.

A slurry cup and gold reflector were used to ensure consistent optical contact and improve spectral repeatability. Measurements were performed under controlled laboratory conditions.

Spectral Preprocessing

Raw spectra were preprocessed to minimize scattering effects, baseline drift, and instrumental noise. Three preprocessing methods were evaluated:

- Standard Normal Variate (SNV)
- Multiplicative Scatter Correction (MSC)
- Savitzky–Golay (S–G) smoothing

The preprocessed spectra were subsequently used for calibration model development.

2.7 Calibration Model Development

Calibration models were developed to predict beef physicochemical characteristics from NIR spectra. Partial Least Squares Regression (PLSR) was used as the primary multivariate calibration technique. Model performance was evaluated using leave-one-out cross-validation implemented in The Unscrambler® (Version 9.7, CAMO Software, Norway).

Model accuracy was assessed using the coefficient of determination (R^2), root mean square error of calibration (RMSEC), and root mean square error of cross-validation (RMSECV). Models with the highest R^2 and lowest prediction errors were considered optimal.

3. Results

3.1 Comparison of Proximate Analysis and NIR Spectroscopy

The physicochemical composition of beef determined by conventional proximate analysis and Near-Infrared (NIR) spectroscopy is presented in Table 2. Proximate analysis produced mean values of $75.52 \pm 6.36\%$ for crude protein, $90.77 \pm 6.90\%$ for moisture, $4.51 \pm 0.78\%$ for ash, and $5.79 \pm 2.60\%$ for fat content. In comparison, NIR spectroscopy estimated $46.80 \pm 6.32\%$ crude protein, $77.97 \pm 4.30\%$ moisture, $5.87 \pm 1.07\%$ ash, and $3.51 \pm 2.20\%$ fat.

Statistical analysis indicated significant differences ($P \leq 0.05$) between proximate analysis and NIR predictions for crude protein, ash, and fat content. However, moisture content did not differ significantly ($P > 0.05$), suggesting that NIR spectroscopy showed relatively better agreement with the reference method for moisture determination.

Table 2. Comparison of proximate analysis and NIR spectroscopy results for beef meat.

Parameter	Proximate Analysis	NIR Spectroscopy	P-value
Crude Protein (%)	75.52 ± 6.36	46.80 ± 6.32	≤ 0.05
Moisture (%)	90.77 ± 6.90	77.97 ± 4.30	> 0.05
Ash (%)	4.51 ± 0.78	5.87 ± 1.07	≤ 0.05
Fat (%)	5.79 ± 2.60	3.51 ± 2.20	≤ 0.05

3.2 Physicochemical Characteristics

The average values of pH, shear force, and water-holding capacity (WHC) are presented in Table 3. The mean pH was 6.02 ± 0.70 , whereas the mean

shear force and WHC were 62.02 ± 2.03 N/kg and $61.92 \pm 18.40\%$, respectively. Shear force and WHC exhibited considerable variation among samples, while pH remained relatively stable.

Table 3. Mean values of selected physicochemical properties of beef meat.

Parameter	Mean $\pm$ SD
pH	6.02 ± 0.70
Shear Force (N/kg)	62.02 ± 2.03
Water Holding Capacity (%)	61.92 ± 18.40

3.3 Instrumental Colour Measurements

Instrumental colour measurements are summarized in Table 4. The average lightness (L^*), redness (a^*), yellowness (b^*), chroma, and hue

values were 40.20 ± 1.80 , 20.12 ± 1.29 , 5.17 ± 1.16 , 19.26 ± 1.21 , and 19.26 ± 1.21 , respectively. The relatively low standard deviations indicate

good consistency in colour measurements among beef samples.

Table 4. Mean instrumental colour values of beef samples.

Parameter	Mean $\pm$ SD
L*	40.20 $\pm$ 1.80
a*	20.12 $\pm$ 1.29
b*	5.17 $\pm$ 1.16
Chroma	19.26 $\pm$ 1.21
Hue	19.26 $\pm$ 1.21

4. Discussion

Near-Infrared (NIR) spectroscopy has emerged as a rapid and non-destructive analytical technique for evaluating meat quality because it provides chemical information based on the interaction of near-infrared radiation with molecular bonds present in proteins, water, and lipids (Beć et al., 2021; Zhang et al., 2022). The present study compared NIR spectroscopy with conventional proximate analysis for predicting the physicochemical characteristics of beef.

The results showed that NIR spectroscopy successfully estimated all measured quality parameters; however, differences were observed between NIR predictions and laboratory reference values. Moisture content exhibited the closest agreement with proximate analysis, as no significant difference was observed between the two methods. Water has strong absorption bands in the near-infrared region, making moisture one of the easiest constituents to predict accurately using NIR spectroscopy. Similar findings have been reported by Tøgersen et al. (2003) and Ripoll et al. (2008), who demonstrated reliable prediction of moisture content in beef using NIR spectroscopy.

In contrast, larger differences were observed for crude protein, fat, and ash content. The lower prediction accuracy for protein may be attributed to biological variation among samples, spectral overlap between chemical constituents, and limitations in calibration model development. Similar observations have been reported by Alomar et al. (2003), who found that protein

prediction is generally less accurate than fat prediction in beef.

Fat content predicted by NIR spectroscopy was lower than that obtained from proximate analysis. Although this difference was statistically significant, NIR still demonstrated the capability to estimate fat concentration rapidly without sample destruction. Previous studies by Prieto et al. (2006), Tøgersen et al. (2003), and Alomar et al. (2003) also reported satisfactory prediction of fat content using NIR spectroscopy when appropriate calibration models were employed.

Ash content also showed significant differences between laboratory measurements and NIR predictions. Since mineral components do not directly absorb near-infrared radiation, ash prediction depends on indirect correlations with organic constituents, which may reduce prediction accuracy. Nevertheless, previous studies have reported acceptable calibration performance for ash prediction using multivariate models (Tøgersen et al., 1999; Alomar et al., 2003).

The average pH value recorded in this study was 6.02 ± 0.70 , which falls within the normal range reported for fresh beef. Muscle pH decreases after slaughter due to post-mortem glycolysis and lactic acid accumulation. Reported pH values for fresh beef generally range between 5.5 and 6.6, depending on muscle type, animal condition, and post-slaughter handling (Parthasarathy et al., 2007). The relatively stable pH values observed in this study suggest acceptable meat quality.

Water-holding capacity and shear force exhibited noticeable variation among samples, reflecting

natural differences in muscle structure and meat quality. Water-holding capacity influences product yield, juiciness, and processing performance, whereas shear force is commonly used as an indicator of tenderness. Variability in these parameters is expected because they are affected by muscle composition, connective tissue content, and post-mortem biochemical changes.

Instrumental colour measurements showed average values of $L = 40.20^*$, $a = 20.12^*$, and $b = 5.17^*$, indicating the characteristic appearance of fresh beef. Colour is one of the primary attributes influencing consumer purchasing decisions. Previous studies have demonstrated that storage conditions, freezing, thawing methods, and

myoglobin oxidation significantly affect beef colour characteristics (Ligonier et al., 2012; Kim et al., 2018).

Overall, the findings indicate that NIR spectroscopy offers a rapid and non-destructive alternative to conventional laboratory analysis for assessing beef quality. Although differences were observed for some physicochemical parameters, the technique demonstrated considerable potential for routine quality evaluation. Further improvement of calibration models using larger and more diverse datasets, together with advanced machine learning algorithms, may further enhance prediction accuracy and support industrial implementation.

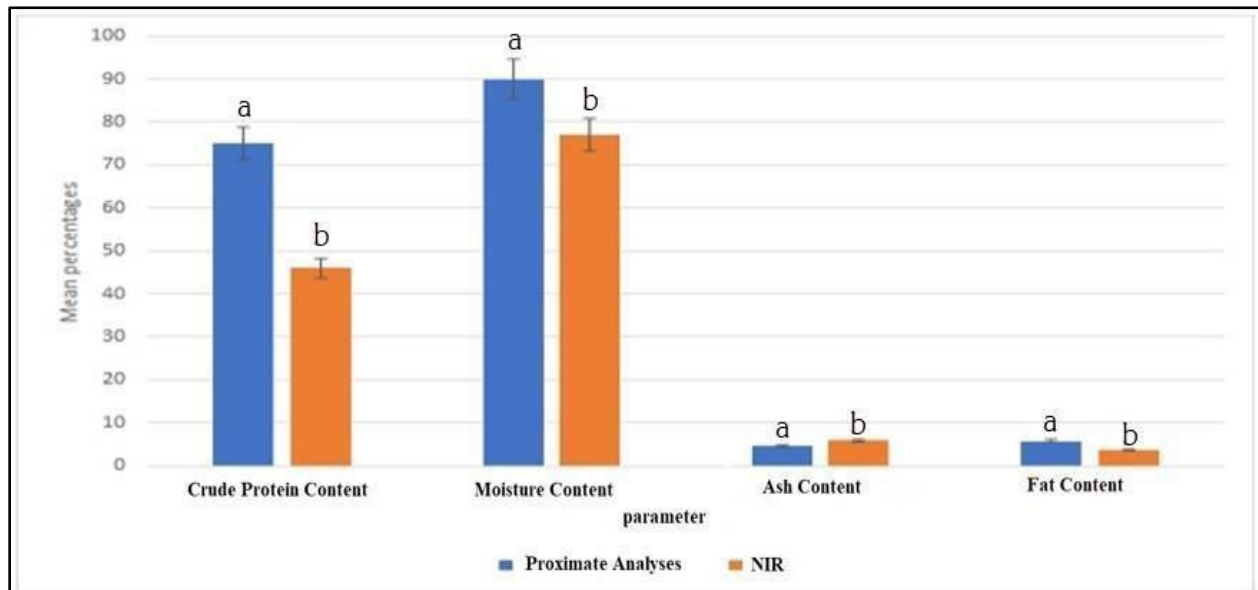


Figure 1. Comparison of physicochemical composition of beef determined by conventional proximate analysis and Near-Infrared (NIR) spectroscopy. Error bars represent standard deviation (mean $\pm$ SD). Different lowercase letters (a, b) above the bars indicate significant differences between methods for the same parameter ($P \leq 0.05$).

Conclusion

The present study demonstrated the applicability of Near-Infrared (NIR) spectroscopy as a fast and non-destructive approach for evaluating the physicochemical quality of beef. Compared with conventional laboratory analyses, NIR spectroscopy provided rapid estimates of moisture, protein, fat, and ash content while requiring minimal sample preparation and preserving sample integrity. Among the evaluated constituents, moisture showed the closest agreement with the reference method, whereas protein, fat, and ash exhibited comparatively larger prediction differences, highlighting the influence of sample variability and the need for further optimization of calibration strategies. The physical quality measurements, including pH, water-holding capacity, shear force, and colour attributes, also confirmed the natural variation in beef quality among the analyzed samples.

These findings indicate that NIR spectroscopy has considerable potential as a practical tool for routine beef quality assessment, particularly in situations where rapid decision-making and high sample throughput are required. Although it cannot completely replace standard laboratory methods, it can substantially reduce analysis time and improve the efficiency of quality monitoring in meat processing operations.

Further studies should expand the calibration dataset to include a wider range of breeds, muscles, production systems, and storage conditions. In addition, integrating advanced machine learning algorithms with optimized spectral preprocessing techniques may improve prediction accuracy and enhance the robustness of calibration models. Such developments would strengthen the application of NIR spectroscopy as a reliable technology for real-time quality evaluation and support the adoption of intelligent quality control systems in the meat industry.

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