Journal of Human Centered Technology
https://www.humentech.utm.my E-ISSN: 2821-3467

Advanced Human-Centered Food Quality Assessment: Second Derivative Linear Prediction of Raw Broiler Shear Force Using Near-Infrared Spectroscopy

Rashidah Ghazali[1], Nur Athirah Syafiqah Noramli[2], Herlina Abdul Rahim[1]*

[1] Faculty of Electrical Engineering, Universiti Teknologi Malaysia, 81310 Skudai, Johor, Malaysia
[2] School of Electrical Engineering, College of Engineering, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia

*Corresponding Author herlina@utm.my

Cite: https://doi.org/10.11113/humentech.v4n2.102 Research Article

Abstract:
This study investigates the application of linear predictive models and a low-cost Near-Infrared Spectroscopy (NIRS) system for non-invasive texture measurement of raw broiler meat, emphasizing its impact on food safety, consumer health, and industrial efficiency. Traditional meat quality assessment methods are often destructive, time-consuming, and labor-intensive, highlighting the need for more efficient, non-invasive alternatives. This research evaluated the effectiveness of Principal Component Regression (PCR) and Partial Least Squares (PLS) in predicting meat texture, demonstrating that the PLS outperformed the PCR with fewer latent variables and higher predictive accuracy. The results showed that the prediction accuracy of the PLS model for shear force estimation reached 64.01% for breast meat and 64.94% for drumstick samples, surpassing the performance of the PCR model. The application of second-order Savitzky-Golay derivative filtering and optimized spectral pre-processing further enhanced the model performance. By eliminating the need for invasive testing, this approach advances smart food technology, providing a fast, cost-effective, and non-destructive solution for automated meat quality assessment. These findings contribute to the development of AI-driven, real-time monitoring systems, improving food processing, supply chain efficiency, and ultimately ensuring better food quality and safety for consumers.

Keywords: Chicken; Near infrared spectroscopy; Texture analyzer; PCR; PLS.

1. INTRODUCTION

Chicken production has grown rapidly since chicken meat was recognized as an affordable and valuable source of protein. To minimize economic losses and ensure the delivery of high-quality products to consumers, quality control measures are essential in meat production. The primary factors that define meat quality include appearance, juiciness, flavor, nutritional content, safety, and texture (1). Among these, tenderness has been identified as the most critical factor affecting consumer satisfaction during consumption (2). Tenderness is described as the force needed to achieve a specific level of deformation or penetration in the product (3).

Traditional methods for assessing meat quality accurately involve manual inspections by human graders (4), instrumental techniques like the Warner-Bratzler shear force test and the Volodkevich Bite Jaws texture analyzer, sensory evaluations, and chemical analyses (2, 5, 6). However, these approaches have several limitations, such as being time-consuming, labor-intensive, destructive to samples, and impractical for online or real-time applications (2, 6).

In comparison, near-infrared spectroscopy (NIRS) has become one of the most effective and advanced tools for continuous monitoring and quality control in the food and agriculture sectors. The development of visible and near-infrared spectroscopy (VIS-NIRS) as a rapid, non-destructive, and real-time technique is increasingly preferred over conventional methods. NIRS has been widely utilized to enhance meat texture assessment and has found applications in predicting the quality of fruits (7, 8) and vegetables, as well as in the meat industry for determining fatty acid content (9), fat levels (10), moisture, and protein content (11) in both raw and cooked products.

Near-infrared spectroscopy offers numerous benefits, including fast measurement speeds, cost-effectiveness, minimal sample preparation, and high accuracy. Moreover, its non-destructive nature enables the direct evaluation of raw meat texture without the need to cook or destroy samples, making it an ideal technique for real-time meat quality assessment.

2. METHODOLOGY

This study involved the acquisition of shear force data using a conventional texture analyzer as a reference and NIR spectroscopy spectra as input data. The correlation between the input and the reference data was analyzed using two

Received 16 February 2025; Accepted 22 March 2025
Available online 06 August 2025

linear models, Principal Component Regression (PCR) and Partial Least Squares (PLS), to evaluate the effectiveness of these models in predicting shear force values based on the NIR spectrum.

Figure 1 outlines the methodology used in this study, starting with data acquisition, where chicken samples were collected and prepared. Next, NIRS and texture analyzer measurements were conducted to capture spectral data and shear force values. In data preprocessing, spectral data were converted, filtered, and outliers removed. Finally, the model development and validation involved applying PCR and PLS models, optimizing parameters, and evaluating accuracy using cross-validation.

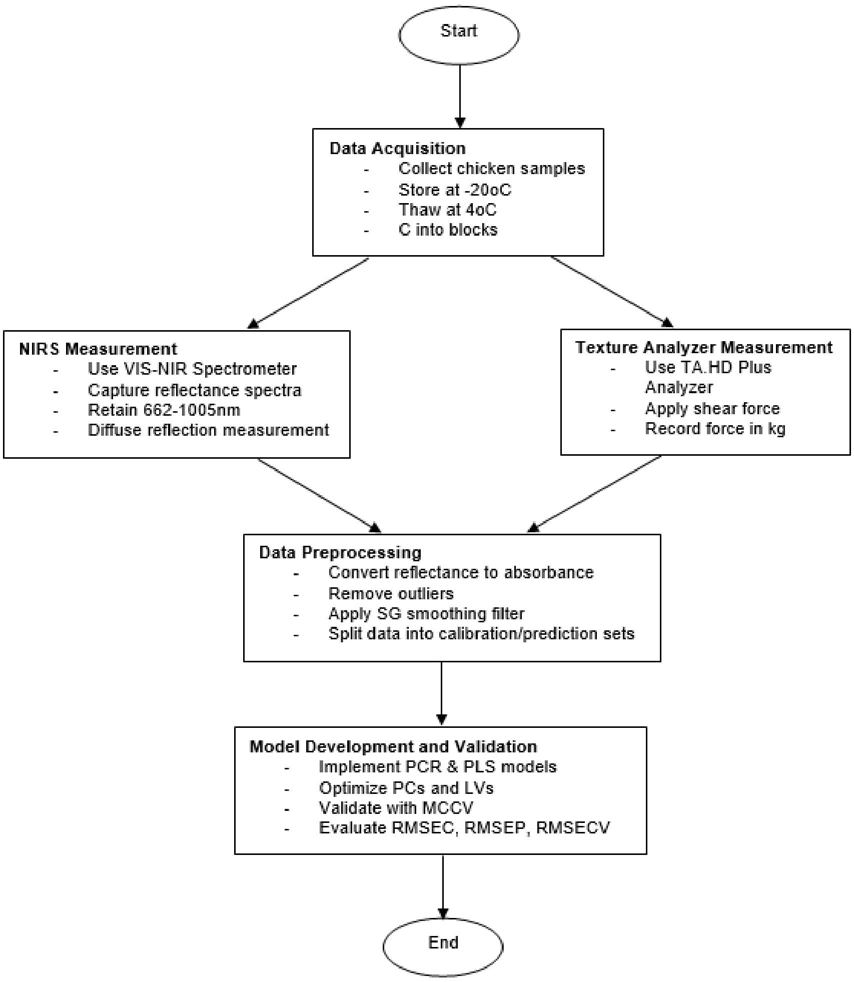

Figure 1. Methodology flowchart for shear force prediction in raw chicken meat.

2.1 Data Acquisition

Ross broilers were commercially bred and harvested from a broiler farm located in Lentang, Dungun, Terengganu, Malaysia. A total of 27 broilers were randomly chosen and slaughtered at 39 days of age, following the guidelines outlined in the Malaysian Standard 1500:2009 for halal food production, preparation, handling, and storage (12). After slaughter, the left-side breast muscles (pectoralis major) and both drumsticks were collected, vacuum-sealed, and stored at -20°C (13). Prior to the experiment, the samples were thawed overnight at 4°C. On the day of the experiment, the raw chicken meat was cut into rectangular blocks measuring 10 mm in thickness, 10 mm in width, and 20 mm in length, with the long axis aligned parallel to the muscle fibers (14, 15). In total, 162 block samples of raw breast meat and 162 blocks of drumstick meat were prepared for spectral acquisition and texture analysis.

2.2 Near Infrared Spectroscopy Measurement

The reflectance spectrum was captured using a VIS-NIR spectrometer (Ocean Optics USB4000 Miniature Fibre Optic Spectrometer, ORNET Sdn. Bhd., Selangor, Malaysia). The spectrometer covered a spectral range from 650 to 1318 nm; however, significant noise was observed at the beginning and end of the spectrum. As a result, only 344 wavelengths within the range of 662 to 1005 nm, at 1 nm intervals, were used for analysis. For diffuse reflection measurements, a reflection probe was positioned at a 90° angle (16) and placed 5 mm away from the chicken meat surface. The spectrometer was operated using the NIRS2 version 3.01 software package (InfraSoft International, State College, PA, USA).

https://doi.org/10.11113/humentech.v4n2.102

2.3 Texture Analyzer Measurement

The texture of raw chicken meat samples was evaluated using a TA.HD Plus Texture Analyzer (Stable Micro Systems, UK) equipped with a Volodkevich bite jaw set (1). Each raw chicken meat block was placed into the texture analyzer's slot before testing. The samples were sheared and compressed once at the center, perpendicular to the direction of the muscle fibers, using a Volodkevich bite jaw, a stainless-steel probe shaped like an incisor, attached to the texture analyzer at a 90° angle (15). The shear force data were recorded in kilograms (kg).

2.4 Data Preprocessing

Data preprocessing involved converting the reflectance spectra into absorbance using the formula log (1/Reflectance), followed by outlier removal, noise filtering, derivation, and data distribution. Outliers were identified and eliminated using externally studentized residuals and leave-one-out cross-validation. Spectral treatment techniques, such as normalization, the Savitzky-Golay (SG) smoothing filter, and the second-order derivative, were applied to smooth the spectral data while simultaneously correcting for baseline shifts and slope effects. The data were then randomly split into calibration and prediction datasets using hold-out cross-validation at a 2:1 ratio.

2.5 PCR and PLS

In this study, two linear models, PCR and PLS, were defined in (1) to predict the shear force values of raw breast meat and drumstick. The performance of these linear models was compared and analyzed based on the applied pre-processing methods. After removing outliers, 134 samples were retained and divided into calibration and prediction sets, with 90 and 44 samples, respectively, for both breast meat and drumstick. The models were represented as:

$$X = TP^T + E$$
$$Y = TQ^T + F$$

where *X* is the matrix of predictors; *Y* is the matrix of references; *T* is the score matrix; *E* and *F* are error term; and *P* and *Q* are the loading matrices.

During the development of both PCR and PLS models, the selections of the number of principal components (PCs) and latent variables (LVs) are critically important and were determined using Monte Carlo cross-validation (MCCV). If the number of PCs or LVs is too small, the regression models may become inaccurate because they fail to capture sufficient measurement information. Conversely, selecting too many PCs or LVs can lead to overfitting, which may degrade the performance of the models.

3. RESULTS AND DISCUSSION

The shear force measurements for breast meat and drumstick samples showed variations influenced by muscle structure, moisture content, and fat distribution. These differences affect meat texture, making shear force a crucial parameter for assessing meat quality. The PLS model demonstrated higher predictive accuracy compared to PCR, reinforcing its effectiveness in estimating shear force values based on NIR spectra. However, some inconsistencies in measurements were observed, highlighting the need for improved data handling and modeling techniques.

Several outliers were identified and removed during data preprocessing. Possible reasons for these outliers include measurement errors, such as inconsistent sample placement in the texture analyzer, biological variability among broilers, and spectral noise caused by ambient light interference or improper probe positioning. Additionally, preprocessing artifacts, such as excessive smoothing or incorrect baseline correction, could introduce deviations in the dataset. Addressing these factors through refined experimental protocols and advanced statistical techniques can enhance model robustness and prediction accuracy.

The Savitzky-Golay (SG) smoothing parameters include the derivative order (DO), polynomial order (PO), and filter length (FL). Higher polynomial orders are more effective at preserving peak heights and widths but may introduce more noise and provide less smoothing (17). For the derivative order, certain polynomial orders produce equivalent results. For instance, a zero derivative yields the same outcome with polynomial orders of zero and one (similarly for second and third orders). Likewise, for the first derivative, polynomial orders of one and two produce identical results (as do third and fourth orders) (18).

The filter length must be chosen carefully to avoid introducing errors or losing critical spectral information (19, 20). Optimizing the filter length in combination with the number of PCR components improves model effectiveness (19). In this study, the derivative order was set to DO = 0, 1, 2; the polynomial order to PO = 1, 2, 3; and the filter length was tested with odd values ranging from 5, 7, 9, until 31. SG smoothing was implemented using the MATLAB function sgolayfilt.

Table 1 presents the optimization of filter length selection for absorbance using the PCR model and Monte Carlo cross-validation (MCCV) for both breast meat and drumstick. The results show that the short-wave near-infrared (SWNIR) region (701–1005 nm) is the most suitable spectral range for breast meat, while the drumstick benefits from a combination of the visible (VIS) and SWNIR regions (662–1005 nm).

For breast meat, the SWNIR region achieves higher accuracy than the VIS-SWNIR region across zero, first, and second derivative orders, with accuracy values of 0.5273, 0.5308, and 0.5598, respectively, and optimal filter lengths of 23, 19, and 21. In contrast, for drumstick, the VIS-SWNIR region outperforms the SWNIR region for zero, first, and second

https://doi.org/10.11113/humentech.v4n2.102

derivative orders, with accuracy values of 0.5016, 0.5155, and 0.5843, respectively, and optimal filter lengths of 21, 19, and 17.

Table 1. Optimization selection of number of filter lengths for absorbance, for breast meat and drumstick across different applications.

Breast Meat						
Spectra Region (nm)	**DO**	**PO**	**FL**	**PC**	**RCV**	**RMSECV**
VIS-SWNIR	0	1	17	9	0.4980	0.8672
662-1005	1	2	9	8	0.5252	0.8510
	2	3	29	8	0.5476	0.8367
SWNIR	0	1	23	10	0.5273	0.8469
700-1005	1	2	19	8	0.5308	0.8475
	2	3	21	6	0.5598	0.8286
Drumstick						
Spectra Region (nm)	**DO**	**PO**	**FL**	**PC**	**RCV**	**RMSECV**
VIS-SWNIR	0	1	21	4	0.5016	0.8651
662-1005	1	2	19	2	0.5155	0.8569
	2	3	17	9	0.5843	0.8115
SWNIR	0	1	11	1	0.4920	0.8740
700-1005	1	2	25	2	0.5003	0.8658
	2	3	19	8	0.5659	0.8245

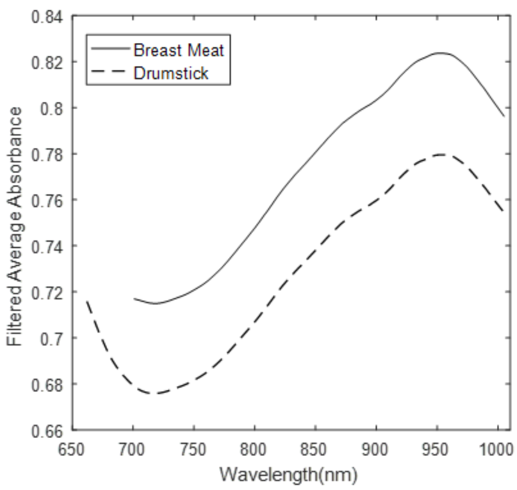

Figure 2. Average filtered absorbance spectra for breast meat and drumstick.

Figure 2 shows the average filtered absorbance spectra for breast meat and drumstick samples. A broad peak was observed between 940 and 990 nm, likely due to the third overtone of OH or water (2, 21, 22). Figure 2 illustrates the processed absorbance spectra for both breast meat and drumstick samples after applying spectral filtering techniques. The spectra reveal key absorption characteristics that correspond to the molecular composition of the meat, highlighting distinct peaks associated with water and other organic components. A broad peak was observed between 940 and 990 nm, likely due to the third overtone of OH or water (2, 21, 22). According to Patel *et al*. (2) and Mamani-Linares *et al*. (23), the visible absorption bands in the 430–700 nm range are associated with myoglobin, oxymyoglobin, metmyoglobin, and deoxymyoglobin, which are the primary heme pigments responsible for meat color (2). However, in the case of breast meat, the visible region is not included, as breast meat samples tend to have a pinkish-white color compared to drumstick samples. Additionally, breast meat contains less fat than drumstick meat.

The baseline shift and slope issues in the absorbance spectra were reduced using the second-order derivative processing method, as shown in Figure 3 for both breast meat and drumstick samples. The drumstick exhibited a high absorption peak around 678 nm, which is associated with hemoglobin. In both spectra, characteristic water absorption bands were identified around 842 nm and 980 nm, corresponding to the second overtone of OH stretching (24-26).

https://doi.org/10.11113/humentech.v4n2.102

Additionally, absorption bands in the 920–950 nm region were related to the third overtone of CH stretching bonds (26, 27). Furthermore, at the third overtone near the 718–760 nm range, absorption bands of CH bonds were also present (28).

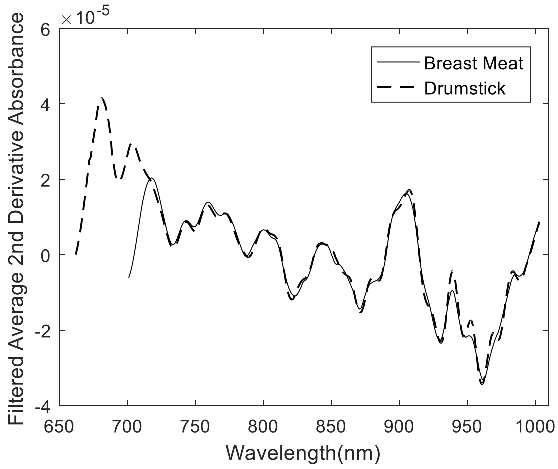

Figure 3. Average filtered second derivative absorbance spectra for breast meat and drumstick.

Table 2 presents the results for the prediction of shear force for breast meat and drumstick using PCR and PLS models. These models were developed using spectral data obtained from the near-infrared (NIR) range, which captures key absorption features related to meat composition and texture. The selection of appropriate spectral regions plays a crucial role in enhancing model accuracy by focusing on wavelengths most relevant to muscle structure and water content.

For breast meat, the models utilized the short-wave near-infrared (SWNIR) region, specifically from 700 to 1005 nm, as this range provided higher predictive accuracy. In contrast, the drumstick model incorporated a broader spectral range, covering both the visible and short-wave near-infrared (VIS-SWNIR) region from 662 to 1005 nm, which helped account for variations in pigmentation and structural differences. The optimal number of principal components (PCs) and latent variables (LVs) for PCR and PLS were selected based on the lowest root mean square error of Monte Carlo cross-validation (RMSECV). Additionally, the condition RMSEC < RMSEP < RMSECV (where the root means square error of calibration (RMSEC) is lower than the root means square error of prediction (RMSEP) and cross-validation (RMSECV)) must be met to prevent overfitting and underfitting. The prediction accuracy of PLS was significantly higher than that of PCR for both breast meat and drumstick samples, achieving values of 0.6401 and 0.6494, respectively. Furthermore, the optimal number of LVs required for PLS prediction was considerably smaller compared to PCR, demonstrating its efficiency.

Table 2. Results of prediction of shear force for breast meat and drumstick using PCR and PLS.

Samples	**Linear Models**	**PC / LV**	**Cross Validation MCCV**	**Calibration**		**Prediction**	
			RMSECV	**RC**	**RMSEC**	**RP**	**RMSEP**
Breast meat	PCR	6	0.8581	0.6398	0.7685	0.6306	0.7761
	PLS	3	0.8390	0.6528	0.7575	0.6401	0.7683
Drumstick	PCR	9	0.8656	0.6557	0.7551	0.6377	0.7703
	PLS	5	0.8661	0.6981	0.7160	0.6494	0.7604

4. CONCLUSION

The performance of both popular linear models, PCR and PLS, demonstrated satisfactory results, achieving an accuracy of approximately 40% for both breast meat and drumstick shear force prediction using the NIR spectrum. The application of the second derivative helped eliminate baseline shift and slope effects in the spectroscopic spectra, thereby increasing the correlation coefficient.

The performance of both PCR and PLS models demonstrated satisfactory results, achieving a prediction accuracy of approximately 64% for breast meat and drumstick shear force using NIR spectra. The application of second derivative preprocessing helped eliminate baseline shifts and slope effects, improving correlation with reference shear force measurements. However, the prediction accuracy remained significantly lower than 80% when using linear models, suggesting potential limitations in the modeling approach.

One possible reason for this limitation could be the spectral region selected for analysis. While the short-wave near-infrared (SWNIR) and visible-short-wave near-infrared (VIS-SWNIR) regions capture key absorption features related to meat composition, they may not fully account for all structural and chemical variations influencing shear force. Expanding the spectral range or incorporating additional wavelengths, along with exploring non-linear models such as machine learning approaches, could enhance prediction accuracy in future studies. Therefore, non-linear models need to be explored to improve the accuracy of shear force prediction using NIR.

AUTHORSHIP CONTRIBUTION STATEMENT

Rashidah Ghazali: writing – original draft, formal analysis; Nur Athirah Syafiqah Noramli: writing – review and editing; Herlina Abdul Rahim: conceptualization, supervision, writing – review and editing.

DATA AVAILABILITY

Data are available within the article.

DECLARATION OF COMPETING INTEREST

All authors declared no competing interest in the publication.

ACKNOWLEDGMENT

The authors would like to thank the Universiti Teknologi Malaysia (UTM) for funding this research with Vote No. (22H01) and Faculty of Electrical Engineering for utmost cooperation.

REFERENCES

(1) Abdul Rahim H, Ghazali R, Sahlan S, Shikh Maidin M. Prediction of texture of raw poultry meat by visible and near–infrared reflectance spetroscopy. Jurnal Teknologi: Special Edition. 2013; 64(5):59–62. https://doi.org/10.11113/jt.v64.2133.

(2) Patel N, Toledo-Alvarado H, Bittante G. Performance of different portable and hand-held near-infrared spectrometers for predicting beef composition and quality characteristics in the abattoir without meat sampling. Meat Sci. 2021; 178:108518. https://doi.org/10.1016/j.meatsci.2021.108518.

(3) Abdul Rahim H, Ghazali R. The application of near-infrared spectroscopy for poultry meat grading. Proceedings of the 2012 IEEE 8th International Colloquium on Signal Processing and its Applications. 2012; 58–62. https://doi.org/10.1109/CSPA.2012.6194691.

(4) Shiranita K, Miyajima T, Takiyama R. Determination of meat quality by texture analysis. Pattern Recognit Lett. 1998; 19(14):1319–1324. https://doi.org/10.1016/S0167-8655(98)00113-5.

(5) Abdul Rahim H, Ghazali R, Sahlan S, Shikh Maidin M. Prediction of texture of raw poultry meat by visible and near-infrared reflectance spectroscopy. Jurnal Teknologi. 2013; 64(5):1–8. https://doi.org/10.11113/jt.v64.2133.

(6) Wang W, Zhang C, Zhang F, Peng Y, Sun J. Real-time and online inspection of multiple pork quality parameters using dual-band visible/near-infrared spectroscopy. Food Anal Methods. 2020; 13(9):1764–1773. https://doi.org/10.1007/s12161-020-01801-8.

(7) Pissard A, Marques EJN, Dardenne P, Lateur M, Pasquini C, Pimentel MF, Fernández Pierna JA, Baeten V. Evaluation of a handheld ultra-compact NIR spectrometer for rapid and non-destructive determination of apple fruit quality. Postharvest Biol Technol. 2021; 172:111375. https://doi.org/10.1016/j.postharvbio.2020.111375.

(8) Chia KS, Abdul Rahim H, Abdul Rahim R. Prediction of soluble solids content of pineapple via non-invasive low-cost visible and shortwave near-infrared spectroscopy and artificial neural network. Biosyst Eng. 2012; 113(2):158–165. https://doi.org/10.1016/j.biosystemseng.2012.07.003.

(9) Rasinska E, Czarniecka-Skubina E, Rutkowska J. Fatty acid and lipid contents differentiation in cuts of rabbit meat. CyTA J Food. 2018; 16(1):807–813. https://doi.org/10.1080/19476337.2018.1488000.

(10) Villar A, Gorritxategi E, Aranzabe E, Fernández S, Otaduy D, Fernández LA. Low-cost visible–near infrared sensor for on-line monitoring of fat and fatty acids content during the manufacturing process of the milk. Food Chem. 2012; 135(4):2756–2760. https://doi.org/10.1016/j.foodchem.2012.07.074.

(11) Abeni F, Bergoglio G. Characterization of different strains of broiler chicken by carcass measurements, chemical and physical parameters and NIRS on breast muscle. Meat Sci. 2001; 57(2):133–137. https://doi.org/10.1016/S0309-1740(00)00084-X.

(12) Jabatan Kemajuan Islam Malaysia. Protocol halal meat and poultry [Internet]. 2021 [cited 2025 Mar 21]. Available from: https://myehalal.halal.gov.my/portal-halal/v1/images/pdf/protocol%20halal%20meat%20poultry.pdf.

(13) Cavitt LC, Youm GW, Meullenet JF, Owens CM, Xiong R. Prediction of poultry meat tenderness using razor blade shear, Allo-Kramer shear, and sarcomere length. J Food Sci. 2004; 69(1):1–8. https://doi.org/10.1111/j.1365-2621.2004.tb17879.x.

(14) Lambe NR, Navajas EA, Bünger L, Fisher AV, Roehe R, Simm G. Prediction of lamb carcass composition and meat quality using combinations of post-mortem measurements. Meat Sci. 2009; 81(4):711–719. https://doi.org/10.1016/j.meatsci.2008.10.025.
(15) Md Saad S, Sazili AQ, Zulkifli I, Nizam Z, Wagiman ZE. Effects of head-only electrical stunning on the physico-chemical characteristics and desmin degradation of broiler breast muscles at different time postmortem. J Anim Vet Adv. 2012; 11(14):2409–2416. https://doi.org/10.3923/javaa.2012.2409.2416.
(16) Ocean Optics I. Non-invasive reflection measurements of the skin, assessing sampling depth by using skin surrogates overview. [Internet]. Photonics Online. [cited 2025 Mar 21]. Available from: https://www.rktech.hu/dokumentaciok/OceanOptics/Application_note/skin_kp.pdf.
(17) Press WH, Teukolsky SA, Vetterling WT, Flannery BP. Savitzky-Golay smoothing filters. In: Vetterling WT, Flannery BP, Press WH, Teukolsky S. Numerical Recipes in C: The Art of Scientific Computing. 2nd ed. Cambridge University Press: Cambridge; 1986. p. 644–649.
(18) Rinnan Å, van den Berg F, Engelsen SB. Review of the most common pre-processing techniques for near-infrared spectra. TrAC Trends Anal Chem. 2009; 28(10):1201–1222. https://doi.org/10.1016/j.trac.2009.07.007.
(19) Chen H, Pan T, Chen J, Lu Q. Waveband selection for NIR spectroscopy analysis of soil organic matter based on SG smoothing and MWPLS methods. Chemom Intell Lab Syst. 2011; 107(1):139–146. https://doi.org/10.1016/j.chemolab.2011.02.008.
(20) Chia KS, Abdul Rahim H, Abdul Rahim R. Evaluation of common pre-processing approaches for visible (VIS) and shortwave near-infrared (SWNIR) spectroscopy in soluble solids content (SSC) assessment. Biosyst Eng. 2013; 115(1):82–88. https://doi.org/10.1016/j.biosystemseng.2013.02.008.
(21) Barbin DF, Badaró AT, Honorato DCB, Ida EY, Shimokomaki M. Identification of turkey meat and processed products using near-infrared spectroscopy. Food Control. 2020; 107:106816. https://doi.org/10.1016/j.foodcont.2019.106816.
(22) Riovanto R, De Marchi M, Cassandro M, Penasa M. Use of near-infrared transmittance spectroscopy to predict fatty acid composition of chicken meat. Food Chem. 2012; 134(4):2459–2464. https://doi.org/10.1016/j.foodchem.2012.04.038.
(23) Mamani-Linares LW, Gallo C, Alomar D. Identification of cattle, llama and horse meat by near-infrared reflectance or transflectance spectroscopy. Meat Sci. 2012; 90(2):378–385. https://doi.org/10.1016/j.meatsci.2011.08.002.
(24) Lambe NR, Clelland N, Draper J, Smith EM, Yates J, Bünger L. Prediction of intramuscular fat in lamb by visible and near-infrared spectroscopy in an abattoir environment. Meat Sci. 2021; 171:108286. https://doi.org/10.1016/j.meatsci.2020.108286.
(25) Grau R, Sánchez AJ, Girón J, Iborra E, Fuentes A, Barat JM. Nondestructive assessment of freshness in packaged sliced chicken breasts using SW-NIR spectroscopy. Food Res Int. 2011; 44(1):331–337. https://doi.org/10.1016/j.foodres.2010.10.011.
(26) Morsy N, Sun D-W. Robust linear and non-linear models of NIR spectroscopy for detection and quantification of adulterants in fresh and frozen-thawed minced beef. Meat Sci. 2013; 93(2):292–302. https://doi.org/10.1016/j.meatsci.2012.09.005.
(27) Zhang J, Liu G, Li Y, Guo M, Pu F, Wang H. Rapid identification of lamb freshness grades using visible and near-infrared spectroscopy (Vis-NIR). J Food Compos Anal. 2022; 111:104590. https://doi.org/10.1016/j.jfca.2022.104590.
(28) Guy F, Prache S, Thomas A, Bauchart D, Andueza D. Prediction of lamb meat fatty acid composition using near-infrared reflectance spectroscopy (NIRS). Food Chem. 2011; 127(3):1280–1286. https://doi.org/10.1016/j.foodchem.2011.01.084.