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Prediction of broiler shear force using near infrared spectroscopy with second derivative linear modeling

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ABSTRACT

This study explores the use of linear predictive models, specifically principal component regression (PCR) and partial least squares (PLS), in combination with a cost-effective near infrared spectroscopy (NIRS) system to non-invasively assess the texture of raw broiler meat. The findings demonstrate that appropriate pre-processing techniques, such as excluding the visible spectrum and applying the second-order Savitzky-Golay (SG) derivative with an optimal filter length (FL), enhance model performance. Notably, the PLS model outperformed PCR, requiring fewer latent variables (LVs) to achieve accurate predictions. This suggests that PLS more effectively captures key spectral features associated with meat texture, making it a promising approach for assessing raw broiler meat quality in a practical, cost-efficient, and non-invasive manner. These results highlight the potential of integrating linear predictive models with NIRS technology for reliable texture analysis in the poultry industry.

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1. INTRODUCTION

The rapid growth of the poultry industry is driven by the low cost of chicken meat as a protein source. However, ensuring meat quality is crucial to minimizing financial losses and providing consumers with high-quality products. The quality of meat is determined by multiple factors, including its appearance, juiciness, flavor, nutritional value, wholesomeness, and texture [1]. Among these, tenderness has been identified as the most critical factor influencing consumer satisfaction [2]. Tenderness is defined as the force required to achieve a certain level of deformation or penetration in meat [3].

Despite the importance of meat tenderness, traditional methods for assessing it present several challenges. These include visual inspection by human graders [4], instrumental techniques such as the Warner-Bratzler shear force and Volodkevich Bite Jaws texture analyzer, sensory evaluation, and chemical testing [2], [5], [6]. While these methods provide accurate results, they are labor-intensive, time-consuming, destructive to samples, and unsuitable for real-time online assessment [2], [6].

An alternative solution is near-infrared spectroscopy (NIRS), which has emerged as a promising, non-invasive, and rapid technique for monitoring and controlling food product quality. NIRS has been widely used in the food and agriculture industries for evaluating various properties, including fatty acid composition [7], fat content [8], moisture levels, and protein concentration [9] in both raw and cooked meat products. This technique offers several advantages, such as high measurement speed, cost-effectiveness, minimal sample preparation, and precise results [10], [11]. Additionally, NIRS enables direct evaluation of raw meat texture without requiring cooking or damaging samples.

Despite its potential, the application of NIRS in predicting broiler meat tenderness remains underexplored. Existing studies have demonstrated its feasibility for meat quality assessment, but further research is needed to optimize its effectiveness for tenderness prediction. Major constraints include variations in meat composition, differences in spectral data interpretations, and the need for robust predictive models that can handle such variability.

This study aims to address these challenges by investigating the capability of low-cost, portable spectroscopy devices in predicting the tenderness of broiler meat early in the processing stage. Specifically, it analyzes NIR spectra from both breast and drumstick meat using linear models such as principal component regression (PCR) and partial least squares (PLS). Additionally, this study compares the performance of two wavelength ranges (662-1005 nm and 700-1005 nm) with three spectral processing techniques (zero-order, first-order, and second-order Savitzky-Golay (SG) derivatives).

By developing a fast, non-invasive, and real-time method for evaluating broiler meat tenderness, this research seeks to enhance quality control processes in the meat industry. The findings could enable producers to monitor and maintain product quality more efficiently, reduce financial losses, and improve consumer satisfaction. The subsequent sections of this paper will elaborate on the methodology, experimental setup, data analysis techniques, results, and their implications for meat quality assessment.

2. METHOD

This study consists of data acquisition of shear force using the conventional texture analyzer as a reference and NIR spectroscopy spectrum as the input data. The correlation between the input and the reference data was analyzed using two linear models, PCR and PLS, to investigate their competence in predicting the shear force value using the NIR spectrum. These models were chosen due to their effectiveness in handling multicollinearity, extracting relevant spectral information, and enhancing predictive accuracy in spectral data analysis.

2.1. Data acquisition

Ross broilers were bred and produced commercially at a broiler farm in Lentang, Dungun, Terengganu, Malaysia. Twenty-seven broilers were randomly selected and slaughtered at 39 days old following the Malaysian standard 1500:2009 for halal food production, preparation, handling, and storage [12]. Samples of the left-side breasts (pectoralis major muscle) and both drumsticks were obtained, vacuum-packed, and stored at -20 °C [13]. Before experimentation, the samples were defrosted overnight at 4 °C. On the experiment day, the uncooked chicken meat specimens were sliced into rectangular shapes measuring 10 mm thick, 10 mm wide, and 20 mm long, with the longest side aligned with the muscle fibers [14], [15]. A total of 162 samples of uncooked breast meat and 162 drumsticks were prepared for spectral data collection and texture measurement. The sample preparation method ensures uniformity and minimizes variability in measurement outcomes.

2.2. Near infrared spectroscopy measurement

A VIS-NIR spectrometer (Ocean optics USB4000 miniature fibre optic spectrometer, ORNET Sdn Bhd, Selangor, Malaysia) was used to obtain the reflectance spectrum. The spectrometer covers a spectrum range of 650 to 1318 nm, but due to significant noise at the spectrum's start and end, only 344 wavelengths between 662 and 1005 nm at 1 nm intervals were retained. A reflection probe was positioned at a 90° angle [16], 5 mm away from the chicken's surface to measure the diffuse reflection. The instrument was operated using the software package NIRS2 version 3.01 (InfraSoft International, State College, PA, USA). The NIR method was selected for its rapid, non-destructive nature and its suitability for real-time meat quality assessment. Additionally, its ability to capture chemical and physical properties of meat makes it a valuable tool for evaluating tenderness.

2.3. Texture analyzer measurement

The texture of uncooked chicken meat samples was evaluated using a TA.HD plus texture analyzer (stable micro systems, UK) equipped with a Volodkevich bite jaws set [1]. Before measuring, each sample of raw chicken meat was placed in the texture analyzer's slot. Each specimen was cut and compressed once at the midpoint and at a right angle to the muscle fibers using a Volodkevich bite jaw (a stainless steel probe resembling a tooth) attached to the texture analyzer at a 90° angle [15]. The shear force data was recorded in kilograms (kg). The use of the Volodkevich bite jaw was chosen due to its effectiveness in simulating the biting action of human teeth and its well-established role in meat tenderness studies. The measurement process was standardized to ensure consistency and reduce experimental error.

2.4. Data preprocessing

Data preprocessing was carried out to improve spectral data quality and enhance the reliability of the predictive models. Reflectance spectra were converted to absorbance by applying the logarithm of the reciprocal of reflectance. To refine the data, anomalies were removed, and noise was minimized using the SG smoothing filter. Baseline shifts and slope variations were corrected using the second-order derivative method. Outliers were identified and excluded based on externally studentized residuals and leave-one-out cross-validation. The dataset was then randomly divided into calibration and prediction subsets in a 2:1 ratio using hold-out cross-validation to ensure an unbiased evaluation. These preprocessing steps are essential for improving model accuracy and maintaining reliable spectral data for regression analysis.

2.5. PCR and PLS

This study employed PCR and PLS for predicting the shear force value of raw breast meat and drumstick samples. These models were selected due to their effectiveness in handling high-dimensional spectral data by reducing redundancy and extracting meaningful information. The mathematical representation of these models is shown in (1) and (2):

$$X = TP^T + E \quad (1)$$

$$X = TQ^T + E \quad (2)$$

where is the matrix of predictors, is the matrix of references, is the score matrix, and are the loading matrices, and represent error terms.

The accuracy of the models relies on the appropriate selection of principal components (PCs) and latent variables (LVs). Monte carlo cross-validation (MCCV) was employed to optimize the number of PCs and LVs. An insufficient number of PCs and LVs may result in underfitting, leading to poor prediction accuracy. Conversely, an excessive number of PCs or LVs may lead to overfitting, reducing the model's generalizability. By systematically tuning these parameters, the study aimed to establish a robust predictive model for real-time, non-destructive assessment of broiler meat tenderness. The validation process ensures that the models provide reliable and reproducible results suitable for practical applications in the poultry industry.

This study consists of data acquisition of shear force using the conventional texture analyzer as reference and NIR spectroscopy spectrum as the input data. The correlation between the input and the reference data was analyzed using two linear models, which are PCR and PLS to investigate the competence of the linear models in predicting the shear force value using NIR spectrum.

3. RESULTS AND DISCUSSION

The SG smoothing parameters, including derivative order (DO), polynomial order (PO), and filter length (FL), play a crucial role in maintaining signal integrity while minimizing noise amplification. Higher POs tend to preserve signal heights and widths more effectively but can amplify noise and reduce smoothing efficiency [17]. Additionally, for any given DO, consecutive POs yield identical coefficient estimates. For instance, a zero-order derivative results in the same outcome for first- and zero-order polynomials, similar to the equivalence between third- and second-order polynomials. Likewise, for the first derivative, first-and second-order polynomials produce similar results, as do third- and fourth-order polynomials [18]. The selection of an appropriate FL is critical to minimizing errors and preserving spectral information [19], [20]. In this study, DOs of 0, 1, and 2 were employed, with POs set at 1, 2, and 3. The FL was systematically varied from 5 to 31 in increments of 2. The MATLAB function sgolayfilt was utilized to implement SG smoothing.

Table 1 presents the optimal FLs for absorbance in PCR modeling and MCCV for breast meat and drumstick samples. The findings highlight that the optimal spectral range for breast meat falls within the shortwave near-infrared (SWNIR) region (701-1005 nm). Conversely, for drumstick meat, the optimal spectral range extends across both the visible (VIS) and SWNIR regions (662-1005 nm). The accuracy in the SWNIR region for breast meat surpasses that in the VIS-SWNIR region, with coefficient values of 0.5273, 0.5308, and 0.5598 for zero, first, and second DOs, respectively. The optimal FLs corresponding to these DOs are 23, 19, and 21. In contrast, drumstick samples exhibit greater accuracy in the VIS-SWNIR region, with respective coefficient values of 0.5016, 0.5155, and 0.5843 for zero, first, and second DO. The corresponding optimal FLs for these results are 21, 19, and 17.

Table 1. The optimization selection of number of FLs for absorbance for breast meat and drumstick

	Spectra region (nm)	DO	PO	FL	PC	RCV	RMSECV
Breast meat	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	**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 1 illustrates the mean absorbance spectra following SG filtering for breast meat and drumstick samples. A pronounced peak is observed between 940 and 990 nm, which is likely attributable to the third overtone of OH or water absorption [2], [21], [22]. Previous studies by [2] and [23] indicate that absorption bands in the 430-700 nm range correspond to myoglobin, oxymyoglobin, metmyoglobin, and deoxymyoglobin-the primary heme pigments responsible for meat coloration [23]. The absence of the visible region in breast meat spectra aligns with its pinkish-to-white coloration, in contrast to drumstick meat, which retains visible absorbance. Additionally, the lower fat content of breast meat compared to drumstick samples is a contributing factor to these spectral differences.

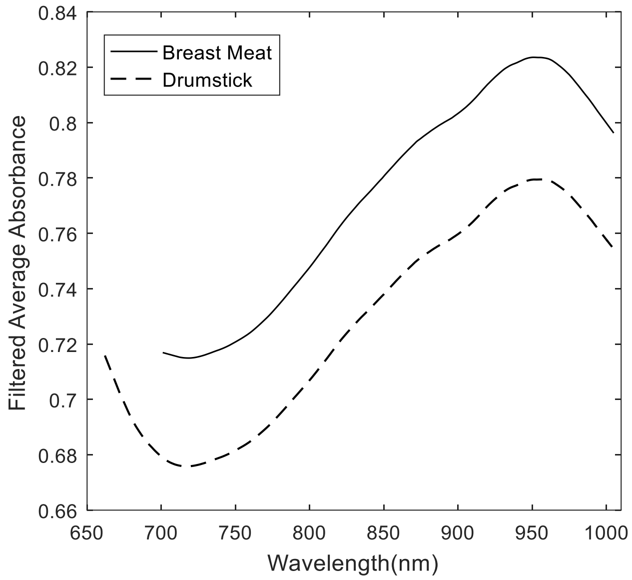

Figure 1. Average filtered absorbance spectra for breast meat and drumstick

Baseline shifts and spectral slope variations were mitigated using second-order derivative processing, as illustrated in Figure 2 for both meat types. Notably, drumstick samples exhibit peak absorption near 678 nm, which corresponds to hemoglobin presence. Furthermore, characteristic water absorption bands appear at approximately 842 nm and 980 nm, representing the OH second stretching overtone [24]-[26]. Additional absorption bands in the 920-950 nm range are linked to the third stretching overtones of CH bonds [26], [27], while CH bond absorption bands also appear in the 718-760 nm range, corresponding to the third overtone [28].

These findings support the study's objectives by confirming the spectral differences between breast meat and drumstick samples, which are attributed to variations in myoglobin content, fat composition, and water absorption properties. Compared to previous studies, the observed spectral bands align with established literature, reinforcing the reliability of the SG smoothing approach used in this research.

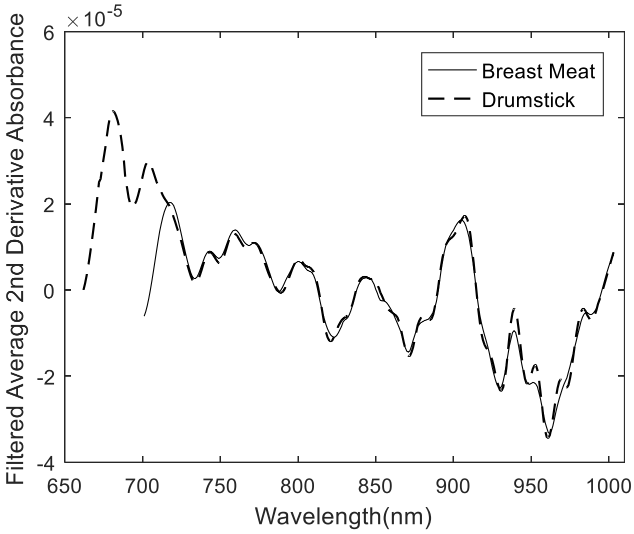

Figure 2. Average filtered second derivative absorbance spectra for breast meat and drumstick

Table 2 summarizes the results of predicting shear force in breast meat and drumsticks using PCR and PLS models. The optimal number of PCs and LVs for PCR and PLS was determined based on the lowest root mean square error values obtained through MCCV (RMSEC < RMSEP < RMSECV). Additionally, to prevent overfitting and underfitting, the root mean square error of calibration had to be lower than that of prediction and cross-validation. The findings indicate that PLS outperforms PCR in prediction accuracy for both breast meat and drumstick samples, achieving prediction coefficients of 0.6401 and 0.6494, respectively. Moreover, the PLS model requires significantly fewer LVs compared to the number of PCs used in PCR, further establishing PLS as the more effective predictive approach.

A potential limitation of this study is the reliance on SG smoothing as the primary preprocessing method. Although effective in enhancing spectral features, alternative methods such as wavelet transformation or standard normal variate (SNV) correction could further improve model performance. Future research should explore a combination of preprocessing techniques to determine the optimal strategy for meat quality assessment.

Table 2. The 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

This study underscores the importance of selecting appropriate SG smoothing parameters to optimize spectral preprocessing for meat quality assessment. The findings highlight the significance of the SWNIR region in breast meat evaluation and the VIS-SWNIR region for drumstick analysis. Furthermore, PLS regression outperforms PCR in shear force prediction due to its higher accuracy and lower model complexity. Future research should focus on refining spectral preprocessing techniques, exploring alternative machine learning approaches, and incorporating advanced validation methodologies to enhance prediction reliability. Additionally, investigating the impact of different preprocessing strategies on other meat quality parameters could further improve spectroscopic analysis in food science applications.

Furthermore, exploring the influence of external factors such as storage conditions, meat aging, and processing techniques on spectral properties could provide a more comprehensive understanding of meat quality variations. Expanding the dataset to include diverse meat sources and integrating deep learning models for spectral data analysis may also enhance predictive accuracy and generalizability in future studies.

4. CONCLUSION

The findings from this study indicate that while the popular linear predictive models, PCR and PLS, have demonstrated satisfactory performance in predicting the shear force of raw broiler meat (both breast and drumstick) using near infrared (NIR) spectroscopy, the accuracy achieved was only around 40%. This level of accuracy, though respectable, is still much lower than the desired 80% target for reliable texture assessment. The application of second-order derivative pre-processing techniques, such as the SG method, was shown to be effective in eliminating the baseline shift and slope effects in the spectroscopic data, thereby improving the correlation coefficient between the NIR spectra and the shear force measurements. This highlights the importance of appropriate data pre-processing for enhancing the performance of linear predictive models. However, the relatively low accuracy achieved by the linear models suggests that there is room for improvement in the predictive capability for raw broiler meat texture assessment. Therefore, the next step in this research would be to explore the use of non-linear predictive models, such as artificial neural networks or support vector machines, to see if they can provide a significant enhancement in the accuracy of shear force prediction using NIR spectroscopy. While the linear models of PCR and PLS have shown promising results, the ultimate goal of achieving an accuracy of 80% or higher in predicting raw broiler meat texture has not yet been met. The investigation of non-linear predictive models holds the potential to further improve the capability of NIR spectroscopy as a fast, non-destructive, and reliable technique for assessing the texture and quality of raw broiler meat products. Future studies should focus on evaluating the performance of non-linear models in order to achieve the desired accuracy levels for practical implementation in the poultry industry.

Additionally, future research should explore hybrid modeling approaches that integrate both linear and non-linear models to maximize prediction accuracy. Investigating the role of deep learning techniques, such as convolutional neural networks (CNNs), may also provide further insights into spectral data interpretation and improve predictive capabilities. Moreover, expanding the dataset to include variations in meat processing conditions, storage duration, and different poultry breeds may help enhance model generalizability. Addressing these aspects will contribute to the development of a more robust and scalable NIR-based meat quality assessment system, ultimately benefiting the poultry industry by ensuring consistent meat quality and reducing the reliance on traditional, time-consuming texture evaluation methods.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Rashidah Ghazali		✓	✓	✓		✓		✓	✓	✓				
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Syahidah Nurani Zulkifli				✓	✓		✓			✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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