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# Broiler meats tenderness prediction using near infrared spectroscopy against non-linear predictive modelling

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**ABSTRACT**

Near infrared (NIR) spectroscopy is a non-invasive analytical technique known for its ability to assess the quality attributes of meat products. However, the linear models utilized, partial least square (PLS) and principal component regression (PCR) achieved unsatisfactory performances of meat physical attributes prediction. Hence, in this research, for its inherent advantages in modelling nonlinear system, artificial neural network (ANN) is augmented to the components of PCR and PLS. Through the augmentation, the principal component neural network (PCNN) and latent variable neural network (LVNN) models are developed. From the results obtained, it shows that PCNN and LVNN successfully surpassed their respective linear versions of PCR and PLS by 70% higher shear force prediction performances. The LVNN proved to achieve the best prediction in breast meat with root mean square error of prediction (RMSEP) of 0.0769 kg and coefficient of determination ($R_P^2$) of 0.8201 whilst for drumsticks, RMSEP=0.1494 kg and $R_P^2$=0.8606. NIR spectroscopy technology integrated with machine learning yields a promising non-invasive technique in predicting the shear force of intact raw broiler meat.



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## 1. INTRODUCTION

Broilers are known for their high protein content, nutritional value, rapid growth, and diverse processed products. However, certain religions or races forbid the consumption of meat, such as beef and pork [1], [2], as a source of protein. Generally, in a typical consumer's perception, tenderness is an important quality attribute which is defined by the ease of mastication. From literature, the meat is indicated as 'tender' when small shear force value is obtained, meanwhile meat is considered 'tough' when larger shear force values are obtained [3], [4]. Numerous techniques have been used to assess meat tenderness in poultry, including instrumental approaches such as the Allo-Kramer, Meullenet-Owen Razor shear force (MORSF), slice shear force (SSF), and Warner-Bratzler shear force (WBSF) methods. However, these methods are invasive, destructive, and time-consuming, requiring extensive calibration and sample preparation.

Typically, effective evaluation of product quality in the food and agriculture sectors is carried out utilizing near infrared (NIR) spectroscopy. NIR spectroscopy can be used without causing harm in a constant way to analyze the chemical, physical, and sensory features of meat products [3], [5], [6]. Optical instruments connected to computers provide fast data collection that enables evaluation of meat quality, despite being limited to a small selected surface area for sampling.

Principal component regression (PCR) and partial least squares (PLS) are both linear multivariate models that heavily rely on reducing data through deriving a small number of orthogonal components or scores, instead of using the entire spectral data for regression analysis [7], [8]. The information is broken down into scores and loadings, which can prevent collinearity problems among variables. Both models can handle multiple variables that exceed the number of samples by compressing and reducing the dimension of spectral data. PCR breaks down spectral variables into principal components (PCs), while PLS breaks down both spectral and reference variables into latent variables (LVs).

Numerous researches have employed linear multivariate analysis alongside NIR spectroscopy to forecast chemical components such as protein, intramuscular fat, and moisture in poultry [5]–[7], [9]–[14]. Nevertheless, linear analysis demonstrated inadequate performance when predicting physical parameters like pH, color, tenderness, and water-holding capacity (WHC) in protein-based foods. In the research conducted by Liao *et al*. [15], employing visible-NIR spectra and a PLS model yielded impressive coefficients of determination ($R^2$=0.82) when forecasting intact pork quality characteristics such as intramuscular fat, protein, and water.

On the other hand, the top model did not have sufficient predictive power for shear force measurement. Even though all parameters in the calibration and validation sets showed an increase in prediction accuracy up to 0.7, the shear force in the validation set had lower accuracy ($R^2$=0.278, root mean square error of prediction (RMSEP)=0.360) than the calibration set. Marchi *et al*. [16] utilized a PLS model for shear force prediction, however the cross-validation outcomes ($R^2$=0.17, root mean squared error of cross-validation (RMSECV)=3.18) were deemed inadequate. Expanding the scanning areas of meat samples could potentially enhance the prediction due to the influence of small scanning areas on inaccurate shear force prediction. Barbin *et al*. [17] failed to accurately predict chicken meat tenderness compared to pH, color, and WHC due to an inadequate linear modeling analysis that could not account for the complexity of meat texture attributes. In the meantime, a number of studies utilizing linear modeling discovered quite satisfactory outcomes in forecasting the tenderness of beef and pork, with R-values ranging from 0.53 to 0.74. Nevertheless, studies on beef, poultry, pork, and lamb have shown unsatisfactory prediction outcomes in linear multivariate analysis, with accuracies under 0.5 when estimating tenderness based on NIR spectral data.

While PCR and PLS models can decrease high-dimensional inputs and remove collinearity, they cannot address nonlinearities present in the data. Nonlinearities in spectral signals may result from light scattering effects in unaltered meat samples [18]. Moreover, factors such as protein content and muscle structure, as well as connective tissue, affect qualities like tenderness, color, pH, and water holding capacity of meat [19]. Nonlinear calibration models are necessary because linear multivariate models cannot capture these nonlinearities. The increased interest in various fields, notably in agriculture and food industry, is due to the capability of artificial neural network (ANN) in modeling highly nonlinear data [20].

Researchers have investigated hybrid models that harness both linear and nonlinear methods to tackle this issue. Methods such as principal component neural network (PCNN) and latent variable neural network (LVNN) utilize the results from PCR and PLS as inputs into an ANN. This merges the data reduction skills of linear models with the nonlinear modeling strength of ANNs, addressing the limitations of individual methods like nonlinearity, redundant spectral bands, and wavelength selection issues [21]. Research has indicated that hybrid models like LVNN are effective in dealing with redundancy and nonlinearity in spectral data to estimate mineral abundance on the moon's surface, performing better than standalone PLS and genetic algorithm (GA)-PLS models [22].

The objective of this research is to evaluate the effectiveness of affordable portable spectroscopy in predicting the tenderness of broiler meat early on, by analyzing NIR spectra from breast meat and drumsticks using both linear (PCR and PLS) and nonlinear (PCNN and LVNN) models. This research also examined the utilization of two diverse subset wavelength intervals (i.e. 662–1,005 nm and 700–1,005 nm). Additionally, it contrasted three distinct spectral pre-processing methods (i.e. zero order, first order, and second order Savitzky-Golay derivatives).

## 2. METHOD

### 2.1. Sample and data collection

Ross broilers were utilized in this study and were raised in a commercial coop with a capacity of 2,200 broilers per coop on a farm in Lentang, Dungun, Terengganu, Malaysia. The broilers were given Huat Lai Feedmill Sdn. Berhad 's commercial pellets for their meals. On day 39, twenty-seven broilers were chosen at random and transported to the broiler processing plant. The sample size is determined using recommendations and resource equation approach outlined in earlier studies [23], [24]. The effectiveness of data analysis relies heavily on the choice of sample sizes. Choosing a sample size with a small number of animals can result in substantial differences in the raw data collected. Nevertheless, excessive waste of animals, along with ethical concerns, poses a problem for extensive sample sizes.

The chickens were housed in crates containing nine chickens each during lairage before being slaughtered and processed according to the regulations outlined in Malaysian Standard 1,500:2,009 for halal food production, preparation, handling, and storage [25]. The pectoralis major muscles on the left side and the pair of drumsticks were extracted from each prepared carcass, then chilled and delivered to Universiti Putra Malaysia in Serdang, Malaysia at a temperature of -20 °C by a specialized cold logistics service. The chilled specimens were kept in a freezer at -20 °C in a Meat Science Laboratory, part of the Department of Animal Science at the Faculty of Agriculture, Universiti Putra Malaysia, located in Serdang, Malaysia.

Before the day of data collection, a total of nine breast meat pieces and nine pairs of drumsticks were thawed overnight at a temperature of 4 °C for 12 hours. Because muscle heterogeneity can lead to high variability in shear force measurements obtained from the same muscle, six samples were collected from breast meat and three samples were collected from drumsticks. The uncooked chicken breast pieces from each broiler carcass were sliced into rectangle strips measuring 10 mm thick × 10 mm wide × 20 mm long with their axis aligned parallel to the muscle fibers [26]–[28]. The drumsticks were boneless before being sliced to the same size. As a result, a total of 108 samples of breast meat and drumsticks were prepared in one day. Every meat sample strip was placed in front of a NIR reflection probe to gather spectrum data, after which the shear force of the strips was tested with the Volokevich Jaw texture analyser. In order to reduce the time gap between the two processes and prevent moisture loss, meat aging, and discoloration, shear force was measured right after acquiring the spectrum [5]. The process of obtaining samples was repeated for the following two days. In total, 324 samples of breast meat and drumsticks were collected over a span of three days for spectroscopic and shear force analysis.

### 2.2. Spectroscopy measurement

A small, affordable handheld visible-short-wave infrared (VIS-SWNIR) spectrometer device, the Ocean Optics USB4000 miniature fibre optic spectrometer (650 to 1,318 nm), manufactured by ORNET Sdn. The device from a company in Malaysia was utilized to gather reflectance spectra from the surface of each broiler meat sample without invasive methods. The light source employed was a Tungsten halogen light (LS-1, Ocean Optics, USA), with a wavelength range spanning from 360 to 2,000 nm. A fiber optic reflectance probe (R400-7-VIS/NIR, Ocean Optics, USA) was employed to send light that was reflected from the surface of the meat to an internal detector. The optical fiber probe includes two connections: one for the light source and one for data collection. In order to measure diffuse reflection, the fiber optic probe was placed vertically at a 90° angle, positioned 5 mm above the surface of the uncooked broiler meat strips [29].

The setup for measuring VIS-SWNIR spectroscopy is shown in Figure 1. Every day, dark and white references were acquired by switching off the light source and capturing a spectrum from a white diffuse reflectance standard (WS-1, Ocean Optics, USA) for optical reference. The spectrometer connected to a laptop computer with the Spectra Suite ® software (Ocean Optics, USA) for capturing spectral data. The reflectance spectrum of a broiler meat sample was obtained using an average of 5 consecutive scans. To improve the signal-to-noise ratio of the obtained spectrum, it was smoothed using a boxcar value of 60. The obtained spectral data was saved on the laptop and analyzed using MATLAB simulation software (MATLAB® Version 7.12.0.635 (R2016a)).

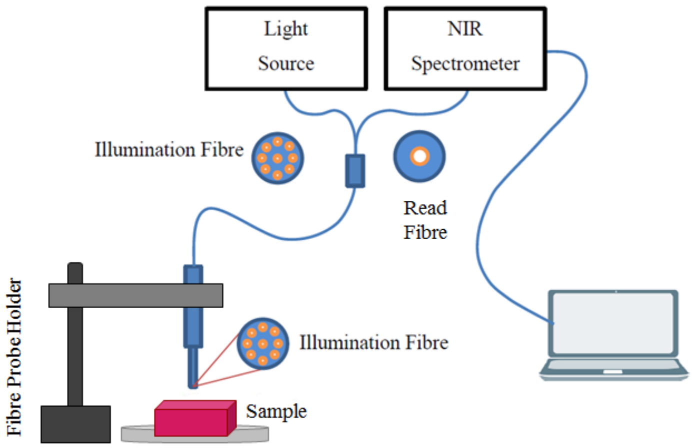


Figure 1. The illustration of VIS-SWNIR spectroscopy measurement

### 2.3. Shear force measurement

The shear force was measured with the help of a computer-aided texture analyser TA system. HD plus TA (Stable Micro Systems, UK) equipped with a Volodkevich Jaw set (stainless steel probe resembling an incisor). The texture analyser was set up with compression for test mode, pre-test, test and post-test speeds of 0.2 cm/sec, a 0.5 cm distance, and auto trigger type calibration. Every broiler strip sample was compressed and sheared once at the center, perpendicular to the muscle fibers' longitudinal orientation [27]. The highest recorded shear force was measured in kilograms (kg). In order to prevent build-up of residues that could affect measurement accuracy, the texture analyser's slot and steel probe were taken out and cleaned after every 8 strips tested. Therefore, the slot and steel probe were reinstalled and the texture analyser underwent recalibration after every 18 measurements. The methods were carried out multiple times while gathering data on shear force of broiler meat samples. The information gathered was stored in an Excel document and analyzed using MATLAB simulation software.

### 2.4. Pre-processing

The spectrometer utilized a TCD1304AP charge-coupled device (CCD) linear image sensor from Toshiba, Japan, to cover a range from 650 to 1,318 nm. Nevertheless, the CCD sensor couldn't detect any wavelengths beyond 1,100 nm, and there was significant noise present at both ends of the captured spectrum. Therefore, a total of 1,741 wavelengths were kept, offering spectral data ranging from about 662 to 1,005 nm. Moreover, the inconsistency in the interval between two neighboring wavelengths was attributed to the analog-to-digital conversion and the reduced efficiency of the spectrometer's grating. An averaging method was used to adjust the spectral data interval to 1 nm.

In order to eliminate unwanted signals resulting from light scattering and random noises, the diffuse reflectance spectra and shear force measurements that were recorded underwent pre-processing data procedures. Possible outlier samples were subsequently pinpointed autonomously using externally studentized residuals with the help of a PCR model and leave-one-out cross-validation. The externally studentized residual was calculated using the variance between the forecasted and actual broiler meat tenderness. Samples where residual values were higher than 1.976, the critical values of the t-distribution, were considered outliers and eliminated, resulting in the exclusion of 16% of breast meat samples and 15.4% of drumstick samples.

In Table 1, the shear force values for breast meat and drumsticks are listed, with potential outliers removed using externally studentized residual. In soft meat samples, the texture analyser requires less shear force to pierce the meat than in tougher meat. This indicates that soft meat has a lower shear force value, while harder meat has a higher shear force value. Additionally, the average, lowest, and highest shear force variability for breast meat was significantly smaller compared to the drumsticks. Breast meat is more tender and has lower shear force compared to drumsticks.

Table 1. The reference shear force values of retained broiler breast meat and drumsticks samples

| Meat types | No. of samples | Mean ± SD (kg) | Range (kg) |
|---|---|---|---|
| Breast meat | 136 | 0.715 ± 0.173 | 0.30 to 1.15 |
| Drumsticks | 137 | 1.045 ± 0.364 | 0.27 to 1.84 |

#### 2.4.1. Spectral pre-processing and calibration

The absorbance spectra were divided into two different wavelength ranges, VIS-SWNIR (662 to 1,005 nm) and SWNIR (700 to 1,005 nm), and analyzed with three mathematical techniques (zero-order, first-order, and second-order Savitzky-Golay (SG) derivative) to investigate if more accurate models could be created for particular traits (breast meat and drumsticks) by focusing on specific spectrum ranges rather than the entire spectrum [30], [31]. The parameters for SG filtering include the derivative order, polynomial order, and filter length. The value of the derivative order was chosen as DO=0, 1, and 2, while the polynomial order was selected as PO=1, 2, and 3. A clear explanation of the appropriate filter length is necessary to maintain the resolution of the derivative signal [30]. Monte Carlo cross-validation (MCCV) was utilized to validate the precision of the PCR model incorporating various pre-processed spectral data, filter length, and number of PCs [30]. MCCV, also known as repeated random subsampling or holdout with random resampling, is a straightforward but efficient method for finding optimal parameters and prediction error. It offers more dependable results than leave-one-out cross-validation (LOOCV) when dealing with a small data set.

The SG derivative coefficients were produced using MATLAB simulation software's built-in matrix routines function, sgolayfilt, in MATLAB version R2016a [32]. One hundred data sets were created with various arrangements and MCCV was conducted using 2-fold Venetian blind cross validation. This method was utilized and cited from Chia *et al.* [30]. The RMSECV was calculated to assess and contrast the PCR performance on various pre-processed spectral data, with filter length ranging from 5 to 31 nm in 2 nm increments and number of PCs ranging from 1 to 15 PCs.

The results of PCR in finding the best number of filter lengths for zero, first and second order SG derivatives on VIS-SWNIR and SWNIR spectra regions are summarized in Table 2. The breast meat had a RMSECV=0.82 with filter length=21 at 6 PCs, achieved by the second-order derivative of SWNIR region, which was smaller than the zero-order and first-order derivatives, including VIS-SWNIR region. In contrast, the drumsticks sample had the lowest RMSECV value of 0.80 and filter length of 21 at 10 PCs for the second-order derivative of VIS-SWNIR region.

Table 2 further demonstrates that utilizing second-order derivative pre-processing in PCR results in better RMSECV performance with a decreased number of PC factors compared to using zero-order and first-order derivatives. To maintain the precision of the derivative signals, it was noticed that a greater-order derivative necessitates a lengthier filter due to the likelihood of noise amplification during the estimation process. When looking at the breast meat SWNIR region and drumsticks VIS-SWNIR region, the filter length required to smooth out noise in the second-order derivative is larger than that needed for the zero-order and first-order derivatives. As a result, the most accurate way to estimate the shear force of drumsticks involved using the visible spectrum. On the other hand, when it came to breast meat, the best approach was to exclude the visible spectrum and use second-order derivative SG pre-processing with a filter length of 21 nm for the best results.

Table 2. Results of PCR models based on different pretreatments using VIS-SWNIR and SWNIR ranges

| Meat type | Spectra region | Pre-processing | Filter length (nm) | Principal components | Root mean square error cross-validation |
|---|---|---|---|---|---|
| Breast meat | VIS-SWNIR | Zero order derivative | 5 | 13 | 0.85 |
| | (662 to 1005 nm) | First order derivative | 9 | 10 | 0.84 |
| | | Second order derivative | 29 | 8 | 0.84 |
| | SWNIR | Zero order derivative | 11 | 10 | 0.85 |
| | (700 to 1005 nm) | First order derivative | 19 | 8 | 0.84 |
| | | Second order derivative | 21 | 6 | 0.82 |
| Drumsticks | VIS-SWNIR | Zero order derivative | 15 | 11 | 0.82 |
| | (662 to 1005 nm) | First order derivative | 17 | 10 | 0.82 |
| | | Second order derivative | 21 | 10 | 0.80 |
| | SWNIR | Zero order derivative | 5 | 11 | 0.83 |
| | (700 to 1005 nm) | First order derivative | 27 | 8 | 0.87 |
| | | Second order derivative | 11 | 10 | 0.83 |

In drumsticks, PCR showed greater enhancement in shear force assessment when including the visible region, measuring between 662 to 700 nm, compared to breast meat, regardless of SG derivative function order. This is due to the higher myoglobin content in drumstick muscles compared to breast meat muscles. The drumstick, being a component of the leg muscles, consists of a higher amount of delicate muscle fibers used primarily for everyday actions like walking [33]. Therefore, a higher amount of myoglobin is necessary to direct oxygen delivery to the working muscle [34]. Furthermore, the high myoglobin content is the cause of the reddish hue in drumstick meat. Consequently, a high level of myoglobin content aids in utilizing the visible and SWNIR wavelengths, specifically between 662 and 1,005 nm, for evaluating drumstick tenderness. In contrast, just the SWNIR area between 700 and 1,005 nm wavelengths is used to evaluate the shear force of breast meat.

Figure 2 displays the average second-order derivative absorbance spectrum for breast meat and drumstick samples obtained from measurements. The secondary derivative shows a significant decrease in the visible spectral range, enabling the distinction of overlapping peaks and uncovering more intense and defined peaks with a reduced bandwidth. The second-order SG derivative shows higher proficiency than zero and first derivatives by offering robust signals with extensive data after eliminating baseline shift and slope effects [12]. The forms of the NIR spectra appear alike, however variations in the spectral information of white meat and red meat in breast and drumsticks can be noticed at specific wavelengths.

Figure 2 shows that the visible region only applies to drumsticks, which have a higher content of myoglobin constituents compared to breast meat samples. Three prominent peaks with high absorbance in the visible spectrum at 662 to 700 nm are linked to the levels of myoglobin in meat and the different forms of myoglobin that determine meat color [35], [36]. The absorption peaks from 700 to 775 nm represent the vibrations of C-H third overtones related to fat or lipid, and O-H third overtones related to the water content of meat samples [35]. Peaks in the range of 775 to 850 nm correspond to the third harmonics of N-H stretching, which are a component of the molecular bonds found in proteins. The distinct absorption peaks in the 850 to 950 nm range are related to the intramuscular fat levels [17], [19], indicating the stretching vibration of C-H thirds overtones. Additionally, the absorbance peaks in the range of 950 to 1,005 nm could be attributed to the presence of O-H second overtone stretching and second overtone N-H stretching [37].

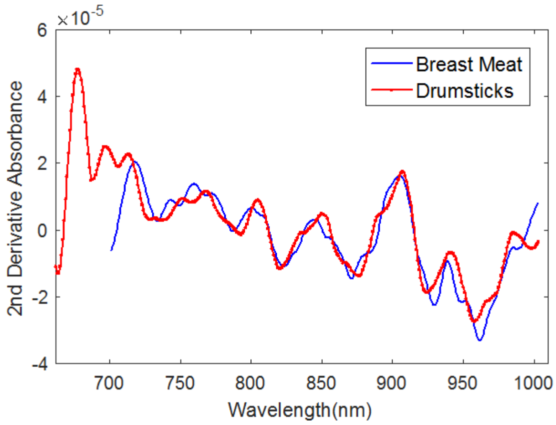


Figure 2. The average second-order derivative absorbance spectra for breast meat and drumsticks

### 2.5. Data analysis

Table 3 presents the descriptive statistics of the calibration and testing data sets for both breast meat and drumsticks. In order to evaluate the predictive performance of the models, the data was divided randomly into a calibration set (comprising 2/3 of the data) and a testing set (comprising 1/3 of the data) using the hold-out cross validation technique. The calibration set was utilized for constructing the predictive models, while the testing sets were used for assessing the predictive performance of the models. In order to prevent overfitting in the PCR and PLS equations, MCCV was conducted with a calibration set split into 50% for training and 50% for validation. The number of PC and LV selected was based on achieving the lowest RMSECV values, as further reduction in error was minimal. The optimization of various factors in constructing nonlinear models (PCNN and LVNN) was fine-tuned using the MCCV method, including the hidden neuron count, learning rate, momentum, and epoch quantity.

Table 3. Calibration and testing statistics for shear force attribute

| Meat types | Sample sets | Sample number | Shear force (kg) | | | |
|---|---|---|---|---|---|---|
| | | | Min | Max | Mean | Standard deviation (SD) |
| Breast meat | Calibration testing | 91 | 0.30 | 1.02 | 0.7209 | 0.1690 |
| | | 45 | 0.30 | 1.15 | 0.7029 | 0.1833 |
| | Total | 136 | 0.30 | 1.15 | 0.7150 | 0.1734 |
| Drumsticks | Calibration | 92 | 0.30 | 1.84 | 1.0624 | 0.3448 |
| | Testing | 45 | 0.27 | 1.74 | 1.0364 | 0.4046 |
| | Total | 137 | 0.27 | 1.84 | 1.0450 | 0.3642 |

The predictive capabilities of calibration models were assessed using $R_C^2$ and $R_P^2$ for calibration and prediction, respectively. RMSEC and RMSEP, along with ratio of performance to deviation (RPD), were also used to evaluate the models. RPD is calculated by dividing the standard deviation (SD) of reference values from the prediction set by the RMSEP. Because it lacks dimensions, RPD is being used more often for quickly assessing a calibration model in NIR spectroscopy. RPD values over 3 are seen as beneficial for quality control tasks but are challenging to achieve; 2.5 to 2.9 are considered acceptable for screening; 2.0 to 2.4 are viewed as inadequate and only suitable for basic screening, while values between 1.5 and 2 are solely for indicating quality [7].

#### 2.5.1. Artificial neural network

The research utilized a three-layer feedforward backpropagation neural network with the Levenberg-Marquardt algorithm, incorporating tan-sigmoid and purelin transfer functions in the hidden and output layers, correspondingly. In the PCNN model, input neurons were the best PC scores from PCR, and in the LVNN model, input neurons were the best LV scores from PLS regression. The output layer consisted of one neuron that represented the predicted shear force (SF) parameter. The input (PCs or LVs) and target (measured SF) data were both normalized to a range of -1 to +1 using the mapminmax function in MATLAB [38], and the pre-processing parameters were saved to re-scale the predicted outputs back to their original scale. The backpropagation training algorithm, trainlm, was utilized along with a MCCV technique to optimize four network parameters (hidden neurons, learning rate, momentum rate, and number of epochs) on the calibration data set [39], split into training and validation subsets. The best network structure was chosen by looking at the lowest mean squared error (MSE) on the validation subset, and the improved network was subsequently trained using the complete calibration dataset and tested with a different testing dataset.

## 3. RESULTS AND DISCUSSION

### 3.1. Linear model

In order to optimize the number of PCs and LVs, the PCR and PLS models was examined using PCs and LVs ranging from 1 to 15. The changes of RMSECV and RMSEC indicates that PCR achieved the optimal performance by having 6 PCs and 10 PCs, respectively. Both models compromised under-fitting and over-fitting results for breast meat and drumsticks. The RMSECV of PLS models radically decreased approaching the lowest error at 3 LVs and 5 LVs for breast meat and drumsticks, respectively. The optimal number of PCs and LVs obtained was evaluated using the prediction set. Based on the prediction results summarised in Table 4, the PLS model achieved better results than PCR, resulting a fewer number of LVs. For instance, PLS ($R_P^2$=0.4959, RMSEP=0.2880) for drumsticks attained slightly higher performances than PCR ($R_P^2$=0.4467, RMSEP=0.3013) with only 5 LVs over 10 PCs data set. However, the calibration ($R_C^2$) and prediction ($R_P^2$) accuracies from both PCR and PLS models for breast meat and drumsticks are still under the 0.8 target accuracy. Both models only managed to estimate the breast meat and drumsticks at the prediction accuracy ($R_P^2$) of 0.37 and 0.50, respectively.

Table 4. Performance of linear and non-linear models in predicting shear force values on breast meat and drumsticks traits

| Meat types | Models | PC/ LV | Input nodes | Parameters: Neuron | LR | MC | Epochs | $R_C^2$ | RMSEC | $R_P^2$ | RMSEP | Slope | Intercept | RPD |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Breast meat | PCR | 6 | | | | | | 0.3796 | 0.1324 | 0.3650 | 0.1450 | 0.41 | 0.42 | 1.26 |
| | PLS | 3 | | | | | | 0.3999 | 0.1302 | 0.3818 | 0.1439 | 0.45 | 0.38 | 1.27 |
| | PCNN | | 6 | 6 | 0.1 | 0.8 | 500 | 0.8233 | 0.0707 | 0.7977 | 0.0815 | 0.8 | 0.14 | 2.24 |
| | LVNN | | 3 | 9 | 0.9 | 0.4 | 400 | 0.8425 | 0.0667 | 0.8201 | 0.0769 | 0.82 | 0.13 | 2.38 |
| Drum sticks | PCR | 10 | | | | | | 0.4502 | 0.2543 | 0.4467 | 0.3013 | 0.43 | 0.56 | 1.34 |
| | PLS | 5 | | | | | | 0.5129 | 0.2393 | 0.4959 | 0.2880 | 0.46 | 0.53 | 1.40 |
| | PCNN | | 10 | 4 | 0.6 | 1.0 | 500 | 0.8525 | 0.1317 | 0.8365 | 0.1618 | 0.84 | 0.17 | 2.50 |
| | LVNN | | 5 | 6 | 0.3 | 0.8 | 300 | 0.8813 | 0.1182 | 0.8606 | 0.1494 | 0.86 | 0.15 | 2.71 |

### 3.2. Nonlinear models

#### 3.2.1. The optimum PCNN design

Instead of utilizing the complete absorbance spectral data, the PCNN utilized the optimal PCs scores derived from PCR as inputs for ANN. For breast meat, the best number of input nodes is 6, while for drumsticks it is 10. The quantity of hidden neuron affects the connections between inputs and outputs and can change based on the particular problem being researched. Using an excessive amount of neurons in the ANN can lead to overfitting, where the model memorizes the training data instead of making accurate predictions. The best number of hidden neurons for breast meat and drumsticks were found to be 6 and 4, respectively, based on the smallest MSE value.

Both the learning rate and momentum rate influence the stability and convergence of the ANN model. Nevertheless, if the learning and momentum rates are too small, it will result in a sluggish converging process, whereas excessively high values can cause network instability and training divergence. In this research, the learning rate and momentum rate were adjusted within the range of 0.1 to 0.9. The best learning rate is 0.1 for breast meat and 0.6 for drumsticks. The momentum rate's impact decreases slowly over time. At momentum levels of 0.8 and 1.0, the network achieved the lowest MSE for breast meat and drumsticks, respectively. The amount of epochs or training cycles plays a vital role in determining the accuracy of network models. Both the breast meat and drumstick had the lowest MSE at 500 iterations. Once all network parameters were established, the PCNN could forecast the samples. Table 4 summarizes the optimized parameters' topology in constructing the PCNN model and the regression outcome.

### 3.2.2. The optimum latent variable neural network design

In addition to utilizing the PCs obtained from PCR, the optimal LVs derived from PLS have also been used as inputs for ANN. The process for creating the best LVNN model closely resembled that of the PCNN model. For breast meat, the ideal number of LVs as input nodes is 3, while for drumsticks it is 5. The best number of hidden neurons for minimizing MSE in breast meat was 9, whereas for drumsticks it was 6. According to the minimum MSE value, the best learning rate and momentum rate for breast meat are 0.9 and 0.4, and for drumsticks are 0.9 and 0.3, respectively. Meanwhile, the ideal number of epochs for breast meat and drumsticks has been set at 400 and 300. The optimized parameters topology for building the LVNN model and the regression outcome are outlined in Table 4.

### 3.3. Prediction of broiler breast meat and drumsticks shear force value

Table 4 summarizes the non-linear prediction outcomes for breast meat and drumsticks, listing the intercept, regression equation slope, root mean square error (RMSE), as well as the calibration ($R_C^2$) and prediction ($R_P^2$) coefficients of determination for all models. The intercept and slope indicate the level of linearity between shear force values and NIR spectroscopy concentration values. A model's linearity is a dependable predictor of its quality of fit because it provides precise quantitative analysis.

While PLS made advancements in comparison to PCR, both methods showed insufficient accuracy in predicting breast meat (0.37 to 0.40) and drumstick (0.45 to 0.51) qualities. Despite achieving good results with optimal PCs and LVs, the low precision, $R^2$, and high RMSE in both calibration and test datasets showed that the predictive power of PCR and PLS was limited, as evidenced by the unequal distribution of equality line test samples. This implies that the model may have been adjusted to account for the inherent noise or error in the data, or there could have been non-linear elements in the spectrum-shear force relationship that were not accurately captured by the linear models. Based on previous research, linear models seem to provide inadequate evaluation of meat tenderness using NIR spectral data. Varying particle sizes in meat result in light-scattering effect, causing nonlinearity in information. Additionally, the RPD value ranging from 1.26 to 1.40 obtained from the linear models is deemed insufficient for the use of VIS-SWNIR spectroscopy in forecasting shear force values, as RPD values <2.0 are not advised for quality control or grading applications.

The LVNN and PCNN models achieved prediction accuracies above 0.8, except for breast meat PCNN prediction ($R_P^2$=0.80). Nonlinear models outperformed linear models in handling complex nonlinear information within spectral data. Using PCs and LVs helps to decrease the total amount of input nodes in ANN and eliminates issues that can occur when using PCR, PLS, or ANN separately. The LVNN and PCNN got rid of repetitive, parallel information found in spectral data, decreased data storage and training time required to reach convergence, and enhanced the ANN model's generalization capability. Furthermore, PCNN and LVNN models achieved a prediction accuracy that was around 70% higher than their linear counterparts, PCR and PLS. The RPD values for PCNN and LVNN in breast meat and drumsticks, ranging from 2.24 to 2.71, indicate that VIS-SWNIR spectroscopy combined with nonlinear models is suitable for screening purposes [7]. This is anticipated because ANN results will outperform linear models for highly nonlinear datasets. The LV-NN had the highest RMSEP and prediction accuracy, $R_P^2$, among predictive models, with PCNN, PLS, and PCR trailing for breast meat and drumsticks. The LVNN model achieved a coefficient of determination greater than 0.8 for both calibration and testing in breast meat ($R_C^2$=0.8425, $R_P^2$=0.8201) and drumsticks ($R_C^2$=0.8813, $R_P^2$=0.8606), demonstrating excellent performance.

## 4. CONCLUSION

This research has effectively confirmed the trustworthiness of affordable and portable NIR spectroscopy with a short range and low intensity. This was done by creating a nonlinear prediction system to predict the tenderness of raw broiler breast meat and drumsticks without the need for invasive methods. The LVNN appears to have a shorter training time than PCNN due to having fewer input nodes, while also outperforming PCNN. These findings suggest that LVNN is superior to PCNN in terms of saving computational resources and reducing training time, as well as in handling nonlinearities, redundancies, and collinearity in input spectral data. Based on overall performance, the models can be ranked in ascending order as PCR, PLS, PCNN, and LVNN. Alternatively, the second-order SG derivative provided valuable insights by removing baseline shift and slope effects, enhancing spectral resolution, and distinguishing overlapping peaks for clearer and more distinct peaks compared to zero-order or first-order SG derivative preprocessing. The results show that only the wavelength from 662 to 700 nm in the visible region gave accurate data for assessing drumsticks shear force. Therefore, the drumsticks are predicted using the visible and SWNIR regions, which have wavelengths between 662 and 1,005 nm. Nevertheless, predictors for the breast meat samples include the SWNIR region with wavelength between 700 and 1,005 nm.

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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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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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