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PREDICTING THE TENDERNESS OF BROILER BREAST FILLETS USING VISIBLE/NEAR-INFRARED SPECTROSCOPY AND MACHINE LEARNING ALGORITHMS

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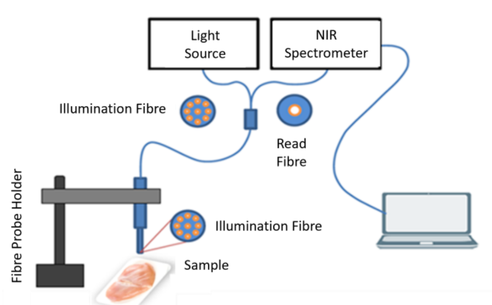
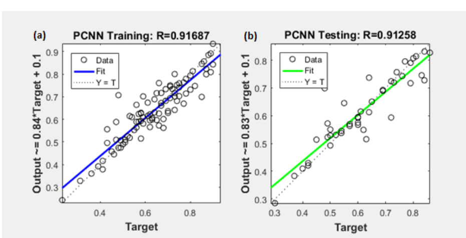
Graphical abstract

System Design



Analysis



Abstract

Chicken, as the most consumed meat worldwide, plays a crucial role in daily protein nutrition. Typically, consumers choose meat based on its tenderness, one of the quality traits in meat selections. In general, assessing the tenderness of chicken meat is commonly labour-intensive and destructive. An alternative approach to traditional methods is NIR spectroscopy, which is non-invasive, rapid, and economical. Portable NIR devices enable real-time, non-destructive meat quality assessment. Hence, this study investigates the effectiveness of a portable NIR spectroscopy system in predicting chicken meat shear force by comparing several machine learning algorithms, which are linear model (PCR) and non-linear model (ANN and PCR-ANN). The result shows prediction accuracy, Rp of 0.64, 0.73, and 0.91 for PCR, ANN, and PCR-ANN models, respectively. The calibration sets, Rc, for all models are 0.65, 0.73, and 0.92 for PCR, ANN, and PCR-ANN, respectively. The PCR-ANN model successfully outperforms both PCR and ANN, indicating it is amenable to non-invasive shear force prediction applications. In conclusion, the PCR-ANN model sufficiently achieved the best performance in predicting chicken meat tenderness using near-infrared spectral data. This study is essential for a number of reasons, including sustaining consumer satisfaction in the food industry, increasing industry returns, and increasing eating quality.

Keywords: Chicken tenderness, Near infrared spectroscopy, principal component regression, artificial neural network, principal components neural network

Abstrak

Ayam, sebagai daging yang paling banyak dimakan di seluruh dunia, memainkan peranan penting dalam pemakanan protein harian. Kebiasaanya, pengguna memilih daging ayam berdasarkan kelembutannya yang merupakan salah satu ciri kualiti dalam pemilihan daging ayam. Secara umumnya, penilaian kelembutan daging ayam memerlukan banyak tenaga kerja dan bersifat merosakkan. Pendekatan alternatif kepada kaedah tradisional adalah spektroskopi NIR, yang tidak invasif, pantas, dan ekonomik. Peranti NIR mudah alih membolehkan penilaian kualiti daging secara masa nyata dan tidak merosakkan. Oleh itu, kajian ini menyiasat keberkesanan sistem spektroskopi NIR mudah alih dalam meramalkan daya ricih daging ayam dengan membandingkan beberapa algoritma pembelajaran mesin, iaitu model linear (PCR) dan model bukan linear. (ANN and PCR-ANN). Keputusan menunjukkan ketepatan ramalan, Rp sebanyak 0.64, 0.73, dan 0.91 untuk model PCR, ANN, dan PCR-ANN, masing-masing. Set kalibrasi, Rc, untuk semua model adalah 0.65, 0.73, dan 0.92 untuk PCR, ANN, dan PCR-

ANN, masing-masing. Model PCR-ANN berjaya mengatasi kedua-dua PCR dan ANN, menunjukkan ia sesuai untuk aplikasi ramalan daya ricih tanpa invasif. Kesimpulannya, model PCR-ANN telah mencapai prestasi terbaik dalam meramalkan kelembutan daging ayam menggunakan data spektrum inframerah hampir. Kajian ini adalah penting atas beberapa sebab, termasuk mengekalkan kepuasan pengguna dalam industri makanan, meningkatkan pulangan industri, dan meningkatkan kualiti pemakanan.

Kata kunci: Kelembutan ayam, Spektroskopi inframerah dekat, regresi komponen utama, rangkaian neural tiruan, rangkaian neural komponen utama

1.0 INTRODUCTION

Chicken is the most consumed meat worldwide, and its quality is vital for providing daily protein nutrition. Tenderness, or shear force, is a key factor influencing consumer choices when purchasing meat (chicken, beef, lamb, and pork) [1], [2], [3], [4], [5]. Traditional methods for evaluating chicken meat quality, such as human inspection (visual assessment and sensory analysis) and instrumental measurements, are subjective, labor-intensive, destructive, time-consuming, and require high expertise [6]. In addition, current methods pose challenges in meeting the demands of modern and high-throughput productions of chicken poultries. Sensory evaluation, gradings, laboratory testing, and chemical analysis are some of the traditional methods used in determining quality level of meat, excalating the complexity of production processes [7].

With technological advancements, there is a need for simpler, faster, and more economical methods for evaluating chicken meat quality [8]. Near-infrared (NIR) spectroscopy is an advanced, non-invasive technology that accurately predicts meat quality. Integrating computing systems with optical devices enables high-speed data acquisition, which is beneficial for assessing meat quality, especially in small surface areas [9], [10], [11]. NIR spectroscopy can simultaneously measure various quality attributes, allowing for quick grading of meat samples [12].

The development of portable NIR devices has enabled real-time assessment of meat samples at any location, keeping the meat intact without the need for mincing for homogeneity. Modern handheld NIR instruments for food and drug quality control are fast, lightweight, and relatively inexpensive compared to stationary devices. Studies have shown the use of NIR spectroscopy in the poultry industry for predicting chicken portions' breed origin [13], [14] and differentiating fresh or frozen poultry meats [15]. When NIR spectroscopy emits radiation through meat samples, overlapping absorption bands are produced, which require chemometrics regression analysis and spectral pre-processing for interpretation. Linear algorithms like Principal Component Regression (PCR) and Partial Least Squares (PLS) are commonly used to predict or classify meat qualities [16]. These algorithms handle highly correlated (multicollinearity) and high-dimensional NIR variables by reducing data dimensionality and performing regression with a few uncorrelated components.

Despite the widespread use of linear algorithms in assessing chemical components in beef, poultry, lamb, and pork, their performance can be degraded by an inability to remove redundant spectral bands effectively and accommodate nonlinear spectral mixing. For instance, predicting tenderness in beef [17], [18], [19], chicken [20], [21], pork [22], and lamb [23] using linear methods has shown unsatisfactory accuracy, with scores below 0.5 in estimating shear force from spectral data.

This study aims to enhance PCR performance in predicting chicken meat tenderness using visible and near-infrared spectral data. To achieve this, Artificial Neural Networks (ANNs), which can handle complex, anti-interference, and nonlinear spectral information, are proposed. The ability of ANNs to model highly nonlinear data has garnered interest in various fields, particularly agriculture and the food industry. Additionally, this study explores integrating the best features of both linear and ANN algorithms to address issues of nonlinearity, redundant spectral bands, and large data dimensions [24], [25], [26], [27], [28], [29]. Hybridizing ANN with linear algorithms (PCR or PLS) resolves the limitations of using these methods independently. In this study, a hybrid Principal Components and Neural Network (PCR-ANN) approach is employed, with Principal Components (PCs) serving as input data for the ANN. This study investigates the effectiveness of a portable near-infrared spectroscopy system paired with machine learning algorithms in predicting shear force in chicken meat, comparing the linear model (PCR) with two nonlinear models (ANN and PCR-ANN).

The article is structured as follows: Section 2 described the methodology used in this work, highlighting the approach and technique used for the meat tenderness based on shear force and prediction modelling. Section 3 provides the details of the results and a discussion, with an evaluation of the calibration sets and prediction accuracy for each model, adequately. Finally, Section 4 concludes this study.

2.0 METHODOLOGY

The flowchart in Figure 1 depicts the key stages used to analyse the quality of chicken breast meat using visible and near-infrared spectroscopy. After obtaining raw spectral data, several procedures are conducted, which are tenderness reference data acquisition, data pre-processing, calibration development and model validation.

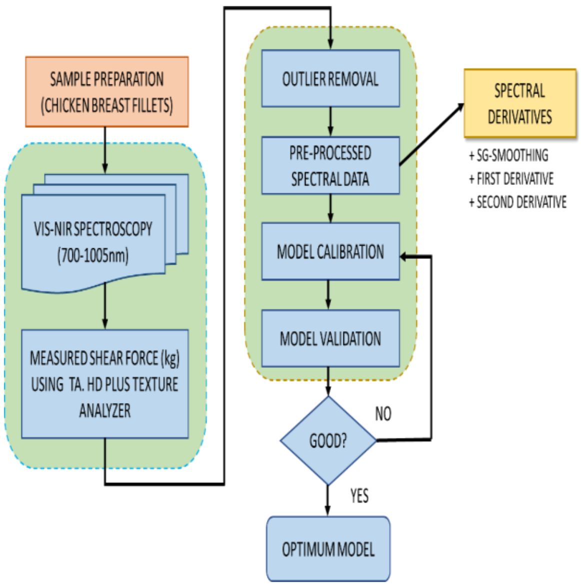


Figure 1 Research flowchart

2.1 Sample Preparation

Slaughtered chicken from Ross breed (n=27) aged 39 days were purchased from a local market in Terengganu, Malaysia. The boneless and skinless left chicken breast fillets (pectoralis major) were excised from each carcass, individually packed, labeled, transported, and stored in a freezer at 20°C at Meat Science Laboratory, Department of Animal Science, Faculty of Agriculture, Universiti Putra Malaysia. On each of three replicate data acquisition days, nine frozen breast fillets were thawed at a temperature of 4°C overnight (12 hours) before measurements on the next day. Each breast muscle was sliced into six rectangular strips (each 10mm thick x 10mm wide x 20mm long) with the axis parallel to the muscle fibers. A total of 162 sample strips from 27 chicken carcasses were used for the study. Each meat sample was first scanned using NIR spectroscopy and then its reference tenderness value was determined using a texture analyzer.

2.2 Spectral Acquisition

In this study, visible and NIR spectra were collected in the diffuse reflectance mode using a visible and near-infrared spectroscopic instrument (Ocean Optics USB4000 Miniature Fiber Optic Spectrometer). Figure 2 illustrated the setup of the visible and near-infrared spectroscopy devices for spectrum acquisition. Each spectrum was an average of 5 scans with a 1 nm interval over the wavelength range between 700 nm and 1005 nm, which implies that 304 data of reflectance were obtained for each sample. The visible region was considered from 380 nm to 780 nm and the NIR region from 780 nm up to 2500 nm. The spectrometer and light source were warmed up for 30 minutes before spectral acquisition began. The reflectance spectra for each chicken meat sample strip were compiled in less than a minute using NIR spectroscopy. 162 readings of visible and NIR reflectance spectra were recorded directly on the middle surface of the meat sample strips over a 3-day data collection period. Reflectance data were transformed into absorbance by calculating the logarithm of the reciprocal of the reflectance values (Absorbance = log 1/Reflectance). All acquired spectral data were stored on a computer and processed using the software MATLAB R2016a (The Math Works, Inc., Massachusetts, USA).

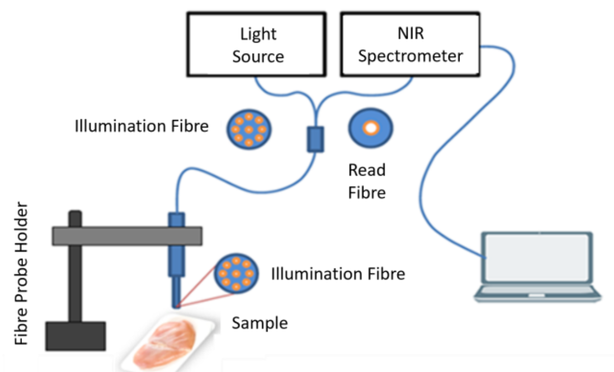


Figure 2 The illustration of visible and near-infrared spectroscopy instrument setup

2.3 Tenderness Measurement

After the spectral acquisition, each sample was used for tenderness determination immediately. The shear force data acquisition was performed using a computer-assisted TA. HD plus Texture Analyzer (Stable Micro Systems, UK) combined with Volodkevich Jaw Set (stainless steel probe in the shape of an incisor). The invasive shear force measurement is performed on the same scanned chicken meat sample strips. Each sample strip was placed in the slot, then compressed and sheared once in the middle, perpendicular to the longitudinal alignment of the muscle fibers. The maximum shear force was recorded in kilograms (kg). After the 18th measurement, the analyzer slot and steel probe were removed and cleaned to prevent the accumulation of chicken strip debris that could interfere with the measurement. The slot and steel probe were then reinstalled, and the analyzer recalibrated. The procedures were repeated until all measurements were completed. 162 shear force data were measured invasively with the Volokevich Jaw Texture Analyzer. The shear force data was exported to MATLAB R2016a (The Math Works, Inc., Massachusetts, USA) for further data analysis.

2.4 Pre-Processing

The spectral data analysis for chicken tenderness prediction was performed in four main steps: outlier removal, pre-treatment of the data, calibration modelling and model evaluation. Using leave-one-out cross-validation, possible outliers were independently detected based on externally studentized residuals. Outliers were defined as sample data with residual values that exceeded the critical threshold of the t-distribution of 1.976. From the data collected, 16% turned out to be outliers and were removed from the dataset. The hold-out validation function in MATLAB software creates randomness by splitting the cleaned data set into two subsets: (1) calibration set (70% data) for the construction and internal cross-validation (using 10-fold cross-validation), and (2) external prediction set (30%) used to validate the predictive capacity of the models.

Spectral data were pre-processed for light scattering, baseline correction and random noise caused by instrumental effects or physical properties (such as particle size and distribution). This treatment is used to reduce data dimensionality, remove redundant information, and improve model performance. In this study, three pre-treatment methods including Savitzky-Golay (SG) smoothing with a moving window of 11, first derivative (FD) based on SG with a second-order polynomial fitting within 17 points moving window and second derivative (SD) based on SG with a third-order polynomial fitting within a moving window of 25 points were separately used. SG-smoothing is widely adopted to filter and eliminate background noise to enhance spectral resolution without distorting the signal tendency. The FD can remove the baseline shift effects while SD performs well in removing both baseline and slope offsets. The most suitable pre-treatment method was selected by comparing the PCR performance for the tenderness estimation.

2.5 Model Calibration and Evaluation

In this study, three prediction methods: one linear algorithm namely Principal component regression (PCR), and two nonlinear models, Artificial neural network (ANN) and The Principal Component Neural Network (PCR-ANN) were applied to correlate the spectra with reference values for the quantitative determination of tenderness value of chicken meat.

PCR is a widely used linear multivariate method that addresses multicollinearity in signals and reduces data dimension by decomposing the spectral variable into principal components (PC). The number of PCs is a key tunable parameter that needs to be optimized to prevent underfitting when insufficient scores are used and overfitting when using too many. The optimum PC was determined by applying 10-fold cross-validation on the calibration data set, where the smallest number of PC at the minimum value of the corresponding root mean square error cross-validation was chosen.

ANN is an alternative multivariate method when there is a suspicion that data is nonlinear, or the interactions of the variables are complex. The neural network structure consists of 3 layers (input, hidden and output layers) consisting of some neurons interconnected by weighted connections. The neuron produces an output signal by passing the weighted sum of the inputs through a non-linear transfer function. In this present work, Trainlm is the network training function that updates weight and bias according to Levenberg-Marquardt optimization. Four ANN network parameters (number of neurons, learning rate (LR), momentum rate (MC) and number of epochs) were systematically optimized through the trial-and-error process using a 10-fold cross-validation approach. The optimal ANN network parameters were chosen based on the lowest mean square error (MSE). The network was retrained with the calibration set and validated with the prediction set using the optimized four parameters.

PCR-ANN combined the PCR data reduction technique with the nonlinear ANN handling capabilities. PCR-ANN reduced the data dimension by using the optimal principal components (PCs) determined from previous PCR as inputs instead of using the full absorption spectral data. The configuration of the PCR-ANN network's parameters and topology is the same as the ANN except for the input layer. The range of network parameters for ANN and PCR-ANN algorithms is shown in Table 1.

Table 1 The range of network parameters for ANN and PCR-ANN

Network Parameters	Settings
Number of neurons	1-10
Learning rate	0.1-1.0
Momentum rate	0.1-1.0
Number of epochs	100-1000
Training function	*Trainlm*

The performance of all three prediction methods was evaluated using the coefficient of correlation at calibration Rc and prediction Rp, the mean square error of calibration (RMSEC) and Prediction (RMSEP) and Performance Deviation Ratio (RPD). RPD was calculated as the standard deviation (SD) of the meat quality trait divided by RMSEP. Models are rated as excellent if the RPD is greater than 2 (RPD > 2), fair if the RPD is between 1.4 and 2 (1.4 < RPD < 2), and unreliable if the RPD is less than 1.4 (RPD < 1.4).

3.0 RESULTS AND DISCUSSION

Table 2 summarizes the descriptive data such as minimum, maximum, mean, and standard deviation (SD) for reference tenderness or shear force values measured by the texture analyzer instrument. The variability of reference shear force values (0.3-1.15 kg) is rather considerable, as evidenced by the data in Table 2. After outliers were removed, the total cleaned data was 136, with 90 for the calibration set and 44 for the prediction set.

Table 2 Reference tenderness of chicken meat measured using texture analyser instrument

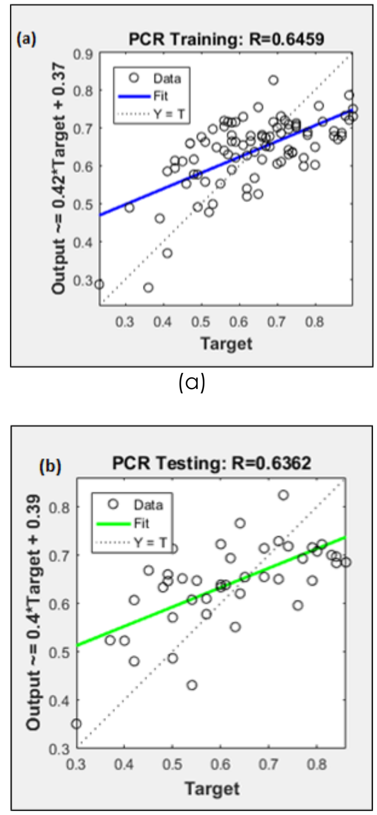
Sample Sets	Sample Numbers	Shear Force (kg)			
		Min	Max	Mean	Standard Deviation (SD)
Calibration	90	0.23	0.90	0.6389	0.1451
Prediction	44	0.30	0.86	0.6177	0.1429
Total	134	0.23	0.90	0.6319	0.1442

A PCR calibration model using full wavelengths was developed for tenderness prediction of breast chicken meat. The prediction statistics and performance of PCR models developed with various spectral processing methods (raw, SG-smoothing, first derivative (FD), and second derivative (SD) are presented in Table 3. Compared to the results of raw spectra, both SG-smoothing and FD offered a little improvement, but the FD had deteriorated performance of the calibration accuracy. SD had the best performance as it gave the highest results both for calibration and prediction sets. Therefore, the SD with a third-order polynomial fitting within a moving window of 25 points was used as the optimal pre-treatment method in this study.

Choosing the right number of principal components (PC) is crucial for developing an accurate PCR model. Selecting too many or too few PC variables may result in unsatisfactory models with poor prediction ability. The model becomes unable to capture the variability in the data because too many PC variables may yield overfitted model while too few variables on the other hand may result in an underfitted model. According to the lowest value of root mean square error cross-validation (RMSECV), five optimal PC were selected for tenderness prediction for the PCR model.

Analysis of the calibration set (between measured and predicted shear force values) in Figure 3(a) shows that R_c of 0.65 was obtained with RMSEC of 0.110. Meanwhile, R_p of 0.365 was obtained with RMSEP of 0.111 and RPD of 1.28 between measured and predicted shear force values in the prediction set as shown in Figure 3(b).

The correlation and R_{PD} values of 1.28 obtained with PCR were insufficient to justify the portable NIR spectroscopy to predict the shear force value of chicken meat (refer to Table 3). The most plausible explanation for this poor performance is that NIR spectral data better correlate with the shear force value in nonlinear space. The same data were analyzed using ANN regression to clarify this point.



(a)

(b)

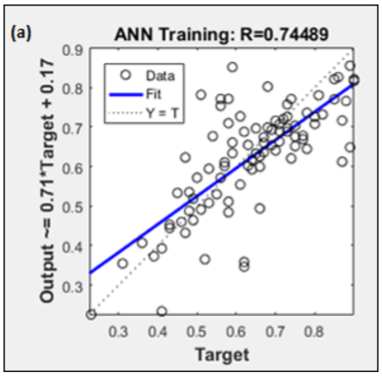
Figure 3 PCR modelling performed with 5 principal components. The measured and predicted shear force are presented as x and y-axis respectively. (a) Calibration and (b) Prediction sets

Table 3 PCR models developed utilizing both raw and pretreated spectral data

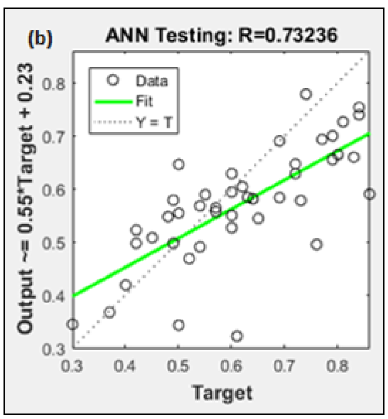
Pre-treatment	PC	RMSEV	R_c	RMSEC	R_p	RMSEP
Raw spectra	7	0.118	0.65	0.109	0.54	0.122
SG-smooting	8	0.120	0.65	0.110	0.59	0.117
FD	6	0.117	0.64	0.110	0.63	0.113
SD	5	0.114	0.65	0.110	0.64	0.111

Four ANN parameters (number of neurons, learning rate (LR), momentum rate (MC) and number of epochs) were systematically optimized through the trial-and-error process using a cross-validation approach. The optimal ANN network parameters were chosen based on the lowest mean square error (MSE). The optimal values of the four parameters for the ANN model are tabulated in Table 4. The network was retrained with the calibration set and validated with the prediction set using the optimized four parameters.

ANN regression outperformed PCR for shear force prediction as shown in Figure 4(a) for the calibration set and Figure 4(b) for the prediction set. It can be noted that the ANN accuracy in the calibration set, R_c compared to the PCR has risen to 0.74 from 0.65. Prediction set accuracy, R_p increased from 0.64 with PCR to 0.73 with ANN. This implies that the relationship between the NIR spectrum and shear force measurement was not only linear, as explained by a PCR model, but may also be non-linear, as explained by an ANN model.



(a)

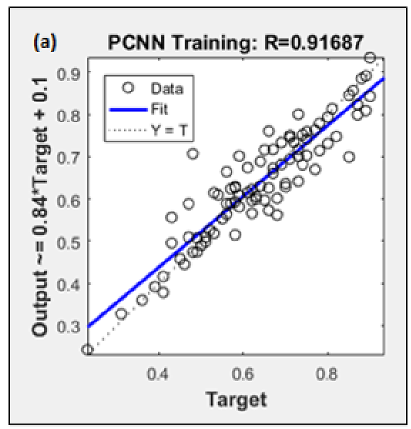


(b)

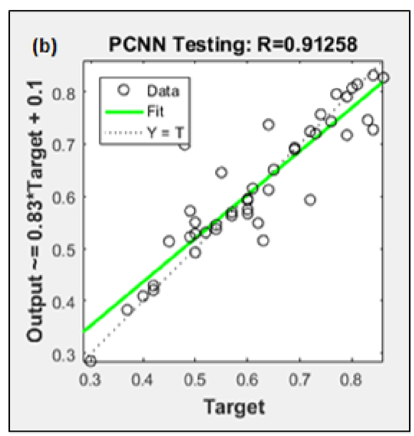
Figure 4 ANN modelling performed using NIR absorbance spectra and shear force value. The measured and predicted shear force are presented as x and y-axis respectively. (a) Calibration and (b) Prediction sets

However, despite its ability to directly analyze high-dimensional spectral data, the ANN achieves only moderate prediction accuracy and RPD values of 1.33, which are still insufficient to justify the potential of portable NIR spectroscopy in predicting the shear force value of chicken meat. ANN cannot eliminate the influence of redundancy and collinearity in high-dimensional spectral data. The performance of the ANN should also be examined by reducing the dimension of the input vectors before the training process. Therefore, another nonlinear model, PCR-ANN, was developed for further performance improvements.

The results of the PCR-ANN model are shown in Figure 5, where Figure 5(a) represents the calibration set and Figure 5(b) represents the prediction data set. As can be seen, the accuracy of the calibration set, R_c successfully reached 0.92 while the prediction set, R_p is 0.91 and R_{PD} is 2.47, indicating that the combination of NIR spectral and hybrid PCR-ANN model is amenable to non-invasive shear force prediction application. Table 5 summarizes the overall performances earned by the PCR, ANN and PCR-ANN models. The PCR-ANN successfully outperforms both the PCR and ANN models. Using PCs as inputs to the PCR-ANN model not only allows intrinsic nonlinearity data to be modelled directly, but also eliminates redundancy, repetition, and collinear inputs that could potentially affect network efficiency and generalization. Furthermore, the PCR-ANN converged earlier in 500 epoch training stages compared to the ANN, which took 700 epochs to converge (see Table 4).



(a)



(b)

Figure 5 PCR-ANN modelling performed with 5 principal components. The measured and predicted shear force are presented as x and y-axis respectively. (a) Calibration and (b) Prediction sets

Table 4 The best network parameters for the ANN and PCR-ANN models

Models	Input Neurons	Parameters			
		Neuron	LR	MC	Epochs
ANN	303	6	0.5	0.6	700
PCNN	44	7	1.0	0.8	500

Table 5 Performance of PCR, ANN and hybrid PCR-ANN models in predicting shear force values of chicken meat

Models	Rc^2	RMSEC	Rp^2	RMSEP	RPD
PCR	0.65	0.1101	0.65	0.109	0.54
ANN	0.74	0.1020	0.65	0.110	0.59
PCR-ANN	0.92	0.0576	0.64	0.110	0.63

4.0 CONCLUSION

The reliability of handheld near-infrared spectroscopy coupled with machine learning algorithms for shear force estimation of intact raw chicken breast fillets was confirmed. This study shows that the hybrid model of PCR-ANN, which combined the linear model (PCR) and nonlinear model (ANN), sufficiently achieved the best performance in predicting chicken meat tenderness using near-infrared spectral data. Aside from outperforming ANN, the hybrid PCR-ANN model requires less training time due to fewer input nodes. The results show that PCR-ANN outperforms ANN and PCR in terms of computational resources and training time, as well as the ability to address nonlinearities, redundancy, and collinearity issues of input spectral data. The predictions of chicken meat tenderness level are beneficial to quality control in food production, automating the evaluation of meat quality based on spectral analysis. In addition, the use of portable NIR devices on the production floor enables fast quality assessments, increasing timely corrective actions when necessary. The NIR-based tenderness predictions are also easily adaptable to the existing Quality Management System (QMS) to enhance traceability and documentation in quality metrics throughout the production processes. However, there are limitations to this study where manual assessment should be conducted by well-trained staff or workers, which can be laborious and impractical for mass production applications. Therefore, for future prospects, integrating real-time data-driven quality control will enable continuous feedback learning to ANN models, adapting to the variations of chicken meat characteristics across different batches.

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Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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