Non-invasive measurement of shear force in chicken meat using near infrared spectroscopy supported by neural network analysis

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ABSTRACT

The aim of the present work was to evaluate the ability of a portable near-infrared (NIR) spectroscopy integrated with machine learning methods to predict the shear force in chicken meat. Considering the benefits of dimension reduction from Principal Component Regression (PCR) and the ability to handle non-linearity from Artificial Neural Network (ANN), these two algorithms were combined. Through the augmentation, the Principal Component Neural Network (PCNN) is developed. The results show that PCNN successfully surpassed the respective versions of PCR and ANN with higher shear force prediction performances. The PCNN proved to achieve the best prediction in breast meat with root mean square error of prediction (RMSEP) of 0.0815 kg and coefficient of determination, ($R_P{}^2$) of 0.7977. NIRS technology integrated with machine learning yield a promising non-invasive technique in predicting the shear force of intact raw chicken meat.

Keywords: Near Infrared (NIR) Spectroscopy, Principal Component Regression (PCR), Artificial Neural Network (ANN), Principal Component Neural Network (PCNN), Shear Force, Chicken Meat

1. Introduction

Chicken is the most consumed meat source in the world, and the quality of chicken meat in supplying protein nutrition in daily life is crucial. Shear force or tenderness has been identified as the key factor influencing consumer choice when purchasing meat sources (chicken, beef, lamb, and pork) [1]. The instrumental techniques used to measure the shear force not only allow measurement after leaving the slaughterhouse and in laboratory settings, but they are also invasive, destructive, and time-consuming to calibrate and in preparing samples. Therefore, this research proposed portable Near Infrared (NIR) Spectroscopy as an accurate, rapid, and non-invasive approach to assess the tenderness of chicken meat without diminishing the carcass value and is suited for routine data collection. The optical instrument coupled with a computer offer potentially high-speed data acquisition that allows decision-making on meat quality, albeit sampled from a selected small surface area only [2]. NIR spectroscopy is capable of non-destructive, hazardous free in a continuous manner to determine the chemical properties (i.e., moisture, fat, protein, intramuscular fat, and fatty acid profile), physical characteristics (i.e., pH, colour, water holding capacity, and tenderness) and sensory characteristics (i.e., juiciness, chewiness, hardness) of meat products [1,3-4].

Principal Component Regression (PCR) and Partial Least Squares (PLS) are popular linear algorithms used to deal with NIRS variables which are often highly correlated (multicollinearity) and has huge dimension. These algorithms utilize data reduction by generating a few uncorrelated components to perform regression in place of the original variables, hence reducing the dimensionality of the input [5]. A large number of studies have verified the ability of NIR spectroscopy combined with linear algorithms to assess the quality of chemical components in beef, poultry, lamb, and pork based on the NIR spectrum [3,4,6]. However, physical parameters (pH, colour, shear force, and water holding capacity) attained unsatisfactory prediction results in beef [7-8], chicken [9-10], pork [11], and lamb [12] with accuracies lower than 0.5 in estimating shear force from spectral data.

To overcome the weakness of the linear algorithm, Artificial Neural Network (ANN) possesses the ability of anti-interference and nonlinear conversation, which means it can cope with complex spectral information to build a robust and sensitive prediction model [13]. The ability of ANN in modelling highly nonlinear data has increased interest in various fields, notably in agriculture and the food industry. Huang et al. achieved high accuracy between 0.93 to 1.00 in the identification of repeatedly frozen pork meat using ANN [14]. Despite its incredible performance, ANN has several flaws: (i) difficulty converging when the input data is large, particularly if using entire spectral data as inputs; (ii) risks in overfitting by including redundant spectral data points; and (iii) long training time. Hence, by integrating the best features of both linear and ANN algorithms, the nonlinearity, redundant spectral band, and huge data dimension problems that arise from using them separately were resolved [15]. For example, by combining PLS and ANN to estimate the abundance of minerals on the lunar surface, the hybrid PLS-ANN model was effective in solving the issues of redundant and nonlinear data in spectral data [16]. To solve the constraints of using the methods independently, a hybrid Principal Component and Neural Network (PCNN) was employed, with the principal components (PCs) serving as input data to the ANN.

The goal of this research is to investigate how effectively a portable near-infrared (NIR) spectroscopy system paired with machine learning algorithms predicts shear force in chicken meat. The comparison between linear model; PCR and two nonlinear models; ANN and PCNN were presented in predicting the shear force value from the NIR spectral data.

2. Methodology

Figure 1 depicts the methodology flow diagram for non-invasive shear force evaluation using NIR spectroscopy. Twenty-seven Ross broiler breeds (39 days old) supplied from a farm in Terengganu, Malaysia were slaughtered and processed in accordance with Malaysian Standard 1500:2009 on halal food production, preparation, handling, and storage. The twenty-seven chicken sample size was chosen using recommendations and the resource equation approach proposed in previous studies [17-18]. The left-side breast fillet was removed from each dressed carcass, individually packed, and stored in a freezer at 20℃ temperatures in a Meat Science Laboratory, Department of Animal Science, Faculty of Agriculture, Universiti Putra Malaysia.

Over the course of three days, nine frozen breast fillets were thawed overnight at 4°C before preparation for measurement. For each breast fillet, six reflectance spectrum (700-1005 nm) data were acquired non-invasively from the surface of the breast fillet using NIR spectroscopy, and six shear force data were acquired invasively using a texture analyzer. During the three days, 162 data (consisting of 162 spectrum data and 162 shear force data) will be acquired for the spectroscopic and shear force measurements. The analysis is performed using the full spectrum data and compared between three algorithms (PCR, ANN, PCNN).

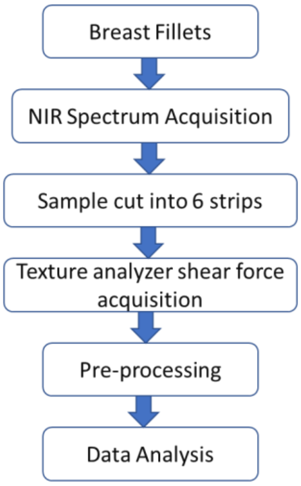


Figure 1. Flow diagram for non-invasive chicken meat shear force assessment using NIR spectroscopy

2.1 Spectral Data Acquisition

Reflectance spectrum in the range of 650nm to 1318nm were collected on the surface of the chicken breast fillets. Since shear force from the same muscle varies significantly due to muscle heterogeneity, six reflectance spectrums were obtained from each breast fillet at six separate locations. An average of five consecutive scans were obtained for each acquired spectrum. A portable visible shortwave near-infrared spectroscopic device (Ocean Optics USB4000 Miniature Fibre Optic Spectrometer (650-1318 nm), ORNET Sdn. Bhd., Selangor, Malaysia) was used to collect the spectrums. The spectrometer and the light source were warmed up for 30 minutes before spectrum acquisition commenced. The device was calibrated first for 100% transmission as a reference spectrum and 0% transmission as a dark spectrum. The reflectance spectrums for each breast fillet were assembled in less than five minutes using NIR spectroscopy. There were

162 raw NIR reflectance spectrums acquired directly from the surface of the breast fillets in a three-day data collection period. All the acquired spectral data were stored in the computer and processed using MATLAB simulation software (MATLAB®Version7.12.0.635 (R2011a)).

2.2 Shear Force Data Acquisition

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 shaped like an incisor). The analyzer was calibrated with the settings of compression for test mode, pre-test speed of 0.2 cm/sec, test speed of 0.2 cm/sec, post-test speed of 0.2 cm/sec distance of 0.5 cm, and auto-trigger type. The invasive shear force measurement is performed on the same scanned breast fillets. Based on the locations scanned using NIR spectroscopy, each breast fillet was cut into six rectangular strips (each measuring 10 mm thick x 10 mm wide x 20 mm long), with the axis oriented parallel to the muscle fibres [19]. Each fillet strip was placed in the slot, then compressed and sheared once in the center, perpendicular to the longitudinal orientation of the muscle fibres [19]. The maximum shear force was recorded in kilograms (kg). After the 18^{th} measurement, the analyzer's slot and steel probe were removed and cleaned to prevent the accumulation of residues that could interfere with the reading. The slot and the steel probe were then reinstalled, and the analyzer was recalibrated. The procedures were repeated until all measurements were completed. There were 162 shear force data measured invasively using the Volokevich Jaw texture analyzer. Shear force data were exported as an Excel file to the MATLAB software for further chemometric analysis.

2.3 Data Analysis

The spectrum and shear force data must first be pre-processed before the non-invasive prediction for chicken meat shear force can be constructed. High noise spectrums from two spectral bands (650-699 nm and 1006-1318 nm) were removed, leaving just 700-1005 nm spectrums for examination. Due to analog-to-digital conversions and a decrease in spectrometer grating intensity, the interval between two neighbouring wavelengths was found to be inconsistent (from 0.21 nm to 0.18 nm between 2 adjacent wavelengths). Hence, the spectrum data interval was fixed to 1 nm using a simple averaging method [20].

The diffuse reflectance spectrums were mathematically transformed into absorbance values using Beer-Lambert's law where Absorbance = log (1/Reflectance). Using a PCR model and leave-one-out cross-validation, possible outlying data were detected independently based on externally studentized residuals [21]. The externally studentized residual was calculated using the difference between the predicted and measured shear force value. Outliers were defined as sample data having residual values that exceeded the t-distribution critical threshold of 1.976 [22,23]. Out of the data collected, 16% were found to be outliers and were removed from the dataset. The total of 136 cleaned NIR spectrums and the shear force measurement data were analyzed with three regression approaches i.e. PCR, ANN and PCNN models.

The hold-out validation creates randomness creates randomness by dividing the cleaned dataset into a calibration set (70%) and a testing set (30%). The calibration set was evaluated using cross-validation (CV) with 50% division for training and validation sets to determine the best number of predictors for PCR as well as the best value for the parameters involved in the construction of the ANN and PCNN. The regression models developed from the calibration set were validated using the testing-set samples. The performances of regression models (PCR, ANN, and PCNN) were appraised using the coefficient of determination in calibration (${R_C}^2$) and testing (${R_P}^2$), root mean square error of calibration (RMSEC), and prediction (RMSEP) as well as the ratio of performance deviation (RPD). RPD was calculated as the standard deviation (SD) of meat quality trait divided by the RMSEP. Models are rated excellent when RPD more than 2 (RPD > 2), fair when RPD between 1.4 and 2 (1.4 < RPD < 2), and nonreliable when RPD less than 1.4 (RPD < 1.4) [24].

3. Result and Discussion

Table 1 presents the descriptive statistics for the calibration set and testing set for the breast fillets after removing outliers based on externally studentized residual.

Table 1. Calibration and testing statistics for shear force measurement

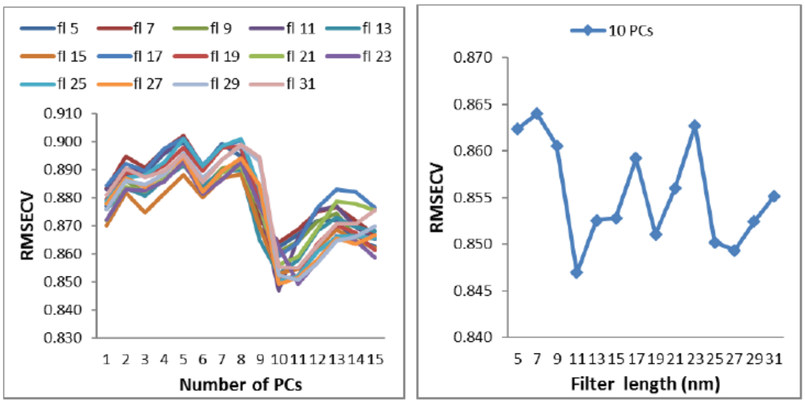
Sample sets	Sample numbers	Shear Force (kg)			
		Min	**Max**	**Mean**	**Standard Deviation (SD)**
Calibration	91	0.30	1.02	0.7209	0.1690
Testing	45	0.30	1.15	0.7029	0.1833
Total	136	0.30	1.15	0.7150	0.1734

3.1 Spectral Data Pre-processing

Spectral preprocessing methods were utilized to reduce light-scattering effect and path-length variation as well as to enhance the quality of the acquire data by eliminating or minimizing the effect of unwanted signal. Three mathematical treatments of Zero-order, 1st-order and 2nd-order SG derivatives were investigated with PCR and cross-validation methods. The zero-order SG derivative (d0) is applied to improve the signal-to-noise ratio of spectral data by smoothing the spectral data, the 1st-order SG derivative (d1) performs d0 and removes the baseline shift effects and the 2nd-order SG derivative, (d2) performs d1 and remove the slope effect, simultaneously [20]. In SG-derivative preprocessing, A proper filter length (FL) clarification is required to preserve the resolution of the derivative signal and to avoid over-fitting or under-fitting performances. The optimum FL was determined at the lowest RMSECV in PCR analysis, where FL varied from 5nm to 31nm (interval of 2nm) is tested with predictor numbers varied from 1 to 15.

Figure 2 shows example of FL determination for zero-order SG derivative. Firstly the optimal number of principal component (PC) is determined by plotting the graph of RMSECV against number of PCs as shown in Figure 2(a). PC of 10 with the lowest RMSECV is selected. Then, the graph of RMSECV against number of FL of the selected PC (which is 10 PCs) is plotted as shown in Figure 2(b) where 11 is the optimal FL based on the lowest RMSECV value. The processes were repeated for the first-order and second-order SG derivatives.

Table 2 shows the results of filter length optimization on SG derivative pre-processing to determine the most efficient spectrum treatment approach. The results show that the 2nd-order SG derivative with a 21nm filter length is the best technique for improving spectrum resolution. As a result, the 2nd-order SG derivative spectral filtering technique is used in both the calibration set and the testing set.



(a) (b)

Figure 2. The RMSECV of zero-order SG derivative versus
(a) number of principal component and (b) number of filter length

Table 2. Filter length optimization of SG derivative pre-processing

Order of Pre-processing	FL[a] (nm)	Number of PC[b]	RMSECV[c]
Zero order D	11	10	0.1475
1st order D	19	8	0.1350
2nd order D	21	6	0.1130

3.2 Linear Regression Modelling

Principal Component Regression (PCR) is a multivariate method, dealing with multicollinearity in signals and reducing data dimension by decomposing the spectral variable into Principal Components (PCs). The number of PCs is a crucial tuneable parameter that must be optimised to reduce prediction model error while also preventing underfitting when insufficient scores are used and overfitting when too many are used. The PCs were determined using cross-validation on the calibration data set.

The results of PCR analysis are presented in Figures 3 and 4. The plot of root mean square error of calibration (RMSEC), root mean square error of prediction (RMSEP) and root mean square error of cross-validation (RMSECV) against the number of principal component (PCs) are presented. The dashed arrow line shows 6 PCs selected as the optimum principal components for PCR as the errors decrease dramatically at 6 PCs. However, it seems the error of RMSEC keep slightly decreasing after 6 PCs. The RMSECV indicated marginal fluctuation occurred when the PC numbers were increased beyond the selected 6 PCs thus, validating the selection for optimal PCs. Later, the PCR model based on 6 PCs was calibrated and tested and the corresponding plots are presented in Figures 4(a) and 4(b), respectively.

Analysis of the calibration set (between measured versus predicted shear force values) in Figure 4(a) shows that a $R_C{}^2$ of 0.3796 was obtained with a RMSEC of 0.1324. Meanwhile, $R_P{}^2$ of 0.3650 was obtained with RMSEP of 0.1450 and RPD of 1.26 between measured versus predicted shear force values in testing set as shown in Figure 4(b). The correlation and RPD values obtained with PCR were insufficient to justify the potential of portable NIR spectroscopy in predicting the shear force value of chicken meat. The most plausible explanation for this poor performance is that NIR spectral data correlates the shear force value better in nonlinear space. The same data was analysed with ANN regression to clarify this point.

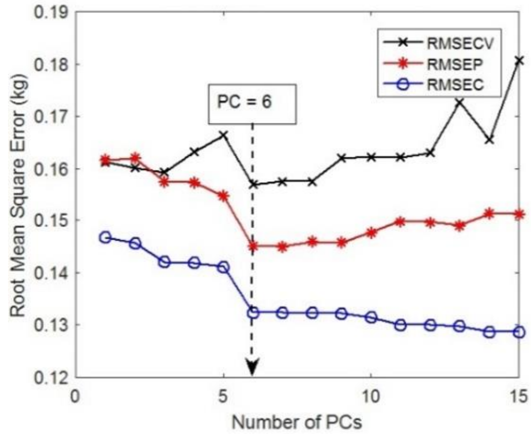
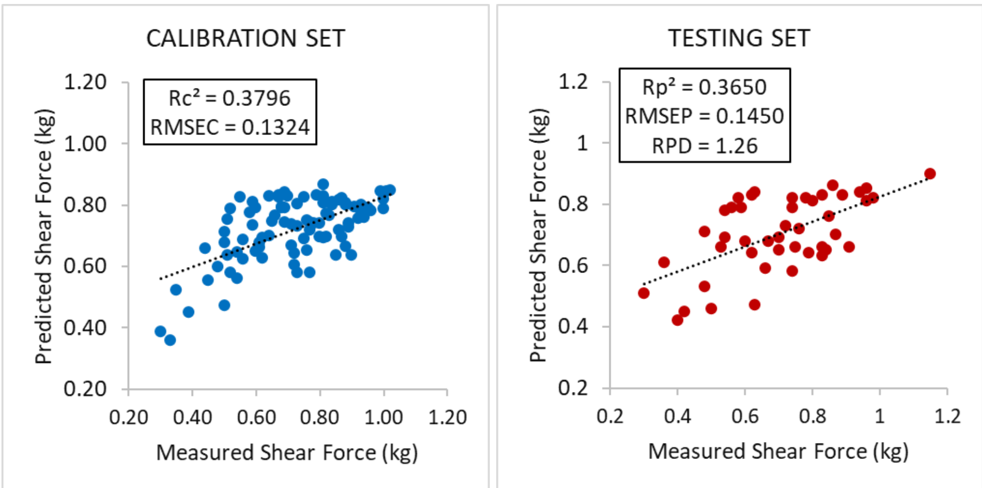


Figure 3. Evolution of root mean squared error of calibration (RMSEC in blue) and root mean squared error of cross-validation (RMSECV in black) with increasing number of principal components (PCs). 6 PCs were selected and highlighted by dashed arrow.



(a) (b)

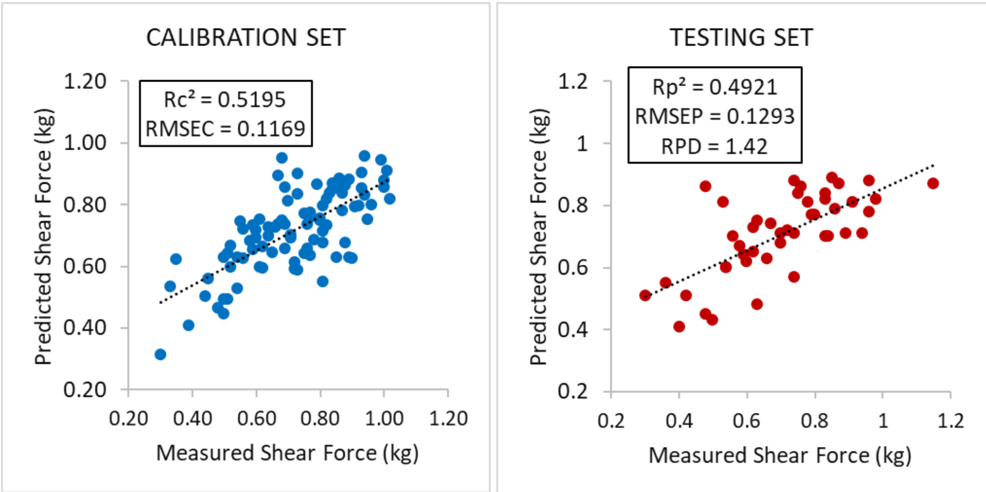
Figure 4. PCR modelling performed with 6 principal components. The measured and predicted shear force are presented as x and y-axis respectively. (a) Calibration set and (b) Testing set

3.3 Nonlinear Regression Modelling

Artificial Neural Network (ANN) is an alternative multivariate method when data are suspected to be nonlinear or the interactions of the variables are complex. The internal structure of an ANN may be modified to simulate complex biological, environmental, and instrument variation since it has an intrinsic capacity for learning and flexibility. The neural network structure consist of 3 layers (input, hidden and output layers) are composed of a series neurons that are linked together through weighted connections. The neuron generates an output signal by passing the weighted sum of the inputs through a non-linear transfer function.

In present work, Trainlm is the network training function that updates weight and bias according to Levenberg-Marquardt optimization. Four ANN parameters (number of neurons, learning rate (LR), momentum rate (MC) and number of epochs) were systematically tuned through the trial-and-error process using cross-validation approach. The optimal ANN network parameters were selected based on the lowest mean square error (MSE). The settings of the four parameters for ANN model are tabulated in Table 3. The network was retrained with the calibration set and validated with the testing set using the optimised four parameters.

ANN regression surpassed PCR for shear force prediction, as shown in Figure 5(a) for the calibration set and Figure 5(b) for the testing set. It can be noted that the ANN accuracy in the calibration set, ${R_C}^2$, increased to 0.5195 when compared to the PCR ${R_C}^2$ of 0.3796. Testing set accuracy, ${R_P}^2$ rose from 0.3650 with PCR to 0.4921 with ANN. This implies that the relationship between NIR spectrum and shear force measurement was not merely linear, as explained by a PCR model, but may also be non-linear, as explained by an ANN model [25]. However, despite its ability to directly analyse high-dimensional spectral data, the ANN only achieves fair prediction accuracy and RPD values of 1.42 still insufficient to justify the potential of portable NIR spectroscopy in predicting the shear force value of chicken meat. The influence of redundancy and collinearity in high-dimensional spectral data cannot be completely removed by ANN. The performance of the ANN should also be investigated by reducing the dimension of the input vectors before the training process. Thus, another nonlinear model, PCNN has been develop for further performance improvements.



(a) (b)

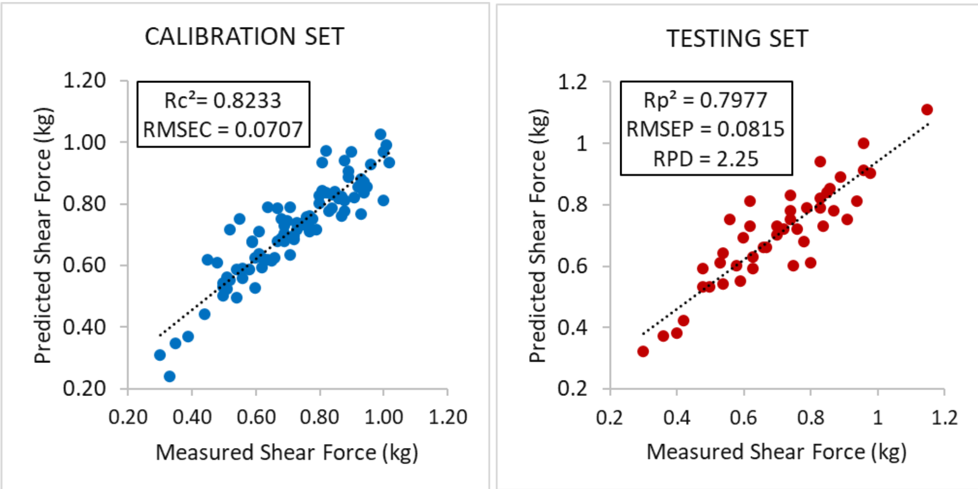
Figure 5. Results of ANN regression performed using NIR absorbance spectra and shear force value. The measured and predicted shear force are presented as x and y-axis respectively. (a) Calibration set and (b) Testing set

The principle components neural network (PCNN) combined the PCR data reduction technique with the ANN nonlinear handling abilities. PCNN reduced the data dimension by using the optimal principal components (PCs) derived from previous PCR as inputs rather than using the full absorbance NIR spectrum. Not only was the number of inputs decreased, but the training process was made considerably faster and less prone to overfitting. The PCNN framework is similar to that of ANN, with the exception of the input data. The settings of the four parameters for PCNN model in Table 3 show that the model required different optimum values for number of hidden neurons, learning rate, momentum rate and number of epochs as compared to ANN.

The results of PCNN model are presented in Figure 6, where Figure 6(a) presents calibration set, and Figure 6(b) presents the testing data set. According to Figure 6, the accuracy of calibration set, ${R_C}^2$ successfully reached 0.8233 while testing set, ${R_P}^2$ is 0.7977 and RPD is 2.25, indicating that the combination of NIR spectral and hybrid PCNN model is suitable for non-invasive shear force prediction application. The PCNN successfully outperforms both the PCR and ANN models. The use of PCs as inputs for PCNN model not only enables it to directly model intrinsic nonlinearities data, but it also eliminates redundancy, repetition, and collinear inputs, which could possibly degrade the efficiency and generalization of the network. Furthermore, the PCNN converged earlier in training stages with 500 epochs compared to the ANN, which required 700 epochs to converge (refer Table 3).

Table 3. Performance of PCR, ANN and hybrid PCNN models in predicting shear force values of chicken meat

Models	PC	Input Nodes	Parameters				R_C^2	RMSEC	R_P^2	RMSEP	RPD
			Neuron	LR	MC	Epochs					
PCR	6						0.3796	0.1324	0.3650	0.1450	1.26
ANN		303	5	0.5	0.9	700	0.5195	0.1169	0.4921	0.1293	1.42
PCNN		6	6	0.1	0.8	500	0.8233	0.0707	0.7977	0.0815	2.25



(a) (b)

Figure 6. Results of PCNN regression performed using 6 principal components as inputs. The measured and predicted shear force are presented as x and y-axis respectively. (a) Calibration set and (b) Testing set

4. Conclusion

The reliability of portable near-infrared spectroscopy paired with machine learning algorithms to estimate the shear force of intact raw chicken breast fillets was confirmed. Aside from outperforming ANN, the hybrid PCNN model appears to require less training time due to fewer input nodes. The results show that PCNN outperforms ANN and PCR in terms of computation resources and training time, as well as the capacity to tackle nonlinearities, redundancy, and collinearity issues of input spectral data. The models' performance is listed in ascending order as PCR, ANN, and PCNN.

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