Jurnal Teknologi

Full Paper

FIRST DERIVATIVE PREDICTION OF RAW BROILER SHEAR FORCE USING VISIBLE SHORT WAVE NEAR INFRARED SPECTROSCOPY

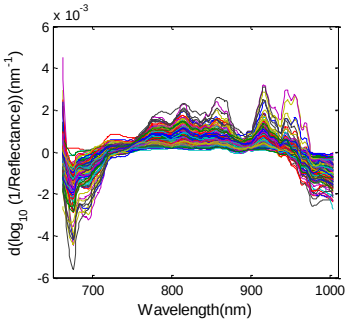
Rashidah Ghazali, Herlina Abdul Rahim*

Department of Control and Mechatronics Engineering, Faculty of Electrical Engineering,Universiti Teknologi Malaysia, 81310 UTM Johor Bahru, Johor, Malaysia

Received
15 December 2015
Received in revised form
30 March 2016
Accepted
30 May 2016

*Corresponding author
herlina@fke.utm.my

Graphical abstract



Abstract

A non-destructive,fast, reliable and low cost technique which is Near-Infrared Spectroscopy (NIRS) is required to replace conventional destructive texture analyser in shear force measurement. The combination of visible and shortwave near infrared (VIS-SWNIR) spectrometer and principal component regression (PCR) to assess the quality attribute of raw broiler meat texture (shear force value (kg)) was investigated. Wavelength region of visible and shortwave 662-1005 nm was selected for prediction after pre-processing. Absorbance spectra was pre-processed using the optimal Savitzky-Golay smoothing mode with 1st order derivative, 2nd degree polynomial and 31 filter points to remove the baseline shift effect. Potential outliers were identified through externally studentised residual approach. The PCR model were trained with 90 samples in calibration and validated with 44 samples in prediction datasets. From the PCR analysis, correlation coefficient of calibration (R_C), the root mean square calibration (RMSEC), correlation coefficient of prediction (R_P) and the root mean square prediction (RMSEP) of visible and shortwave (662-1005 nm) with 4 principal components were 0.4645,0.0898, 0.4231 and 0.0945. The predicted results can be improved by applying the 2nd order derivative and the non-linear model.

Keywords: Broilers, near infrared spectroscopy, texture analyser, PCR

1.0 INTRODUCTION

In meat production, quality control procedures were carried out in order to reduce economic losses and also to supply high quality products for the consumers. Most highlighted value of meat production mainly depends on the appearance, juiciness, flavour, nutritional value, wholesomeness and texture of meat [1]. Conventional techniques for accurate assessment of meat quality use instrumental methods (for example, Warner-Bratzler shear force and Volodkevich Bite Jaws texture analyser), sensory evaluation or chemical analyses [2]–[4]. However, these techniques are destructive, time consuming and not suitable for online application [3], [4]. On the contrary, the development of visible and near infrared spectroscopy for fast, non-destructive and online techniques is desired to replace the conventional methods. Therefore, study on the ability of visible/NIR spectroscopy for the prediction of raw broiler meat texture from two regions, visible and shortwave near infrared (VIS-SWNIR) at range 662-1000 nm and shortwave near infrared (SWNIR) at range 700-1005 nm were investigated.

2.0 MATERIALS AND METHODS

2.1 Sample Preparation

Ross broilers were bred and harvested commercially from broiler farm in Lentang, Dungun, Terengganu, Malaysia. Broilers were fed with commercial pellet diets. Twenty seven broilers were randomly selected and slaughtered at the age of 39 days according to the guidelines of Malaysian Standard 1500:2009 on halal food production, preparation, handling and storage respectively [5]. Afterwards, the left-side breasts (pectoralis major muscle) were taken and vacuum-packed and kept frozen under -20°C temperature [6]. The breast meats were thawed at a temperature of 4°C overnight before the experiment day. The next day, the raw breast meats from each chicken carcass were cut into rectangular blocks with a dimension of 10 mm-thick x 10 mm-wide x 20 mm-long with the long axis in the direction of the muscle fibres [7], [8]. Seven blocks samples from each raw breast meat were cut for spectra acquisition and texture measurement.

2.2 Experimental Instrumentation

A total of 189 diffuse reflectance spectra and measured shear force of raw breast meats were acquired using near-infrared spectroscopy and texture analyser.

2.2.1 VIS-SWNIR Spectroscopic Measurement

The reflectance spectrum of the raw broiler breast meats were collected using VIS-NIR spectrometer (Ocean Optics USB4000 Miniature Fibre Optic Spectrometer, ORNET Sdn. Bhd., Selangor, Malaysia). The spectrometer is able to provide spectrum range from 650 to 1318 nm but substantial noise existed at the beginning and the end of the acquired spectrum. Therefore, only 344 wavelengths, ranging from 662 to 1005 nm at 1nm intervals were retained. For the diffuse reflection measurement, a reflection probe was positioned at 90° angle [9] and 5mm from the surface of the chicken. The instrument was operated by the software package NIRS2 version 3.01 (InfraSoft International, State College, PA, USA).

2.2.2 Volodkevich Bite Jaws Texture Measurement

The measured shear force was obtained immediately after the spectra acquisition of raw breast meat. The textural assessment of raw chicken meat samples were conducted using TA.HD plus Texture Analyser (Stable Micro Systems, UK) fitted with Volodkevich bite jaws set [1]. Each raw chicken meat block samples were placed into the texture analyser slot before measurement. Each sample was sheared and compressed once in the centre and perpendicular to the longitudinal direction of the fibres using a Volodkevich bite jaw (stainless steel probe shaped like an incisor) fitted to the texture analyser at an angle of 90° [8]. The sheared force data was recorded in kilograms (kg).

2.2.3 Data Analysis

Data analysis was performed using MATLAB (version 7.12.0.635 (R2011a), The Mathworks, Inc.). The reflectance spectra were converted into absorbance as log (1/Reflectance). Spectra pre-treatment of normalization, Savitzky-Golay (SG) smoothing filter and first order derivative were applied to smooth the spectral data and remove baseline shift effects. All samples were randomly divided into calibration and prediction sets using the hold-out cross validation at ration 2:1.

Principal component regression (PCR) analysis was used in predicting raw broiler shear force from VIS-SWNIR spectra. PCR is a combination of principal component analysis (PCA) and multiple linear regression (MLR) [10]. Firstly, PCA decomposed the spectral data matrix using singular value decomposition (SVD) into column-mode eigenvectors, singular values, and row-mode eigenvectors. The product of column-mode eigenvectors and singular values are called as principal components (PC), were used as the input variables of calibration models. In order to determine the optimal number of PC, a graph of root mean square error (RMSE) versus the number of PC was plotted. The optimal number of PC was used as the input of MLR to perform PCR. The performance of PCR model was evaluated by correlation coefficient (R) and root mean square error (RMSE) between the measured and the predicted values for the calibration and prediction data sets.

3.0 RESULTS AND DISCUSSION

3.1 Pre-processing

The absorbance spectra were smoothed by applying first derivative and SG smoothing with polynomial order of 1 and 2 for zero order and first order and also filter length of 5 and 27 for zero and first order. Leave-one-out cross validation (LOOCV) and externally studentised residuals were used to identify the outliers. The residuals values that exceeds the critical values of the t-distribution will be outcast as the outliers and the data will be removed. This procedure will be repeated until the highest correlation coefficient of cross-validation (RCV) and lowestroot mean square errorof cross-validation (RMSECV) obtained. The data retain of 134 indicates the highest RCV = 0.37 and the lowest RMSECV = 0.93.

SG smoothing parameters include the derivative order (DO), polynomial order (PO) and filter length (FI). Higher polynomial orders filters are best at preserving heights and widths but tends to increase noise and less smoothing [11]. For derivative order, two subsequent polynomial orders will give the same estimate of coefficients. For zero derivative, zero and

first polynomial order will give the same answer (as will second and third order). Meanwhile, for first derivative, first and second polynomial order will give the same answer (as will the third and fourth order) [12]. The number of filter lengths should be determined appropriately to avoid increase of errors and lose of information in the spectra [13], [14]. Thus, the optimization selection of number of filter lengths combined with PCR number of components will be more effective [13]. In this paper, the order of derivatives was set as DO = 0,1, polynomial order was set as 1,2 and the number of filter lengths was set odd as 5,7,9,...,31. SG smoothing was performed by the MATLAB function sgolayfilt.

LOOCV was considered to ensure the model neither over nor under-fit. In LOOCV, the size of validation set is one and the number of validation equals to the number of samples. In the first validation, first sample was retained from the dataset and the remaining data were train to build a model which was then applied to the retained sample. The retained sample was the reintroduced, the second sample was retained and calibration and prediction process was repeated.

Table 1 illustrated the optimization selection of number of filter lengths using PCR model and LOOCV. The result showed that for both the VIS-SWNIR region (662-1005nm) and SWNIR region (700-1005nm) the optimum filter length for zero and first derivative are found to be 5 and 31. The RCV of zero derivative for the VIS-SWNIR (RCV = 0.353) is higher than the SWNIR region (RCV = 0.326). However, RCV and RMSECV of VIS-SWNIR and SWNIR only differ by 0.013 where PC = 4, RCV = 0.371 and RMSECV = 0.928 for VIS-SWNIR compared to the SWNIR region that require number of PC = 6, RCV = 0.358 and RMSECV = 0.935.Therefore, the absorbance at 662-1005nm spectra region was selected for the continuation of PCR model for shear force prediction.

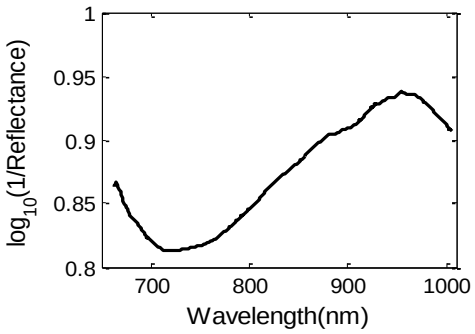
Table 1 The optimization selection of number of filter lengths

Spectra region (nm)	DO[a]	PO[b]	FL[c]	PC[d]	RCV[e]	RMSECV[f]
662-1005	0	1	5	5	0.353	0.936
	1	2	31	4	0.371	0.928
700-1005	0	1	5	7	0.326	0.950
	1	2	31	6	0.358	0.935

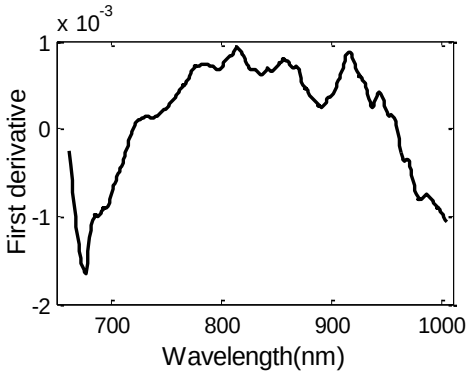
[a] DO: Derivative order
[b] PO: Polynomial order
[c] FL: Filter length
[d] PC: Principal components
[e] RCV : Correlation coefficient of cross-validation
[f] RMSECV : Root mean square error of cross-validation

3.2 Spectra Characterization

Figure 1(a) shows the acquired average absorbance (log10 (1/R)) spectra that contains both visible and SWNIR spectra. In the absorbance spectrum, it was observed a broad peak located between 940 and 990 nm, probably due to the third overtone of OH or water that absorbs at this wavelengths range [4], [15], [16]. The visible regions have absorption bands in the range 430 to 700 nm related myoglobin, oxymyoglobin, metmyoglobin and deoxymyoglobin [4], [17]. The spectral features in the visible region are similar for both chicken and meat because both contain the myoglobin protein, which is the primary heme pigment responsible for colour of meat [4].



(a) Average log10 (1/Reflectance) spectra



(b) Average first derivative spectra

Figure 1 Average log10 (1/Reflectance) (a) and First derivative (b) of visible and short wave near infrared spectra for raw broiler breast meat samples

The baseline shift problem in the absorbance spectra is reduced by the first order derivative processing method as in Figure 1(b). In the first derivative treatment, absorption band around 678 nm were related to haemoglobin and around 842 nm related to water [18]. Moreover, characteristic bands profile of water were identified in the region of 980 nm related to OH second stretching overtone [19], [20]. In addition, absorption bands between the region of 920 to 950 nm related to third stretching overtones of CH bonds [20], [21]. Furthermore, atthe third overtone nearly at the range between 718 to 760 nm, absorption bands of CH bonds also existed [22].

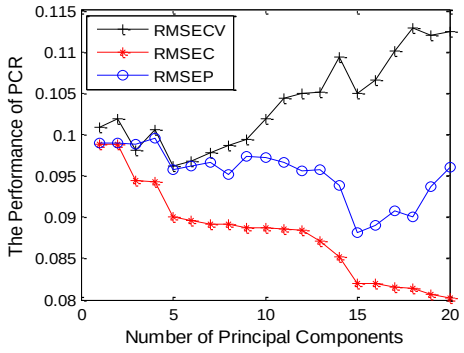
3.2 Prediction of Shear Force from VIS-SWNIR Spectra

Table 2 summaries the descriptive statistics measured of shear force values after excluding 55 potential outliers based on externally studentised residual. The shear force values of 134 raw broiler meat samples were approximately normally distributed around a mean value of 0.6748 kg and a standard deviation of 0.1015 kg.

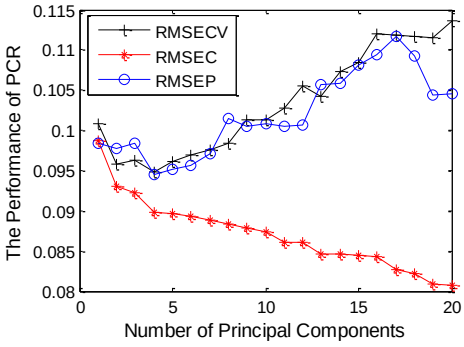
Table 2 Descriptive statistics of data sets

Data set	Number of Samples	Shear Force (kg)			
		Min	Max	Mean	Standard Deviation
Calibration	90	0.45	0.89	0.6791	0.1019
Prediction	44	0.50	0.88	0.6659	0.1013
All samples	134	0.45	0.89	0.6748	0.1015

Figure 2(a) and 2(b) show the plot of root mean square error (RMSE) versus the number of PC to determine the optimal number of PC for zero derivative and first derivative for VIS-SWNIR region.



(a) Root mean square error (RMSE) versus the number of PC for zero derivative



(b) Root mean square error (RMSE) versus the number of PC for first derivative

Figure 2 Plot of root mean square error (RMSE) versus the number of PC for zero derivative (a) and first derivative (b) for VIS-SWNIR region

The optimal number of PC for zero derivative is five while for the first derivative is four. The optimal number of PC was used as the input of MLR to perform PCR to determine the correlation coefficient (R) and root mean square error (RMSE) between the measured and the predicted values for the calibration and prediction data sets. Table 3 showed the calibration and prediction results for raw broiler meat prediction using PCR for absorbance at the range 662-1005 nm. The pre-processing treatment used was zero and first order derivative with SG smoothing.

Table 3 Results for the prediction of shear force in Ross broiler samples using principal component regression

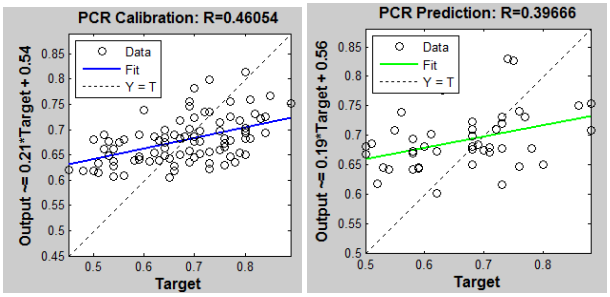
Spectral region (nm)	VIS-SWNIR 662-1005	
DO[a]	0	1
PO[b]	1	2
FI[c]	5	31
PC[d]	5	4
***RC*[e]**	0.4605	0.4645
***RP*[f]**	0.3967	0.4231
RMSEC[g]	0.0900	0.0898
RMSEP [h]	0.0957	0.0945
RMSECV[i]	0.0961	0.0948

[a] DO : Derivative order
[b] PO: Polynomial order
[c] FI: Filter length
[d] PC: Principal components
[e] R_C : Correlation coefficient of calibration
[f] R_P : Correlation coefficient of prediction
[g] RMSEC : Root mean square error of calibration
[h] RMSEP : Root mean square error of prediction
[i] RMSECV: Root mean square error of cross validation

Polynomial order for zero and first derivatives were set as 1 and 2 while the filter length for zero and first derivatives were 5 and 31 as were discovered from optimization selection of number of filter lengths for absorbance using PCR model and LOOCV.

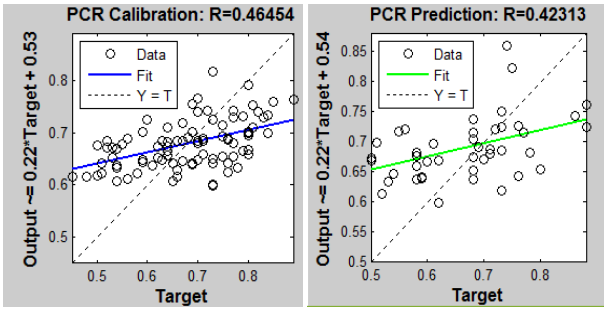
The result indicated that the spectral region of VIS-SWNIR with first order derivative produced better accuracy for both calibration and prediction where RC = 0.4645 and RP = 0.4231 with PC = 4 compared to VIS-SWNIR with zero order derivative where RC = 0.4605 and RP = 0.3967 with PC = 5. Figure 3(a) and 3(b) show the scatter plot for both PCR Calibration and Prediction for zero derivative while Figure 4(a) and 4(b) show the scatter plot of first derivative for VIS-SWNIR region.

Both Figure 3 and 4 showed that all the points were scattered far away from the target line. This verified the poor results for the PCR Calibration and Prediction for both zero and first derivative of VIS-SWNIR region.



3(a) 3(b)

Figure 3 Scatter plot for zero order derivative VIS-SWNIR for PCR Calibration (a) and PCR Prediction (b) datasets



4(a) 4(b)

Figure 4 Scatter plot for first order derivative VIS-SWNIR for PCR Calibration (a) and PCR Prediction (b) datasets

Apparently, the results for zero and first derivative of VIS-SWNIR region were dissatisfied because the accuracies were lower than 80%. Therefore, other pre-processing techniques and models need to be applied in order to improve the prediction of the VIS-SWNIR to predict the shear force of raw broiler meat samples. It is suggested that the second derivative pre-treatment and non-linear model to be applied to improve the accuracies of the prediction [20], [23].

4.0 CONCLUSION

From the following study, it can be concluded that the first derivative pre-processing eliminated the base line shift effect in the VIS-SWNIR spectroscopic spectral. However, the prediction results stated that the accuracies for spectral region of 662-100 nm were lower than 80% and need to be improved. Therefore, second derivative and non-linear model need to be applied to improve the accuracies of the VIS-SWNIR prediction in the shear force values for intact raw broiler meat samples.

Acknowledgement

The authors wish to thank the Ministry of Higher Education of Malaysia (MOHE) and Universiti Teknologi Malaysia (UTM) for financing this research with Vote No. (12H20).

References

[1] Ghazali, R., Abdul Rahim, H., Shikh Maidin, M. and Sahlan, S. 2013. Low Cost Visible/Near-Infrared Reflectance Spectroscopy for Raw Poultry Meat Texture Prediction. *World Academy of Science, Engineering and Technology*. 77: 486-491.

[2] Ghazali, R., Abdul Rahim, H., Shikh Maidin, M. and Sahlan, S. 2013. Prediction of Texture of Raw Poultry Meat by Visible and Near-Infrared. *Journal of Technology*. 64: 59-62.

[3] Liao, Y.-T., Fan, Y.-X. and Cheng, F. 2010. On-line Prediction Of Fresh Pork Quality Using Visible/Near-Infrared Reflectance Spectroscopy. *Meat Science*. 86: 901-907.

[4] Liu, Y., Lyon, B. G., Windham, W. R., Realini, C. E., Pringle, T. D. D. and Duckett, S. 2003. Prediction Of Color, Texture, And Sensory Characteristics Of Beef Steaks By Visible And Near Infrared Reflectance Spectroscopy. A Feasibility Study. *Meat Science*. 65: 1107-1115.

[5] Department of Islamic Development Malaysia. 2009. Malaysian Protocol for the Halal Meat and Poultry Productions.

[6] Cavitt, L. C., Youm, G. W., Meullenet, J. F., Owens, C. M., and Xiong, R. 2004. Prediction of Poultry Meat Tenderness Using Razor Blade Shear, Allo–Kramer Shear, and Sarcomere Length. *Journal of Food Science*. 69: 11-15.

[7] Lambe, N. R., Navajas, E. A., Bünger, L., Fisher, A. V., Roehe, R., and Simm, G. 2009. Prediction Of Lamb Carcass Composition And Meat Quality Using Combinations Of Post-Mortem Measurements. *Meat Science*. 81: 711-719.

[8] Salwani, M. S., Sazili, A. Q., Zulkifli, I., Nizam, Z., and Zul Edham, W. 2012. Effects of Head-Only Electrical Stunning on the Physico-Chemical Characteristics and Desmin Degradation of Broiler Breast Musles of Different Time Postmoterm. *Journal of Animal and Veterinary Advance*. 11: 2409-2416.

[9] Ocean Optics, I. 2012. Non-Invasive Reflection Measurements of the Skin, Assessing Sampling Depth by Using Skin Surrogates. *Photonics Online*. 727-733.

[10] Chia, K. S., Abdul Rahim, H., and Abdul Rahim, R. 2012. Neural Network And Principal Component Regression In Non-Destructive Soluble Solids Content Assessment: A Comparison. *Journal of Zhejiang University-Science B*. 13: 145-151.

[11] Press, W. H., Flannery, B. P., Teukolsky, S. A., and Vetterling, W. T. 1993. *Savitzky-Golay Smoothing Filters*. Numerical Recipes in FORTRAN 77: The Art of Science Computing. 2nd Ed. Cambridge: University Press.

[12] Rinnan, A., Berg, F.v.d., and Engelsen, S. B. 2009. Review Of The Most Common Pre-Processing Techniques For Near-Infrared Spectra. *Trends in Analytical Chemistry*. 28: 1201-1222.

[13] Chen, H., Pan, T., Chen, J., and Lu, Q. 2011. Waveband Selection For NIR Spectroscopy Analysis Of Soil Organic Matter Based On SG Smoothing And MWPLS Methods. *Chemometrics and Intelligent Laboratory Systems*. 107: 139-146.

[14] Chia, K. S., Abdul Rahim, H. and Abdul Rahim, R. 2013. Evaluation Of Common Pre-Processing Approaches For Visible (VIS) And Shortwave Near Infrared (SWNIR) Spectroscopy In Soluble Solids Content (SSC) Assessment. *Biosystems Engineering*. 115: 82-88.

[15] Cozzolino, D. and Murray, I. 2004. Identification Of Animal Meat Muscles By Visible And Near Infrared Reflectance Spectroscopy. *LWT-Food Science and Technology*. 37: 447-452.

[16] Riovanto, R., De Marchi, M., Cassandro, M. and Penasa, M. 2012. Use Of Near Infrared Transmittance Spectroscopy To Predict Fatty Acid Composition Of Chicken Meat. *Food Chemistry*. 134: 2459-64.

[17] Mamani-Linares, L. W., Gallo, C. and Alomar, D. 2012. Identification Of Cattle, Llama And Horse Meat By Near

Infrared Reflectance Or Transflectance Spectroscopy. *Meat Sci*ence. 90: 378-385.

[18] Cozzolino, D., De Mattos, D. and Vaz Martins, D. 2002. Visible/near Infrared Reflectance Spectroscopy For Predicting Composition And Tracing System Of Production Of Beef Muscle. *Animal Science*. 74: 477-484.

[19] Grau, R., Sánchez, A. J., Girón, J., Iborra, E., Fuentes, A. and Barat, J. M. 2011. Nondestructive Assessment Of Freshness In Packaged Sliced Chicken Breasts Using SW-NIR Spectroscopy. *Food Research International*. 44: 331-337.

[20] Morsy, N. and Sun, D.-W. 2013. Robust linear and non-linear models of NIR spectroscopy for detection and quantification of adulterants in fresh and frozen-thawed minced beef. *Meat Science*. 93: 292–302.

[21] Andrés, S., Murray, I., Navajas, E. A., Fisher, A. V., Lambe, N. R., and Bünger, L. 2007. Prediction Of Sensory Characteristics Of Lamb Meat Samples By Near Infrared Reflectance Spectroscopy. *Meat Science*. 76: 509-516.

[22] Guy, F., Prache, S., Thomas, A., Bauchart, D. and Andueza, D. 2011. Prediction Of Lamb Meat Fatty Acid Composition Using Near-Infrared Reflectance Spectroscopy (NIRS). *Food Chemistry*. 127: 1280-1286.

[23] Chia, K.S., Abdul Rahim, H. and Abdul Rahim, R. 2012. Prediction Of Soluble Solids Content Of Pineapple Via Non-Invasive Low Cost Visible And Shortwave Near Infrared Spectroscopy And Artificial Neural Network. *Biosystems Engineering*. 1