Banana Quality Attribute Prediction and Ripeness Classification Using Support Vector Machine

Segun E. Adebayo
Universiti Putra Malaysia, Department of Biological and Agricultural Engineering, Serdang, Malaysia
Email: oluvictor4life@yahoo.com

Norhashila Hashim, Khalina Abdan, Marsyita Hanafi and Manuela Zude-Sasse
Department of Biological and Agricultural Engineering, Faculty of Engineering, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia
Department of Computer and Communication Engineering, Faculty of Engineering, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia
Leibniz-Institute for Agricultural and BioeconomyEngineering Potsdam-Bornim (ATB), Max-Eyth-Allee 100, 14469 Potsdam-Bornim, Germany
Email: {norhashila, khalina, marsyita}@upm.edu.my, mzude@atb-potsdam.de

***Abstract*—Five laser diodes of 532, 660, 785, 830 and 1060 nm laser light backscattering imaging (LLBI) were employed for quality attribute prediction and ripening stage classification of banana. A support vector machine (SVM) was tested to establish the theoretical prediction and classification models to predict chlorophyll, elasticity and soluble solids content (SSC) and also to classify the bananas into six ripening stages. The classification was set up with six ripening stages 2-7. Wavelengths of 532, 660 and 785 nm gave high correlation coefficients both for banana quality prediction and ripeness classification. The results show that the highest correlation coefficients of 0.912, 0.945 and 0.872 were obtained for chlorophyll, elasticity and SSC at 785, 660 nm respectively. An overall classification accuracy of 92.5 % was recorded at 830nm. These results show that LLBI with the SVM model can be used for non-destructive estimation of banana quality attributes and the subsequent ripeness classification.**

***Index Terms*—laser diodes, banana, elasticity, ripeness, chlorophyll, quality**

I. Introduction

Banana, which originated from India in Eastern Asia, has over 1000 varieties and has been cultivated in approximately 135 countries in the world with the Cavendish banana as the most cultivated and common variety. Banana is one of the world's top leading food crops apart from rice, maize and wheat [1]. It is widely consumed with about ninety percent of production consumed in or around the production areas in Asia, Latin America and Africa [1], [2]. Banana has been used in other forms such as in the production of puree, jams, wines, pastries, desserts, sorbet ice-creams and cream products [3], [4].

Since attention is at present focused on quality and safety of fruit for consumption, concerted efforts in technologies that will estimate the qualities of banana become a vital concern [5], [6]. Currently, banana sorting is done manually using colour as the main quality attribute [7]. Banana is a climacteric fruit which is harvested at the optimum stage of maturity to achieve effective ripening and good eating quality [8], [9]. Many methods are currently employed to determine these qualities. However these methods are mostly destructive and also subjective because their operation is human dependent which could give inconsistent results. To address these shortcomings, non-destructive optical-based methods are receiving greater consideration.

Laser light backscattering imaging (LLBI) is an emerging technology that is non-destructive and suited for measurement of fruit quality attributes. Its operation is fast, requires less sample preparation and allows for multiple measurements of various attributes concurrently [10]-[12]. Some research works has been reported using LLBI, for example; Ref. [11] reported the use of LLBI to discriminate decaying citrus from sound ones; Ref. [13] reported the application of LLBI to predict the mechanical properties of selected horticultural crops; Ref. [14] reported a work on the potential of LLBI to monitor chilling injuries in banana. Although quite a few numbers of works have been done using LLBI in postharvest handling, an extension of the research works is still required in order to verify its potential. Thus, the objective of this work is to determine the application of LLBI to predict the elasticity, SSC and chlorophyll and ripening stages of banana by using support vector machine (SVM) as a prediction and classification model.

II. Materials and Methods

A. Sample Preparations

Banana at ripening stage 2 were collected at a ripening facility in Potsdam, Germany. The bananas were stored at 14 ℃ which was the recommended temperature for

Manuscript received September 26, 2016; revised October 25, 2016..

doi: 10.18178/ijfe.3.1.42-47

storage [15], [16]. Two hundred and seventy fingers of bananas with uniform size and free from any defects, contamination and disease were used for this work. The backscattering images of the bananas for ripening stage 2 were acquired immediately and subsequent measurements of the other ripening stages were completed as each of the ripening stages were reached. Forty five banana fingers were measured non-destructively at each measuring stage and the same samples were used for destructive measurements.

A ΔA meter was used for the pigment measurement (Chlorophyll). The ΔA index is a measure of the chlorophyll content in a fruit, in other words, it is a measure of its ripeness state. The index decreases in value during the ripening process and reaches very low values till the ripening is complete. The ΔA meter measurement was undertaken on both sides of the banana at the central area and the mean value of the readings was recorded.

The elasticity test was performed on the banana fingers using a TA.XT Plus Texture Analyser (Stable Micro Systems, Godalming Surrey UK) with a 12 mm diameter ball probe. Sample firmness was measured at three different points on the banana fingers at both edges and the central area. The average was then recorded. The SSC of banana was measured at room temperature using a digital handheld refractometer (DR 301-95; A. Kruss Optronic Germany). Three different positions on the banana finger, both edges and the central areas, were used. Samples were taken from those positions then mashed and the mashed pulp placed on a clean dry refractometer prism and readings were taken directly. The SSC recorded for a banana finger was the average of the three readings taken. The SSC was expressed as %Brix. The destructive test followed immediately after the acquiring backscattering images.

B. *Laser Light Backscattering Imaging System*

The imaging system used for the research was developed and assembled by the Leibniz-Institute for Agricultural Engineering, Potsdam-Bornim (ATB), Germany [10]. The system comprised of a CCD camera made in Japan (CV-A50IR, JAI Ltd, Japan) with a zoom lens F2.5 and focal length 18-108 mm (12VG1040 ASIR-SQ, Tamron Co. Ltd, Japan), and a desktop computer for controlling the camera and for image capture and storage. The images were captured using five solid-state laser diode modules simultaneously. The five laser diodes wavelengths were 532, 660, 785, 830, 1060 nm with power ratings of between 10 to 85 mW which also served as light sources. The camera captured the fraction of backscattered light from the surface of the fruit and transferred it to the computer. The setup of the LLBI system is shown in Fig. 1.

Acquisition of the images was done in the dark to prevent direct illumination from the outside which may result in interference. Images of 720 × 576 pixel with a resolution of 0.133 mm/pixel were acquired. The laser diodes were positioned to direct the laser beam of 1 mm towards the top of the fruit [17]. The incident angles of the diodes varied between 5 ° and 15 ° with respect to the vertical axis. Ref. [18] recommended that to obtain an image that is symmetrical with respect to the incident point the incident angle and beam size must be small. The images were acquired by manually placing each banana finger on the fruit platform on the system with the point to measure facing the camera. Five images were captured simultaneously for each of the fruit. Therefore a total of 1350 images were captured for 270 banana fingers.

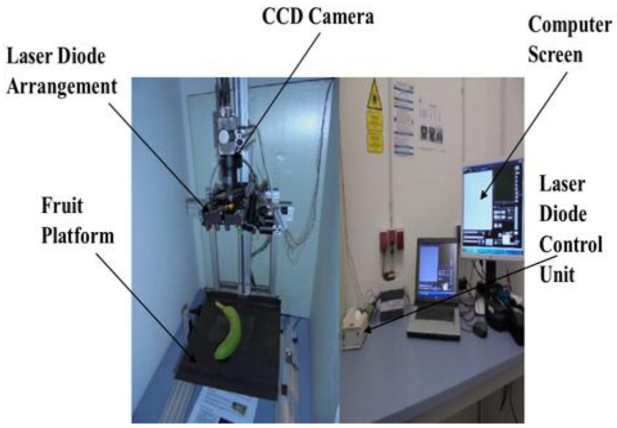

Figure 1. LLBI System showing the CCD and laser diodes.

C. *Prediction and Classification Algorithms*

SVM is a supervised machine learning technique that has a demonstrated capability in many areas of biological analysis [19], [20]. SVM was established on the principle of structural risk minimisation and has been tested to be an impressive and potent method for both classification and regression. SVM is not limited to separating entities into correct classes but also possesses the ability to pinpoint instances whose class is not backed by the data [21]. Ref. [22] employed SVM for the classification of astringent persimmon into unripe, mid-ripe, ripe and overripe fruits.

A total of 270 banana fingers were used for the analysis. 192 samples representing 70 % comprised of 32 samples from each ripening stage were used for model training and the remaining 78 samples representing 30 % were used to test the models. The models were developed using leave-one-out cross validation. The performance of the regression models for the attribute predictions were evaluated using standard error of calibration (SEC) and standard error of prediction (SEP) and the coefficient of determination (r^2). Ref. [23] reported that a model could be considered good when the r^2 is high and low SEC and SEP values with a minimum difference between both parameters. These criteria were used to evaluate the performance of the models as shown in the following equations 1, 2 and 3:

$$SEC = \sqrt{\frac{1}{I_c - 1}\sum_{i=1}^{Ic}(?_i - y_i)^2} \ . \qquad (1)$$

$$SEP = \sqrt{\frac{1}{I_p - 1}\sum_{i=1}^{Ip}(?_i - y_i - bias)^2} \ . \qquad (2)$$

$$bias = \frac{1}{I_P}\sum_{i=1}^{n}(?_i - y_i) \quad (3)$$

where $ý_i$ is the attribute value predicted by the model for fruit number i; y_i is the attribute measured value for the fruit number i; I_c is the number of samples used to build the model; I_P is the number of samples in the test set. For the classification, the performance of the classifiers was undertaken using specificity and sensitivity.

D. *Specificity*

Specificity is the capability of a classifier to correctly preclude classes or individuals that do not belong to a particular class. It is usually expressed as false positive result. The more specific a classification is, the fewer “false-positive” results it produces. A false-positive result often leads to misclassification. Even though few if any classifiers succeed in classifying correctly 100 % of the time, it is necessary that the classifier should produce only a small proportion of false-positive or false-negative results.

$$Specificity = \frac{TN}{TN + FP} \quad (4)$$

where TN is true negative, FP is false negative.

E. *Sensitivity*

Sensitivity is the capability of a classifier to correctly identify classes or individuals belonging to a particular class. It is usually expressed as false-negative result. The fewer the false-negative results a classifier produces the more sensitive the classifier is. A false-negative result refuses to classify an individual to a class even though it belongs to that class.

$$Sensitivity = \frac{TP}{TP + FN} \quad (5)$$

where TP is true positive, FN is false positive.

F. *Classification of Banana into Six Ripening Stages*

For the classification of the ripening stages, samples of each ripening stage were divided at random into two groups. Some 70 % of the 270 samples, which is 192, was used for model development and training while the remaining 30 % was used for model testing. In order to achieve better evaluation results for the models the training and test operations were repeated ten times. The averages of the ten times are reported in this report.

G. *Statistical Analysis*

The image and statistical analyses were carried out using Matlab R2015b (The MathWorks Inc., Natick, MA, USA) and WEKA.

III. Results and Discussion

A. *Chlorophyll Prediction*

From Table I, the r^2 values of 0.867, 0.91, 0.912, 0.899 and 0.88 were achieved for 532, 660, 785, 830 and 1060 nm respectively. The wavelengths of 660 and 750 nm gave the highest r^2 values. The results also show that the difference between the SEC and SEP is very small which implies that the model prediction is good. It should be noted that the wavelength at which higher correlation occurs is within the visible range and therefore these wavelengths in the visible range provide more information as regards to chlorophyll absorption. During ripening, the chloroplast is de-differentiated and there is degradation of the chlorophyll which is responsible for colour changes in most fruits, particularly in banana, thus changing from green in the earlier stage of ripening to yellow in the latter stages of ripening [24].

TABLE I. Regression Performance of SVM Models for Predicting Chlorophyll, Firmness and SSC

Parameter	**Wavelength (nm)**	**Calibration**		**Prediction**	
		SEC	**r^2**	**SEP**	**r^2**
Chlorophyll	532	0.071	0.909	0.068	0.867
	660	0.065	0.932	0.061	0.91
	785	0.066	0.912	0.062	0.912
	830	0.064	0.905	0.061	0.899
	1060	0.068	0.903	0.068	0.88
Elasticity	532	0.418	0.925	0.417	0.929
	660	0.331	0.922	0.327	0.945
	785	0.525	0.921	0.521	0.937
	830	0.357	0.921	0.354	0.932
	1060	0.376	0.922	0.375	0.938
SSC	532	2.494	0.891	2.402	0.828
	660	1.988	0.932	1.971	0.872
	785	2.718	0.856	2.5585	0.831
	830	2.688	0.852	2.576	0.832
	1060	2.765	0.874	2.638	0.809

B. *Elasticity Prediction*

Elasticity has been reported to decrease with increasing ripeness in fruits, and banana is not an exception. During ripening there is pigment accumulation and changes in the cell wall which results in the softening of the fruit, thereby leading to decreasing firmness as ripening proceeds [24]. The firmness of the banana reduces with increasing ripening stage. The SVM model gave high r^2 for firmness prediction for all the wavelengths with 660 nm recording the highest value with 0.946.

C. *SSC Prediction*

As fruit ripens there is increase in soluble pectic polysaccharide that accompanies the softening of the fruit tissue. The changes in wall properties that occur during ripening result in modification of water relations in fruit tissues and this leads to solute reorganisation between the tissue compartments. For the SSC prediction, the SVM model gave r^2 values of 0.828, 0.872, 0.831, 0.832 and 0.809 for 532, 660, 785, 830 and 1060 nm wavelengths respectively. It was also noted that the 660 nm wavelength gave the highest r^2 and the difference between the SEC and SEP were all small for all the wavelengths that were used. This implies that the prediction model is good.

From Table II to Table VI, the confusion matrixes of the classification show that most of the errors are due to the samples being misclassified to the adjacent classes.

TABLE II. CLASSIFICATION RESULT USING SVM WITH BACKSCATTERING DATA AT 532 NM

Ripening Stage	Number[a]	Ripening Stage[b]						FN Error Rate(%)	FP Error Rate(%)
		RP2	RP3	RP4	RP5	RP6	RP7		
RP2	110	100 (110)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0	0
RP3	130	0 (0)	100 (130)	0 (0)	0 (0)	0 (0)	0 (0)	0	0
RP4	120	0 (0)	0 (0)	75 (90)	16.7 (20)	8.5 (10)	0 (0)	25	5.5
RP5	120	0 (0)	0 (0)	25 (30)	50 (60)	25 (30)	0 (0)	50	5.5
RP6	80	0 (0)	0 (0)	0 (0)	12.5 (10)	87.5 (70)	0 (0)	12.5	6.8
RP7	110	0 (0)	0 (0)	0 (0)	0 (0)	9.1 (10)	90.9 (100)	9.1	0

[a] The number of samples used for the test of each ripening stage multiplied by the number of runs (10 runs).
[b] Ripeness stages in percentage with sample number for 10 runs in brackets.

TABLE III. CLASSIFICATION RESULT USING SVM WITH BACKSCATTERING DATA AT 660 NM

Ripening Stage	Number[a]	Ripening Stage[b]						FN Error Rate(%)	FP Error Rate(%)
		RP2	RP3	RP4	RP5	RP6	RP7		
RP2	110	100 (110)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0	0
RP3	130	0 (0)	100 (130)	0 (0)	0 (0)	0 (0)	0 (0)	0	0
RP4	120	0 (0)	0 (0)	83.3 (100)	16.7 (20)	0 (0)	0 (0)	16.7	3.6
RP5	120	0 (0)	0 (0)	16.7 (20)	66.7 (80)	16.7 (20)	0 (0)	33.3	7.3
RP6	80	0 (0)	0 (0)	0 (0)	25 (20)	75 (60)	0 (0)	22	5.1
RP7	110	0 (0)	0 (0)	0 (0)	0 (0)	9.1 (10)	90.9 (100)	9.1	0

[a] The number of samples used for the test of each ripening stage multiplied by the number of runs (10 runs).
[b] Ripeness stages in percentage with sample number for 10 runs in brackets.

TABLE IV. CLASSIFICATION RESULT USING SVM WITH BACKSCATTERING DATA AT 785 NM

Ripening Stage	Number[a]	Ripening Stage[b]						FN Error Rate(%)	FP Error Rate(%)
		RP2	RP3	RP4	RP5	RP6	RP7		
RP2	110	100 (110)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0	0
RP3	130	0 (0)	84.6 (110)	15.4 (20)	0 (0)	0 (0)	0 (0)	15.4	0
RP4	120	0 (0)	0 (0)	83.3 (100)	16.7 (20)	0 (0)	0 (0)	16.7	7.3
RP5	120	0 (0)	0 (0)	16.7 (20)	83.3 (100)	0 (0)	0 (0)	16.7	5.5
RP6	80	0 (0)	0 (0)	0 (0)	12.5 (10)	87.5 (70)	0 (0)	12.5	0
RP7	110	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	100 (110)	0	0

[a] The number of samples used for the test of each ripening stage multiplied by the number of runs (10 runs).
[b] Ripeness stages in percentage with sample number for 10 runs in brackets.

TABLE V. CLASSIFICATION RESULT USING SVM WITH BACKSCATTERING DATA AT 830 NM

Ripening Stage	Number[a]	Ripening Stage[b]						FN Error Rate(%)	FP Error Rate(%)
		RP2	RP3	RP4	RP5	RP6	RP7		
RP2	110	100 (110)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0	0
RP3	130	0 (0)	92.3 (120)	7.7 (10)	0 (0)	0 (0)	0 (0)	7.7	0
RP4	120	0 (0)	0 (0)	100 (120)	0 (0)	0 (0)	0 (0)	0	7.3
RP5	120	0 (0)	0 (0)	25 (30)	66.7 (80)	8.3 (10)	0 (0)	33.3	0
RP6	80	0 (0)	0 (0)	0 (0)	0 (0)	100 (80)	0 (0)	0	1.7
RP7	110	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	100 (110)	0	0

[a] The number of samples used for the test of each ripening stage multiplied by the number of runs (10 runs).
[b] Ripeness stages in percentage with sample number for 10 runs in brackets.

TABLE VI. CLASSIFICATION RESULT USING SVM WITH BACKSCATTERING DATA AT 1060 NM

Ripening Stage	Number[a]	Ripening Stage[b]						FN Error Rate(%)	FP Error Rate(%)
		RP2	RP3	RP4	RP5	RP6	RP7		
RP2	110	100 (110)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0	0
RP3	130	0 (0)	69.2 (90)	30.8 (40)	0 (0)	0 (0)	0 (0)	30.8	1.9
RP4	120	0 (0)	8.3 (10)	75 (90)	16.7 (20)	0 (0)	0 (0)	25	14.5
RP5	120	0 (0)	0 (0)	33.3 (40)	41.7 (50)	25 (30)	0 (0)	58.3	9.1
RP6	80	0 (0)	0 (0)	0 (0)	25 (20)	75 (60)	0 (0)	25	5.1
RP7	110	0 (0)	0 (0)	0 (0)	9.1 (10)	0 (0)	90.9 (100)	9.1	0

[a] The number of samples used for the test of each ripening stage multiplied by the number of runs (10 runs).
[b] Ripeness stages in percentage with sample number for 10 runs in brackets.

In summary, the 830 nm wavelength shows the lowest misclassified errors with 92.5 % correct classification (Table VII). The lowest correct classification was scored by 1060 nm with 74.6 % while 532, 660 and 785 nm show quite good classification results with 83.6 %, 86.6 % and 89.6 % respectively.

TABLE VII. TYPE SIZES FOR CAMERA-READY PAPERS

Wavelength (nm)	Performance (%)
532	83.6
660	86.6
785	89.6
830	92.5
1060	74.6

IV. CONCLUSION

In this paper, the backscattering data with reference measurements using five laser diodes of wavelength 523, 660, 785, 830 and 1060 nm were used to predict quality attributes and to discriminate banana into different ripening stages. An SVM model was built both to predict the quality attributes of banana and also to classify the banana into different ripening stages. It was discovered that wavelengths of 532, 660 and 785 nm gave consistent results with all the models evaluated. In conclusion, this study has shown that backscattering imaging could be an effective and efficient means for analysis of banana quality attributes and ripening stages.

ACKNOWLEDGMENT

The authors are grateful for the financial support received from the Ministry of Science, Technology and Innovation, Malaysia under a Science Fund research grant (Vot number: 5450728).

REFERENCES

[1] Aurore, B. Parfait. and L. Fahrasmane, “Bananas, Raw Materials for making Processed Food Products,” *Trends in Food Science & Technology*, vol. 20, no. 2, pp. 78-91, October, 2009.

[2] P. Arias, “The World Banana Economy,” *Food & Agriculture Org. 2003.*, vol. 1, pp. 78-80, 1985-2002.

[3] S. Carreno and L. Aristizabal, “Utilisation de Bananes Plantain pour Produire du vin. Info Musa,” vol. 12, no. 1, pp. 2-4, 2003.

[4] P. I. Akubor, S. O. Obio, K. A. Nwadomere and E. Obiomah. “Production and Quality Evaluation of Banana Wine,” *Plant Foods for Human Nutrition*, vol. 58, no . 3, pp. 1-6, September, 2003.

[5] L. Lunadei, P. Galleguillos, B. Diezma, L. Lleo and L. Ruiz-Garcia. “A Multispectral Vision System to Evaluate Enzymatic Browning in Fresh-cut Apple Slices,” *Postharvest Biology and Technology*, vol. 60, no. 3, pp. 225-234, August, 2011.

[6] D. Lorente. et al, “Recent Advances and Applications of Hyperspectral Imaging for Fruit and Vegetable Quality Assessment,” *Food and Bioprocess Technology*, vol. 5, no. 4, pp. 1121-1142, May, 2012.

[7] C. J. Studman. “Computers and Electronics in Postharvest Technology—a review,” C*omputers and Electronics in Agriculture*, vol. 30, no. 1, pp. 109-124, February, 2001.

[8] A. A. Kader. “Flavor Quality of Fruits and Vegetables,” *Journal of the Science of Food and Agriculture*, vol. 88, no. 11, pp. 1863-1868, June, 2008.

[9] A. A. Kader, “Postharvest Technology of Horticultural Crops,” *UCANR Publications*, vol. 33, no. 11, pp. 8-10, 2002.

[10] L. Baranyai and M. Zude. “Analysis of Laser Light Propagation in Kiwifruit using Backscattering Imaging and Monte Carlo Simulation,” *Computers and Electronics in Agriculture*, vol. 69, no. 1, pp. 33-39, July, 2009.

[11] D. Lorente. et al. “Early Decay Detection in Citrus Fruit using Laser-light Backscattering Imaging,” *Postharvest Biology and Technology*, vol. 86, pp. 424-430, August, 2013.

[12] M. Zude, B. Herold, J-M. Roger, V. Bellon-Maurel and S. “Landahl. Non-destructive Tests on the Prediction of Apple Fruit Flesh Firmness and Soluble Solids Content on Tree and in Shelf Life,” *Journal of Food Engineering*, vol. 77, no. 2, pp. 254-260, August, 2005.

[13] K. Mollazade, et al. “Analysis of Texture-based Features for Predicting Mechanical Properties of Horticultural Products by Laser Light Backscattering Imaging,” *Computers and Electronics in Agriculture*, vol. 98, pp. 34-45, August, 2013.

[14] N. Hashim, et al. “An Approach for Monitoring the Chilling Injury Appearance in Bananas by Means of Backscattering Imaging,” *Journal of Food Engineering*, vol. 116, no. 1, pp. 28-36, December, 2012.

[15] Y. Jiang, D. C. Joyce, W. Jiang and W. Lu. “Effects of Chilling Temperatures on Ethylene Binding by Banana Fruit,” *Plant Growth Regulation*, vol. 43, no. 2, pp. 109-115, June, 2004.

[16] T. B. T. Nguyen, S. Ketsa and W. G. van Doorn, “Relationship between Browning and the Activities of Polyphenoloxidase and Phenylalanine Ammonia Lyase in Banana Peel during Low Temperature Storage,” *Postharvest Biology and Technology*, vol. 30, no. 2, pp. 187-193, November, 2003.

[17] D. Lorente, M. Zude, C. Idler, J. Gomez-Sanchis and J. Blasco, “Laser-light Backscattering Imaging for Early Decay Detection in Citrus Fruit using both a Statistical and a Physical Model,” *Journal of Food Engineering*, vol. 154, pp. 76-85, January, 2015.

[18] K. Mollazade, M. Omid, F. A. Tab and S. S. Mohtasebi, "Principles and Applications of Light Backscattering Imaging in Quality Evaluation of Agro-food Products: a review," *Food and Bioprocess Technology*, vol. 5, no. 5, pp. 1465-1485, July, 2012.

[19] M. P. Brown, et al., "Knowledge-based Analysis of Microarray Gene Expression Data by using Support Vector Machines," *in Proc. of the National Academy of Sciences*, vol. 97, no. 1, pp. 262-267, 2000.

[20] A. Zien, et al. "Engineering Support Vector Machine Kernels that Recognize Translation Initiation Sites. Bioinformatics," vol. 16, no. 9, pp. 799-807, March, 2000.

[21] T. S. Furey, et al. "Support Vector Machine Classification and Validation of Cancer Tissue Samples using Microarray Expression Data," *Bioinformatics*, vol. 16, no. 10, pp. 906-914, May, 2000.

[22] X. Wei, F. Liu, Z. Qiu, Y. Shao and Y. He, "Ripeness Classification of Astringent Persimmon using Hyperspectral Imaging Technique," *Food and Bioprocess Technology*, vol. 7, no. 5, pp. 1371-1380, May, 2014.

[23] C. Liu, et al. "Application of Multispectral Imaging to Determine Quality Attributes and Ripeness Stage in Strawberry Fruit," *PloS one*, vol. 9, no. 2, pp. e87818, February, 2014.

[24] R. B. H. Wills, W. B. McGlasson, D. Graham and D. C. Joyce, "Postharvest: An Introduction to the Physiology and Handling of Fruit," *Vegetables and Ornamentals*, *CABI.*, pp. 23-26, 2007.

Segun E. Adebayo, an academic staff of the Federal University of Technology, Minna, Niger State, Nigeria was born in Oyo, Oyo State, Nigeria on 4th of July, 1976. Adebayo obtained B.Eng from the Federal University of Technology, Minna, Niger State Nigeria in 2006. He was awarded M.Sc from the University of Ibadan, Ibadan, Oyo State Nigeria in 2010 and currently a Ph.D student in Agricultural Process Engineering, Universiti Putra Malaysia, Serdang, Selangor, Malaysia. He is a member of Nigerian Institution of Agricultural Engineers (NIAE). He is also a member of International Association of Engineers IAENG.

Norhashila Hashim obtained her Ph.D in Biomechanical Engineering, from Universiti Putra Malaysia (UPM), Serdang, Selangor, Malaysia in 2013. She is a senior academic staff of the Department of Biological and Agricultural Engineering, Faculty of Engineering, UPM. With three years experience in teaching and research, she has authored a number of publications. Her research interest includes postharvest engineering, agricultural process engineering and non-destructive testing.

Khalina Abdan is an associate professor and a former Head of Department, Biological & Agricultural Engineering and Head of Laboratory, Institute of Tropical Forestry and Forest Products, UPM. She has more than 15 years experience in research and teaching. Her research interest are biocomposite and agricultural properties.

Marsyita Hanafi is currently a senior lecturer in Department of Computer and Communication Systems Engineering, Faculty of Engineering, UPM. She obtained her PhD from Imperial College London, UK. She has more than 5 years experiences in research and teaching. Her research interest are optical Devices, Biometrics, Security, Image Processing and Machine Learning.

Manuela Zude-Sasse obtained her Ph.D. in Fruit Physiology from Technical University Berlin in 2003. She is a group leader in the Department of Horticultural Engineering at the Leibniz Institute for Agricultural Engineering and Bioeconomy (ATB) Potsdam Bornim, Germany and a professor at the Beuth University of Applied Sciences Berlin, Germany. Prof. Zude-Sasse is a Prof. Dr. Manuela Zude is a board member of the following journals: Biosystems Engineering, Food and Bioprocess Technology and Postharvest Biology and Technology, a vice chair of CIGR WG on image processing, VDI/VDE standardization committee for sensor solutions, and in the CP (Falkensee, Germany) company.