Scientific Papers. Series B, Horticulture. Vol. LXV, No. 1, 2021
Print ISSN 2285-5653, CD-ROM ISSN 2285-5661, Online ISSN 2286-1580, ISSN-L 2285-5653

HYPERSPECTRAL IMAGING SYSTEM FOR MATURITY STAGE CLASSIFICATION OF DURIAN PULP USING BAYESIAN OPTIMIZED MACHINE LEARNING ALGORITHMS

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Abstract

Non-destructive classification of fruits based on the maturity stage is beneficial to the consumer and fruit industry. Improper ripening can lead to low eating quality and economic loss for the producers. In this research, a hyperspectral image (HSI) of durian pulp was obtained using a reflectance-based system. The mean raw spectra of the durian pulp were extracted and pre-treated using standard normal variate (SNV). An assessment of maturity stage classification (unripe, ripe, and overripe) on the full wavelength (900-1600 nm) was performed. The comparison among the machine learning (ML) algorithms (random forest (RF), support vector machine (SVM), and k Nearest Neighbours (kNN)) was carried out, where the hyperparameters were tuned using Bayesian optimization and the 3-fold cross-validation method. The samples were split into training (70%) and test (30%) set using stratified random sampling. In terms of overall classification accuracy and kappa coefficient, SVM (88.5%, 0.83) performed better than RF (84.6%, 0.77) and kNN (73.1%, 0.59). The results show that the classifiers (SVM and RF) can fairly differentiate the ripening stage of durian pulp using HSI.

***Key words**: durian, hyperspectral imaging, maturity, machine learning, Bayesian optimization.*

INTRODUCTION

In Southeast Asian countries, durian is known as "the king of fruits". Durian is produced and consumed highly in Malaysia, Indonesia, Singapore, Thailand, the Philippines, and China (Siriphanich, 2011). Durian is popular for its appearance, taste, and distinct odor. Thailand is considered to be one of the largest durian producing country, as well as an exporter to the international market among the countries in the Association of Southeast Asian Nations (ASEAN) (Maninang et al., 2011; Somton et al., 2015). In some countries such as Malaysia, the fruit is likely to be consumed fully ripe with a soft texture and strong odor, whereas the majority of people from Thailand prefer just ripe fruit with a firm texture and mild odor (Siriphanich, 2011). The traditional methods for identifying the ripeness and maturity of durian before harvesting includes mostly visual inspection and destructive techniques (Ketsa et al., 2020). Uneven ripeness due to harvesting immature fruits develop low eating quality, and even after ripening, the fruit lacks the quality characteristic: aroma and flavour (Ketsa et al., 2020). Identifying the correct maturity is one of the biggest challenges that durian producers are facing currently.

Spectroscopy and imaging techniques have been applied on several fruits and vegetables for quality monitoring. Recently, hyperspectral imaging (HSI) is more in use for quality inspection as it integrates both, spectroscopy and imaging techniques (Park & Lu, 2015). Application of HSI has been done for decades in several fruits such as strawberry, peach, pear, banana, etc (Elmasry et al., 2007; Haiyan Cen, Renfu Lu, Fernando A. Mendoza, 2011; Khodabakhshian & Emadi, 2018; Rajkumar et al., 2012). HSI generates 3-dimensional hypercube where the first two dimensions contains spatial information and the last dimension stores the spectral information. Based on an approach in which the spatial information is acquired, the HSI sensor are classified into point scanning (whiskbroom), line scanning (push broom), and area scanning

(tunable filter). In pushbroom system configuration either the object or the imaging unit is moving which gives an advantage to be used in online systems for industrial application (Liu et al., 2007).
Similar to spectroscopic technique, HSI images are first preprocessed and then the classification/regression algorithms are implemented for classification and regression task along with feature extraction and dimensionality reduction. Machine learning algorithms such as support vector machine (SVM), random forest (RF), k nearest neighbor (kNN), discriminant analysis (linear discriminant analysis (LDA), partial least squares discriminant analysis(PLS-DA)) are popular for classification and regression analysis. In machine learning, some parameters control the learning process known as hyperparameters. Hyperparameter optimization can be done manually or with automatic search methods. One of the famous hyperparameter optimization methods is Bayesian optimization. It combines prior information about the unknown function with sample information, to obtain posterior information of the function distribution by using the Bayesian formula (Wu et al., 2019). Based on this posterior information, the optimal parameters combination can be known where the function outputs the optimal value (Wu et al., 2019). Bayesian optimization was proved to be a promising method to find the best hyperparameters for widely used machine learning models such as RF, SVM, and neural networks (NN) (Jones, 2001). Hyperparameter for SVM such as soft margin constant (C) should not be not too high or low. It has to be considered that large values for C lead to few training errors and narrow margin, whereas small values generate a larger margin, at the cost of more errors and more training points situated inside the margin (Eitrich & Lang, 2006). Similarly, the number of estimator trees (n-estimator) is one of the important parameters to be optimized in RF. If the value is too high for n-estimators, the strength can be improved but at the same time the error rate due to high inter tree correlation increases (Wu et al., 2019). If the value is low, the inter tree correlation and strength of individual tree goes down (Wu et al., 2019). Therefore, a proper optimization method plays a critical role in obtaining a good classification model with minimal error in machine learning.
The main objective of this research is to identify the potential of HSI system for the ripeness classification of the durian pulp by using machine learning algorithms: SVM, RF, and kNN. The hyperparameter tuning is performed by using Bayesian optimization for machine learning algorithms.

MATERIALS AND METHODS

Durian samples were collected from Trat Province, the eastern part of Thailand. The fruits were harvested at 99, 106, 113, 120, 127, and 134 days after anthesis (DAA). The total number of whole fruit harvested was 50 with each fruit consisting of approximately 5 to 6 pulps. In total, 260 pulps were used for the experiment. The experiment was conducted 2 days after the harvesting date. The fruits were divided in terms of ripeness level as unripe (99-106 DAA), ripe (113-120 DAA), and overripe (127-134 DAA).
The image was acquired using a pushbroom HSI system with a wavelength range from 900-1600 nm and the spectral resolution of 3.2 nm. The HSI system included an imaging spectrograph (Imspector N17E Specim, Spectral Imaging Ltd., Oulu, Finland) with a CCD camera (Xeva 992, Xenics Infrared Solutions, Belgium), and two 500 W tungsten–halogen light sources (Lowel Light Inc., New York, United States of America) at an angle of 45 degrees. The system was controlled by Specim's LUMO Software Suite (Spectral Imaging Ltd., Oulu, Finland). The integration time was set as 6. The pulp was placed on the translation stage moving at the speed of 10 mm s^{-1} and was guided by the bar on both sides to make it stable during the scan.
After hyperspectral image acquisition, the radiometric calibration was done. The white reference and dark reference acquired for each image in the HSI system were used for the radiometric calibration. To capture the white reference, the spectralon with relative reflectance of 99% was used. In the HSI system, the dark reference image was captured by the system automatically by closing the shutter of a camera.

$$R = \frac{Io - D}{W - D} \quad (1)$$

where R is the relative reflectance image, Io is the raw reflectance image, D is the dark reference image, and W is the white reference image.

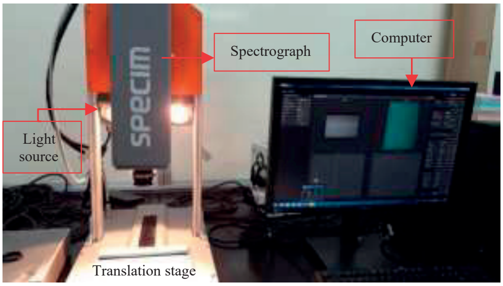

Figure 1. Image acquisition using hyperspectral imaging of durian intact fruit

The area of interest (AOI), pixels representing pulp region, was extracted from each radiometically corrected image. Since the durian pulp was supported by two guiding bars (Figure 2a) while scanning, a normalized difference index (NDR) (Equation 2) was computed to separate pulp from the bars and background (translation stage). Two wavelengths with high reflectance (1205 nm) and low reflectance (1450 nm) were selected for NDR computation.

$$NDR = \frac{(R_{1075.67} - R_{1450.18})}{(R_{1075.67} + R_{1450.18})} \quad (2)$$

The binary threshold operation was then applied to NDR image to separate the pulp from the background as shown in Figure 2b.

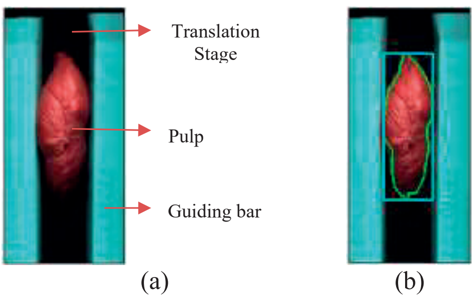

Figure 2. Raw image acquired from hyperspectral imaging (a) Masked image by binary masking and morphological filter.

The threshold value was set to 0.5, with values greater than 0.5 representing the pulp. The morphological filters (dilation and erosion) were then applied to the binary image to extract the pulp pixels. From the extracted AOI, the mean spectra were calculated from every pixel within the boundary of the AOI.

The obtained mean spectra was then preprocessed using standard normal variate (SNV) technique as it minimizes the effects of scattering, particle size, and the difference in the global intensities of the signals (Barnes et al., 1993; Roger et al., 2020)

Supervised machine learning algorithms: SVM, RF, and kNN, were applied on the preprocessed mean spectra of durian pulp. The classification models were developed in Python 3.8 using Scikit-learn machine learning library. The hyperparameters: soft-margin constant (C), and gamma (γ) for SVM, the number of estimators trees in the forest (n-estimator), the number of features to consider for the best split, the maximum depth of the tree for RF, and number of neighbors (n) to calculate the nearest neighbor for kNN, were optimized by Bayesian optimization. In the case of SVM, the radial bias function (RBF) kernel function was used. The distance metrics in kNN was set as euculidean. The sample set was divided randomly into a training set and the test set in the ratio of 70:30. Overall accuracy (Equation 3), precision (Equation 4), recall (Equation 5), and Kappa coefficient (Equation 6) values were used to analyze the performance of each machine learning classifier. The Kappa coefficient measures the actual agreement (indicated by the diagonal elements of the confusion matrix) minus chance agreement (indicate by the product of the row and column marginal). It measures how the classification performs as compared to the reference data (Fung & Ledrew, 1988).

$$\text{Overall Accuracy (\%)} = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \quad (3)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

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

$$\text{Kappa coefficeint} = \frac{p_o - p_e}{1 - p_e} \quad (6)$$

		Predicted Class	
		Positive	Negative
Actual Class	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

Figure 3. Confusion matrix

Where, TP is true positive, TN is true negative, FP is false positive and FN is false negative, p_o is the empirical probability of agreement on the label assigned to any sample, p_e is the expected agreement when both annotators assign labels randomly.

RESULTS AND DISCUSSIONS

The average raw spectra from the extracted AOI of the pulp are shown in Figure 4. With the change in path length due to the different sizes of the sample, the raw spectra showed a baseline shift. Therefore, the SNV preprocessing was applied in the raw spectra to improve the spectral characteristics. The SNV pretreated spectra show a dominant peak of water at the wavelength of 970 nm and 1205 nm (Figure 5). This wavelength represents O-H stretching due to the first overtone of water. Also, at 1450 nm there is a significantly lower reflectance band which represents the band of water and starch.

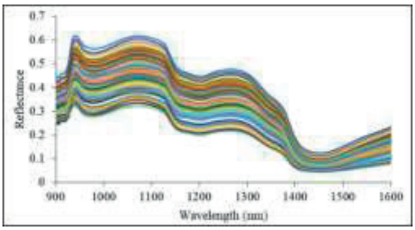

Figure 4. Average raw spectra of durian pulp

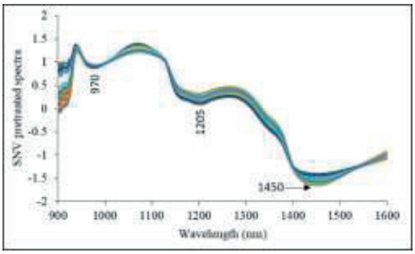

Figure 5. SNV pretreated spectra of durian pulp

Table 1 shows the selection of hyperparameters for SVM, RF, and kNN using Bayesian optimization.

Table 1. Selection of hyperparameters for SVM, RF, and kNN using Bayesian optimization

Classifiers		Hyperparmeter		
Support vector machine		C	gamma	Kernel function
	Input	0.01-1000	0.1-100	Radial base function, Linear, Polynomial
	Output	53	0.4	Radial base function
Random forest		n-estimator	Maximum feature	Maximum depth
	Input	25-500	2-20	2-20
	Output	93	8	14
k nearest neighbor		n- neighbor		Distance
	Input	2-20		Euclidean (default)
	Output	10		Euclidean

The best classification performance from the optimized hyperparameter classification models from SVM, RF, and kNN in terms of training accuracy, cross-validation accuracy, and test accuracy is shown in Table 2. SVM showed the highest test accuracy (91.8%) among three machine learning classifiers. The training accuracy of RF was significantly (100%) higher but the 3 fold cross-validation (86.8%) and test accuracy (84.6%) do not show the good performance of the RF model. Meanwhile, kNN obtained the lowest accuracy among all the machine learning classifiers.

Table 2. Performance of machine learning classifiers using Bayesian optimization

Classifiers	Training accuracy	3-fold cross validation accuracy	Overall accuracy
Support vector machine	91.8%	87.9%	88.5%
Random forest	100%	86.8	84.6%
k nearest neighbour	84.1%	81.3%	73.1%

Table 3 shows the precision, recall and kappa coefficient of test set. Figure 6 shows the confusion matrix from each ML classifiers. The number of overripe, ripe and unripe in the test set were 21, 28 and 29, respectively, which is represented in confusion matrix. The precision, recall and kappa coefficient of overripe samples are higher for all classification models. With the advancement of the maturity stage, the moisture content of the pulp decrease. The significant difference in the moisture content between overripe samples and the other samples may have resulted in classification metrics value of overripe samples. The inter-class confusion between ripe and unripe can be seen for all the classification models with more classification error in the case of kNN. The similar spectral characteristics of ripe and unripe sample must have influenced the classification performance of kNN.

Table 3. Precision, recall and kappa coefficient obtained from the classification model by different machine learning classifiers

Classifiers		Precision	Recall	kappa coefficient
Support vector machine	Overripe	0.95	0.95	0.83
	Ripe	0.86	0.86	
	Unripe	0.86	0.86	
Random forest	Overripe	0.90	0.90	0.77
	Ripe	0.80	0.86	
	Unripe	0.85	0.79	
k nearest neighbor	Overripe	0.86	0.90	0.59
	Ripe	0.68	0.68	
	Unripe	0.68	0.66	

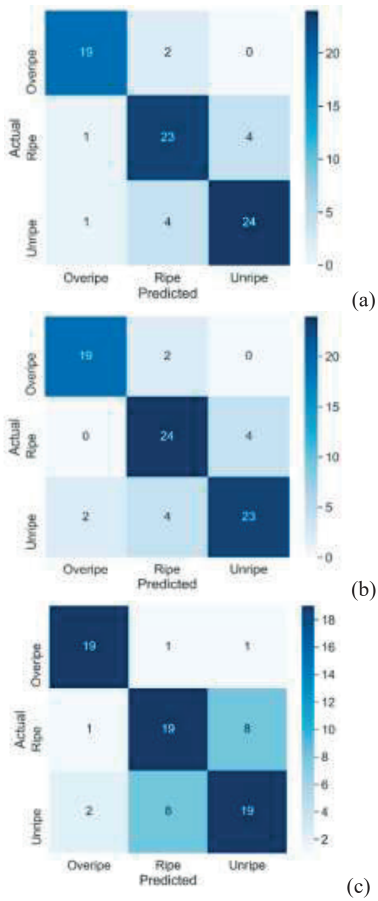

Figure 6. Confusion matrix from classification model of support vector machine (a), random forest (b), and k nearest neighbors (c)

Several supervised and unsupervised classification algorithms have been used for the maturity classification of fruits. The ripeness classification model of pear using short near-infrared (425-1000 nm) by three classification model soft independent modeling of class analogy (SIMCA), LDA, and PLS-DA were compared by Khodabakhshian & Emadi, 2018. The overall classification result showed that PLS-DA attained the best correct classification accuracy of 87.86% for pear ripeness classification (Khodabakhshian & Emadi, 2018). Hyperspectral image of navel oranges was obtained using the diffuse transmittance imaging-based system and a multispectral index was developed to identify the maturity with the hyperspectral technique by Wei et al., 2017. Linear discriminant analysis and kNN were used to classify the three maturity stages of navel orange, among which kNN attained the highest correct classification rate of 96.0%. Classification of maturity stages of cherry fruits by using the HSI system in the NIR region (874-1734 nm) was done by Li et al., 2018. The result showed the best correct classification ratio of 96.4% by the LDA classifier (Li et al., 2018). For different fruits, different machine learning algorithms showed the best results for maturity classification.

Durian maturity was evaluated by minimal destruction based on electrical impedance measurement (Kuson & Terdwongworakul, 2013). According to the findings of Kuson & Terdwongworakul (2013), selected impedance parameters using a stepwise regression could be used to classify durian samples into an immature class and mature class with less accuracy of 83.3%. Similarly, the research done by Timkhum & Terdwongworakul (2012) showed a good result to identify the characteristic changes in the durian spine with maturity using visible spectroscopy. Their result showed the best accuracy of 94.7% into only four maturity classes from 113-134 DAA. Tantisopharak et al. (2016) identified the potential of natural frequency due to electromagnetic scattering properties of durian to identify the fruit maturity. The findings shows that, the changes in natural frequencies were associated with the maturity of the fruit which resulted in a variation of resonant frequencies for classification of durian according to its maturity stages (Tantisopharak et al., 2016).

Several researches have been conducted on durian intact fruit and pulp for maturity identification and internal properties evaluation. However, the research using the HSI system had not been performed for the maturity classification of durian pulp. The results from this research show the potential to use the HSI system for ripeness classification. The result from SVM shows an overall accuracy of 88.5%, which is comparable to other researches that have been done.

CONCLUSIONS

The potential of the HSI pushbroom system with a spectral range from 900-1600nm for ripeness classification of durian pulp was evaluated in this research. The mean spectra extracted from the area of interest were preprocessed using SNV. Three machine learning classifiers: SVM, RF, and kNN were used for developing the ripeness classification of durian pulp where Bayesian optimization was used for tuning the the associated hyperparameters. SVM showed best classification with the training, cross-validation, and overall accuracy of 91.8 %, 87.9%, and 88.5%, respectively. The result shows the potential of the HSI system combined with machine learning algorithms for the ripeness classification of durian pulp. However, the overall accuracy should be improved further using more samples and applying other machine learning as well as deep learning approaches. Different wavelength selection algorithms: successive projection algorithm (SPA), genetics algorithm (GA), and competitive adaptive reweighted sampling (CARS), will be applied further for feature extraction and dimensionality reduction for improvement of classification performance.

ACKNOWLEDGEMENTS

The author would like to acknowledge NIR Spectroscopy Research Centre for Agricultural Product and Food (www.nirsresearch.com) and the Department of Agricultural Engineering, Faculty of Engineering, Kasetsart University Kamphaengsaen Campus for providing the necessary equipment for conducting the experiment. We would like to acknowledge King Mongkut's Institute of Technology Ladkrabang for the support.

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