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Prediction and classification of soluble solid contents to determine the maturity level of watermelon using visible and shortwave near infrared spectroscopy

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Abstract

The present work investigated the potential application of a portable and low-cost spectroscopic technique to predict the soluble solid content (SSC) for determining the maturity level of watermelons. A total of 63 watermelon samples were used in the present work, representing three different maturity levels: unmatured, matured, and over-matured. Before spectral acquisition, each watermelon sample was cut into half, producing 126 fruit portions. Visible shortwave near infrared (VSNIR) spectrometer was used to record the spectral data from the skin surface of each portion. The SSC of each portion was measured using a digital refractometer. Partial least square (PLS) regression method was used to establish both calibration and prediction models to predict the SSC values from the watermelon samples. Support vector machine (SVM) classifier was used to categorise spectral data into the respective maturity levels. Results showed that the coefficient of determination (R^2) values for calibration models of unmatured, matured, and over-matured were 0.65, 0.81, and 0.78, respectively. For the prediction model, the R^2 values for unmatured, matured, and over-matured were 0.60, 0.74, and 0.76, respectively. The SVM yielded good classification accuracy of 85%. The present work demonstrated that the proposed spectroscopic method could be applied to predict and classify the maturity level of watermelons based on their skin condition.

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Introduction

Watermelon (*Citrullus lanatus*) is a popular edible fruit. It is usually eaten fresh, or processed into fruit juice since it contains approximately 93% water of its total mass. Globally, watermelon is the most produced fruit, with an average annual production of 93.7 million tons (Liu *et al.*, 2018). It is a nutritional fruit which contains vitamins, mineral salts, antioxidant, lycopene, and specific amino acids (Sultana and Ashraf, 2019). The demand for watermelon is always high due to its nutritional value and delicious taste.

For the commercial market, watermelon with good quality is always preferred by consumers. The external quality attributes of watermelon such as shape, weight, and rind and flesh colours are important preference components for consumers to purchase the fruit (Kyriacou *et al.*, 2018). Recently, in addition to the external quality factors, consumers also consider the internal quality features such as the fruit's sugar and nutritional contents (Musacchi and Serra, 2018). Sugar content, which is commonly measured as soluble solid content (SSC) in °Brix value, is the best indicator for the internal quality of watermelon, and strongly related to the fruit's maturity level (Kyriacou *et al.*, 2018).

Watermelon should be harvested as soon as it reaches maturity to preserve its premium quality. Therefore, the determination of the optimum maturity level of watermelon is a critical task during harvest. Conventionally, the maturity level of watermelon is estimated by farm workers based on several indices such as the vine tendrils which should begin browning and drying, the skin with less glossiness, appearance of ground spot yellowness, and

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production of a dull sound when the fruit is thumped (Sun *et al.*, 2010). However, these manual assessments are time-consuming, tedious, less efficient, and subjected to human errors (Ali *et al.*, 2017). Therefore, an application of fast, automatic, and non-destructive technology to determine the maturity level of watermelon is critically needed.

Numerous non-destructive methods for determining the internal quality attributes of watermelons have been published, including electrical and magnetic (Kato, 1997; Nelson *et al.*, 2007), X-ray (Tollner, 1993), acoustic and dynamic (Abbaszadeh *et al.*, 2015), and near-infrared spectroscopy (Jie *et al.*, 2014; Tamburini *et al.*, 2017). Even though these laboratory methods were accurate and reliable, they are typically fragile and expensive, thus requiring careful handling, and are not suitable for assessing maturity level of watermelon *in situ*.

Currently, due to its excellent measurement performance, visible and shortwave near-infrared (VSNIR) spectroscopy has gained attention as a low-cost and non-destructive sensing technique for assessing the internal quality of fruits such as mandarins (McGlone *et al.*, 2003), mangoes (Saranwong *et al.*, 2004), kiwifruits (Clark *et al.*, 2004), apples (Mendoza *et al.*, 2015), pineapples (Chia *et al.*, 2012), and sugarcanes (Nawi *et al.*, 2013). These studies employed VSNIR spectroscopy due to its ability to perform rapid non-destructive measurement, and measure multiple parameters concurrently (Alfatni *et al.*, 2013). However, the application of this technology for predicting SSC values of watermelon has never been conducted before.

The use of VSNIR spectroscopy will generate many raw spectral data. Therefore, chemometric analysis is required to remove unwanted and irrelevant information from the raw spectral data before developing regression and classification models. Data classification is an important procedure in chemometric analysis to reduce data dimensionality, optimise data processing time, and enhance data generalisation by reducing prediction and over-fitting (Kumar *et al.*, 2016). Common classification algorithms in agricultural research include support vector machines (Jie *et al.*, 2019), artificial neural networks (Nawi *et al.*, 2013), finite element model (Abbaszadeh *et al.*, 2014), and K-nearest neighbour method (Abbaszadeh *et al.*, 2015). Support vector machine (SVM) is one of the most popular classification methods, and greatly recognised due to its excellent performance in dealing with high-dimensional data (Khaled *et al.*, 2018).

Therefore, the objectives of the present work were (1) to investigate the possibility of using VSNIR spectroscopy to predict SSC levels of watermelon samples using PLS regression model, and (2) to classify spectral data of watermelon samples into three maturity levels using SVM.

Materials and methods

Sample preparation

Sixty-three watermelon samples of Red Seedless variety representing three different maturity levels, namely unmatured (21 samples), matured (21 samples), and over-matured (21 samples) were purchased from a local farm in Bangi, Selangor, Malaysia. The watermelons were harvested by a well-trained farm worker at 60, 65, and 70 days after planting to represent unmatured, matured, and over-matured categories, respectively. Sixty-five days after planting was an optimal harvest date for this variety (Ali *et al.*, 2017). The samples were then cleaned, weighed, and transported directly to the laboratory.

Prior to sample preparation, the samples were stored in a chiller at 8°C and 85% relative humidity. The watermelon samples were placed on a bench until they reached thermal equilibrium. Paper towels were used to remove dirt and moisture from the skin surface of the samples before the measurement was performed. Kato (1997) reported that the sweetness distribution of the flesh varies from the centre to the rind of the watermelon. Therefore, to investigate the variation of skin characteristics and sugar distribution, the watermelon samples were cut into halves, thus producing 126 sub-sample portions. Then, to average this variation, each portion was divided into top, middle, and bottom (Figure 1). Three measurements on spectra and SSC were performed on each section before they were averaged for further analysis. The average value of the spectral and SSC data from these three portions was used to determine each portion's spectral and CCS value.

Reflectance measurement

The spectral data of each watermelon portion was collected using a visible near-infrared (VSNIR) spectrometer (Ocean Optic HR4000, Ocean Optics

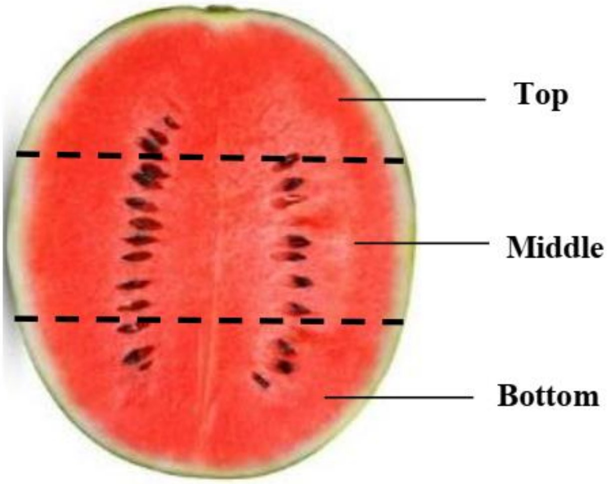

Figure 1. Division of three sections (top, middle, and bottom) on a portion of watermelon sample.

Inc., Dunedin, Florida). This miniature fibre optic spectrometer came with a charge-coupled device (CCD) detector. This spectrometer worked in the wavelength region ranging from 200 to 1100 nm with an optical resolution of 0.025 nm. A tungsten halogen light source (HL-2000 12VDC (15 W), Ocean Optics Inc., USA) was used to illuminate both visible and NIR regions during the measurement.

A measuring box (1 × 1 × 1 m) with light-proof characteristics was developed and utilised to block the light source, sensor, and samples from ambient light. All surfaces inside the box were also covered with black cloth to reduce the influence of background surfaces on spectral data (Wu *et al.*, 2008). The scanning distance was kept constant at 2 cm by placing the probe on a probe holder at a 90° angle. The spectral measurement of watermelon was collected from the outer skin surface of each portion. The reflectance measurement technique was chosen because this technique did not require any contact with the samples. A white reference (WS-1 Diffuse Reflectance Standard) and black reference were recorded prior to spectral measurement. Spectrasuite software (Ocean Optic Inc.) was installed in a computer for collecting, observing, and processing the spectral data.

Measurement for sugar content

After the spectral measurement, each section from the individual watermelon portion was squeezed to extract the juice samples. The SSC value of each section was measured using a digital refractometer (Pal-1, Atago Co, Tokyo, Japan) three times, and averaged.

Pre-processing of spectral data

The purpose of data pre-processing is to obtain the highest correlation between concentration values and spectral data, as well as to improve spectral features and eliminate irrelevant variation and noise in the data (Jayaselan *et al.*, 2018). The spectral data were pre-processed before using partial least square (PLS) regression modelling to obtain better prediction accuracy. Different pre-processing techniques which could affect the performance of the PLS models were evaluated in the present work including smoothing by moving average, multiplicative scatter correction (MSC), baseline offset correction (BOC), first and second derivatives, standard normal variate (SNV) transformation, and mean normalisation. Preliminary trials found that BOC was the best pre-processing technique for the present work. The pre-processing treatment was performed using Unscrambler X version 10.3 software (CAMO Process, AS, Oslo, Norway).

Development of calibration and validation models

Principal component analysis (PCA) was applied before establishing the PLS regression models to reduce the dimensionality of spectral data, remove the noise, and determine the optimum number of latent variables (Wu *et al.*, 2008). PCA is a chemometric method that searches for directions in multivariate space, and uses them as a new axis known as principal component (PCs) which can be used as new variables to represent the original data. PCA was also used to identify the potential spectral outliers. The spectral outliers were identified and eliminated before developing the PLS model. The outliers were identified from the samples which showed an apparent residual variance in the influence plot. Based on the spectral data from 126 watermelon samples, six spectral data represented six samples (5%) were identified as outliers, and they were removed from the analysis. Hence, only 120 spectral data and SSC values were used for further analysis.

The spectral data were analysed using the PLS regression method to establish calibration and prediction models. In establishing the PLS, the PCs were applied to simplify the relationship between the response and predictors variables. To determine the optimum number of PCs, full cross-validation (leave-out) was applied to prevent the over-fitting of the model. Ten PCs were used for the analysis. Both PCA and PLS modelling were run using Unscrambler X version 10.3 software (CAMO Process, AS, Oslo, Norway). Before calibration, samples were divided into two sets; 75% of the samples were applied to establish the calibration model. The remaining (25%) samples were used to validate the predictive equation (validation set). In the validation set, one out of four samples was selected from the whole set to cover the whole range of SSC values in every set.

Root mean square error of calibration (RMSEC) and the coefficient of determination for calibration (R^2) were calculated to measure the performance of PLS model during calibration. In contrast, the root means square error of prediction (RMSEP) and the coefficient of determination for prediction (R^2) were calculated to measure the performance of validation samples. The models that yielded a low RMSEC and RMSEP, and a high R^2 for both calibration and prediction models may be considered a good regression model.

Classification using support vector machine

Classification algorithm based on SVM has been widely adopted in spectroscopic measurement. SVM is a machine-learning technique based on statistical-learning theory which transforms initial input space into higher-dimensional feature space in searching for an optimal separating hyperplane (Kavzoglu and Colkesen, 2009). The performance of the SVM classifier depends on the kernel functions such as linear, sigmoid, polynomial, and radial basis function (RBF). The grid search technique was used to obtain the optimum performance of the model using the RBF modelling. The RBF modelling was chosen in the present work due to its superiority. For the classification task, the optimal parameter used in the RBF for a kernel width (γ) was 10, while the regularisation (C) parameter was 16.

SVM algorithm was employed to classify the spectral data of watermelon samples into three different maturity levels. After removing the outliers, a total of 59 samples (21 unmatured samples, 18 matured samples, and 20 over-matured samples) were used as inputs for SVM classification. From the whole data samples, 65% were applied for training, while the remaining 35% were applied for prediction. Three optimum wavebands at 550, 680, and 760 nm, which could be correlated to lycopene, chlorophyll, and third overtone of sugar, respectively, were selected for the classification modelling.

In the present work, an analysis software (Waikato Environment for Knowledge Analysis (WEKA), version 3.6, Hamilton, New Zealand) was used to develop SVM algorithm and perform feature selection (Khaled *et al.*, 2018). Feature selections are commonly applied to reduce data dimensionality because they reduce the data's complexity, improve prediction performance, and are easy to interpret. The optimum wavebands of the spectrum selection may also decrease the volume of processed spectrum data, and increase the classification efficiency. For the determination of statistically significant differences between two data set of the samples, analysis of variance (ANOVA) was performed using the SAS software (Version 9.4, SAS Institute, Cary, NC, USA).

Results and discussion

Statistical characteristic and spectral pattern

Table 1 shows the statistical characteristics of SSC values for the watermelon samples at different maturity levels. The SSC value in watermelon was influenced by the level of its maturity (Kyriacou *et al.*, 2018). The matured watermelons contained the highest SSC value (7.13 °Brix) while the unmatured samples contained the lowest (6 °Brix). As the fruit maturity level progressed and sugar content increased, SSC also increased due to the hydrolysis of sucrose to invert sugars (Salamat *et al.*, 2013). The result of the ANOVA test confirmed that there was a significant difference in SSC at different maturity levels at p < 0.05, based on the least significant difference (LSD) test.

Table 1. Statistical characteristics of the SSC (°Brix) value for watermelon at different maturity levels.

Maturity level	Max.	Min.	Mean	Std. Dev
Unmatured	7.18	4.5	6.00	0.66
Matured	8.10	5.61	7.13	0.65
Over-matured	8.47	5.00	6.71	0.68

Std. Dev. = standard deviation.

Typical reflectance spectra for the watermelon samples at different maturity levels are presented in Figure 2. It was observed that all curves which represented different maturity levels exhibited similar patterns with varying values of reflectance. A graph with a similar pattern for apples was reported by Liu and Ying (2005). From Figure 2, prominent peaks are seen at 550, 675, and 760 nm, all of which could be related to the maturity level of the watermelon. For example, the peak around 675 nm could be correlated to chlorophyll content in the skin of watermelon, while significant absorption around 760 nm could be correlated to sugar content which was represented by a stretching of the third overtone of O-H (Merzlyak *et al.*, 2003). Typically, unmatured fruit had a higher chlorophyll content than matured fruit because the chlorophyll content will decrease as the fruit ripens.

The absorption pattern at 760 nm indicated that the watermelon has different SSC values at different maturity levels. These differences were because SSC will increase as the maturity increases. An increase in SSC was due to the accumulation of carbohydrate to reducing sugar and decreasing the acidity (Oliveira *et al.*, 2015). Another pronounced peak at 550 nm can be used to measure the presence of lycopene content (red pigment) of the watermelon (Sánchez *et al.*, 2014). This lycopene content varies at different maturity levels since the concentration of lycopene is low during the early stage of fruit development, and increases as the fruits ripen. Therefore, it is envisaged that the level of chlorophyll, SSC, and lycopene can be used to predict the maturity of watermelon.

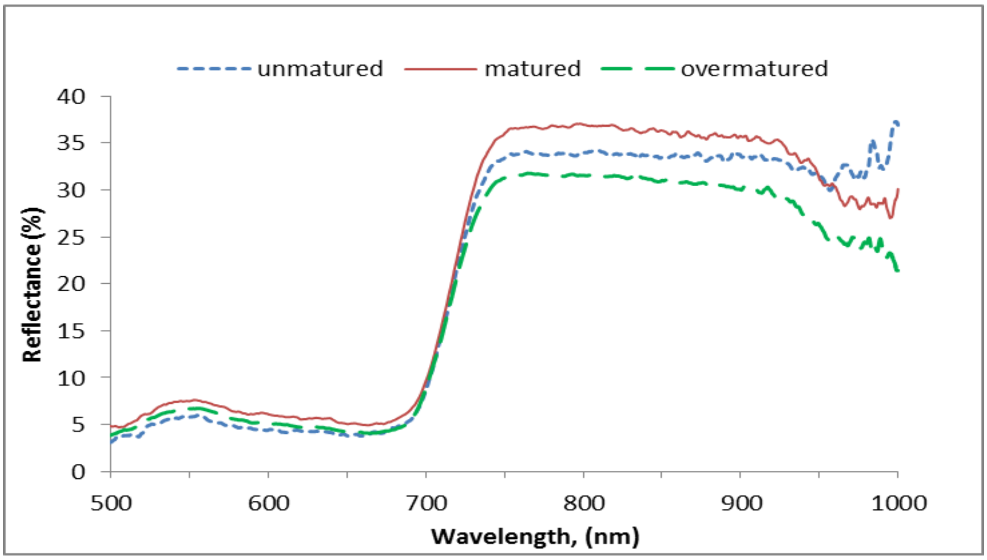

Figure 2. Typical reflectance spectrum for watermelon samples at different maturity levels.

Prediction of SSC from watermelon samples

In the present work, the BOC technique was used to pre-process the spectral data before they were used in the PLS regression method. PLS regression method was applied in the development of the calibration and prediction models. The values of R^2, RMSEC, and RMSEP were used to evaluate the performances of the models. Table 2 shows the performance of the calibration and prediction models in predicting SSC values to determine the maturity levels of the watermelon samples from the spectral data collected from the outer skin of the fruits. Table 2 shows that the R^2 values for prediction models of unmatured, matured, and over-matured were 0.60, 0.74, and 0.76, respectively. These data indicated that the spectroscopic method could yield better prediction accuracy when it was used for matured and over-matured crops. This finding is logical since the PLS models were developed between spectral data and SSC. From the data, it can be said that unmatured watermelon contained less SSC as compared to matured watermelon.

Table 2. Performance of the calibration and prediction models in predicting the SSC (°Brix) values at different maturity levels.

Maturity level	Calibration		Prediction	
	RMSEC (°Brix)	R^2	RMSEP (°Brix)	R^2
Unmatured	0.49	0.65	0.69	0.60
Matured	0.30	0.81	0.34	0.74
Over-matured	0.48	0.78	0.64	0.76

From the reflectance data, the value of R^2 for SSC attained in the present work was relatively better than that obtained by Jie *et al.* (2014), who reported R^2 value of 0.66 in predicting SSC from watermelon samples using the transmittance technique. The prediction accuracy reported in the present work for matured (R^2 = 0.74) and over-matured (R^2 = 0.76) categories was also higher than the prediction accuracy (R^2 = 0.71) reported by Tamburini *et al.* (2017) who employed an online NIR spectrometer in the range of 700 - 1900 nm to predict total soluble solids of intact melons. The results reported herein were also better than that published by de Oliveira *et al.* (2014) who used NIR spectroscopy to measure the SSC of passion fruit with R^2 of 0.63. However, the results reported herein was lower than the result (R^2 = 0.93) reported by Khodabakhshian *et al.* (2017) in estimating the sugar content of pomegranate. In conclusion, the present work demonstrated that the level of SSC in watermelon could be predicted using a VSNIR spectrometer.

Maturity classification by support vector machine (SVM)

Table 3 shows the classification results generated by SVM classifier. The model showed an excellent overall prediction accuracy of 85%. Table 3 also shows that two main classes representing over-matured and unmatured levels achieved 80 and 100% accuracy, respectively. However, the matured level yielded a lower accuracy of 75%. A lower accuracy occurred because this maturity level had SSC values that were borderline between other maturity levels. Overall, this finding was better than the result reported by Baki *et al.* (2010) who employed Multi-Layer Perceptron (MLP) neural network for discriminating ripe and unripe watermelons with an accuracy of 77.3%. In another study, better accuracy of 86.96% for watermelon maturity classification was obtained when band magnitude vector (BMV) and probabilistic neural network (PNN) methods were employed (Zhang *et al.,* 2010). In conclusion, the results reported herein implied that the VSNIR spectroscopy in combination with SVM classifier could be a promising technology to classify maturity levels of watermelon non-destructively.

Table 3. Classification results using SVM.

Maturity level	No. of sample	No. of correctly classified sample	Prediction accuracy (%)
Unmatured	21	21	100
Matured	18	14	75
Over-matured	20	16	80
Overall accuracy (%)			**85**

Conclusion

The low-cost, portable, and non-destructive spectroscopic method was successfully employed in the present work to evaluate SSC from watermelon samples at different levels of maturity. Results showed that the R^2 values of the prediction model for unmatured, matured, and over-matured were 0.60, 0.74, and 0.76, respectively. The SVM classifier used to classify SSC data into three maturity categories gave a good classification performance, ranging from 75 to 100% accuracy, with an overall accuracy of 85%. Results also indicated that the proposed method was feasible for predicting and classifying the maturity level of the watermelons based on SSC values. The VSNIR spectroscopy technique employed in the present work could also be potentially applied for an automated and online grading or sorting system. The accuracy of the prediction model could be increased by increasing the number of samples. In contrast, the use of the deep learning method might increase the accuracy of the classification result.

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