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Near infrared hyperspectral imaging for predicting water activity of dehydrated pineapples

By

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Abstract

Water activity (a_w) of dehydrated pineapple is one of the most important quality factors that must be determined in the routine operation of a factory. A non-destructive technique for detecting a_w of dehydrated pineapples in the factory is required. Near infrared hyperspectral imaging (NIR-HSI) that has previously been shown to be a possible non-destructive, rapid, accurate and robust method was used in this study. The model for a_w was established using partial least square regression (PLSR). Spectra in the wavelength of 935–1720 nm of samples were measured by using NIR-HSI and preprocessing methods tested before model establishment. The accuracy of the prediction model for a_w gave a correlation coefficient of prediction (R_p) of 0.72 and root mean square error of prediction (RMSEP) of 0.0054. Results showed that NIR-HSI could possibly be used for determining a_w of dehydrated pineapple non-destructively and could be incorporated into the production process for online grading in dehydration factories.

Index Terms—fruit, spectra, model, quality, non-destructive

Introduction

Pineapples (Ananas comosus L.) are grown in both tropical and subtropical climates and they rank third among non-citrus fruits in production; following bananas and mangoes [1]. Global pineapple production has progressively increased by over 3% annually over the past 9 years, reaching approximately 27.9 million tonnes in 2019. The major producers are Brazil, Philippines, Thailand, Costa Rica, Indonesia, India and China [2]. Pineapples are marketed in various forms including fresh fruit as well as being processed into juice, canned slices or pieces, fresh-cut [3] and lately as dehydrated snacks [4].

The quality of any processed fruit depends on the quality of the fresh fruit to be processed as well as the conditions during processing and an interaction of the two. Batches of fruit delivered to the factory may vary and processing may require modifications in order to maintain optimum quality. Therefore, factories apply constant monitoring of random samples as the fruit arrive as well as monitoring throughout processing. However, monitoring is inconvenient, destructive, time consuming and labor intensive, therefore a non-destructive, quick procedure would speed the process, be more cost-effective and should be more reliable since every fruit is monitored not just a random sample [5], [6]. For consistent production of high-quality products from fruit, which constantly vary, any method that can help to achieve this would be very valuable to the industry.

NIR-HSI has previously been shown to be a technique that can be used for non-destructive and non-contact analysis of foods. The use of NIR-HSI enables the capture of both spatial and spectral data for determining product quality for example in: eggs [7], limes [8], cakes [9], tapioca starch [10], pulse flour [11], infant formula [12], chrysanthemum bud tea (hangbaiju) [13], black tea [14] and durian pulp [15]. The preferred method is to use a chemometrics and PLSR to extract significant data in order to develop a linear model for the prediction of dependent variables from a large number of independent variables [16]. Therefore, NIR-HSI was selected for testing the prediction of water activity of dehydrated pineapples in this research, since it is a feasible analytical method that should fulfill these requirements, because it is non-destructive and non-contact and enables for the capture of both spatial and spectral data for determining product quality.

Materials and methods

Dehydrated Pineapple Preparation

Different batches of commercial sliced dehydrated pineapple were obtained from a dehydration fruit factory in Kanchanaburi Province of Thailand. Each sample was visually inspected to ensure they were of good appearance and without any visible flaws.

Spectral data

Each dehydrated pineapple slice was scanned using a NIR-HSI system. The system consisted of a push-broom-laboratory-based sisu CHEMA system with a hyperspectral camera (Specim Fx17, Spectral Imaging Ltd, Oulu, Finland) in a reflectance mode in the wavelength of 935–1720 nm, which consisted of 224 spectral bands. Each sample was positioned on the scanner tray and passed through the camera's field of view with a position speed 20 mm/s and a scanning speed at 15 mm/s, using a stepper motor. The camera’s field was illuminated by lamps on both the left and right sides of the sample. A white reference image was measured using a Spectralon bar and a black reference image was measured while the shutter was closed (Figure 1).

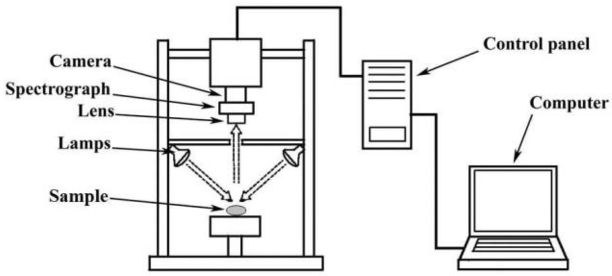

Figure 1. *Schematic of the NIR-HSI system.*

Water activity

For the determination of water activity (a_w) the AOAC method [13] using a water activity meter (4TE, Aqualab©, USA) was employed. The water activity meter was first calibrated using the calibration standard (distilled water), which showed, as predicted, the a_w of distilled water of 1.000 ±0.003. Determination of a_w was done by weighing 1 g of sample, placing the sample in a water activity measuring cup and placing the cup containing the sample the water activity meter. The value of a_w was displayed in the water activity meter and it sounded "beep" when the measurement was done.

Data Analysis

The NIR-HSI system's scanning outputs covered both the sample and background spectra. Principal component analysis (PCA) was used to remove the background data, leaving only the region of interest (ROI), which was only the sample spectra. ROI spectra of each sample were then averaged and utilized in the study. The acquired a_w was defined as the dependent variables, whereas the sample spectra were defined as the independent variables. This information was used to create a calibration model. Samples were divided into calibration and prediction groups. To select the optimal calibration model, spectral pretreatments included Savitzky-Golay smoothing, first and second derivatives, standard normal variate (SNV), multiplicative scatter correction (MSC) and combinations were performed and evaluated on each sample in the calibration group. PLSR was used to build the calibration models for a_w from spectra that were preprocessed using spectral pretreatments and then selected for the best calibration model in the optimal conditions by considering lowest root mean square error of cross validation (RMSECV), high correlation coefficient of cross validation (R_{cv}) and the lowest number, and number of latent variables (LV). The best calibration model for a_w was validated by samples in the calibration group in order to determine the model's performance by considering the root mean square of calibration (RMSEC) and the correlation coefficient of calibration (R_c). The best calibration model for a_w were also tested using the samples in the prediction group to evaluate the accuracy by considering RMSEP and R_p. The robustness of the calibration model was determined by the similarity of RMSEC and RMSEP. The data was statistically analysed using the Unscrambler X Version 10.5.1 (CAMO, Osla, Norway) and UmBio Evince HSI analysis software (Prediktera Evince, version 2.7.5, Sweden).

Results and Disscussions

The feature of the average ROI spectra from all the samples in the wavelength range of 935–1720 nm that were used for establishing the calibration model for a_w was shown in Figure 2. Samples based on a_w were divided into two groups of low and high levels. Also, the spectra of each group were averaged and plotted (Figure 3), indicating that the average spectra of high levels of a_w had a larger absorbance value than lower levels. That clearly showed that higher absorbance occurred in samples with higher a_w was due to the influence of water in samples, that is a_w influenced absorbance spectra.

In order to reduce noise and detect and eliminate overlapping peaks, the second derivative spectral pretreatment was investigated (Figure 4). The averaged second derivative spectra showed distinct peaks in the negative bands about 964, 1154, 1342 and 1460 nm, which has previously been shown to be aligned to the water absorption peak [14], showing that water was the major constituent in dehydrated pineapples. In order to develop the calibration model, the dehydrated pineapple samples were divided into the calibration and the prediction groups (Table 1), with the samples for a_w in the prediction group were in the calibration group's range, with a close standard deviation between groups.

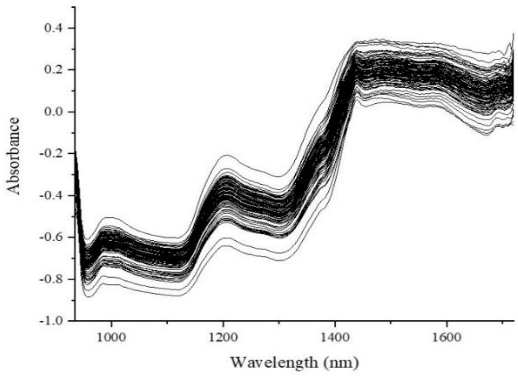

Figure 2. *Average ROI spectra of dehydrated pineapples.*

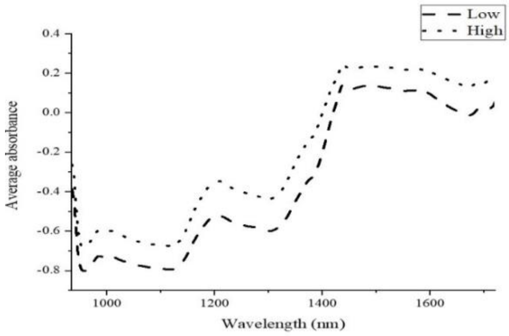

Figure 3. *Averaged spectra of low and high a_w of dehydrated pineapples.*

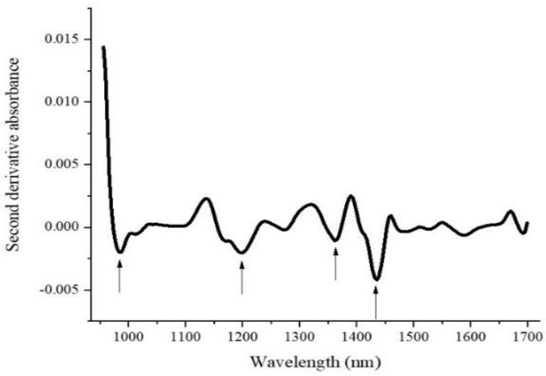

Figure 4. *Average second derivative spectra of dehydrated pineapples.*

Although several spectral pretreatments applied to the spectra of samples in order to minimize noise and reduce the shift in the base line, it was shown that its original spectra gave the best calibration model (Table 2), therefore the original spectra were therefore utilized to predict a_w of dehydrated pineapples in this study. The calibration model was then tested in order to determine the accuracy by the samples of the prediction group for a_w. The calibration model was shown to give acceptable results for predicting a_w (R_p= 0.72, RMSEP= 0.0054) (Table 3). The calibration model also achieved good robustness as indicated by the values of RMSEC and RMSEP, which were close. The scatter plots for a_w (Figure 5) showed that the calibration model was validated by the samples in the calibration group and illustrates the accuracy of the calibration model for a_w when it was tested using the samples in the prediction group (Figure 6). This effect indicates that using NIR-HSI for predicting a_w of dehydrated pineapples gave acceptable accuracy and could be used in a non-destructive online grading system for quality control in a pineapple fruit dehydration factory.

Table 1. *a of dehydrated pineapples in the calibration and the prediction group*

	a_w	
	Calibration group	**Prediction group**
Sample	90	40
Range	0.567 – 0.608	0.569 – 0.604
Average	0.588	0.587
Standard deviation	0.008	0.008

Table 2. *Spectral pretreatments for PLSR models for a_w of dehydrated pineapples*

Pretreatments	a_w **Latent variable**	**Correlation coefficient of cross validation**	**Root mean square error of cross validation**
Original	2	0.73	0.0053
Smoothing	2	0.72	0.0053
1st Derivative	1	0.70	0.0055
2nd Derivative	2	0.70	0.0056
MSC	2	0.68	0.0056
SNV	2	0.69	0.0056
Smoothing + MSC	2	0.69	0.0056
Smoothing + SNV	2	0.68	0.0056

Smoothing = Savitzky-Golay smoothing, 1st derivative = Savitzky-Golay first derivative differentiation, 2nd derivative = Savitzky-Golay second derivative differentiation, MSC= Multiplicative scatter correction, SNV= Standard normal variate.

Table 3. *PLSR results of dehydrated pineapple's a_w in calibration and prediction group*

Pa	**Pre**	**LV**	**Sample group** Calibration group N			Prediction group N		
			N	$\mathbf{R_c}$	**RMSEC**	**N**	$\mathbf{R_p}$	**RMSEP**
a_w	Original	2	90	0.73	0.0053	40	0.72	0.0054

Pre= Pre-treatment, LV = latent variables, N= Number of samples, R_C= Correlation coefficient of calibration, RMSEC= Root mean square error of calibration, R_P= Correlation coefficient of prediction, RMSEP= Root mean square error of prediction.

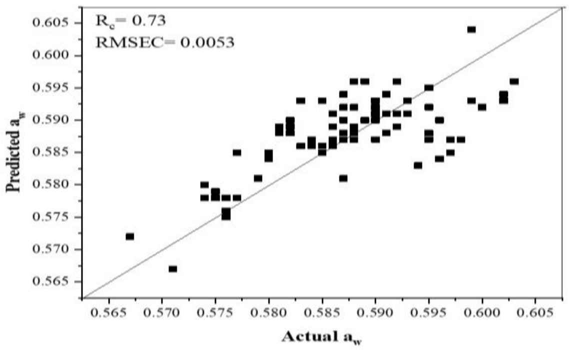

Figure 5. *Scatter plot of actual and predicted a_w of dehydrated pineapples in the calibration group.*

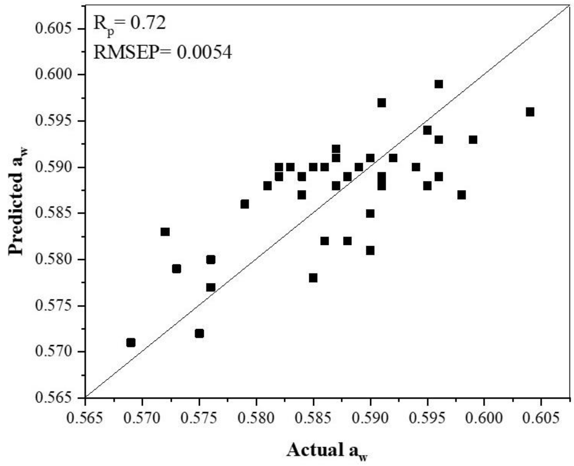

Figure 6. *Scatter plot of actual and predicted a_w of dehydrated pineapples in the prediction group.*

Conclusion

The calibration model for water activity of dehydrated pineapples was established by using averaged original data of the region of interest spectra using partial least square regression. The results showed that the calibration model by obtained from near infrared hyperspectral imaging showed an acceptable performance and accuracy for predicting water activity of dehydrated pineapples. It was therefore concluded that near infrared hyperspectral imaging could be used as a non-destructive, rapid, and reliable technique for detecting water activity of dehydrated pineapples, which is considered to be one of the most important quality factors of the finished output product before sending to customers.

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