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Research Article

Near Infrared Hyperspectral Imaging for Predicting Quality of Dehydrated Ginger

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Abstract

The quality of any food product processed from fruit and vegetables can vary depending mainly on the quality of raw material and their processing. Near infrared hyperspectral imaging (NIR-HSI) has been shown to be a reliable and effective method of online monitoring of food products and was therefore tested on dehydrated ginger. The quality parameters of the dehydrated ginger assessed were hardness and total soluble solids (TSS). The models for hardness and TSS were established using partial least square regression (PLSR). Spectral pretreatments were tested in order to get better precision of the models. The accuracy of the prediction models for hardness was achieved correlation coefficient of prediction (Rp) of 0.79 and root mean square error of prediction (RMSEP) of 3.13 N and for TSS was Rp= 0.82 and RMSEP= 2.25%. Results showed that NIR-HSI has the possibility for determining hardness and TSS of dehydrated ginger non-destructively and could possibly to be used as part of the production process for online grading in dehydration factories.

Keywords: *hyperspectral imaging, near infrared, quality, spectra*

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Introduction

Ginger (*Zingiber officinale*) is a native of Asia where has been grown since ancient times and from where it has been exported to Europe in its dried form for centuries. *Z. officinale* is a perennial herb with a fleshy rhizome that is used as a spice, as a preserve and has medicinal properties. It is sold fresh, but also as preserved ginger, crystallized ginger and dried ginger. Ginger has many uses as a flavoring as well as in traditional medicine, because of both its volatile and non-volatile compounds including gingerols, shogaols and zingerone [1], [2]. Total world production of ginger in 2019 was estimated by FAO as 4,081,374 tonnes. The major producers are India, Nigeria, China, Nepal, Indonesia and Thailand [3]. Fresh ginger contains some 85-95% water and when dried ginger is produced, the process can affect its quality including taste, texture, color, nutrient content and consumers acceptability [4], [5].

In a factory that produces dried fruit the fresh fruit the provides the raw material can vary day-to-day, therefore constant quality analysis is required. Traditionally quality analysis is on a sample basis of each batch, but this method is disruptive, time consuming, labor intensive and may require certain materials or chemicals. Therefore, a non-destructive method that is rapid, analyses all the throughput has the potential to the more cost-effective and maintain high and more consistent standards [6], [7].

Of possible analytical methods that could meet these criteria near infrared hyperspectral imaging (NIR-HSI) was selected as it is non-destructive and non-contact and allows collections of both spatial and spectral data for predicting product quality. NIR-HSI has previously been applied for quality analysis of cakes [8], tapioca starch [9], eggs [10], limes [11], beef jerky [12], jujubes [13] and cucumbers [14]. The optimum method is to analyze the information produced by NIR-HSI instrument using a chemometrics method such as partial least square regression (PLSR) to extract the important data and create a linear model prediction of dependent variable from an abundant number of independent variables [15]. Therefore, NIR-HSI tested for predicting quality of dehydrated ginger non-destructively. The textural attribute of hardness and the chemical attribute of total soluble solids (TSS) are critical qualities of dehydrated ginger, therefore predicting these two attributes was selected for testing in the current study.

Materials and methods

A. Dehydrated Ginger Preparation

The commercial dehydrated ginger samples that were used in the experiments were from various lots produced from Thai ginger in a fruit dehydration factory at Kanchanaburi Province, Thailand. Samples were inspected visual to ensure they were without flaws and of good appearance.

B. Spectral Data Acquisition

Each sample was scanned in reflectance mode in the wavelength of 935–1720 nm and consisted of 224 spectral bands using a push-broom-laboratory-based sisu CHEMA system which supported a hyperspectral camera (Specim Fx17, Spectral Imaging Ltd, Oulu, Finland). Each sample was positioned on the moving table and passed through the camera's

field of view with a position speed 20 mm/s and scanning speed at 15 mm/s using a stepper motor. Six halogen lamps were used in the illumination unit. The samples and two references were taken in each scanning, one a dark reference which captured when the lid was on the camera during a closed shutter and the other a white reference using a white reference bar.

C. Physical and Chemical Qualities Analysis

The hardness of each individual sample was measured using a texture analyzer (TA-XT Plus, Stable Micro Systems Ltd., UK) with a 2 mm diameter cylinder probe, a crosshead speed of 1 mm/s, and a 25 kg load cell. When the probe was withdrawn from the sample, the same speed was used. To determine the hardness of each material, the maximum peak force during the first compression was observed as previously reported [16]. The TSS was measured, using the AOAC method [17], by taking a 5 g of samples of each batch of dehydrated ginger, adding 95 ml of deionized water, homogenizing using a homogenizer (IKA, T25 digital ULTRA-TURRAX®, Germany) and then filtering. The filtered solution was then tested using a digital refractometer (PR101, Palette Series, Atago Co., Ltd., Tokyo, Japan).

D. Data Analysis

The scanning results from the NIR-HSI system included both the sample and background spectra. The background data was eliminated using principal component analysis (PCA) leaving only the region of interest (ROI). The ROI spectra of each sample were then averaged and used for the analysis. The acquired data of hardness and TSS were defined as dependent variables and the spectra of the sample as the independent variables. Those data were plotted into a calibration and a prediction set. The spectral pretreatments including Savitzky-Golay smoothing, first and second derivatives, standard normal variate (SNV), multiplicative scatter correction (MSC) and the combinations were applied and observed in order to determine the best calibration model. The calibration models for hardness and TSS were created using PLSR. The determination of the best calibration model of each dependent variable was considered by the correlation coefficient of cross validation (R_{cv}) with highest number, root mean square error of cross validation (RMSECV) with the lowest number and number of latent variables (LV) also observed. In order to measure the model's capability, both correlation coefficient of calibration (R_c) and root mean square of calibration (RMSEC) were considered, which were acquired by validation of selected calibration models for dependent variables were tested with the samples themselves in the calibration set. Also, the calibration models were tested with the samples in the prediction set to test the model’s accuracy considering the correlation coefficient of prediction (R_p) and root mean square of prediction (RMSEP). Similar value of RMSEC and RMSEP were the test to determine whether the models were robust. All of the data were statistically analyzed using the Unscrambler software (CAMO, Osla, Norway) and UmBio Evince HSI analysis software (Prediktera Evince, version 2.7.5, Sweden).

Results And Dısscussıons

The average spectra of ROI from all of the samples achieved in the wavelength ranged between 920-1720 nm were used to establish the calibration models (Fig. 1). The hardness and TSS of dehydrated ginger were classified into low and high content and the spectra of

each group was averaged as shown in Fig. 2, which shows that the average spectra of high level of hardness and TSS had higher absorbance value than lower levels.

The second derivative spectral pretreatment were performed in order to eliminate the noise and identify and overcome overlapping peaks (Fig. 3). The averaged second derivative spectra showed clear peaks in the negative bands around at 964, 1342, 1460 nm, which corresponded to absorption peak of water and the peak at 1195 nm corresponded to the absorbance bands of glucose [18], [19] indicating that water and sugar were the main components in dehydrated ginger.

The dehydrated ginger samples were separated into calibration and prediction sets in order to create the calibration model (Table 1). The samples for hardness and TSS in prediction set in the range of calibration set with a close standard deviation between calibration and prediction set.

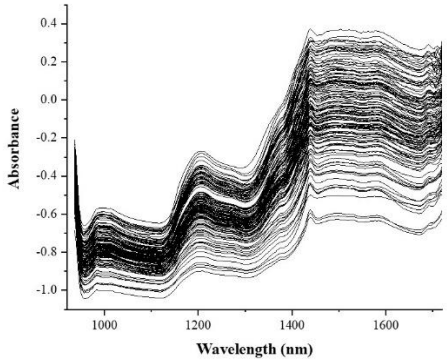

FIGURE 1. The average spectra of ROI from dehydrated gingers.

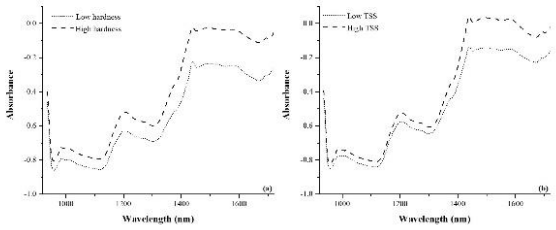

FIGURE 2. The averaged spectra of low and high hardness (a) and low and high TSS (b) of dehydrated ginger.

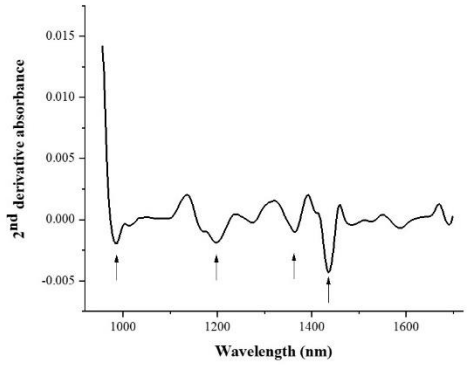

FIGURE 3. Average second derivative spectra of dehydrated ginger.

Different kinds of spectral pretreatments were applied to the spectra of samples in the calibration set in order to eliminate noise and reduce the shift in base line. The best calibration models were achieved by applying smoothing pretreatment for both hardness and TSS (Table 2). Thus, smoothing pretreatment was then used for predicting hardness and TSS of dehydrated gingers.

The calibration models that were created using the preprocessed spectra together with the smoothing pretreatment were then tested in order to determine the accuracy by the samples in the prediction set for both hardness and TSS. The models obtained acceptable results for predicting both hardness (R_p= 0.79, RMSEP= 3.13 N) and TSS (R_p= 0.82, RMSEP= 2.25%) (Table 3). The prediction models achieved also showed robust models as the value of RMSEC and RMSEP were close for both hardness and TSS.

The performance of calibration models, shown by the scatter plots for hardness (Fig. 4(a)) and TSS (Fig. 5(a)) show that the accuracy that was achieved by applying the calibration models to the samples in prediction set. The visualization of the accuracy of the calibration models are shown in Fig. 4(b) for hardness and Fig. 5(b) for TSS. These results showed that using NIR-HSI resulted in good performance and accuracy for predicting the hardness and TSS of dehydrated ginger and implies that it could be applied for use as a non-destructive online grading system for quality control during the production process for dehydrated ginger and possibly for other dehydrated fruit.

TABLE 1. The data of dehydrated ginger in calibration and prediction set

	Hardness (N)		TSS (%)	
	CS	PS	CS	PS
Number	128	63	133	67
Range	2.42-35.42	3.10-26.46	65-84	65-84
Mean	10.94	10.63	77.18	77.25
SD	5.67	5.09	4.09	3.93

TSS= Total soluble solids, CS= Calibration set

PS= Prediction set, SD= Standard deviation

TABLE 2. Spectral pretreatment results of dehydrated ginger's hardness and TSS

Pretreatments	Hardness (N)			TSS (%)		
	LV	R_{cv}	RMSECV	LV	R_{cv}	RMSECV
Original	6	0.74	3.85	6	0.73	2.79
Smoothing	**7**	**0.76**	**3.67**	**9**	**0.77**	**2.61**
1st Derivative	9	0.75	3.79	5	0.73	2.80
2nd Derivative	9	0.76	3.71	4	0.72	2.83
MSC	5	0.75	3.75	5	0.76	2.66
SNV	5	0.74	3.79	5	0.75	2.69
Smoothing + 1st Derivative	4	0.72	3.93	4	0.74	2.76
Smoothing + 2nd Derivative	4	0.66	4.23	4	0.73	2.78

TSS= Total soluble solids, LV= Latent variable,

R_{cv}= Correlation coefficient of cross validation,

RMSECV= Root mean square error of cross validation,

MSC= Multiplicative scatter correction,

SNV= Standard normal variate.

TABLE 3. PLSR results of dehydrated ginger's hardness and TSS in calibration and prediction set

Para-meters	Pre-treatments	LV	Sample set					
			Calibration Set			Prediction Set		
			N	R_c	RMSEC	N	R_p	RMSEP
Hardness	Smoothing	7	128	0.82	3.27 N	63	0.79	3.13 N
TSS	Smoothing	9	133	0.84	2.23%	67	0.82	2.25%

TSS= Total soluble solids, 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.

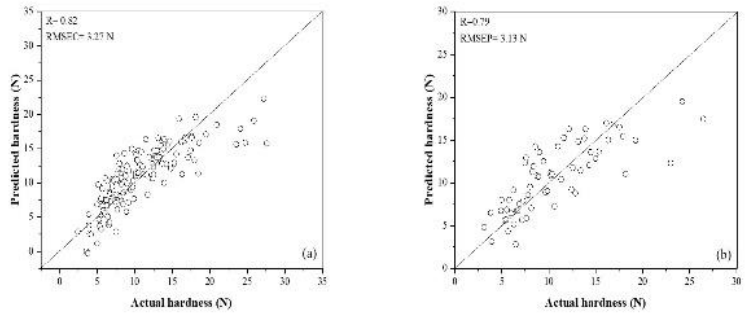

FIGURE 4. Actual and predicted hardness in the calibration set (a) and prediction set (b) of dehydrated ginger visualized in scatter plots.

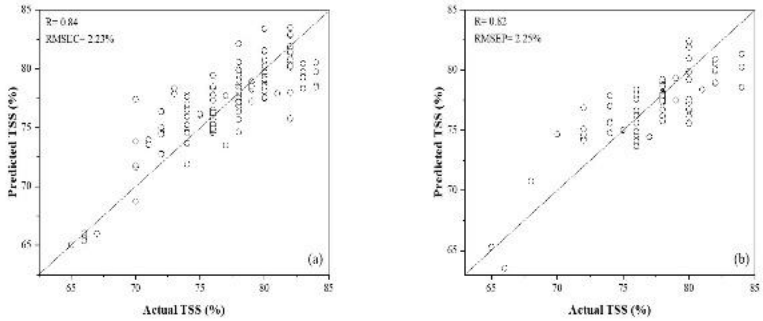

FIGURE 5. Actual and predicted TSS in the calibration set (a) and prediction set (b) of dehydrated ginger visualized in scatter plots.

Conclusıon

The calibration models constructed using PLSR from average spectra with the smoothing spectral pretreatment of data from NIR-HSI equipment, could be used to predicting quality of

dehydrated ginger. It was indicated that NIR-HSI had an acceptable performance and accuracy for prediction the hardness and TSS of dehydrated ginger, which could possibly to be applied as a non-destructive, rapid and reliable quality control method in commercial manufacturing process line of dehydrated fruit factories.

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