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Performance Comparison of Two Portable Near-infrared Devices for Rapid Authentication of Aceh Aromatic Rice ‘Sigupai’

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ABSTRACT

Sigupai rice, Indonesia local aromatic rice varieties grown in South-West region of Aceh, is highly valued for its fragrance and quality, making it susceptible to adulteration. This study compares the performance of two portable Near-infrared (NIR) devices, SCiO and NeoSpectra, for rapid authentication of Sigupai rice. We evaluated 86 samples for qualitative analysis (i.e. authentic vs adulterated rice) and 44 samples for quantitative analysis (i.e. the level of adulteration). For the qualitative analysis using partial least squares-discriminant analysis (PLS-DA), the best estimation model could differentiate authentic and adulterated samples with an accuracy, sensitivity, specificity, and false positive rates of 89.29%, 92.86%, 85.71% and 14.29% for the NeoSpectra and 97.44%, 100%, 94.87%, and 5.13% for the SCiO, respectively at the validation stage. For quantitative analysis using partial least squares-regression (PLS-R), the best estimation model could estimate the level of adulteration with a coefficient of determination (R^2), RMSEP, RPD, and consistency values of 0.92, 1.50%, 5.93 and 100.69% for the NeoSpectra and 0.96, 1.31%, 6.83 and 104.78% for the SCiO. Both portable NIR devices could be used as a rapid analysis tool for the authenticity of Sigupai rice with high accuracy. However, in this study the SCiO device showed a better performance.

1. INTRODUCTION

In several countries, there are aromatic rice varieties that are well known for their unique characteristics and flavors that make them have high economic value, such as jasmine rice (Thailand), basmati rice (India/Pakistan), and Japonica rice (Japan) (Verma *et al*., 2019). Likewise in Indonesia, several aromatic rice varieties are quite well known, one of which is Sigupai, a local aromatic which is grown in the South-West region of Aceh Province, Indonesia (Jalil *et al*., 2022). This aromatic rice has superior characteristics including long grains, soft texture, producing a distinctive aroma and taste when cooked, and resistance to drought but also has several weaknesses including low yields, long harvesting time and high plant architecture (Bakhtiar *et al*., 2011). The Sigupai variety is also widely used as a parent plant in plant breeding programs aimed at obtaining superior aromatic rice (Deski *et al*., 2023; Gusmelly *et al*., 2024). Besides the aromatic feature of Sigupai exploited during breeding, breeders employed it for the adaptative characteristics of biotic and abiotic stressors (Hayati & Efendi, 2021), particularly in this era of devasting climatic change. These adaptive features are a plus to this variety to meet Indonesia’s rice sufficiency and food security.

In general, the high economic value of various aromatic rice makes it a target for counterfeiting or adulteration, where lower-quality rice is mixed with or substituted for the authentic aromatic rice. This not only deceives consumers but also undermines the integrity of the agricultural market. To address this challenge, accurate and efficient methods for authenticating aromatic rice are essential. Various approaches have been used to authenticate aromatic rice varieties. These methods include near-infrared (NIR) reflectance spectroscopy (Kim *et al*., 2003; Teye *et al*., 2019; Doan *et al*., 2021), hyperspectral imaging (Edris *et al*., 2024), multispectral imaging (Liu *et al*., 2021), handheld near-infrared spectroscopy combined with electronic nose (e-nose) Aznan *et al*. (2022) etc. Each of these methods has its strengths and limitations, but they all demonstrate the potential for rapid and non-destructive rice authentication. Among these various methods, spectroscopy-based approach, especially NIR spectroscopy, is one of the most widely adopted method. NIR spectroscopy works by measuring the absorption of near-infrared light by the sample, providing a spectral fingerprint that can predict the chemical content or distinguish between different samples based on their chemical composition.

Recent advancements in portable near-infrared (NIR) spectroscopy offer promising solutions for rapid, non-destructive analysis and authentication of agri-food products. The presence of portable devices has brought significant progress regarding the use of NIR spectroscopy technology, especially its use for rapid analysis that can be carried out in loco or directly in the field (Folli *et al*., 2022). Therefore, recently this technology has been being widely adopted. This technology has been applied successfully for authentication or quality assurance of various agri-food products e.g. extra virgin olive oil (Borghi *et al*., 2020), chicken meat (Parastar *et al*., 2020; Rakhmawati *et al*., 2023), milk (Uusitalo *et al*., 2019), online assessment of changes occurring in fresh beef quality (Njume *et al*., 2021). Extensive use of this technology in rice authentication for the last twenty years has been reviewed by Wadood *et al*., (2022). Portable NIR spectrometer devices are also robust to distinct adulteration of powdered rice of various proportion (Teye & Amuah, 2022). Doan *et al*., (2021) used SCiO handheld spectrometer with partial least squares-discriminant analysis (PLS-DA), and soft independent modeling of class analogies (SIMCA) to identify fraud in mixing high quality rice from cheap rice.

There are various commercial portable NIR devices on the market including SCiO, NeoSpectra, Viavi MicroNIR, Felix 750, SCiO, NIRscan, Trinamix, or Linksqure (Sagita *et al*., 2024). In general, those portable NIR devices can be divided into two groups based on their effective operating wavelength, short wave near-infrared (SWNIR) and long wave near-infrared (LWNIR) based devices. This study aims to compare the performance of two portable NIR devices, SCiO and NeoSpectra, for a rapid authentication of Sigupai aromatic rice especially for on-site inspection. These two devices work at different NIR wavelength ranges. The SCiO device works on SWNIR while the NeoSpectra device works on LWNIR. By evaluating their performance in identifying authentic rice from the adulterated samples, it can be used as reference to determine the most reliable tool for field use by farmers, traders, and quality control agencies. The outcomes of this comparison will not only provide insights into the best practices for rice authentication, but also contribute to safeguarding the authenticity of Sigupai rice, thereby protecting both consumers and producers from the adverse effects of adulteration.

2. MATERIAL AND METHOD

2.1. Rice Sample

The Sigupai aromatic rice used in this study was obtained from one of the rice mills in South-West region of Aceh Province, Indonesia. As an adulterant, Inpari rice was used which was obtained from the Public Company of Logistics Agency (Perusahaan Umum Badan Urusan Logistik – Perum Bulog) Aceh. Inpari rice was chosen because this variety has physical characteristics similar to Sigupai rice but with lower quality and a cheaper price. The comparison of visual appearance of Sigupai and Inpari rice is shown in Figure 1.

To get the adulterated rice sample, Inpari rice as the adulterant was intentionally mixed with the authentic Sigupai rice. Before the mixing, all the rice samples were sorted to remove impurities. The level of adulteration (AL) was calculated based on the weight of Sigupai rice (WS) and the weight of Inpari rice as the adulterant (WI) using Eq. (1):

$$AL = \frac{W_I}{(W_S + W_I)} \times 100\% \tag{1}$$

(a) **(b)**

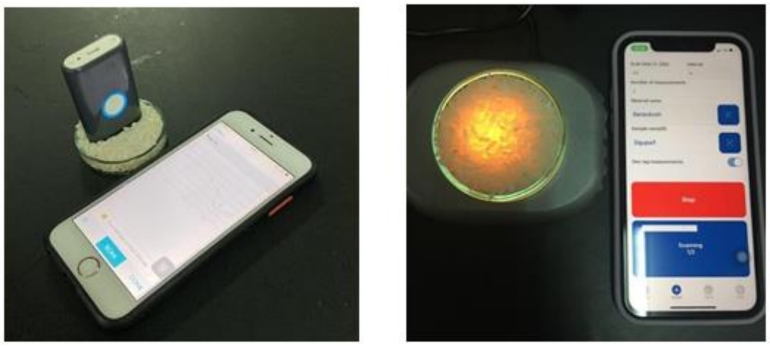
Figure 1. Rice sample: a) Sigupai and b) Inpari rice variety.

In total there were 44 samples of rice mixture with various adulteration level in the range of 0-30% (w/w). These rice mixtures were then used to create two sets of samples. The first data set was used in developing classification model to qualitatively differentiate authentic aromatic rice from adulterated rice. This set included 43 samples of adulterated rice with adulteration levels in the range of 1-30% and 43 samples of authentic Sigupai rice, making a total of 86 samples. The second data set was used in developing a predictive model to quantitatively predict the level of adulteration in a rice sample. In this case, it was 44 samples rice with adulteration levels in the range of 0-30% which have been previously prepared.

2.2. Acquisition of Near-infrared Spectra

In this study, two portable near-infrared devices SCiO (Consumer Physics, San Francisco, USA) and NeoSpectra (Si-Ware, Cairo, Egypt) were used to acquire spectral data of rice samples. SCiO has an effective wavelength of 740-1070 nm with a spectral resolution of 1 nm and NeoSpectra has an effective wavelength of 1350-2550 nm with a spectral resolution of 9 nm. In each spectra measurement, SCiO produces 331 data points, while NeoSpectra produces 257 data points. Each portable spectrometer device is connected to smartphone via Bluetooth and is operated using a special built-in mobile application. To obtain a valid measurement results, the SCiO and NeoSpectra devices need to be calibrated first. Calibration of the device is carried out by pointing the device at the standard white reference provided by the manufacturer and then select the calibration menu on the application. After calibration completed, the device is ready to be used for acquisition of spectral data.

The setup of spectra acquisition is shown in Figure 2. For spectra measurement, 20 g of rice sample was weighted using analytical balance (Mettler Toledo PM 4800, USA) and then it was put on an 80 mm in diameter petri dish creating a pile of rice samples with a thickness of 15 mm. The spectra measurement was carried out three times for each sample and then averaged. The measurements were carried out at room temperature. For each measurement, the



(a) **(b)**

Figure 2. Setup for spectra acquisition of rice sample: a) SCiO and b) NeoSpectra portable spectrometer.

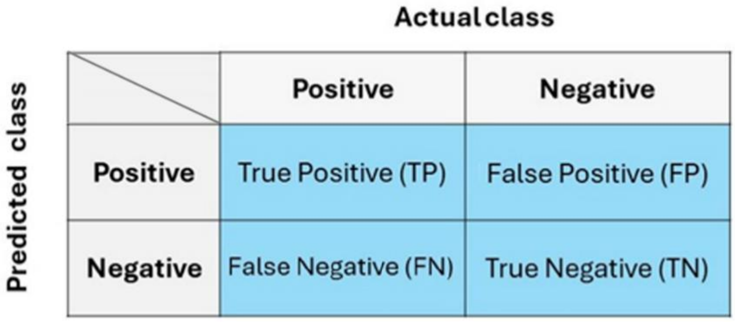
typical scanning time is about 2-5 seconds. The reflectance data is then saved to the cloud and available for download in *.csv format for subsequent analysis.

2.3. Data Analysis

Spectra data of rice sample imported from the cloud were then analyzed using Unscrambler X 10.4 software (CAMO, Oslo, Norway). The analysis carried out using multivariate analysis to develop models for classifying authentic or adulterated rice and determining adulteration levels in rice samples.

2.3.1. Classification Model of Authentic and Adulterated Rice

The first model developed was a classification model for authentic rice and adulterated rice. The analysis was carried out to develop a prediction model based on partial least squares-discriminant analysis (PLS-DA). PLS-DA is a statistical technique commonly used for discriminant analysis and classification in chemometrics. It is a variant of partial least squares-regression (PLS-R) that is specifically designed for classification problems where the dependent variable is categorical (Fordellone *et al*., 2019). PLS-DA is a powerful tool for handling high-dimensional data and is widely used in various fields such as food analysis, medical diagnosis, and forensic science (Lee *et al*., 2018).



Actual class

Predicted class	Positive	Negative
Positive	True Positive (TP)	False Positive (FP)
Negative	False Negative (FN)	True Negative (TN)

Figure 3. Confusion matrix for evaluation of the model performance to predict authentic vs adulterated rice sample.

The model was developed using 86 samples data consisting of 43 samples of authentic rice and 43 samples of adulterated rice with variations in the adulteration level of 1-30%. All data was then divided randomly with a proportion of 2/3 for calibration (58 data) and 1/3 for validation (28 data). During development of the PLS-DA model, the authentic Sigupai rice was assigned as 1 and the adulterated rice was assigned as 0. For the class assignment based on output of the model, a threshold value of 0.5 was applied. The performance of the developed model was then evaluated using confusion matrix (Figure 3) followed by calculation of accuracy, sensitivity, specificity, and false positive rate (FPR) using equation (2)-(5) based on prediction data denoted as True Positive (TP) where authentic Sigupai rice correctly predicted as authentic rice; True Negative (TN) where adulterated rice correctly predicted as adulterated rice; False Positive (FP) where adulterated rice incorrectly predicted as authentic rice; and False Negative (FN) where authentic rice incorrectly predicted as adulterated rice. A predictive model is considered of good quality if accuracy, sensitivity, and specificity are close to 100%, while FPR is close to 0%.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{2}$$

$$Sensitivity = \frac{TP}{TP+FP} \tag{3}$$

$$Specificity = \frac{TP}{TP+FN} \tag{4}$$

$$FPR = \frac{FP}{FP+TN} \tag{5}$$

2.3.2. Predictive Model of the Level of Adulteration

The second model developed was a prediction model of the level of adulteration in a rice sample. The model was developed using data obtained from 44 samples of adulterated rice with variations in the adulteration level of 0-30%. All data was then divided randomly with a proportion of 2/3 for calibration (29 data) and 1/3 for validation (15 data). The analysis was carried out using partial least square regression (PLS-R). PLS-R is a widely used chemometric technique which is applied in spectra data analysis to remove redundancy, making use of variables with the most representative chemical information of the sample. The PLS regression model is developed from a data set when the number of variables exceeds the number of samples by a linear combination of the spectra data and the measured analyst. It operates by first, decomposing the spectra data to obtain the principal components (PCs) of the main variables and the evaluation of the contribution of each PCs to the model (Xie *et al*., 2018). The original spectra data acquired by the SCiO and NeoSpectra portable NIR devices were correlated with the authentic rice and adulterated rice proportions. Apart from original spectra, spectra data that has undergone pre-treatment including smoothing, de-trending, standard normal variate (SNV), multiplicative scatter correction (MSC), and derivatives were also used to obtain the best estimation model. The use of pre-treatment is intended to improve data quality by eliminating scattering effects, noise that occurs during measurements and to enhance the information contained in the spectral data.

Performance of the developed model was then evaluated using three parameters, coefficient of determination (R^2), root mean square error of calibration (RMSEC), root mean square error of prediction (RMSEP), ratio of prediction to deviation (RPD), and consistency. These metrics are determined using equations (6-9), respectively. A predictive model is considered of good quality if R^2 is close to 1 and the RMSE value is close to zero. Williams & Sobering (1996) recommend an RPD values >2.5 and >3.0 for models with a good and excellent prediction accuracy, respectively. Consistency in the range 80-110% is desirable and it indicates there is no underfitting or overfitting with the developed model.

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y}_i)^2} \tag{6}$$

$$RMSE_{C/P} = \sqrt{\frac{\sum_{i=1}^{N} (\hat{y}_i - y_i)^2}{N}} \tag{7}$$

$$RPD = \frac{SD}{RMSE_P} \tag{8}$$

$$Consistency = \frac{RMSE_C}{RMSE_P} \times 100\% \tag{9}$$

where *i* represents index of the data; N represents number of the data; $y_i, \hat{y}_i,$ and $\bar{y}_i$ represent actual value, predicted value, and average value of the *i*-th data; and *SD* represents standard deviation of the data. Furthermore, a limit of detection (*LOD*) analysis was also carried out for the best selected model for each Portable NIR device using the following equation:

$$LOD = \frac{3.3 \times \sigma}{m} \tag{10}$$

where σ represents standard error of blanks which is approximated as intercept of the regression line and and *m* represents slope of the regression line of the calibration dataset.

3. 3. RESULT AND DISCUSSION

3.1. Characteristic of Near-infrared Spectra

Figure 4 shows the acquired rice spectral data using SCiO and NeoSpectra portable spectrometer. Figure 4 shows the absorbance spectra, calculated from reflectance spectra data (R) as log (1/R), of Sigupai and Inpari rice. To observe more clearly the comparison of the two spectra and to avoid bias, both spectra have been pre-treated with baseline shift correction. Based on the figure, both spectra have a quite similar profile with several peaks and valleys at certain wavelengths although they vary in term of intensity. Several absorbance peaks were observed at wavelengths of 926

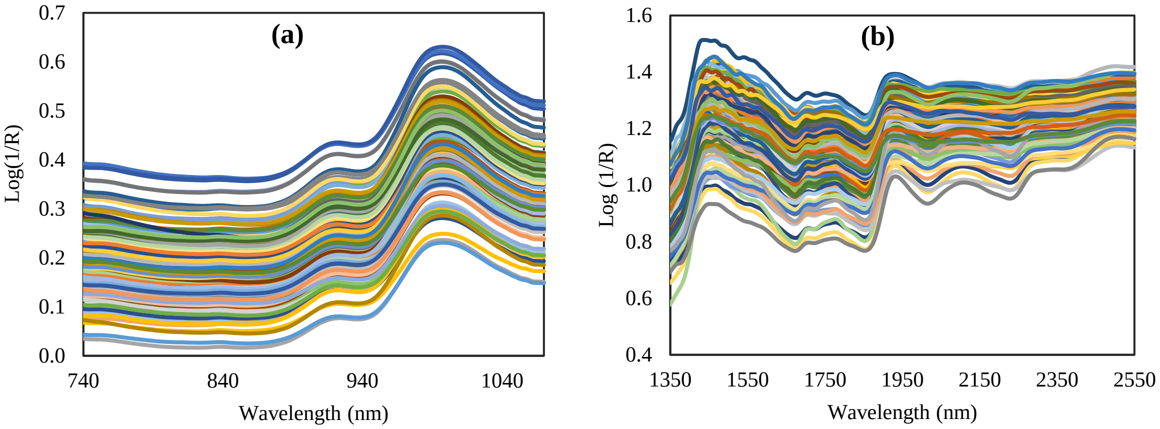


Figure 4. Spectra of rice sample acquired using: a) SCiO, and b) NeoSpectra portable spectrometer.

and 999 nm for the SCiO device; 1472, 1760, 1943, 2100, 2300, and 2515 nm for NeoSpectra devices. These results are similar to the findings in other related studies (Osborne, 2006; Chen *et al*., 2008; Chen *et al*., 2018; Burestan *et al*. 2020) that in rice grain and flour samples there were main absorption peaks and corresponding chemical fingerprints observed at wavelength of 998 nm (the O-H or N-H second overtone), 1457 and 1573 nm (the O-H and N-H first overtone), 1752 nm (the C-H first overtone), 1938 and 2100 nm (the O-H and N-H combinations), and 2295 nm (the C-H combinations).

A similar spectra profile typical to rice measured using SCiO was reported by (Teye & Amuah, 2022), who revealed that the NIR region between 1039-1054, and 1055-1070 nm are C-H bonds and N-H amide bonds of symmetric stretching associated with the combination of starch, amylose, amylopectin, cellulose, and protein in rice. Also, the absorption peak at 2100 nm is used in the rice industry to quantify protein (Liu *et al*., 2014). A similar spectra profile typical to rice measured using NeoSpectra was reported by Liu *et al*. (2020), but the wavelength range (1000-2500 nm) differed slightly with this study (1350-2550 nm). The absorption peak at 1472 and 1943 nm are attributed to the combination of first overtone of O-H and C-H stretching mode of amylose molecules (Sampaio *et al*., 2018; Shinzawa & Mizukado, 2018). The absorption peaks at 2300 and 2515 nm are related to the combinations of C-H stretching and deformation associated with the aleurone layer (carbohydrates) covering the surface of intact rice grain (Tamura *et al*., 2016).

Among other chemical contents, amylose content is one of the ingredients that plays an important role in distinguishing between Sigupai rice and Inpari rice. Sigupai rice has a medium amylose content of 20.92%, while Inpari rice has a low amylose content of 17.54% (Chairunnisak *et al*. 2021). According to Sattari (2015) rice can be classified as having high, low, and medium amylose levels. High amylose levels (>25%) generally produce rice that is dry when cooked and often becomes hard after cooling. Low amylose content (15-20%) produces fluffier and sticky rice. Moderate amylose content (20-25%) produces rice that is fluffier but not sticky, and is widely liked by most consumers.

3.2. Classification Model of Authentic and Adulterated Rice

The first model developed is a model that qualitatively predicts whether a rice sample being analyzed is authentic or adulterated. As mentioned previously, apart from the original spectra data, several pre-treatments were also carried out to remove noise and to enhance the information contained in the spectra data. Figure 5 shows spectra data that has been processed with several pre-treatments. Table 1 shows a summary of the performance of the developed models. Next, the obtained model was validated using another dataset that was not used in the calibration stage. This was done to evaluate the generalization ability of the model developed in analyzing rice authenticity. Validation results are shown in Table 2. Based on all the parameters evaluated, it can be concluded that for both NIR devices the first derivative pre-treatment produces the model with the best performance.

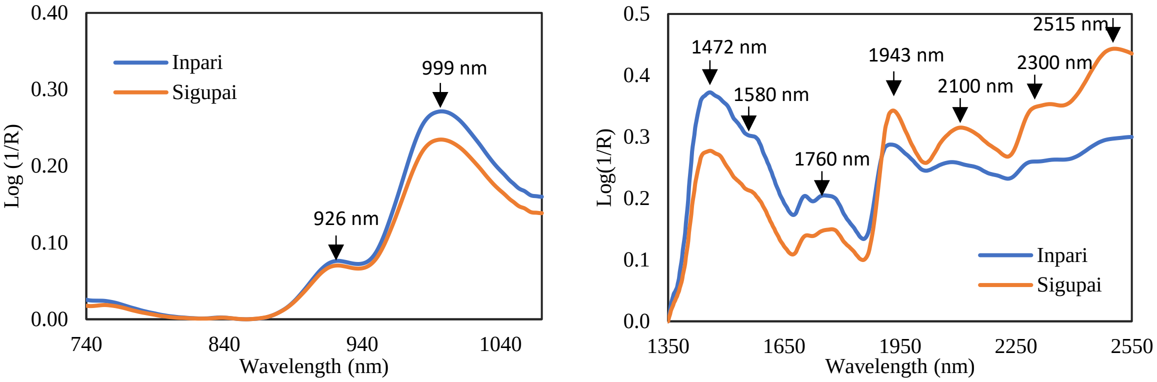


Figure 5. Spectra of Sigupai vs. Inpari rice using: a) SCiO, and b) NeoSpectra portable spectrometer (Note: the spectra were corrected using baseline shift correction).

Table 1. Calibration of predictive models in distinguishing the authentic from adulterated rice sample

Device	Pre-treatment	PLS Factor	Accuracy (%)	Sensitivity (%)	Specificity (%)	FPR (%)
SCiO	Original	10	100.0	100.0	100.0	0.0
	Smoothing SG	10	100.0	100.0	100.0	0.0
	1st Derivative SG	7	100.0	100.0	100.0	0.0
	SNV	10	99.4	100.0	98.9	1.1
	Detrending	9	100.0	100.0	100.0	0.0
	MSC	8	99.4	100.0	98.9	1.1
NeoSpectra	Original	10	100.0	100.0	100.0	0.0
	Smoothing SG	7	100.0	100.0	100.0	0.0
	1st Derivative SG	8	100.0	100.0	100.0	0.0
	SNV	10	99.4	100.0	98.9	1.1
	Detrending	6	100.0	100.0	100.0	0.0
	MSC	13	99.4	100.0	98.9	1.1

Table 2. Validation of predictive models in distinguishing authentic from adulterated rice sample

Device	Pre-treatment	PLS Factor	Accuracy (%)	Sensitivity (%)	Specificity (%)	FPR (%)
SCiO	Original	10	97.4	100.0	94.9	5.1
	Smoothing SG	10	99.4	100.0	94.9	5.1
	1st Derivative SG	7	100.0	100.0	100.0	0.0
	SNV	10	100.0	100.0	100.0	0.0
	Detrending	9	100.0	100.0	100.0	0.0
	MSC	8	100.0	100.0	100.0	0.0
NeoSpectra	Original	10	89.3	92.9	85.7	14.3
	Smoothing SG	7	85.7	78.6	92.9	7.1
	1st Derivative SG	8	89.3	92.9	85.7	14.3
	SNV	10	85.7	85.7	85.7	14.3
	Detrending	6	78.6	64.3	92.9	7.1
	MSC	13	82.1	78.6	85.7	14.3

Table 3. Confusion matrix of prediction performance using the best developed model

Device	Predicted Class	Actual Class		Overall Accuracy (%)
		Authentic	Adulterated	
SCiO	Authentic	14	0	100.0
	Adulterated	0	14	
NeoSpectra	Authentic	13	2	89.3
	Adulterated	1	12	

In more detail, the performance of the best model obtained using first derivative pre-treatment is shown as a confusion matrix (Table 3). Based on the data, both portable NIR devices could detect the authenticity of Sigupai rice with an overall accuracy of 89.3% and 100% for NeoSpectra and SCiO, respectively. Furthermore, in the case of NeoSpectra there were two samples of adulterated rice which were incorrectly predicted as authentic rice. These two data are samples with adulteration levels of 3.80% and 2.0%. Therefore, it can be concluded that NeoSpectra using the PLS-DA method is able to predict the authenticity of Sigupai rice when mixed above 4%, while SCiO is able to predict all adulteration levels from 0-30%.

3.3. Prediction Model of the Level of Adulteration

The second model developed is a model that quantitatively predicts the level of adulteration in an analyzed rice sample. This model is primarily intended for inspection purposes regarding rice quality in the field by relevant agencies as part of consumer protection efforts. Table 4 shows a summary of the prediction model derived from both original spectra data and pre-treated data at the calibration stage. As with the previous analysis, the model obtained was also validated using another dataset that was not used in the calibration stage.

Table 4. Summary of predictive models in estimating level of adulteration of rice sample

Device	Pre-treatment	PLS Factor	R²_cal	R²_val	RMSE$_C$ (%)	RMSE$_P$ (%)	RPD	Consistency (%)
SCiO	Original	9	0.94	0.92	2.10	1.98	4.50	105.84
	Smoothing SG	6	0.88	0.83	3.01	2.97	3.77	101.39
	1st Derivative SG	7	0.98	0.96	1.37	1.31	6.83	104.78
	SNV	8	0.92	0.86	2.50	2.33	3.83	107.18
	Detrending	4	0.94	0.90	2.29	2.32	3.84	98.60
	MSC	8	0.92	0.90	2.49	2.26	3.95	110.21
NeoSpectra	Original	9	0.69	0.59	4.76	4.35	2.06	109.47
	Smoothing SG	11	0.86	0.67	3.67	3.43	2.60	107.06
	1st Derivative SG	9	0.98	0.92	1.52	1.50	5.93	100.69
	SNV	12	0.96	0.86	1.93	1.85	4.83	104.29
	Detrending	4	0.86	0.67	3.10	2.85	2.63	108.77
	MSC	12	0.98	0.94	1.60	1.49	6.00	105.84

In general, most of the models met the criteria as good prediction models. However, the best prediction model for both NIR devices was obtained using pre-treatment first derivative. For the SCiO device, the best model has R², RMSEP, RPD, and consistency of 0.96, 1.31%, 6.83 and 104.8%. Meanwhile, for the NeoSpectra device the values are 0.92, 1.50%, 5.93 and 100.7%. Based on these parameter values, it can be concluded that both devices can be used to predict adulteration levels in rice samples with high accuracy. An RPD value > 3 also indicates that this model is reliable. Apart from that, the consistency value is in the range of 80-110%, which indicates that there is no overfitting or underfitting with the model developed. Figure 6 shows a scatter plot of adulteration levels on predicted samples and actual values based on the best model for each portable NIR device.

From the regression trendline (Figure 7), the limit of detection (LOD) of the developed model also can be calculated using formula (10). The LOD for the SCiO and NeoSpectra are 9.79% and 10.63% respectively. This is maybe one of reasons for the previous classification results where the prediction model for NeoSpectra incorrectly classified rice samples with adulteration levels of 2.0% and 3.8% as authentic rice because these adulteration levels are below the LOD value. However further analysis is needed considering that this is not the case for the SCiO even though both devices have nearly identical LOD values. However, both models have shown a good performance and suitable for practical use considering that in the field the level of adulteration carried out is certainly far above the LOD value. This is because people who commit adulteration certainly expect great benefits from the illegal actions they carry out.

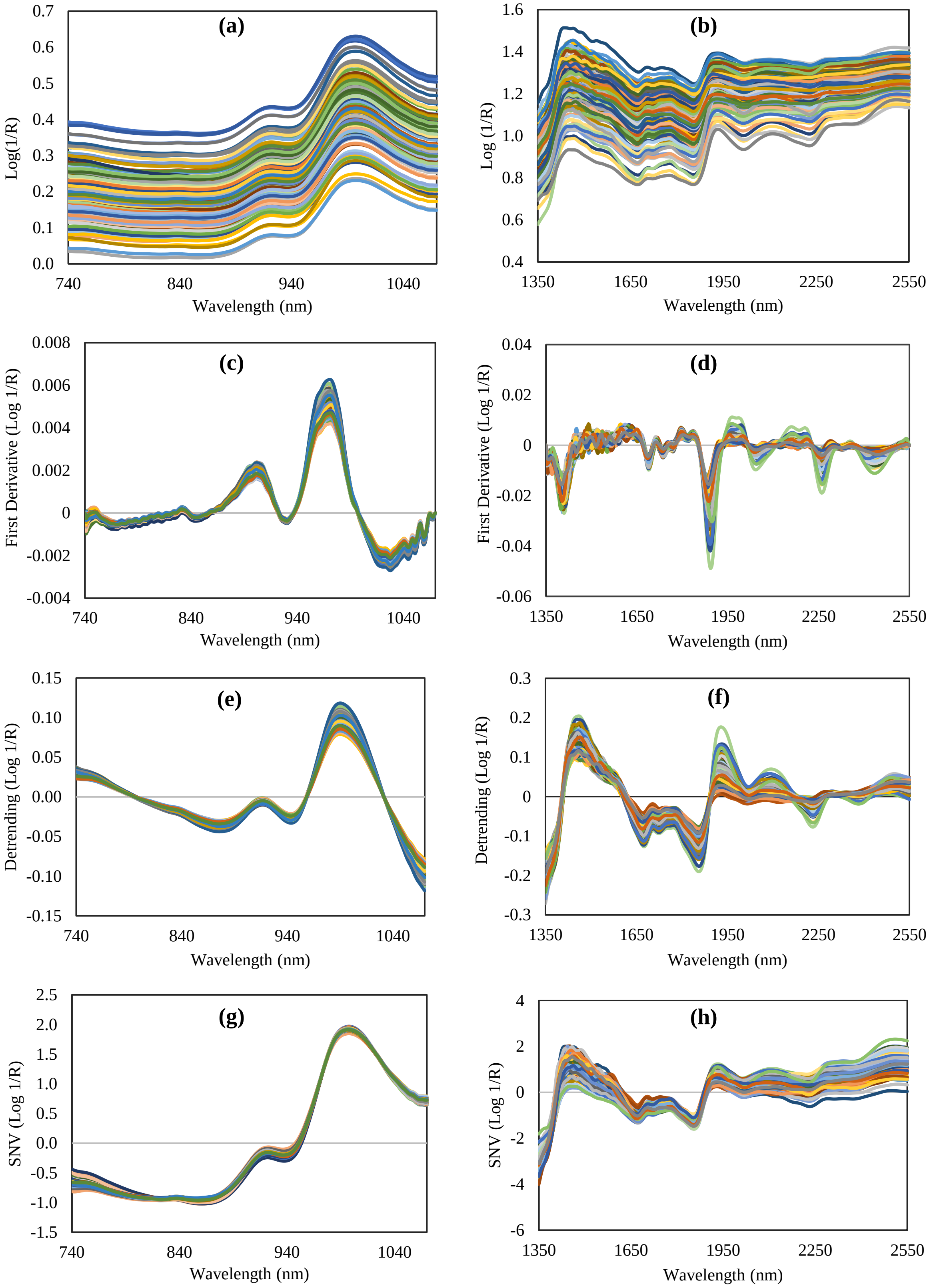


Figure 6. Spectra data processed with various pre-treatments including smoothing, first derivative SG, detrending, and SNV for SCiO (a,c,e,g) and NeoSpectra (b,d,f,h) portable spectrometer.

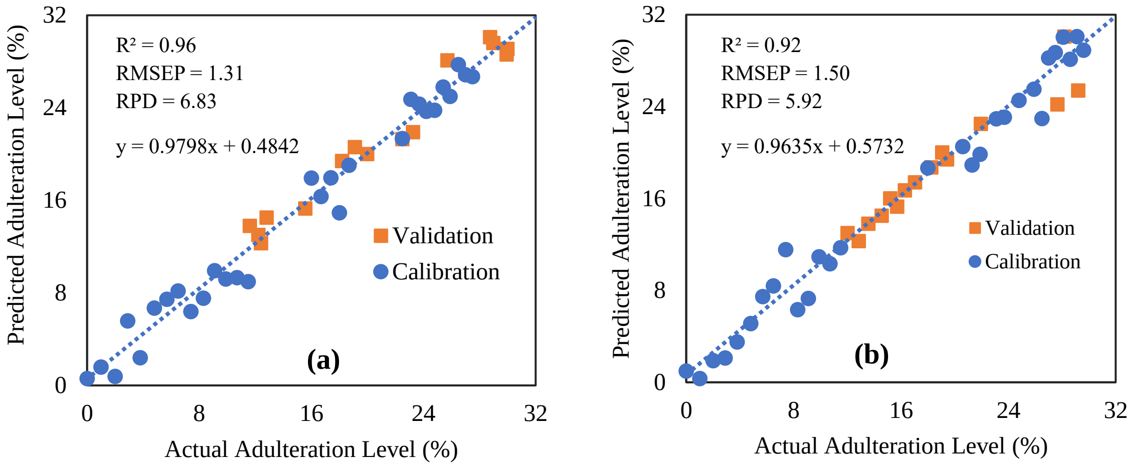


Figure 7. Scatter plot of actual vs predicted adulteration level of rice sampe from the best developed model: a) SCiO, and b) NeoSpectra portable NIR device.

Based on the analysis carried out, it is proven that the two portable NIR devices can be used for the authentication process of Sigupai aromatic rice, both to differentiate qualitatively between authentic or adulterated rice samples, as well as for further analysis related to estimating the level of adulteration. However, the SCiO device shows better performance than the NeoSpectra device. This may be caused by the different characteristic of the two devices. The SCiO operates at SWNIR, while NeoSpectra operates at LWNIR. NIR energy in the SWNIR region has a stronger penetration and a lower heating, in contrast to that in the LWNIR region (Guo *et al*., 2016). Therefore, the light can penetrate deeper and acquire more information about the samples.

The future direction of this research is to integrate the model that has been developed into a mobile application so that it is easy to use especially for on-site inspection by control agencies, farmers, distributors, and sales agents which is beneficial for restoring the trust and confidence level of quality in the supply chain. Apart from that, it is also an interesting opportunity to further explore the use of different chemometrics methods including machine learning that can improve the performance of the predictive model.

4. CONCLUSIONS

This research compares the performance of two commercial portable NIR devices for authenticating Sigupai rice, a local Aceh aromatic rice that has unique characteristics and high economic value. For the qualitative analysis of the authenticity of aromatic rice based on partial least squares-discriminant analysis (PLS-DA), the best estimation model obtained had accuracy, sensitivity, specificity and false positive rates (FPR) at the validation stage of 89.29%, 92.86%, 85.71% and 14.29% for the NeoSpectra device and 97.44%, 100%, 94.87%, and 5.13% for the SCiO device, respectively. For quantitative analysis of estimating the level of aromatic rice adulteration based on partial least squares-regression (PLS-R), the best estimation model obtained has coefficient of determination (R^2), RMSEP, RPD, and consistency values of 0.92, 1.50%, 5.93 and 100.69% for the NeoSpectra device and 0.96, 1.31%, 6.83 and 104.78% for the SCiO device. Both portable near-infrared spectrometer devices, NeoSpectra and SCiO, have the potential to be used as a rapid analysis tool for the authenticity of Sigupai aromatic rice with high accuracy. However, in this study the SCiO device showed a better performance compared to the NeoSpectra device. Further research could be conducted by increasing the sample size and using to validate the application of these devices by actors in the rice supply chain: farmers, traders, and quality control agencies.

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