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Non-destructive Prediction of Brix Value in Sugarcane Based on Portable NIR Spectroscopy

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Abstract

The quality of sugarcane in the plantation is the most important information for farmers and sugar factories for assessing the maturity of sugarcane and determining the optimal harvest schedule. The brix value is used as a quality index in the sugar industry and is an important parameter for the evaluation of cane quality and maturity. Traditional methods of determining brix involve time-consuming and labor-intensive processes, often involving destructive sampling. To overcome these challenges, this study proposes a non-destructive approach using portable near-infrared (NIR) spectroscopy to predict the sugar content in sugarcane stalks. The main objective of this study was to develop a nondestructive prediction model for the brix value in sugarcane using portable NIR spectroscopy. Data processing involved two models: Partial Least Squares (PLS) and an Artificial Neural Network (ANN), along with various data pre-treatment techniques. The PLS model showed an improvement in prediction accuracy with data pre-treatment, especially with the Savitzky-Golay method (R^2 = 0.755, RMSEP = 1.22%, RMSEP = 1.43%, CV = 6.13%, and RPD = 2.02). In addition, the ANN model combined with Principal Component Analysis (PCA) showed high predictive performance when sugarcane was 11 months old (R^2 = 0.797, RMSEC = 0.56%, RMSEP = 0.87%, CV = 3.04%, and RPD = 2.96).

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1. Introduction

Sugar content in sugarcane, which is usually measured in brix or *pol*, is the main parameter that determines the quality and maturity of sugarcane. This brix or *pol* value determines the yield of sugarcane produced (Subiyanto 2023). In general, the mechanism for determining the yield of sugarcane consists of three parts: weighing sugarcane, analysis of samples in the laboratory, and weighing of sugar. Currently, the determination of sugar yield relies on laboratory chemical analysis. Although laboratory analysis provides accurate results compared to human sensory judgment, this method damages the sample, takes a long time, and is expensive (Huck et al., 2005).

Sugarcane productivity in Indonesia currently ranges from 70 to 75 tons/ha with a sugar yield of approximately 7-8%. This productivity is still relatively low compared with the potential productivity

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of sugarcane, which ideally exceeds 100 tons/ha (Magandi & Purwono, 2019). Sugarcane productivity is also influenced by several factors, such as land type, variety, pests, diseases, and age at sugarcane maturity (Wahyuni & Astuti, 2022). The characteristics and quality of the varieties affect the quality of sugarcane juice produced (Sutrisno, 2009). In addition, the quality of sugarcane juice is also influenced by the slash-load-transport mechanism (Khamidatullailiyah et al., 2020), as well as the time of sugarcane milling, especially if there is a delay in milling (Hanka & Santosa, 2021).

Sugar mills require information regarding the brix value before the harvest season to determine the optimal harvest date. To date, the brix value has been determined in the field by taking samples of sugarcane and conducting destructive analysis by collecting sugarcane juice from sugarcane and measuring it using a refractometer. This type of measurement is not only detrimental because it is destructive but also requires special skills to take sugarcane juice samples and read the refractometer. Therefore, it is necessary to develop an alternative method that is both practical and reliable.

Near infrared (NIR) based instruments can be used as an alternative to non-destructive, quick, and accurate measurements of brix values in sugarcane. The use of these instruments can help to optimize the harvest scheduling and general management. The NIR technology has been widely used to determine sugarcane quality (Taira et al., 2013). Many previous studies have analyzed sugarcane juice samples using NIR spectroscopy. Sverzut et al. (1987) reported the potential of spectroscopy evaluation of brix, *pol*, fiber, sugar and moisture content in sugarcane samples.

In recent years, NIR technology has gained popularity for the analysis of chemical contents, including brix, in various agricultural and food products. NIR spectroscopy enables non-destructive analysis of the chemical content of materials. One type of NIR that is often used is the benchtop type, which is commonly used in laboratories and has an effective wavelength in the range of 1000 - 2500 nm. However, the benchtop type has disadvantages, including a large size, relatively expensive price, and operation requiring special skills. Therefore, with advances in electronics and manufacturing, a new model known as handheld or portable NIR spectroscopy has been developed (Widyaningrum et al., 2022). Portable NIR devices, such as SCiO, have emerged as potential tools for nondestructive brix measurements. This device is small and can be easily operated by operators in the field.

This study aimed to develop a nondestructive brix estimation model for sugarcane based on portable NIR spectroscopy and evaluate the performance of the model obtained. Model development was carried out using approaches commonly used in spectral data analysis, namely, partial least square regression (PLSR) and artificial neural networks (ANN). In addition, the most appropriate pre-treatment of the spectral data was analyzed to obtain the best-performing estimation model.

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2. Research Materials and Methods

2.1 Sample Preparation Method

Data were collected directly from plantations owned by PT Rajawali II Unit PG Sindang Laut, Cirebon Regency. Spectrum data were measured for sugarcane with three levels of planting age: 9, 10, and 11 months. Sugarcane samples were determined by selecting sugarcane with as many as 10 stems for each planting age and then measuring the height and diameter of the sugarcane stem. This study aimed to determine the effects of sugarcane height and diameter on the brix capacity of sugarcane stems. Scanning was performed using a portable NIR spectroscopy tool (SCiO) to obtain spectral data. Spectral measurements were performed on three parts of the sugarcane stem (base/bottom, middle, and tip/top), and each part of the sugarcane stem was measured three times. Sugarcane juice was collected, and total soluble solids (TSS) were measured in % brix using a Hanna Instrument HI96804 digital refractometer (Hanna Instrument, Japan) with a measurement accuracy of 0.2 % brix. Spectrum measurements were performed at the same point as the TSS-measured part of the sample. This was performed to maintain consistency of the data. The procedure for measuring the spectrum and TSS is shown in Figure 1.

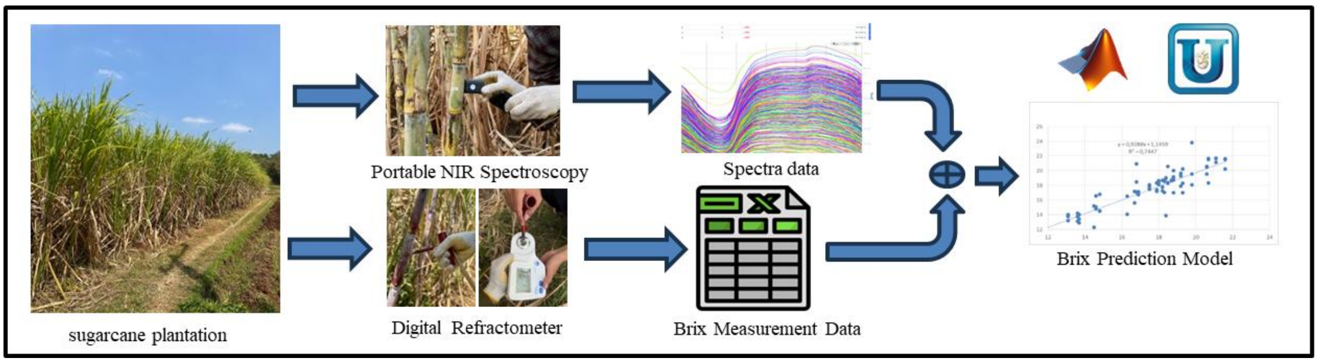

Figure 1. Spectrum measurement procedure using portable NIR spectroscopy and brix measurement using refractometer.

2.2 Data Processing Method

Data processing was conducted with two multivariate analysis approaches, namely Partial Least Square Regression (PLSR) and Principal Component Analysis (PCA) using Unscrambler X software and Artificial Neural Network (ANN) using Matlab software. PLSR is a data dimension reduction technique similar to Principal Component Regression (PCR) that aims to identify the most important factors in predicting and interpreting data. The difference is that PLSR actively incorporates the response variables in the dimensionality reduction process, improving the model's capabilities compared to PCR. PCR focuses on the variation in predictors, whereas PLSR focuses on the covariance between responses and predictors. PLSR works by balancing the information between the predictors and response, thus reducing the influence of irrelevant predictors on the variance of the data. Additionally, the prediction error estimate was improved through a cross-validation process (Hanis, 2008).

The PLS calibration method is a multivariate approach used to estimate the chemical content of a material. In the calibration stage, PLS was used to identify the relationship between the chemical content of the material and the NIR reflectance data. The PCA method is a dimension reduction by projecting the original data into a new space, focusing on maximizing data variation so that most of the information remains in a few key components.

The spectral data were also subjected to a pre-treatment analysis, which is useful for interpreting the NIR spectral data from various special waves that may have influential characteristics. Through pre-treatment, it is possible to obtain estimates that are more accurate than those obtained using the original NIR spectrum data. Pre-treatment also aims to reduce disturbances and interferences that may occur in the measured spectrum data to obtain accurate and stable data. Common methods include normalization, standard normal variate (SNV), Multiplicative Scatter Correction (MSC), de-trending, and Savitzky–Golay smoothing (Ana et al., 2021).

Artificial Neural Network (ANN) is an approach to information processing inspired by the biological nervous system processes information. This technique has a unique information-processing structure that varies for each application. An ANN consists of a large number of information-processing elements called neurons, which are interconnected and work together to solve certain problems, such as classification or prediction. In this study, the Neural Network Fitting Tool provided by MATLAB was used, which is a simple network in which data flows from input to output. MATLAB uses the tansig activation function (tangent sigmoid) with an ANN structure consisting of input, hidden, and output layers. An ANN is a machine-learning method that works on the principle of internal self-adjustment of control parameters and can be used to recognize complex nonlinear relationships between input and output datasets (Fei & Lu, 2018).

2.3 Calibration Modeling and Model Accuracy Evaluation

The brix content was predicted using PLS and ANN models built based on predicted brix data from NIR (Variable X) and reference brix data from a refractometer (Variable Y). The accuracy of the calibration model was evaluated by examining relevant statistical parameters including the Coefficient of Determination (R^2), Root Mean Square Error of Calibration (RMSEC), Root Mean Square Error of Prediction (RMSEP), and Ratio of Prediction to Deviation (RPD). The coefficient of determination is a statistical measure used to evaluate how well a regression model predicts actual data. In the context of linear regression, R^2 describes the ability of the regression model to explain the dependent variable using the independent variables. The R^2 values range from 0 to 1. If the value is

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close to one, the independent variables provide almost all the information needed to predict the dependent variable; otherwise, if the value decreases, the ability of the independent variables to explain the dependent variable is quite limited. Testing for food ingredients can be said to be successful in the range of 95% and above; in the–80-95% range, it can be said to be good; and in the 70-80 range it can be said to be quite good. The coefficient of determination was calculated using Equation 1.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \quad (1)$$

where R²: Coefficient of Determination, with a range of values ranging from 0 to 1, y_i: True value or value of the i data point, $\hat{y}_i$: Model predicted value for the i data point, $\bar{y}$: Average of all true values (y_i) in the data set.

The next step was to determine the Root Mean Square Error (RMSE). RMSE is the difference between the estimated and true values. The RMSE value was considered good if it was close to zero. The next parameter to consider was the Coefficient of Variation (CV). CV shows the magnitude of the error value that occurs compared to the average measurement analysis results in the laboratory (reference data). CV values were calculated using Equation 3.

$$RMSE = \sqrt{\frac{\sum(y_{nirs} - y_{ref})^2}{n}} \quad (2)$$

$$CV = \frac{RMSE}{\underline{y}_{ref}} \times 100\% \quad (3)$$

where yref: Actual TPT content (%brix), ynirs: NIR predicted TPT content (%brix), n: Number of samples.

Another statistical parameter used in the analysis was the ratio of predictive value to deviation (RPD). An RPD value above 1.5 indicates that the accuracy of the resulting model is very good (Rosita et al., 2016). The RPD value was calculated using Equation 4.

$$RPD = \frac{SD}{RMSEP} \quad (4)$$

where SD: Standard Deviation (%brix), RMSEP: Root Mean Square Error of Prediction (%brix).

3. Results and Discussion

3.1 Data Spectrum NIR

Raw or original spectra are the result of taking NIR spectra in the wavelength range 740-1070 nm. The brix reflectance of sugarcane samples was measured between 740 and 1070 nm using portable NIR spectroscopy. Figure 2(a) presents the original reflectance spectra (before pre-treatment) of the

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NIR measurements of the sugarcane. The brix content was characterized at wavelengths of 920-1040 nm based on the original spectra (Lengkey et al., 2020). In this wavelength range, peaks and valleys are observed in the spectrum. These peaks and valleys indicate the presence of chemicals in the materials at certain wavelengths. The absorption of wavelengths by a particular chemical substance can be observed by the appearance of peaks and valleys in the near-infrared (NIR) reflectance curve. The more intense the interaction of NIR waves with the chemical components in the material, the more peaks and valleys formed in the spectrum. The chemical components of the material affected the characteristics of the peaks and valleys in the observed NIR spectrum. The brix spectrum of sugarcane is shown in Figure 2(a).

The spectrum in Figure 2(a) appears to contain outliers. Outliers are usually caused by several factors, such as the use of equipment for a long time, and thus spectrum taking becomes ineffective. Outliers in the brix spectrum of sugarcane can be identified by the shape of the spectrum, which is far from most other data points in a set of data. Spectra containing outliers can be resolved by pretreating the spectral data.

The results of the spectral refinement process with the first derivative Savitzky-Golay (SG) pre-treatment are shown in Figure 2(b). The spectra of brix content in sugarcane after correction with SG form a pattern that looks slim and has a clearer peak than the original spectra, especially for brix content. This is because the first derivative functions as a separator of chemical components that experience overlapping (overlapping) (Lengkey et al. 2020). Another pre-treatment in the form of normalized (NO) is shown in Figure 2(c). The normalized pre-treatment forms a pattern similar to the original spectra, with a smaller value range between the spectra. Normalized pre-treatment serves to reduce the range of reflectance values in the 0-1 range to reduce the effect of differences in sample particle size (Lengkey et al., 2020). The use of Standard Normal Variate (SNV) pre-treatment aims to reduce the influence of wave interference (noise). The SNV pre-treatment succeeded in reducing the scatter effects of the spectrum so that the resulting brix spectrum appeared clearer. As shown in Figure 2 (d), the brix spectrum after SNV pre-treatment appeared denser and cleaner from noise. Multiplicative Scatter Correction (MSC) is used as one of the important initial spectrum testing stages to minimize the multiplicative effects of light scattering. MSC is a transformation method used to compensate for additive and multiplicative effects in spectrum data. MSC works by separating the effects of physical light scattering from chemical light reflectance. The MSC spectrum appears better than the original spectrum because the noise in the raw spectrum is reduced, as shown in Figure 2(e), and the use of de-trending pre-treatment on the data can eliminate the nonlinear trends contained in the spectrum. As shown in Figure 2(f), the de-trending pretreated brix spectrum shows a typical change in the characteristics of the spectrum, with reduced noise that appears denser than the original spectrum.

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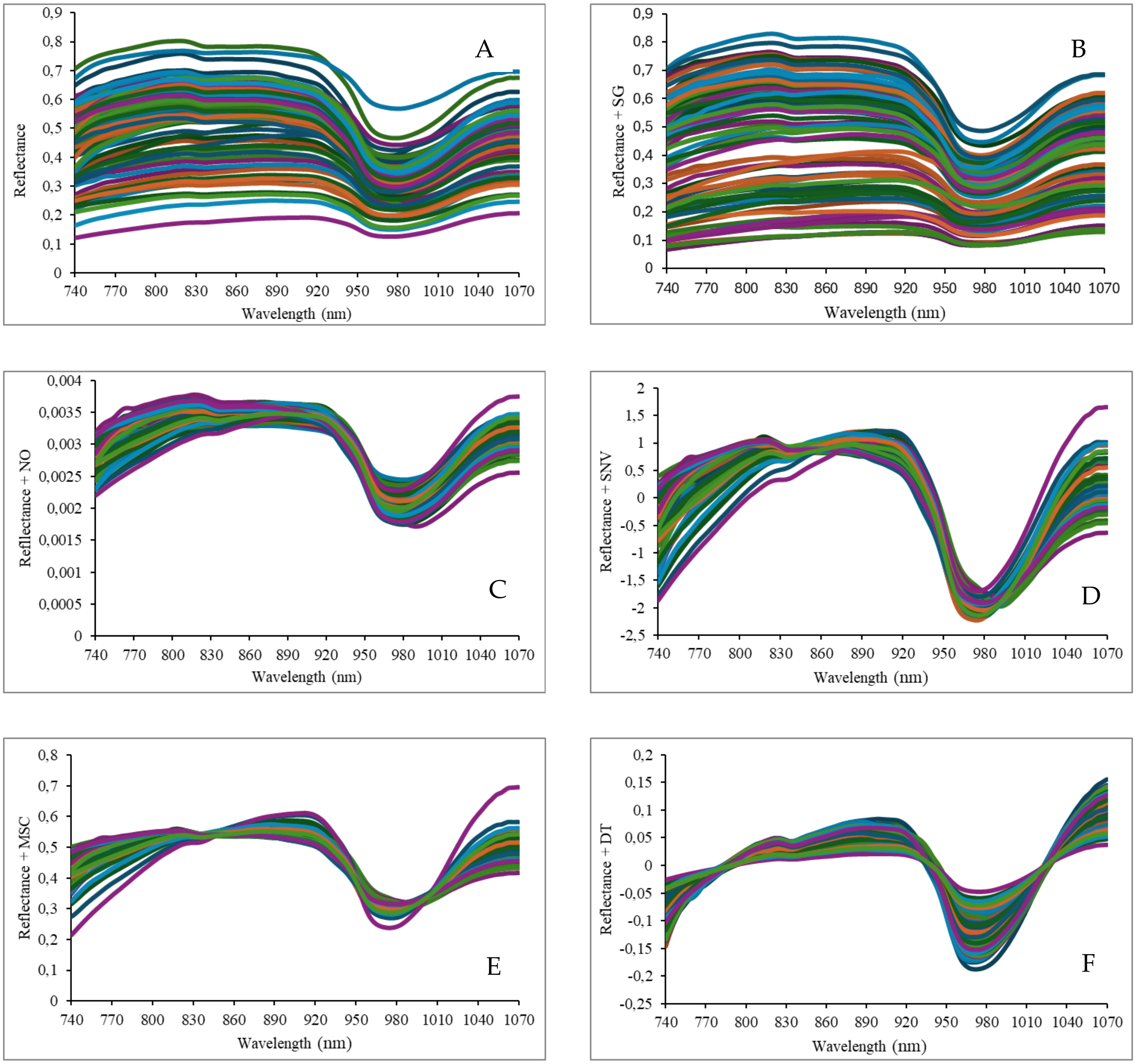

Figure 2. (a) spectrum original (NO); (b) pre-treatment Smoothing Savitzky-Golay (SG); (c) pre-treatment Normalization (NO); (d) pre-treatment Standard Normal Variate (SNV); (e) pre-treatment Multiplicative Scatter Correction (MSC); (f) pre-treatment De-trending.

Table 1. Interpretation results of PLS calibration model development for sugarcane brix content prediction.

PSJT941 Variety	Treatment	Factor	R^2	RMSEC (%brix)	RMSEP (%brix)	CV (%)	RPD
9 months age	Original	7	0.630	2.05	1.99	12.35	1.64
	Normalize	7	0.630	2.05	2.06	12.35	1.64
	SNV	6	0.552	2.25	2.23	13.60	1.49
	MSC	7	0.630	2.05	2.15	12.35	1.64
	DT	7	0.630	2.05	1.57	12.35	1.64
	SG	**8**	**0.657**	**1.97**	**1.94**	**11.89**	**1.71**
10 months age	Original	2	0.732	1.30	1.43	6.53	1.89
	Normalize	2	0.725	1.29	2.96	6.49	1.91
	SNV	2	0.613	1.53	23.25	7.70	1.61
	MSC	2	0.675	1.40	39.28	7.05	1.75
	DT	2	0.721	1.30	1.78	6.53	1.89
	SG	**2**	**0.755**	**1.22**	**1.43**	**6.13**	**2.02**
11 months age	Original	10	0.737	0.71	1.29	3.80	1.95
	Normalize	10	0.711	0.75	1.23	3.99	1.86
	SNV	**11**	**0.768**	**0.67**	**14.87**	**3.57**	**2.07**
	MSC	10	0.737	0.71	1.23	3.80	1.95
	DT	9	0.715	0.74	1.27	3.96	1.89
	SG	10	0.737	0.72	1.30	3.80	1.95

Table 1 explains the PLS results and pre-treatment of the spectrum data from each age of sugarcane planting. At the age of nine months, sugarcane planting data obtained from the original spectrum that had not been resolved using treatment had a Coefficient of Determination (R^2) value of 0.630. According to Karoui et al. (2006), a value of 0.630 shows a poor prediction because only 0.50-0.65 of variable Y can be explained by variable X, the RMSEC value is 2.05%, the RMSEP value is 1.99%, the CV value is 12.35%, and the RPD value is 1.64. After the treatment data on the spectrum of 9-month-old sugarcane, there was no significant increase in the R^2 value, and Savitzky-Golay pre-treatment was the best among the treatments, with an R^2 value of 0.657, RMSEC of 1.97%, RMSEP of 1.94%, CV of 11.98%, and RPD value of 1.71 (Figure 3).

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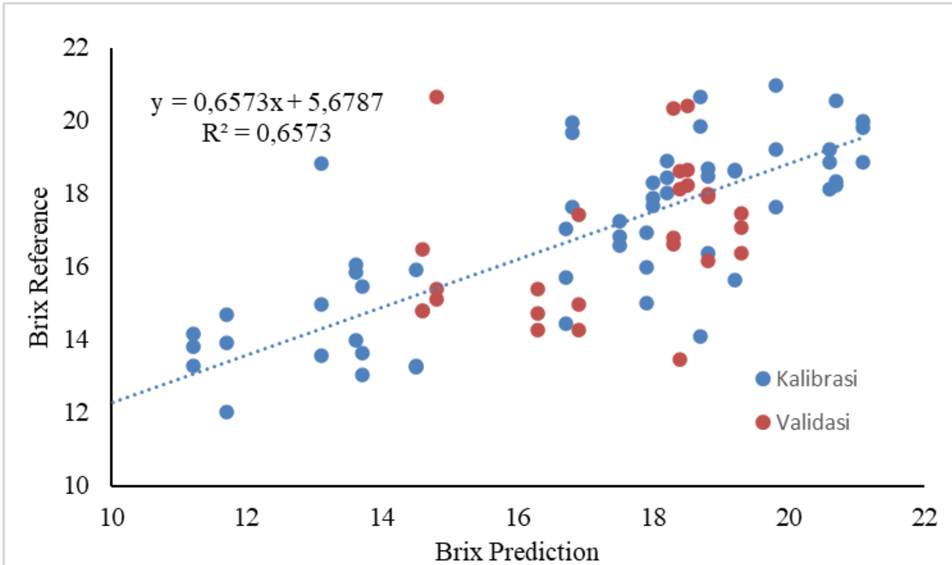

Figure 3. Plot of 9-month-old brix values using Savitzky-golay smoothing treatment.

The coefficient of determination continued to increase as sugarcane grew, and there was an increase in the planting age of the sugarcane. When the sugarcane entered the planting age of 10 months, the R^2 value increased by 0.732 for the original spectrum, and after the Savitzky–Golay smoothing treatment, the R^2 value became 0.755 (Figure 4), which was slightly better than the original spectrum. Savitzky-Golay is a data smoothing technique used in PLS analysis, the purpose of which is to reduce noise and fluctuations in the spectrum or measured chemical data (Chen et al., 2013).

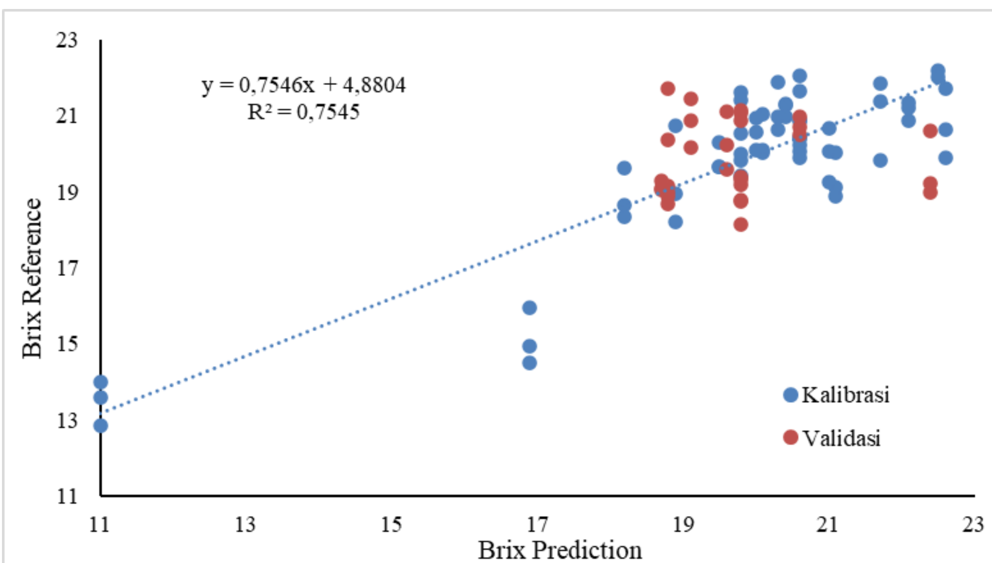

Figure 4. Plot of 10-month-old brix values using Savitzky-Golay smoothing treatment.

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At the planting age of 11 months, the R^2 value increased to 0.737 before the treatment. The best R^2 value was obtained for the SNV treatment, which amounted to 0.768 (Figure 5) with an RMSEC of 0.67%. The SNV is a transformation that eliminates the renewal effect of the spectrum by concentrating and scaling the individual spectra.

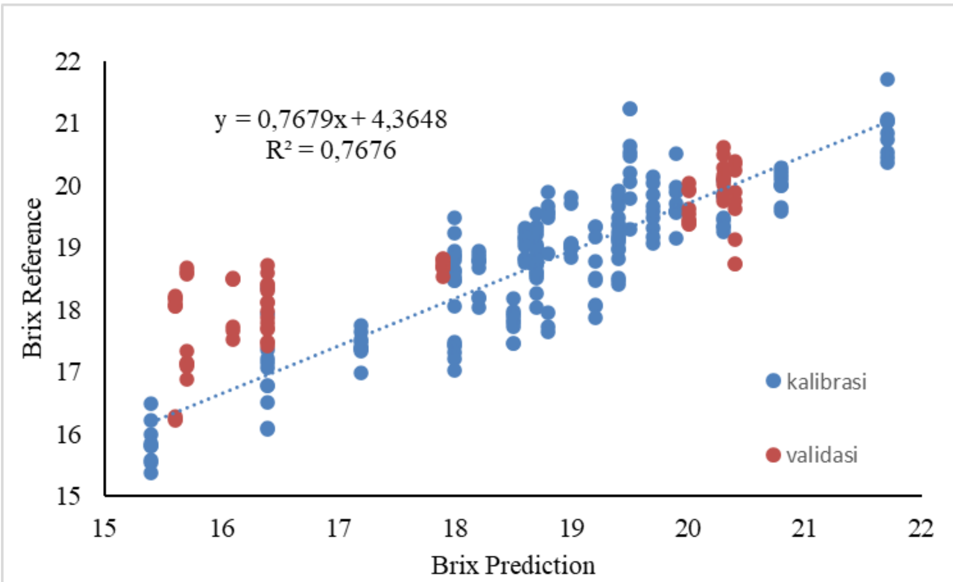

Figure 5. 11-month-old brix values plot using Standard Normal Variate (SNV) treatment.

3.2 Estimation of sugarcane brix content using Artificial Neural Network

An ANN is an information processing method inspired by the manner in which the biological nervous system processes information. The structure of information processing in ANNs is unique, and varies depending on the application. In an ANN, many neurons are interconnected and work together to solve a specific problem such as classification or prediction.

Table 2. Interpretation results of model development using Artificial Neural Network (ANN).

Age	Input ANN	R^2	RMSEC (%brix)	RMSEP (%brix)	CV (%)	RPD
9 months	PCA_SG_9	0.745	1.14	0.99	6.71	2.66
10 months	PCA_SG_10	0.734	0.80	0.75	4.05	2.61
11 months	PCA_SNV_11	0.797	0.56	0.87	3.04	2.96

Based on Table 2, it can be seen that the ANN input uses spectral data from Principal Component Analysis (PCA). In general, this technique is a multivariate interpretation method in which loadings are selected to maximize the explanation of diversity in the variables. The goal of the principal

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components is to explain as much variance in the data as possible through linear combinations, which are found to be mutually independent and lead to the greatest variance.

Table 2 shows the results of spectrum data processing using the Artificial Neural Network model. The R^2 value obtained for sugarcane with a planting age of nine months was 0.745, with an RMSEC value of 1.14%, RMSEP value of 0.99%, CV value of 6.71%, and RPD value of 2.66. According to Safitri (2016), if the R^2 value obtained is close to 1, it is classified as a very strong relationship.

The coefficient of determination R^2 obtained in sugarcane with a planting age of 10 months was 0.734, with an RMSEC value of 0.80%, RMSEP value of 0.75%, CV value of 4.05%, and RPD value of 2.61. The R^2 value increased in sugarcane aged 11 months to 0.797, with an RMSEC value of 0.56%, RMSEP value of 0.87%, CV value of 3.04%, and RPD value of 2.96. According to Nicola et al. (2007), if the obtained RPD value is> 2, it is classified as a good prediction (good performance).

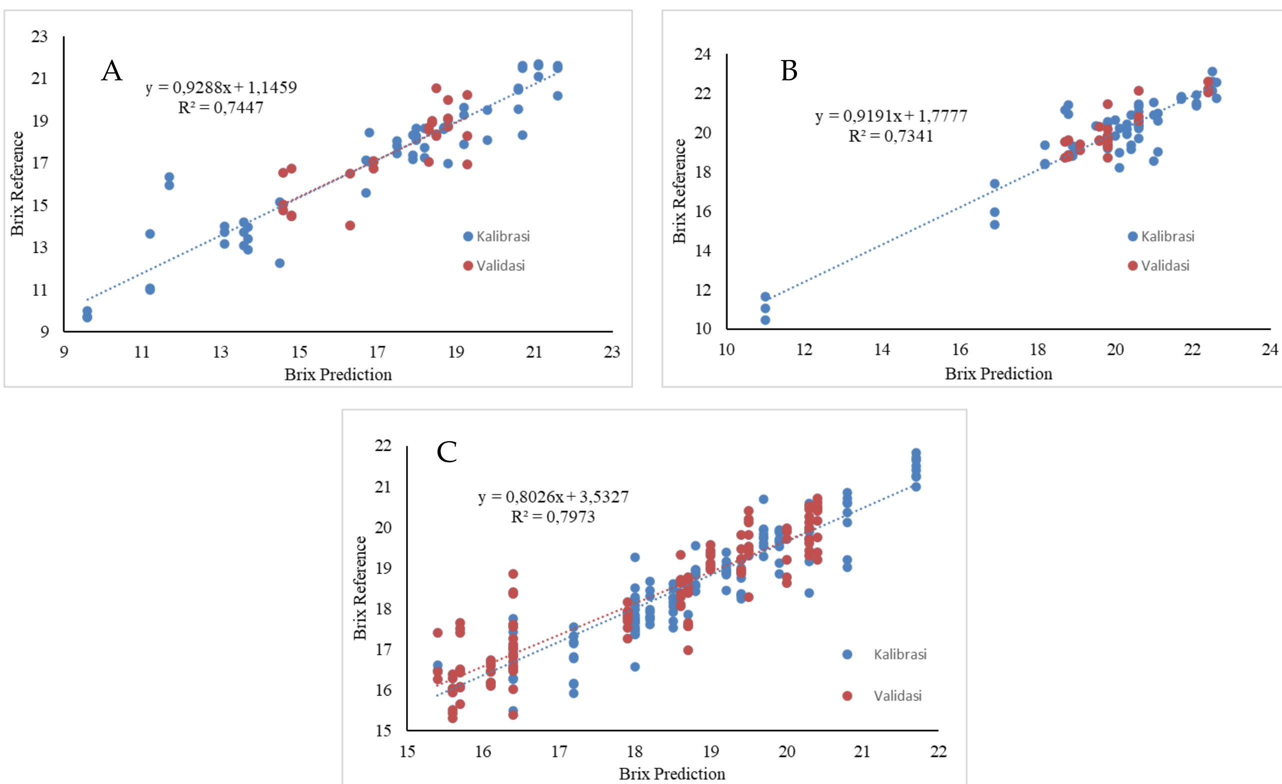

Figure 6. Plot of brix content in sugarcane using Artificial Neural Network (ANN) model; (a) 9 months old; (b) 10 months old; (c) 11 months old.

Figure 6 shows the predicted brix content plot using the PCA-ANN. The high coefficient of determination R^2 obtained for 11-month-old sugarcane was 0.797, the RMSEC value was 0.56%, the RMSEP value was 0.87%, the CV value was 3.04%, and the RPD value was 2.96, indicating that the model could predict the brix content well in sugarcane plants. In accordance with the research of Williams and Sobering (1996), an RPD value >2.40 indicates the good quality of a model.

4. Conclusion

The development of a nondestructive brix estimation model in sugarcane based on portable NIR spectroscopy can predict brix well, and the use of NIR with proper pre-treatment can effectively improve the prediction of brix content in sugarcane stalks. At the age of 9 months, prediction using the original spectrum produced an R^2 value of 0.630 with an RPD value of 1.64, indicating poor prediction. After pre-treatment using the Savitzky-Golay method, the R^2 value increased to 0.675, with an RPD value of 1.71. At the age of 10 months, the R^2 value after pre-treatment with Savitzky-Golay was better than the original spectrum, which was 0.755 with an RPD value of 2.02. The PLS model showed the best R^2 value at 11 months after pre-treatment with SNV, with an R^2 value of 0.768 and an RPD value of 2.07 after pre-treatment with SNV. The ANN model showed better performance than PLS in predicting brix content, and the best model was found at 11 months of sugarcane cultivation with an R^2 value of 0.797 and RPD value of 2.96. Both the PLS and ANN models in this study could be used to accurately predict the brix content.

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