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Rapid Analysis of ICUMSA Value of Cane Sugar Using Multi-Channel Spectra Sensor Based-Portable Device

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Abstract

One of important quality parameters of white crystal cane sugar is its color, which is measured as the ICUMSA value referring to the standard method established by the International Commission for Uniform Methods of Sugar Analysis (ICUMSA). It is usually measured in a laboratory using a complex and lengthy chemical analysis method. To overcome this challenge, this research attempts to explore the potential use of multi-channel spectral sensors in the UV-Vis-NIR region as an alternative method to predict the ICUMSA value. The proposed portable device uses an AS7265X sensor as the main component. The spectra data of 60 cane sugar samples were collected using the proposed device followed by measurements of ICUMSA value in the laboratory using standard methods as reference. The prediction using partial least squares regression (PLSR) model achieved $R^2 = 0.896$, RMSEC = 0.072%, RMSEP = 0.103%, CV = 26.087%, and RPD = 3.104. The multiple linear regression (MLR) model achieved $R^2 = 0.910$, RMSEC = 0.067%, RMSEP = 0.111%, CV = 24.328%, and RPD = 3.328. The artificial neural network (ANN) model achieved $R^2 = 0.999$, RMSEC = 0.004%, RMSEP = 0.037%, CV = 1.433% and RPD = 9.543. This result indicates that the developed PLSR, MLR, and ANN models can predict the ICUMSA value well with ANN as the best model. It also can be concluded that the proposed portable device can be an alternative for rapid analysis of ICUMSA value.

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1. Introduction

The sugar-processing industry plays an important role in providing raw materials for various types of food, beverages, and pharmaceutical products (Nopiyasari, 2016). Therefore, sugar quality control is important for ensuring consumer satisfaction, food safety, compliance with applicable regulations, and building consumer trust. One of the parameters used to measure sugar quality is the color of the sugar solution, known as the ICUMSA value, which refers to the measurement method established by the International Commission for Uniform Methods of Sugar Analysis (ICUMSA). Industrial standards usually require the ICUMSA level of sugar to remain at a certain value. For example, SNI 3140.3:2010 on white crystal sugar (gula kristal putih - GKP) stipulates that for GKP-1,

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the ICUMSA value is in the range of 81-200 IU and GKP-2 is in the range of 201-300 IU (Indonesian National Standardization Agency, 2010).

ICUMSA measurements are generally carried out in the laboratory using several complex and time-consuming chemical procedures; therefore, measurement results cannot be obtained quickly (Ariani, 2018). This can reduce the factory's ability to monitor and control the product quality in real time. There is also another potential loss if the sugar produced does not meet the set quality standards and needs to be reprocessed. Therefore, an alternative method that is faster, more efficient, and reliable for measuring ICUMSA is needed.

Related to this, spectroscopy technology in the ultraviolet, visible, and near-infrared (UV-Vis-NIR) wavelength range can be a promising alternative. This technology utilizes the interaction between electromagnetic waves and the molecular structure of a sample, especially from organic materials (Hadiwijaya et al., 2020). Based on this interaction, the physicochemical characteristics of materials related to product quality can be predicted. The advantages of spectroscopic technology include fast and simultaneous measurement without complicated sample preparation or the use of additional chemicals (Hadiwijaya et al., 2020). In previous research, this technology has also proven to be reliable for estimating ICUMSA values (Wening, 2021). However, this research still uses bench-top-type NIR instruments, which are relatively expensive, quite large, and difficult to use for on-site analysis. Currently, with the development of instrumentation technology, portable NIR instruments have been developed and widely used in various fields (Widyaningrum et al., 2022), including cane sugar quality analysis (Aparatana et al., 2023).

This study aimed to develop an alternative method for predicting ICUMSA values of white crystal sugar using a portable device based on the multi-channel spectral sensor AS7265X. This sensor has a wide spectral data-reading range, covering 18 wavelength channels in the ultraviolet (UV), visible (Vis), and near-infrared (NIR) ranges, enabling the collection of comprehensive spectral information. In a previous study, this sensor successfully detected the addition of cane sugar to granulated coconut sugar (sugar made from coconut tree sap) with high accuracy. This tool could classify pure coconut sugar and coconut sugar mixed with cane sugar with 100% accuracy and identify the concentration level of cane sugar with 96% accuracy (Sulistyo et al., 2023). The proposed system is expected to overcome complex and time-consuming ICUMSA measurements in the laboratory, allowing the sugar industry to measure ICUMSA quickly and efficiently. In addition, by using this developed tool, the sugar industry can monitor the level of sugar purity in real time and take the necessary actions if the ICUMSA value exceeds the set standard.

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2. Materials and Methods

The tool used in this study was a portable multi-channel spectral sensor device (Sagita et al., 2024) modified for sugar spectrum measurement, with the SparkFun Triad Spectrometry AS7265X sensor (Figure 1) covering wavelengths of 410-940 nm. In addition, the proposed system also measured the fluorescence data by using the integrated UV LED as excitation light source and measured the fluorescence emission in the visible region using AS72651 spectrometer, giving six additional spectral data. Summary of the spectral data/channel is listed in Table 1. The SparkFun Triad AS7265X sensor uses multiple single LEDs, namely, a 405 nm LED for ultraviolet spectral analysis, a 5700k white LED that emits visible light spectrum, and an 875 nm LED that emits light in the NIR region (Daurai et al., 2023). A laptop/computer for data processing, Unscrambler X software (CAMO Software, Norway), and MATLAB software (Mathworks, US) were used for spectrum data analysis. The materials used in the study were 60 samples of sugar with various ICUMSA values obtained from PT PG Rajawali II Unit PG Sindang Laut and traditional markets around Bogor. A flowchart of this study is shown in Figure 2.

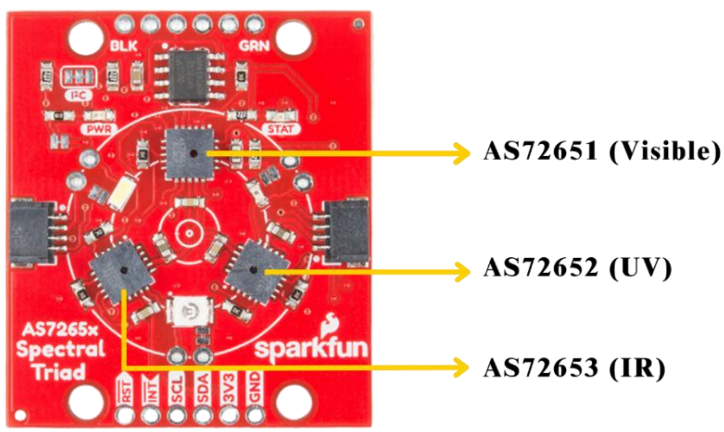

Figure 1. AS7265x chipset with three sensors (UV, Visible, and IR).

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Table 1. The 18 Channel spectral response.

No	Channel	Wavelength (nm)	No	Channel	Wavelength (nm)	No	Channel	Wavelength (nm)
1.	A	410	9.	R	610	17.	K	900
2.	B	435	10.	I	645	18.	L	940
3.	C	460	11.	S	680	19.	F1	405/560
4.	D	485	12.	J	705	20.	F2	405/585
5.	E	510	13.	T	730	21.	F3	405/610
6.	F	535	14.	U	760	22.	F4	405/645
7	G	560	15.	V	810	23.	F5	405/680
8.	H	585	16.	W	860	24	F6	405/705

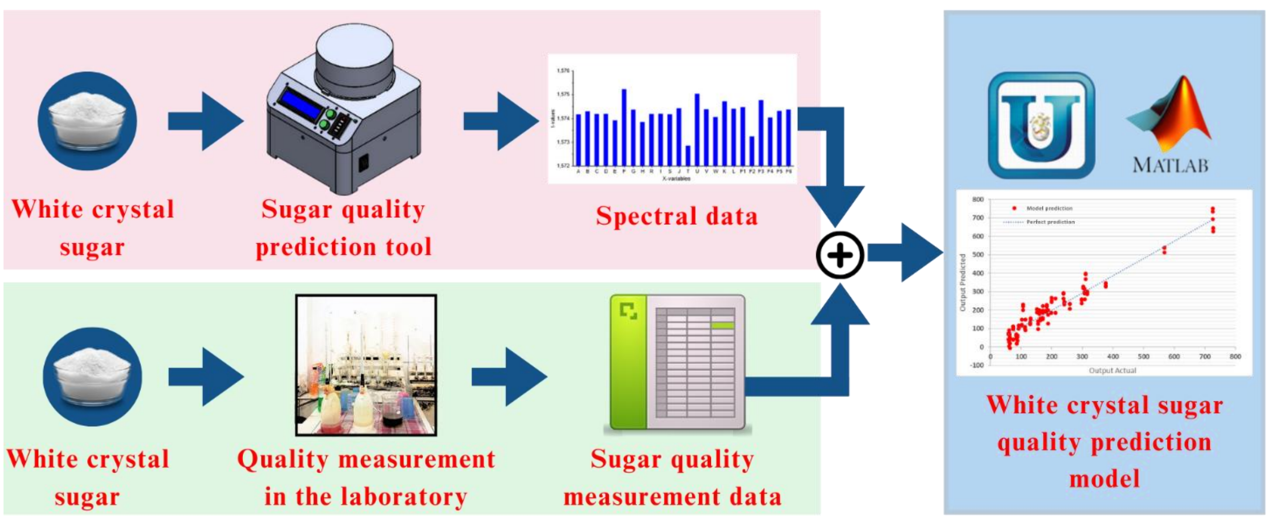

Figure 2. Research flow chart.

2.1 Spectral Data Acquisition

ICUMSA measurements were carried out on 60 cane sugar samples with various ICUMSA values, which were obtained from PT. PG Rajawali II Unit PG. Sindang Laut and traditional markets around Bogor. ICUMSA measurements were made on 40 g of white crystal sugar per sample using a glass petri dish and then analyzed with a portable multichannel spectral sensor connected to Google Sheets to obtain spectral data. The spectral data then can be downloaded for further analysis.

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2.2 ICUMSA Measurement

ICUMSA data reference measurements were performed at the PT PG Rajawali II Unit PG Sindang Laut quality control laboratory using the standard method (Indonesian National Standardization Agency, 2010) by dissolving 50 g of crystal sugar in distilled water or 50 ml of pure water, followed by the addition of 1 g of *Kieselguhr* to remove turbidity. A spectrophotometer with wavelengths of 420 and 560 nm was used to measure the absorbance of the color of the solution (Sari et al., 2024). Subsequently, the solids (g/ml) contained in the solution were calculated based on RDS (%), density, and ρ (kg/m3). The RDS was determined using a refractometer. Then the ICUMSA value is calculated using equation 2.

$$\text{Solids } (c) = \frac{RDS\ x\ \rho}{10^5} \tag{1}$$

$$\text{ICUMSA value (IU)} = \frac{1000\ x\ As}{b\ x\ c} \tag{2}$$

Where:

RDS = relative density scale (%)

As = absorbance

b = cuvette thickness (cm)

2.3 Data Processing Method

At this stage, mathematical models or algorithms were developed to predict the ICUMSA values in cane sugar. These models use light spectrum data measured by a portable device as the basis for prediction. A prediction model is a tool used to understand and predict the relationship between the input data (light spectrum) and the output (ICUMSA value) of sugar samples.

In this study, three prediction models were used for data processing, namely partial least squares regression (PLSR), multiple linear regression (MLR), and artificial neural network (ANN). Based on previous research (Wening, 2021), the development of the PLSR model for NIRS has potential as an alternative method for analyzing the quality of white crystal sugar for *pol*, color, weight loss, and grain size parameters. The use of MLR and ANN models has also been studied to predict ICUMSA values using ash, color, and vacuum temperature as input variables (Erdem, 2022).

The partial least squares regression (PLSR) model is a multivariate statistical approach applied to analyze the relationship between two sets of variables: the independent variable (spectral data) and the dependent variable (ICUMSA value). PLSR aims to identify and exploit the linear relationship between two sets of variables by minimizing the dimensionality of the independent variables, resulting in an efficient prediction model.

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The multiple linear regression (MLR) model is a statistical approach used to quantify the linear relationship between one or more independent variables (spectral data) and the dependent variable (ICUMSA value) (Muhayat et al., 2022). Using MLR, we can identify the extent to which independent variables affect the ICUMSA value and make predictions based on this linear relationship.

Meanwhile, artificial neural network (ANN) is a mathematical model inspired by the structure of human neural networks (Suleman & Palupi, 2023). This model was used to handle the more complex and non-linear relationships between the input and output variables. An ANN involves a training process that allows the network to learn patterns in the data, thus making more accurate predictions.

2.4 Calibration and Prediction

The model performance is determined by looking at several matrices, namely the root mean square error (RMSE), coefficient of determination (R^2), and the residual of predictive of deviation (RPD). This model performance evaluation will help assess the extent to which these models can accurately predict the ICUMSA value of cane sugar.

The root mean square error (RMSE) was used to measure the extent to which the accuracy of a model's forecast results was close to the true value (Aryani et al., 2020). In this study, the RMSE was used to measure the extent to which prediction models such as multiple linear regression (MLR), partial least squares regression (PLSR), and artificial neural network (ANN) approach the true value of ICUMSA values in cane sugar. The lower the RMSE value, the better is the performance of the model in predicting the ICUMSA values accurately. The root mean square error (RMSE) formula is given by Equations 3 and 4:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

$$RMSE\ (\%) = \frac{RMSE}{y_{max}} \times 100\% \tag{4}$$

Where:

$RMSE$ = root mean square error
n = Total number of data points in the data set
$\sum_{i=1}^{n}$ = sum operation from the first data point (*i*=1) to the n data point
y_i = Actual value of the *i*-th data point
$\hat{y}_i$ = Model predicted value for the *i*-th data point
y_{max} = maximum value in data set

The coefficient of determination (R^2) is the ratio of the variability of the modeled values to that of the original data values. In general, R^2 is used as information for the fit of a model (Aulia et al., 2013).

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The predictive models in research such as MLR, PLS, and ANN fit the data and how well they explain variations in ICUMSA values for cane sugar. The higher the R^2, the better the model explains the variation in the data, which indicates that these models may be suitable for use in predicting ICUMSA values for cane sugar. The R^2 formula is shown in Equation 5:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \tag{5}$$

Where:

R^2 = Coefficient of determination, with a range of values ranging from 0 to 1
y_i = True value or value of the i-th 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

RPD (Residual of predictive of deviation) is an evaluation metric used to measure the extent to which prediction models are able to predict ICUMSA values in cane sugar by considering variability or deviation from reference data. The higher the RPD value, the better the model (Wiradinata et al., 2021) for predicting the ICUMSA value by considering the variability in the reference data. The RPD formula is shown in Equation 6:

$$RPD = \frac{SD}{RMSEP} \tag{6}$$

$$SD = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{7}$$

Where:

RPD = residual of predictive of deviation
SD = standard deviation
$RMSEP$ = root mean square error of prediction
n = total number of samples in the study
y_i = true value or value of the-i data point
$\bar{y}$ = average of all true values y_i in the data set

The results of the performance evaluation of the three models will help determine a better and more suitable model to be implemented in a portable device. This method supports the research objective of developing a system that can accurately predict ICUMSA values by using multi-channel spectral sensors. The model with the best performance is the appropriate choice for integration into a portable device.

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3. Results and Discussions

3.1 Spectral Data Samples

Spectral data were obtained from the measurement of cane sugar samples using a multi-channel spectral sensor in the wavelength range of 410–940 nm, for a total of 18 channels in reflectance mode (channels A to L), with an additional six channels in fluorescence mode (channels F1 to F6), as shown in Figure 3. Fluorescence is the emission of light by a substance after it absorbs light or other electromagnetic radiation (Hefniati et al., 2020).

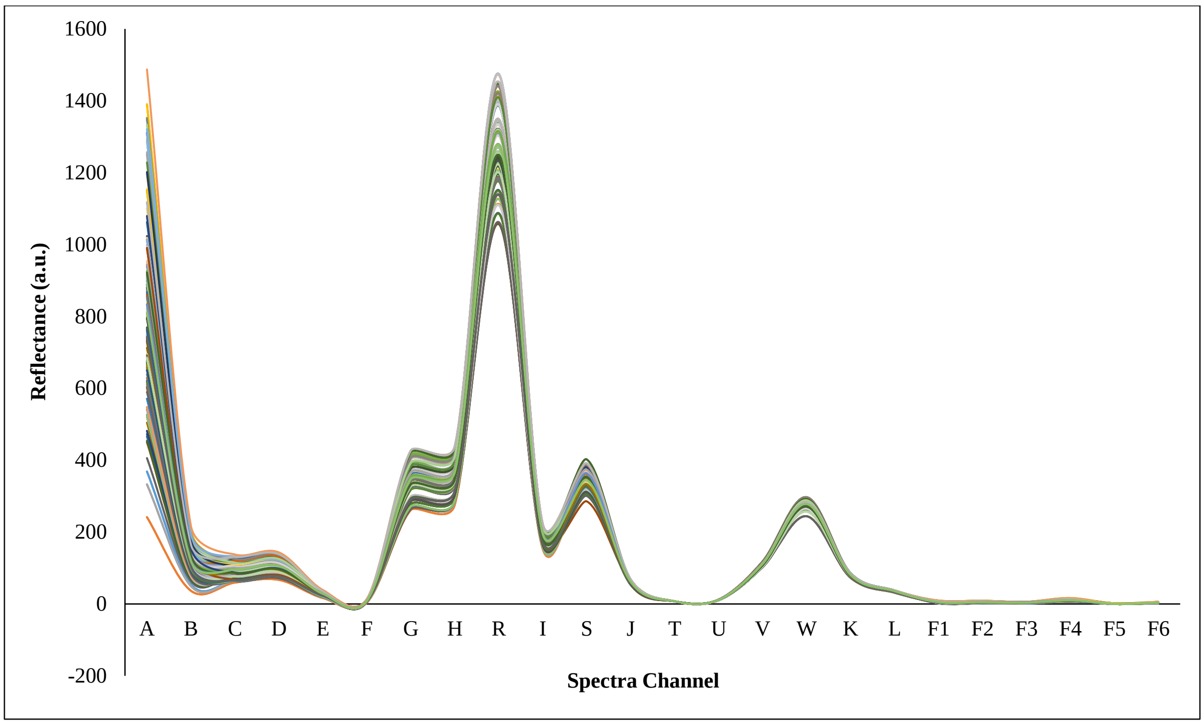

Figure 3. Original spectral data of cane sugar samples.

The valleys formed at several wavelengths indicate the absorption of the dominant chemical compounds contained in the cane sugar. Channels A–F show that reflectance data in the UV region are lower than those of visible light. This indicates that the sugar absorbs more light, usually due to the presence of impurities, pigments, or remnants of organic matter such as molasses. The greater the amount of contamination or dyes in the sugar, the lower the reflectance in this channel. In channels G to J, the visible light (Vis) spectrum has valleys, indicating insignificant light absorption. The color of a product affects its reflectance under visible light. A high reflectance peak at this wavelength indicates a low absorption value, that mainly due to color the cane (i.e., light/white color).

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In channels T to L, which are NIRS channels, there is a decrease in the reflectance (valley). The higher the content of chemical components, such as sucrose, glucose, fructose, or water, the more light is absorbed by the sample and involves a decrease in reflectance. Therefore, the valley in this NIR channel indicates that the sugar sample contained a significant amount of these chemical components. In channels F1 to F6, which are fluorescence channels, there was no significant fluorescence emission at these wavelengths, indicating that the compound was not excited by the UV light.

3.2 ICUMSA Measurement Data in Laboratory

The ICUMSA values describe the cleanliness of sugars. The lower the ICUMSA value, the better the sugar quality and white color (Taufiqi & Aksioma, 2018). Based on the measurement results of 60 sugar samples tested in the laboratory using the standard method, the data diversity shown in Table 2 indicates the differences in the production process and quality of the raw sugar materials. These measurement data were used as reference data to validate the ICUMSA values using a multichannel spectral sensor.

Table 2. ICUMSA Measurement Data from the Laboratory.

Total Sample	ICUMSA value (IU)		Average	Standard Deviation
	Minimum	Maximum		
60	59.03	727.08	204.28	145.72

3.3 Calibration and Predicted ICUMSA Values Results

This study used three analytical methods to develop a prediction model for ICUMSA values in cane sugar, namely, Partial Least Squares Regression (PLSR), Multiple Linear Regression (MLR), and Artificial Neural Network (ANN). Detail of the ANN's hyperparameters are shown in Table 3. Sixty samples were used in this study, with 70% (42 samples) used for calibration and 30% (18 samples) for validation. The ANN model used a more detailed data distribution, with 70% (42 samples) of the data used for training, 15% (9 samples) for validation, and 15% (9 samples) for testing.

Table 4 shows the results of processing spectral data predicting ICUMSA values using PLSR, MLR, and ANN. The PLSR model produced a coefficient of determination (R^2) of 0.896, indicating that the model is quite good at explaining data variability. The root mean square error of calibration (RMSEC) value was 0.072%, and the root mean square error of prediction (RMSEP) was 0.103%, which shows the variation between calibration and prediction. The Coefficient of Variation (CV) was 26.087% and the reciprocal predictive of deviation (RPD) was 3.104, indicating a fairly good model performance,

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and this model also met the standard (RPD>2) (Hernaman et al., 2021). A scatter plot of predicted and actual ICUMSA values from the laboratory tests on the PLSR model is shown in Figure 4.

Table 3. Hyperparameter Artificial Neural Network.

Algorithm	Parameters	Variable
Artificial Neural Network	*Hidden layer*	46
	Activation function	*Sigmoid, linear*
	Training algorithm	*Levenberg-Marquardt (trainml)*
	Learning rate	*Adaptive*
	Epochs	1000
	Data division function	*Dividerand*
	Data division ratio	0.7, 0.15, 0.15

Table 4. Statistical data of ICUMSA value prediction with PLSR, MLR and ANN.

Model	Factor	R^2	RMSEC (%)	RMSEP (%)	CV (%)	RPD
PLSR	9	0.896	0.072	0.103	26.087	3.104
MLR		0.910	0.067	0.111	24.328	3.328
ANN		0.999	0.004	0.037	1.433	9.543

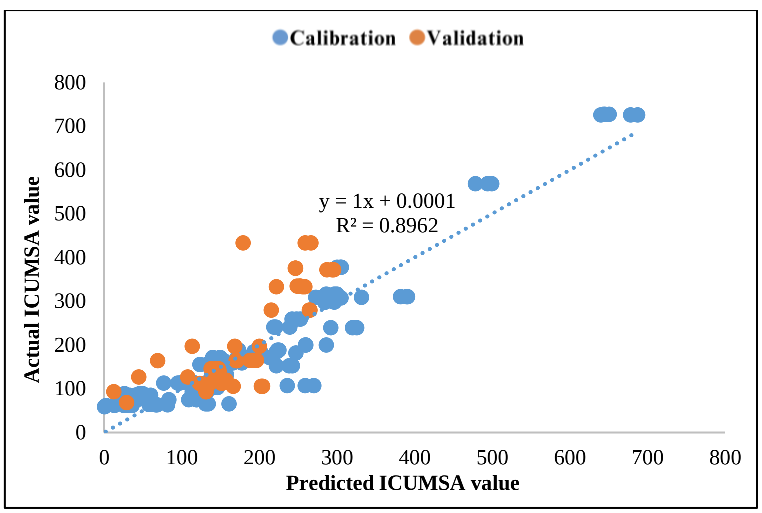

Figure 4. Plot of predicted vs actual ICUMSA value for the PLS model.

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Table 3 shows the results of processing spectral data predicting ICUMSA values with the MLR model (R^2 = 0.910), the MLR model shows a better ability than PLSR in explaining data variability. The data used in this model consist of 24 variables, namely data from 24 channels of the AS7265X sensor consisting of UV, Vis, NIR, and fluorescence channels. The RMSEC and RMSEP values were 0.067% and 1.111 %, respectively, showing variations in calibration and prediction. The CV and RPD values were 24.328% and 3.328 %, respectively, indicating good model performance.

The MLR model showed better performance than the PLSR model. This is because the MLR model provides direct regression coefficients that can be interpreted as the effect of each independent variable on the dependent variable, whereas PLSR uses latent variables, which are linear combinations of independent variables, and requires additional analysis to predict the dependent variable, making interpretation more complex (Irwan & Adam, 2015). A scatter plot of the predicted ICUMSA values and ICUMSA values from the laboratory tests on the MLR model is shown in Figure 5.

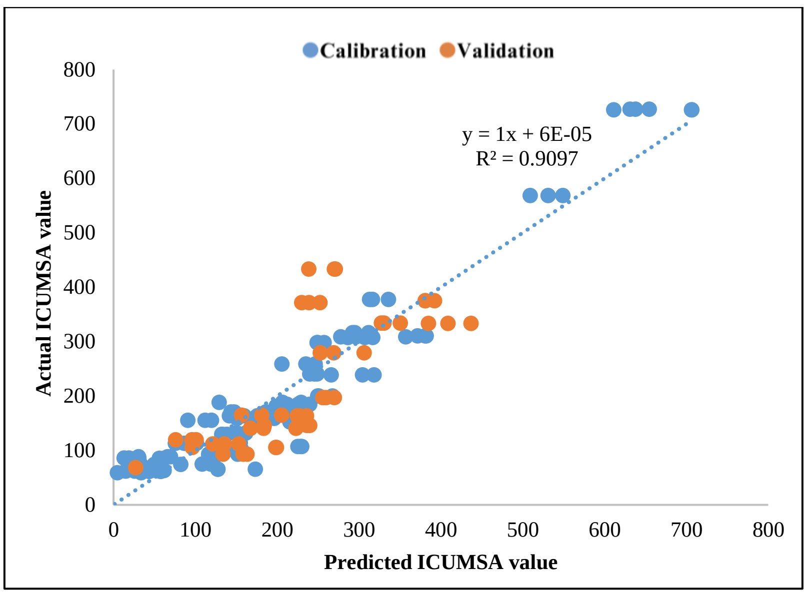

Figure 5. Plot of predicted vs actual ICUMSA value for the MLR model.

Table 3 shows the results of the spectral data processing prediction of ICUMSA values with the ANN model with a very high R^2 value of 0.999, and shows that the model is in good agreement with the observed data. With an RMSEC value of 0.004% and including relatively low, the model had good accuracy in predicting the ICUMSA value in calibration, and the RMSEP value obtained was 0.037%. The low CV value of 1.433% indicated that the model prediction results were consistent. The RPD obtained was 9.543 and included a high value, indicating that the ANN model had excellent predictive ability.

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The ANN models showed better performance than the MLR and PLSR models. This is because ANN has the ability to detect complex non-linear relationship interactions in data (Bhakti, 2019), whereas PLSR and MLR can only model the linear relationships between independent and dependent variables (Erdem, 2022). A scatter plot of the predicted ICUMSA values and ICUMSA values from the laboratory tests on the ANN model is shown in Figure 6.

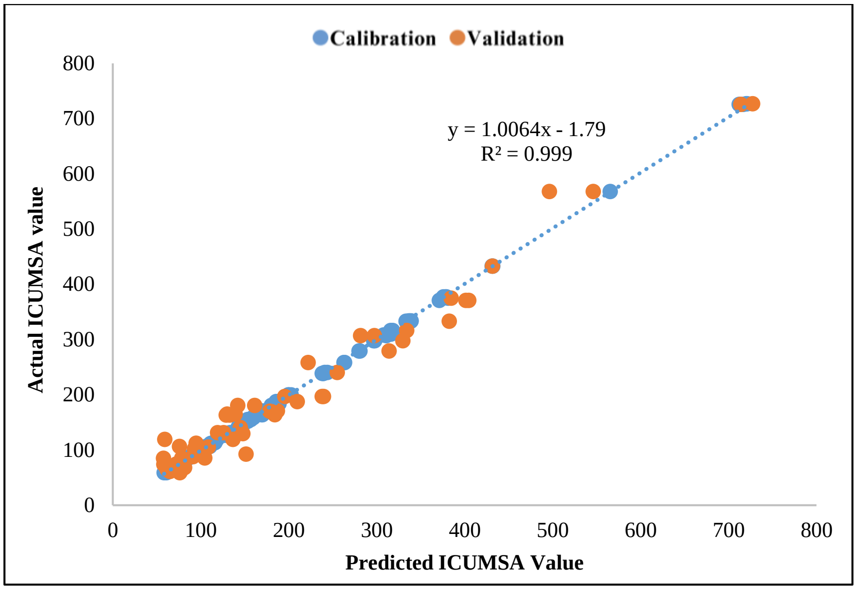

Figure 6. Plot of predicted vs actual ICUMSA value for the ANN model.

4. Conclusion

The color of cane sugar is a key indicator in determining the quality of the final product; to measure this quality, the ICUMSA parameter was used. In this study, an alternative system was developed to predict the ICUMSA value by applying a multichannel spectral sensor. The results showed that multichannel spectral sensors can be used to predict ICUMSA values in crystal sugars. The prediction values with the PLSR model achieved $R^2 = 0.896$, RMSEC = 0.072%, RMSEP = 0.103%, CV = 26.087%, and PRD = 3.104. For MLR prediction, $R^2 = 0.910$, RMSEC = 0.067%, RMSEP = 1.111%, CV = 24.328% and RPD = 3.328. Prediction of ICUMSA value using the ANN model performed better with $R^2 = 0.999$, RMSEC=0.004%, RMSEP=0.07%, CV=1.433%, and RPD = 9.543. Overall, the portable tool developed provides predictions of ICUMSA values with sufficient accuracy, with ANN being the most superior method for accurately predicting ICUMSA values.

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