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# NIR-Based Predictive Modelling for the Quantification of Sucrose, Glucose, and Fructose in Brown Sugar from Oil Palm Trunk Sap

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**ABSTRACT**

*Using oil palm trunk sap as a raw material for brown sugar is an innovative alternative for local product diversification. However, craftsmen's limited access to laboratory analysis methods is challenging to maintain product quality consistency. This study aims to evaluate the feasibility of using near-infrared spectroscopy (NIRS) combined with chemometric modelling for the estimation of sucrose, glucose, and fructose content in brown sugar derived from oil palm trunk sap. This method combines destructive analysis using high-performance liquid chromatography (HPLC) as a reference with non-destructive NIRS analysis and partial least squares regression (PLSR) modelling. The prediction model performed very well for glucose with an $R^2$ of 0.991, while for sucrose it was 0.850 and fructose 0.860. However, the relatively high values of SEC and SEP and the low prediction consistency (<20%) indicate that the current chemometric strategy is not yet fully adequate, suggesting the need for a larger and more process-representative sample set, more rigorous consideration of sample representativeness and laboratory reference uncertainty (SEL), and the inclusion of laboratory reference error (SEL) from HPLC data to enable more robust and reliable model development. These findings indicate that NIRS has potential as a fast and non-destructive method for brown sugar quality control, but further development is needed to make the model more reliable under various production conditions.*

## 1. INTRODUCTION

The production of brown sugar from various vegetable sources has received increasing attention and efforts to diversify raw materials and increase the added value of local commodities (Siswati *et al*., 2022). Brown sugar is an important sweetener in various culinary applications and the food industry (Liu *et al*., 2021). Generally, brown sugar is made from palm sap (*Arenga pinnata*) (Upadhyaya & Sonawane, 2023). Still, utilising oil palm trunk sap (*Elaeis guineensis*) as an alternative is just beginning to be developed (Nurdjanah *et al*., 2024). This innovation opens up opportunities to utilize oil palm trunk waste from 25-year-old trees that are no longer productive in producing oil (Dirkes *et al*., 2021).

The utilisation of oil palm trunks for brown sugar production has been implemented in Pegajahan Village, Serdang Bedagai Regency, North Sumatra. Villagers independently manage the business of making brown sugar from oil palm sap using traditional techniques (Simbolon *et al*., 2021). Although production is quite high, limited access to laboratory facilities and chemical analysis techniques causes craftsmen to rely on subjective experience, so product quality is often inconsistent, making it difficult to expand the market (Sarkar *et al*., 2023).

Measurement of sugar content, such as sucrose, glucose, and fructose, is important to determine the quality of brown sugar (Wardani *et al*., 2020). High-performance liquid chromatography (HPLC) is a commonly used, accurate method (Soyseven *et al*., 2022; Veena *et al*., 2018), but it is costly, time-consuming, and destructive (Deewatthanawong *et al*., 2023). This condition makes the method less efficient for craftsmen in the field. Because of this, an alternative method that is more practical, fast, and non-destructive is needed (Alves *et al*., 2024).

Near-infrared spectroscopy (NIR) is a promising technology for quantitatively analysing various components in food products (Cozzolino, 2021; Johnson *et al*., 2023). Based on the interaction of light with molecules, NIR can identify and quantify sugar components quickly and non-destructively (Cornehl *et al*., 2024). The working principle involves measuring reflected or absorbed light at specific wavelengths, with the spectral results analyzed using statistical models (Vranić *et al*., 2020). The technology is suited to craftsmen as it does not require much sample preparation, although its effectiveness greatly depends on the calibration model's quality (Qiao *et al*., 2023).

The development of predictive models using partial least squares regression (PLSR) is key to interfacing NIR spectral data with the actual content of sucrose, glucose, and fructose (He *et al*., 2022). PLSR establishes linear relationships between independent and dependent variables through latent variables (Liu *et al*., 2022). Predictive modelling requires diverse sample data as well as thorough validation (Maraphum *et al*., 2022) and as a result, is widely applied for NIR-based quality control of food products (Parrenin *et al*., 2024).

Several previous studies have proven the success of NIR in detecting sugar content in foods such as fruits (Borras *et al*., 2022), vegetables (Fodor *et al*., 2024), as well as non-alcoholic beverages, including tea, cocoa and coffee (Makmuang, 2018). However, specific studies on palm trunk brown sugar are still very limited. This suggests a research gap that can be filled by developing an NIR-based oil palm trunk brown sugar method. Thus, this study aims to assess the feasibility and preliminary quantitative capability of near-infrared spectroscopy combined with chemometric modelling for the estimation of sucrose, glucose, and fructose in brown sugar produced from oil palm trunk sap.

## 2. MATERIALS AND METHODS

In this study, brown sugar samples from oil palm trunks were randomly collected from several sugar craftsperson who applied varying treatments, such as differences in tree age and processing methods. These conditions reflect natural variations in the field, and thus the treatments were not experimentally controlled. Each sample was analyzed using both destructive HPLC and non-destructive NIR methods to develop and validate a predictive model capable of estimating sugar content quickly and accurately without damaging the samples (Jaywant *et al*., 2022). A total of 10 brown sugar samples were collected from different traditional sugar craftsperson in Pegajahan Village, Serdang Bedagai Regency, North Sumatra, representing natural variability in raw material sources and traditional processing practices. The number of samples was considered sufficient for a feasibility study aimed at exploring the potential of MicroNIR for sugar quantification, rather than for developing a fully robust and generalizable prediction model. All analyses were conducted at the Food Science and Technology Laboratory, IPB University.

### 2.1. Sample Preparation

Samples of brown sugar were obtained from 10 traditional sugar craftsperson in Pegajahan Village, Pegajahan District, Serdang Bedagai Regency, North Sumatra. Samples used in this study were as many as 10 brown sugar samples from different sugar craftsmen. This brown sugar was produced from the sap of old oil palm trunks (20–25 years old) that have been cut down (Nuryawan *et al*., 2022). Figure 1a shows the trunk of an oil palm tree that has been peeled and is ready to be tapped, while Figure 1b shows a sample of brown sugar from the trunk of an oil palm.

The sap tapping was done by cutting the end of the felled oil palm trunk until the sap drips and is collected in a container. This tapping process was generally carried out in the morning and evening because the quality of sap significantly decreases after it is released. In this study, the farmers used dried jackfruit wood and slaked lime (calcium hydroxide) as traditional preservatives during the tapping process to maintain the sap quality (Ansar *et al*., 2022; Syahidah *et al*., 2023). After that, the sap was cooked in an iron cauldron over a firewood stove until the water content was reduced to thick, concentrated palm sap locally called *juruh* (Putra *et al*., 2024). The *juruh* was cooked on a firewood


Figure 1. (a) Palm trunk and (b) sample of brown sugar

stove until the water content was sufficiently reduced. Although the temperature and cooking time may vary depending on the traditional practices of each sugar maker, generally the cooking process was carried out at 100–120 °C for about 2 to 3 h (Sarkar *et al*., 2023). During the cooking process, white crystal sugar was added to the juruh to enhance sweetness and facilitate crystallization. The *juruh* was then poured into bamboo moulds until it hardened into solid brown sugar. The resulting brown sugar was packed in plastic and wrapped in cardboard to prevent physical damage and maintain humidity during transportation to the laboratory for further analysis.

### 2.2. Instruments and Chemical Materials

This study used laboratory equipment such as a MicroNIR OnSite Spectrometer, equipped with a linear variable filter and a 128-pixel InGaAs photodiode array detector and operating in the wavelength range of 950–1650 nm, and a Reversed-Phase type HPLC system made by Shimadzu (Japan) equipped with a multi-wavelength detector (MWD), a C18 column (15 cm × 4.6 mm, 5 µm), and a 20 µL sample loop. Support equipment included an analytical balance, vortex mixer, water bath, screw-capped test tubes, Whatman filter paper, glass funnel, Erlenmeyer, sample vials, 0.45 µm PVDF membrane, and a syringe for filtration and sample injection into the HPLC. The used materials were standard sucrose, glucose, and fructose (≥99%) from the Laboratory of the Department of Food Science and Technology of IPB University, as well as reagents such as acetonitrile, $H_2SO_4$ solution, ethanol, and aquabidestilata, which were stored at room temperature and protected from direct light.

### 2.3. Sugar Content Analysis using HPLC

Sucrose, glucose, and fructose levels were analysed using HPLC with a modified method based on McCleary & McLoughlin (2023). A total of 2 grams of brown sugar samples were dissolved in 20 mL of 75% ethanol, homogenized using a vortex, and then heated in a water bath at 60°C for 30 minutes to extract the sugar. After cooling, the solution was transferred into a 50 mL volumetric flask and diluted with aquabidest up to the calibration mark, then homogenized again. The solution was filtered through Whatman No.1 filter papers, then filtered with a 0.45 µm syringe filter. 20 µL of filtrate was injected into the HPLC system with a mobile phase of a mixture of acetonitrile and $H_2SO_4$ 4 mM (5:95, v/v) to separate sucrose, glucose, and fructose (Soyseven *et al*., 2023; Sutar *et al*., 2021; Tiwari *et al*., 2023). HPLC analysis data is utilised as a reference in the validation process of the predictive model developed using the NIR method (Mayr *et al*., 2021).

### 2.4. Near-Infrared (NIR) Spectrum

The NIR spectra of brown sugar samples from oil palm trunks were measured using a MicroNIR OnSite Spectrometer, which operates at a wavelength range of 950–1650 nm and is equipped with a 128-pixel InGaAs photodiode array detector. Prior to spectral acquisition, instrument verification and background scan were performed by acquiring a white reference spectrum using a Spectralon™ reflectance standard (approximately 99% diffuse reflectance) and a dark reference spectrum with the internal light source switched off, in accordance with the standard operating procedure of the MicroNIR device. (Gorla *et al*., 2023). Measurements were conducted by positioning the MicroNIR probe perpendicular to the sample surface at room temperature, with the sensor placed in direct contact without applying additional pressure beyond the sensor weight. Near-infrared light was emitted onto the surface, partially absorbed by the chemical components and partially reflected. The reflected signal was captured by the optical system and received by the detector, which recorded vibration frequencies representing the interaction between electromagnetic waves and chemical compounds such as sucrose, glucose, and fructose. The analog signals were then converted into digital form and analyzed using the built-in Software MicroNIR Pro, which also performed initial spectral processing such as signal amplification and noise reduction (Pierre & Wiencek, 2023). Each sample was scanned at two different points, and the spectra were averaged to improve data representativity.

### 2.5. Regression

The prediction model was developed using the partial least squares regression (PLSR) method, which utilised NIR spectrum data and HPLC analysis results as references. PLSR is a data analysis method often used to manage high-dimensional data, especially in NIR spectrum datasets (Silalahi *et al*., 2021). A total of 10 samples were used for calibration model development. Spectral acquisition, spectral pre-processing, chemometric modelling, and regression analysis were performed using MicroNIR Pro software. Prior to model construction, NIR spectra were pre-processed to minimize scattering effects and baseline variability. Standard normal variate (SNV) transformation combined with first derivative preprocessing (Savitzky–Golay) was applied, as commonly recommended for food-related NIR applications to enhance spectral resolution and improve model interpretability. Model performance was evaluated using the coefficient of determination ($R^2$), standard error of calibration (SEC), standard error of prediction (SEP), and prediction consistency. The PLSR model was constructed using seven latent variables (factors), which were selected to minimize the root mean square error of cross-validation (RMSECV). Due to the limited number of samples ($n = 10$), model validation was carried out using leave-one-out cross-validation (LOO-CV), in which each sample was iteratively excluded from the calibration set and used as a validation sample. Consequently, the calibration and validation sets were not fully independent, and this limitation should be considered when interpreting the predictive performance of the model. These statistical parameters were used to assess the feasibility and predictive capability of the developed NIR–PLSR models for estimating sucrose, glucose, and fructose contents in brown sugar samples (Riza *et al*., 2023; Bala *et al*., 2022).

## 3. RESULTS AND DISCUSSION

### 3.1. Analysis of Destructive Test Data

The destructive analysis used the HPLC method to determine the sugar content in oil palm trunk brown sugar, which includes sucrose, glucose, and fructose (Soyseven *et al*., 2022). As shown in Figure 2, the chromatogram results showed a clear performance between these sugar components through the HPLC technique. Each peak on the chromatogram represents the retention time of each sugar type, which is obtained based on the interaction between the molecules in the sample and the stationary phase in the HPLC column (Luo *et al*., 2024).

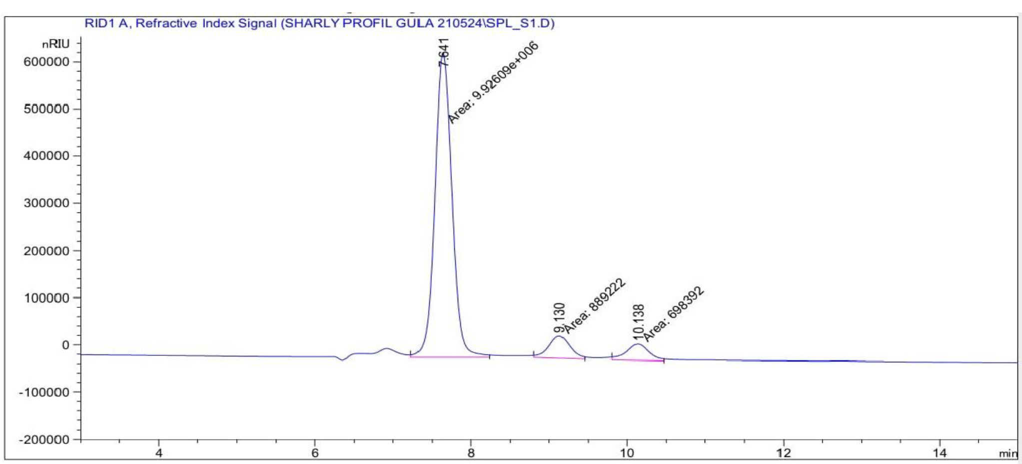


Figure 2. Representative HPLC chromatogram of a brown sugar sample showing the peaks of sucrose, glucose, and fructose

As shown in Figure 2, the first peak indicates the presence of sucrose, which has its own retention time and distinguishes it from glucose and fructose. The next peak depicts glucose, which was successfully separated well, followed by fructose, which forms its peak on the chromatogram (Saad *et al*., 2020). Each peak reflects the specific concentration of sugar contained in the brown sugar sample. In general, the separation results through chromatography show high effectiveness in detecting and identifying types of sugar quantitatively (Rodrigues *et al*., 2021). The separation technique provides detailed information on the sugar composition, which can be used as a basis for the development of sugar content prediction models through the NIRS approach (Larson *et al*., 2023; Nelum *et al*., 2023).

Table 1 shows destructive measurement results for brown sugar from oil palm trunks. Sucrose is the main sugar with an average of 87.08 g/100g (SD 4.85), followed by glucose at 26.75 g/100g (SD 6.26), and fructose at 15.30 g/100g (SD 4.67). According to a study by Alves *et al. (2024)*, sucrose is the primary component of palm sugar. Furthermore, research by Sarkar *et al.* (2023) indicates that the production process of palm sugar can influence the levels of reducing sugars such as glucose and fructose. Variations in sugar content in palm sugar may be affected by factors such as cooking temperature and duration, which can lead to the inversion of sucrose into reducing sugars.

Figure 3a shows the raw spectrum of the palm trunk brown sugar sample, while Figure 3b shows the spectrum that has been pre-treated using the standard normal variate (SNV) method. Applying the SNV technique intends to reduce disturbances such as scale differences and systematic shifts in the data, resulting in more uniform and suitable spectra for further analysis. This process can improve data quality and the accuracy of NIR-based predictive models (Zahir *et al*., 2022). This is supported by previous research, such as Deewatthanawong *et al*. (2023), which demonstrated that the application of first derivative and standard normal variate (SNV) pre-processing can enhance spectral interpretability and reduce scattering effects in near-infrared analysis of chemical components. Sánchez *et al*. (2020) found that the NIRS approach needs data processing, such as first derivative and SNV, to monitor fruit ripeness in real-time effectively. This indicates that similar techniques could be used in the brown sugar industry to continuously monitor product quality without damaging the samples. Therefore, data pre-processing in NIRS analysis not only improves the accuracy of the results but also enables its wide application in the food sector.

HPLC testing of oil palm trunk brown sugar samples provided detailed information on the content of each sugar type. The predicted results compared to reference values are shown in Figures 3c to 3e, representing brown sugar's sucrose, glucose, and fructose content, respectively. The range of sucrose concentrations detected was between 78.14 and 93.92 g/100 g, glucose between 17.14 and 36.03 g/100 g, and fructose between 9.15 and 22.73 g/100 g. The differences in these values also indicate the variation in sugar composition between samples. The variation is because the brown sugar samples were obtained from various artisans, each of whom may apply different production methods. This indicates the influence of several factors, such as the processing method used, the temperature during the cooking process from *juruh* to brown sugar, the additives, and the proportion of the ingredients used (Alves *et al*., 2024).

In Figures 3c and 3b, the sucrose and fructose prediction results exhibit several outliers, which may be attributed to spectral variability caused by sample heterogeneity, surface irregularities, or limitations of the calibration model arising from the small sample size. Meanwhile, in the glucose prediction shown in Figure 3e, the validation points spread far from the ideal line, especially at high concentrations. This pattern indicates that the predictive model has not accurately captured the variation of glucose spectra at that concentration range (Deewatthanawong *et al*., 2023).

The selection of tree age is a key factor in determining the quality and yield of brown sugar produced from palm trunk sap. Trees aged 10 to 20 years typically produce the highest sap volume due to optimal photosynthetic activity and carbohydrate storage (Pradiko *et al*., 2023; Wardani *et al*., 2020). Although sap production declines in older trees above 20 years, utilizing these trunks, commonly removed during replanting programs, remains economically viable. Despite lower sap yields, older trunks can be processed sustainably into value added products such as brown sugar, supporting resource efficiency and waste reduction.

Table 1. Quantitative analysis of sucrose, glucose, and fructose in brown sugar

| Parameter | Number of Sample (*n*) | Mean (g/100g) | Minimum (g/100g) | Maximum (g/100g) | Range (g/100g) | SD |
|---|---|---|---|---|---|---|
| Sucrose | 10 | 87.0767 | 78.1446 | 93.9288 | 78.1446 – 93.9288 | 4.8494 |
| Glucose | 10 | 26.7453 | 17.1423 | 36.0369 | 17.1423 – 36.0369 | 6.2567 |
| Fructose | 10 | 15.2952 | 9.1552 | 22.7362 | 9.1552 – 22.7362 | 4.6688 |

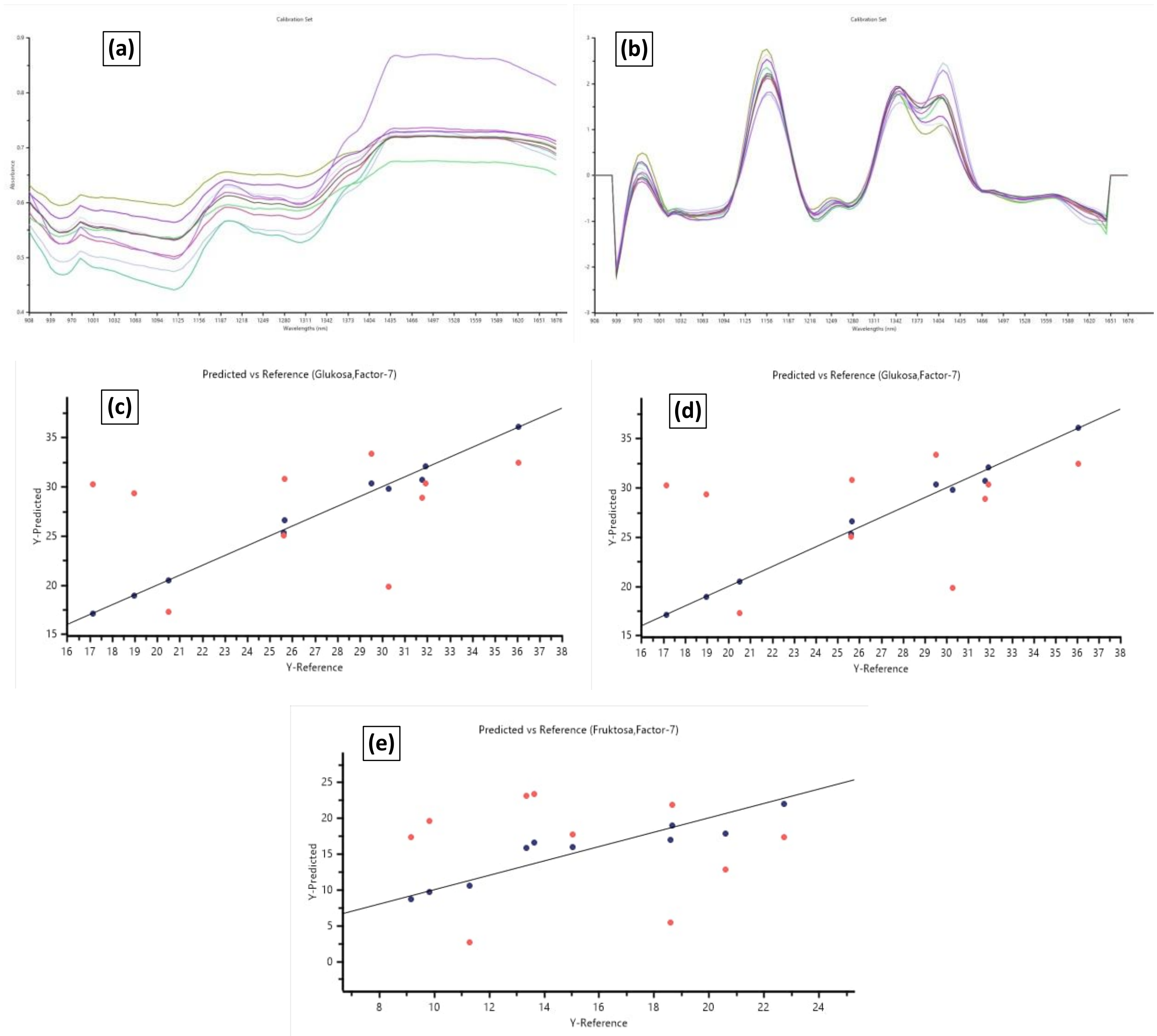


Figure 3. (a) NIR spectrum of brown sugar sample, (b) pre-processed data SNV & first derivative , (c) prediction and reference plot of sucrose, (d) glucose, and (e) fructose

Based on the research results, the analysis of sugar content in brown sugar from oil palm stems using the HPLC method is used as reference data in building a prediction model for sap analysis using NIRS (Sringarm *et al*., 2022). The comparison between the destructive analysis results and the NIRS data showed a fairly high agreement, as illustrated in Figure 3. The graph displays the relationship between the reference and predicted values, which shows the similarity of the results from both approaches. This indicates that the NIRS technique has promising potential as a predictive tool for determining sucrose, glucose, and fructose levels in oil palm trunk brown sugar. Although NIRS is a faster and more practical non-destructive analytical method, its accuracy is comparable to the HPLC method. With efficiency and ease of operation, NIRS can be a reliable alternative for sugar content analysis without significantly compromising accuracy (Solihin *et al*., 2024).

### 3.2. Analysis of NIRS Data Processing Using PLSR

PLS is an iterative estimation process utilizing the variance relationship between independent and dependent variables. The main goal of PLS is to construct several components that can capture important information from the independent variables to predict the response variable (Liu *et al*., 2022). In the analysis of NIRS data, pre-treatment using standard normal variate (SNV) is carried out to improve the accuracy and stability of the calibration results, considering that the resulting spectrum still contains interference or noise (Zahir *et al*., 2022). An ideal NIRS calibration model is characterized by $R^2$ value close to 1, as well as low SEP and SEC values close to zero, with consistency of results between 80 to 110% (Heil & Schmidhalter, 2021). The success of optimal calibration is strongly influenced by selecting appropriate pre-treatment methods and the number of samples that adequately represent the population (Daba *et al*., 2022).

The results obtained in Table 3 show the development of Partial least squares regression (PLSR) models to predict sucrose, glucose, and fructose levels in oil palm trunk brown sugar samples. This method constructs a calibration model that displays spectral information with results from a reference method while identifying the largest variations present in both types of data (Lackey *et al*., 2023). Processing the sucrose, glucose, and fructose data by a factor of 7 resulted in $R^2$ values of 0.850, 0.991, and 0.860, respectively. Concerning oil palm trunk sap samples, NIRS predictions accounted for the $R^2$ values contributions, which sucrose, glucose, and fructose valued at 85%, 99.1%, and 86%, respectively. This is supported by research from Prasetyo *et al.* (2024), obtaining coefficient of determination results that reached $R2 > 0.8$ for the prediction of sugar content in cocoa beans. These results highlight the high predictive accuracy of the PLS method, especially for glucose with an almost perfect $R^2$ value, indicating that the model is very effective in capturing data variation (Fu *et al*., 2023). However, for sucrose and fructose, the obtained $R^2$ values suggest that the current calibration is still preliminary and would benefit from further refinement, such as expanding the sample set to better represent process variability and systematically evaluating alternative spectral pre-processing strategies to enhance model robustness rather than merely increasing predictive accuracy. In addition, consideration of the laboratory reference error (SEL) from HPLC measurements is necessary to properly interpret model performance and avoid overestimation of predictive capability. This is because the availability of extensive baseline data is essential for developing robust and accurate NIR predictions (Parrini *et al*., 2018). In addition, variation is also related to each artisan's production practices, which are tailored to market demand and consumer characteristics (Alves *et al*., 2024).

Table 3. Results of data processing for sucrose, glucose, and fructose using the PLSR method

| **Parameter** | ***n*** | **Factor** | **Calibration** | | | **Validation** | | **Consistency (%)** |
|---|---|---|---|---|---|---|---|---|
| | | | **$R^2$** | **SEC** | **RMSEC** | **SEP** | **RMSECV** | |
| Sucrose | 10 | 7 | 0.850 | 1.874 | 1.778 | 14.445 | 13.705 | 0.13 |
| Glucose | 10 | 7 | 0.991 | 0.584 | 0.554 | 7.1025 | 6.812 | 0.08 |
| Fructose | 10 | 7 | 0.860 | 1.741 | 1.652 | 8.823 | 8.408 | 0.20 |

Notes: n: sample; $R^2$: Coefficient of determination; SEC: Standard Error of Calibration; SEP: Standard Error of Prediction; RMSEC: Root Mean Square Error Calibration; RMSECV: Root Mean Square Error Cross Validation; Consistency (%) = RMSEC/RMSECV: lower values indicate overfitting, while values closer to 1 indicate model stability.

Meanwhile, the SEC and SEP values are relatively high for each sucrose, glucose, and fructose parameter. The SEC values for sucrose, glucose, and fructose were 1.874, 0.584, and 1.741, respectively, while the SEP values were 14.445, 7.1025, and 8.823. This high error can be caused by sample heterogeneity, brown sugar texture variations, or environmental factors during NIRS spectral acquisition, such as ambient temperature fluctuation (Sadergaski *et al*., 2023; Sánchez *et al*., 2020). However, the influence of ambient temperature fluctuation is mitigated in the MicroNIR through a built-in Temperature Baseline Normalization (TBN) feature, which is designed to maintain spectral stability within the rated operating range of 0–40 °C when the default integration time is applied (VIAVI Solutions Inc., 2023). The noticeably lower SEC values compared to the much higher SEP values indicate that the developed PLSR models are likely affected by overfitting, a common issue when calibration models are developed using a limited number of samples and validated through cross-validation rather than independent test sets. Under such conditions, the model may fit the calibration data well but exhibit reduced predictive capability during validation. In addition, high SEP values indicate overfitting, where the model is too specific to the calibration data and less able to predict new data accurately, especially for the sucrose parameter as a component of the NIRS spectrum. Especially in the sucrose parameter as the dominant component, the sucrose spectrum has the potential to experience saturation due to strong O-

H bonds, thus reducing detection sensitivity (Beć *et al*., 2020). This corroborates Amankwaah *et al*. (2024), who developed an NIRS calibration curve for sugar concentration in roasted sweet potato and noted that sample uniformity and texture non-uniformity can affect the calibration model accuracy.

Using the given values of SEC and SEP for sucrose, glucose, and fructose parameters, a consistency calculation was conducted relative to the percentage of SEC and SEP. The results demonstrate a remarkably low consistency value of 13%, 8%, and 20%, indicating that this model is likely forecasting using a very weak relationship among the parameters, thus making it unreliable and lacking trustworthiness. This condition is most likely caused by the limited number of calibration samples, which impacts the model's generalization ability. This is supported by the findings of Li *et al*. (2022), who explained that an insufficient number of samples can increase the risk of overfitting and reduce the accuracy of predictions against new data. Furthermore, Gariglio *et al*. (2024) also emphasized that a small gap between RMSEC and RMSECV signifies stability and low overfitting risk, while a bigger gap may reflect some form of overfitting or underfitting. Thus, augmenting the quantity and variety of samples and applying more refined spectrum preprocessing techniques is fundamental to enhancing the reliability and consistency of the predictive models (Daba *et al*., 2022).

## 4. CONCLUSION

This study evaluated the feasibility of using near-infrared spectroscopy (NIRS) combined with PLSR to estimate sucrose, glucose, and fructose content in brown sugar derived from oil palm trunk sap. The model was built using PLSR concerning HPLC analysis results. Results showed excellent performance for glucose ($R^2$ = 0.991) and fair performance for sucrose (0.850) and fructose (0.860), demonstrating the potential of NIR as a rapid and non-destructive method for quality control in the field. However, the high SEC and SEP values and prediction consistency below 20% indicate that the model is not yet stable and still prone to overfitting due to the limited number of samples.

This research offers a practical solution for sugar artisans constrained by laboratory access, with NIRS enabling direct analysis in the field. However, further development is needed, such as increasing sample variation and optimizing spectrum pre-treatment to improve model accuracy and reliability. Exploration of the influence of production processes and environmental factors on the sugar profile is also important to make the predictive model more representative. The findings demonstrate the potential of MicroNIR as a rapid and non-destructive analytical tool, which can be further developed into a robust predictive model through the inclusion of a larger and more diverse sample set in future studies.

## AUTHOR CONTRIBUTION STATEMENT

| Author | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| SCAS | ✓ | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | | |
| DH | ✓ | ✓ | | ✓ | | | ✓ | | | ✓ | ✓ | ✓ | ✓ | ✓ |
| FSB | ✓ | ✓ | | ✓ | | | | | | ✓ | | ✓ | | |
| YWS | | | | ✓ | | | | | | ✓ | | ✓ | ✓ | ✓ |
| IAI | | ✓ | ✓ | ✓ | ✓ | | | ✓ | | ✓ | ✓ | | | |
| NR | | | ✓ | ✓ | | | | | | ✓ | ✓ | | | |

C: Conceptualisation
M: Methodology
So: Software
Va: Validation
Fo: Formal Analysis
I: Investigation
D: Data Curation
R: Resources
O: Writing - Original Draft
E: Writing - Review & Editing
Vi: Visualization
Su: Supervision
Fu: Funding Acquisition
P: Project Administration

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