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Classification of Arabica Coffee Beans Based on Starters Type with Honey Processing Using Multi-channel Spectral Sensor

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Abstract

Coffee is one of important agricultural commodities in Indonesia, contributing as an income source for farmers and a major export revenue. The specialty coffee industry has begun to utilize microorganisms (starter) in the fermentation process, including the honey process, to obtain a distinctive flavour. However, the use of various starters in this process produces coffee bean with similar color, making it difficult to determine the authenticity of the type of starter used. This research aims to classify arabica coffee beans processed with different types of starters using multi-channel spectral sensor to ensure product quality and authenticity. This research used arabica coffee beans, in the form of green beans, processed with three types of starters, namely Saccharomyces cerevisiae, Lactobacillus sp, and Rhizopus oryzae. Multi-channel spectral sensor was used to acquire the spectra data of coffee sample processed with different starters. The data was then analysed using multivariate analysis based on Partial Least Square – Discriminant Analysis (PLS-DA). In the calibration stage, PLS-DA model built using de-trending pre-treatment was able to predict the type of starter very well, with accuracy, sensitivity, specificity, and precision values, reaching 97%, 95%, 96%, 95%, respectively. This result is also confirmed during validation stage where the built PLS-DA model could predict the type of starter with accuracy, sensitivity, specificity, and precision values, reaching 100%.

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1. Introduction

Coffee is one of the most important agricultural commodities in Indonesia, serving as a source of income for farmers and the fourth-largest contributor to foreign exchange after palm oil, rubber, and cocoa. The most widely traded coffee types are arabica, robusta, and liberica, all of which have distinct characteristics in terms of flavor, aroma, and selling price (Aryadi et al., 2021). The quality of arabica coffee can be improved by the addition of microbial cultures during fermentation. Coffee fermentation is one method used to reduce the caffeine content in coffee. The purpose of coffee fermentation is to remove the mucilage layer that still clings to beans. Decomposition of the mucilage layer during coffee bean fermentation occurs because of the metabolic activity of microorganisms originating from the environment. Mucilage is rich in pectin and sugar. Mucilage serves as a source of nutrients for

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microorganisms during fermentation. One of the fermentation processes in coffee is called honey processing (Rabani & Fitriani., 2022).

Currently, the processing of coffee using microorganisms (starters) has become a trend in the specialty coffee industry because it creates unique flavors. The use of starters in the honey process for Arabica coffee results in beans of similar colors, making product authentication difficult. Additional approaches such as chemical analysis are required to ensure the authenticity of the product (Kembaren & Muchsin., 2021). The identification of honey-processed coffee bean often encounters obstacles owing to the subjectivity of assessments, which rely on visual observation and individual experience, as well as the lack of understanding among industry players regarding objective parameters in coffee bean classification. Therefore, an appropriate decision support system is required to analyse and address this issue. Conventional (chemical) methods for classifying Arabica coffee beans are considered expensive and time-consuming; therefore, a non-destructive method is needed as a more efficient and accurate solution (Sugianti et al., 2016). The classification of honey-processed Arabica coffee using various starters needs to be conducted to determine the influence of each starter on the flavor, color, and aroma of coffee. This process helps to determine the type of starter used to ensure consistent quality and flavor characteristics.

The multi-channel spectral sensor has a wide wavelength range, covering the ultraviolet-visible (UV-Vis) and near-infrared (NIR) regions, thus enabling comprehensive spectral information collection. Its modular nature and small size allow the development of portable and inexpensive spectroscopy-based instruments. Portable spectroscopy has been widely studied in various fields, including non-destructive quality evaluation technology of agricultural products using portable NIR (Widyaningrum et al., 2022). Masyitah et al. (2023) used portable NIR for authentication of Aceh special rice (sigupai variety). This technology has also been used to estimate the content of caffeine, theobromine, theophylline and chlorogenic acid in roasted coffee (Huck et al., 2005). It has also been employed to estimate caffeine content in Gayo Arabica coffee beans (Rosita et al., 2016), as well as to predict caffeine content (Ayu et al., 2020), trigonelline, and chlorogenic acid in green Bondowoso Arabica coffee (Madi et al., 2018). Given the potential use of this spectroscopy-based technology, it is possible to utilize it for identifying the coffee bean processed using the honey method based on the type of starter non-destructively through their spectral characteristics. This study aims to develop a classification model for honey-processed Arabica coffee beans based on the starter type using a multi-channel spectral sensor. The developed method has the potential to become an innovative and efficient solution to support the processing of high-quality coffee while helping coffee industry practitioners maintain product consistency and prevent mis-labelling.

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2. Materials and Methods

2.1 Tools and Materials

The tools used in this study were a multi-channel spectral sensor, a laptop with Microsoft Excel (Microsoft, USA) and Unscrambler version 10.4 (CAMO Software, Norway) for spectral data analysis. The material used in this study was honey-processed arabica coffee beans obtained from PT Java Frinsa, Pengalengan, Bandung, which were fermented using three starters: *Saccharomyces cerevisiae*, *Lactobacillus sp*., and *Rhizopus oryzae*. A flowchart of the research method is shown in Figure 1.

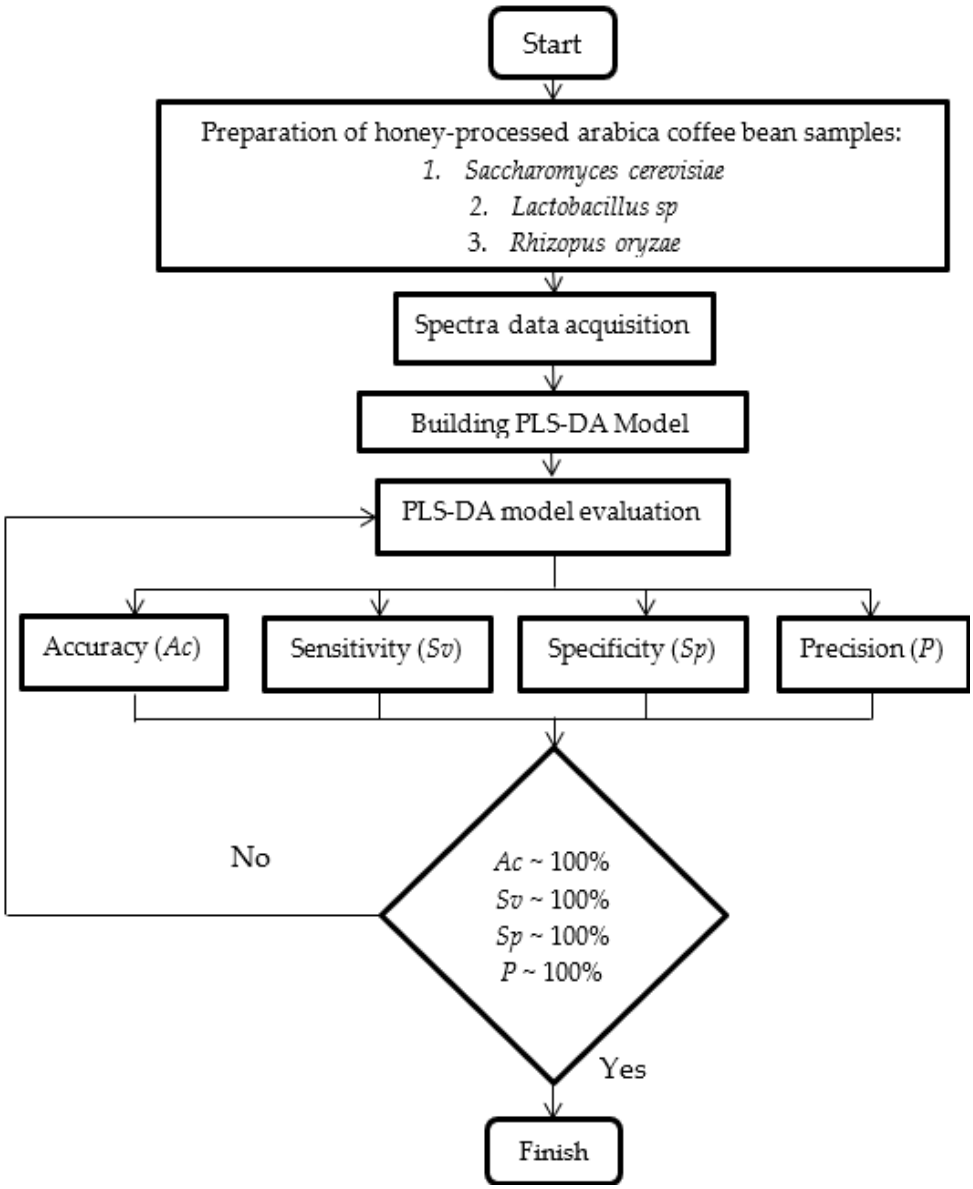

Figure 1. Research flowchart.

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2.2 Sample Preparation

The samples used in this study were arabica coffee in the form of green beans processed using the honey method with three types of starters: *Saccharomyces cerevisiae*, *Lactobacillus sp*, and *Rhizopus oryzae*, each weighing 1.5 kg. For each type of starter, 60 samples were prepared, bringing the total to 180 samples. Each sample consisted of 40 grams of coffee beans, evenly and tightly placed in a petri dish in four stacked layers. This was intended to obtain the optimal spectral measurement data (Rosita et al., 2016). The arabica coffee samples are shown in Figure 2.

Figure 2. Samples of honey-processed arabica coffee beans processed with three starters: (a) *Saccharomyces cerevisiae*, (b) *Lactobacillus sp*, and (c) *Rhizopus oryzae*.

2.3 Spectral Data Acquisition

The process of acquiring spectral data for coffee beans uses a multi-channel spectral sensor that operates within the spectral range of 410–940 nm in accordance with the specifications of the AS7265X sensor (Sagita et al., 2024). Each measurement was performed in triplicate, and the results were averaged. The multi-channel spectral sensor used in this study was factory-calibrated and was equipped with a self-calibration system. This system allows the sensor to adjust and correct its spectral response automatically without requiring additional external calibration. With the self-calibration feature, the sensor was able to maintain measurement accuracy and consistency under various conditions, ensuring reliable spectral analysis in the classification of arabica coffee beans. The multi-channel spectra sensor AS7265X and the device used for the acquisition of coffee sample spectra are shown in Figure 3 and 4.

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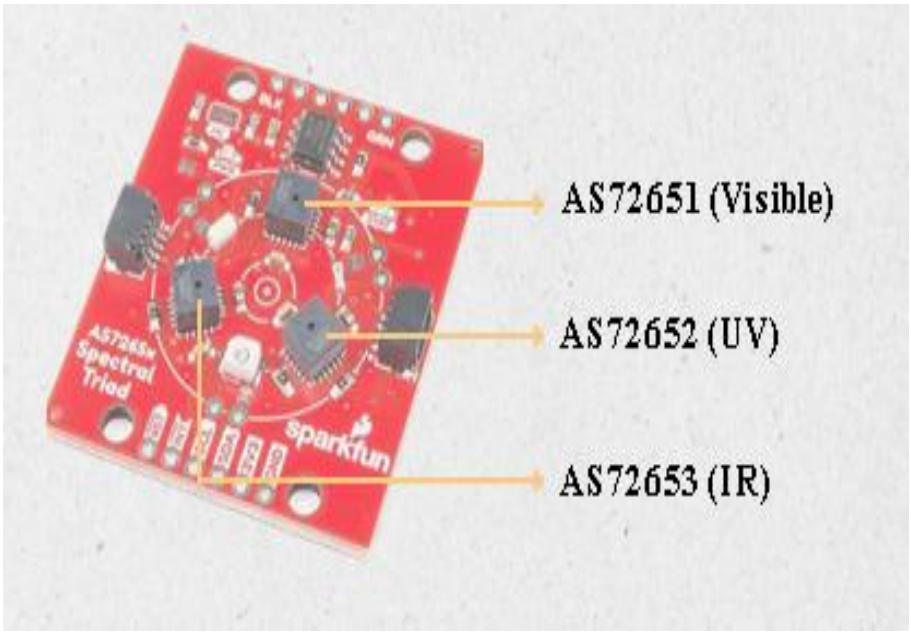
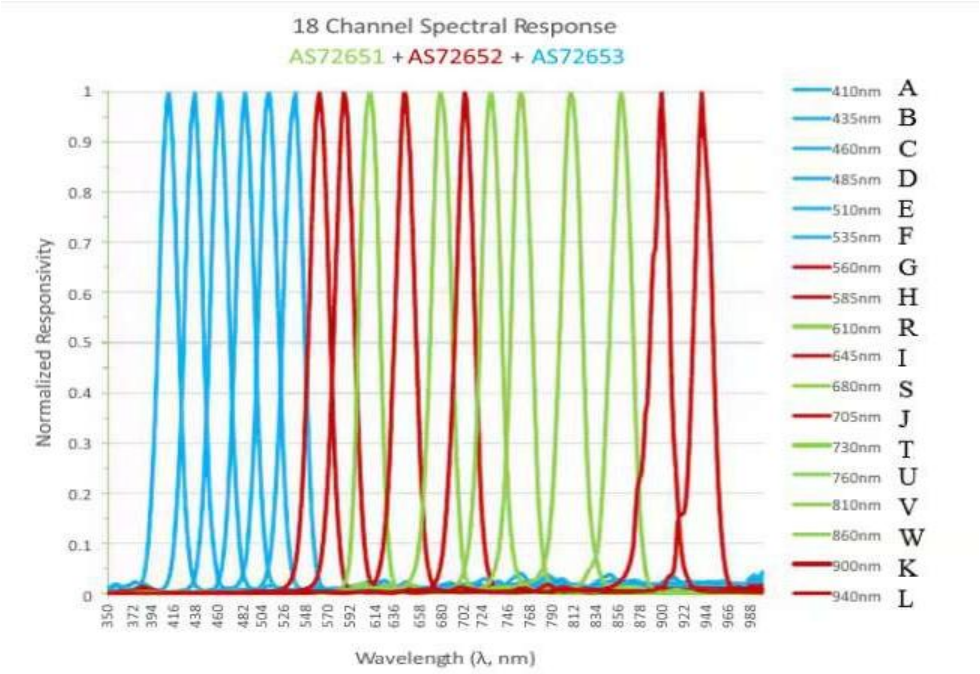


(a)



(b)

Figure 3. (a) Multi-channel spectral sensor and (b) Specific wavelength for each channel.

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Figure 4. Spectral data acquisition device.

2.4 Development of Coffe Beans Classification Model

At this stage, a mathematical model was developed for the classification of arabica coffee beans processed with various types of starters, using spectral data to build a classification model with 150 calibration data and 30 validation data. Data processing of the spectra in this study was conducted using Microsoft Excel and the Unscrambler 10.4. In addition to the original spectral data (without pre-treatment), spectral data processed with several pre-treatments were used to reduce noise and sharpen the information contained in the spectral data to improve the accuracy and stability of the developed prediction model. This approach is common and has proven to be effective in improving the model performance, as demonstrated in the research conducted by Ahmar et al. (2024). Four types of pre-treatments were used in this study: standard normal variate (SNV), multiplicative scatter correction (MSC), baseline correction, and de-trending.

This study used a classification data processing model based on multivariate analysis, namely partial least squares-discriminant analysis (PLS-DA). PLS-DA classifies data using a regression analysis approach, where class or group of the data are represented as numerical data. The results of PLS-DA analysis need to be rounded off to determine the accuracy of data grouping (Suhandy & Yulia, 2017). PLS-DA was calculated using the non-linear iterative partial least squares (NIPALS) algorithm, with spectral data as the predictor (X) and coffee type/class data as the response (Y) (Yulia et al., 2023).

This study uses five PLS-DA models with pre-treated data and one model with untreated data, with the following details: PLS-DA1 is the PLS-DA model with original data, PLS-DA2 is the PLS-DA model with SNV pre-treated data, PLS-DA3 is the PLS-DA model with MSC pre-treated data, PLS-

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DA4 is the PLS-DA model with baseline correction pre-treated data, and PLS-DA5 is the PLS-DA model with de-trending pre-treated data. Table 1 presents the models used in each scenario, where the five models consist of data with and without pre-treatment.

Table 1. Classification model.

Data Code	Model
1 = Original data (without pre-treatment)	PLS-DA1
2 = Data with SNV pre-treatment	PLS-DA2
3 = Data with MSC pre-treatment	PLS-DA3
4 = Data with Baseline pre-treatment	PLS-DA4
5 = Data with De-trending pre-treatment	PLS-DA5

2.5 Model Evaluation Using Confusion Matrix

Model evaluation aims to assess the model's ability to distinguish between different classes or groups within the dataset. This evaluation process involves several parameters such as accuracy, sensitivity, specificity, and precision. To obtain the values for these evaluation parameters, the prediction results of the model were entered into a confusion matrix. The confusion matrix divides the data into four categories: true positive (TP), true negative (TN), false positive (FP), and false negative (FN) (Permadi & Gumilang, 2024). Model evaluation using the confusion matrix can be performed using Equations 1–4, and the confusion matrix table is shown in Table 2.

Tabel 2. Confusion matrix.

Prediction Class	Actual Class	
	True	False
True	TP	FP
False	FN	TN

$$Accuracy\ (Ac) = \frac{TP+TN}{TP+FN+FP+FN} \text{ x } 100\% \quad (1)$$

$$Sensitivity\ (Sv) = \frac{TP}{TP+FN} \text{ x } 100\% \quad (2)$$

$$Spesificity\ (Sp) = \frac{TP}{FP+TN} \text{ x } 100\% \quad (3)$$

$$Precision\ (P) = \frac{TP}{FP+TP} x\ 100\% \quad (4)$$

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Accuracy is the total number of true positives (TP) and true negatives (TN) divided by the total number of data points. The accuracy indicates the level of correctness of the model created; the higher the accuracy value, the better the model. The sensitivity is the ratio of the number of true positives (TP) to the sum of true negatives (TN) and false negatives (FN). The sensitivity percentage indicates the model's ability to recognize samples belonging to the correct class. Specificity is the ratio of the number of true negatives (TN) to the sum of false positives (FP) and true negatives (TN). Specificity illustrates the ability of the model to direct the samples to the correct class. Therefore, the higher the specificity percentage, the better the model is for identifying samples that do not belong to a class. Precision is the ratio of the number of true positives (TP) to the sum of false positives (FP) and true positives (TP). Precision provides information on how many of the cases predicted as positive by the model are positive.

3. Results and Discussion

3.1 Spectral Data Acquisition

The reflectance spectral data of arabica coffee beans processed using the honey method with various types of starters were measured at wavelengths of 410–940 nm using a multi-channel spectral sensor. The spectrum was measured using 18 channels, including channels A–L, and six additional channels (F1-F6). Channels F1-F6 were used to detect fluorescence emissions that occurred upon UV LED excitation. The original spectral data of arabica coffee beans are shown in Figure 5, and the average spectrum graph of arabica coffee beans from the three starters are shown in Figure 6.

From both graphs, several peaks and valleys can be seen, indicating interactions between the electromagnetic waves at certain wavelengths and the sample. In the UV wavelength range, this is thought to be related to the content of active compounds such as phenols or proteins. In the VIS wavelength range, this is closely related to the color of the sample. This color is closely associated with chemical changes during fermentation in the honey processing method. Furthermore, in the NIR wavelength range, this is related to the water, fat, and carbohydrate contents, which contribute to the aroma and flavor of the coffee. No fluorescence emission was observed in channels F1-F6. This may be because the UV LED used was not suitable for exciting the fluorescent compounds present in the sample. The LED lamp used in this study was the original lamp from the sensor module manufacturer. Adjustments or replacement with other UV lamp with specific wavelength may be necessary to properly excite the fluorescence emission from the coffee samples.

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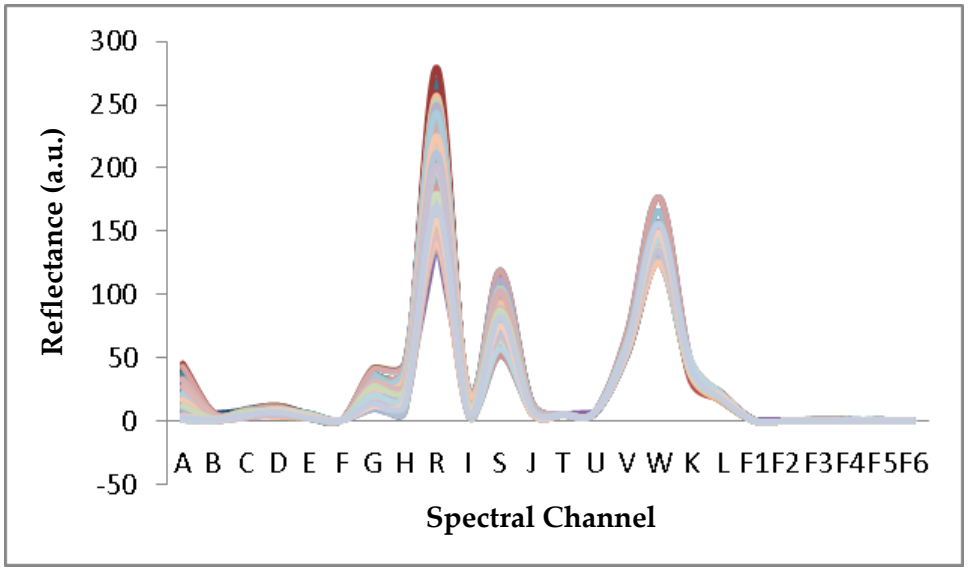

Figure 5. Original spectral data of arabica coffee beans

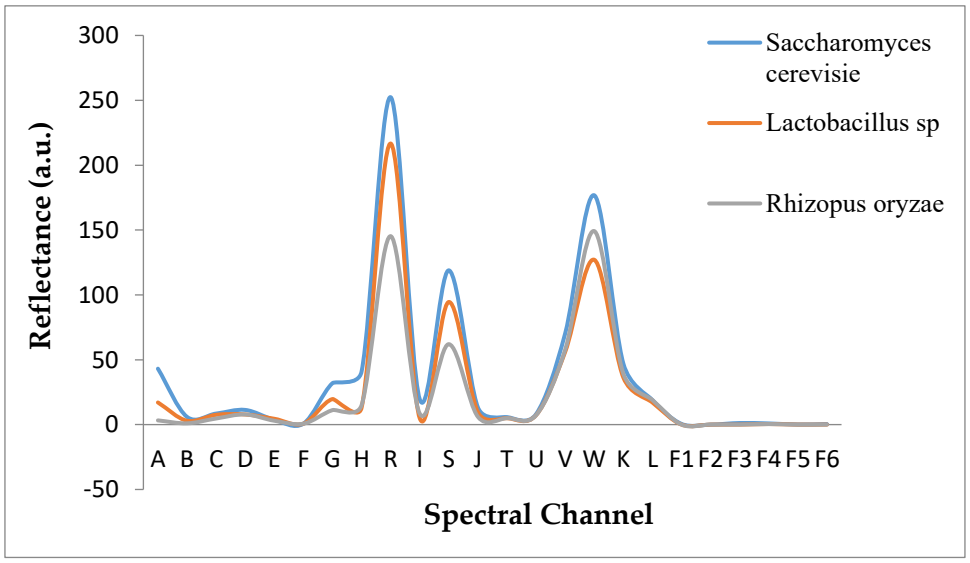

Figure 6. Average spectral data of arabica coffee beans processed with three starters

3.2 Development of a PLS-DA Model for Classification of Arabica Coffee Beans

Figure 7 shows the score plot from the Partial Least Squares-Discriminant Analysis (PLS-DA) used to classify arabica coffee beans processed by the honey method using three types of starters: *Saccharomyces cerevisiae*, *Lactobacillus sp*., and *Rhizopus oryzae*. The horizontal axis (Factor-1) explains 86% of the data variance, while the vertical axis (Factor-2) explains 4% of the variance, so the total variance explained by these two factors reaches 90%.

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The overlap between the *Saccharomyces cerevisiae* and *Lactobacillus sp*. starter groups likely occurs because of similarities in the chemical or physical characteristics of the fermentation products generated by both microbes. These two starters produce similar metabolites, such as organic acids, volatile compounds, and other bioactive components, which influence the spectral signals in a similar manner. Additionally, the data pre-treatment methods used may not have fully eliminated non-characteristic variability, thereby reducing the model's ability to clearly distinguish between the two groups. Environmental factors during fermentation, such as temperature, humidity, and fermentation time, may also contribute to the similarity of spectral profiles, resulting in an overlap in this score plot.

The score plot of each group's distribution on the graph shows that coffee samples with *Rhizopus oryzae* are positioned on the right side of the graph and are significantly separated from the other two groups. This indicates a striking difference in the spectral characteristics of honey-processed coffee prepared using *Rhizopus oryzae* and the other two starters. Meanwhile, the *Saccharomyces cerevisiae* and *Lactobacillus sp*. groups appeared closer together but still displayed some boundary between groups. This separation pattern suggests that the spectral approach based on a multi-channel spectral sensor used in this study is capable of classifying starter types, even though Arabica coffee beans have a similar color.

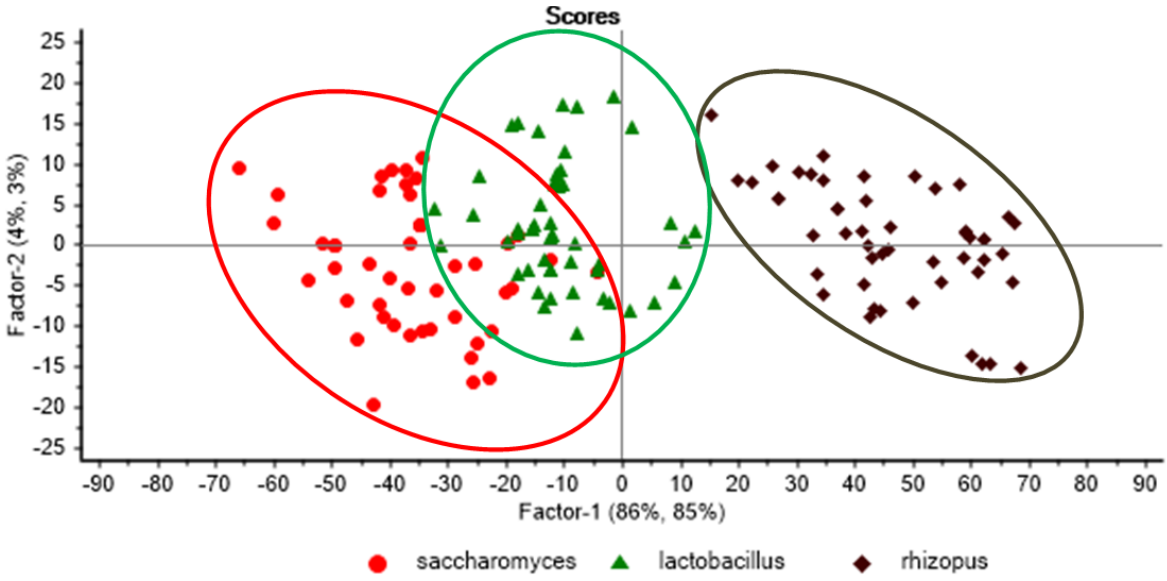

Figure 7. PLS-DA5 analysis score plot.

3.3 Evaluation of the PLS-DA Model Using a Confusion Matrix for the Calibration Dataset

Table 3 shows the best model, namely the PLS-DA5 model, which is the model with detrending pre-treatment on the calibration dataset. Some data experienced misclassification between the classes. A total of 45 *Saccharomyces cerevisiae* data were correctly classified, but five others were incorrectly

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classified as *Lactobacillus sp*. Conversely, in the *Lactobacillus sp* class, 47 data points were correctly classified, whereas three data points were incorrectly identified as *Saccharomyces cerevisiae*. For *Rhizopus oryzae*, all 50 data points were classified correctly without any prediction errors, indicating a fairly good model performance. Research conducted by Suhandy & Yulia (2017) showed that the PLS-DA model has a very high classification accuracy, with 100% accuracy in distinguishing peaberry coffee samples from regular coffee. The results of this study confirm that applying the PLS-DA model with proper pre-treatment plays an important role in improving the classification accuracy of arabica coffee beans.

Table 3. Confusion matrix for starter classification results using the PLS-DA model on the calibration dataset (n=150).

Model	Prediction Data	Actual Data		
		Saccharomyces cerevisiae	*Lactobacillus sp*	*Rhizopus oryzae*
PLS-DA1	*Saccharomyces cerevisiae*	45	5	0
	Lactobacillus sp	3	47	0
	Rhizopus oryzae	0	3	47
PLS-DA2	*Saccharomyces cerevisiae*	47	3	0
	Lactobacillus sp	6	44	0
	Rhizopus oryzae	0	1	49
PLS-DA3	*Saccharomyces cerevisiae*	42	8	0
	Lactobacillus sp	6	44	0
	Rhizopus oryzae	0	1	49
PLS-DA4	*Saccharomyces cerevisiae*	43	7	0
	Lactobacillus sp	3	47	0
	Rhizopus oryzae	0	3	47
PLS-DA5	*Saccharomyces cerevisiae*	45	5	0
	Lactobacillus sp	2	48	0
	Rhizopus oryzae	0	0	50

The *Saccharomyces cerevisiae* starter converts sugars into alcohol and organic acids, while *Lactobacillus sp* ferments sugars into lactic acid. Both starters produce volatile compounds that affect the aroma and flavor complexity of arabica coffee (Winanti and Handoko., 2024). The *Rhizopus oryzae* starter breaks down complex polysaccharides, such as pectin and cellulose, in the coffee mucilage

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layer through pectinase and cellulase enzymes. This starter also accelerates the breakdown of fibers and proteins and enriches secondary metabolites that form volatile compounds, thereby influencing the aroma and taste of arabica coffee (Nuryana et al., 2018).

Table 4. Classification model performance using the PLS-DA model on the calibration dataset (n=150).

Model	Accuracy %	Sensitivity %	Spesificity %	Precition %
PLS-DA1	95	93	94	95
PLS-DA2	96	93	95	94
PLS-DA3	93	90	92	91
PLS-DA4	94	92	93	93
PLS-DA5	97	95	96	95

Table 4 shows the performance of the best model, namely the PLS-DA5 model, which is the model with detrending pre-treatment in classifying arabica coffee beans with various starters fermented using the honey method. The de-trending pre-treatment significantly improves the model's ability to analyze spectra by removing long-term trends that can obscure important information in the data.

The PLS-DA5 model with detrending pre-treatment demonstrated good performance with an accuracy of 97%, sensitivity of 95%, specificity of 96%, and precision of 95%. These results indicate that the model is capable of accurately classifying samples, for both identifying positive and negative samples. Furthermore, the validity of the results is strengthened through comparison with the study by Masyitah et al. (2019), which showed that detrending pre-treatment was effective with an accuracy of up to 87%. The study results indicate that the application of appropriate pre-treatment plays an important role in increasing the accuracy of arabica coffee bean classification.

3.4 Evaluation of the PLS-DA Model Using a Confusion Matrix for the Validation Dataset

Table 5 shows that the best model is the PLSDA5 model, which is the model with pre-treatment detrending on the validation dataset, where it achieved a value of 10 data points for all starter types without any prediction errors. The detrending pre-treatment is effective in removing complex trends, improving spectral signal quality, and handling data variability. The classification of Arabica coffee beans becomes more accurate and reliable with the application of appropriate pre-treatment. The results of this study affirm that de-trending is the most effective method for improving classification accuracy. This finding is also in line with research conducted by Aprilia et al. (2021), who reported successful achievement of 100% accuracy by using detrending pre-treatment for classification of chili powder antioxidant activity.

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Table 5. Confusion matrix for starter classification results using the PLS-DA model on the validation dataset (n=30).

Model	Prediction Data	Actual Data		
		Saccharomyces cerevisiae	*Lactobacillus sp*	*Rhizopus oryzae*
PLS-DA1	*Saccharomyces cerevisiae*	10	0	0
	Lactobacillus sp	0	10	0
	Rhizopus oryzae	0	1	9
PLS-DA2	*Saccharomyces cerevisiae*	9	1	0
	Lactobacillus sp	2	8	0
	Rhizopus oryzae	0	0	10
PLS-DA3	*Saccharomyces cerevisiae*	10	0	0
	Lactobacillus sp	0	10	0
	Rhizopus oryzae	0	1	9
PLS-DA4	*Saccharomyces cerevisiae*	9	1	0
	Lactobacillus sp	2	8	0
	Rhizopus oryzae	0	0	10
PLS-DA5	*Saccharomyces cerevisiae*	10	0	0
	Lactobacillus sp	0	10	0
	Rhizopus oryzae	0	1	9

Table 6. Classification model performance using PLS-DA on the validation dataset (n=30).

Model	Accuracy %	Sensitivity %	Spesificity %	Precition %
PLS-DA1	98	97	98	100
PLS-DA2	93	90	96	90
PLS-DA3	98	97	98	100
PLS-DA4	98	97	98	100
PLS-DA5	100	100	100	100

4. Conclusion

In this study, a multi-channel spectral sensor using the PLS-DA method successfully classified arabica coffee beans processed using the honey method with three types of starters: *Saccharomyces cerevisiae*, *Lactobacillus sp*., and *Rhizopus oryzae*. The PLS-DA model built with de-trending pre-

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treatment showed an excellent ability to predict the calibration data of arabica coffee beans based on the type of starter, with accuracy, sensitivity, specificity, and precision values reaching 97%, 95%, 96%, and 95%, respectively. In addition, the PLS-DA model successfully predicted validation samples of arabica coffee beans by type of starter with very high performance, achieving accuracy, sensitivity, specificity, and precision values of 100%. These results indicate that arabica coffee beans processed by the honey method using various types of starters can be classified non-destructively using a multi-channel spectral sensor through the application of the PLS-DA model.

Suggestion

Future research should conduct a chemical content analysis of Arabica coffee using three types of starters, namely *Saccharomyces cerevisiae*, *Lactobacillus sp*., and *Rhizopus oryzae*, which are fermented using the honey method, to provide deeper insights into the influence of each starter on coffee quality.

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