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Research Article

Classification of Natural and Carbide-Ripened Cavendish Bananas Using Portable Vis-NIR Multispectral Sensor

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Abstract

Cavendish banana (Musa acuminata Cavendish) is a climacteric fruit that ripens rapidly after harvest, requiring accurate monitoring to maintain postharvest quality. In Indonesia, calcium carbide is still frequently used to accelerate ripening, although this practice can reduce fruit quality and raise safety concerns. Laboratory-grade spectrophotometers are effective for spectral characterization but are costly and limited to controlled environments, restricting their applicability for practical postharvest evaluation. To address this limitation, this study employed visible and near infrared (Vis-NIR) spectroscopy using the portable and low-cost AS7265X multispectral sensor to classify bananas ripened under different conditions. Spectral data were collected across 410 to 940 nanometers from three treatments, including naturally ripened fruit and fruit ripened with calcium carbide at 32 grams and 96 grams per kilogram of banana, with thirty samples in each group. The spectral irradiance curves showed clear differences, where naturally ripened bananas displayed smoother and lower intensity patterns than carbide-treated fruit. Linear Discriminant Analysis (LDA) was applied to the spectral data and successfully classified all ripening categories with 100% accuracy for both training and test datasets. The model's performance, evaluated using a confusion matrix, confirmed the perfect classification, indicating that the AS7265X multispectral sensor integrated with LDA offers a reliable, low-cost, and non-destructive approach for assessing banana ripening methods in postharvest quality evaluation.

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1. Introduction

Banana is one of Indonesia's most important horticultural commodities cultivated throughout tropical regions and serving as a key source of income for rural households as well as a major contributor to the country's fruit production volume (Suryanti et al., 2017). Among the existing cultivars, the Cavendish banana (Musa acuminata Cavendish) is highly preferred in Indonesian

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commercial markets because of its stable yield, uniform size, bright yellow peel, and good transport resistance, which make it suitable for both national and export distribution (Andriani & Rahayu, 2023). The fruit provides a vital source of carbohydrates, vitamins, and minerals that support nutritional security. Its economic value, however, depends on proper postharvest handling and ripening management since physiological changes after harvest determine consumer acceptance and shelf life (Safitri, 2022). Cavendish bananas are climacteric fruits that undergo a rapid increase in respiration and ethylene production at maturity, initiating a sequence of biochemical processes including chlorophyll degradation, carotenoid synthesis, starch hydrolysis, and cell wall softening. These transformations influence peel color, sweetness, and aroma, which are the main visual and sensory indicators of ripeness. Maintaining these characteristics through controlled ripening management is essential for ensuring consistent quality and minimizing postharvest losses. However, under practical conditions, natural ripening is often slow and uneven (Wardani & Dewi, 2017), leading to the use of artificial chemical agents to accelerate the process (Melasari, 2016).

In Indonesia, calcium carbide is still widely applied by small and medium-scale fruit traders to achieve uniform ripening before marketing (Wekti & Khanifa, 2019). When reacting with moisture, calcium carbide releases acetylene gas, which acts as an ethylene analogue that stimulates fruit ripening. This practice is favored for its low cost and local availability but poses several health and quality concerns. Commercial calcium carbide often contains impurities such as arsenic and phosphorus hydride, which can penetrate fruit tissues and reduce safety for consumption (Okeke et al., 2022). Prolonged exposure to high doses may also diminish nutritional value and alter texture, aroma, and sugar composition (Nuhu et al., 2020). According to Nuhu et al. (2020), carbide concentrations of 32 grams and 64 grams per kilogram of fruit remain within the safe range established by the Food and Agriculture Organization, while higher doses such as 96 grams per kilogram may lower nutrient retention and elevate phosphorus residues beyond permissible limits. Despite these risks, the method continues to be used in Indonesia to satisfy market demand for bright and evenly colored fruit.

Detecting whether bananas have ripened naturally or through chemical induction is essential for ensuring consumer safety (Okeke et al., 2022) and improving quality assurance in the postharvest supply chain. Visual evaluation is insufficient because external color does not always indicate internal biochemical conditions; chemical ripening can produce good color but reduce internal quality (Wardani & Dewi, 2017). Ripening involves molecular and structural transformations affecting pigment concentration, water distribution, and sugar content, which are not visible to the human eye. Visible and near infrared spectroscopy has been extensively applied to analyze these internal changes by observing the interaction between light and fruit tissue. The visible region between 400 and 700 nanometers (Austin et al., 2021) corresponds to pigment degradation and carotenoid formation, while the near infrared region between 700 and 2500 nanometers (Cozzolino, 2025) relates to the absorption

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DOI: 10.19028/jtep.014.3.364-379

of O-H, C-H, and N-H bonds, which indicate the presence of moisture, starch, and sugar (Amoriello et al., 2025). Although accurate, conventional spectrophotometers are expensive, immobile, and require controlled laboratory conditions that limit their practical use for rapid assessment in the field. The need for portable, low-cost, and non-destructive optical alternatives (Amoriello et al., 2025) has therefore become increasingly important, particularly for agricultural applications in developing countries (Moinard et al., 2021).

Recent advances in optical sensing have introduced compact instruments capable of reproducing the analytical performance of laboratory spectrophotometers (Hasanzadeh et al., 2022; Walsh et al., 2020). Among these, the AS7265X multispectral sensor has emerged as a promising tool for visible and near infrared spectral analysis in agricultural produce. It records irradiance across eighteen discrete wavelengths ranging from 410 to 940 nanometers using three integrated optical modules that contain interference filters and silicon photodiodes (AMS, 2018). Each module is calibrated to deliver accurate digital irradiance values through a standard communication interface, eliminating the need for signal converters or complex optics. The inclusion of an internal illumination source and temperature correction mechanism improves measurement stability during variable environmental conditions (Hasanzadeh et al., 2022). The sensor connects to microcontrollers such as the ESP32 through an I2C communication channel, enabling real-time data acquisition and spectral processing in the field (Kusumah & Pradana, 2019; Nizam et al., 2022). The AS7265X operates on a reflectance principle where incident light interacts with fruit tissues and the reflected irradiance is measured as spectral data (Wang et al., 2023). It integrates three chips, namely AS72651, AS72652, and AS72653, that collectively cover blue to green, red, and near infrared regions, providing broad optical coverage for both qualitative and quantitative fruit analysis (AMS, 2018). Its compact size, low energy requirement, and adaptability to field environments make it suitable for small-scale and postharvest quality monitoring systems (Moinard et al., 2021; Daurai et al., 2023; Amoriello et al., 2025). In fruit assessment, the AS7265X can detect spectral variations related to pigment breakdown, water redistribution, and sugar accumulation, which are major biochemical transformations occurring during ripening (Huang et al., 2024; Cozzolino, 2025).

This study was conducted to implement a cost-effective Vis NIR spectroscopy approach using the AS7265X multispectral sensor for assessing the ripening stages of Cavendish bananas subjected to different treatments, including natural ripening and artificial ripening using calcium carbide at 32 grams and 96 grams per kilogram of fruit. Spectral irradiance data obtained from the sensor were analyzed using Linear Discriminant Analysis (LDA) to classify the ripening categories. LDA was selected because it reduces the dimensionality of spectral variables while maximizing class separation by forming linear combinations that highlight the variance between groups. This approach enhances the interpretability of spectral patterns and supports robust discrimination of ripening treatments (Wang et al., 2023). The model was validated using a confusion matrix, which quantified performance

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indicators including accuracy, precision, recall, and F1 score to evaluate predictive reliability (Moinard et al., 2021). The integration of the AS7265X sensor with Linear Discriminant Analysis provides an accessible and non-destructive method for identifying fruit ripening status. The results of this work are expected to demonstrate the potential of low-cost multispectral sensing for improving postharvest quality control and supporting data-driven agricultural innovation in Indonesia.

2. Material and Methods

2.1 Study Sample preparation and ripening treatments

Cavendish bananas (Musa acuminata Cavendish) were acquired from a farmer's plantation in Pariaman. The fruit was harvested at maturity level two, indicating it was unripe and green, and then transported to the Laboratory of Food and Agricultural Product Processing Engineering (LTPPHP) at Andalas University. Upon arrival, all bananas were sorted and graded according to SNI No. 01-6946-2003 Class A criteria to ensure uniformity. All selected samples had a finger length between 17 and 20 cm.

A total of 90 graded bananas were selected for the experiment. These were divided into three distinct treatment groups of 30 samples each. The first group served as the control and consisted of bananas that were stored and allowed to ripen naturally without any chemical intervention. The second and third groups were subjected to artificial ripening using calcium carbide at doses of 32 g/kg and 96 g/kg, respectively, following doses used in previous research (Nuhu et al., 2020). For these carbide treatments, the precise dose was calculated based on each banana's individual weight. The measured carbide was then wrapped in a piece of cloth, slightly dampened with water to initiate acetylene gas release (Mubarak et al., 2021), and placed at the base of a sealed, plain cardboard box measuring 22x15x10 cm. Each banana was ripened in its own individual box for a period of 72 hours.

2.2 Spectral data acquisition system

A portable spectral measurement system was constructed to acquire data for this study. The core of the system was the Sparkfun Triad Spectroscopy Sensor AS7265X, which detects light across 18 distinct channels within the visible and near infrared spectrum, from 410 nm to 940 nm. The system operated on a reflectance basis. The sensor's integrated light source illuminated the sample, and the sensor then measured the intensity of the reflected light, which was converted to digital spectral data (Wang et al., 2023). The AS7265X sensor was interfaced with an ESP32 microcontroller using an I2C communication protocol (Pandey et al., 2018). This involved connecting the sensor's SCL and SDA pins to the ESP32's GPIO22 and GPIO21 ports, respectively. A USB connection to a laptop provided power to the system and served as the data logging interface, as illustrated in Figure 1.

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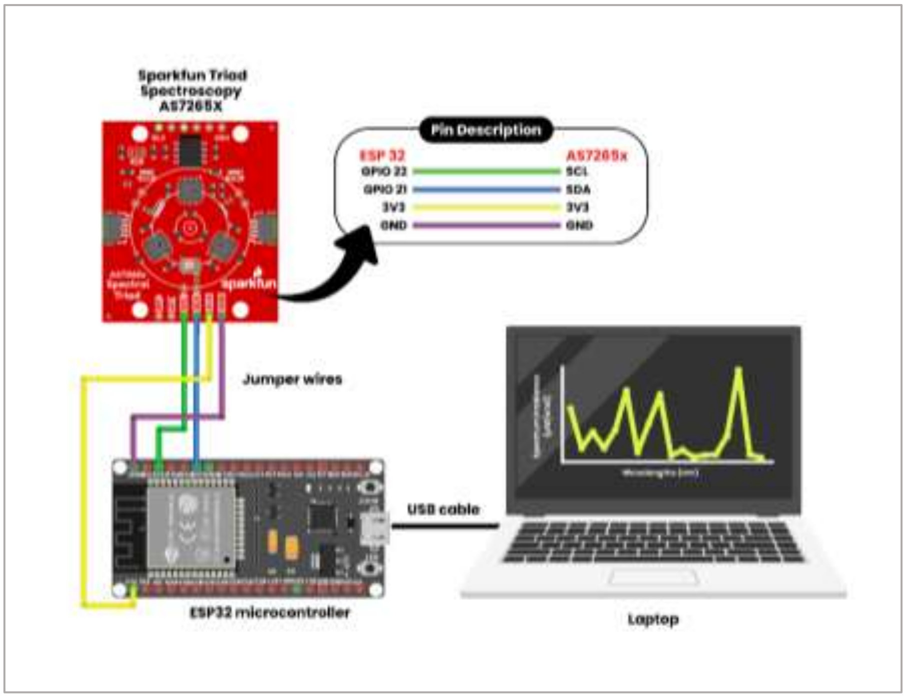

Figure 1. Schematic of the AS7265X and ESP32 spectral acquisition system.

2.3 Sensor calibration

To validate the performance of the sensor, its readings were calibrated against a high precision laboratory instrument. This calibration used an Ocean Optics Flame-T-VIS-NIR spectrophotometer, which operates in a wavelength range from 345.219 nm to 1033.424 nm. This calibration was conducted at the Biophysics Laboratory, Gadjah Mada University, using the setup shown in Figure 2.

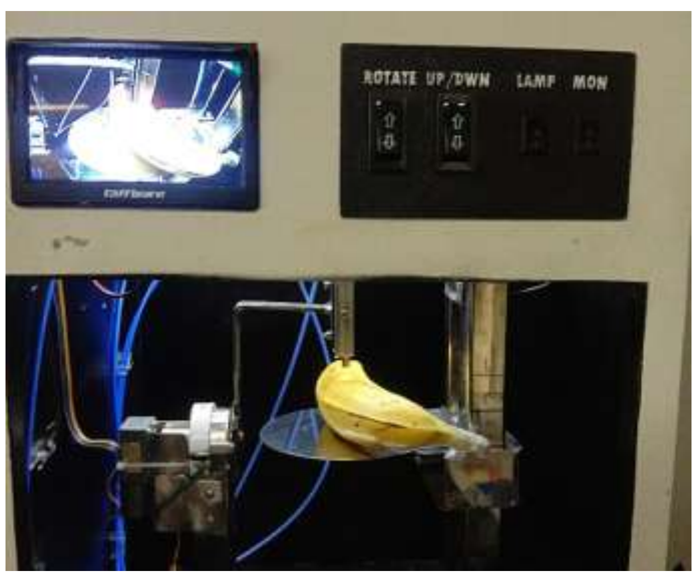

Figure 2. Laboratory setup for sensor calibration against the Flame-T-VIS-NIR spectrophotometer.

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The process involved comparing the irradiance patterns from the AS7265X with the reflectance values from the spectrophotometer under identical measurement conditions, including sample position, distance, and angle. All calibration measurements were performed in a dark room to prevent interference from external light. Raw intensity data from the AS7265X was normalized using a white reference standard (Nguyen et al., 2020).

$$\hat{I}_i = \frac{I_i}{I_{i0}} \quad (1)$$

Description: i = wavelength, $\hat{I}_i$ = normalized interactance response, I_i = interactance response, I_{i0} = white calibration value

2.4 Measurement procedure

All spectral measurements for the experiment were conducted in a dark room. This precaution ensured that the sensor only recorded light reflected from its own source, thereby eliminating ambient light contamination (Tran & Fukuzawa, 2020). Each banana was positioned perpendicular to the sensor at a close proximity, specifically less than 1 cm as shown in Figure 3, to maximize the intensity of the reflected signal (Pahlawan et al., 2021).

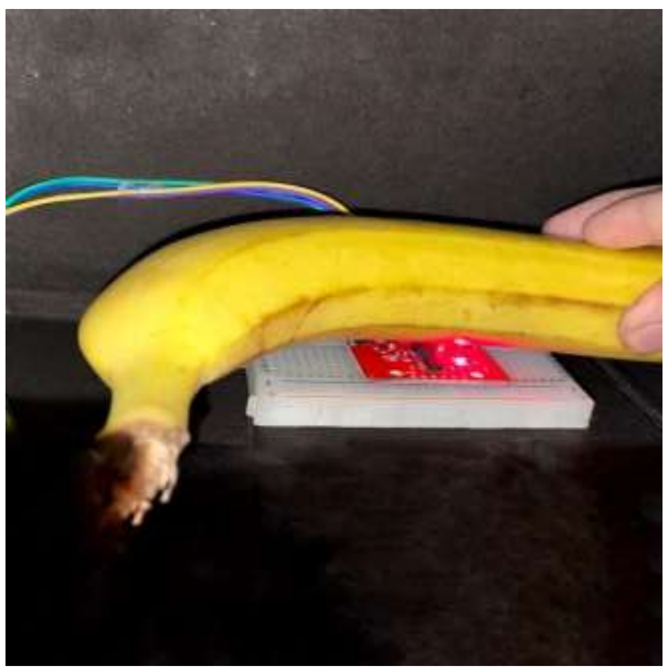

Figure 3. Sample measurement position less than 1 cm from the sensor.

For each banana sample, measurements were taken at two points, one on the upper surface and one on the lower surface. The resulting spectral data from these two points were then averaged to create one representative spectrum for that sample. An initial measurement was taken of all bananas

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in their unripe state before treatments were applied. A second and final measurement was conducted after the 72-hours ripening period concluded.

The measurement process was controlled by a C++ program running on the Arduino IDE, which operated the sensor via the ESP32. Spectral data was streamed in real time to the connected laptop and automatically captured in Microsoft Excel using PLX DAQ software. This method allowed the 18 channel irradiance data for every reading to be saved efficiently for later analysis.

2.5 Statistical analysis and classification.

For statistical analysis, Linear Discriminant Analysis (LDA) was employed to classify the banana samples based on their ripening treatment. LDA is a supervised classification method well suited for this application, as it effectively reduces the dimensionality of the data while maximizing the separation between the predefined classes. The 18 spectral irradiance values from the sensor served as the independent variables. The ripening category, either naturally ripened, carbide 32 g/kg, or carbide 96 g/kg, was set as the dependent grouping variable.

The analysis was performed using OriginPro software. The complete dataset of 90 samples was partitioned into a training set, containing 2/3 of the data, and a test set, containing the remaining 1/3. This approach is considered near optimal for datasets of this size (Dobbin & Simon, 2011). The training data was used to build the classification model, while the test data was used to validate its performance (Kotu & Deshpande, 2019). The model's effectiveness was evaluated using a Confusion Matrix. From this matrix, key performance metrics including accuracy, precision, recall, and F1 score were calculated to quantify its ability to reliably distinguish between the ripening methods.

3. Results and Discussion

3.1 Sensor calibration

Before analyzing the banana samples, a critical calibration step was performed to validate the low-cost AS7265X sensor against a high-precision, laboratory-grade Vis-NIR spectrophotometer. This process is essential because while laboratory instruments are precise, they are costly and immobile, limiting their use in the field. Portable sensors offer a practical alternative, but their data must be proven to be relevant and comparable to standard laboratory analyses (Wang et al., 2022).

The spectral patterns from both devices are shown in Figure 4. The graph shows that while the absolute reflectance values from the AS7265X are generally lower, the overall spectral pattern closely follows that of the high-precision spectrophotometer. Both instruments successfully capture the key spectral features, including the dip in the green region and the sharp, continuous rise into the near-infrared (NIR) region. This difference in absolute values is an expected and well-understood phenomenon. It can be attributed to the sensor's wider Full Width at Half Maximum (FWHM) of 20 nm, which captures a broader, averaged signal, whereas the laboratory instrument measures a much narrower, more precise point (Brazile et al., 2006).

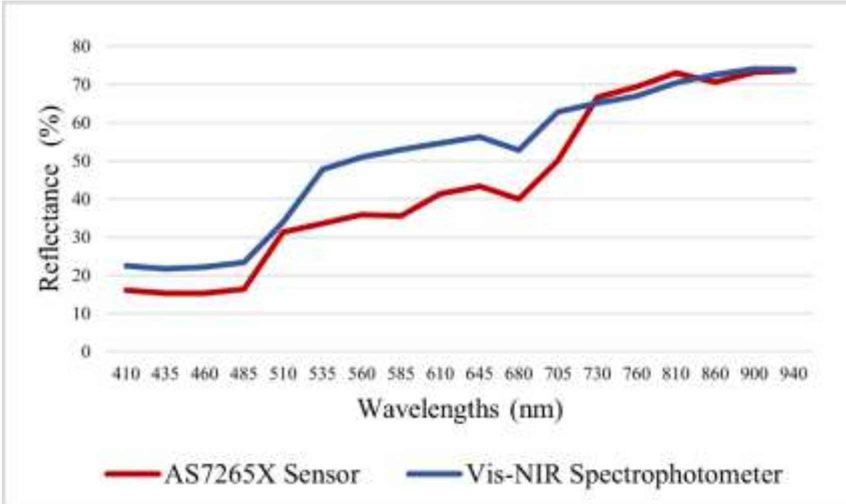

Figure 4. Sensor calibration comparing AS7265X and Vis-NIR spectrophotometer.

To quantify this relationship, the reflectance values from the 18 channels of the sensor were plotted against the corresponding values from the spectrophotometer, as shown in Figure 5. In this plot, the horizontal axis marks the AS7265X sensor reading and the vertical axis marks the paired Vis-NIR spectrophotometer reading for the same eighteen channels, so each point corresponds to one channel measured by both instruments. The resulting correlation is exceptionally strong, with a coefficient of determination (R^2) of 0.9155. This high R^2 value indicates a robust linear relationship and strong predictive capability (Noguera et al., 2022). This validation confirms that the AS7265X sensor, despite its low cost, can reliably follow the spectral patterns of the laboratory standard and is a suitable instrument for this research.

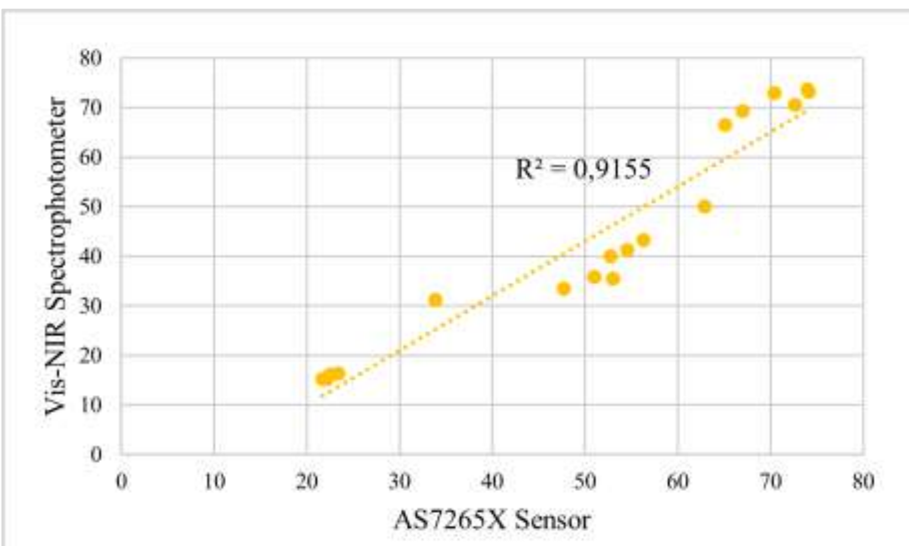

Figure 5. Correlation plot for sensor calibration.

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3.2 Spectral characteristics of ripening treatments.

The analysis of the banana samples revealed distinct spectral signatures for each of the three ripening methods. These spectral fingerprints are the basis for the classification model. Responses in the visible spectrum (410-700 nm) are dominated by pigments like chlorophyll and carotenoids, while the NIR region (750-940 nm) is influenced by water and organic compounds, allowing for a non-destructive assessment of internal quality (Walsh et al., 2020; Wang et al., 2022).

The spectral profile for naturally ripened bananas is shown in Figure 6. This profile is defined by two key characteristics. In the visible spectrum, the irradiance values are relatively low and fluctuating. This pattern reflects the gradual, natural degradation of chlorophyll and the corresponding emergence of carotenoid pigments, which is the hallmark of a complete physiological ripening process (Huang et al., 2024). The spectrum is dominated by a single, massive peak in the NIR region at 860 nm. This strong NIR peak is associated with advanced tissue softening and the conversion of starch to simple sugars like glucose and fructose, which are strongly detected in this range (Huang et al., 2024; Omar et al., 2012).

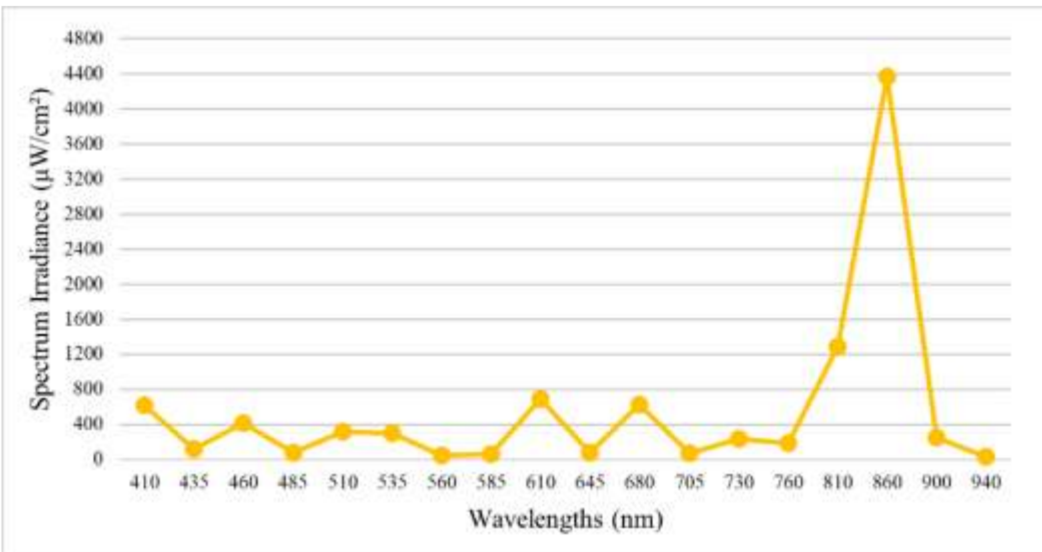

Figure 6. Spectral irradiance curve for naturally ripened bananas.

The spectral profiles for the two carbide-treated groups are shown in Figure 7. These spectra show a fundamental difference from the natural process. In the visible spectrum, both the 32 g/kg and 96 g/kg doses produced much higher irradiance peaks than the natural fruit at 410 nm, 535 nm, and 610 nm. This high-intensity response indicates that the acetylene gas forces a rapid, aggressive, and chemically distinct change in the peel's pigments, resulting in a brighter visual appearance. This aligns with findings that carbide-induced ripening accelerates chlorophyll degradation (Roy et al., 2021). In the NIR spectrum, both doses also show a strong peak at 860 nm, but the peaks are distinct. The 32

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g/kg dose peaks at 4267 µW/cm², while the 96 g/kg dose peaks highest of all at 4749 µW/cm². The 96 g/kg dose, being higher, results in reduced light absorption and may be indicative of overripe conditions (Adebayo et al., 2016).

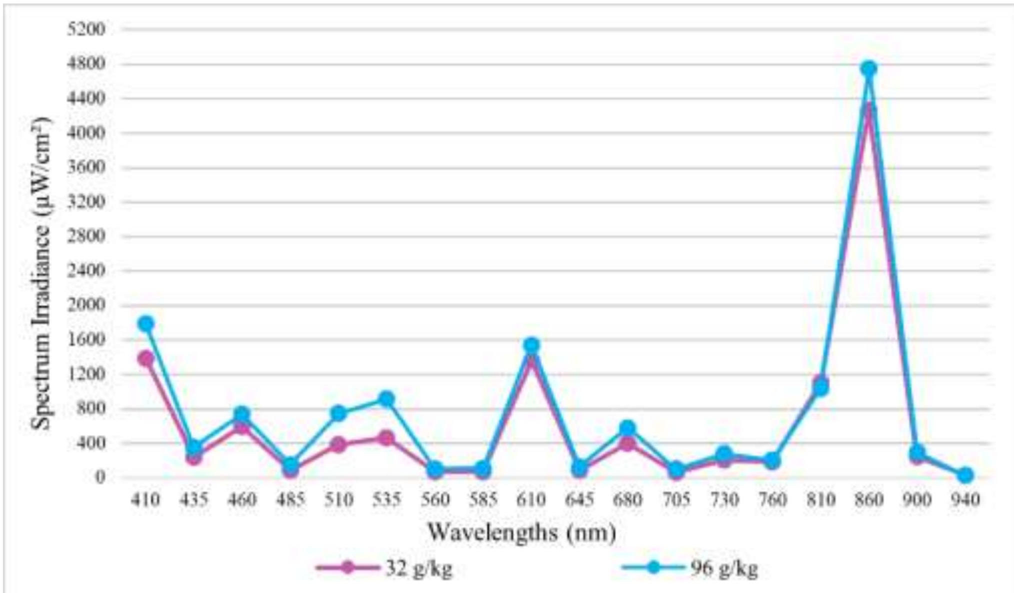

Figure 7. Spectral irradiance curves for carbide-treated bananas.

3.3 Comparative spectral analysis

The overlay of all three spectral signatures in Figure 8 makes the spectral distinctions that enable classification visually evident. The graph shows two primary methods for separating the groups. First, the carbide-treated bananas can be distinguished from the naturally ripened group by using the visible spectrum. The irradiance values for natural fruit are low, while for both carbide groups, they are significantly higher. This supports the finding that carbide ripening is highly "visual" (Firmansyah et al., 2022). In other words, the elevated visible-region peaks at 410 nm, 535 nm, and 610 nm mainly reflect a rapid, externally driven change in peel pigmentation, since acetylene gas forces chlorophyll breakdown at the fruit surface without necessarily advancing the internal biochemical changes at the same pace, as captured by the NIR region. Second, the three groups can be differentiated using the NIR peak at 860 nm. The 96 g/kg dose is the highest 4749 µW/cm², the naturally ripened peak is in the middle, and the 32 g/kg dose is the lowest 4267 µW/cm². The 32 g/kg dose falls below the naturally ripened fruit rather than above it, suggesting that the lower carbide dose mainly accelerated visible pigment change without driving the same degree of internal starch to sugar conversion reached through natural ripening. This combination of unique identifiers in both the visible and NIR ranges provides a robust, separable fingerprint for each of the three classes.

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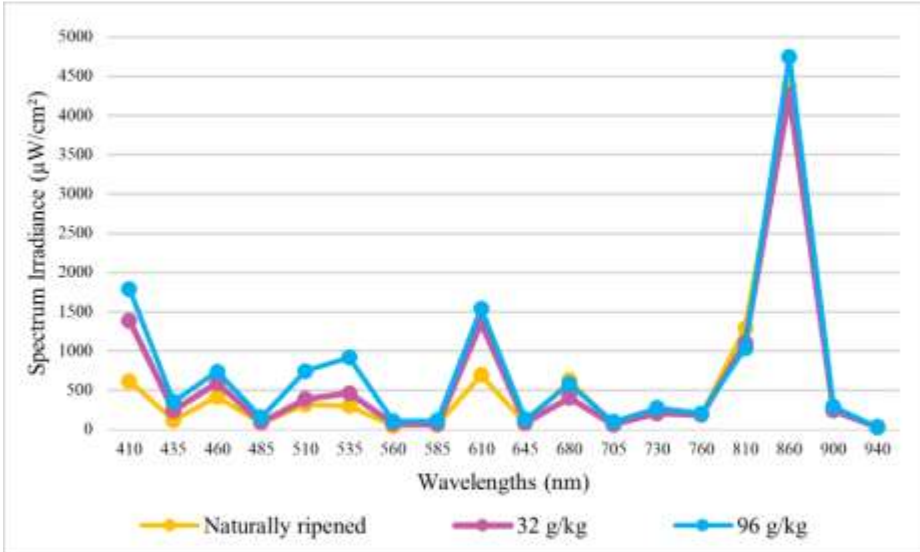

Figure 8. Comparative spectral irradiance curves for all three ripening treatments.

3.4 Classification using linear discriminant analysis (LDA).

To statistically quantify these observed spectral differences, a Linear Discriminant Analysis (LDA) was applied. The LDA model was trained using 2/3 of the dataset and validated on the remaining 1/3 test set. The classification results were definitive, achieving 100% accuracy for both training and testing. The LDA scatter plot in Figure 9 visually confirms this perfect separation.

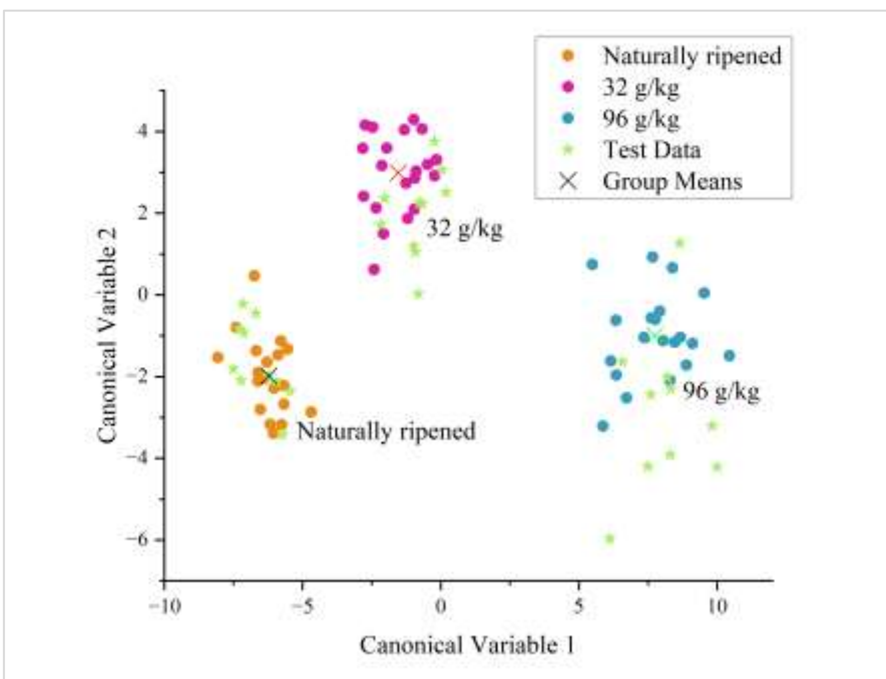

Figure 9. LDA scatter plot for the three ripening classes.

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The two axes, Canonical Variable 1 and Canonical Variable 2, represent the linear combinations of the 18 spectral channels that best separate the classes 1. Canonical Variable 1, the x-axis, appears to be the primary driver for separating the 96 g/kg group. This group is clustered far to the right with positive values around +6 to +10, while both the 32 g/kg and naturally ripened groups have negative values. Canonical Variable 2, the y-axis, then perfectly separates the remaining two groups. The 32 g/kg group is clustered in positive y-values, while the naturally ripened group is clustered in negative y-values. The "Test Data" points, marked as green stars, for each category fall perfectly within their respective clusters, demonstrating the model's high predictive power.

The numerical performance on the test data is detailed in the confusion matrix in Figure 10. The matrix shows a perfect diagonal, with 10 out of 10 samples for all three classes being correctly identified. This 100% accuracy confirms that the spectral signatures for each group are unique and highly separable, allowing the model to build perfect classification boundaries.

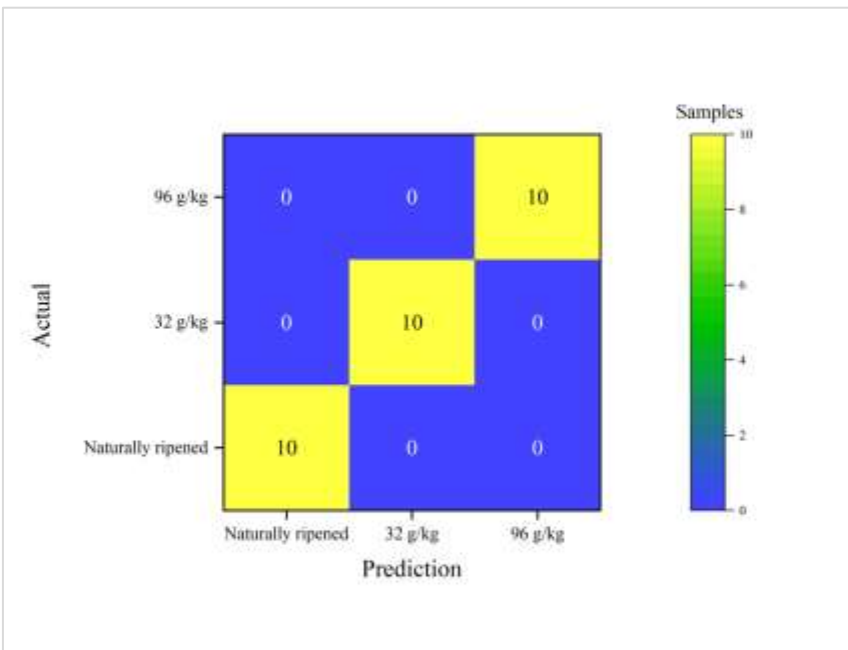

Figure 10. Confusion matrix for the LDA test dataset.

4. Conclusion

This study assessed the potential of a low-cost, portable AS7265X multispectral sensor to classify Cavendish bananas ripened under different conditions. The objective was to classify bananas ripened naturally against those ripened with calcium carbide at two doses, using the AS7265X sensor. [2S4.1]The results demonstrated clear and significant differences in the spectral patterns of bananas from the three treatment groups: naturally ripened, 32 g/kg carbide, and 96 g/kg carbide. Naturally ripened bananas exhibited distinct, lower-intensity curves in the visible spectrum, while the carbide-

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treated groups showed unique, high-intensity signatures in both the visible and near-infrared regions. Leveraging these separable spectral fingerprints, a Linear Discriminant Analysis model successfully classified all samples with 100% accuracy for both the training and test datasets. These findings confirm that the AS7265X sensor, when integrated with LDA, provides a reliable, cost-effective, and non-destructive method for differentiating between natural and artificial ripening methods, presenting a viable solution for enhancing postharvest quality control.

5. AI Writing Statement

This manuscript was written entirely by the author without the use of generative artificial intelligence (AI) tools or AI-assisted technology. All stages of research, writing, and revision were carried out independently by the author. The author bears full responsibility for the originality, accuracy, and scientific integrity of this manuscript.

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