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Investigating the capability of near-infrared spectroscopy to measure cassava tuber deterioration levels

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Abstract

This research aims to develop a model for assessing the deterioration level of cassava roots using near-infrared spectroscopy techniques. The study focuses on evaluating the capability of measuring the deterioration level of cassava roots from the Kasetsart 50 variety, harvested from a cassava field at ages of 9 and 12 months after planting, with a total of 42 roots. Additionally, samples were collected from a cassava field in Dunsat Subdistrict, Kranuan District, Khon Kaen Province, at the age of 10 months, totaling 21 roots. The model was constructed by scanning within the wavelength range of 500-1100 nm, using a detector installed on the side and connected to the Mini-NIR spectrometer. The data obtained were analyzed for physical and chemical properties over different storage periods. The analysis included brightness (L), color intensity, dry matter content (DMC), and starch content (SC) using ANOVA test. Significant differences were found at a confidence level of 95% for L, a*, b*, SC, and DMC, while the color intensity b* showed no significant difference. The spectroscopic measurements with the NIR Spectrometer indicated important changes in properties. In developing the K-Nearest Neighbors (KNN) model, it was found that using the raw spectrum yielded the highest accuracy at 69%, reflecting the ability to predict the deterioration of cassava roots in the future. This study not only contributes significantly to the knowledge of cassava root deterioration but also provides a recommendation for developing techniques to assess the quality and freshness of agricultural products in the future.

Keywords: Cassava, Starch content, Dry matter content, Storage, Deterioration.

1. Introduction

Cassava (*Manihot esculenta Crantz*) is currently recognized as one of Thailand, it most significant economic crops due to its high adaptability, low input requirements, and extensive cultivation across various regions of the country [1]. According to the Office of Agricultural Economics (OAE) [2], under the Ministry of Agriculture and Cooperatives, the total export volume of cassava and cassava-derived products in 2023 reached approximately 8 million metric tons, with an estimated export value of 120 billion Thai baht [3]. Further data from the same agency concerning agricultural exports for industrial use in 2023 revealed the following cassava-based product export volumes and values: Tapioca starch: 2 million metric tons, valued at approximately 49 billion THB, The production volumes and estimated values of key cassava-related products are as follows: sago production amounted to 30,000 metric tons, with an approximate value of 1.1 billion THB; modified tapioca starch reached 900,000 metric tons, valued at around 30 billion THB; cassava pellets totaled 90,000 metric tons, corresponding to an estimated value of 926 million THB; and cassava chips production was 4.39 million metric tons, valued at approximately 3.879 billion THB [4].

These figures clearly illustrate that cassava and its processed forms are among Thailand's leading agricultural exports in terms of both volume and economic value [2].

Cassava is widely cultivated due to its resilience to varying environmental conditions and its ability to grow in marginal soils. The trend in global and domestic demand for cassava products has shown consistent growth, driven by their versatile applications across multiple industrial sectors. Primarily, cassava roots are processed into cassava chips, pellets, and tapioca starch, which serve as feedstocks for various downstream industries [5].

Specifically, cassava chips and pellets are widely used in the production of animal feed, ethanol, and industrial alcohol, while tapioca starch plays a critical role in paper, plywood, food, sweeteners, and adhesive industries. This industrial versatility underscores the strategic importance of cassava in both agricultural sustainability and agro-industrial development in Thailand [6].

The methods used for harvesting, handling, and storage of cassava roots prior to processing significantly influence the quality, properties, and yield of the final product. One of the most critical quality parameters of cassava roots is freshness. Factors influencing the rate of deterioration include cultivar, harvest season, root age, postharvest interval, and storage conditions [7].

Different cassava cultivars exhibit varying rates of deterioration. For example, Rayong 3 and Rayong 60 tend to deteriorate more rapidly compared to Rayong 5, Rayong 90, Sriracha 1, and Kasetsart 50, particularly during the rainy season. Another key factor contributing to deterioration is the time elapsed after harvest. Ideally, cassava roots should be delivered to processing plants immediately after harvesting. Within the first two days, the roots typically remain intact; however, if left for more than four days, significant spoilage or dehydration occurs.

Cassava is harvested in two main seasons in Thailand: the dry season since November–March and the rainy season since April–October. April poses challenges due to high temperatures and the onset of rain. After harvesting, storage conditions become the final major factor influencing deterioration. Farmers usually sell cassava roots to collection yards, where the roots are stored in open-air environments, often on concrete surfaces. During the rainy season, cassava roots are found to deteriorate more rapidly than in the dry season. Spoilage not only affects market value, but also consumer acceptance of cassava-derived products.

Cassava continues to be one of Thailand's top economic crops and is cultivated extensively. Thus, maintaining its quality is crucial, as it directly impacts industrial processing efficiency and starch quality. A significant issue in cassava processing is postharvest deterioration, primarily caused by delayed harvest and inefficient transport logistics. This often results in cassava being left in the fields or held by smallholder farmers, who sell through middlemen and must wait until quantities justify transport costs. Consequently, part of the harvest may deteriorate before reaching the factory.

Currently, there is no standardized instrument for assessing the degree of deterioration in cassava roots. Existing tools are limited to starch content measurement. As a result, substandard roots are sometimes processed, affecting overall product quality. Nowadays, NIR is being used to assess the quality of agricultural products [8-9].

To address this issue, the present study investigates the use of NIR spectroscopy as a non-destructive technique for evaluating cassava root deterioration. By directing NIR light into cassava samples, the molecular bonds absorb energy and undergo vibrational changes. The resulting NIR spectral data are then processed to determine deterioration levels. This technique holds promise for the development of real-time, accurate assessment tools for the cassava processing industry, ultimately enhancing product quality and reducing postharvest losses.

2. Materials and methods

2.1 Sample preparation

The cassava samples used in this experiment were harvested from 8 to 12 months of age, which is considered the optimal harvest period. The cultivar selected for the study was Kasetsart 50, a widely cultivated variety in Thailand. This cultivar is favored by farmers due to its high yield, robust stems, dense tuber formation, and ease of harvesting. Additionally, it contains a high starch content in the tuberous roots and is suitable for cultivation across various regions of the country.

Based on these characteristics, the study utilized Kasetsart 50 cassava roots at 9 and 12 months of age, with 21 samples collected for each age group as shown in Figure 1. The samples were obtained from a cassava farm located in Muang Klang Village, Non Kok Subdistrict, Kaset Sombun District, Chaiyaphum Province, Thailand.

Figure 1 Cassava sample harvested for this experiment

2.2 NIR scanning

Figure 2 shows a schematic diagram of the NIR experimental design. Before measurements were taken, each sample was trimmed at the bottom and top parts of the stalks due to the reducing effects of weight loss, wherewith water within the stalks would evaporate.

Figure 3 shows a schematic drawing of the NIR measurement system, which includes a portable mini-spectrometer TM-UV/VIS: C10082CB-01 (HAMAMATSU Corporation, Shizuoka, Japan) and a light source (100-W tungsten halogen lamp), which has been set up in a dark experimental box (60 cm x 60cm x 60 cm). The scanning process was conducted on the central portion of each cassava tuber. For each sample, three points around the central region were scanned. At each point, data were collected three times, and the average value was calculated for that point. Each day, three cassava roots were scanned, resulting in nine spectral lines per day (3 roots × 3 scan points). This scanning protocol was repeated for each month, yielding a total of 189 spectra across the three-month sampling period.

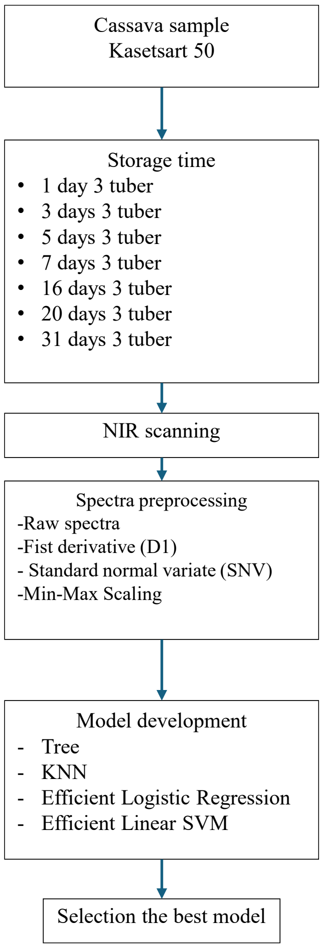

Figure 2 Experiment schematic diagrams

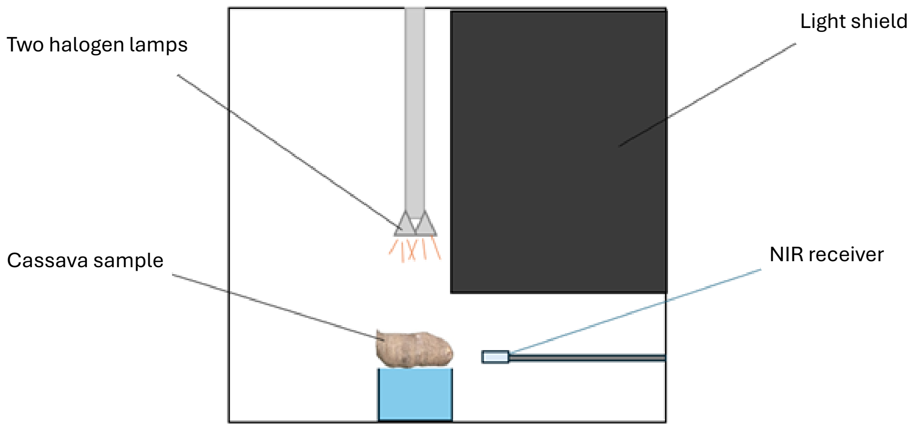

Figure 3 The equipment set up for scanning cassava roots.

2.3 Color measurement

After the spectral scanning was completed, the color of the cassava flesh was analyzed to evaluate potential correlations between visual quality and internal deterioration. The cassava roots were carefully cut open at the exact region previously scanned, ensuring consistency in sample location. A colorimeter (WR10 Colorimeter, Shenzhen Wave Optoelectronics Technology Co., Ltd., Buji Street, Longgang, Shenzhen, China) was used to measure the color properties, and the results were recorded in terms of CIELAB color space parameters: L, a*, and b*. These parameters offer a standardized, quantitative method to describe color. The L value indicates the lightness of the sample, with values ranging from 0 (black) to 100 (white), allowing assessment of brightness or discoloration due to spoilage. The a* value represents chromaticity on the green (−a*) to red (+a*) axis, which can signal biochemical changes during deterioration. The b* value represents chromaticity on the blue (−b*) to yellow (+b*) axis, often influenced by enzymatic reactions or dehydration. By analyzing these three parameters, the study aimed to objectively quantify visible changes in the cassava flesh associated with aging or degradation, thereby providing additional validation for NIR spectral data.

2.4 Determination of cassava starch and dry matter content

After scanning sample, the cut section of each cassava root was divided into two portions for determining starch and dry matter content (DMC). One portion was used to determine the DMC, while the other was used to measure the SC. These analyses were conducted to quantify the physicochemical properties of the cassava samples, which are essential indicators of root quality and are commonly used in both agricultural and industrial evaluation. The separation of the scanned tissue into distinct portions ensured that both measurements were derived from the same representative area, maintaining consistency and accuracy in the dataset.

2.4.1 Starch content

The sample's peel was first removed, and its weight was measured using a digital balance with a precision of 0.001 g (AE-ADAM, Adam Equipment Inc., New York, USA). For cassava samples, which have a specific gravity (SG) greater than water, a rope was used for suspension during the weighing process. In contrast, if the SG of a sample were less than that of water, a rigid stick would be used instead. To determine the SG, the sample was weighed both in air and when submerged in water using a texture analyzer (EZ-LX, Shimadzu, Kyoto, Japan). A schematic diagram illustrating this low-volume SG measurement technique was presented in Figure 2. The SG was then calculated using Equation 1. This procedure was followed by Maraphum et al. [10]

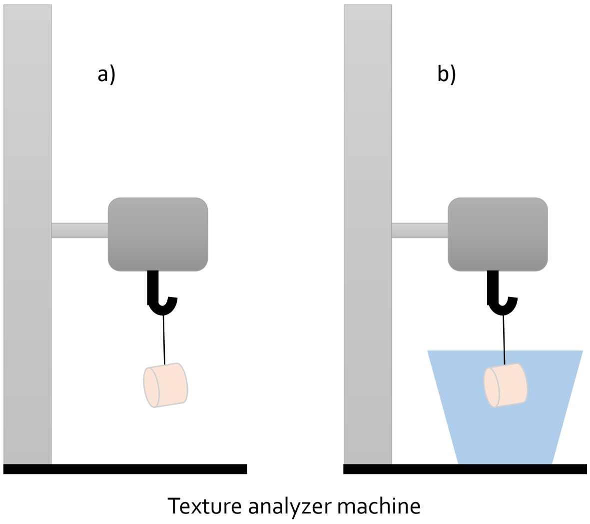

Figure 2 The schematic diagram of the cassava measurement system. a) Weighting sample in air b) Weighting sample in water

$$SG = \frac{W_a}{W_a - W_w} \quad (1)$$

Where Wa and Ww are the weights of the sample in air and water, respectively.

Then, the SG will be using them for determine the starch content (SC) as shown in Equation 2 by calculate Wholey and Booth equation [11].

$$SC\ (\%) = 159.1 \times SG - 147.0 \quad (2)$$

2.4.2 Dry matter content

The cassava samples were cut into small pieces and placed in drying flasks, then placed for dried in a hot air oven at a temperature of 70°C for 48 h to ensure complete evaporation of moisture from the samples. After drying, the samples were transferred to a desiccator to remove any remaining moisture and prevent reabsorption from the air. The DMC was then determined based on the difference in weight before and after drying (Equation 3).

$$DMC\ (\%) = \frac{W_f}{W_i} \times 100 \quad (3)$$

Where W_i is the weight of the sample at the initial stage (%), W_f is the weight of the sample at the final stage (after drying) and DMC is the dry matter content (%).

2.5 Spectra preprocessing

All spectral data obtained from the cassava samples were analyzed using MATLAB program version R2024a (MathWorks, Natick, MA, USA). Prior to model development, spectra were preprocessed using four commonly employed techniques including raw spectrum, standard normal variate (SNV), first derivative (D1), and Min-Max scaling. These preprocessing methods were used to normalize the data, reduce baseline variation, and enhance signal features to improve classification performance [12].

To identify the optimal model for classifying the level of cassava deterioration, a total of 11 supervised machine learning algorithms were implemented such as Fine Tree, Medium Tree, Coarse Tree, Fine K-Nearest Neighbors (KNN), Medium KNN, Coarse KNN, Cubic KNN, Weighted KNN, efficient logistic regression, and efficient linear support vector machine (SVM). Each model was trained and validated using cross-validation techniques to evaluate classification accuracy, precision, recall, and F1-score. The complete model development pipeline is illustrated in Figure 3, outlining data preprocessing, model training, and evaluation steps.

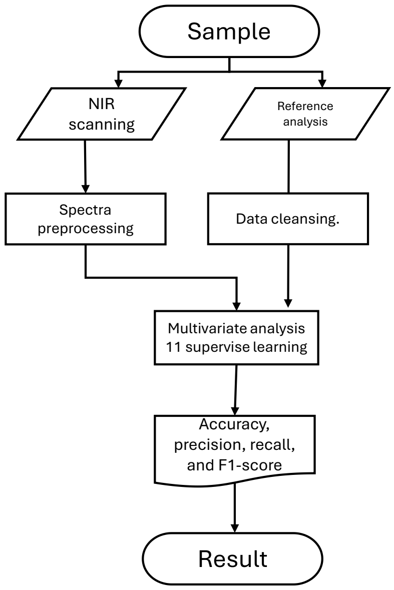

Figure 3 The model development pipeline using machine learning.

2.6 Model performance evaluation

To evaluate the performance of the best-performing model, spectral data were randomly selected using completely randomized design (CRD) and used for prediction testing. Model accuracy was assessed using four key performance metrics including of accuracy, Recall, Precision, and Specificity as shown in Equations 4-7, respectively. These indicators play a crucial role in evaluating the effectiveness of machine learning algorithms and classification systems, as outlined below:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{5}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{6}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{7}$$

To quantitatively assess the performance of the classification model, several evaluation metrics were employed, all derived from the confusion matrix. The fundamental components of this matrix include true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). A TP refers to a case in which the model correctly identifies a positive instance, whereas a TN denotes a correctly identified negative instance. A FP occurs when a negative instance is incorrectly classified as positive, and an FN arises when a positive instance is incorrectly classified as negative. These components serve as the basis for calculating standard performance metrics, including accuracy, precision, recall, specificity, and the F1-score (Equation 8). Collectively, these metrics provide a comprehensive evaluation of the model's predictive capabilities, particularly in imbalanced or domain-sensitive classification tasks.

$$\text{F1} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \tag{8}$$

3. Results and discussion

This study investigated the capability to assess the deterioration levels of cassava tubers (Kasetsart 50), which were subjected to different storage durations. The results of data analysis obtained from the experimental process are presented to address the research objectives.

3.1 Physical and Chemical Properties

Analysis of Color (L, a*, b*), SC, and DMC of cassava tubers at different storage periods. The differences in color parameters, SC, and DMC of cassava tubers stored for various durations were analyzed. The summarized results are presented in Table 1.

Table 1 ANOVA result in color parameters (L, a*, b*), SC, and DMC of cassava tubers

Parameter	F	df1	df2	p-value	Significance
L	6.02	6	24	< .001	*
a*	2.88	6	24	0.029	ns
b*	1.69	6	24.5	0.165	ns
SC (%)	5.81	6	23.8	< .001	*
DMC (%)	1.97	6	24.8	0.108	*

ns: not significant,

Table 1 summarizes the results of ANOVA performed on various quality parameters of cassava tubers. Statistically significant differences among groups were observed for the L value ($p < 0.001$), the a* value with p-value equal to 0.029, and SC gave p-value < 0.001. These results indicate that there were significant effects of treatment or genotype on lightness, red-green chromaticity, and starch content. On the other hand, b* value ($p = 0.165$) and DMC ($p = 0.108$) did not show statistically significant differences at the 0.05 level, suggesting uniformity among groups in terms of yellow-blue chromaticity and DMC.

From the result of Table 1, it was found that the b* color parameter showed no statistically significant difference, as indicated by a p-value greater than 0.05. However, the L, a*, DMC, and SC values exhibited statistically significant differences at the 95% confidence level.

A result of ANOVA was conducted to examine the differences in physical and chemical properties of cassava tubers under varying storage durations. To determine which specific groups differed significantly, Tukey's Honestly Significant Difference (HSD) post-hoc test was employed, assuming equal variances among the groups. The level of significance was set at $p < 0.05$. This was displayed in Table 2.

Table 2 The result of ANOVA

Day	L		a		b		SC		DMC	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	80.63	1.229	0.586	0.643	16.637	1.83	21.37	5.476	34.541	4.667
3	78.92	2.309	0.656	0.517	13.892	3.181	18.261	5.412	27.473	4.553
5	81.949	1.397	0.632	0.438	15.821	1.461	15.693	14.444	31.775	3.921
7	77.961	3.899	0.616	0.3	15.726	1.749	13.743	13.586	30.03	7.679
16	78.801	5.931	1.557	1.658	16.592	3.406	21.136	5.556	28.039	5.774
20	69.228	8.239	3.963	3.513	17.678	4.537	19.803	7.885	29.851	6.489
31	71.096	11.751	4.686	4.081	18.658	3.648	12.374	2.425	30.204	6.434

3.2 statistical data of cassava sample

The results of color measurements of cassava tubers were obtained using a color meter. The measurements are illustrated in Figures 4. The Figure 4 displayed the analysis revealed that the lightness (L) value of cassava tuber flesh varied across different storage durations. Specifically, the L value tended to decrease as the storage time increased. This reduction in lightness indicates a progressive darkening of the cassava flesh over time. Such changes are likely associated with physiological deterioration or internal chemical transformations within the tuber, such as enzymatic browning or oxidative reactions. These findings suggest that lightness measurement could serve as a potential indicator for assessing the degree of postharvest deterioration in cassava roots.

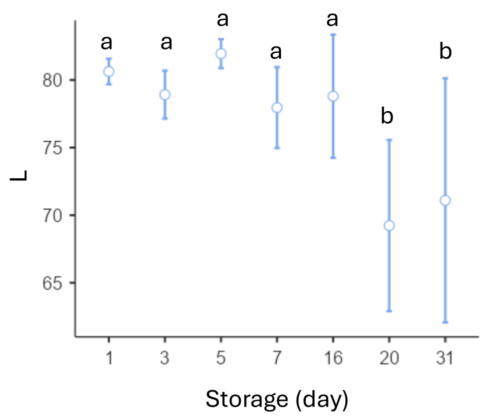

Figure 4 Shows the results of the analysis of the brightness (L) of cassava roots

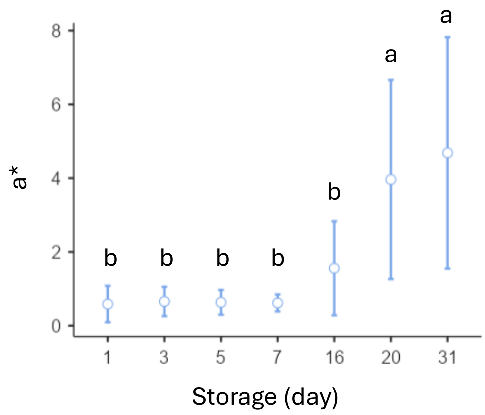

Figure 5 The results of the color intensity (a) analysis of cassava roots, where the color a value indicates the intensity of the red-green shade in cassava roots

Figure 5 The analysis revealed that the a* value, representing the red-green color intensity, changed significantly at certain stages of the storage period. This indicates that the cassava tubers tend to undergo slight color changes as the storage time increases. The variation in the a* value may be attributed to oxidative reactions or other physiological processes that lead to pigment degradation or transformation within the cassava tissue. These findings suggest that a* is a sensitive indicator of subtle quality changes in cassava tubers during postharvest storage.

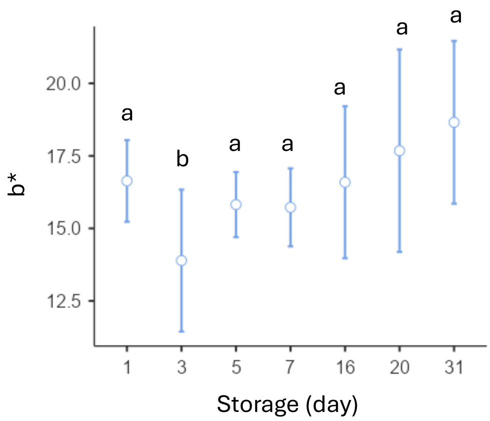

Figure 6 Changes in the b* color value of cassava tubers during different storage durations

Figure 6 explained that on the first day, the initial b* value was relatively high, indicating a notable yellow coloration. However, by day 3, there was a slight reduction in the b* value, accompanied by increased variability. Between days 3 and 7, the b* value remains relatively stable but low, suggesting a temporary suppression or plateau in yellow pigmentation. From day 10 onward, a gradual increase in the b* value is observed, with the most pronounced rise occurring between days 18 and 31. This increase may be associated with the accumulation of chemical changes in the cassava tissue as storage progresses. The wider error bars toward the later storage days (especially days 20 and 31) indicate greater variation among samples, possibly reflecting differential responses to storage conditions or physiological heterogeneity among tubers.

Therefore, this trend suggests that storage duration significantly influences the yellow chromaticity of cassava tubers. The observed fluctuations in the b* value may be related to internal quality changes, enzymatic activity, or postharvest deterioration.

3.3 Statistics of starch and dry matter content in cassava

Figure 7 displayed the result of cassava SC in different time storage period. Based on the analysis of SC, it was found that SC significantly changed during certain storage periods. The SC value showed a decreasing trend as the storage duration increased, indicating starch degradation within the cassava tubers. This reduction may be attributed to decomposition processes that convert starch into other compounds. The decline in starch content over time, therefore, serves as an indicator of the progressive deterioration of cassava tubers during prolonged storage. Figure 8 displays the result of DMC in cassava tubers in different time storage periods. According to the analysis, the DMC showed statistically significant changes across different storage durations. The DMC values tended to decrease as the storage period increased, indicating a loss of solids or certain nutrients within the cassava tubers. This reduction in DMC may result from chemical deterioration, such as the breakdown of organic compounds within the tubers, which occur due to biochemical reactions taking place during storage.

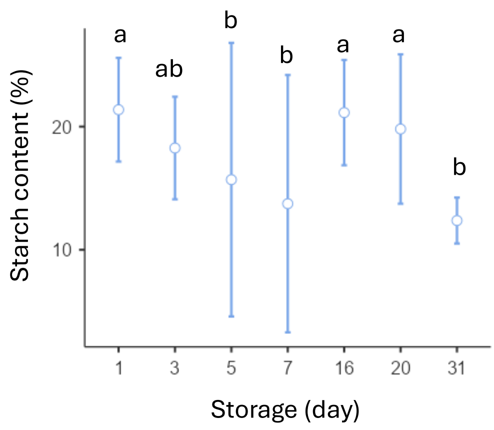

Figure 7 Starch content in cassava tubers at different storage periods

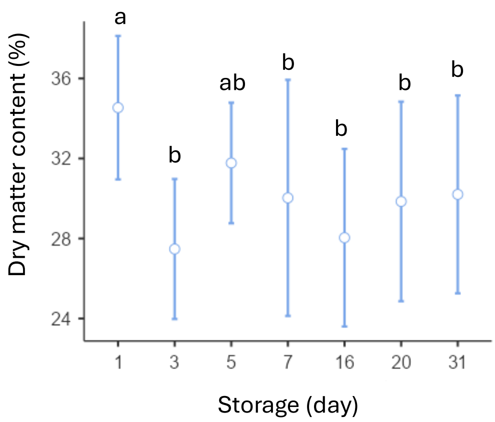

Figure 8 Result of DMC in cassava tubers in different time storage period

3.4 NIR spectra profile

Figure 8 displayed the raw reflectance NIR spectral measurement analysis was conducted at the central part of the cassava tuber using a Mini NIR spectrometer, operating within a wavelength range of 500–1100 nm.

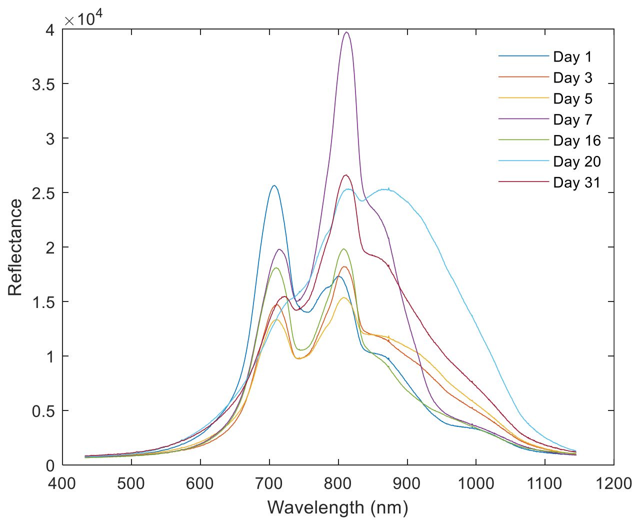

Figure 9 NIR spectra profile obtained from cassava tuber.

From the raw spectra in Figure 9, it can be observed that the reflectance values change across different wavelengths as the storage duration increases. This indicates alterations in the chemical composition or physical properties of the cassava tubers over time. These spectral changes can be utilized to develop predictive models for assessing the level of cassava deterioration.

3.5 Classification of cassava deterioration via machine learning

The analysis revealed that the KNN model provided the highest prediction accuracy. The KNN model using raw spectrum data achieved an accuracy of 69%. The model developed by using preprocessed spectra via SNV and D1 showed slightly lower accuracies of 59.7% and 64.3%, respectively. The model using Min-Max scaling resulted in the lowest accuracy at 60.5%. Therefore, the use of raw spectrum data yielded the most accurate predictive performance compared to other preprocessing methods in the analysis of cassava tubers based on storage duration.

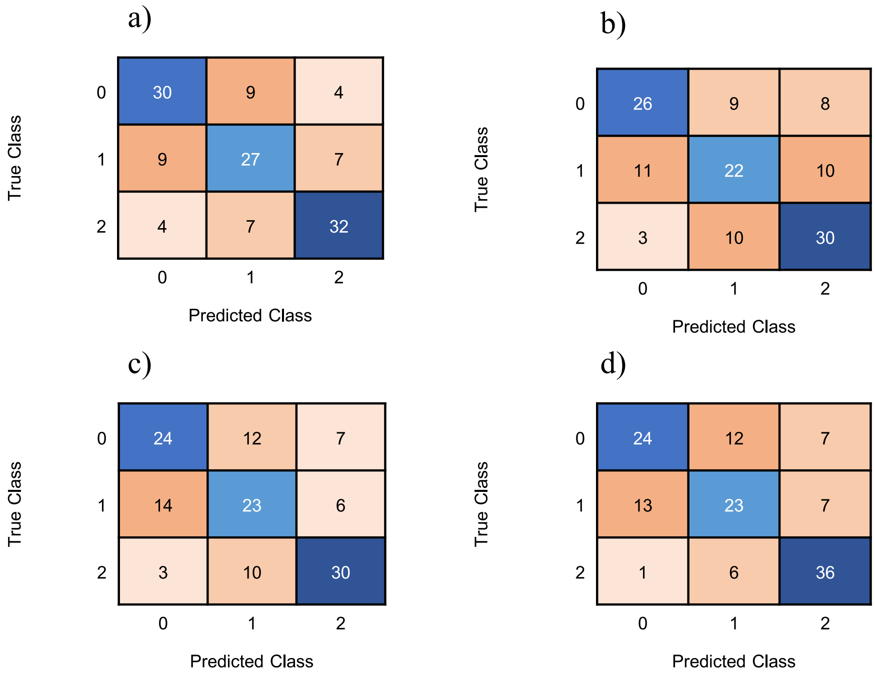

Figure 10 Figures a), b), c), and d) present the analysis results of the predictive models developed using the KNN algorithm, in which raw spectra were employed to build the models for predicting the deterioration levels of cassava tubers over different storage durations.

The predictive model for classifying the deterioration levels of cassava tubers was developed using KNN method. The classification results were divided into three groups: Group 0: Fresh cassava tubers with no visible signs of spoilage. Class 1 indicates moderately deteriorated tubers showing initial changes such as slight discoloration or texture changes. Class 2 indicated severely deteriorated tubers with evident spoilage, including darkening, softening. These classifications were based on visual inspection, colorimetric data (L, a* , b* values), and physicochemical indicators such as SC and DMC, supported by expert judgment and literature guidance.

From the analysis, the KNN models using Min-Max scaling and D1 preprocessing achieved higher accuracy compared to other methods, especially in terms of Recall and Precision. This indicates that the predictions of these models are more accurate and consistent in correctly identifying true results from the data. This information is shown in Table 3

Table 3 Performance of model classification

Performance metrics	raw spectrum	Min-max	SNV	D1
Accuracy	0.6964	0.7273	0.6667	0.7273
Recall	0.6316	0.7222	0.7000	0.7500
Precision	0.7059	0.7647	0.7368	0.7895
Specificity	0.6667	0.7500	0.7000	0.7619

Results indicate a substantial improvement in KNN performance with appropriate preprocessing. Min-max scaling significantly enhanced all metrics compared to the raw spectrum, demonstrating its effectiveness in normalizing feature ranges. The D1 method yielded the highest overall performance, achieving superior recall, precision, and specificity, alongside accuracy comparable to Min-max scaling. SNV, while offering some improvements over raw data in terms of precision and recall, generally showed slightly lower accuracy. These findings underscore the critical role of data preprocessing in optimizing distance-based algorithms such as KNN, highlighting that techniques such as Min-max scaling and D1 could significantly improve classification model efficacy. Further research into the specific characteristics of D1 and its generalizability across diverse datasets would be beneficial.

4. Conclusions

This study investigated the potential of NIR spectroscopy in reflectance mode to assess the deterioration levels of Kasetsart 50 cassava tubers during different storage durations. Key physical and chemical properties such as color (L, a*, b*), SC, and DMC were analyzed. Significant changes in L, a*, SC, and DMC were observed as storage time increased, indicating measurable deterioration. Spectral data from each sample were preprocessed using raw spectrum, Min-Max normalization, SNV, and D1, and were used to develop classification models using KNN. Among the models, those using Min-Max and D1 preprocessing achieved the highest prediction accuracy of 72.73%, demonstrating the effectiveness of these methods in deterioration detection. These findings highlight the usefulness of NIR spectroscopy combined with machine learning as a rapid, non-destructive approach for monitoring postharvest quality in cassava and potentially other root crops.

5. Acknowledgements

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