Evaluating the ripening stages of *Musa acuminata* × *balbisiana* (Saba) using 2D-image analysis

ILYSSA MARIE D. MOSO, SEAN RAFAEL L. PUDA, PIA O. TIMAAN, and MARIA DEANNA B. JOLITO

Philippine Science High School Western Visayas Campus - Department of Science and Technology (DOST-PSHSWVC), Brgy. Bito-on, Jaro, Iloilo City 5000, Philippines

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Abstract

Saba banana is one of the Philippines' main export products but has a fast ripening process which affects its quality and marketability. Most instruments utilized in measuring banana quality are destructive. However, few have used 2D-image analysis in assessing the ripeness of the banana. This paper presents the evaluation of the ripening stage of Saba banana using 2D-image analysis as an alternative, non-destructive method. The 120 banana images were pre-processed by obtaining the mask to remove the background, retaining only the region of interest, which was further converted into HSV and Grayscale. Ninety of the processed images were utilized as training data sets and the rest as testing data sets for the Support Vector Machine (SVM) where the overall agreement is 70%. The researchers recommend that future studies increase the texture features of the Gray Level Co-occurrence Matrix (GLCM) Analysis to improve the performance of the SVM.

Introduction. - Bananas are the top traded fruit worldwide, and it is one of the top fruit exports of the Philippines [1]. Therefore, it is important to ensure the quality (appearance, texture, flavor, and nutritive values) of the banana being exported and consumed locally because it affects their profitability [2].

There are four major cultivars of bananas in the Philippines and *Musa acuminata x balbisiana* (Saba) is one of the country's main products [22]. It is rich in vitamins and minerals and is also included in many Filipino dishes. *M. acuminata x balbisiana* is also used as a supplement or an alternative staple food from rice and corn in rural areas [3]. There was also a lack of research articles involving the analysis of the different ripening stages of this specific variety of banana using 2D image analysis. Bananas tend to be eaten at their mature stage which is why they are usually harvested at the mature green stage and remain without significant changes depending on the temperature, humidity, and age of the banana at the time of harvest. This is because the ripening process of bananas is irreversible once it starts because it brings about physical and chemical changes to the bananas [4]. It can be observed with the alterations in the fruit texture, the changes in the peel color (usually from green to yellow), the appearance of brown spots, and the synthesis of volatile components [5]. Bananas are known to have seven stages in the ripening process, as seen in Table 1, which are usually assessed through visual comparison of the colors of the peels [6]. As the banana ripens, its shape, size, color, and texture change which are observed by producers to decide when to harvest, transport, and sell the fruit [7]. The ability to identify maturity will help farmers optimize the harvesting phase [8].

Table 1. The stages of banana ripening based on peel color [6].

Ripening stage		Banana peel color
Unripe	1	Dark Green
	2	Light green, traces of yellow
Ripe	3	More green than yellow
	4	More yellow than green
	5	Green tip and yellow
	6	All yellow
Overripe	7	Yellow, flecked with brown

The usual methods for determining fruit quality involve destructive and time-consuming measures such as evaluation of dry matter content, total soluble solids content, sugar content, and juice acidity. Thus, non-destructive alternatives such as image analysis are encouraged [12]. As manual inspections tend to be tedious, subjective, and non-uniform, image analysis using different image processing techniques has been

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used to assess and evaluate the ripening process of bananas. Techniques such as the use of colorimeters [11], feature extraction and texture analysis [7], imaging and spectroscopy [12], color histogram [7], and many others have been used over the past few years. Many algorithms have also been utilized for the purpose of identifying the different ripening stages of bananas such as the use of the Gray Level Co-occurrence Matrix (GLCM) for processing; Support Vector Machine (SVM) and K-nearest Neighbor (KNN) for recognition [13]; Fuzzy Color Histogram (FCH) and Movement Imagination (MI) methods for feature extraction [14]; Artificial Neural Network (ANN) to increase quality detection [15], and many others have been proven to be effective and usable in real-life applications. There are also new and efficient techniques that are based on the Hue Saturation Value (HSV) colorspace, development of brown spots, and texture analysis of the banana. According to Tichkule and Gawali [20], non-destructive applications that can use texture analysis techniques on the products are good alternatives for effective food quality assessment because they contain information on the color and geometric structure of the fruit.

The results of this study will benefit researchers who aim to further enhance the use of 2D-image analysis as a non-destructive assessor of quality.

This study aimed to predict the ripening stages (unripe, ripe, and overripe) of *Musa acuminata x balbisiana* (Saba) using 2D-image analysis. Specifically, it aimed to:

(i) analyze the ripe, unripe, overripe stages of Saba banana by applying the Hue Saturation Value (HSV) and Grey-level Co-occurrence Matrix (GLCM) feature extraction techniques.

(ii) compare the HSV of the unripe, ripe, and overripe Saba bananas using histograms.

(iii) determine the different ripening stages of the bananas using the SVM.

Methods. - The Saba bananas were acquired from the local farmers in Leganes, Iloilo, Philippines. The samples were grouped into ripe, unripe, and overripe stages by. This research utilized 120 banana samples overall, 40 for each ripening stage. From each ripening stage, ten of the images were processed while the rest were used to train the SVM. The images were converted into binary images [7]. Next, the images underwent image segmentation which produced the original picture without the background [8]. For the feature extraction, the HSV color space was used to categorize each pixel based on its color and brightness and the GLCM was used in measuring the texture of the image. The final process utilized an SVM to differentiate the ripe, unripe, and overripe bananas [7].

Program Implementation. The Python programming language of version 3.7.10 was implemented through Google Colaboratory which was mounted onto specific Google Drive folders where the acquired images were uploaded.

Sample Collection. The Saba banana samples collected in Leganes, Iloilo were identified and grouped by a qualified banana farmer. Six hands of bananas which were classified as unripe, ripe, and overripe were collected. Unripe bananas are green (stage 1 - stage 2), ripe bananas are usually yellow (stage 5 - stage 6) and overripe bananas are yellow with brown spots (stage 7) [8]. Forty (40) individual bananas were chosen from each ripening stage having 120 samples in total.

Image Acquisition. Images of the samples were acquired inside an enclosed black cardboard box by taking photos using a mobile phone model Vivo 1806 with a 9.8MP camera which was attached to a phone stand 19 cm above the surface of the black cloth. The picture was taken in a room with a temperature of 302°C [17] and with one major source of white light being an LED ring light [12]. Overall, 120 pictures were taken and transferred from the mobile phone to a Google Drive folder in JPEG format [18].

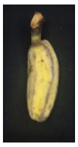
Table 2. The camera control settings used during image acquisition.

Variable	Settings
Image Size	2160 x 4560
Magnification	1.0x
Flash	No Flash
Image Type	JPEG
Aperture	f/2.0

Table 3. The specifications of the LED Ring light used during image acquisition.

Variable	Settings
Brand	SANYK
Model	10 inches live fill light
Outer Ring Size	26cm
Light	Cold Light
Dimmable	Yes
Color Temperature	2700-7000K
Color Rendering Index	RA/CRI:80
Overall lumens	600-1300LM
Number of Lamp Beads	120PCSA
Working Power Supply	DC 5V/1A
Power	12W/24W
Lamp Bead Model	2835 LED
Light Angle	120

Table 4. Raw images of three *Musa acuminata x balbisiana* samples from each ripening stage (unripe, ripe, and overripe).

Samples	Unripe	Ripe	Overripe
1			
2			
3			

Projected Area Estimation. The bananas were cut into six planes in the longitudinal axis. Each perpendicular cut was measured using a Vernier caliper, while the internal and external lengths of the bananas were measured using a flexible ruler [10]. The area of the banana was calculated by solving for the summation of the individual elements: the mean value of the ring thickness, area of the sectoral frustum, and center of the curvature.

Pre-processing. The images were converted into the HSV colorspace. Afterwards, it was converted into grayscale and further converted into binary images which served as segmentation masks [19].

Image Segmentation. Using the segmentation masks, the RGB banana images were separated from the unwanted regions where only the regions of interest were kept [8] which are the areas of the images that were used for analysis [20].

Feature Extraction. The study focused on measuring the sample images' color and texture features. The HSV method was used to evaluate the color, amount of color, and brightness of the images. Afterwards, the HSV values were extracted and plotted into a histogram for each ripening stage where the data was analyzed [7]. The GLCM was used to investigate the texture, specifically, the contrast and homogeneity of the pixels [7,12].

Recognition. The SVM model was trained using 90 testing images with 30 from each ripening stage. The SVM was then used in order to predict the ripening stages of the Saba bananas based on the data sets from the feature extraction process [7].

Data Analysis. The classification of bananas based on their ripening stages was analyzed using the HSV and GLCM for color and texture features, respectively. For the HSV extraction, the data obtained were from the colors of the pixels generated from the HSV color space. These pixels were plotted on a histogram. The GLCM extraction focused on obtaining the value for the contrast [8] and homogeneity [12] using the following formulas:

$$\text{Contrast} = \frac{\sigma}{(\alpha_4)^{0.25}}, \text{ and } \alpha_4 = \frac{\mu_4}{\sigma^4}$$

Where μ_4 is the fourth moment about the mean, and σ^2 is the variance.

$$\text{Homogeneity} = \sum_{i=1}^{K} \sum_{j=1}^{K} \frac{P_{ij}}{1+|i-j|}$$

Where K is the size of the co-occurrence matrix, P_{ij} is the estimate of the probability of a pair of points having values that satisfy an operator, and i and j are values of intensity.

The contrast and homogeneity values were then placed on a matrix and were sorted into pairs according to their banana sample [21]. Using Microsoft Excel, the mean and standard deviation of the texture values were calculated. The SVM was used to compare its predictions with the actual ripening stages of the samples.

Safety procedure. The mandated safety protocols of the LGUs for the COVID-19 were followed during the conduct of the data gathering by the researchers.

Results and Discussion. - Figures 1, 2, and 3 show the average hue, saturation, and intensity values from the ten segmented unripe, ripe, and overripe banana images, respectively, which were obtained from the HSV color feature extraction process. The hue values for the unripe stage are between the range of 90 to 110, while the ripe and overripe stages have hue values in between the range of 50 to 70 with the ripe banana samples having the highest frequency of pixels and the overripe bananas having the lowest frequency of pixels. For the saturation, ripe bananas had the highest saturation value being 0.6 - 0.8 while unripe bananas had the lowest saturation ranging only from 0.4 - 0.6. Lastly, for the intensity, the unripe bananas have the most diverse range of brightness from 50 to 250 while the overripe bananas had the least diverse range of brightness from 150 to 200.

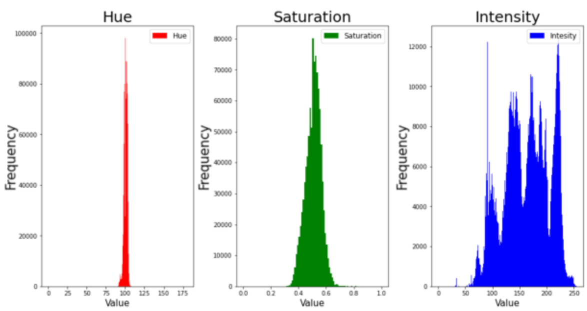


Figure 1. The average HSV histogram of the unripe samples.

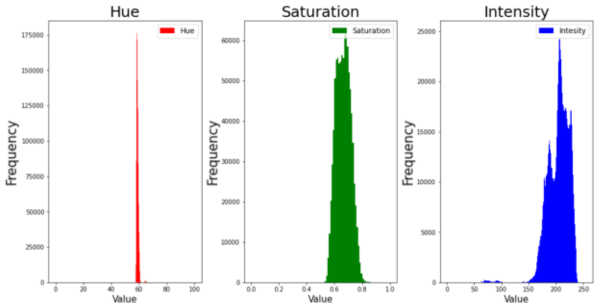


Figure 2. The average HSV histogram of the ripe samples.

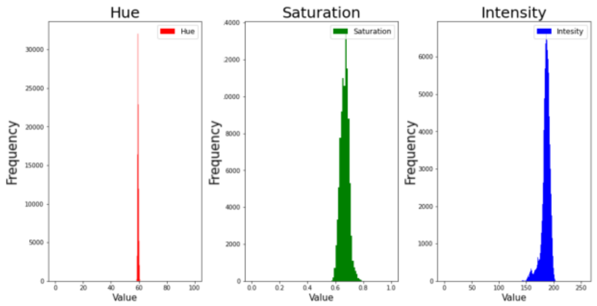


Figure 3. The average HSV histogram of the overripe samples.

The contrast and homogeneity values were obtained using Python in Google Colaboratory, meanwhile, Microsoft Excel was used to calculate the mean of the values and their standard deviation. Normalization of data was done to obtain the best performance for the system with values between zero and one [23]. From Table 4, the overripe bananas have obtained the lowest normalized texture feature value for contrast and homogeneity. The unripe and ripe bananas obtained the highest normalized values for contrast and homogeneity, respectively.

Table 5. The normalized feature vector for the unripe, ripe, and overripe Saba bananas using GLCM Feature Extraction.

Texture Feature	Contrast	STD. DEV	Homogeneity	STD. DEV
Unripe	0.22	0.24	0.25	0.20
Ripe	0.21	0.25	0.29	0.12
Overripe	0.19	0.27	0.21	0.25

Figures 4, 5, and 6 are histograms that present the average red, green, and blue values of the ten unripe, ripe, and overripe banana samples that were analyzed during the HSV color feature extraction process, respectively. On the right side of the plots, the unripe samples have more green pixels than red pixels as evidenced by the higher peak around the 150-color range, while the ripe samples were the other way around having a stronger peak towards the 250-color range. On the other hand, the overripe samples have much more red, green, and blue pixels on the left side of the plot.

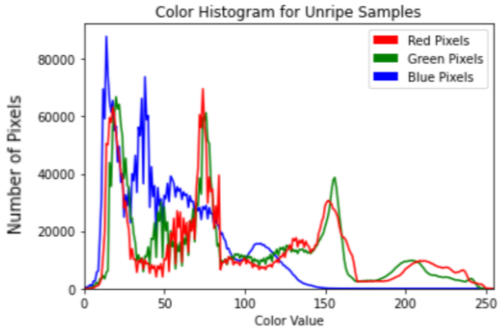


Figure 4. The average color histogram for the unripe samples.

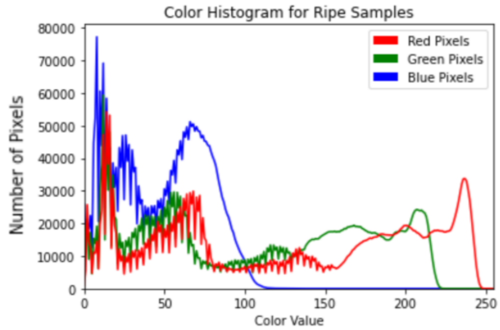


Figure 5. The average color histogram for the ripe samples.

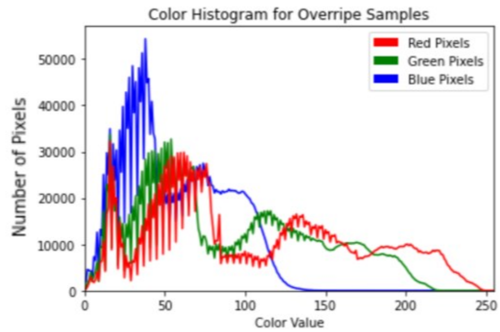


Figure 6. The average color histogram for the overripe samples.

The average values of the histograms in Figures 4, 5, and 6 have a high frequency of dark blue pixels as evidenced by the strong peaks of the blue line reaching over 50,000 pixels from the 0-50 range. This indicates that there may be high amounts of shadows that were included in the images during the HSV color extraction. However, the frequency of the blue pixels in all three histograms was reduced to zero as the color value rose, which means that there were no light blue pixels in the banana images. In contrast to the reduced amount of blue pixels, the right side of the histograms has higher amounts of red and green pixels.

Specifically, the unripe samples had more green pixels than the ripe and overripe samples while the ripe sample had more red pixels than the unripe and overripe samples. Moreover, the unripe samples have the least amount of red and green pixels on the ride side of the plot but have higher values of red, green, and blue pixels on the left side.

An SVM is a supervised learning method that analyzes data and recognizes patterns that are useful in data classification [24]. Random forest was used to classify the images based on the SVM model. The classification was conducted in Colaboratory using python as a programming language.

Table 6. The confusion matrix resulting from the classification of the ripening stages of the Saba bananas using an SVM Classifier.

Actual Stage	Predicted Stage			Sensitivity (%)
	1	2	3	
Unripe	**5**	2	3	50
Ripe	0	**10**	0	100
Overripe	0	4	**6**	60
Precision (%)	100	62.5	66.7	Overall Correctness = **70%**

In Table 5, the confusion matrix presented was used to evaluate the SVM system. The total samples that were processed in the system were 30 bananas, ten from each ripening stage. The system has an overall agreement of 70%. The system classified 10 out of the 10 samples of the ripe bananas correctly (100% sensitivity). Analyzing the errors, 4 out of 10 samples of overripe bananas were misclassified as ripe. This means that the banana samples between the ripe and overripe stages have a similar texture and color features. In a study conducted by Mazen and Nashat (2019), they had made an SVM that achieved an overall agreement of 96.6%. In their study, they used another image feature to differentiate between the different ripening stages—Ripening Factor (RF)—which was not included in this study. RF is the banana's ripeness factor where the total area of the brown spots is divided by the total area of the banana [10]. The maximum value of precision, which is a proportion of the predicted positive ripening stage that was correctly identified, in the classifier is from the unripe stage with 100%. The maximum value of sensitivity, which is the ability of the prediction model to select the instance of a certain ripening stage from the dataset, is reached by the ripe stage with 100%. Table 5 proves this fact because 10 out of 10 banana samples were classified in the correct stage.

Limitations. The limitations of this study include the color range threshold for the image segmentation as the study only used the visual chart provided by Soltani et al. (2019) due to the lack of previous literature involving Saba bananas. Furthermore, only the basic color values of yellow, green, and brown were used for the image segmentation process due to a lack of previous literature regarding the color ranges of Saba bananas.

Conclusion. - The color and texture features from the 90 images that were used to train SVM were able to achieve a 70% overall agreement in classifying the 30 Saba banana samples into unripe, ripe, and overripe classes. Nevertheless, the SVM was still able to garner a 100% accuracy rating for the ripe banana images. Hence, 2D-image analysis has the potential to be a non-destructive alternative in classifying the ripening stages of Saba banana as well as other similar fruits in the food industry, but can always be improved further in the future.

Recommendations. - It is recommended to use the official or actual color ranges of the different stages of bananas depending on their species, as this study was not able to find the color chart for the species used in this study -Saba banana. Moreover, it is recommended to apply more than two texture features for the GLCM analysis such as correlation, energy, entropy, dissimilarity, and other image features such as the Ripeness factor to achieve the best performance for the SVM [23]. Additionally, it is also advisable to use classifiers other than the SVM such as Artificial Neural Network [23] to attain a suitable classifier with the best performance depending on the research design process. Lastly, the researchers emphasize the importance of adding more samples to increase the number of images for the training dataset to also increase the performance of the system [24].

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