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Non-invasive Transport Tier Classification of Banana 'Señorita' (musa acuminata) Using Machine Learning Techniques

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***Abstract*—The lack of a transport quality forecasting system in farming and sorting facilities of indigenous varieties of bananas is aiding the increase of food waste generation in the country. This in turn decreases agriculture sustainability and imposes economic losses to farmers. Musa acuminata 'Señorita' are diploid cultivars of bananas originating in the Philippines. This study aims to develop a machine learning-based system that classifies Musa acuminata 'Señorita' bananas into their transport tiers: (I) for interprovincial distribution, (II) for intra provincial distribution, or (III) subject for rejection. The model is trained and went through 7 machine learning classifiers to identify which model is the most compatible with the system design. The application of external parameters such as size, girth, weight, maturity stage, and RGB parameters can be the foundation to develop a machine learning-based banana transport tier classifier that accurately monitors and determines how long they can travel based on their maturity level. Among the seven models, Logistic Regression, Linear Discriminant Analysis, Decision Tree Classifier, Gaussian Naive Bayes, and Support Vector Machine attained a classification accuracy of 100 %. The development of this system can aid in the proper distribution of produce and help uplift the country's agriculture and economic sustainability.**

Keywords*—*musa acuminata, señorita banana, machine learning, transport classification, fruit maturity detection

I. Introduction

The world's growing population requires agricultural sustainability for guaranteed food security and hunger abolition. To feed the growing population, food production must be increased by 60-110 % globally by 2050. However, this rapid production may also lead to the increasing probability of food waste or food loss, which pertains to edibles that remained unconsumed due to certain circumstances such as spoilage, expiration, or unproper storage system. More specifically, crops such as vegetables and fruits tend to stale quickly. Making them a large contributor to the world's food waste [1].

An example of this is one of the most significant fruits found in the Philippines which are bananas. Bananas are extensively consumed for their nutritional value as they are rich in numerous health benefits that serve as protection against cell damage and various human diseases [2]. Because of this, banana production in the country is prevalent and competitive under both local trade, export trade, and import substitution scenarios [3]. However, not all the available produce is sold as about 60% of banana biomass remains as waste and around 114.08 million metric tons (MMT) of waste-loss are generated after harvest, causing dilemmas in the environment such as emission of harmful greenhouse gases.[4] Therefore, it is important to identify the transport quality better fitted for a bananas' maturity stage.

Thus, methods are curated to determine a bananas' post-harvest maturity and freshness. A recent study in 2022 used two deep learning techniques namely, Convolutional Neural Networks and AlexNet to determine the best deep learning algorithm most compatible for the forecasting of banana fruit maturity and shelf-life quality. The researchers concluded that CNN is the optimal algorithm for banana fruit maturity and quality classification. [5]. Meanwhile, in 2019 and 2020, two studies recognized the importance of the evaluation or estimation of the changing process of bananas. It is explained that the Cavendish Banana has four consecutive maturity stages which vary from a dark green banana, a yellow banana with hints of green, an all-yellow banana, and a purely yellow banana with brown spots, respectively [6]. Another method is the usage of transfer learning which established the connection between the freshness of a fruit and its storage dates. The model was able to detect banana freshness with 98.92% accuracy, which is significantly higher than the human capacity [7].

Other published papers put concern about Banana Strain detection in conjunction with identifying its quality. In 2021, five strains of different bananas are classified and identified with 96.8% performance accuracy. These are the cavendish, shabri, red, lady finger and green banana. [8].

However, there is a lack of variety within the species of banana used in the studies. Only a specific type of banana, which is the Cavendish, was frequently used as subject for fruit maturity and quality monitoring as it is the most common and available globally. The parameters manually taken such as size were also recorded dependent on a single banana from a whole hand, leading for the raw data to be less accurate.

With this in consideration, the researchers chose *Musa acuminata* Señorita cultivar as the focus of the study to monitor a systematic model that predicts the maturity and trading grade by incorporation of machine learning techniques based on several parameters such as RGB color indexes, measured finger size, weight, and mean circumference. These parameters will be used as a guide to classify Señorita bananas, which has a significantly fragile peel that is dependent on their maturity level, into different tiers: **(TIER I)** for interprovincial distribution (Up to 5 days), **(TIER II)** for intraprovincial distribution (Up to 3 days), and **(TIER III)** for rejected class.

TABLE I. TRANSPORT TIER

Transport tier	Transport Life (Days)	Distribution
I	Up to 5	Interprovincial
II	Up to 3	Intraprovincial
III	0-1	Rejected

A. Objectives of the Study

This project aims to classify the transportability of bananas through image processing and multiple machine learning techniques by considering their maturity, size, girth, weight, R, G, and B values. Specifically, the study aims to:

A.1. identify the best combination of features to determine the transportability of bananas.

A.2. accurately predict the transportability of bananas using selected parameters and identify which machine learning technique is best suited for the system.

B. Significance of the Study

The study will contribute to the United Nations Sustainable Development Goals (UN SDG) as the monitoring and classification of bananas' transportability based on their maturity level will ensure responsible production and consumption of goods, which would then limit excessive food waste pollution. The introduction of Señorita banana to the interprovincial and intra provincial trade market will improve the Philippine's economic growth, more specifically Region-IV Calabarzon, as said species of the fruit is mainly produced and transported from the area. The project will serve as a basis and encouragement to pioneer fruit quality inspection in the community to aid in preventing food loss, which is directly correlated to global hunger.

C. Assumptions, Scope, and Delimitations

There are many claims that the use of Machine Learning algorithms has a positive impact in the economy, agricultural management, efficient monitoring of resources, and improved environmental state [9]. Specifically, the banana supply chain has become a recent area of focus for research that applies Machine Learning in smart agriculture [10] Due to bananas having a high rate of deterioration, farmers must determine the fruit's maturity stage to minimize losses during the post-harvest process [11].

The scope of the study primarily focuses on a specific species of banana called Senorita, as there is limited information available that is dedicated to said species. Parameters included in the selection of features that have a sufficient correlation to the transportability of said bananas are size, weight, maturity, girth, R, G, and B color spectrum.

Other species of bananas are not included in the study. The fruit is classified in only 3 transport tiers namely: interprovincial, intra provincial, and rejected respectively.

II. REVIEW OF RELATED LITERATURE AND WORKS

The parameters chosen to determine the transportability of Senorita bananas are maturity, girth, weight, size, and R, G, and B colors. The maturity of bananas is a leading factor to accomplish the aim of this research as it has a big effect on the fruit's quality, marketability, and shelf life after it has been harvested [12]. Meanwhile, size and RGB are the most frequently observed qualities when evaluating banana quality. The Red, Green, and Blue color system enhances the accuracy of image processing and determines hue frequency values that can visually predict a banana's maturity level when incorporated to machine or deep learning techniques [13]. Similarly, a change in the size and girth of a banana is a great indicator of its species and aids in age-bunch control [14]. This is showcased in a study which classified post-harvest grading based on the parameters mentioned along with surface analysis [15]. Lastly, fruit yield is represented by hand weight which is significant to the cost evaluation of its distribution [16]. With these in mind, the selected parameters are further investigated on the following studies:

A. External Parameters

The stage of maturity is vital to the quality, marketability, and shelf life of bananas after they have been picked. Color, size, and defects are the most frequently observed qualities when evaluating banana quality. These are either currently classified manually or individually studied by past researchers.

The study [17] conducted a study in the Philippines that resulted in a system that accurately sorts bananas by cultivar and grade. Image processing with the main algorithms K-Means clustering and HOG feature extraction makes this possible. In 2019, a group of researchers took a similar approach. Using optical imaging techniques, the peel color characteristic is more suitable for determining the various phases of banana fruit maturity due to its simplicity and precision [18].

For determining which type of machine learning model is best for determining banana ripeness or quality, Zhang et al.'s [19] study stated that the CNN model provides a crucial indicator to show the banana ripeness that works well for both a coarse and fine-grained classification of the fruit's ripening stages.

B. RGB Parameter

A common parameter integrated into existing studies and observations about fruit quality is the RGB system. The RGB colors, red, green, and blue, can determine the specification of hues in a standardized way which can be easily recognized by human eyes. The combination of these three shades creates a three-dimensional coordinate system wherein a single point represents each color. RGB, HSV, HSI, and L*a*b color models are the most commonly available color spaces [20].

Relatively, to achieve a more accurate RGB-based prediction, Chen, et. al. [21] wrote a study comparing different tobacco leaves' skewness distribution as well as computing the mean, median, mode, and kurtosis, which showed greater accuracy.

The benefits of both RGB and hyperspectral imaging in the classification of bananas can also be used to model the classification of other horticultural crops [22]. With regards to farm postharvest procedures, the multi-input model's rapid processing time may be more efficient. Another study integrated an image recognition system using a hyperspectral camera. The corresponding images taken are rendered with a set of RGB images under it to build and feed the neural network model that will be the basis of prediction for the sample's quality [23].

In 2022, an RGB-based system was used for classifying fruit stages. Stages are as follows: young, swelling, white-mature, premature, and mature. The results of the observation were based on the quantified pigmentation and key color changes of the fruit [24]. In the same year, a study performed image segmentation and color transformation where the input image's RGB color space is converted into Lab color space, which is a color system with dimension for lightness (black to white) on a scale (zero to 100) [25].

III. Methodology

Application of image processing in agriculture has been a growing research area during the past years. In this study, Image processing techniques used concerned the following steps: image acquisition, pre-processing of raw data and image segmentation, and extraction of features. Fig. 1 shows the methodological framework used in the study.

A. Image Acquisition

The subject of this study is the *Musa acuminata* (AA Group) 'Señorita'. The data gathering process started with the preparation of the bananas to be used for image acquisition. Using the 12 MP camera of an iPhone 8 and an

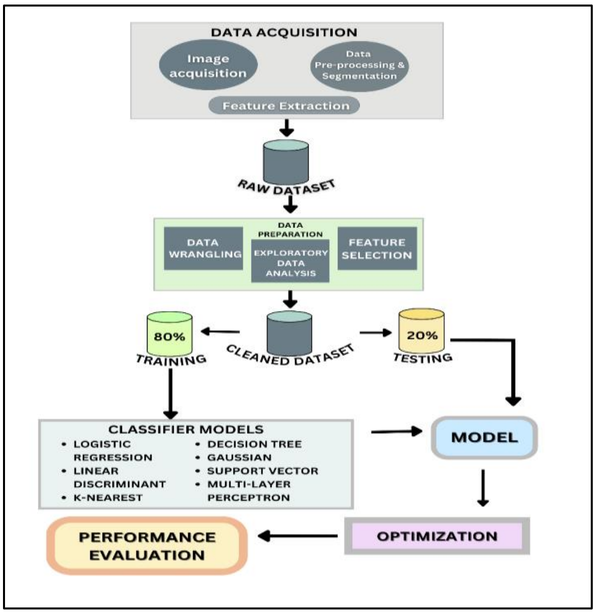

Fig. 1. Methodological Framework that Summarizes the Entire Systematic Process of the Study

LED bar light illumination against a plain white background, the raw images of the Señorita bananas are recorded with 50 samples for each class of banana (class 1, class2, and class 3) giving us 150 samples per class. Image augmentation is performed by photographing in two orientations (front and back). The total number of bananas amounted to 300 samples which were photographed in a way that the overall values and conditions of the sample are captured.

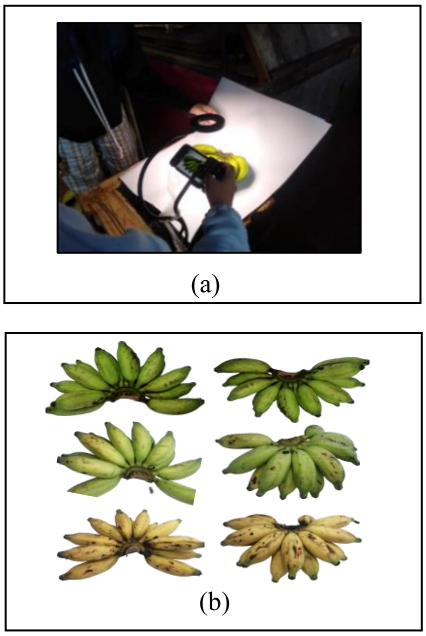

Fig. 2. (a) Actual photographing of samples in two orientations (Front and Back) and (b) raw image samples of Señorita bananas.

The following information in Table II regarding maturity time frames and visual cues of the bananas according to the seller and supplier's perspectives was also acquired.

TABLE II. MATURITY TIME FRAMES WITH INDICATED PARAMETERS

Banana Maturity Level	Parameters		
	Maturity in Days	*Days in Transport*	*Color*
Unmature	1-2	Up to 5 days	Green
Partially Mature	3-5	Up to 3 days	Green with some yellow parts
Mature	6-7	Reject / immediate dispatch	Yellow to Dark Yellow with Black and Brown Specks

B. Data Preprocessing and Segmentation

The images will go through pre-processing, where image enhancement takes place for photographs that have existing noises or interference. The raw images were labeled "1uf.jpg 1ub.jpg, 1pmf.jpg, 1pmb.jpg, 1mf.jpg, 1mb.jpg, etc." indicating the maturity stage (u,pm,m), and banana orientation(front, back). In this stage, image segmentation, or the separation of the background from the actual sample, is done using binary thresholding. Hidden details are extracted to increase low contrasts in some images to produce an output whose pixels are significantly enhanced for RGB recognition, and mechanism.

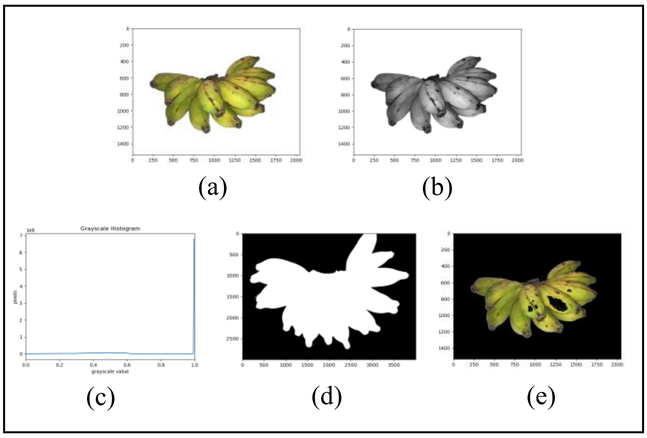

Fig. 3. Process of Image segmentation via Binary Thresholding: (a) Original image, (b) grayscale conversion, and blurring to denoise (c) histogram creation of the gray scaled and blurred image (d) create a binary mask based on the threshold values (e) Background Subtraction using the binary mask

C. Feature extraction

A total of 7 parameters are acquired namely: size_mm, weight, girth_mm, orientation, and the individual R, G, B color indexes. Banana farmer's mode of banana classification is typically based on banana size, making it a significant parameter along with its color indexes. Related literature limitations concerning dimension extraction via image processing of banana images, manual measurement was implemented. The size parameter is measured in millimeters (mm), the weight of the bananas was measured using a standard weighing scale and recorded in kilograms (kg), the girth was measured by measuring the average circumference of each finger in a bunch in millimeters (mm). Finally, the extraction of the RGB values for each raw image sample is executed using the OpenCV library as shown in Fig. 4.

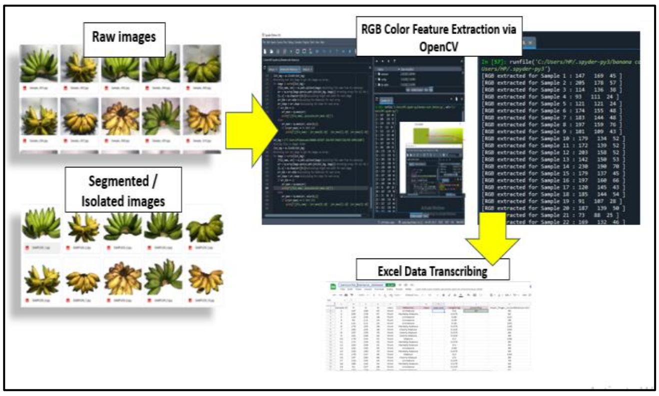

Fig. 4. RGB values extraction via OpenCV

RGB color space is the most common color space where colors are represented by the three primary colors (red, green, and blue). For each component, the value ranges between 0 and 255, where black is represented with the tuple (0, 0, 0) while (255, 255, 255) are the values for the white color. After going through the process of elimination of noise and background via Binary Thresholding, the RGB values of the Señorita banana images were extracted.

The approach was to feed the images using cv2.imread() function. This function reads the image then a NumPy array representing the image is returned. The cv2.split() function is then used to split the image into its three-color channels. This function takes an input image as an argument and returns a tuple containing the three-color channels.

E. Feature Selection

Several methods of feature selection, such as recursive feature elimination, univariate selection, and feature importance are performed to further identify the best features to be incorporated in the machine learning model. Table III summarized the results of the three featue selection methods. It suggests that variables which are significant in predicting the class are maturity, girth_mm, size_mm, RGB features.

TABLE III. HOLD-OUT VALIDATION USING SELECTED FEATURES (OPTIMIZED PARAMETERS)

	Univariate	**Recursive**	**Feature Importance**
Features Selected	maturity G B R girth_mm size_mm	girth_mm weight_kg maturity B G R	maturity girth_mm size_mm B G weight_kg

To justify that only these features are relevant for the prediction of class, the researchers provided supporting related literature and works and used a correlation matrix to evaluate the correlation between the features that were selected, as highly correlated features can lead to problems such as multicollinearity in some models. Weight is correlated to maturity and size, as shown in the matrix in Fig. 5. Weight may not have a direct relationship with the target variable or class, and its high ranking in the plot may be due to its correlation with other features that are more relevant. In such cases, weight may not provide any additional information helpful for class prediction.

	R	G	B	Maturity	weight_kg	size_mm	girth_mm	class
R	1.000000	0.874686	0.860450	-0.221167	0.053634	0.120576	0.159454	0.221167
G	0.874686	1.000000	0.879099	0.205829	0.173329	0.112134	-0.169008	-0.205829
B	0.860450	0.879099	1.000000	-0.014162	0.137416	0.141576	0.037547	0.014162
Maturity	-0.221167	0.205829	-0.014162	1.000000	0.341039	-0.025463	-0.767764	-1.000000
weight_kg	0.053634	0.173329	0.137416	0.341039	1.000000	0.488631	-0.310271	-0.341039
size_mm	0.120576	0.112134	0.141576	-0.025463	0.488631	1.000000	-0.031830	0.025463
girth_mm	0.159454	-0.169008	0.037547	-0.767764	-0.310271	-0.031830	1.000000	0.767764
class	0.221167	-0.205829	0.014162	-1.000000	-0.341039	0.025463	0.767764	1.000000

Fig. 5. Correlation between Variables

F. Machine Learning

The machine learning process has two main parts: the training and testing of dataset. During the training phase, 80 % of the dataset is trained to create a machine learning model. Seven classification models are used: logistic regression, linear discriminant analysis, K-nearest neighbors, decision tree classifier, gaussian naïve bayes, support vector machine and multi-layer perceptron classifier. Training validation ensures that there will be no overfitting of data and the process is generalized. The remaining 20 % is treated as the test dataset which is used for testing the model. The model prediction is evaluated through performance metrics like precision, recall, f1-score, and accuracy.

G. Optimization of Parameters

Machine learning optimization refers to the process of iteratively increasing the accuracy and decreasing the level of error of a machine learning model. Machine learning models learn to generalize and predict new live data based on knowledge gained from training data. The GridSearchCV was used to find the best parameters for each machine learning model.

IV. Results and Discussion

Table IV summarizes the list of parameters and their optimal values for each machine learning model. These parameters were determined using the GridSearchCV function. All parameters of each not included in the optimization process are considered using their default values.

TABLE IV. BEST PARAMETERS FOR EACH MACHINE LEARNING MODELS

Machine Learning Model	Optimized Parameters
Logistic Regression	C: 100, penalty: l1, random_state:0, solver: liblinear
Linear Discriminant Analysis	shrinkage: auto, solver: lsqr
K-nearest Neighbors	algorithm: auto, leaf_size: 10, n_neighbors: 6, weights: distance
Decision Tree Classifier	criterion: gini, max_depth: 2, min_samples_leaf: 1, min_samples_split: 2
Gaussian Naïve Bayes	var_smoothing: 1e-09
Support Vector Machine	C: 0.1, decision_function_shape: ovo,kernel: linear
Multi-layer Perceptron Classifier	activation: logistic, alpha: 0.0001, hidden_layer_sizes: (100, 100), learning_rate: constant, random_state: 0, solver: adam

Table V and VI shows the performance of the models with optimal parameters using selected features. Five out of seven models obtained an accuracy of 100 % after the cross-validation and hold-out validation namely: logistic regression, linear discriminant analysis, decision tree, Gaussian Naïve Bayes, and support vector machine.

TABLE V. CROSS VALIDATION USING SELECTED FEATURES (OPTIMIZED PARAMETERS)

Machine Learning Model	Accuracy Result
Logistic Regression	1.000000
Linear Discriminant Analysis	1.000000
K-Nearest Neighbors	0.893333
Decision Tree	1.000000
Gaussian Naive Bayes	1.000000
Support Vector Machine	0.993333
Multi-layer Perceptron Classifier	0.966667

TABLE VI. HOLD-OUT VALIDATION USING SELECTED FEATURES (OPTIMIZED PARAMETERS)

Machine Learning Model	Precision	Recall	F1-score	Accuracy
Logistic Regression	1.00	1.00	1.00	1.00
Linear Discriminant Analysis	1.00	1.00	1.00	1.00
K-nearest Neighbors	0.86	0.86	0.86	0.85
Decision Tree	1.00	1.00	1.00	1.00
Gaussian Naïve Bayes	1.00	1.00	1.00	1.00
Support Vector Machine	1.00	1.00	1.00	1.00
Multi-layer Perceptron	0.97	0.97	0.97	0.97

V. Conclusion

This section provides a summary of the project and a restatement of its primary outcome, i.e., what was learned and what was accomplished. At the conclusion of the test, the deliverability prediction accuracy for bananas was determined given seven parameters, including size_mm, weight, girth_mm, orientation, and the R, G, and B color indexes of bananas.

A satisfactory classification using machine learning was achieved from the seven machine learning models. Each model's best parameter combination is determined by optimization. Among the seven models, Logistic Regression, Linear Discriminant Analysis, Decision Tree Classifier, Gaussian Naive Bayes, and Support Vector Machine attained a classification accuracy of 100 %. The maturity and size parameters are classified as good predictors of banana class for its deliverability.

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