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Automated Pili Fruit Sorting Device using L-SVM Image Classification Model

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Abstract - Bicol is famous because it is one of the regions in Southeast Asia where the indigenous pili trees (scientific name: canarium ovatum) are growing. One of the precious products from the pili tree is the pili fruit. The properties of the pili pulp, especially its color, make it possible to be sorted automatically. The study's primary purpose is to create an automated device that can sort fresh harvested pili fruits according to their maturity using digital image processing. The proposed system used a low-cost digital camera for image acquisition, Linear Support Vector Machine (L-SVM) as the classification algorithm, a microcontroller, a servo motor, an automatic pili feeder, and a conveyor belt system. Two hundred (200) pili fruit images were collected as training data, and 50 sample pili fruits were used for real-time testing. One hundred seventeen (117) of the images for training were ripe pili fruits, and 83 were a mixture of unripe and almost ripe pili. A total of nine (9) fruits were misclassified out of the 200 samples during validation, having an overall average accuracy of 95.5%. Misclassifications were observed from varying colors of almost ripe pili samples and the defects or deformations on the pulp of the sample pili fruits. Real-time testing resulted in all 50 pili samples having one misclassification only, leading to an accuracy of 98.0%. The test images comprised 25 combined unripe and almost ripe pili and 25 ripe pili fruits. The system can classify approximately 720 pili fruits in an hour which is efficient enough to help the farmers process the fruits after harvest. Ultimately, the device is also applicable to sort fruits with similar properties as the pili since the algorithm only evaluates and classifies the maturity utilizing the mean and standard deviation of the segmented binary images of the pulp.

Keywords: *Automated Sorting, Fruit Sorting, Pili Fruit Sorting, SVM Model*

INTRODUCTION

Bicol Region is famous because it is one of the regions in Southeast Asia where the indigenous pili trees (known in the scientific world as Canarium ovatum) are growing. The production of what they call java nut became one of the trademarks of Bicol, and that is why private and public sectors are eager to spearhead innovations towards the improvement of the pili industry in the province. The emergence of industries that use pili as one of their main products impacts pili production in the region that challenges the pili growers to be more competitive to meet the market needs. Due to the numerous products generated from the pili pulp, sorting them according to maturity is one of the laborious tasks the harvesters face. Pili Industry confronts problems with the slow progress of technology and incomplete end-to-end automation of the processes during post-harvest. After the pili fruits are harvested from the tree, the next step is sorting them out according to maturity. This process is done manually in the current setup, requiring human resources to separate the ripe fruits and unripe ones into different containers. Manual sorting may take 2-3 seconds per pili fruit, and it also depends on the sorting skills of the person doing the task. Although human beings can classify ripeness immediately, there are still chances that our judgment is wrong due to blurred vision, stress, poor eyesight, and other uncontrollable human factors. This step must be mechanized if the goal is to automate the pili production process fully.

Evaluating the available machines for pili processing in Bicol, automated sorting of pili fruits according to color or maturity is missing. The assessment of the advantages and disadvantages of the prior methodology from the current studies will make the proposed system more efficient. The classification accuracy and performance offered by the individual and modular IR and color sensors are not very reliable as they depend on the individual photodiodes' sensitivity. The random color of pili fruits from green, light purple, and dark purple will not allow the sensors to detect its color quickly and accurately. A simple image processing model must be implemented since it does not need high computing power and is very reliable for real-time classification and sorting.

The study's primary purpose is to create an automated device that can sort harvested pili fruits according to their maturity. The specific objectives of the study are: (1)harness the properties of the pili pulp and sort them based on ripeness using an image processing and classification model, (2)provide a definite result of the Linear-Support Vector Machine's (L-SVM) performance, accuracy, and learning rate, (3) disclose the sorting rate of the device to assess if it is comparable to the speed of manual sorting, and (4)assess the cost of the device if small-pili harvesters can consider it for procurement.

RELATED LITERATURE

Current studies provided different approaches in sorting objects, from detection, classification, and eventually separating them according to specific qualities. Soloman [1] shared great insights about the importance of color vision in realizing essential agricultural and industrial applications such as color-based inspection, detection, classification, and sorting. Humans can efficiently deal with multi-colored objects, intricate patterns, and random orientations under normal or poor lighting conditions. Fully automated color-based sorting machines should be trained and tested to perform with almost the same capabilities as humans. In order to obtain this objective, a refined machine learning or image processing and classification model should be designed to perform the designated task.

Embuscado [2] has revealed promising technologies for pili processing in his article. Some offices in Bicol collaborated to identify the problems related to the pili industry and gave birth to the development of mechanized devices and equipment. To enumerate some, the harvester with cutter and collecting net, de-pulping machine, pili nutcracker, tesla removal machine, and oil extractor. Assessing the available devices, automated sorting of pili fruits according to color or maturity, size, shape, and quality is missing.

Batra et al. [3] developed a simple, efficient, and affordable tomato sorting machine that helps get good-quality ripe tomatoes without human error. The machine separates ripe and unripe tomatoes utilizing IR, color, weight sensors, a microprocessor, a servo motor, and a conveyor belt system. Their study opened the possibility of using cheap and simple devices to perform essential industry applications. Low-cost cameras nowadays can offer better imaging performance and hold more opportunities for further image processing and analysis due to the variability of the colors on the fruit pulp.

Alaya et al. [4] stated that Arduino could be developed so that the combined light intensities reflected from the product and frequency of the wavelength can be converted from the RGB space to the HSL domain. The study proposed a sorting machine of the coated chocolate candy. An Arduino directs the machine to command the servo, stepper motor, and color sensor TCS3200. The research could not resolve the only limitation of classifying colors at shorter ranges (i.e., yellow and orange). This issue can significantly impact the system's performance as candies usually have bright colors, and yellow and orange are some.

Capucao et al. [5] created a system to detect ripe pili fruits using the Haar-like features, Adaboost classifier, and color analysis to establish a dataset of canarium ovatum with a phantom IV professional drone attached with a 20-megapixel camera as a means for image acquisition. The result of the pili fruit detection using this method is not yet sufficient to estimate how many pili fruits are ripe and are expected to be harvested. Only the top and front view of the pili tree was captured, and multiple detections of pili fruits caused this restriction. Their recommendation is to perform the pili fruit maturity detection and classification after fruits are harvested and under controlled lighting.

Sharif et al. [6] stated that enhancing the pre-processing methods would improve the segmentation accuracy in return. Their study focused on creating a hybrid method of detecting and classifying diseases on citrus plants consisting of two primary phases: detecting lesion spots on the citrus fruits and leaves and classifying citrus diseases. Their investigation showed that a good pre-processing method is needed to obtain better results during classification.

Sakr et al. [7] proved that SVM is more advantageous than using a Convolutional Neural Network (AlexNet) in separating waste categories, specifically plastic, paper, and metal. The analysis of two different models showed a big difference in which method is appropriate for every scenario. The use of AlexNet requires sophisticated hardware such as GPU to train the model and preserve high accuracy output. Compared to SVM, the model does not require a lot of computing power to train the model – thus, it delivered more than AlexNet.The best model tested from the output of AlexNet has an accuracy of 83%. On the other hand, SVM delivered 94.8% accuracy, which is way higher than that of AlexNet.

The work of Pascual et al. [8] regarding the automated detection of rice plant diseases presented the results of using two different classification models, namely, the SVM and Random Forest algorithm. Results show that the blue pixels that are indicators of rice disease and the SVM as its classifier have yielded better outcomes than the other model. Finally, the study of Ayllon et al. [9] about fruit maturity detection shared insights that fruits is the ninth (9^{th}) most exported good in the Philippines. The researchers utilized Convolutional Neural Networks through Image Processing to determine the fruit maturity of bananas, mango, and calamansi. They classified said fruits into three categories for the fruit maturity as pre-matured, matured, and over-matured.

METHODOLOGY

A. Proposed Device's Conceptual Framework

Fig. 1 demonstrates the conceptual framework of the proposed system. The properties of the pili pulp, especially its color, make it possible to be sorted automatically through the assembly of hardware supported by software elements. The system's inputs were fresh pili fruits dropped by the automatic pili feeder to the conveyor belt system and the snapshots of the pili fruits on the detection platform captured by the low-cost digital camera. Image pre-processing was necessary to extract the ripe and unripe pili features into two classes. The process stage contains the (1)segmented images using the morphological structuring element method, (2)comparison of the mean and standard deviation of the segmented image with the validation database, (3)classification result using the L-SVM image classification model, and (4)initialization of the triggers of the microcontroller and the servo motor. The output of the system was the sorted ripe and unripe pili fruits.

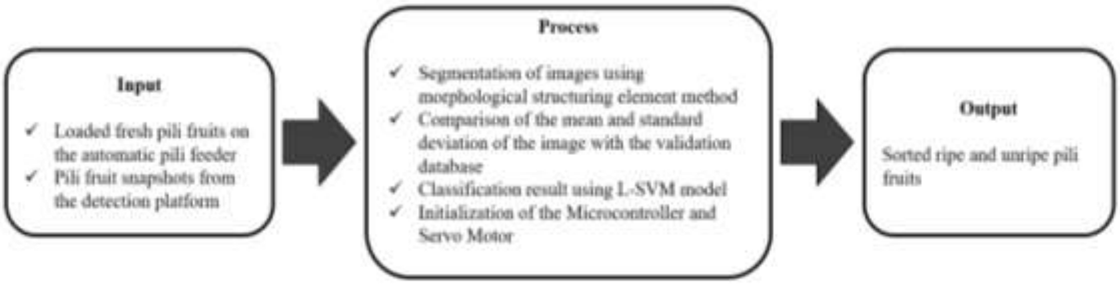


Fig. 1. Automated Pili Fruit Sorting Device using L-SVM Image Classification Model Conceptual Framework.

B. Image Acquisition and Dataset

The study has collected 200 images of fresh pili fruits under uniform distance and controlled lighting using a 320x240 pixels A4Tech digital camera. Proper lighting was secured using two 13W led lamps to eliminate unnecessary shadows in the region of interest (ROI). The camera was positioned at the height of 0.28 meters, and both lamp tips were at 0.19 meters from the conveyor belt. A total of 50 ripe and unripe pili fruits were selected for real-time testing and served as the input for the assessment of the actual accuracy of the device. Eighty-three (83) were used for training, and 25 for testing are the combined samples of unripe and almost ripe pili fruits. One hundred seventeen (117) images used for training and 25 images for testing are the samples for the ripe ones. The two-hundred pili images were fed to MatLab as the training validation database, where the test samples were compared for real-time classification. Fig. 2 shows the three major stages of the pili fruit. Images (a) and (c) illustrate the unripe pili having a green pulp and the ripe pili, black, respectively. The variability of pulp's color, especially when it is almost ripe, as shown in (b), puts the use of individual color and infrared sensors at a disadvantage compared to using digital cameras for color detection. Part of the system's design was to position the digital camera at such a height that it could capture the moving pili fruits in the conveyor, eliminating any unnecessary objects and components that may affect the image classification.

a) unripe pili b) almost ripe pili c) ripe pili

Fig. 2 Sample images acquired for training the L-SVM Classifier.

C. Image Classification using L-SVM Model

Linear Support Vector Machine (L-SVM) is an image processing algorithm used in classification. The concept is to find a suitable learning boundary while maximizing the margin or distance between the closest learning samples (the support vectors) corresponding to the classes. In the case of pili fruit sorting, the model was designed to separate the ripe and unripe pili fruits. Numerous SVMs are available in Matlab as classification learner apps; however, the L-SVM best suits the classification requirement for a two-class data set. The program includes converting the colored image to its binary equivalent using the global thresholding technique. Thresholding is a type of image segmentation where the pixels of an image are changed to make the image easier to analyze. In thresholding, an image should be converted from color or grayscale into a binary image that is simply black and white. For Global Thresholding, the Threshold (T) is constant and applies to the whole image. Equation (1) shows the function of how thresholding is performed.

$$g(x,y) = \begin{cases} 1, \ if\ f(x,y) > T \\ 0, \ if\ f(x,y) \leq T \end{cases} \quad (1)$$

where $g(x,y)$ is the output pixel, $f(x,y)$ is the input pixel and T is the threshold value.

The initial estimate of the threshold is generated after the RGB image is converted to grayscale and adjusted through contrast stretching. What happens is that each pixel is compared to the threshold value. If the individual pixel is greater than T, it will be considered one or white. If the pixel value is less than or equal to T, the output value will be zero or black after thresholding [10]. Moreover, a morphological segmentation technique used a structuring element to break narrow bridges and eliminate thin structures on the captured images before proceeding to the classification section. Implementing the "opening" morphological segmentation differed between the segmented images for unripe and ripe pili fruits. The mathematical equations below represent the morphological segmentation.

$$A \ \Theta \ B = \{z | B_z \subseteq A\}, \ Erosion \quad (2)$$

$$A \oplus B = \{z | \hat{B}_z \ \cap \ A \subseteq A\}, \ Dilation \quad (3)$$

$$A \circ B = \{(A \ \Theta \ B) \oplus B\}, \ Opening \quad (4)$$

where A is the original set and B is the structuring element. The opening method (4) requires both erosion (2) and dilation (3) process. For erosion, the set of points z such that the structuring element (B) translated by a vector (z) fits fully inside the original set (A). On the other hand, dilation finds pixels such that shifted structuring element (B) has any overlap with the original set. The opening starts with erosion, followed by dilation.

The first step of implementing L-SVM is to evaluate the extracted features from the segmented images [11]. Those are the mean and standard deviation. The mean (μ) was computed as the average of the pixels on the entire image (5),

$$\mu = \frac{\sum x_i}{n} \tag{5}$$

and the standard deviation was computed using the fundamental formula (6) below,

$$\sigma = \sqrt{\frac{\sum(x_i - \mu)^2}{n}} \tag{6}$$

where σ is the standard deviation of the image, x_i is the value of each pixel, μ is the mean of the image, and n is the sum of the pixels on the entire image.

The next step is to determine the support vectors. Support vectors denoted by $(\tilde{s_1}, \tilde{s_2}, \& \tilde{s_3})$ on the sample formula are data points closer to the decision boundary and influence the position and orientation of the hyperplane (7) & (8). Data points falling on either side of the hyperplane can be attributed to different classes. Once the support vectors are selected, a bias of (1) will be added to the features creating a 3x1 matrix. After solving the dot product of the matrices, three equations are generated, thus the variables $(\alpha_1, \alpha_2, \& \alpha_3)$ can be computed.

$$\alpha_1 \tilde{s_1} \cdot \tilde{s_1} + \alpha_2 \tilde{s_2} \cdot \tilde{s_1} + \alpha_3 \tilde{s_3} \cdot \tilde{s_1} = 1 \tag{7}$$

$$\alpha_1 \tilde{s_1} \cdot \tilde{s_2} + \alpha_2 \tilde{s_2} \cdot \tilde{s_2} + \alpha_3 \tilde{s_3} \cdot \tilde{s_2} = 2 \tag{8}$$

where α_1, α_2, & α_3 are the variables for computing the weight vector and $\tilde{s_1}, \tilde{s_2}, \& \tilde{s_3}$ are the support vectors with bias. The weight vector is made up of a 1x3 matrix. The elements on the first two rows are the weight, and the element on the third row is the bias. The weight vector was computed using the equation (9) below.

$$\tilde{w} = \sum_i \alpha_i \tilde{s_i} \tag{9}$$

For the L-SVM model, the hyperplane equation looks the same as the slope of the line equation, which is y=mx+b, where m is the slope and b is the y-intercept. Equation (10) shows the hyperplane function.

$$y = wx + b \tag{10}$$

the weight vector (w) signifies the slope of the hyperplane, and the bias (b) is the y-intercept of the line. Using these support vectors, we maximize the margin of the classifier. Deleting the support vectors will change the position of the hyperplane. These are the points that helped build the L-SVM. The Matlab code also contains commands for the webcam to capture a snapshot under a specified time and triggers the Arduino and servo motor to eventually guide the pili fruits to their respective containers. The system used 11th Gen Intel(R) Core(TM) i5-1135G7 to run the program in Matlab.

D. Microcontroller and Actuation System

A microcontroller is used in programming and robotics due to its user-friendly or easy-to-use setting. Like any microcontroller, an Arduino is a circuit board with a chip programmed to perform desired tasks. It collects information from the computer program and finally triggers the circuit or machine to execute the specified command. Arduino Uno was used in this study to interface the system's input (sensing section) and output (actuation section) which is the servo motor. Servo Motor SG90 was the actuator used to swing the sorting chute to its appropriate position. The Arduino board was connected to a computer using USB 2.0 Cable Type A/B. The servo motor was connected to the Digital pin 3 of the Arduino board, including its supply voltage with a position set to 0.5 as its default angle. If the classification model resulted in a ripe pili fruit, the servo motor's position would change to 0.25 angle. Hence, if the classification resulted in unripe pili, the angle would change to 0.60.

E. Conveyor Belt System

Belt conveyors are thick rubber bands stretched at high tension and threaded through a brush of rolling components, moving at the desired speed to carry materials from one place to another. The conveyor belt system was responsible for transporting the pili fruits from the reservoir to the detection platform until they reach the containers after sorting. A 0.63 x 0.29 x 0.13 meters conveyor system was improvised to run by a 680W impact drill connected to a 220V AC supply. The design was bearingless, making the construction simpler and more affordable than the usual conveyor belt setup. The rollers were fabricated with ¾" PVC Pipes and 10" Water Filter Cartridges. The conveyor belt was made of 0.02 meters elastic bandage cloth, wide enough to avoid the pili fruit from moving out of track and falling off the conveyor.

F. Automatic Pili Feeder

The automatic pili feeder was linked to a DH48S-S timer connected to a 220V supply and a fabricated roller setup using a 12V DC motor to drop pili fruits one by one to the conveyor belt for a specified time. The timer will turn the DC motor for 0.1 seconds for a pili fruit to drop from the reservoir to the conveyor belt and then turns off for 5 seconds to make way for the pili fruit to be classified and reach its designated container. A 12V Dimmer was necessary as part of the feeder and was connected in series with the motor so that strong spins will be prohibited that may cause the pili fruits to trickle out of the platform. The succeeding pili fruit drops on the next cycle of the timer. The process will repeat until all pili fruits loaded on the automatic pili feeder are sorted.

G. National Standard Used

The ISO 21183-1 set the light conveyor belt systems' principal characteristics and applications. Based on the review, light conveyor belt systems are usually found in chemicals, pharmaceuticals, cosmetics, food, agriculture, wood, and tobacco. They are mostly used in indoor applications and outdoors under cover [12]. The assessment of the different light conveyor belt systems, their characteristics, designs, and applications guided the research to implement the most appropriate belt system to transport the pili fruits from the automatic pili feeder down to the sorting containers.

H. System's Process Flow

This research implemented the process flow as demonstrated in Fig. 3 to obtain the set of objectives of the study.

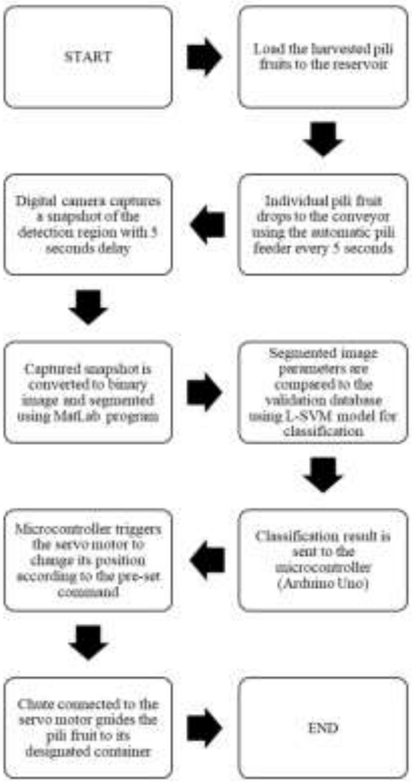


Fig. 3 Process flow of the proposed system.

The process begins from the pili reservoir linked to the automatic pili feeder, where the harvested pili fruits are loaded. The individual dropping of the pili fruits is controlled by the DH48S-S timer and the roller setup. The cycle relay timer automatically uses 2 watts of power, switches the DC motor on by 0.1 seconds, and turns off 5 seconds. An additional device was used to control the DC motor. A 12V Dimmer was connected in series with the motor so that strong spins will be prohibited that may cause the pili fruits to trickle out of the platform. Once the pili are dropped successfully to the platform, they will move and pass through the detection stage. The camera is connected to a computer that runs MatLab codes to determine the mean and standard deviation of the segmented pili fruit images. The L-SVM model implemented in MatLab determines the boundary and maximizes the margin so that for every test image, the model compares its parameters to the pili validation database. The MatLab code has a command to control the response of the servo motor for each pili fruit that was captured. The servo motor was connected to the digital pin 3 and 5V power inputs of the Arduino Uno responsible for guiding the pili fruits into the designated containers through a sliding chute. Finally, designated round plastic containers for the ripe and unripe pili used for sorting were placed at the end of the conveyor line to separate the classified ripe and unripe pili fruits. Fig. 4 displays the prototype of the proposed device.

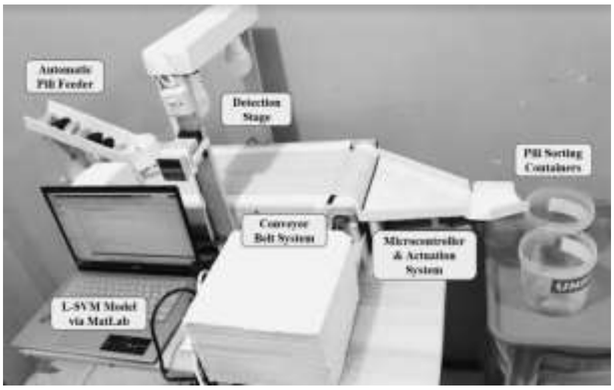


Fig. 4 Prototype of the Automated Pili Fruit Sorting Device.

I. Data Analysis

The equations below express the calculation of the validation and testing accuracy of the classification model.

$$TPR = \frac{CC}{TS} \tag{11}$$

$$FNR = \frac{MC}{TS} \tag{12}$$

$$OVA = \frac{CC_{combined}}{TS_{combined}} \tag{13}$$

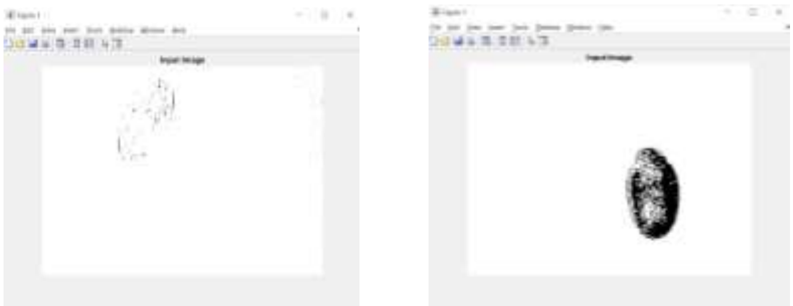
Where, TPR (True Positive Rate) is the percentage of the correct classification, and FNR (False Negative Rate) is the percentage of the misclassification. CC is the number of correct classifications, and MC is the number of misclassification. TS is the total number of samples for each class. OVA is the overall validation accuracy, the ratio of the combined number of correct classification, and the combined number of ripe and unripe pili samples.

RESULTS AND DISCUSSIONS

The proposed setup of the automated pili fruit sorter using the L-SVM Classification model showed satisfactory results based on the validation and testing outcomes of the model. The succeeding discussions provided the results and the procedures performed to sort the pili fruits.

A. Results of the Pre-processing using Morphological Segmentation Technique

Classifying the pili fruits require pre-processing techniques to efficiently obtain the mean and standard deviation of the sample pili fruits. Fig. 5 shows the output of the segmentation using the morphological structuring element.



a) Segmented Unripe Pili   b) Segmented Ripe Pili

Fig. 5 Sample segmentation output using morphological structuring element method.

The segmented images exhibited a huge difference where the unripe pili displayed a small portion of black compared to the ripe pili, which showed the black color covering the entire pili area. Mathematically, the average segmented mean of an unripe pili fruit was 0.987, and its average standard deviation was 0.089. On the other hand, the average segmented mean and standard deviation of ripe pili fruits were 0.961 and 0.154, respectively. This finding proved that a simple classification model could be implemented to classify the pili fruits into two different maturity classes in real-time.

B. Training Validation Result of the L-SVM Image Classification Model

The significant margin or gap between the parameters of the sample data will justify why the Linear SVM delivered exemplar results in classifying the maturity of the pili fruits. The numbers provided were gathered from the 200 images to train the model. One hundred seventeen (117) of the images for training were ripe pili fruits, and 83 were unripe and almost ripe pili. The validation accuracy of the model was evaluated using the True Positive Rates (TPR) and False Negative Rates (FNR). The TPR was 92.8% and 97.4% for the unripe and ripe pili fruit classes. On the other hand, 7.2% for the unripe and 2.6% for the ripe class were the algorithm's FNR. Six (6) fruits were misclassified as ripe though they should be unripe, and three (3) samples were misclassified as unripe; they should be in the ripe class. Nine (9) out of 200 samples were misclassified during validation, having an average training accuracy of 95.5%. Additionally, it took 6.19 seconds to complete the training validation. The issue was due to the property of the pulp of almost ripe pili, which has nearly parametric values as with the ripe pili fruits. Other factors such as deformations, irregularities in the pulp, and extrinsic defects also caused misclassifications and were not corrected nor eliminated during the segmentation process.

C. Test Result of the Automated Pili Fruit Sorting Device

Although the model's validation accuracy was 95.5%, the overall real-time test accuracy obtained was still great at 98.0%. A total of fifty (50) pili fruits were used for testing, composed of 25 combined unripe and almost ripe pili and 25 ripe pili fruits, as shown in Table I.

The table includes the classification accuracy for both pili classes. With the classification rate of roughly 5 seconds, including the travel time of the pili fruit in the conveyor and sliding chute, the system can classify approximately 720 pili fruits in an hour – which is efficient enough to help the pili farmers process the fruits with minimal human intervention after harvest.

Table I. Overall Test Data Confusion Matrix

No. of Samples	Ripe Pili Fruit Class		
	Correct Sorting	Incorrect Sorting	Accuracy
25	25	0	100.0%

(a) Classification accuracy for the Ripe Pili Fruit Class.

No. of Samples	Unripe Pili Fruit Class		
	Correct Sorting	Incorrect Detection	Correct Sorting
25	24	1	96.0%

(b) Classification accuracy for the Unripe Pili Fruit Class.

No. of Samples	Combined Class		
	Correct Sorting	Incorrect Detection	Correct Sorting
50	49	1	98.0%

(c) Overall classification accuracy for the combined pili fruit samples.

CONCLUSION AND FUTURE WORKS

The method to harness the properties of the pili pulp to sort them according to ripeness was performed using the combination of multiple devices. Using a computer and MatLab version R2021a software, the Linear Support Vector Machine (L-SVM) Classification Model, an image processing and classification model, served as the backbone for categorizing the ripe and unripe pili fruits. With the help of a digital camera to capture images, a microcontroller (Arduino Uno) connected with a servo motor used as actuation devices, an automatic pili feeder, and a conveyor belt system for transporting the pili fruits from beginning through the end, the automation of the pili fruit sorting developed into a novel work.

The L-SVM showed an exemplar performance in classifying the maturity of the pili fruits. The sorting rate of the device is approximately 5 seconds per pili fruit making it 720 pili fruits in an hour. The sorting rate of the proposed device is lower than the manual sorting rate; however, this automation will benefit the pili growers as they will no longer need to dedicate many efforts or hire a resource to sort the harvested pili fruits. The system's performance can be enhanced by using more sophisticated and high specification detection components such as the camera, which can perform multiple detections.

Regarding the economical aspect, an amount of ₱4,544.00 was spent to create the prototype of the proposed device. Based on the cost assessment, the Automated Pili Sorting Device is still reasonably priced compared to the existing small-scale fruit sorting machines in the market ranging from ₱50,000.00 - ₱300,000.00. The largest expenditure made on the device was from the conveyor belt system. The conveyor belt system can be procured as a whole and in bulk for wide-range production and will lessen the cost of creating the sorting device.

The bearingless conveyor belt setup powered by an impact drill can be replaced with a conveyor composed of a motor, bearings, speed control, and belts for a more stable performance versus using the improvised setup. The impact drill was very unstable because it speeds up after running for a prolonged period. The alignment of the drill's shaft and one of the conveyor tubes made it difficult for the proposed setup to maintain its speed.

Other classification models can also be reviewed to compare L-SVM regarding the validation accuracy and processing time as part of future endeavors. The possibility of multiple detections of pili fruits is promising to tremendously improve the device's sorting rate. Ultimately, the device is also applicable to sort fruits with similar properties as the pili since the algorithm only evaluates and classifies the maturity utilizing the mean and standard deviation of the segmented images of the pili pulp.

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