Jackfruit Maturity Classification Using Uniform Local Binary Pattern and Support Vector Machine

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***Abstract*—According to the Philippine National Standards (PNS), mature jackfruit are defined by their spines being separated far apart and well-developed. Such maturity feature is present in many local cultivars in the Philippines, specifically within the Magnolia jackfruit variety. We developed a maturity classification system based on the Uniform Local Binary Pattern (ULBP) operator as the texture descriptor and the Support Vector Machine (SVM) as the classification model. Initially, the Region of Interest (ROI) was extracted from the captured image to emphasize the jackfruit's rind. Then, the ULBP operator was used to detect and capture local texture patterns exhibited by the spines. The Hue histogram was also extracted to incorporate the rind's discoloration. Finally, the extracted features were concatenated to generate the final feature vector. A total of 240 images were utilized to train the system for jackfruit maturity classification. The proposed methodology yielded an accuracy of 93.33% for Magnolia's immature and mature classes.**

Keywords—image processing, SVM, ULBP, jackfruit maturity classification, confusion matrix

I. Introduction

According to the Philippine Statistics Authority (PSA), about 13.8 thousand ha of land in the Philippines have been planted with jackfruit (*Artocarpus heterophyllus*) over the past two years. Jackfruit is known for its various economic utilities, including meat alternatives, medicinal applications, and animal fodder. According to the Philippine National Standards (PNS), mature jackfruit is defined through the change in the rind's texture about spines that are separated far apart and well-developed. The rind's discoloration could also be taken as a maturity-indicating characteristic. Immature jackfruit is green to greenish at an earlier stage and yellowish-green to yellowish as it advances in maturity [1]. Despite these significant changes in jackfruit's physical characteristics, limited research has been done on its maturity classification based on image processing techniques.

We used the Uniform Local Binary Pattern (ULBP) as the texture descriptor for jackfruit maturity classification. ULBP descriptor is rotation invariant, supports multi-resolution methods, and accumulates uniform patterns from calculated textures. In contrast with its predecessor Local Binary Pattern (LBP) algorithm, the separation of uniform patterns in ULBP allows effective generalization with minimal data loss in the image [2]. This texture algorithm has been applied to various image processing studies, such as the ethnicity recognition algorithm [3], lychee fruit detection system [4], and cirrhosis liver recognition [5]. Another example of texture descriptor is Disorganization Indicator Based on Component, wherein an image's texture is characterized based on its intuitive properties. These components include energy, contrast, entropy, homogeneity, dissimilarity, and maximum probability. The texture descriptor was used in the Aedes Aegypti detection system, yielding an 80% accuracy using image processing techniques [6].

According to studies, LBP-based descriptors have shown higher accuracy with Support Vector Machine (SVM) than other machine learning classifiers [7,8]. SVM is also effectively utilized in recent studies involving color space analysis [9−11], text recognition models [12], image processing [6,13], and gas-based sensors [14,15]. In the study of Black Sigatoka disease detection on banana leaf [16], the performance of SVM in comparison with ShuffleNet V2 and Convolutional Neural Network (CNN), showed a slight difference in percentage accuracy with 93.33 and 95.00% for SVM and ShuffleNet V2 CNN. Additionally, SVM can adapt to non-linearly separable data using various kernel functions. Using the one-vs-rest strategy allows the determination of Linear and Sigmoid kernel functions with the highest accuracy of 81%, compared to Polynomial and RBF, with less than 60% yielded accuracy [17].

The existing approach for jackfruit maturity classification is based on its chemical composition, including chemometric analysis [18] and physicochemical properties [19]. Existing methodologies require the destructive testing of the samples, which can be prevented with non-destructive methods, namely texture feature analysis with ULBP descriptor and machine learning methods such as SVM classifier. The lack of a publicly available dataset might also be attributed to limited research done on jackfruit maturity classification.

This study's objective was to utilize the Uniform Local Binary Pattern (ULBP) operator for texture feature analysis and SVM as the classification model. We implemented the proposed hardware based on a Raspberry Pi 3 B+ platform with a camera module and LCD, the ULBP operator, and SVM for training and testing procedures. We evaluated the performance of the system using the confusion matrix and percentage accuracy. The study will benefit the field of jackfruit cultivation by developing a reliable maturity classification system with a non-destructive method.

The developed model in this study was used for the mature and immature classification of the Magnolia jackfruit variety. Jackfruit samples with irregular discoloration, handling damage, and skin diseases will be excluded. The dataset was limited to Magnolia jackfruit images captured from local suppliers and public markets in the Philippines.

II. Methodology

A. Conceptual Framework

The system captured an image of a jackfruit using the input camera (Fig. 1). The whole fruit was fitted in the frame. Once the image of the jackfruit was captured and saved in JPEG file format. From the image, the ROI with 564x564 pixels from its center was extracted. To analyze the spine density, the ULBP operator was used to capture the uniform and non-uniform texture patterns from the ROI. Additionally, the Hue histogram of the ROI was extracted for the rind's discoloration. The acquired histograms were concatenated to generate the final feature vector. The jackfruit's maturity was classified using SVM based on the final feature vector. We defined mature jackfruit wherein the spines were separated far apart and well-developed with the rind color containing mostly yellowish green to yellow. Finally, the GUI displayed the captured image with an overlay text, indicating whether the captured jackfruit is immature or mature.

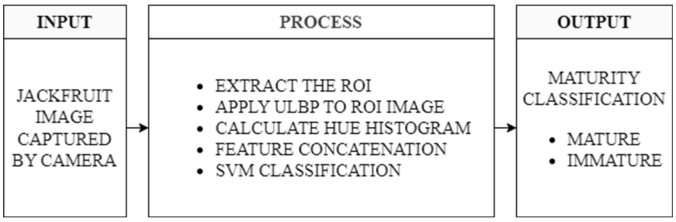


Fig. 1. Conceptual framework.

B. Hardware Development

Figure 2 shows the hardware components diagram for the study. The central controller was Raspberry Pi 3 Model B+. This handheld computer operated at 1.4GHz clock speed with 1GB SDRAM for image processing. For the system's input, the official Pi Camera V2 was used. We calibrated the camera's lens to improve focus from captured images. A power bank with a 20,000 mAh battery capacity was used for the proposed hardware. A compatible 5V/3A Micro USB power cable was adopted to ensure optimal power delivery. We used an official Raspberry Pi 3.5 inches TFT Display. The display featured 480 × 320 resolution, 16-bit color pixels, and a resistive touch overlay. The LCD was designed to fit with Raspberry Pi Model B+ for housing purposes. The system's Graphical User Interface (GUI) displayed the camera preview, control buttons, and the jackfruit's maturity classification.

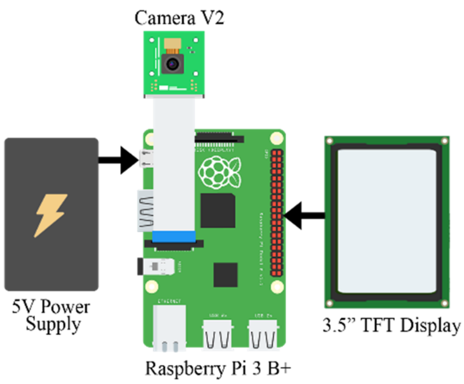


Fig. 2. Diagram of hardware.

C. System Program

Figure 3 shows the system program flowchart. The first process was to capture a jackfruit image using the input camera. Then, the captured image was saved with 960 × 1280 resolution in a JPEG file format. The image was loaded to extract the ROI by cropping an area of 564x564 from its center. ROI extraction highlighted the spine density from the center of the jackfruit's rind while reducing noise and computational complexity using higher dimensions with the ULBP operator.

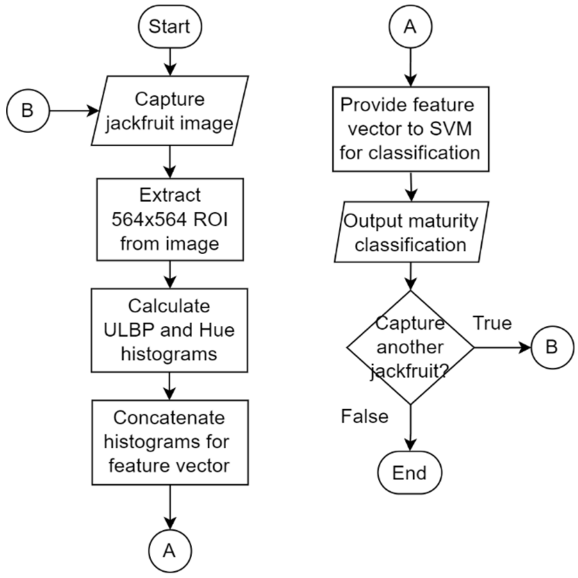


Fig. 3. Flowchart of system program.

In this study, the texture properties of the jackfruit served as the primary feature vector. The texture feature was extracted by the ULBP operator using (1). The superscript $riu2$ means that the operator is unrotated, and the subscript P and R are for the neighborhood parameters point and radius, respectively. The non-uniform and uniform patterns are detected using (2), the sum of all signed differences following the binary thresholding. If the calculated binary code had at most two transitions from one to zero or vice versa, it was considered a uniform pattern; otherwise, the non-uniform pattern is segregated into the last bin.

$$LBP_{P,R}^{riu2} = \left\{ \begin{array}{ll} \sum_{p=0}^{P-1} s(i_p - i_c) \; if \; U(LBP_{P,R}) \leq 2 & \\ P+1 & otherwise, \end{array} \right\} \quad (1)$$

$$U(LBP_{P,R}) = |\, s(i_{P-1} - i_c) - s(i_0 - i_c)\,| + \sum_{p=1}^{P-1} s(i_p - i_c) - s(i_{p-1} - i_c) \quad (2)$$

The rind's discoloration from green to yellow was employed, wherein the Hue histogram was extracted from the ROI. Then, the Hue histogram with 64 bins was concatenated with ULBP via horizontal stacking. The concatenated histograms represented the extracted features of the jackfruit as a final feature vector. Then, the SVM model classified jackfruit maturity based on the generated final feature vector. The SVM also predicted the maturity of the captured jackfruit image. Finally, the system's GUI displayed the predicted maturity as an overlay text on the input image. The processed image, alongside its maturity, were saved in a folder.

D. Training Program

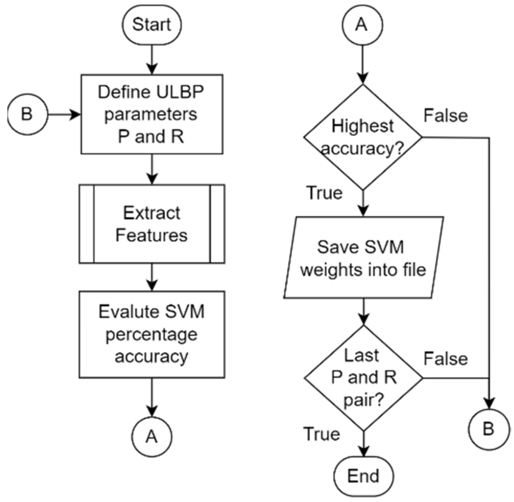


Fig. 4. Flowchart of training program.

Figure 4 shows the training program flowchart of the study. To effectively detect uniform and non-uniform texture patterns, the neighborhood parameters were evaluated in terms of accuracy. The parameters P and R were stored in two separate arrays, where the points were paired with the radius in the one-vs-rest approach. The ULBP used the current value for P and R when training the SVM model. Upon achieving a higher accuracy than the previous result, the trained model saved the result into a file via the Joblib library. The previous accuracy was reset as new images were processed, allowing the program to save the model with the highest accuracy for every point in the array. Lastly, the previous accuracy was initialized to 80% by the researchers. The training program proceeded until the last pair of P and R were evaluated.

Sklearn library provided an accuracy metric score (3) to evaluate the SVM's accuracy. This equation was used to determine the yielded accuracy score for every pair of points and radius. In this way, a total of 60 sample images for both mature and immature jackfruit classes were analyzed. Additionally, the ground truth of the sample images was stored in an array. In this equation, the variable y is the actual maturity of the sample image, and $\hat{y}$ is the predicted maturity of the system. The actual and predicted maturity comparison table will be shown in the results.

$$accuracy(y, \hat{y}) = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} 1(\hat{y}_i = y_i) \quad (3)$$

Features from the training images were extracted by a function depicted in Fig. 5. In this process, the images underwent ROI extraction, feature extraction, and feature concatenation for the final feature vector. The final feature vector acted as a data point for the SVM during training. The SVM constantly adjusted its weights as more training data was provided. Once all the training images were processed, the model was evaluated in terms of accuracy, as previously discussed. The training employed supervised learning and binary classification for immature and mature jackfruit classes. Since the computing resources of Raspberry Pi were limited, an external computer was used to accelerate the training process.

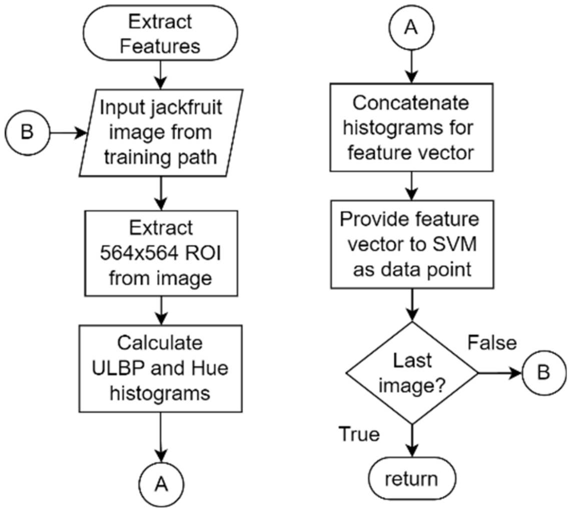


Fig. 5. Flowchart of extracted features function.

E. Experimental Setup

The experimental setup for the study is shown in Fig. 6. The capture button was pressed at the bottom center of the screen to capture an image. Automatic light balancing mode was configured for lighting scenarios with the default value set autonomously. Based on the illustration, the jackfruit image was maximized in the frame, and the camera's direction was perpendicular to the jackfruit's surface. The luminance must be high enough to properly distinguish the physical features of the fruit. Finally, the jackfruit's maturity classification was displayed at the top left part of the screen.

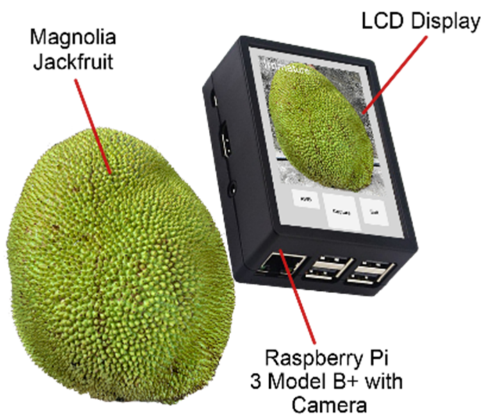
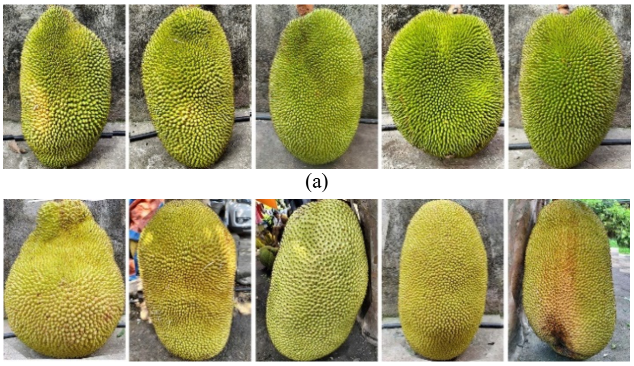


Fig. 6. Experimental setup.

F. Data Gathering

For data gathering, several criteria were implemented. First, jackfruit with sustained damage from improper handling or skin disease were not considered. However, multiple sides of the jackfruit were used to avoid areas with the damage. Second, the jackfruit must not be obscured. Sufficient lighting was mandatory with the correct angle. An evenly cut jackfruit (vertically) was allowed except for other cutting methods as it affected the natural shape or contour. These criteria were applied to mature and immature jackfruit samples. Figure 7 shows an example of mature and immature Magnolia jackfruit samples for the dataset.



(a)

(b)

Fig. 7. Dataset Images: Immature jackfruit samples (a) and mature jackfruit samples (b), captured with no obstruction, upright, and in ideal lighting conditions.

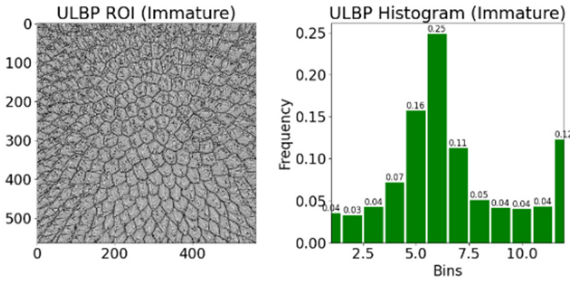
Images used for the dataset were captured using a mobile device. To ensure pixel consistency and reduce computational complexity, captured images were downscaled to 960 ×1280 pixels. Simple data augmentation was used to increase the dataset size and improve generalization. The augmentation process included vertical and horizontal flips. A total of 300 images were generated for the dataset using data augmentation. For the test and train split, 120 images were used for training and 60 images for testing from both mature and immature classes.

III. RESULT AND DISCUSSION

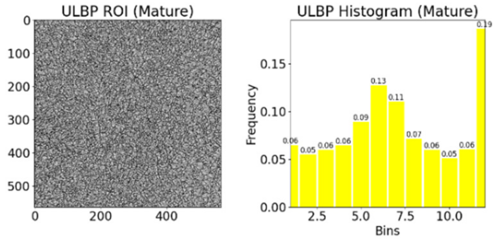
Table I shows the highest accuracy achieved for every neighborhood pair (P, R) based on Sklearn's accuracy score (3). Distinctive texture patterns were effectively captured by limiting the radius parameter to two. A small number for radius allowed the ULBP operator to capture crucial texture patterns from the ROI that were otherwise undetectable from using higher resolutions. Similarly, higher points required a higher radius to achieve the same level of accuracy as seen in the table. The highest accuracy was achieved using the neighborhood parameters (10, 2), yielding a 93.33% prediction accuracy.

TABLE I. ULBP OPTIMAL NEIGHBORHOOD PARAMETERS

No.	Neighborhood Parameters		Accuracy
	Points	Radius	
1	8	2	91.67%
2	9	2	90.00%
3	**10**	**2**	**93.33%**
4	11	2	91.67%
5	12	2	91.67%
6	13	6	91.67%
7	14	6	90.00%
8	15	8	91.67%
9	16	6	88.33%



(a)

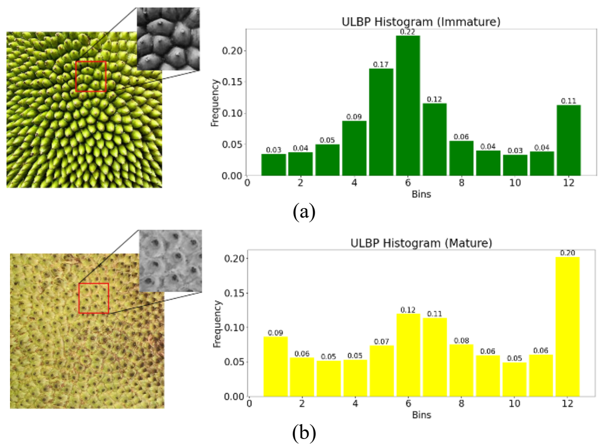


(b)

Fig. 8. ULBP texture analysis result of ROI: Notable differences in captured textures between immature jackfruit samples (a) characterized by texture uniformity and mature samples (b) with non-uniformity.

The extracted texture features extracted using the ULBP operator are shown in Fig. 8 for both mature and immature classes. The spines with immature samples were more visible and consistent, translating to higher texture uniformity and less texture pattern variations. On the other hand, the spine in the mature sample was diminished, exhibiting texture with fewer discernable patterns and non-uniform characteristics. This phenomenon was attributed to spine flattening and spreading conditions as the jackfruit matures, resulting in spines being virtually undetectable with ULBP due to the limited presence of edges and corners. The non-uniform patterns are segregated at the last bin using (2) and the ULBP operator. Therefore, the ULBP texture analysis result showed that the mature class featured more non-uniform patterns than the immature class, with a yield of 0.19 and 0.12, respectively. Additionally, the immature class had the highest number of detected uniform patterns with the highest peak of 0.25, based on the results.

In applying the ULBP operator, Fig. 9 reveals that a small area consistently showed the overall texture of the larger ROI. Similar to earlier results, non-uniform patterns are still dominant in the mature class, while the most detected uniform patterns were still observed in the immature class. The overall shape of the histogram is also recognizable, with the immature class being close to a normal distribution and the mature class with reduced intensities, wherein no significant peaks or troughs are observed. The consistency in results suggested that the proposed method is stable and robust at capturing intrinsic texture patterns distributed throughout the ROI, irrespective of minor variations from the sampled area. This also implied that the optimal neighborhood parameters (10,2) from Table I effectively generalized across rind texture variations with minimal sensitivity.

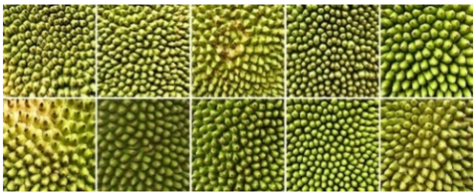


(a)

(b)

Fig. 9. ULBP Texture Analysis of Sampled Area: Immature jackfruit class (a) with consistent normal distribution and mature jackfruit class (b) with reduced intensities.

Figure 10 shows the extracted ROI from the immature and mature jackfruit test images used in Table II. Based on the extracted ROI of the immature class, shadows were present between the spines, constituting the detected edges and corners from ULBP. These shadows were then reduced with spine spreading and flattening from the mature class, translating to ULBP histogram with less uniform patterns and high variability. The misclassifications were attributed to the similarity of the rind's color from the Hue histogram. Additionally, artificial ripening processes, such as with the use of chemical (Ethrel), can alter or change the natural physiological changes of jackfruit such as variations in texture, such as flattening and spreading, can also affect the system's accuracy in this way.



(a)

(b)

Fig. 10. Extracted ROI Images: Immature jackfruit (a) with high spine density with a greenish hue, and mature jackfruit (b) with a yellowish hue and evident spine spreading.

TABLE II. ACTUAL AND PREDICTED CLASSIFICATION

Image No.	Actual	Predicted	Image No.	Actual	Predicted
1	Immature	Immature	31	Mature	Mature
2	Immature	Immature	32	Mature	Mature
3	Immature	Immature	33	Mature	Mature
4	Immature	Immature	34	Mature	Mature
5	Immature	Immature	35	Mature	Mature
6	Immature	Immature	36	Mature	Mature
7	Immature	Immature	37	Mature	Immature
8	Immature	Immature	38	Mature	Immature
9	Immature	Immature	39	Mature	Mature
10	Immature	Immature	40	Mature	Mature
11	Immature	Immature	41	Mature	Mature
12	Immature	Immature	42	Mature	Mature
13	Immature	Immature	43	Mature	Immature
14	Immature	Immature	44	Mature	Mature
15	Immature	Immature	45	Mature	Mature
16	Immature	Mature	46	Mature	Mature
17	Immature	Immature	47	Mature	Mature
18	Immature	Immature	48	Mature	Mature
19	Immature	Immature	49	Mature	Mature
20	Immature	Immature	50	Mature	Mature
21	Immature	Immature	51	Mature	Mature
22	Immature	Immature	52	Mature	Mature
23	Immature	Immature	53	Mature	Mature
24	Immature	Immature	54	Mature	Mature
25	Immature	Immature	55	Mature	Mature
26	Immature	Immature	56	Mature	Mature
27	Immature	Immature	57	Mature	Mature
28	Immature	Immature	58	Mature	Mature
29	Immature	Immature	59	Mature	Mature
30	Immature	Immature	60	Mature	Mature

Table II shows the actual versus predicted classification of the proposed system. Of 30 immature Magnolia jackfruit samples, only one image was misclassified as a mature class. For the mature jackfruit samples, three images were misclassified as immature, as seen from the table. Then, Table II is used to generate the confusion matrix in Table III.

TABLE III. CONFUSION MATRIX FOR JACKFRUIT MATURITY

$n = 60$		Predicted Maturity	
		Immature	**Mature**
Actual	**Immature**	29	1
	Mature	3	27

For the confusion matrix, the rows represent the actual maturity classification of the jackfruit, while the column represents the predicted maturity of the system. A total of 30 images for both mature and immature classes were used, wherein 27 mature and 29 immature jackfruits were correctly classified by the system. (4) is the equation to calculate accuracy of the system based on the confusion matrix table.

$$\begin{aligned} \%Accuracy &= \frac{TP + TN}{TP + TN + FP + FN} \\ &= \frac{29 + 27}{29 + 27 + 1 + 3} = 93.33\% \end{aligned} \quad (4)$$

IV. CONCLUSION AND RECOMMENDATION

We demonstrated the feasibility of a Magnolia jackfruit maturity classification system with image processing techniques. Based on Philippine National Standards (PNS) for mature jackfruit, we analyzed the textures of the jackfruit based on the Uniform Local Binary Pattern (ULBP) operator for feature extraction. To incorporate the rind's discoloration, the Hue histogram was concatenated with the ULBP histogram to generate the final feature vector. The acquired feature vector was input to the trained Support Vector Machine (SVM) model to classify the jackfruit as whether it is mature or immature. The proposed methodology achieved 93.33% accuracy.

The dataset needs to be expanded with more Magnolia jackfruit images for jackfruit maturity classification based on deep learning algorithms. Other variants of the LBP-based algorithm can also be experimented with, including multi-scale local binary pattern (M-LBP) with multiple scales of the input image to capture texture patterns at different resolutions. Segmentation techniques also need to be applied to isolate the jackfruit from the background, covering more feature extraction areas than Region of Interest (ROI) extraction. Additionally, most training images were captured with a camera distance of less than 45.72 cm from the samples. This virtually limits the proposed system to reliably classify jackfruit images in larger sizes. Therefore, the fruit's length and width need to be included other than the camera's distance to improve the system's reliability.

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