

Classification of Jackfruit Fruit Damage Using Color Texture Features and Backpropagation Neural Network

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Abstract— An accessible and cost-effective technology for plant pest and disease diagnosis could be beneficial for the farmers to be equipped with the technical know-how in producing high quality and quantity of crop yields. This study presents an implementation of image processing and machine learning techniques in building a predictive model for a computer-based and a mobile-based classification of jackfruit fruit damages caused by pests (fruit borer and fruit fly) and diseases (*rhizopus* fruit rot and *sclerotium* fruit rot). First, captured images of healthy, and infected fruit were split into two datasets: 60% for training and 40% for the testing phase, wherein each set contains five different classes. Then pre-processing methods such as cropping, scaling, and median filtering were applied that would make these images appropriate for information extraction. Next, 13 *Haralick* texture features were extracted from color co-occurrence matrices generated from Hue, Saturation, and Luminance color components of pre-processed images. Through Pearson's correlation approach, texture features such as uniformity, variance, sum average, sum entropy, and entropy were selected as significant descriptors for training the classification model using a backpropagation learning algorithm. Lastly, basic evaluation metrics such as accuracy, precision, sensitivity, specificity, and Cohen's kappa were computed to determine the performance of the model in recognizing the type of fruit damage on an unforeseen dataset. As a result, an overall accuracy rate of 93.42% and a kappa value of 0.9146 were obtained. In addition, the developed application displays suggestions on the proper pest control or disease management of the identified damage on the fruit surface of jackfruit.

Keywords— jackfruit; backpropagation neural network; color co-occurrence matrix; texture feature.

I. INTRODUCTION

Jackfruit (*Artocarpus heterophyllus* Lam.) is one of the high values and priority fruit crops in the Philippines, particularly in the Visayas region, wherein major growing areas are in Western, Central, and Eastern Visayas [1]. It has the potential to provide a sustainable livelihood for farmers through the domestic market and export opportunities. Its primary economic product, the fruit, can be consumed both when mature and immature [2]. With its importance, several programs by the government agencies are being promoted to boost its production, optimize its processing, and improve its productivity.

However, the jackfruit industry of the country has been significantly affected by various threats, as reflected in Fig. 1 [3] of which the susceptibility of jackfruit to boring insects and plant diseases, as well as the lack of sufficient knowledge and technical skills of farmers on the proper cultural management, have been identified as major causes

of crop yield loss [4]. With the move to expand jackfruit production and with the increasing demand for its fresh and processed products, it is essential to effectively identify the incidence of pests and diseases specifically at an early stage to implement proper control or management strategies.

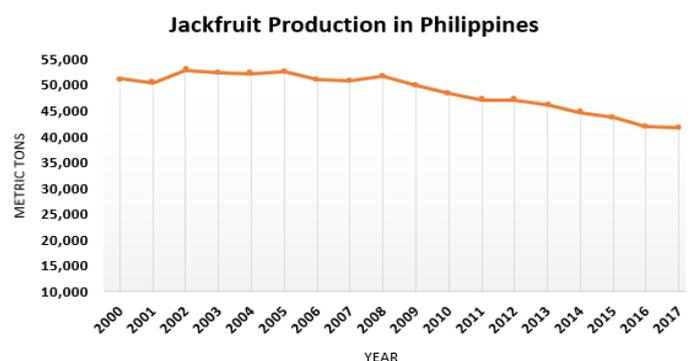


Fig. 1 Total production (MT) of jackfruit in the Philippines, 2000 – 2017

One of the challenges faced by jackfruit growers is to obtain the necessary information because experts are not always available, and the disease diagnosis through laboratory tests is costly. In cases like these, technological advancement plays a significant role in providing solutions in an accurate and timely manner and in improving the status of the agricultural sector in general. The application of computer vision and machine learning has been proven to be beneficial in the field of precision agriculture. Several studies have carried out algorithms of an artificial neural network like backpropagation were able to attain promising results. Image processing methods and backpropagation neural network were carried out in paper [5] wherein color features were considered as descriptors in detecting groundnut leaf diseases. The authors in [6] used as well the backpropagation algorithm in predicting rice plant diseases based on extracted features such as the fraction of infected part, mean values, the standard deviation of RGB, and mean values of HS. Also, in the study [7] in which they applied two-stage backpropagation neural network in detecting citrus Huanglongbing disease through color and texture features. Furthermore, other previous studies [8], [9], presented a scheme that uses mobile phones for efficient and real-time plant disease recognition.

Incorporating such techniques in developing a cost-effective and accessible technology for diagnosing jackfruit pest infestations and disease infections could assist the farmers in producing high quality and quantity of crop yields. Automated recognition of disease occurrence on a jackfruit trunk was initiated using fuzzy logic classifier in [10] and using Naïve Bayes classifier in [11]. While for this study, a method for automatic detection and classification of damages on a fruit part was proposed. This would enable low-cost and speedy access to human expertise in identifying jackfruit pests and diseases as well as the different approaches in controlling and managing them.

II. MATERIALS AND METHOD

The conceptual framework of this study is shown in Fig. 2, wherein the gathered dataset underwent image processing and machine learning methods to establish a model that is capable of recognizing jackfruit fruit damages caused by pests and diseases when deployed in a computer or mobile device for its actual application.

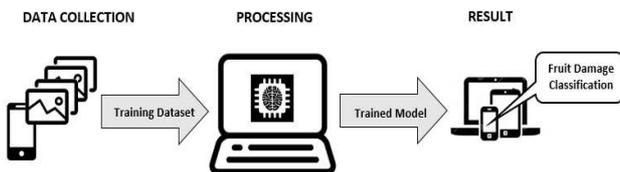


Fig. 2 Conceptual framework of the study

Whereas, Fig. 3 demonstrates the different processes involved in building the classification model, which include the application of image pre-processing techniques, extraction of image information, selection of significant features, and training the model using supervised machine learning algorithm (backpropagation). On the other hand, during the testing phase, the same image pre-processing techniques were applied, and only convenient features were

extracted from sample images in a new dataset, for which the trained model made its prediction. The performance of the model in classifying the image as belonging to the correct category was verified by computing basic evaluation metrics such as accuracy, precision, sensitivity, specificity, and Cohen's kappa.

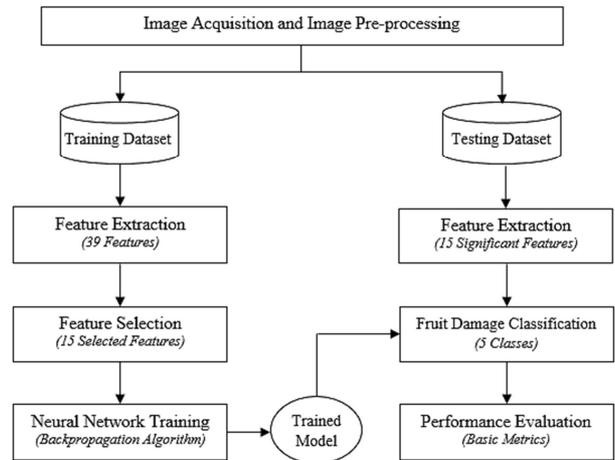


Fig. 3 The system architecture of jackfruit fruit damage recognizer

A. Image Acquisition and Image Pre-processing

The dataset of this study is composed of fruit images, both healthy and with disease infection or pest infestation, which were captured in jackfruit orchards in Leyte, the Philippines, using digital or cellphone camera. Jackfruit damages (Fig. 4), which can be visually determined from the outer surface of the fruit, were covered. These include fruit borer infestation wherein the damage in the edible part is caused by the reddish-brown caterpillar that bores a tunnel into the fruit associated with a mass of excreta, which then eventually get rotten due to the entrance of rainwater [12]. Fruit fly infestation for which the pest lays its eggs under the skin of the fruit and the larvae work their way into the fruit, causing damage on the tissues and pre-disposing them to rot [13]. *Rhizopus* fruit rot wherein white aerial mycelia and grayish-black spores engulf the fruit [14]. And, *Sclerotium* fruit rot which develops symptoms such as coarse white mycelium with sclerotia spreading over the fruit surface [15].

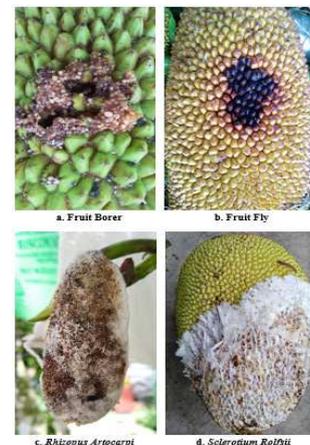


Fig. 4 Jackfruit fruit damages caused by pests and diseases

The acquired 380 jackfruit images were grouped into two sets, wherein 60% of its totality was used as a training dataset while the remaining 40% was used as a testing dataset. The dataset has five different classes; four classes represented fruit damages and another class for healthy fruit. Table I shows the number of images in each class used for the training and the testing phases of the classification model.

TABLE I
DATASET FOR JACKFRUIT FRUIT DAMAGE CLASSIFICATION

| Class | Number of Images | | Total (Class) |
|---------------------------|------------------|------------|---------------|
| | Training | Testing | |
| Healthy | 48 | 32 | 80 |
| Fruit Borer | 54 | 36 | 90 |
| Fruit Fly | 24 | 16 | 40 |
| <i>Rhizopus Artocarpi</i> | 30 | 20 | 50 |
| <i>Sclerotium Rolfsii</i> | 72 | 48 | 120 |
| Total (Dataset) | 228 | 152 | 380 |

Then a sequence of pre-processing techniques was performed that would make these images appropriate for extracting related information. The said techniques include cropping to emphasize the region of interest, scaling to reduce image size and applying the median filter as noise removal operation to improve image quality.

B. Feature Extraction and Feature Selection

Feature extraction on images in a training dataset was performed with texture analysis using Color Co-occurrence Matrix (CCM) method. This method, which was applied in the studies [16], [17] and [18], both measures the color distribution in an image and considers the spatial interaction between pixels. For this study, the process involved a transformation of Red, Green, and Blue (RGB) into Hue, Saturation, and Luminance (HSL) color space representation using (1), (2), and (3).

The R, G, B values were divided by 255 to change the range from 0-255 into 0-1: [19]

$$R' = R / 255$$

$$G' = G / 255$$

$$B' = B / 255$$

$$C_{max} = \max(R', G', B')$$

$$C_{min} = \min(R', G', B')$$

Hue calculation:

$$H = \begin{cases} 0 & , \text{if } C_{max} = C_{min} \\ 60^\circ \times \left(0 + \frac{G' - B'}{C_{max} - C_{min}} \right) & , \text{if } C_{max} = R' \\ 60^\circ \times \left(2 + \frac{B' - R'}{C_{max} - C_{min}} \right) & , \text{if } C_{max} = G' \\ 60^\circ \times \left(4 + \frac{R' - G'}{C_{max} - C_{min}} \right) & , \text{if } C_{max} = B' \end{cases} \quad (1)$$

Luminance calculation:

$$L = (C_{max} + C_{min}) / 2 \quad (2)$$

Saturation calculation:

$$S = \begin{cases} (C_{max} - C_{min}) / (C_{max} + C_{min}) & , \text{if } L < 0.5 \\ (C_{max} - C_{min}) / (2 - C_{max} - C_{min}) & , \text{otherwise} \end{cases} \quad (3)$$

Next, 3 color co-occurrence matrices were generated, one for each component of HSL. Afterward, a set of 13 *Haralick* descriptors [20] was computed from each matrix resulting into a total of 39 (3 x 13) extracted features which were then stored into the database alongside with its corresponding label based on the domain expert's specification and plant disease diagnostic test.

Finally, feature selection using Pearson's correlation technique was carried out to find out the suitable discriminating texture features which can be used for attaining accurate classification. As a result, features such as uniformity, variance, sum average, sum entropy, and entropy of the three matrices were considered for training the model. These were extracted using the following equations:

$$\text{uniformity} = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p(i,j)^2 \quad (4)$$

$$\text{variance} = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} (i - \mu)^2 p(i, j) \quad (5)$$

$$\text{sum average} = \sum_{i=2}^{2N_g} ip_{x+y}(i) \quad (6)$$

$$\text{sum entropy} = - \sum_{i=2}^{2N_g} p_{x+y}(i) \log \{ p_{x+y}(i) \} \quad (7)$$

$$\text{entropy} = - \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p(i,j) \log(p(i,j)) \quad (8)$$

C. Training and Classification Phase

The backpropagation algorithm was used for training the fruit damage classification model of which its architecture is shown in Fig. 5. The neural network contains 15 input neurons that represent the selected texture features, 45 hidden neurons, and five output neurons, which signify the image classification. The training process involved forward and backward propagation while repeatedly adjusting the weights of the connections in the network to minimize a measure of the difference between the actual output and the desired output of the network [21]. Aside from the weights, the biases of the hidden and output layers are also updated. The minimum value of the Mean Square Error (MSE) function was then considered as a solution to the learning problem. For this model, the maximum allowed error was 10^{-5} .

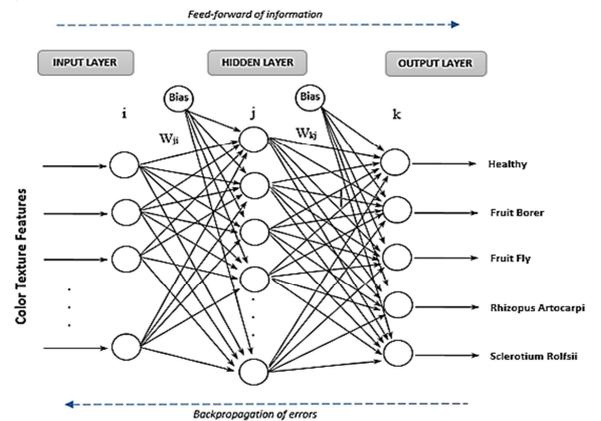


Fig. 5 The backpropagation neural network architecture of the study

III. RESULTS AND DISCUSSION

Table II illustrates the resulting image with a dimension of 300x300 after the conduct of pre-processing methods. The

table also reflects the characteristic differences among classes.

TABLE II
CLASS SAMPLE IMAGE

| Class | Healthy | Fruit Borer | Fruit Fly | <i>Rhizopus Artocarpi</i> | <i>Sclerotium Rolfsii</i> |
|--------------|---|---|---|---|---|
| Image Sample |  |  |  |  |  |

The figure (Fig. 6) below illustrates the graphical user interface of the computer application for building the fruit damage classification model, which was developed using a C# programming language. It displays the results of 3x3 median filtering application and feature extraction on the

uploaded image. Initially, all 13 *Haralick* texture features were extracted from the CCM of each HSL color plane, which then needs to be labeled with the type of fruit damage before saving them into the MySQL database.

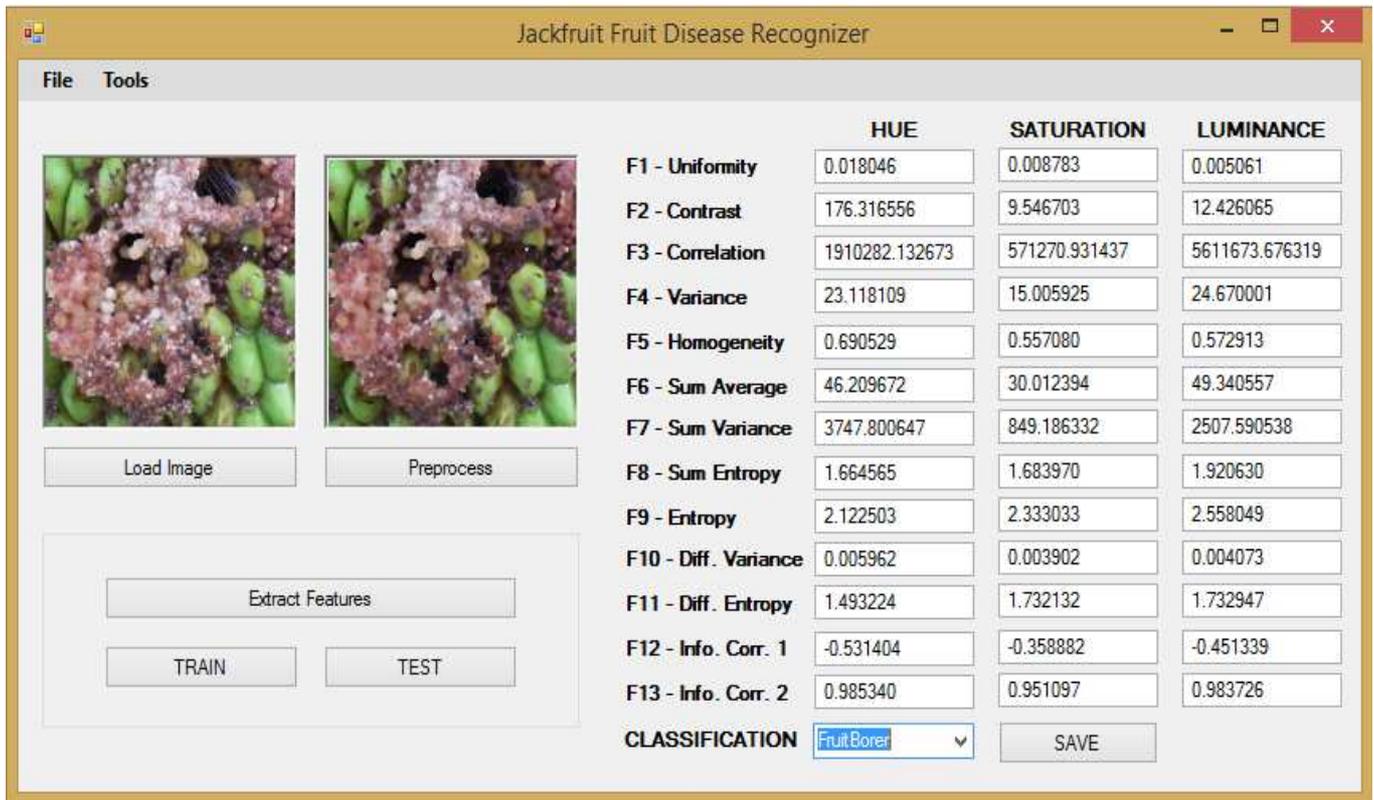


Fig. 6 User interface for building the fruit damage classification model.

However, only 5 of them were selected as the most relevant features to the predictive model, which, in effect, reduces as well as the computation time and complexity of the model. These include uniformity (F1), variance (F4), sum average (F6), sum entropy (F8) and entropy (F9). Table III depicts the computed feature values from H, S, and L

color components of sample images. Each row represents the extracted 15 features from an image that was tagged with its corresponding class type. During the training phase, the backpropagation neural network iteratively learned from this labeled dataset to establish a model that can make correct predictions on unforeseen data.

TABLE III
SAMPLE COLOR TEXTURE FEATURE VALUES

| Image No | HUE | | | | | SATURATION | | | | | LUMINANCE | | | | | Class |
|----------|-------|--------|---------|-------|-------|------------|--------|--------|-------|-------|-----------|--------|--------|-------|-------|------------|
| | F1 | F4 | F6 | F8 | F9 | F1 | F4 | F6 | F8 | F9 | F1 | F4 | F6 | F8 | F9 | |
| 1 | 0.224 | 10.934 | 21.870 | 0.842 | 0.937 | 0.009 | 43.506 | 87.013 | 1.852 | 2.622 | 0.016 | 20.262 | 40.525 | 1.705 | 2.127 | Healthy |
| 2 | 0.059 | 8.542 | 17.085 | 1.243 | 1.485 | 0.008 | 19.162 | 38.324 | 1.703 | 2.344 | 0.007 | 24.535 | 49.071 | 1.832 | 2.417 | Healthy |
| 3 | 0.107 | 7.762 | 15.525 | 1.046 | 1.206 | 0.004 | 31.917 | 63.835 | 1.884 | 2.665 | 0.009 | 23.706 | 47.412 | 1.784 | 2.343 | Healthy |
| 49 | 0.028 | 18.238 | 36.462 | 1.572 | 1.927 | 0.013 | 14.667 | 29.334 | 1.599 | 2.122 | 0.006 | 25.743 | 51.487 | 1.918 | 2.448 | Borer |
| 50 | 0.018 | 23.118 | 46.210 | 1.665 | 2.123 | 0.009 | 15.006 | 30.012 | 1.684 | 2.333 | 0.005 | 24.670 | 49.341 | 1.921 | 2.558 | Borer |
| 51 | 0.019 | 22.434 | 44.864 | 1.731 | 2.155 | 0.009 | 15.692 | 31.384 | 1.665 | 2.339 | 0.005 | 22.481 | 44.962 | 1.896 | 2.507 | Borer |
| 103 | 0.009 | 40.131 | 80.254 | 1.764 | 2.352 | 0.009 | 12.539 | 25.079 | 1.672 | 2.385 | 0.006 | 19.664 | 39.329 | 1.909 | 2.603 | Fly |
| 104 | 0.013 | 28.317 | 56.623 | 1.772 | 2.236 | 0.008 | 15.240 | 30.481 | 1.756 | 2.416 | 0.007 | 20.424 | 40.849 | 1.941 | 2.484 | Fly |
| 105 | 0.023 | 26.313 | 52.624 | 1.675 | 2.018 | 0.009 | 13.688 | 27.377 | 1.658 | 2.284 | 0.006 | 19.827 | 39.654 | 1.845 | 2.489 | Fly |
| 127 | 0.032 | 47.724 | 95.448 | 1.500 | 1.723 | 0.054 | 8.337 | 16.674 | 1.265 | 1.533 | 0.016 | 20.022 | 40.045 | 1.617 | 2.054 | Rhizopus |
| 128 | 0.014 | 41.525 | 83.043 | 1.747 | 2.167 | 0.084 | 4.144 | 8.284 | 1.089 | 1.278 | 0.024 | 18.143 | 36.286 | 1.547 | 1.870 | Rhizopus |
| 129 | 0.034 | 50.528 | 101.051 | 1.397 | 1.743 | 0.009 | 11.832 | 23.665 | 1.606 | 2.406 | 0.003 | 24.015 | 48.030 | 1.931 | 2.945 | Rhizopus |
| 157 | 0.013 | 21.723 | 43.434 | 1.812 | 2.380 | 0.030 | 7.877 | 15.740 | 1.530 | 2.077 | 0.008 | 23.886 | 47.773 | 1.793 | 2.336 | Sclerotium |
| 158 | 0.015 | 17.101 | 34.199 | 1.746 | 2.367 | 0.007 | 12.811 | 25.617 | 1.787 | 2.576 | 0.007 | 25.522 | 51.045 | 1.817 | 2.387 | Sclerotium |
| 228 | 0.050 | 9.936 | 19.873 | 1.421 | 1.683 | 0.027 | 9.062 | 18.121 | 1.589 | 1.977 | 0.012 | 30.068 | 60.137 | 1.754 | 2.201 | Sclerotium |

Afterward, the trained model was verified on every image from the testing dataset. The results are indicated in Table IV, wherein values in the diagonal elements represent the number of images that are accurately predicted from the total of each class. In contrast, values in the off-diagonal elements are incorrect predictions.

TABLE IV
CONFUSION MATRIX

| Class | Healthy | Fruit Borer | Fruit Fly | Rhizopus Artocarp | Sclerotium Rolfii | Actual Total |
|-------------------|---------|-------------|-----------|-------------------|-------------------|--------------|
| Healthy | 32 | 0 | 0 | 0 | 0 | 32 |
| Fruit Borer | 0 | 33 | 1 | 0 | 2 | 36 |
| Fruit Fly | 0 | 3 | 12 | 1 | 0 | 16 |
| Rhizopus Artocarp | 0 | 0 | 0 | 20 | 0 | 20 |
| Sclerotium Rolfii | 0 | 3 | 0 | 0 | 45 | 48 |
| Predicted Total | 32 | 39 | 13 | 21 | 47 | 152 |

Table V summarizes the four outcomes of classification that can be derived from the confusion matrix. These values are useful in computing the performance measures of the model.

TABLE V
CLASSIFICATION OUTCOMES

| Class | TP | TN | FP | FN |
|--------------------------|----|-----|----|----|
| Healthy | 32 | 120 | 0 | 0 |
| Fruit Borer | 33 | 110 | 6 | 3 |
| Fruit Fly | 12 | 135 | 1 | 4 |
| <i>Rhizopus Artocarp</i> | 20 | 131 | 1 | 0 |
| <i>Sclerotium Rolfii</i> | 45 | 102 | 2 | 3 |

Then the percentage of correct predictions was calculated using the equation below, which resulted in an accuracy rate of 93.42%.

$$\text{Accuracy} = \frac{\text{number of correct predictions}}{\text{total number of predictions}} \times 100 \quad (9)$$

$$\text{Accuracy} = \frac{32 + 33 + 12 + 20 + 45}{152} \times 100 = 93.42$$

Other basic metrics [22] such as precision (10), sensitivity (11), and specificity (12) were computed to further evaluate the performance of the model.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (10)$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (11)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (12)$$

where:

True positive (TP) – correct positive prediction

True negative (TN) – correct negative prediction

False positive (FP) – incorrect positive prediction

False negative (FN) – incorrect negative prediction

From the results shown in Table VI, the sensitivity of fruit fly class is 75%, which is the proportion of images with fruit fly infestation that were correctly predicted by the model as having the said damage. The rate is relatively low as compared to the other classes. However, the model is 92.31% precise on its prediction for images, which had the fruit fly damage as well as obtained a higher specificity rate of 99.26%. Moreover, it is notable that the model performs well in classifying the healthy class as it was able to achieve a 100% rate for all three performance measures. The result implies that the recognizer was able to correctly classify the jackfruit image, whether it is healthy or affected with any of the pests or diseases.

TABLE VI
PERFORMANCE EVALUATION RESULTS

| Class | Precision | Sensitivity | Specificity |
|---------------------------|-----------|-------------|-------------|
| Healthy | 100.00% | 100.00% | 100.00% |
| Fruit Borer | 84.62% | 91.67% | 94.83% |
| Fruit Fly | 92.31% | 75.00% | 99.26% |
| <i>Rhizopus Artocarp</i> | 95.24% | 100.00% | 99.24% |
| <i>Sclerotium Rolfsii</i> | 95.74% | 93.75% | 98.08% |

The graphical representation of the classification results for each class is displayed in Fig. 7. It emphasizes that the model obtained the highest percentage value in recognizing the healthy class in terms of precision and specificity, also in terms of sensitivity together with the *rhizopus artocarp* class. On the other hand, the lowest performance of the model was observed in the fruit borer class with respect to precision and specificity while the fruit fly class for sensitivity evaluation metric.

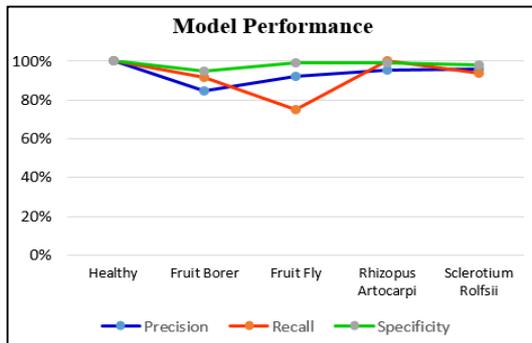


Fig. 7 Graphical representation of model performance

The performance of the model was further verified by computing the Cohen's kappa value using (13) [23]

$$\text{kappa} = \frac{\text{accuracy} - \text{baseline}}{1 - \text{baseline}} \quad (13)$$

where:

$$\text{baseline} = \sum_{i=1}^k \frac{a_{ix} \times a_{xi}}{N^2}$$

a_{ix} – total predicted value per class

a_{xi} – total actual value per class

N – total number of predictions

Considering the values indicated in the confusion matrix, the calculation of kappa for this study is as follows:

$$\begin{aligned} \text{baseline} &= \frac{32 \times 32}{152^2} + \frac{39 \times 36}{152^2} + \frac{13 \times 16}{152^2} + \frac{21 \times 20}{152^2} + \frac{47 \times 48}{152^2} \\ &= 0.2299 \end{aligned}$$

$$\text{kappa} = \frac{0.9342 - 0.2299}{1 - 0.2299} = 0.9146$$

As a result, kappa gives a value of 0.9146, indicating an almost perfect agreement based on the interpretation shown in Table VII. This signifies the better performance of the model in predicting the actual data.

TABLE VII
INTERPRETATION OF COHEN'S KAPPA VALUES [24]

| Kappa Statistic | Strength of Agreement |
|-----------------|-----------------------|
| < 0.00 | Poor |
| 0.00 – 0.20 | Slight |
| 0.21 – 0.40 | Fair |
| 0.41 – 0.60 | Moderate |
| 0.61 – 0.80 | Substantial |
| > 0.81 – 0.99 | Almost perfect |
| 1.00 | Perfect |

The application, where the trained model was deployed, must forms: computer-based and mobile-based. The computer-based application (Fig. 8), which was developed using C# programming language, allows the user to upload a fruit image that needs to be classified. While, the mobile-based application (Fig. 9), developed using Android Studio, provides an option to either capture using the camera or browse from the storage, an image of infected or infested jackfruit fruit as well as requires to crop the portion of the region of interest. Subsequently, the model determines the incidence and type of fruit damage. Lastly, it displays the prediction outcome along with the corresponding details and suggested management strategies.

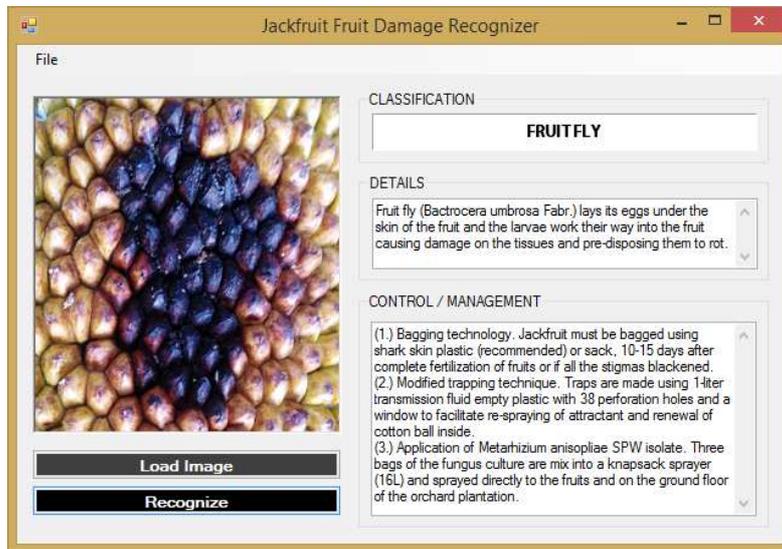


Fig. 8 Computer-based jackfruit fruit damage recognizer

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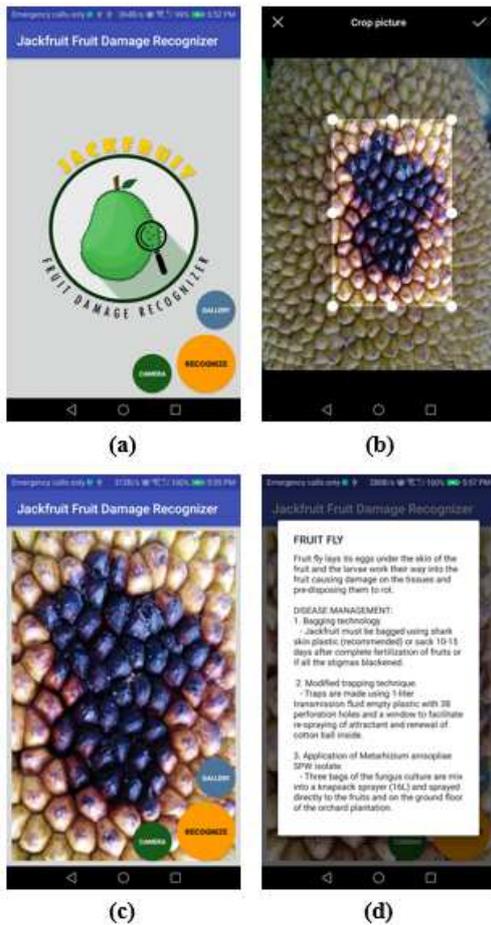


Fig 9. Mobile-based jackfruit fruit damage recognizer

IV. CONCLUSION

A trained classification model deployed in a computer-based and an Android-based mobile application for jackfruit fruit damage recognition was presented. In this study, 5 *Haralick* texture features which were extracted from the color co-occurrence matrices computed from HSL color components were identified as relevant descriptors for the backpropagation neural network. The experimental result shows that the model is 93.42% accurate in detecting and classifying the damage that affects the fruit part.

Although visual inspection by human experts and laboratory tests are more reliable, the application developed in this study could serve as a supplemental method for the jackfruit growers to reduce the spread of the fruit damage and facilitate in their decision-making on what appropriate pest control or disease management to adopt.

Likewise, an extension of this study can be made that may improve the performance of the model, such as increasing the number of the training dataset, segmenting the image, adding features, or applying other machine learning techniques. Also, to cover additional fruit damages such as fruit cracking, fruit bronzing, etc. and diseases that affect other jackfruit parts.

Further studies can also be made by implementing the application to work on other mobile platforms and to include a feature that would store information such as the location, date, and time of capturing the jackfruit image sample.

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