

## An Explorative Analysis on the Machine-Vision-Based Disease Recognition of Three Available Fruits of Bangladesh

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Bangladesh, being a densely populated country, hinges on agriculture for the security of finance and food to a large extent. Hence, both the fruits' quantity and quality turn out to be very important, which can be degraded due to the attacks of various diseases. Automated fruit disease recognition can help fruit farmers, especially remote farmers, for whom adequate cultivation support is required. Two daunting problems, namely disease detection, and disease classification are raised by automated fruit disease recognition. In this research, we conduct an intense investigation of the applicability of automated recognition of the diseases of three available Bangladeshi local fruits, viz. guava, jackfruit, and papaya. After exerting four notable segmentation algorithms, *K*-means clustering segmentation algorithm is selected to segregate the disease-contaminated parts from a fruit image. Then some discriminatory features are extracted from these disease-contaminated parts. Nine noteworthy classification algorithms are applied for disease classification to thoroughly get the measure of their merits. It is observed that random forest outperforms the eight other classifiers by disclosing an accuracy of 96.8% and 89.59% for guava and jackfruit, respectively, whereas support vector machine attains an

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accuracy of 94.9% for papaya, which can be claimed good as well as attractive for forthcoming research.

*Keywords:* Fruit disease; image segmentation; subjective evaluation; feature extraction; classification model; performance metric.

1. Introduction

The majority of the people of Bangladesh, an agronomical country, directly or indirectly lean on agriculture. The agronomical division conducts impressive deeds for the unified financial growth of Bangladesh. It provides, according to the record disclosed by the World Bank,<sup>1</sup> more than 39% of the overall employment of Bangladesh. Moreover, this division supplies 14.74% to the GDP of the entire country as per the World Bank.<sup>2</sup> Hence the agronomical division has been provided the utmost importance in Bangladesh, a densely populated country, to get rid of the food deficit.<sup>3</sup> So, the agricultural production quality needs to be controlled with adequate care for financial growth and food security. A significant component of quality is fault-free production. It is a recommendation to the readers to be mindful that our context is presumed as an expert system for agro-medical, where it starts with an image of a diseased fruit or leaf captured with a mobile phone or other hand-held device and identifies the disease. Among a large number of fruits, we have chosen guava, jackfruit, and papaya — three available local fruits in Bangladesh. They are commonly produced in firm lands as well as yards by inexperienced gardeners being pictorially exhibited in Fig. 1. The overall fruit production in Bangladesh has been enhanced by 11.5% over about the last two decades as reported by FAO in Ref. 4. It is further reported in Ref. 4 that Bangladesh has also been second in jackfruit production and eighth in guava production, where papaya is also on the list of

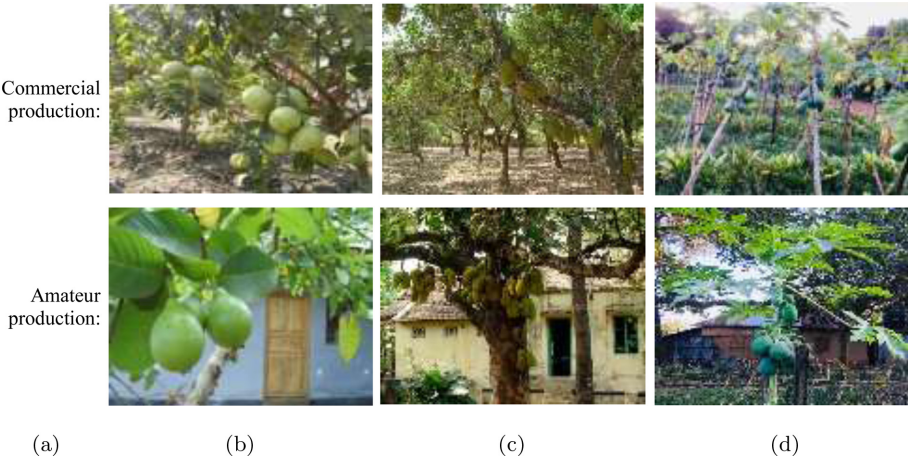


Fig. 1. Yielding of three of the local fruits in Bangladesh: (a) Mode of yielding. (b) Guava yielding. (c) Jackfruit yielding. (d) Papaya yielding.

fast-growing fruits. The fruit production in the country including these local fruits, i.e., guava, jackfruit, and papaya is affected by different types of diseases of both fruits and leaves that result in considerable damages during the cultivation and postharvest period as per the report in Hassan *et al.* in Ref. 5. As a result, farmers entail a mass economic loss.

In this research, we conduct, applying a computer vision approach, a rigorous investigation of the applicability of automated recognition of the diseases of some available local fruits (including leaves) of Bangladesh in the same frame. An agro-medical expert system, as shown in Fig. 2, is conceived that deals with an image of guava, jackfruit or papaya, and recognizes the infecting disease together with the infected portion(s). Some distinguishing features, which have been put forward and displayed for the fruit disease recognition by Habib *et al.*,<sup>7</sup> are utilized in this research. Digital image processing operations are put into action to extract the features, which are used in the subsequent classification. The fruit disease classification has been carried out with nine noteworthy classifiers to evaluate and compare their performances in the amount of seven comprehensive metrics.

In essence, the major contributions of this paper are

- An endeavor to explore the feasibility of the solution to the problem of automated Bangladeshi local fruits, especially guava disease recognition in the same frame for the first time.
- A rigorous subjective exploration of different segmentation techniques as well as classifiers on the subject of disease recognition of local fruits, especially guava to expedite upcoming research.
- The presentation of a very promising performance achieved by our proposed computer vision method on the image data set of local fruit, especially guava diseases prepared in this research.
- In essence, successful deployment of off-the-rack techniques to resolve the problem of automated recognition of local fruit, especially guava diseases.

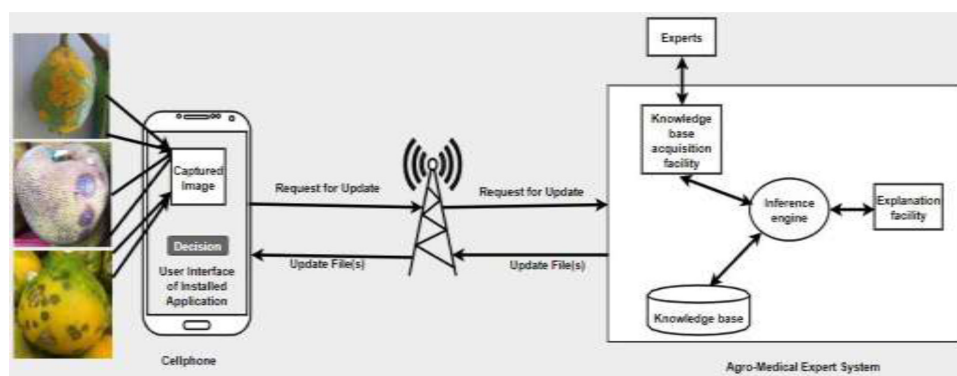


Fig. 2. An agro-medical expert system to recognize local fruit disease.

## 2. Related Works

Automated, i.e., computer-vision-based recognition of fruit diseases can be divided into two individual problem areas, such as disease identification, and classification. A considerable number of researchers have confined their works to disease detection only, whereas the rest number of the researches concentrates on both disease detection and disease classification. It has been observed that a small number of works have been performed on the machine-vision-based recognition of Bangladeshi local fruit diseases. However, some efforts have been given on the machine-vision-based recognition of some other fruits' diseases.

Samajpati and Degadwala<sup>6</sup> introduced a hybrid, i.e., feature-fusion-based disease recognition of apple. They have only dealt with the three types of apple disease. Their feature set has been comprised of 13 distinct features, all of which have been selected depending on color and texture. The image of the infected portion of an apple has been segmented by using a clustering-based segmentation algorithm named *K*-means clustering, and thereafter the selected features have been extracted before employing them to classify the diseases using a random forest classification algorithm. They have used very few datasets to compute the performance of the work. They have dealt with 70 and ten images for training and testing purposes, respectively in classification. The magnitude of accuracy attained moves in the range of 60–100% owing to the uses of different fusion of features. Many issues have made this work disputable despite its being the first endeavor for machine-vision-based recognition of apple disease. Habib *et al.*<sup>7</sup> have proposed a computer vision method to recognize papaya diseases. The data set has been comprised of 129 images. They have dealt with ten features. The features have been extracted after using the segmentation algorithm, namely *K*-means clustering to split up the disease-infested portion. Three classifiers have been tried to perform the classification, where support vector machines (SVMs) present 95.2% of accuracy which is surpassing the other two classifiers. Thereafter this research work has been expanded by Habib *et al.* in Ref. 8 introducing six more noteworthy classifiers, but SVM retains the top position by surpassing all other classifiers. Majumder *et al.*<sup>9</sup> have applied the computer vision method the same as the method proposed in Ref. 7 on a carrot. Using 202 images of six classes (five for disease types and one for disease-free), they have attained 96% accuracy. Kumar and Suhas<sup>10</sup> have claimed to apply a computer-vision method for recognizing diseases of ten different fruits, but it, in sooth, has been disputable and obscure to readers owing to the absence of many significant details. For example, the disease names have not been disclosed. They have been used for 243 images for testing purposes though no required information was provided in the training. Nevertheless, the classification accuracy that they have obtained quantifies to 87.47%, which seems to be fishy. Likewise, weak work has been done by Chopade and Bhagyashri<sup>11</sup> for detecting diseases only rather than classifying them. They have not used any systematic method like computer vision for detecting diseases. Thereby, no information of feature and classifier has not been disclosed in their work. The only

information that they have shared, which seems fuzzy, is histogram-dependent segmentation for fruit-leaf-disease recognition. Rozario *et al.*<sup>12</sup> have put some techniques based on digital image processing for the detection of the defects of vegetables and fruits, e.g., bananas, apples, potatoes, and tomatoes. No classification technique has been applied in their research work.

A 3D-image-based work has been performed by Hosen *et al.*<sup>13</sup> by applying the color-segmentation-based method for fruit-fault detection. They have only concentrated on recognizing the faulty part from the fruits, e.g., banana, apple, and orange rather than applying any classifier to recognize the specific fruit disease. Habib *et al.*<sup>14</sup> have utilized a computer vision method to recognize jackfruit disease with 360 jackfruit images. They have dealt with a set of ten features in agglomeration. *K*-means clustering segmentation algorithm has been used by them to split up the disease-infested part to extract the features. After employing three classifiers, SVMs have been found presenting 88.67% accuracy outdoing the other two classifiers. Thereafter, their work<sup>14</sup> has exhaustively been prolonged by Habib *et al.*<sup>15</sup> by employing nine noteworthy classifiers with 480 images of jackfruits, where random forest secures the best position exhibiting 89.59% accuracy. Some works other than those just discussed have been performed encompassing leaf diseases only. Batule *et al.*<sup>18</sup> have handled with only the leaf disease recognition, where *K*-means clustering has been employed to compute features, and thereafter noise removal technique is used for disease detection. They have claimed that they would attempt to put SVM into action in the future even though the information has been provided for neither feature set nor SVM classifier. Thereby, many significant issues remain unclear in their paper. In the same manner, Howlader *et al.*<sup>16</sup> have made use of a deep convolution neural network with 2,705 images to recognize diseases of guava leaf only. Although they have got a good accuracy of 98.74%, deploying a deep neural network makes the model complexity expensive. A different work has been performed by Ahmed *et al.*<sup>17</sup> from a distinguishing perspective to forecast the amount of potato blight disease based on some environmental points, e.g., minimum temperature, maximum temperature, wind speed, amount of rainfall, and relative humidity by using statistical regression.

### 3. Research Methodology

#### 3.1. Method applied

The method that has been taken for finding the solution of machine-vision-based recognition of Bangladeshi local fruit disease is portrayed in Fig. 3 in the form of a block diagram. The method begins, with the observation of Fig. 3, including the different color images of diseased guava, jackfruit, and papaya. A transformation holds from this color image into a fixed-size image by applying a method called bicubic interpolation.<sup>19</sup> Holding that  $I$  is the values of intensity, and  $I_x$ ,  $I_y$  and  $I_{xy}$  are the derivatives, which can be respectively encountered at all of the four corners of

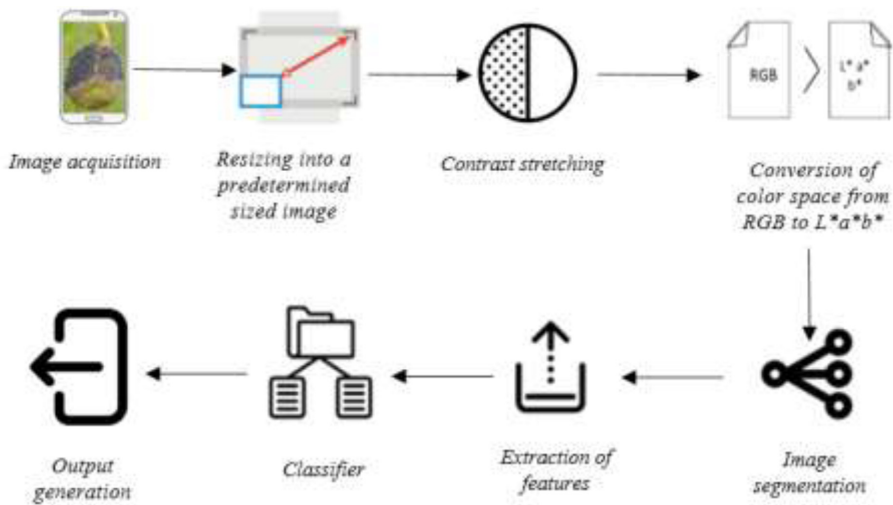


Fig. 3. Pictorial diagram for solving the problem of automated recognition of local fruit diseases.

the unit square  $(0, 0)$ ,  $(0, 1)$ ,  $(1, 0)$ , and  $(1, 1)$ , The surface of interpolated intensity can be shown as follows:

$$s(x, y) = \sum_{m=0}^3 \sum_{n=0}^3 c_{mn} x^m y^n, \quad (1)$$

where  $c_{mn}$  are the coefficients.

Then the image contrast is accentuated by exerting the technique called histogram equalization. Assuming  $n$  be the column-wise pixel frequency, i.e., width,  $m$  be the row-wise pixel frequency, i.e., height,  $c_g$  be the frequency of pixels being color intensity  $I_g$ , and  $v$  be the frequency of legitimate level of color intensity in an image, each pixel containing color intensity  $I_g$  is charted into a similar type of pixel enduring color intensity  $I'_g$  by employing the technique histogram equalization. Thus, the color-mapped image is built as follows<sup>20</sup>:

$$I'_g = T(I_g) = \frac{v-1}{mn} \sum_{i=0}^g c_i, \quad (2)$$

where  $g = 0, 1, \dots, v-1$ .

Then this enhanced image passes through a transformation from RGB to  $L^*a^*b^*$  color space since the  $K$ -means clustering algorithm exhibits better enough performance in segmentation, as asserted by Burney and Tariq,<sup>21</sup> of images in  $L^*a^*b^*$  color space than in RGB. The transformation is completed, as defined in Ref. 22, from RGB color space to CIE (International Commission on Illumination) another color space named XYZ color space. Consequently, the image is split into



several areas by employing the  $K$ -means clustering segmentation, which is a color-based segmentation technique. This is very much challenging because the diseased parts of images are non-geometric in nature and could be very small as well as similar to fruits and/or leaves. The selection of the  $K$ -means clustering algorithm is not a grotesque one, rather after applying four notable segmentation algorithms, namely Otsu's method, fuzzy  $C$ -means clustering,  $K$ -means clustering, and region growing. However, disease-infested portions are thus segregated from disease-free portions. From the infested parts, two different feature types are elected respectively- co-occurrence matrix and statistical, which comprises the feature vector. These two feature-types are going to be described in-depth in the next section of the contents (Sec. 3.2). Thereafter, the feature vectors thus computed are inputted to several noteworthy classification models for training first and later testing. These classification models are C4.5,  $k$ -nearest neighbors ( $k$ -NN), repeated incremental pruning to produce error reduction (RIPPER), backpropagation neural network (BPN), Naïve Bayes, SVMs, logistic regression, counter propagation neural network (CPN), and random forest which all belong to the category of classical machine learning. Not even a single deep learning model is used due to the midget size of the data set of each of the three fruits, i.e., guava, jackfruit, and papaya. However, all of these classifiers are thoroughly looked into for the most suitable model configuration. Then they are exhaustively checked out with the test data set in terms of several performance metrics to determine the best-performing classification model. During performance inspection, accuracy cannot be solely asserted as a precise metric for determining the exact classification performance of the model since it might have not been entirely befitted for measuring the performance of classification with the unbalanced set of data, i.e., there are several cases in numerous classes vary extensively. There exist many other metrics depending on the confusion matrix of models, as described in Refs. 23 and 24, to measure the classification performance of each of the models. A two-dimensional binary confusion matrix calculates the abundance of true positives (TPs), false positives (FPs), true negatives (TNs), and false negatives (FNs) for a two-class problem. For a more-than-two, i.e. multiclass problem, and the confusion matrix ( $\mathbf{C}$ ) can be presented using the following equations:

$$\mathbf{C} = [e_{ij}]_{n \times n}. \quad (3)$$

It would be easily discovered by observing the confusion matrix  $\mathbf{C}$  for the multiple classes, it is comfortably discovered that it is a square matrix of dimension  $n \times n$  (where  $n > 2$ ), and possesses  $n$  number of rows and  $n$  number of columns resulting in  $n^2$  records in total. There is no direct method for calculating the amount of TPs, FPs, TNs and FNs in the multi-class problem. As per the rules stated in Ref. 25, the numbers of TPs, FPs, TNs, and FNs for class  $c$  are calculated in the following way:

$$\text{TP}_c = e_{cc}, \quad (4)$$

$$FP_c = \sum_{\substack{i=1, \\ i \neq c}}^n e_{ic}, \quad (5)$$

$$FN_c = \sum_{\substack{i=1, \\ i \neq c}}^n e_{ci}, \quad (6)$$

$$TN_c = \sum_{\substack{i=1, \\ i \neq c}}^n \sum_{\substack{j=1, \\ j \neq c}}^n e_{ij}. \quad (7)$$

Moving with the technique mentioned above, the concluding confusion matrix turns into a two-dimensional square matrix, which comprises the average results of all of the  $n$  ( $n > 2$ ) confusion matrices for every class of the problem. After establishing this concluding confusion matrix into operation, accuracy, TP rate (TPR) or sensitivity, TN rate (TNR) or specificity,  $F_1$ -score, precision, FP rate (FPR), and FN rate (FNR) are estimated for a specific classifier. After performing the training of each of the classifiers, we have used the test data set for measuring the overall classification performance matrices depending on the two-dimensional confusion matrix. The performance evaluation matrices of all the classifiers namely accuracy, sensitivity, specificity, precision,  $F_1$ -score, FPR, and FNR are estimated in rates is represented as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100\%, \quad (8)$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \times 100\%, \quad (9)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \times 100\%, \quad (10)$$

$$\text{Precision} = \frac{TP}{TP + FP} \times 100\%, \quad (11)$$

$$F_1\text{score} = \frac{2 \times TP}{2 \times TP + FP + FN} \times 100\%, \quad (12)$$

$$\text{FPR} = \frac{FP}{TN + FP} \times 100\%, \quad (13)$$

$$\text{FNR} = \frac{FN}{TP + FN} \times 100\%. \quad (14)$$

We apply the cross-validation approach, as defined in Refs. 23 and 24, to find the performances of the classifiers which are applied on the subject of performance metrics exhibited in equations in between (8)–(14). Finally, we achieve the most significant classifier for automatic of recognition fruit disease namely papaya, jack-fruit, and guava after analyzing the results in different ways.



### 3.2. Disease and feature description

Ocular inspection of diseases is one of the most important steps to develop a system because it assists someone to correctly understand the distinctive considerations of the defects and gives him effective features. In this study, we principally deal with four diseases of each of the three fruits guava, jackfruit, and papaya, which are common all over Bangladesh. They are shown pictorially in Fig. 4.

Two types of features have been used in our research, respectively, gray-level co-occurrence matrix (GLCM) as well as statistical features. We have built our set of features by selecting from both feature types. Classification models mainly work based on the feature set to classify accurately. Habib and Rokonzaman<sup>26</sup> exhibited effective research that is done to identify textile defects. They perform the classification using extraordinary statistical features. Consequently, we have selected this feature which is worked effectively as proved in Ref. 26. Five statistical features have selected for our work, i.e., standard deviation ( $\sigma$ ), variance ( $\sigma^2$ ), mean ( $\mu$ ), kurtosis ( $\kappa$ ), and skewness ( $\gamma$ ). If faulty portion(s) contains  $n$  number of pixels, where the gray-scale intensity of the pixel is  $I$ , and  $\bar{I}$ ,  $I_\sigma$ , and  $I_M$  are the mean, standard deviation, and mode of the gray-scale intensity



Fig. 4. Four common diseases of each of three of the available local fruits in Bangladesh. (a) Guava. (b) Jackfruit. (c) Papaya.

of every pixel individually, these features can be presented in the following equations:

$$\text{Standard deviation } (\sigma): \sigma = \sqrt{\frac{\sum_{i=1}^n (I_i - \bar{I})^2}{n}}, \quad (15)$$

$$\text{Mean } (\mu): \mu = \frac{1}{n} \sum_{i=1}^n I_i, \quad (16)$$

$$\text{Variance } (\sigma^2): \sigma^2 = \frac{1}{n} \sum_{i=1}^n (I_i - \bar{I})^2, \quad (17)$$

$$\text{Skewness } (\gamma): \gamma = \frac{\bar{I} - I_M}{I_\sigma}, \quad (18)$$

$$\text{Kurtosis } (\kappa): \kappa = \frac{\frac{1}{n} \sum_{i=1}^n (I_i - \bar{I})^4}{\left(\frac{1}{n} \sum_{i=1}^n (I_i - \bar{I})^2\right)^2} - 3. \quad (19)$$

Haralick *et al.*<sup>27</sup> asserted that GLCM features also worked remarkably in this context. They have determined that this set of features is most significant to recognize the diseased portions from the original images which provide a visualization intensity variation at the pixel of the application by investigating the relationship between 2 pixels at an identical time. Let  $f(x, y)$  is a two-dimensional grey-scale image of size  $K \times L$  pixels with  $l_f$  grey levels. Let us assume that  $(p_1, q_1)$  and  $(p_2, q_2)$  are two pixels in  $f(x, y)$ , the distance is  $h$  and the  $\phi$  is the angle between the two and the ordinate. Therefore, according to Ref. 25, a GLCM  $P(i, j, h, \phi)$  appears in the given equation

$$P(i, j, h, \phi) = |\{(p_1, q_1), (p_2, q_2) \in K \times L : h, \phi, f(p_1, q_1) = i, f(p_2, q_2) = j\}|. \quad (20)$$

We have also implemented five types of GLCM features, i.e., individually contrast ( $C$ ), entropy ( $S$ ), energy ( $E$ ), correlation ( $\rho$ ), and homogeneity ( $H$ ), whose detailed description for the readers can be found in Ref. 7. All of these features are equated here, where  $P(i, j)$  is the  $(i, j)$ th entry of the estimated GLCM;  $l_g$  is the total amount of grey levels in an image; and  $s_x$ ,  $s_y$ , and  $m_x$ ,  $m_y$  are the standard deviations and means of the row and column sums of the GLCM.

$$\text{Contrast } (C): C = \sum_{i=0}^{l_g-1} \sum_{j=0}^{l_g-1} (i - j)^2 P(i, j), \quad (21)$$

$$\text{Correlation } (\rho): \rho = \frac{\sum_{i=0}^{l_g-1} \sum_{j=0}^{l_g-1} ijP(i, j) - \mu_x \mu_y}{\sigma_x \sigma_y}, \quad (22)$$

$$\text{Entropy } (S) : S = - \sum_{i=0}^{l_g-1} \sum_{j=0}^{l_g-1} P(i, j) \log P(i, j), \quad (23)$$

$$\text{Energy } (E) : E = \sum_{i=0}^{l_g-1} \sum_{j=0}^{l_g-1} P(i, j)^2, \quad (24)$$

$$\text{Homogeneity } (H) : H = \sum_{i=0}^{l_g-1} \sum_{j=0}^{l_g-1} \frac{P(i, j)}{1 + (i - j)^2}. \quad (25)$$

#### 4. Experimental Evaluation

We perform a profound exploration on machine vision-based local fruit disease recognition as depicted in Fig. 3. It originates with the hypothesis that personage, i.e., a farmhand, who needs to identify the disease of fruits accurately takes an image of fruits using a smartphone or other handheld devices. Respecting the distinct people from various backgrounds and contexts, we have resized the originally captured image. Then this image is converted into a fixed-size image of  $300 \times 300$  pixels. This fixed-sized image has been chosen by taking the different configurations of diverse smartphone and handheld devices into account. Then color intensity mapping is used to enhance the contrast of the image i.e., histogram equalization. Following the contrast-enhanced color, the image is segregated into different areas applying the segmentation algorithm i.e.,  $K$ -means clustering. This algorithm is selected based on the results of the objective evaluation performed in Ref. 28 as well as the subjective evaluation performed by us in this paper. Since the objective evaluation is already performed, only the subjective evaluation is performed in this work. In our subjective evaluation, the segmentation results are judged by 20 human evaluators, who are all university students. Each evaluator is provided with 15 images of each disease of each of the three local fruits and a quality metric (QM) that varies on a scale of 0–10. The evaluators meticulously observe the images and give marks, i.e., value of QM. Final results are produced by averaging all marks. Figure 5 shows pictorial, i.e., qualitative as well as quantitative performances of the four segmentation algorithms on a sample disease of each of three local fruits. Moreover, Tables 1 and 2 exhibit the results obtained in detail. It is observed from Tables 1 and 2 that the  $K$ -means clustering algorithm performs better than the three other segmentation algorithms.

So, it is better to use the  $K$ -means clustering algorithm. In this way, disease-affected portions are segregated from disease-free portions by employing a segmentation algorithm i.e.,  $K$ -means clustering. The step-by-step outcomes of differences of the images of a disease of the three local fruits, i.e., guava, jackfruit, and papaya are exhibited in Fig. 6. Segmentation of images is the most important part of the machine vision-based work because feature qualities depend on the segmentation of images which can lead to classify the image accurately. So, image segmentation is a

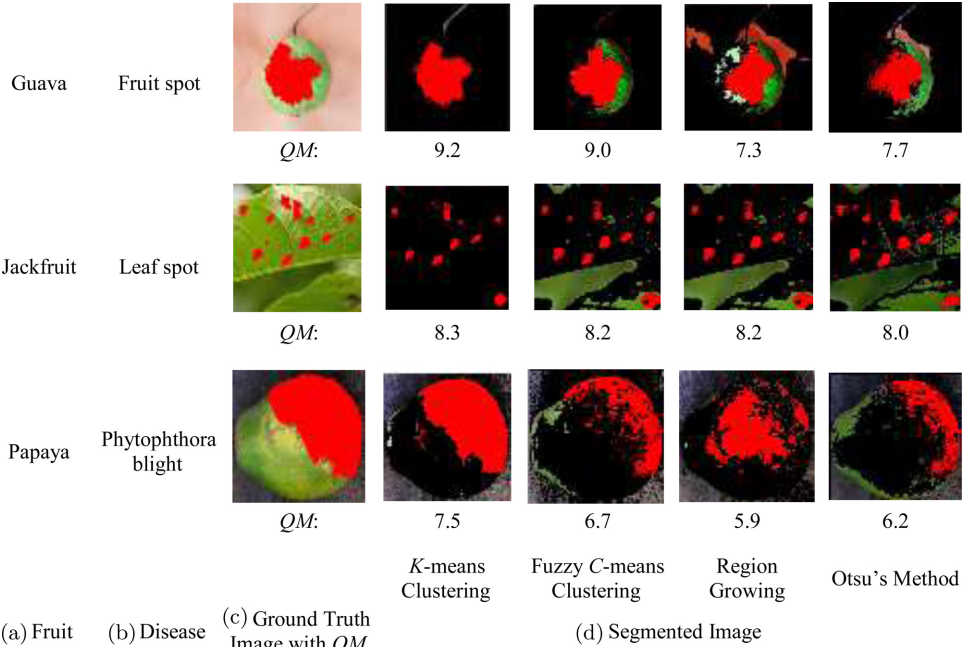


Fig. 5. Subjective evaluation of performances of different segmentation algorithms on a sample disease of each of three local fruits. (a) Local fruits. (b) A sample disease of each of the three local fruits. (c) Manual ground truth images with corresponding value of QM. (d) Segmented images of a disease of each of three local fruits after applying the four algorithms — *K*-means clustering, fuzzy *C*-means clustering, region growing and Otsu's method.

required part of this research. Figure 7 illustrates a pair of test images of each of the three fruits, i.e., guava, jackfruit, and papaya (two are healthy and two are disease-infested), where all the extracted features are presented. Among all the pairs of images, one is correctly recognized and the other is not recognized accurately.

We have used a total of 500, 480, and 125 color images of both diseased and disease-free guava, jackfruit, and papaya, respectively. A huge percentage of the images are collected locally and the rest of the part of the images are collected from the internet. The class-wise image data is shown in Table 3. The cross-validation<sup>23,24</sup> method is used for evaluation purposes. According to the cross-validation method, total data is split into ten parts, nine parts used for training and one part used for testing purposes. So, it is clear that we have applied the ten-fold cross-validation method. After completing the training, test data set are used to measure the performance of the nine classifiers. Our single multi-class confusion matrix contains five classes but we built a five binary (2 classes) confusion matrix which is already explained in Refs. 29 and 30. After constructed the final binary matrix, the stepwise experiments are done that are given in Table 4.

At this period of experimentation, we have applied in total nine extremely asserted classifiers, viz. C4.5, *k*-NN, logistic regression, RIPPER, Naïve Bayes SVMs,

Table 1. Performances expressed by each of the segmentation algorithms applied.

Segmentation algorithm	QM											
	Guava				Jackfruit				Papaya			
	Fruit		Stylar		Rhizopus		Pest and		Phytophthora		Powdery	
	Anthracnose	spot	Red	end	rot	rot	disease	spot	disease	blight	mildew	Black spot
Region growing	6.2	7.3	8.7	4.9	9.2	9.2	9.1	8.3	8.7	5.9	8.5	9.1
K-means clustering	8.1	9.2	9.0	8.2	9.3	9.3	9.2	8.4	9.2	7.5	8.6	9.0
Fuzzy C-means clustering	8.0	9.0	8.4	5.7	9.1	9.1	8.9	8.1	7.9	6.7	6.7	8.5
Otsu's method	6.7	7.7	7.9	7.9	8.9	8.9	8.3	8.1	8.3	6.2	6.4	8.2

Table 2. Performance of all segmentation algorithms used in the amount of QM.

Segmentation algorithm	Criterion	QM
Region growing	Guava	6.8
	Jackfruit	8.8
	Papaya	7.8
	Total	7.8
K-means clustering	Guava	8.6
	Jackfruit	9.0
	Papaya	8.3
	Total	8.6
Fuzzy c-means clustering	Guava	7.8
	Jackfruit	8.5
	Papaya	7.3
	Total	7.9
Otsu's method	Guava	7.6
	Jackfruit	8.4
	Papaya	7.0
	Total	7.6

random forest, CPN, and BPN, which have been chosen consciously to include a wider range of classifiers. By dint of training processes, the values of all related parameters of all these classifiers are set. The results are determined analytically estimating the classifier performance. They are shown in several noticeable

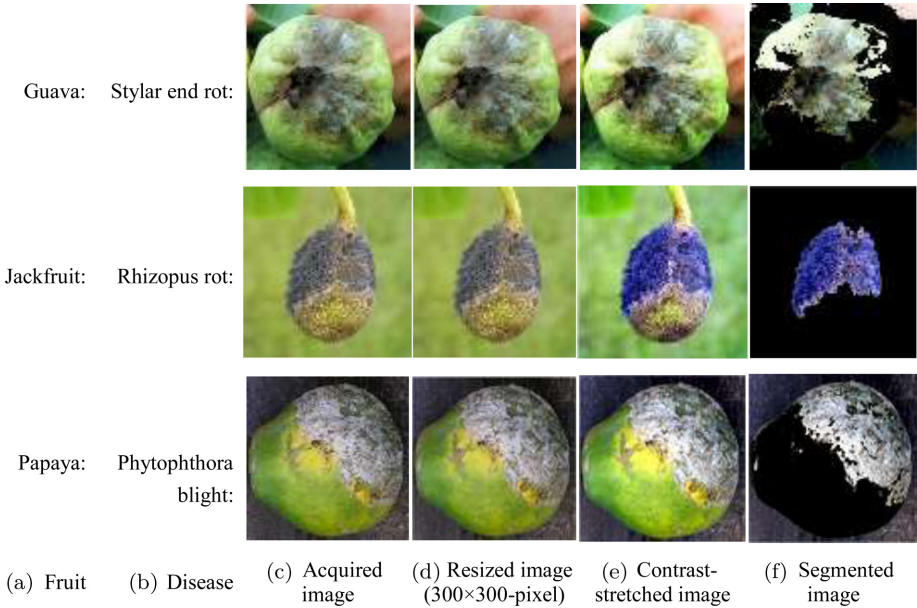


Fig. 6. Stepwise alterations of images. (a) Fruit. (b) Disease. (c) Captured image. (d) Resized image (300 × 300 pixels). (e) Contrast-stretched image. (f) Disease-affected segmented areas.



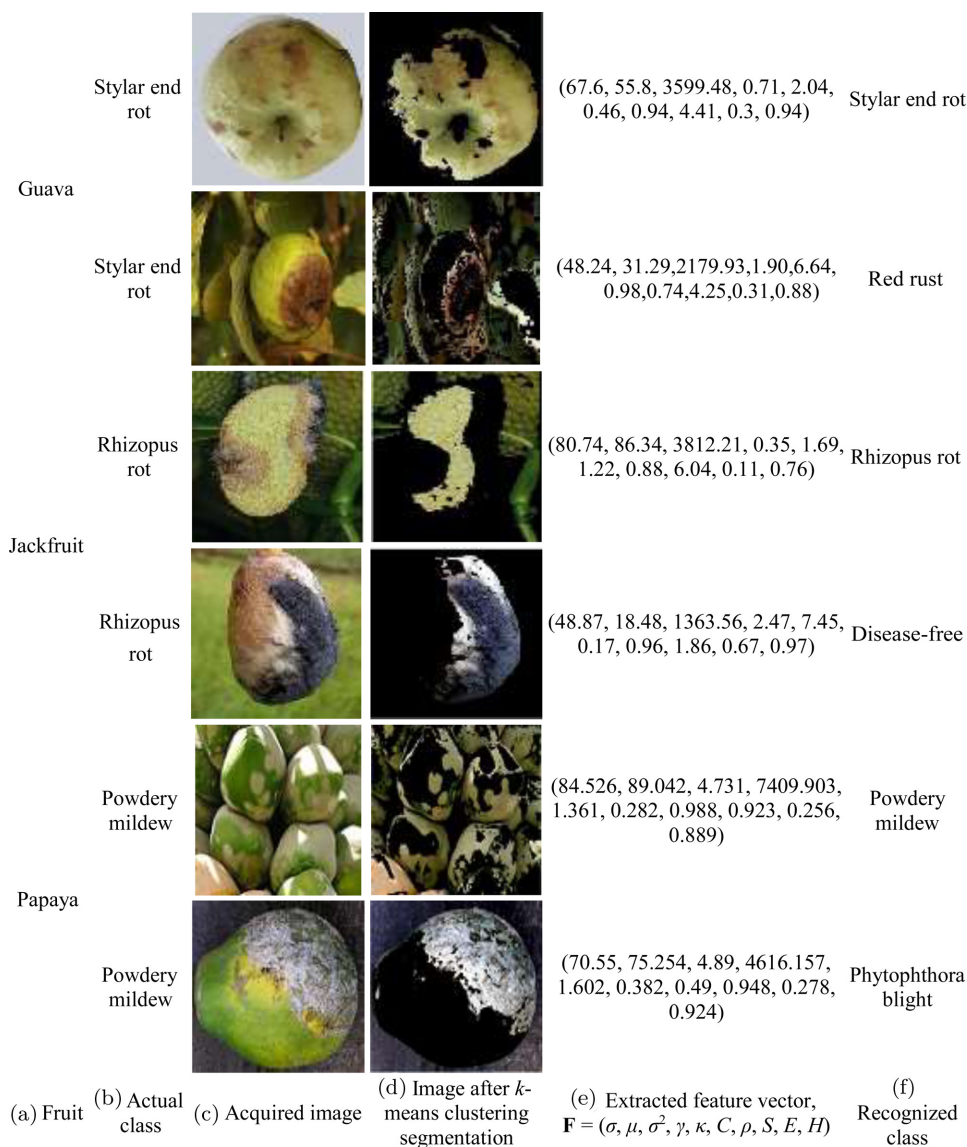


Fig. 7. Representation of all the extracted features from three pairs of diseased fruit images, where three images are correctly identified and the other three of the images are erroneously recognized. (a) Diseased fruits, (b) Collected image, (c) Segmentation of images by using  $K$ -means clustering algorithm, (d) Feature vector  $\mathbf{F}$  extracted. (e) recognition of disease or disease-free fruits.

performance metrics, i.e., accuracy, sensitivity, specificity, precision,  $F_1$ -score, FPR, and FNR, as presented in (8)–(14) sequentially and given in Table 5. Besides, the accuracy achieved by each of the classifiers has also been computed separately for all of the fruit diseases i.e., guava, jackfruit, and papaya that is given in Table 6.



Table 3. The disease-wise distribution of the collected data sets of all three local fruits.

Guava		Jackfruit		Papaya	
Class	Frequency	Class	Frequency	Class	Frequency
Anthracnose	100	Leaf spot	104	Anthracnose	24
Disease-free	100	Disease-free	115	Black spot	24
Fruit spot	100	Pest and disease	88	Disease-free	29
Red rust	100	Pink disease	74	Phytophthora blight	24
Stylar end rot	100	Rhizopus rot	98	Powdery mildew	24
Total	500	Total	480	Total	125

Table 4. Synopsis of stepwise experiments carried out.

Coverage area	Experimental stride	Adopted technique/ algorithm	Method/parameter/instance used
Digital image processing	Preprocessing	Resizing	Bicubic interpolation
	Preprocessing	Contrast stretching	Histogram equalization
Digital image processing	Segmentation	<i>k</i> -means clustering	<i>L</i> * <i>a</i> * <i>b</i> * color space
Machine learning	Classification	C4.5	Decision tree
		RIPPER	Rule based
		<i>k</i> -NN	Instance based
		Naïve Bayes	Bayesian
		Logistic regression	Linear modeling
		SVMs	
		Random forest	Ensemble
		BPN	Shallow neural networks
		CPN	

It is remarked from Table 5 that random forest classifier turns significant over all of the other nine classifiers employed in the amount of all metrics selected for the cases of guava and jackfruit although SVMs take the place in the case of papaya. This happens because the random forest is an ensemble classification model which builds multiple models and then combines them to produce improved results. Hence random forest generally generates more accurate solutions than a single model would. A very effective classifier is SVM which generally outperforms all other classifiers when there is a clear margin of separation between classes. In the case of papaya, the size of the data set is only 125, where the number of overlapping points is very small and there exists a clear margin of separation between classes. This is why SVMs stand first leaving the random forest behind in the second position. Likewise, the same scenario exists for all other metrics. This is delineated in Table 5. On the contrary, the poorest performances are exhibited by Naïve Bayes, logistic regression and *k*-NN for the cases of guava, jackfruit, and papaya, respectively. Although the highest accuracy (96.8%) is exhibited by random forest for the case of guava, promising accuracy is also disclosed by SVMs, CPN, and C4.5. Likewise, the highest accuracy is obtained for the cases of jackfruit and papaya by random forest (89.59%)

Table 5. The performances of the nine classifiers applied in recognition of the three local fruits in terms of seven comprehensive metrics.

Classifier	Fruit	Metric						
		Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	$F_1$ -score (%)	FPR (%)	FNR (%)
C4.5	Guava	89.40	73.40	93.40	73.56	73.47	6.6	26.60
	Jackfruit	82.92	54.47	88.91	55.13	54.80	11.09	45.53
	Papaya	93.60	84.05	96.02	84.09	83.92	3.98	15.95
RIPPER	Guava	84.08	61.00	89.85	60.40	60.62	10.15	39.00
	Jackfruit	79.92	48.75	87.16	52.24	50.43	12.84	51.25
	Papaya	78.88	47.44	86.83	47.45	47.20	13.17	52.56
$k$ -NN	Guava	84.76	61.00	90.70	62.46	61.44	9.30	39.00
	Jackfruit	75.70	39.43	84.64	42.90	41.09	15.36	60.57
	Papaya	72.16	30.52	82.62	30.67	30.46	17.38	69.48
Naïve Bayes	Guava	81.24	53.00	88.30	53.53	52.39	11.70	47.00
	Jackfruit	80.12	51.06	87.53	45.34	48.03	12.47	48.94
	Papaya	76.32	41.90	85.05	41.47	41.29	14.95	58.10
Logistic regression	Guava	84.89	63.20	90.30	62.98	62.84	9.70	36.80
	Jackfruit	74.83	35.60	84.04	37.45	36.50	15.96	64.40
	Papaya	75.59	39.25	84.65	39.31	38.80	15.35	60.75
SVMs	Guava	90.48	76.40	94.00	76.30	76.32	6.00	23.60
	Jackfruit	87.92	69.29	92.46	69.32	69.31	7.54	30.71
	Papaya	94.90	87.17	96.85	87.32	87.02	3.15	12.83
Random forest	Guava	96.80	92.20	98.05	92.22	92.2	1.95	7.80
	Jackfruit	89.59	74.20	93.51	73.61	73.90	6.49	25.80
	Papaya	89.73	74.86	93.60	75.34	74.60	6.40	25.14
BPN	Guava	88.80	72.60	92.85	72.25	72.23	7.15	27.40
	Jackfruit	83.17	56.64	89.44	56.28	56.46	10.56	43.36
	Papaya	88.96	73.79	92.85	72.94	72.79	7.15	26.21
CPN	Guava	93.68	84.17	96.05	84.27	84.19	3.95	15.83
	Jackfruit	85.68	60.52	91.15	64.70	62.54	8.85	39.48
	Papaya	90.08	75.60	93.86	76.79	75.27	6.14	24.40

and SVMs (94.9%), respectively, whereas promising accuracy is also exhibited by SVMs, CPN, BPN and C4.5. Random forest outperforms all other classifiers for the cases of both jackfruit and papaya attaining the highest accuracy of 96.8% for the case of guava. This happens because the color appearance of guava is smoother and more uniform than that of jackfruit and papaya. This holds for the case of their diseases too. Hence, it is also observed from Table 6 that the maximum accuracy for an individual disease is exhibited by random forest for fruit spot of guava and it quantifies 98%. Likewise, it quantifies 92.5% by random forest and 95.2% by SVMs for rhizopus rot of jackfruit and phytophthora blight of papaya, respectively. In this case too, as stated earlier, random forest outperforms all other classifiers for all disease classes of both jackfruit and papaya attaining the highest accuracy of 98% for fruit spot of guava. Taking all these observations into account as well as considering all seven metrics, we can assert that the random forest performs the finest among all of the nine classifiers used concerning the recognition of guava diseases.

Table 6. Class-wise accuracy of the nine classifiers used in recognition of the three local fruits.

Fruit	Disease	Classifier (disease and disease-free)								
		C4.5 (%)	RIPPER (%)	k-NN (%)	Naïve Bayes (%)	Logistic regression (%)	SVMs (%)	Random forest (%)	BPNN (%)	CPNN (%)
Guava	Anthraxnose	88.00	89.20	83.40	82.20	86.60	92.00	96.40	90.00	93.40
	Disease-free	88.40	86.00	83.60	78.60	81.20	88.00	96.80	89.20	93.80
	Fruit spot	87.40	84.20	84.40	82.80	82.40	90.60	98.00	85.60	94.20
	Red rust	90.80	82.60	87.60	83.00	89.64	93.00	96.60	90.60	92.80
Jackfruit	Stylar end rot	92.40	78.40	84.80	79.60	84.60	88.80	96.60	88.60	94.20
	Rhizopus rot	82.92	75.63	70.42	76.25	72.50	89.38	92.50	84.79	85.68
	Pest and disease	81.67	85.21	82.23	80.83	76.67	87.71	88.96	81.67	87.29
	Pink disease	83.33	87.29	81.25	86.25	83.75	87.08	90.83	83.54	82.92
Papaya	Leaf spot	80.83	81.04	71.25	79.79	69.17	88.13	88.75	82.70	85.42
	Disease-free	82.92	70.42	73.33	77.50	72.08	87.29	86.88	83.13	86.45
	Anthraxnose	92.80	76.80	69.60	72.80	72.36	93.70	88.80	86.40	88.00
	Black spot	94.40	80.00	72.00	76.80	74.40	95.20	89.43	88.80	90.40
Phytophthora blight	Disease-free	94.40	78.40	71.20	76.80	76.80	96.00	91.20	91.20	92.00
	Phytophthora blight	93.60	80.00	72.80	78.40	76.00	95.20	91.20	88.00	89.60
	Powdery mildew	92.80	79.20	75.20	76.80	78.40	94.40	88.00	90.40	90.40

## 5. Conclusion and Future Work

The applicability of automated recognition of the diseases of some available local fruits, i.e., guava, jackfruit, and papaya have been profoundly delved in the same frame of computer vision in this paper. Ten features of two types have been engaged to recognize the diseases of guava, jackfruit, and papaya. For extracting the features, digital image processing techniques have been put into action. These features are thereafter input to nine noteworthy classifiers. The best results have been found with random forest and SVMs. Despite the scarcity of profound research work on the recognition of the diseases of these three local fruits, it can assert that our method performs comprehensively well achieving an accuracy of 96.8%, 89.59%, and 94.9% for guava, jackfruit, and papaya, respectively. There exists a rigorous allusion of future research works on local fruit disease recognition to cover an enormous range of diseases of much more than three local fruits.

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