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## An in-depth exploration of automated jackfruit disease recognition

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### ABSTRACT

Bangladesh extensively depends on agriculture for the economy as well as food security owing to its huge population. In this connection, it becomes very important to efficiently grow plants and increase their yields. Quantity and quality of fruits can be degraded having attacked by various diseases. It is a matter of fact that not even a single research work has been conducted for automated recognition of jackfruit diseases to facilitate those distant farmers who need proper cultivation support. Presuming that our context is the recognition of jackfruit diseases, two challenging problems are mainly raised, i.e. detection of diseases and classification of diseases. In this research, we perform an in-depth investigation of an agro-medical expert system, which proceeds with a digital image acquired with a cellphone or other handheld device and recognizes the disease. Exhaustive experiments have been performed to assess the feasibility of our intended expert system. At first, a discriminatory feature set is selected. *k*-means clustering segmentation is put into action to detect disease-affected regions of an image of a disease-attacked jackfruit and extract the features from these regions. Then classification of the diseases is accomplished by using nine off-the-shelf classification algorithms in order to thoroughly assess the merits of the classifiers in the index of seven prominent performance metrics. Random forest is found outperforming all other classifiers to the amount of all metrics used by attaining an accuracy approaching to 90%. On the contrary, logistic regression shows not only the poorest result of an accuracy approaching to 75% but also some other poorest metric-values.

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### 1. Introduction

Bangladesh is an agricultural country, where the lion's share of the people depends on agriculture directly or indirectly. The agriculture sector performs remarkable feats for the entire economic development of Bangladesh. It supplies more than 39% of the total employment of Bangladesh as per the data provided by the World Bank ([Bangladesh: Employment in agriculture](#)). Moreover, the agricultural sector contributes 14.74% to the country's GDP according to the data provided by the World Bank ([Bangladesh: GDP share of agriculture](#)). This sector includes crops, animal farming, forests, and fishing. It is consequently essential to have a sustainable, valu-

able, and environment-friendly agricultural system for ensuring the long-term security of food for the people of Bangladesh – a densely populated country. Hence the agricultural sector has been given the highest priority by the current government in order to make Bangladesh self-sufficient in food. So, we have to maintain the agricultural product with proper care for ensuring food security. One of the important aspects of quality is the disease-free product. The readers are presumed to keep it in mind that our context is the recognition of jackfruit diseases. We propose an agro-medical expert system, which proceeds with an image acquired with a cellphone or other handheld device and not only detects the disease-affected part(s) of the product but also recognizes the disease. Among various agricultural goods, we have taken jackfruit, the national fruit of Bangladesh. It is extensively produced in farmland as well as a home-side garden by amateur gardeners as illustrated in [Fig. 1](#). In the area of cultivation, jackfruit ranks are third and in the area of production, Bangladesh ranked second among all the fruits. Annual jackfruit production of Bangladesh is 469,500 tons from the 25,110 ha of land under jackfruit. In Bangladesh, it accounts for approximately 22% of the entire fruit production ([Jackfruit](#)). Jackfruit is attacked by various types of diseases

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**Fig. 1.** Production of jackfruits in Bangladesh: (a) Large-scale jackfruit production by professional farmer. (b) Home-side jackfruit production by amateur gardener.

that causing significant damage during the cultivation period. Consequently, farmers bear the immense economic loss. It has been published in a survey (Rahman and Afroz, 2016) that about 66% of jackfruit trees are infested with fungal disease, which causes a decrease in the lifetime of the affected trees resulting in losses in terms of quality as well as quantity of jackfruit. Moreover, Haq (2006) opined that post-harvest losses of jackfruit can be as much as 30–34%.

In this paper, we deeply conduct exploratory analysis on automatic disease recognition of jackfruit following a computer vision approach. We put forward an agro-medical expert system that processes a digital image of jackfruit and recognizes the affecting disease along with the contaminated part(s). A set of discriminatory features has already been proposed and demonstrated for recognizing fruit diseases by Habib et al. (2018). These features are used in our research too. For the sake of the extraction of features, image processing techniques are used and the classification of diseases has been performed using nine prominent classification algorithms to the amount of seven performance metrics so that the merits of the classifiers can be assessed and compared.

To summarize, the main contributions of our research work are:

- The first attempt to solve the problem of automated jackfruit disease recognition.
- Systematically formation of a strong base of discriminatory features for classifiers in order to successfully classify jackfruit diseases.
- An in-depth exploration of different classification in the context of jackfruit disease recognition in order to facilitate future research.
- A demonstration that our proposed approach has a very competitive performance on the data set of images of jackfruit diseases built in this paper.

## 2. Related works

Automated, i.e. machine vision based fruit disease recognition system can be disintegrated into two problem domains, particularly the detection of diseases and classification of diseases. A remarkable number of researchers define their works only for the detection of diseases, whereas some researches incorporate the field of both disease detection and classification. We come to know, as a matter of fact, that not a single work has been performed for automated jackfruit disease recognition. However, some endeavors have been performed for automated some other fruits disease recognition, for example papaya, apple, guava and so on. Moreover, there have been some endeavors in order for automatically detecting or recognizing vegetable disease recognition, for example lemon, bean, tomato, and so on.

Samajpati and Degadwala (2016) have proposed a hybrid procedure, i.e. fusion of features, for fruit disease recognition in the context of apple. Although this is the first step for automated apple disease recognition, some issues have made it questionable. They have prepared their feature set using thirteen distinct features. All of the features are chosen based on texture and color. Only three apple diseases are dealt with in their work. The defected part of an apple image has been separated by applying *k*-means clustering segmentation, and then texture and color features are employed all together to classify the diseases with the help of random forest classifier. In the case of classification, seventy images and ten images have been used for training and testing, respectively. The level of accuracy attained varies from 60% to 100% because different fusion of features has been used. Habib et al. (2018) introduce a computer vision approach in order for recognizing papaya diseases. One hundred and twenty-nine images are used in their work. They have worked with a feature set of two types of features accumulating ten features in total. They have deployed the *k*-means clustering algorithm to segment out the disease-attacked part so that the features can be extracted. Three classifiers have separately been used for getting the classification task done. It has been found that support vector machines (SVMs) exhibits an accuracy of 95.2% beating the other two classifiers. Although this work (Habib et al., 2018) is then extended by Habib et al. (2020) using six more prominent classifiers, SVM remains the best by outperforming all other classifiers, whereas *k*-NN performs the worst showing 71.11% accuracy. Kumar and Suhas (2016) have deployed a computer vision approach in order to recognize diseases of some distinct fruits. In sooth, their work has been questionable and vague to readers because some important information is missing. It has been claimed by them that ten distinct fruits have been used for detecting diseases, but the disease names have not been presented in their work. They have used two hundred and forty-three images for testing. Their work has been presented as cluttered. Due to the missing of some important information, their obtained classification accuracy should be refused even though it is 87.47%. Chopade and Bhagyashri (2016) have completed poor research work to detect disease only other than the classification. They have not used a computer vision approach to detect the disease, and for this reason, neither feature nor classifier has not been presented in their work. They have just presented segmentation based on the histogram to recognize fruit leaf disease. Consequently, we can say that their attempt is not an acceptable one to detect fruit disease. Rozario et al. (2016) have worked on fruits and vegetable detection using image-processing techniques. Their work mainly focused on detecting the defects of fruits and only vegetables and fruits, i.e. banana, apple, potato, and tomato. No classifier has been used in their work. Hosen et al. (2018) have done another work using a

color-segmentation-based approach to detect the fruits. They have also focused their work on only detects the faulty portion of the fruits i.e. apple, banana, and orange from 3D images. They have used a 3D image of the fruits. Working with 3D images is algorithmically complicated and time-consuming. Moreover, they have used any classifier to detect the particular disease name from the input images.

Some work has been done to detect or recognize leaf disease only. Mokhtar et al. (2015) have worked on the detection of tomato leaf disease. Their data set consists of eight hundred (800) images of healthy and diseased tomato leaves. They have used a large number of gray-level co-occurrence matrix (GLCM) features for binary classification. They have used SVMs with different kernel functions in order to categorize binary classes bypassing the process of segmentation. Bypassing segmentation involves bypassing the problem of automatic fruit recognition, which is dealt with in (Mia et al., 2019), for example. Moreover, despite having achieved an accuracy of 99.83% by the SVM with a linear kernel, their research method and limited application domain have made their work feeble. Batule et al. (2016) have dealt with the disease recognition of leaf, but their work is very much uninformed and questionable. They have used  $k$ -means clustering to extract features and then they performed a noise removal technique to detect the disease. But some important information is missing from their work. They have completed their work by asserting that they will try to use SVM in the future. They have not presented either feature set or SVM classifier. In the same fashion, Naik and Sivappagari (2016) have come up with a promiscuous work on recognition of diseases of leaves of some fruits and vegetables, e.g. mango, guava, bean and lemon. They have worked with a very small number of features. SVM and neural network (NN) have been separately used for classification, where NN has exhibited better results. Nonetheless, inconsistent descriptions and missing of many important details have rendered their work feeble.

### 3. System architecture

The delineation of the structural design of the proposed agro-medical expert system for recognizing jackfruit diseases is performed through Fig. 2. Someone, e.g. a farmer or a gardener is presumed to capture an image of an apprehensively disease-attacked jackfruit with a cellphone or other handheld device, in which the mobile application of the agro-medical expert system has already been installed. Then he/she inputs the image to the installed application. The system renders its decision using its expertise. The entire agro-medical expert system will reside in a distant server. The installed application of the expert system can send a request for update(s) to the server through the Internet and get itself updated. The entire agro-medical expert system consists of some integrated components that are related among themselves.

They are an inference engine, a knowledge base, a knowledge base acquisition facility and an explanation facility. The inference engine handles the entire workflow inside the agro-medical expert system. To provide the expertise all of the components work together. The inference engine is the very component that coordinates the knowledge flow to other segments of the expert system. It is the part of the expert system which delivers predictions, suggestions, and answers in a way similar to a human expert.

## 4. Research methodology

### 4.1. Approach followed

The block diagram of the entire approach adopted for solving the problem of machine vision based jackfruit disease recognition is delineated in Fig. 3. It can be seen from Fig. 3 that the approach begins with a color image of a diseased jackfruit. First, a conversion from this image turns up into a predetermined-size image applying bicubic interpolation (Keys, 1981). Presuming that  $I$  is the intensity values, and  $I_x$ ,  $I_y$  and  $I_{xy}$  are the differential coefficients that can be perceived at the quad corners (1, 1), (1, 0), (0, 1), and (0, 0) of the unit square, the interpolated intensity surface is written in the following way:

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

where  $c_{mn}$  is a coefficient.

Then the contrast of the image is stretched by applying the histogram equalization technique. By letting  $n$  be the count of pixels through the column, i.e. width,  $m$  be the count of pixels through the row, i.e. height,  $c_k$  be the count of pixels containing color intensity  $I_k$ , and  $l$  be the count of permissible color intensity levels in the image, and then mapping each of the pixels containing color intensity  $I_k$  into a corresponding pixel containing color intensity  $I'_k$  applying histogram equalization, the color-mapped image is found in the following way (Gonzales and Woods, 2008).

$$I'_k = T(I_k) = \frac{l-1}{mn} \sum_{i=0}^k c_i \quad (2)$$

where  $k = 0, 1, \dots, l-1$ .

Then this image undergoes a conversion from RGB color space to  $L^*a^*b^*$  color space because it has been asserted by Burney and Tariq (Burney and Tariq, 2014) that the  $k$ -means clustering algorithm outperforms in segmenting images in  $L^*a^*b^*$  color space than that in RGB color space. At first, the conversion is performed, as described in Color Conversion Algorithms, from RGB color space to CIE (International Commission on Illumination) XYZ color space in the following way:

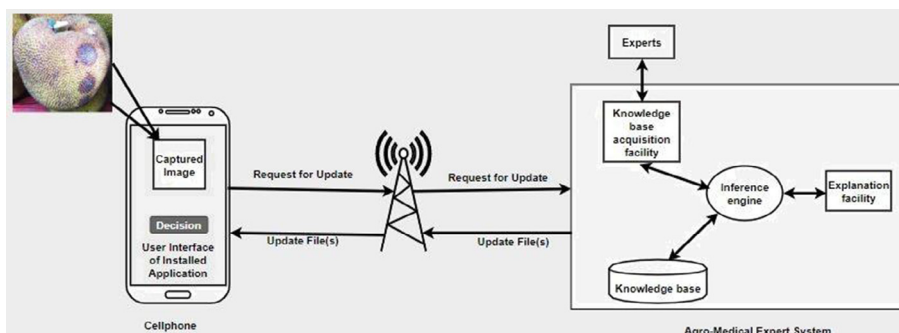


Fig. 2. Proposed structural design of the agro-medical expert system.

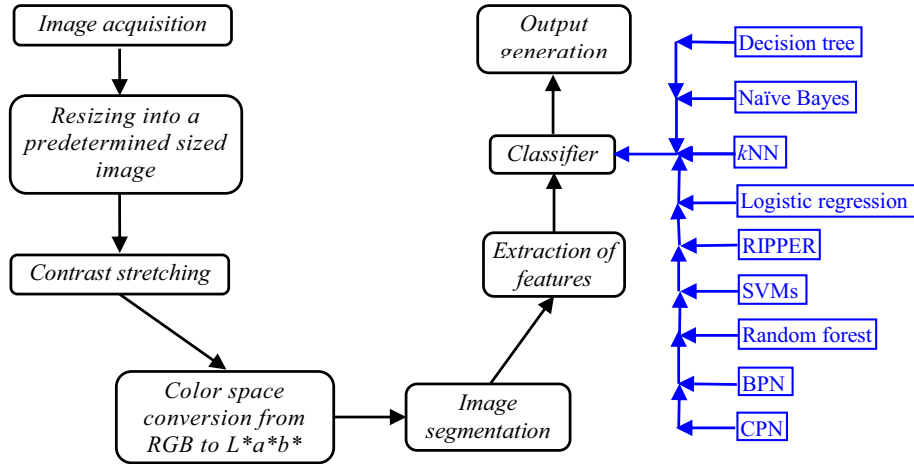


Fig. 3. Approach for solving the automated jackfruit disease recognition problem.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 3.240479 \times 10^0 & -1.53715 \times 10^0 & -4.98535 \times 10^{-1} \\ -9.69256 \times 10^{-1} & 1.875992 \times 10^0 & 4.1556 \times 10^{-2} \\ 5.5648 \times 10^{-2} & -2.04043 \times 10^{-1} & 1.057311 \end{bmatrix} \times \begin{bmatrix} R \\ G \\ B \end{bmatrix}. \quad (3)$$

In order for transforming XYZ color space into  $L^*a^*b^*$  color space,  $X_w$ ,  $Y_w$  and  $Z_w$  have been presumed the tristimulus values of the reference white color. If it is presumed more that

$$f(t) = \begin{cases} t^{\frac{1}{3}} & \text{if } t > 8.856 \times 10^{-3} \\ 7.787t + \frac{16}{116} & \text{if } t \leq 8.856 \times 10^{-3} \end{cases}, \quad (4)$$

we can equate  $L^*$ ,  $a^*$  and  $b^*$  in the following way as described in [Color Conversion Algorithms](#).

$$L^* = \begin{cases} 116\left(\frac{Y}{Y_w}\right)^{\frac{1}{3}} - 16 & \text{if } \frac{Y}{Y_w} > 8.856 \times 10^{-3} \\ 903.3 \frac{Y}{Y_w} & \text{if } \frac{Y}{Y_w} \leq 8.856 \times 10^{-3} \end{cases}. \quad (5)$$

$$a^* = 500f\left(\frac{X}{X_w}\right) - 500f\left(\frac{Y}{Y_w}\right). \quad (6)$$

$$b^* = 200f\left(\frac{Y}{Y_w}\right) - 200f\left(\frac{Z}{Z_w}\right). \quad (7)$$

The image is then segmented into some regions by applying the  $k$ -means clustering method ([Habib et al., 2018](#)). Thus, disease-attacked parts are separated from disease-free parts. From the attacked portion, feature vectors including two types of features are constructed - co-occurrence feature and statistical. Shortly, these features are being explained in detail in the following section ([Section 4.2](#)).

The feature vectors extracted in the above way are fed to some classifiers in order for training and then testing. Nine state-of-the-art classifiers are chosen from a number of off-the-shelf classifiers. They are C4.5, Repeated Incremental Pruning to Produce Error Reduction (RIPPER),  $k$ -nearest neighbors ( $k$ NN), naïve Bayes, logistic regression, support vector machines (SVMs), backpropagation neural network (BPN), counterpropagation neural network (CPN) and random forest. They are thoroughly examined with the test data set built to the amount of several performance metrics so that the most suitable classification model can be found out.

In the arena of performance analysis, accuracy cannot be claimed a rigorous metric for the measurement of the actual performance of a classifier, because it may not be well fitted for estimating classification patterns obtained from the imbalanced set of

data, i.e. the numbers of examples in various classes differ widely. There are some other evaluation matrices based on the ([Confusion Matrix](#)), as stated in ([Tan et al., 2006](#)) and ([Han et al., 2012](#)), for measuring the performance of a classifier. A binary ([Confusion Matrix](#)) states the number of true positives (TPs), false negatives (FNs), false positives (FPs), and true negatives (TNs) for a 2-class problem. For a multiclass, i.e. more than 2-class problems, the ([Confusion Matrix](#)) ( $M$ ) is written as follows:

$$M = [e_{ij}]_{n \times n}. \quad (8)$$

It can be easily noticed that the multiclass ([Confusion Matrix](#))  $M$  is an  $n \times n$  ( $n > 2$ ) square matrix. It has  $n$  rows and  $n$  columns, which results in  $n^2$  entries in total. For the multi-class matrix, there is no straightforward way to compute the number of FPs, FN, TPs, and TNs. According to the rules for multi-class matrix as stated in ([Confusion Matrix](#)), the values of TPs, FN, FP, and TNs for class  $i$  are computed as:

$$TP_i = e_{ii}. \quad (9)$$

$$FP_i = \sum_{\substack{j=1, \\ j \neq i}}^n e_{ji}. \quad (10)$$

$$FN_i = \sum_{\substack{j=1, \\ j \neq i}}^n e_{ij}. \quad (11)$$

$$TN_i = \sum_{\substack{j=1, \\ j \neq i}}^n \sum_{\substack{k=1, \\ k \neq i}}^n e_{jk}. \quad (12)$$

Progressing with this procedure, the final ([Confusion Matrix](#)) arrives in the form of a square matrix of dimension  $2 \times 2$  and includes the average amounts of the  $n$  confusion matrices for each class. By putting this final ([Confusion Matrix](#)) into action, accuracy (recognition rate), error rate (misclassification rate), sensitivity (true positive rate), specificity (true negative rate), precision, FPR (false positive rate) and FNR (false negative rate) are computed for a classifier ([Tan et al., 2006](#); [Han et al., 2012](#)). After training a classifier, a test data set is used for evaluating the performance to the amount of performance metrics based on the ([Confusion Matrix](#)). The performance evaluation metrics, namely accuracy, error rate, sensitivity, specificity, precision, FPR, and FNR are computed in percentage in the following way:

$$\text{Accuracy} = \left( \frac{TP + TN}{TP + FP + FN + TN} \times 100 \right) \%. \quad (13)$$

$$\text{Error rate} = \left( \frac{FP + FN}{TP + FP + FN + TN} \times 100 \right) \%. \quad (14)$$

$$\text{Sensitivity} = \left( \frac{TP}{TP + FN} \times 100 \right) \%. \quad (15)$$

$$\text{Specificity} = \left( \frac{TN}{FP + TN} \times 100 \right) \%. \quad (16)$$

$$\text{Precision} = \left( \frac{TP}{TP + FP} \times 100 \right) \%. \quad (17)$$

$$\text{FPR} = \left( \frac{FP}{FP + TN} \times 100 \right) \%. \quad (18)$$

$$\text{FNR} = \left( \frac{FN}{TP + FN} \times 100 \right) \%. \quad (19)$$

We use the cross-validation method, as described in [Tan et al. \(2006\)](#) and [Han et al. \(2012\)](#), in order to find the performances of the classification models used in terms of the performance metrics shown in equations (13)–(19). We further use receiver operating characteristic (ROC) curves and consider the areas under them to assess the degree of separability of the nine classifiers used. Finally, we come to the conclusion about the most suitable classifier in the context of automatic jackfruit disease recognition after methodically comparing the measures in different directions.

#### 4.2. Description of diseases and features

Visual examination of diseases is an important step in the system development because it helps us to accurately know the distinguishing factors of the defects and provides us bases of suitable features. In this research, we are mainly conducting four diseases of jackfruits which are common all over Bangladesh. They are pest disease, rhizopus rot, pink disease, and leaf spot. Sample images of all these disease-attacked jackfruits are shown in [Fig. 4](#).

We have used two types of features, namely statistical features and GLCM features. We have made our feature set by picking features from these two feature types. The feature set is used to recognize the diseases based on the various classifiers. [Habib and Rokonzaman \(2011\)](#) presented a quality work, which is done in the context of textile defect recognition. They have used remarkable statistical features in their work. Following this work, we have taken fascinating discriminatory statistical features whose efficiency has been proved in [Habib and Rokonzaman \(2011\)](#). In this work, we have chosen five statistical features, i.e. namely standard deviation ( $\sigma$ ), mean ( $\mu$ ), variance ( $\sigma^2$ ), skewness ( $\gamma$ ), and kurtosis ( $\kappa$ ). If there are  $n$  pixels in the faulty region(s), where  $I$  is the

gray-scale intensity of a pixel, and  $\bar{I}$ ,  $I_M$ ,  $I_\sigma$  are the mean, mode, and standard deviation of gray-scale intensity of all pixels respectively, the corresponding equations of these features are as follows:

$$\text{Standard deviation } (\sigma) : \sigma = \sqrt{\frac{\sum_{i=1}^n (I_i - \bar{I})^2}{n}}. \quad (20)$$

$$\text{Mean } (\mu) : \mu = \frac{1}{n} \sum_{i=1}^n I_i. \quad (21)$$

$$\text{Variance } (\sigma^2) : \sigma^2 = \frac{1}{n} \sum_{i=1}^n (I_i - \bar{I})^2. \quad (22)$$

$$\text{Skewness } (\gamma) : \gamma = \frac{\bar{I} - I_M}{I_\sigma}. \quad (23)$$

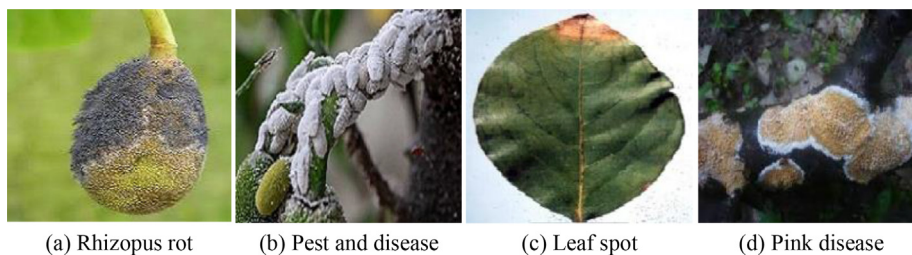
$$\text{Kurtosis } (\kappa) : \kappa = \frac{\frac{1}{n} \sum_{i=1}^n (I_i - \bar{I})^4}{\left( \frac{1}{n} \sum_{i=1}^n (I_i - \bar{I})^2 \right)^2} - 3. \quad (24)$$

We have also selected some GLCM features which are stated by [Haralick \(1973\)](#). They have shown that GLCM features are very much useful to detect the faulty part from the image because they give an example of the intensity variation at the pixel of concentration by analyzing the relation within two pixels at the same time. Let  $g(x, y)$  be a two-dimensional grey-scale image of size  $K \times L$  pixels with  $l_g$  grey levels. Let us assume that  $(p_1, q_1)$  and  $(p_2, q_2)$  are two pixels in  $g(x, y)$ , the distance is  $r$  and the angle between the two and the ordinate is  $\alpha$ . Then, as stated in [Naikwadiand, 2013](#), a GLCM  $P(i, j, r, \alpha)$  arrives in the following form of the equation:

$$P(i, j, r, \alpha) = |\{(p_1, q_1), (p_2, q_2) \in K \times L : r, \alpha, g(p_1, q_1) = i, g(p_2, q_2) = j\}|. \quad (25)$$

So, we used five GLCM features, i.e. namely contrast ( $C$ ), correlation ( $\rho$ ), entropy ( $S$ ), energy ( $E$ ), and homogeneity ( $H$ ) in our work. The reader can also go through [Habib et al., 2018](#) to know more about these features. The corresponding equations of these features are as follows, where  $P(i, j)$  is the  $(i, j)$ -th entry of the computed GLCM;  $l_g$  is the total number of grey levels in the image; and  $\mu_x$ ,  $\mu_y$ , and  $\sigma_x$ ,  $\sigma_y$  are the means and standard deviations of the row and column sums of the GLCM.

$$\text{Contrast } (C) : C = \sum_{i=0}^{l_g-1} \sum_{j=0}^{l_g-1} (i-j)^2 P(i, j). \quad (26)$$



**Fig. 4.** Four very much common diseases of jackfruit in Bangladesh. (a) Rhizopus rot. (b) Pest and disease. (c) Leaf spot. (d) Pink disease.

$$\text{Correlation } (\rho) : \rho = \frac{\sum_{i=0}^{l_g-1} \sum_{j=0}^{l_g-1} ijP(i,j) - \mu_x\mu_y}{\sigma_x\sigma_y}. \tag{27}$$

$$\text{Entropy } (S) : S = - \sum_{i=0}^{l_g-1} \sum_{j=0}^{l_g-1} P(i,j)\log P(i,j). \tag{28}$$

$$\text{Energy } (E) : E = \sum_{i=0}^{l_g-1} \sum_{j=0}^{l_g-1} P(i,j)^2. \tag{29}$$

$$\text{Homogeneity } (H) : H = \sum_{i=0}^{l_g-1} \sum_{j=0}^{l_g-1} \frac{P(i,j)}{1 + (i-j)^2}. \tag{30}$$

### 5. Experimental evaluation

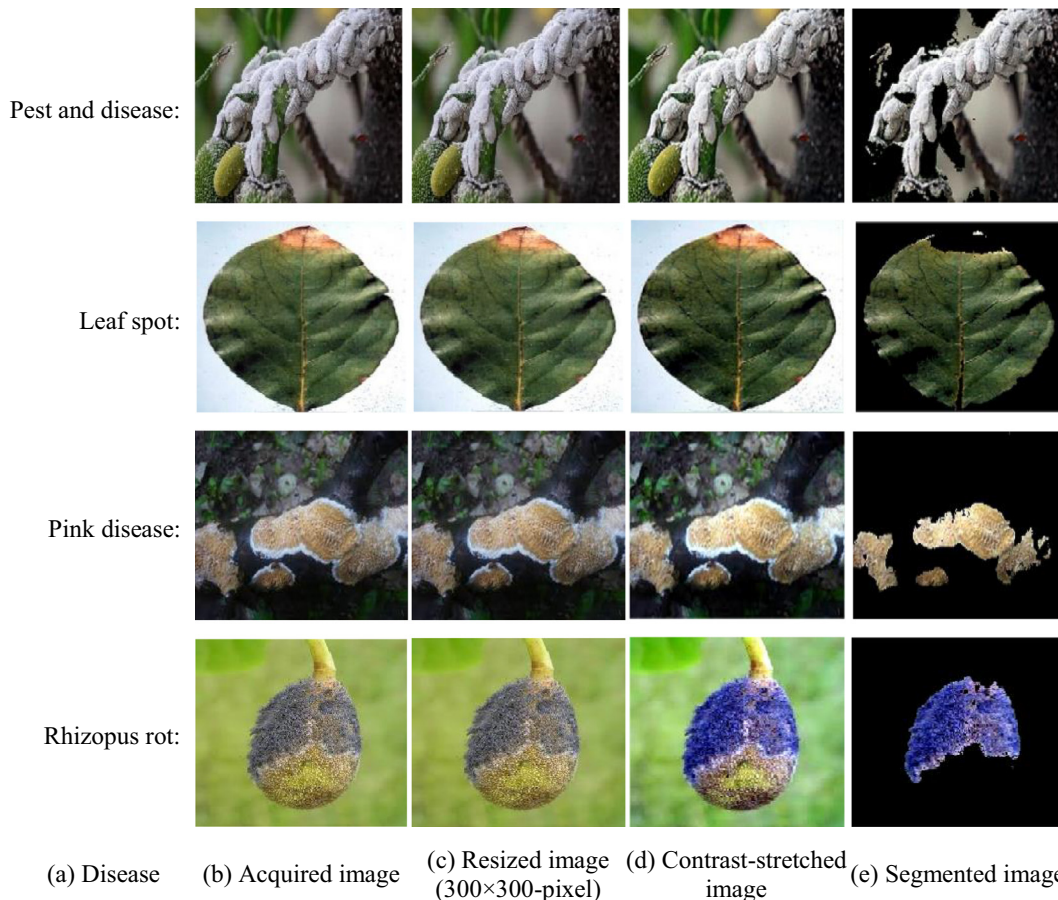
We present an in-depth investigation following our approach for automated jackfruit disease recognition as illustrated in Fig. 3. It commences with the presumption that somebody, i.e. a farmer or a gardener, who wants to recognize jackfruit diseases properly, captures a jackfruit image using a smart cellphone or a handheld device. Considering the different people from different contexts and backgrounds, we have resized the original image inputted. Then the resized image is transformed into a predetermined-size image of 300 × 300 pixels. This predetermined size has been chosen by pondering over the varying configuration of different handheld devices. Contrast stretching of the image is

**Table 1**  
k-means clustering segmented region for different diseases relative to ground truth.

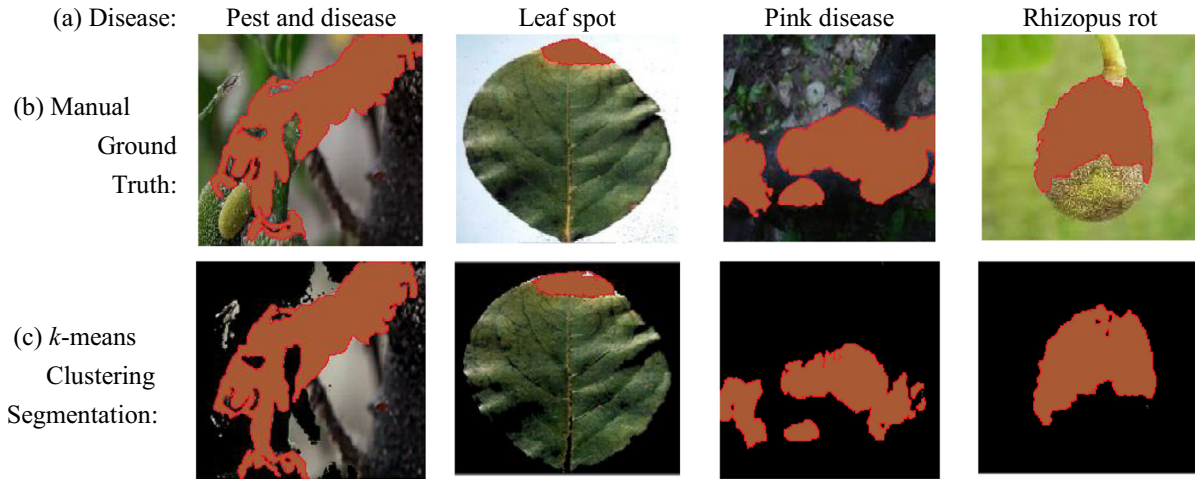
Disease	Ground Truth Region	Separated Region Relative to Ground Truth	Aberrated Region Relative to Ground Truth
Pest and disease	100%	96.08%	-3.93%
Leaf spot	100%	124.28%	+24.22%
Pink disease	100%	67.15%	-32.85%
Rhizopus rot	100%	91.62%	-8.38%
Total	100%	94.77%	17.34%

accomplished using color intensity mapping, i.e. histogram equalization. Thereafter the contrast-enhanced color image is segmented out into some regions using k-means clustering because the k-means clustering algorithm outperforms other off-the-shelf segmentation algorithms, which is provided in Rozario et al. (2016). In this way, disease-affected portions are isolated from disease-free portions. The stepwise effects of changes in the images of all disease types are shown in Fig. 5.

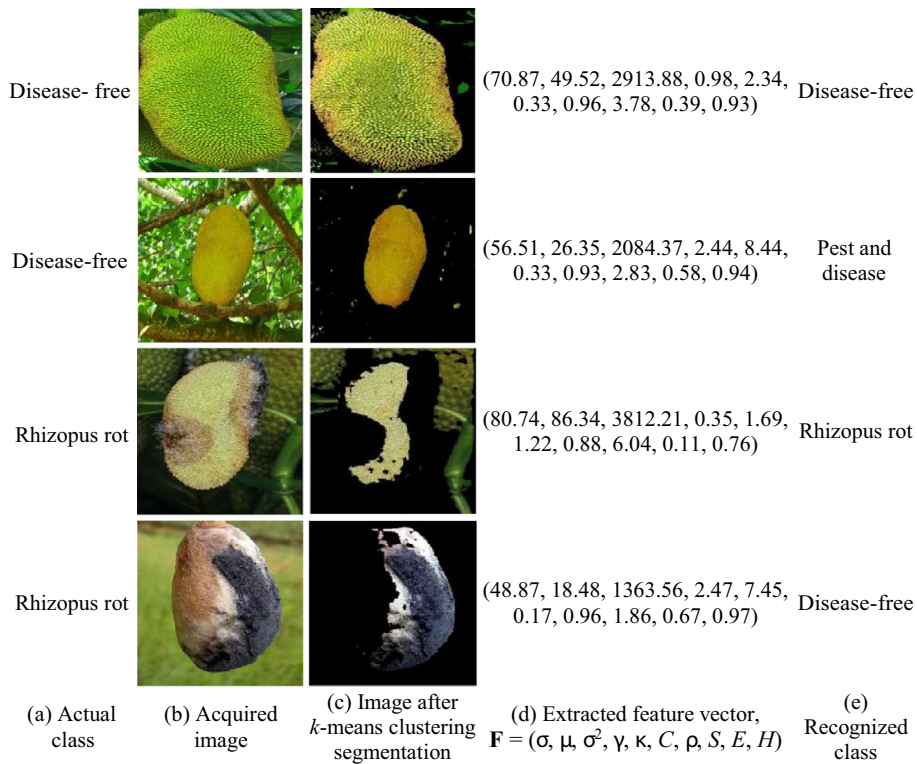
Image segmentation is a crucial step in this machine vision based work since quality feature extraction depends on the quality image segmentation. In order for evaluating the performance of the k-means clustering segmentation algorithm, ground truth images, which are manually labeled, are put into action. The results of performance for different jackfruit diseases along with the ground truth are quantitatively provided in Table 1 and pictorially shown in Fig. 6. We observe from Table 1 that pest and disease, pink disease and rhizopus rot are shrunk and only leaf spot is stretched relative to ground truth image. We also observe that segmentation performance is the most accurate (96.08%) in the case of pest



**Fig. 5.** (a) Disease, (b) Acquired image, (c) Resized image (300 × 300 pixels), (d) Contrast-stretched image, (e) Disease-affected segmented areas.



**Fig. 6.** Segmentation performance results for different diseases compared to ground truth. (a) Disease. (b) Manually outlined ground truth of the affected portions of jackfruit. (c) Affected portions of jackfruit computed by using *k*-means clustering.



**Fig. 7.** Illustration of all features extracted from a pair of disease-free jackfruit images and a pair of disease-attacked jackfruit images, where two are correctly recognized and the other two are incorrectly recognized. (a) Attacking disease, (b) Acquired image, (c) Image segmented applying *k*-means clustering, (d) Extracted feature vector **F**. (e) Recognized disease.

and disease and the most erroneous (32.85% error) in the case of the pink disease. Moreover, Fig. 7 illustrates four test images of jackfruits (two are disease-free and two are disease-affected), where all of the four feature vectors extracted are provided. Of the first two images of disease-free jackfruits, one is recognized correctly and another is recognized incorrectly. Likewise, one is recognized correctly and another is recognized incorrectly of the last two images of disease-attacked jackfruits.

We have used a total of four hundred and eighty (480) color images of both diseased and disease-free jackfruits. It is very difficult to gather a such number of images since jackfruit is a seasonal

fruit. The lion share of the entire image data is gathered locally using different cameras of different resolutions and the remaining parts are from the Internet. Different cameras of different resolutions are used taking this factor into account that a farmer or a gardener is presumed to capture an image of an apprehensively disease-attacked jackfruit or its leaf with a cellphone or other handheld device. The class-wise distribution of the gathered data set is shown in Table 2. The classes are the diseases discussed earlier in Section 4.2 (Description of Diseases and Features) along with the class disease-free. This class of images consists of flawless jackfruits only. However, the entire image data set is divided into two

**Table 2**

The class-wise distribution of the collected data set.

Class	Frequency
Rhizopus rot	98
Pest and disease	88
Pink disease	74
Leaf spot	104
Disease-free	116
Total	480

portions, i.e. training and testing. For evaluation, we have used the method of cross-validation (Tan et al., 2006); (Han et al., 2012). According to this method, each feature vector is used nine times for training and exactly once for testing, which purports that we use ten-fold cross-validation. After using different values, ten is found, for which error is minimized. When the data set training

comes to an end, the performances of some classifiers are measured using the test data set. In the course of this process, the single multiclass (5 classes) (Confusion Matrix) and resulting five binary (2 classes) confusion matrices are formed according to the method described in (Confusion Matrix). Then the final binary (Confusion Matrix) is constructed.

At this point of experimentation, we need to use some classifiers. We use nine highly pronounced classifiers in total. They are C4.5, RIPPER, kNN, naïve Bayes, logistic regression, SVMs, random forest, BPN and CPN. They have not been selected whimsically, rather deliberately in order to cover a larger range of classifiers. The values of all relevant parameters of all these classification models are fixed through training processes, which are shown in Table 3. The results are found after experimentally evaluating the performances of all these classifiers. They are expressed in different prominent performance evaluation metrics, i.e. accuracy, error rate, sensitivity, specificity, precision, FPR and FNR, as shown in the equations (13)–(19) respectively and provided in Table 4. Also, we

**Table 3**

Detailed specifications of the nine classifiers used.

Classifier	Specifications
C4.5	Splitting criterion: Gain ratio, $GR = \frac{\Delta_{info}}{Split\ Info} = \frac{\Delta_{info}}{-\sum_{k=1}^s p(v_k) \lg P(v_k)}$ .
RIPPER	Rule building metric = FOIL's information gain = $p_1 (\lg \frac{p_1}{p_1+n_1} - \lg \frac{p_0}{p_0+n_0})$ . Number of data used for pruning = 3. Pruning metric = $(p - n)(p + n)^{-1}$ .
kNN	Metric: Manhattan distance, $d_M = \sum_{i=1}^{10}  x_i - f_i $ . Weight vector, $\mathbf{W} = (w_1, w_2, w_3, \dots, w_{10}) = (1)_1 \times n$ . $k = 3$ .
Naïve Bayes	Gaussian (normal) distribution: Mean, $\mu = 0$ . Variance, $\sigma^2 = 1$ . Probability density function, $pdf(x) = \frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$ .
Logistic regression	Model: Multinomial Logistic function: $logit(p) = \ln p - \ln(1 - p)$ .
SVMs	Kernel: Linear function $C = 250043$ .
Random forest	Size of each bag = Percentage of training data size = 100%. Maximum height of the tree = unrestricted integer. Number of the attributes randomly chosen = 0.
BPN	Network topology: Fully connected two-layered feedforward (10-15-5) Transfer function: Sigmoid function, $s_c(x) = (1 + e^{-\alpha x})^{-1}$ . Learning rate, $\gamma = 0.27$ . Momentum rate, $\alpha = 0.21$ .
CPN	Network topology: Fully connected two-layered feedforward (10-11-5) Layer 1 2: Training algorithm: Unsupervised learning (Kohonen) Transfer function: $f(z) = \begin{cases} 1, & \text{if } z = \underset{x}{\operatorname{argmin}} \sqrt{\sum_{i=1}^{10} (x_i - f_i)^2} \\ 0, & \text{otherwise} \end{cases}$ . Learning rate, $\gamma_{1 2} = 0.35$ . Layer 2 3: Training algorithm: Supervised learning (Grossberg) Transfer function: $f_c(x) = cx$ , where $c = 1$ . Learning rate, $\gamma_{2 3} = 0.25$ .

**Table 4**

Metric-wise performance of all classifiers used.

Classifier	Accuracy	Error Rate	Sensitivity	Specificity	Precision	FPR	FNR
C4.5	82.92%	17.08%	54.47%	88.91%	55.13%	11.09%	45.53%
RIPPER	79.92%	20.08%	48.75%	87.16%	52.24%	12.84%	51.25%
kNN	75.70%	24.30%	39.43%	84.64%	42.90%	15.36%	60.57%
Naïve Bayes	80.12%	19.88%	51.06%	87.53%	45.34%	12.47%	48.94%
Logistic regression	74.83%	25.17%	35.60%	84.04%	37.45%	15.96%	64.40%
SVMs	87.92%	12.08%	69.29%	92.46%	69.32%	7.54%	30.71%
Random forest	89.59%	10.41%	74.20%	93.51%	73.61%	6.49%	25.80%
BPN	83.17%	16.83%	56.64%	89.44%	56.28%	10.56%	43.36%
CPN	85.68%	14.32%	60.52%	91.15%	64.70%	8.85%	39.48%



**Table 5**

Class-wise (disease and disease-free) accuracy of all classifiers used.

Classifier	Class (Disease and Disease-Free)				
	Rhizopus Rot	Pest and Disease	Pink Disease	Leaf Spot	Disease-Free
C4.5	82.92%	81.67%	83.33%	80.83%	82.92%
RIPPER	75.63%	85.21%	87.29%	81.04%	70.42%
kNN	70.42%	82.23%	81.25%	71.25%	73.33%
Naïve Bayes	76.25%	80.83%	86.25%	79.79%	77.50%
Logistic regression	72.50%	76.67%	83.75%	69.17%	72.08%
SVMs	89.38%	87.71%	87.08%	88.13%	87.29%
Random forest	92.50%	88.96%	90.83%	88.75%	86.88%
BPN	84.79%	81.67%	83.54%	82.70%	83.13%
CPN	86.31%	87.29%	82.92%	85.42%	86.45%

**Table 6**

Comparative results between our work and other recent works.

Work Done	Object (s) Dealt with	Problem Domain	Size of Data Set	Segmentation Algorithm	Classification Status	No. of Feature	Classifier	Accuracy
This work	Jackfruit(both fruit and leaf)	Recognition	480 images	k-means clustering	✓	10	Random forest	89.59%
Habib et al. (2018)	Papaya (both fruit and leaf)	Recognition	126 images	k-means clustering	✓	10	SVMs	90.15%
Samajpati and Degadwala (2016)	Apple (only fruit)	Recognition	80 images	k-means clustering	✓	13	Random forest	(60–100)%
Habib et al. (2020)	Papaya (both fruit and leaf)	Recognition	129 images	k-means clustering	✓	10	Linear SVMs	95.2%
Kumar and Suhas (2016)	Fruit	Recognition	243 images	k-means clustering	✓	NM	k-nearest neighbor	87.47%
Chopaade and Bhagyashri (2016)	Papaya, mango, banana (only leaf)	Detection	NM	C-means clustering	×	NA	NA	NA
Mokhtar, et al. (2015)	Leaf (NM)	Detection	800 images	Histogram based thresholding	✓	36	Linear SVM	NA
Rozario et al., (2016)	Apple, banana, tomato (only fruit)	Detection	63 images	Manual cropping	×	NA	NA	NM
				Modified k-means clustering				
				Otsu method				

<sup>1</sup>NM: Not Mentioned.<sup>2</sup>NA: Not Applicable.

have calculated the accuracy achieved by each classifier individually for all of the diseases of jackfruits, which is provided in Table 5.

It is noticed from Table 4 that random forest becomes preponderant over all other classifiers used in terms of all metrics considered, where that of logistic regression is the poorest. Although the highest accuracy (89.59%) and the lowest error rate (10.41%) are achieved by random forest, promising accuracy and error rate are also exhibited by SVMs, CPN, and BPN. For the five metrics considered except accuracy, SVMs, CPN and BPN outperform all other classifiers, where C4.5 resides in the middle position by leaving four classifiers back. We also notice from Table 5 that the highest accuracy for an individual disease class is achieved by random forest for rhizopus rot and it quantifies 92.5%. In opposite to this, the lowest accuracy for an individual disease class is shown by kNN for rhizopus rot and RIPPER for disease-free class quantifying 70.42%. Statistical significance of results purports the existence of an effect, whereas practical significance indicates the degree of the effect. Knowledge and expertise of the research area are applied to determine whether the effect is big enough to be meaningful in the real world. Pondering over all of the seven metrics, we can claim that the random forest functions the best among all nine classifiers in the context of automated jackfruit disease recognition.

## 6. Comparative discussion of results

To assess the qualities of the proposed agro-medical expert system for identifying diseases of jackfruit, it needs to compare the results of some recently published relevant research works. It has been already mentioned in Section 2 that not a single work has been done focusing on the diseases of jackfruit. The barrenness

of research work on jackfruit disease recognition renders it arduous to fairly compare the merits of our approach. On the contrary, most of the relevant paper works are confined to the illustration of notions of machine vision strategy for recognition of fruit diseases except the delivers of adequate numerical results and their comparison with that of other similar works. It has been noticed that some inspiring efforts have been made in fruit disease recognition research for the past few years, but rigorous performance evaluation based on practical indications is still inadequate. Concerning this situation, we have tried out to review the numerical results related to fruit disease recognition to evaluate the comparative merits of our work. Table 6 shows a comparative view of all methods of different works including our work. Concerning the scenario depicted in Table 6, our obtained accuracy of near about 90% can be claimed to be both good and promising enough.

## 7. Conclusion and future work

An exhaustive exploration of a machine vision based agro-medical expert system, especially focused on jackfruit, has been performed. We have used two sets of features comprising of ten members in total to recognize jackfruit diseases. Image processing techniques have been engaged to extract the features, which are then fed to nine classifiers separately. We have been able to find the expected results with the random forest classifier. Despite the barrenness of research work on jackfruit disease recognition, we can claim our system to perform comprehensively well. Our achieved accuracy is 89.52%. which is both good and promising. The research work done and results achieved in this paper purport the existence of plenty of potential for automated jackfruit disease

recognition. There remain enormous future works on jackfruit disease recognition to address a much broader variety of jackfruit diseases with a very large set of data. It is earnestly expected that this endeavor would subsume some other local fruits, e.g. mango, watermelon, custard apple etc., rather than confining jackfruit only.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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