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Computer Vision Based Local Fruit Recognition

Md. Robel Mia, Md. Jueal Mia, Anup Majumder, Soummo Supriya, Md. Tarek Habib

Abstract*: Bangladesh is an agricultural country having a tropical monsoon climate. A large variety of tropical and sub-tropical fruits abound in Bangladesh. People of Bangladesh are fruit-lovers too. Currently, most of the people of this country are failing to recognize many of the rare local fruits and the number of this portion of people is increasing day by day. Thus, not only the natural heritage but also good sources of food are being diminished. Performing a machine vision based recognition of these fruits can help people recognize them. In this paper, we perform an in-depth exploration of a computer vision approach for recognizing rare local fruits of Bangladesh. A number of rare local fruits are classified based on the features extracted from their images. For our experiment, we have used a total of 480 images of 6 rare local fruits. We perform some preprocessing on the captured image and then expected features are extracted using image segmentation. Classification of the fruits is accomplished using support vector machines (SVMs). We have achieved 94.79% classification accuracy, which is not only good but also promising for future research.

Keywords*: Computer vision, Feature extraction, Image segmentation, Local fruit, Performance metrics, Support vector machine (SVM).

I. INTRODUCTION

Bangladesh is a developing country, where the leading portion of the population directly or indirectly depends on agriculture. In the overall economic development of Bangladesh, the agriculture sector plays an important role. Agriculture sector provides employment to around 47% of people in our country. Also, it has a great¬ contribution to the GDP comprising 16% on the whole [1]. The fruit and vegetable sector is one of the largest and diverse economic areas in Bangladesh agriculture. A vast variety of tropical and sub-tropical fruits abound with Bangladesh. According to BAU-GPC Bangladesh has a total of 70 varieties of fruits [2]. Generally, 9 major and 48 minor fruits are produced in this country [3]. Cultivation of Fruit has been recognized as a vast part of practicing agriculture in Bangladesh. The fruit is a fundamental source of nutriment. After completing our demand, Bangladeshi fruit has been exporting to a different country all over the world. According to the Food and Agriculture Organization (FAO) of the UN, the fruit production rate of Bangladesh among the worlds is increased highly. Seemingly it is the 10th largest tropical fruit producer in the world [4]. Commercially fruits trees are planted along roads and in yards. But many types of fruits are becoming scarce now. Most of the people of this generation in Bangladesh not only fail to recognize some rare fruits but also do not know the names. As they do not know the names, they always suffer to recognize fruits. Moreover, due to the lack of recognizing different type of local fruits, a vital part of the cultural heritage of Bangladesh is being diminished. Jackfruit is the national fruit of Bangladesh. Major fruits, such as jackfruit, mango, banana, papaya, pineapple, litchi, and jujube are manufactured on 79% of the cropped area [5]. Except all the major fruits, there lots of local tropical fruits in Bangladesh such as amla, amra, chamble, coffe plum, sugar-apple, bilombo, elephant apple, orboroi, sapota, kamranga, keya, monkey jack, musk melon, zamrul, wood apple etc. Although each of these fruits is of distinguishing size, shape and color, it is a very tough job to recognize them individually with a machine.

In this paper, a computer vision based expert system is proposed which works on the captured image through mobile or handheld device and determines what fruits it is. Among a lot of local fruits, we have chosen 6 fruits, namely amla (amloki), sugar-apple (ata), bilombo, elephant apple (chalta), orboroi, sapota (sopheda) for our experiment. We perform preprocessing on the captured image than expected feature is extracted using segmentation. After segmentation, classification of fruits is done using support vector machines (SVMs).

The content of this paper is organized as follows: In Section II, the similarity works have discussed with background study. In Section III, the system architecture, data collection, fruits, feature and the proposed models are discussed. In Section IV, the experimental evaluations are described. In Section V, the result analysis is discussed. Finally, In Section VI, the future work and the synopsis of the conclusion are described.

II. LITERATURE REVIEW

There are a lot of research work has been done based on fruit disease detection and recognition and confine their work for only fruit recognition whereas very few works have been done based on computer vision based approach for fruit recognition and specially for local fruit.

Hussain et al. [6] proposed an algorithm based on deep convolution neural network for fruit recognition where their contribution is to build a database of fruit image of only 15 categories which is very few compared with the huge categories of fruits and so on.

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Md. Robel Mia, Department of CSE, Daffodil International University, Dhaka, Bangladesh**,** mia15-5538@diu.edu.bd

Md. Jueal Mia, Department of CSE, Daffodil International University, Dhaka, Bangladesh, mjueal02@gmail.com

Anup Majumder, Department of CSE, Jahangirnagar University, Dhaka, Bangladesh, anupju.cse20@gmail.com

Soummo Supriya, Department of CSE, Daffodil International University, Dhaka, Bangladesh, soummo.cse@gmail.com

Md. Tarek Habib, Department of CSE, Jahangirnagar University, Daffodil International University, Bangladesh, md.tarekhabib@yahoo.com

Although their work has a high accuracy of 99% but the algorithm learns optimal features by adaption process without extracting any features. Notable thing is that their work is not compared with others algorithm thus it could be easily validated their proposed algorithm for fruit recognition. Lak et al. [7] used machine vision approach for recognizing apple fruit under natural luminance. To process the images that they have used two algorithms like combination of color and shape analysis and edge detection whereas edge detection was not successful. In this work their goal is to find red apples but dataset is about quite low of 30 images only and no lighting control was employed to standardize luminance. Even though two algorithms have been used to detect red apples but color-shape based model could detect the apple fruits in the accuracy of 83.33%. Arivazhagan et al. [8] developed a computer vision approach to detect fruit using four very basic features of intensity, color, shape and texture and the proposed model has been performed by the minimum distance classifier based upon co-occurrence and the statistical features. They have recognized the fruits using the dataset size of about 2635 fruits from 15 classes. In this fruit recognition process, they have classified the fruits using minimum distance criterion and not mentioned the accuracy of the proposed methodology. Jana et al. [9] developed a methodology to classify different types of fruits using texture and color features based on statistical color features and gray-level co-occurrence matrix (GLCM). To classify the fruits images, SVMs are used in the methodology. Their work is done with two types, namely texture and color, features but not mentioned any data size as well as the accuracy result using the classifier. Sang et al. [10] presented a methodology for recognizing and figuring fruits from the images in cluttered greenhouses and formed a two-stage approach to determine and count fruits. Even though the method is developed using a huge dataset of 28000 color images of fruits and plants using SVM as classifier and the model performs a correlation of 74.2% externally any linear improvement for a comprehensive dataset. Zawbaa et al. [11] derived an automated fruit recognition scheme for classifying several fruits varieties extracting two features by shape and color features and scale invariant feature transform (SIFT) features. To classify the images, they have used support vector machine (SVM) and *k*-nearest neighbors (*k*-NN) algorithms. Their introduced model is developed by utilizing the dataset of 178 fruits images and that classifiers achieved several accuracies for different types of fruits and so on.

Astuti et al. [12] proposed a comparison technique with an artificial neural network for classifying fruits using SVM based on their shapes. In this research work, Fast Fourier Transform (FFT) is extracted and later applied as input to the SVM-based identifier. No segmentation method is mentioned here and ANN provides 66.7% classification in training frames that means the ANN not correctly classifies all of the fruits. Zhang and Wu [13] in their research work recommended a classification system based on a multi-class kernel support vector machine (*k*SVM) and classify 18 different categories of fruits. For feature extraction purpose, they applied the fruit images using split-and-merge segmentation algorithm. The entire works has been done over the dataset of 1653 fruit images and the method gets the accuracy of 88.2%.

Rocha et al. [14] presented an automated approach to classify fruit and vegetables by extracting the statistical features. This work has been done based on a super market data and the image background is subtracted by using *k*-means algorithm. Although they have introduced a super-market dataset of 2633 images to implement the system their work didn't mention the accuracy of the classification result. Shivaji et al. [15] classify fruit images according to the size, quality, color and health by developing an embedded based system. To classify two steps has been followed by them those are color and edge detection but no classification algorithm and the success rate is mentioned in the proposed system. A machine vision based fruit classification technique has been proposed by Zawbaa et al. [16] and Naik and Patel [17]. In these research works, fruit classification and grading are discussed over a small size of dataset. Random forest classifier is used here and then it is compared with only *k*-NN and SVM.Sekar et al. [18] discussed a computer vision approach for fruit classification. In their research work they have analyzed different fruit disease detection techniques as well as their advantages and disadvantage. Several classifiers models and features are discussed in their work but they did not propose a computer vision approach for classifying or detecting fruits or fruits diseases and so on. Hossain et al. [19] classify fruits using deep learning technique for industrial applications. The proposed model is based on convolutional neural network and pre-trained VGG-16 (also called OxfordNet) deep learning model. Here clear fruits images and general fruit images two datasets were used. In this research work a good level of accuracy is achieved but they have not compared with other classifiers.

III. SYSTEM ARCHITECTURE

The system architecture of a computer vision-based expert system for recognizing the rare fruits is shown in Fig. 1. It arises with the assumption that someone, i.e. a person who does not know the names of the fruit properly or a user can capture an image of fruit using a smartphone or device, where proposed system application is already installed. Then using mobile application user will send the captured image to our proposed expert system which is placed in the back-end server. From the front-end software or application, image is received through the internet. Then it is sent to the back-end server, where our expert system is installed. Based on the input image, the system sends its acknowledgment to the user. The user can find the feedback from the front-end mobile application.

IV. RESEARCH METHODOLOGY

There are numerous steps in image processing which are being used for classification of fruits. Fig. 2 shows a machine vision based solution framework for the recognition of fruits. Our expert system starts with the image of fruit. The image of the fruit is obtained locally and from the Internet. Firstly, using bicubic interpolation the color image of fruit is transformed into a fixed-sized image [20]. Let us assume that I is the intensity

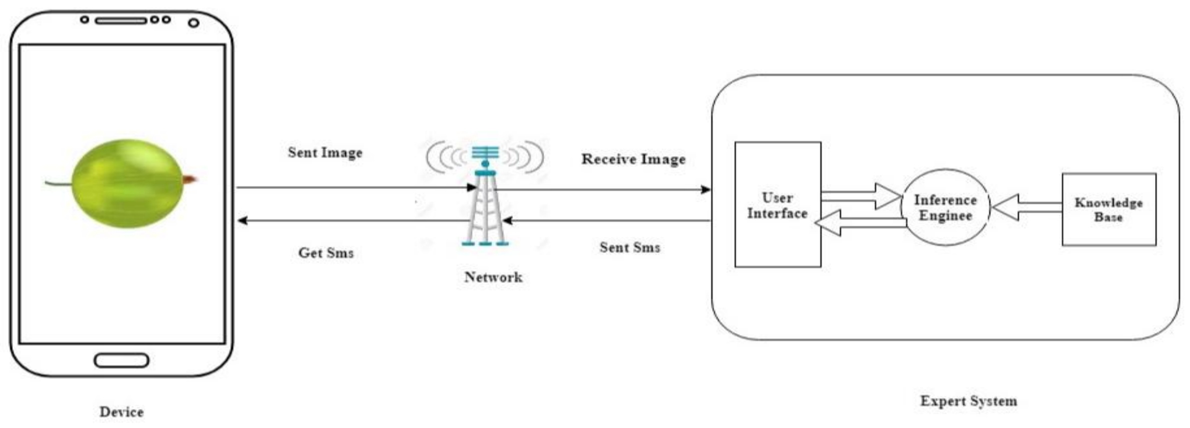


Fig. 1. The architecture of machine vision based expert system for fruit recognition.

values, and p_x, p_y and p_{xy} are the derivatives, which can be recognized at the four corners (1, 1), (1, 0), (0, 1), and (0, 0) of the unit square. Then the interpolated surface intensity can be written as:

$$p(x,y) = \sum_{i=0}^{3}\sum_{j=0}^{3} a_{ij}\, x^i y^j, \qquad (1)$$

where a_{ij} are coefficients.

Then using histogram equalization technique, the contrast of the image is enhanced. Let us assume that the number of rows (height) in pixels is R, the number of columns (width) in pixels is C, the number of pixels, which have intensity of color r_k, is n_k, and the total size of achievable intensity levels of color in the image is L; then the color-mapped or prepared image is achieved by mapping each pixel with the intensity of color r_k into a similar pixel with color intensity s_k using the following equation.

$$s_k = T(r_k) = \frac{L-1}{CR}\sum_{j=0}^{k} n_j, \qquad (2)$$

where $k = 0, 1, \ldots\ldots, L$-1.

After contrast enhancement, conversion of RGB color space is performed to achieve $L^*a^*b^*$ color space. Tariq et al. [21] stated that k-means clustering segments image quite better in $L^*a^*b^*$ space than in RGB space. Transformation of RGB color space to CIE (International Commission on Illumination) XYZ color space as can be written as the following equation according to [22].

$$\begin{bmatrix} P \\ Q \\ Z \end{bmatrix} = \begin{bmatrix} 3.240479 & -1.537150 & -0.498535 \\ -0.969256 & 1.875992 & 0.041556 \\ 0.055648 & -0.204043 & 1.057311 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \qquad (3)$$

In order to transform into $L^*a^*b^*$ color space from XYZ color space, we suppose that the tri-stimulus values of the reference white are P_n, Q_n, and Z_n. The assumption can be written in the following way.

$$f(t) = \begin{cases} t^{\frac{1}{3}} & if\ t > 0.008856 \\ 7.787\,t + \dfrac{16}{116} & if\ t \leq 0.008856 \end{cases}. \qquad (4)$$

Then, according to [22], the calculation of L*, a*, and b* can be written as:

$$L^* = \begin{cases} 116\left(\dfrac{Q}{Q_n}\right)^{\frac{1}{3}} - 16 & if\ \dfrac{Q}{Q_n} > 0.008856 \\ 903.3\,\dfrac{Q}{Q_n} & if\ \dfrac{Q}{Q_n} \leq 0.008856 \end{cases}. \qquad (5)$$

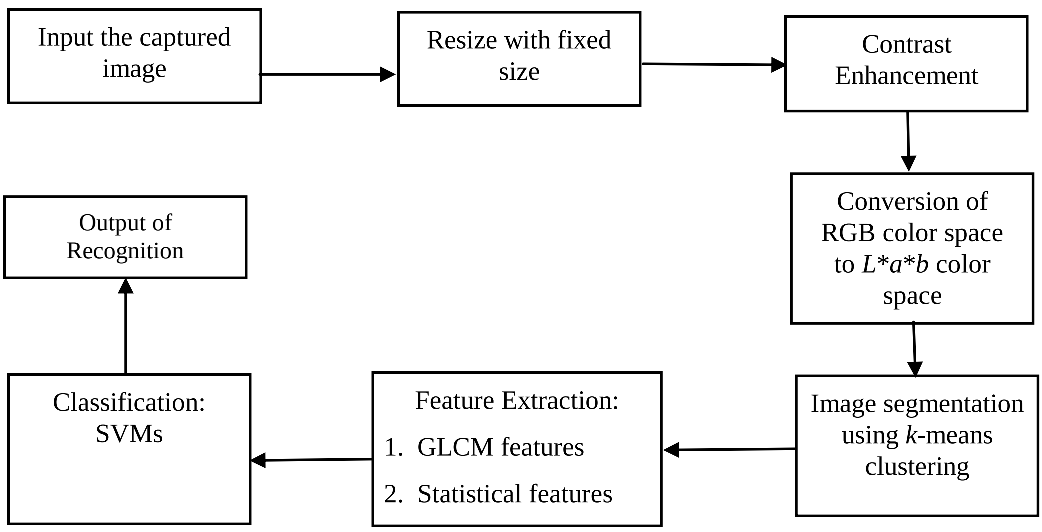


Fig. 2. Methodology for local fruit recognition system.

$$a^* = 500\left(f\left(\frac{P}{P_n}\right) - f\left(\frac{Q}{Q_n}\right)\right). \quad (6)$$

$$b^* = 200\left(f\left(\frac{Q}{Q_n}\right) - f\left(\frac{Z}{Z_n}\right)\right). \quad (7)$$

Then the image segmentation of fruit is done with the help of *k*-means clustering method. Thus, all the parts of the fruit are differentiated individually. From the segmentation, two types of feature vectors are obtained, one is statistical and other is the GLCM feature. In the next section (Section 5), two types of features are described in detail.

The accomplished feature vectors are applied to SVMs. Classification of data is a frequent task in machine learning. SVMs is a machine learning algorithm. It is also called linear classifier. It plays an important role in the field of biological science. SVMs is established to provide huge accuracy and ordinarily betters than other classifiers. SVMs basically designed for the classification of binary problems, but its handle multiclass problem too that is our main problem. If the classifiers produce binary output, two basic strategies are used. In the first strategy, classifier among one and the K − 1 other classes are trained (in entire classifiers K). This is called the 1-r (one-against-rest) approach. The one-against-rest (1-*r*) approaches including the number of SVMs can be used to overcome this type of problem [23]. By using training data set, SVMs are trained. Then test data can be used to measure the performance of the classifier. For analyzing the performance of a classifier, efficiency is not an accurate metric because that may not be suitably fitted for estimating classification types acquired from imbalanced data sets, i.e. the numbers of observations in different classes differ extensively. So, we can say that for precisely evaluate the performance of a classifier, not only efficiency but also required some other metrics [23] and [24]. For a binary decision the confusion matrix, i.e. 2-class problem summarizes the number of true positives (TPs), false positives (FPs), true negatives (TNs), and false negatives (FNs). In the multiclass purpose, i.e. longer than 2-class problems, the resulting confusion matrix dimension is $n \times n$ ($n > 2$). That is known that n is the matrix rows and n is the matrix columns and total entries are $n \times n$. Using that matrix, the number of TPs, FPs, TNs , FNs does not calculate shortly. According to the aforementioned procedure, the values of TPs, FPs, TNs, FNs for class *i* can be calculated as [25]:

$$TP_i = a_{ii}. \quad (8)$$

$$FP_i = \sum_{j=1, j\neq i}^{n} a_{ji}. \quad (9)$$

$$FN_i = \sum_{j=1, j\neq i}^{n} a_{ij}. \quad (10)$$

$$TN_i = \sum_{j=1, j\neq i}^{n} \sum_{k=1, k\neq i}^{n} a_{jk}. \quad (11)$$

By using this procedure, the final confusion matrix dimension is 2 × 2, that n confusion matrices for every class holds the average values. For the statistical classification, we can use a confusion matrix which also known as the error matrix. The accuracy, precision, specificity, sensitivity, FPR (false positive rate), and FNR (false negative rate) of the expert system are calculated by using confusion matrix [25]. We split our data into two distinct sets.one is training data set other is testing data set. We keep the maximum number of data in our training data set. As per our expert system, data can be trained by the SVMs. With the help of test data set the performance of the system is measured in terms of these metrics. In this way, SVMs can classify the name of the fruit from the image. From the confusion matrix accuracy, specificity, precision, sensitivity, FPR, and FNR are calculated in percentage as follows:

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \times 100\%. \quad (12)$$

$$Precision = \frac{TP}{TP+FP} \times 100\% \quad (13)$$

$$Specificity = \frac{TN}{FP+TN} \times 100\% \quad (14)$$

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

$$FNR = \frac{FN}{FN+TP} \times 100\%. \quad (16)$$

$$FPR = \frac{FP}{FP+TN} \times 100\%. \quad (17)$$

In order to estimate the overall performance of our classifier with the evaluation metrics equations are shown in (12), (13), (14), (15), (16) and (17). For comparing the relative performance, we can use receiver operating characteristic (ROC) curves.

V. DESCRIPTION OF LOCAL FRUITS AND FEATURES

A. Description of Local Fruits

A large variety of tropical and sub-tropical fruits abound in Bangladesh. Generally, 9 major and 48 minor fruits are produced in this country. Except for all the major fruits, there are lots of fruit in our country. But now most of the fruits are becoming rare now. So, it is high time for retrieving the cultural heritage of Bangladesh. We use six fruits, e.g. amla (amloki), sugar-apple (ata), bilombo, elephant apple (chalta), orboroi, sapota (sopheda) as shown in Fig. 3, in our experiment.

- Amla (আমলকী): Amloki (আমলকী, pronounced *amloki*) words come from the Sanskrit language. Amla is a popular and useful fruit in Bangladesh. Amloki Supports healthy metabolism, digestion, and elimination. It also nourishes the heart and respiratory system. There are many other advantages.
- Sugar-apple (আতা): Suger-appple (আতা, pronounced *ata*) is very much favorite to Bangladeshi people. That fruit has the ability to provide adequate calcium in order to keep body bones strong and strong.

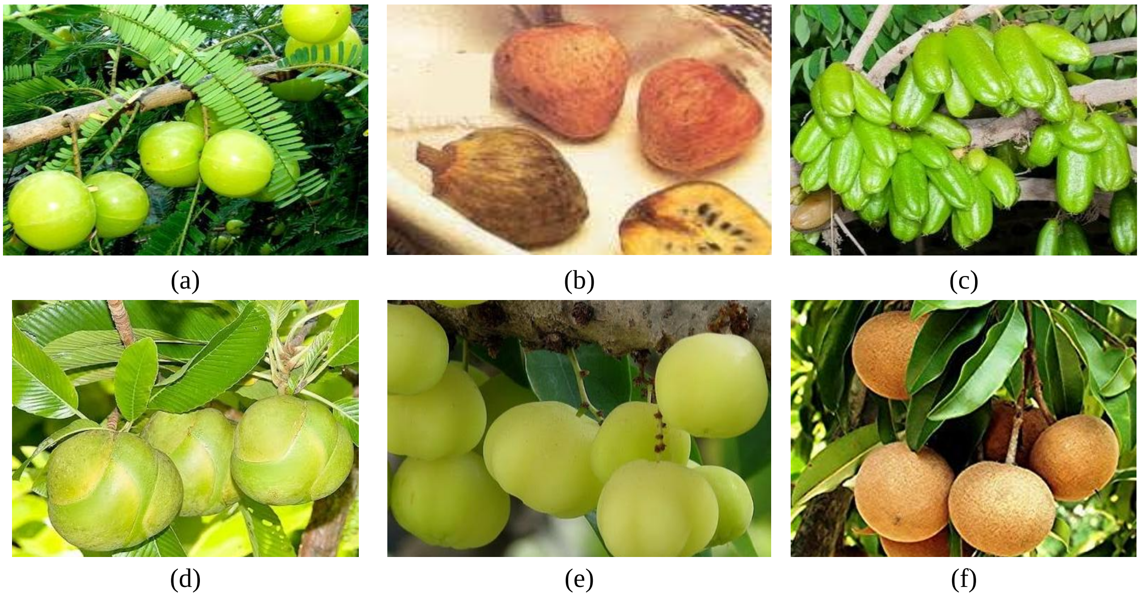


Fig. 3. Some rare local fruits of Bangladesh. (a) Amla. (b) Sugar-apple. (c) Bilombo. (d) Elephant apple. (e) Orboroi. (f) Sapota.

- Bilombo (বিলম্ব): Another rare fruit is Bilombo (বিলম্ব, pronounced *bilombo*). The fruit seems to be effective against coughs and thrush.
- Elephant apple (চালতা): Elephant apple (চালতা, pronounced *chalta*) can only found in the rural area. That fruit also provides nourishment.
- Orboroi (অড়বড়ই): Orboroi (অড়বড়ই, pronounced *orboroi*) contains vitamin C that provide nutriment.
- Sapota (সফেদা): Scientific name of sapota (সফেদা, pronounced *sopheda*) is manilkara zapota. This fruit is very sweet, calorie and delicate loaded fruit.

Although each of these fruits is of distinguishing size, shape and color, it is a very tough job to recognize them individually with a machine. In this paper we can recognize all the following fruits and our accuracy level better enough. Although each of these fruits is of distinguishing size, shape and color, it is a very tough job to recognize them individually with a machine. In this paper we can recognize all the following fruits and our accuracy level better enough.

B. Description of Features

In this research, we select two feature set one is the gray-level co-occurrence matrix (GLCM) and other is statistical features to recognize the fruits. Statistical features quality in the context of textile fabric defect recognition is shown in [26]. From that research, we have chosen some statistical feature to recognize the fruits. All the features are presented in [26]. All features are described precisely here.

- Mean (μ): If we represent object regions by N number of pixels, Background or object free regions by M number of pixels, and GS is a gray-scale color intensity of a pixel in object regions. The equation can be written as follows:

$$\mu = \frac{\sum_{i=1}^{N} GS_i}{N}. \quad (18)$$

- Standard deviation (σ): If we represent object regions by N number of pixels, where μ is the mean gray-scale color intensity and GS represent the gray-scale color intensity of a pixel individually, then the equation is presented as follows:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(GS_i-\mu)^2}{N}} \quad (19)$$

- Variance (σ^2): If we represent object regions by N number of pixels, where μ is the mean gray-scale color intensity and GS represents the gray-scale color intensity of a pixel individually, then the variance equation is presented as follows:

$$\sigma^2 = \frac{\sum_{i=1}^{N}(GS_i-\mu)^2}{N}. \quad (20)$$

- Kurtosis (κ): If we represent object regions by N number of pixels, where μ is the mean gray-scale color intensity and GS represent the gray-scale color intensity of a pixel individually, then the equation is presented as follows:

$$\kappa = \frac{\frac{1}{N}\sum_{i=1}^{N}(GS_i-\mu)^4}{\left(\frac{1}{N}\sum_{i=1}^{N}(GS_i-\mu)^2\right)^2} - 3. \quad (21)$$

- Skewness (γ): If we represent deviation, mean, and mode of color intensity of all pixels of the gray-scale image in object regions are using Mo, μ, and σ individually, then

$$\gamma = \frac{\mu - Mo}{\sigma}. \quad (22)$$

Haralick et. al. [27] proposed with the statistical features, a number of GLCM features is used. GLCM features have been confirmed to be a beneficial method of extracting textural features from numerous images. At the same time by considering the relation between two pixels GLCM provides a measure of the variation in intensity at the pixel of interest. The features are presented here.

Let us think that $f(x, y)$ be a two-dimensional digital image of size $A \times B$ pixels with L is the number of gray levels. We also assume that (x_1, y_1) and (x_2, y_2) are two pixels in $f(x, y)$, the d is the distance and the angle between the ordinate and two is θ. As per [27] the GLCM $P(i, j, d, \theta)$ is presented as:

$$P(i, j, d, \theta) = |\{(x_1, y_1), (x_2, y_2) \in A \times B: d, \theta, f(x_1, y_1) = i, f(x_2, y_2) = j\}| \quad (23)$$

In this work, we used 5 GLCM features, namely correlation (ρ), energy (E), contrast (C), homogeneity (H), and entropy (S). All of their corresponding equations are shown below (24) - (28).

Contrast: $$C = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}(i-j)^2 P(i,j). \quad (24)$$

Correlation: $$\rho = \frac{\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} i.j.P(i,j) - \mu_x\mu_y}{\sigma_x.\sigma_y} \quad (25)$$

Energy: $$E = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} P(i,j)^2. \quad (26)$$

Entropy: $$S = -\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} P(i,j)\, logP(i,j) \quad (27)$$

Homogeneity: $$H = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}\frac{P(i,j)}{1+(i-j)^2}, \quad (28)$$

Where μ_x, μ_y, σ_x and σ_y are the sum of required and variance values for the row and column matrix entries, respectively.

VI. EEPERIMENTAL EVALUATION

Machine vision based expert system for fruit recognition is shown in Fig. 2. At first, we have taken 480 color images of six rare fruits that are captured by a different person with a different angle as well as a different size. Different size image is used for our experiment considering the different people. Then all the images are sent to our proposed system for further procedure as shown in Fig. 1.

First, the image is resized into an image of the size of 350×300 pixels. Using color intensity mapping, contrast enhancement of the image is completed. Then using k-means clustering color image is segmented into the number of clusters. k-means clustering works better than other existing segmentation algorithms shown in [28]. Thus, the portion of the fruits or object is extracted from the background of the image. The stepwise changes of images for recognition of fruits is shown in Fig. 4. From this way we can say that our expert systems provide better results.

Good quality of segmentation is required since it affects the performance of subsequent steps. Good quality of segmentation leads to good quality of feature extraction. This is why, good quality of segmentation is needed for improving the performance of the expert system. We have taken 480 color images of 6 different local fruits for our experiment. Experimental outcomes from feature extraction is shown in Fig. 5.

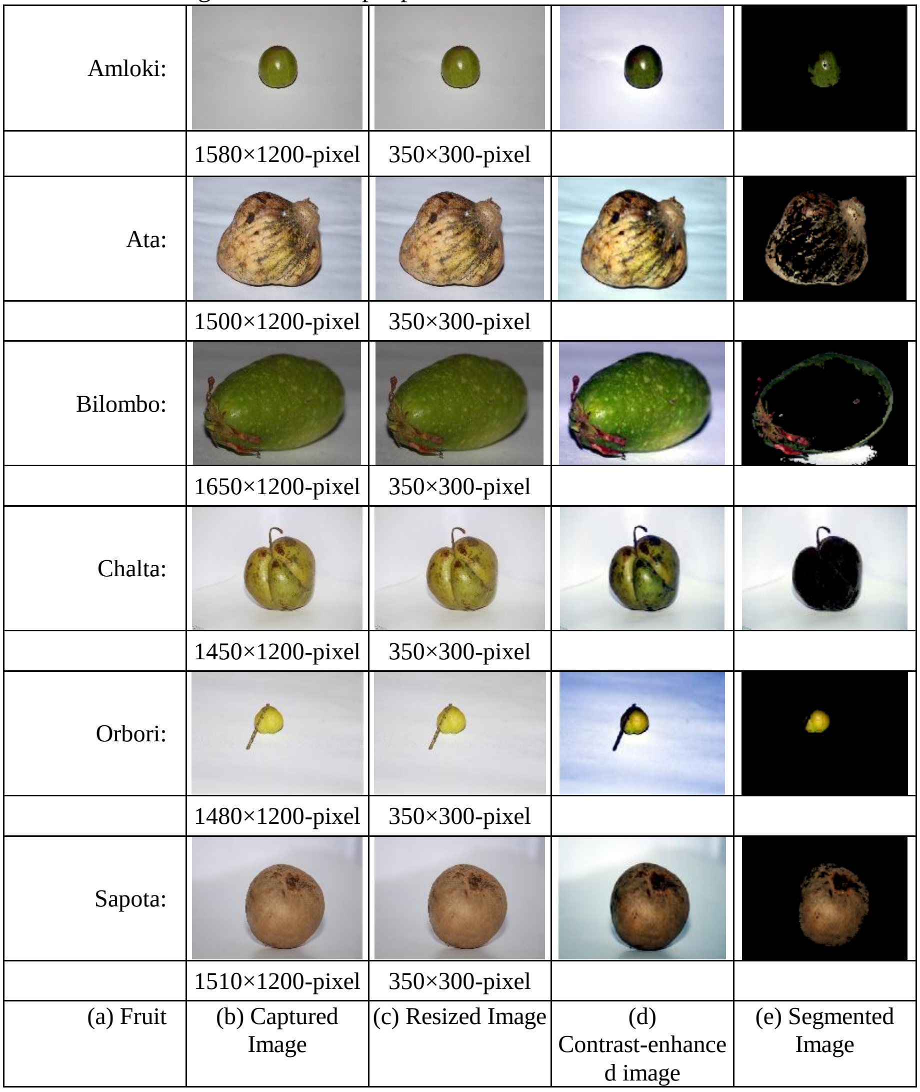


Fig. 4. Stepwise changes of the image of each fruit. (a) Fruit. (b) Captured image. (c) Resized image. (d) Contrast-enhanced image. (e) Segmented object, i.e. fruit.

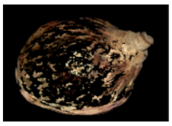
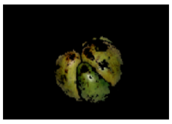
(a) Actual fruit	(b) Captured local fruit image	(c) Segmented image using *k*-means clustering	(d) Extracted feature vector, $\mathbf{x} = (\mu, \sigma, S, \sigma^2, \kappa, \gamma, C, \rho, E, H)$	(e) Recognized fruit
Ata			(2.695625, 2589.128498, 5.690043, 1.935101, 1.037653, 0.785316, 0.520784, 0.907741, 27.340983, 54.564659)	Ata
Ata			(0.929067, 1164.681455, 22.603302, 4.414895, 0.308578, 0.868906, 0.832502, 0.965669, 9.434153, 37.963223)	Orboroi
Chalta			(0.750338, 382.32926, 25.932449, 4.793352, 0.110631, 0.858441, 0.863379, 0.980128, 4.830485, 21.557279)	Chalta
Chalta			(4.915386, 6095.101053, 2.167585, -1.048911, 0.205882, 0.988767, 0.536782, 0.972747, 179.645797, 105.119756)	Ata

Fig. 5. Extracted feature from some fruits, where most them are classified correctly and rest of them are misclassified. (a) Name of actual fruit, (b) Captured image, (c) After segmentation using *k*-means clustering, (d) Extracted feature vector. (e) Recognized fruit

. Table 1. The multiclass confusion matrix.

		Predicted					
		Amloki	Ata	Bilombo	Chalta	Orbori	Sapota
Actual	Amloki	33	0	5	0	0	0
	Ata	3	47	0	2	0	0
	Bilombu	7	0	32	3	0	0
	Chalta	3	0	2	36	0	0
	Orbori	2	2	2	2	27	0
	Sapota	3	0	2	2	0	25

Entire sample data are split into two parts, namely testing part and training part. For selecting the training and testing data, we used the holdout method [29]. Based on the holdout method we choose about two-thirds data as training data set and the rest of them are used for testing sample data. There are many problems arises during experiments using those data. We have chosen the data validation set to avoid low training and generalization error. It is also known as overfitting problem. According to this approach, the original training data set are divided into two subsets. First one is used for training data set, while the other one is used for data validation. From all the training data we have taken two-thirds as training set for building classifier and the rest of the image are used for error correction. To access the highest performance classifier, we apply holdout methods for the five times repeatedly. After the training of the data set, we measure the performance of the system using the test data set. From all the results, we can calculate the average value for build multiclass confusion matrices [25] as shown in Table 1 and Table 2.

this perspective, we have to use the classifier. So, we used a linear SVM classifier. If the data set for training is $\{(\mathbf{x}_1, d_1), (\mathbf{x}_2, d_2), \ldots, (\mathbf{x}_{84}, d_{84})\}$, where $\mathbf{x}_i = (\mu, \sigma, S, \sigma^2, \kappa, \gamma, C, \rho, E, H)$ is the input vector; $d_i = \pm 1$. For maximizing the objective function, Lagrange of multipliers $\{\alpha_1, \alpha_2, \ldots, \alpha_{84}\}$ is calculated as follows:

$$Q(\alpha) = \sum_{i=1}^{28} \alpha_i - \frac{1}{2}\sum_{i=1}^{28}\sum_{j=1}^{28} \alpha_i \alpha_j d_i d_j \mathbf{x}_i^T \mathbf{x}_j. \quad (29)$$

Subject to the restrictions

$$(1)\ \sum_{i=1}^{28} \alpha_i d_i = 0$$

$$(2)\ 0 \le \alpha_i \le C \quad for\ i = 1, 2, \quad (30)$$

Where positive parameter C working as an upper-bound value of α_i.

C is the special numeric value for our experiment. In the training process all the parameters of SVM are fitted. Four kernels have been used namely polynomial, linear, Gaussian, and sigmoid. Due to the simplicity of the linear kernel, we have used it. Step by step procedure of our experiment has been shown in Table 3.

For measuring the performance of all the classifier, we have calculated average specificity, accuracy, precision, FNR, FPR that are shown in Table 4. Also, we have calculated the accuracy level for all the fruits individually.

Table 3. Summary of stepwise experiments performed.

Experiment Step	Method/Parameter Used
Resizing	Bicubic interpolation
Contrast enhancement	Histogram equalization
k-means clustering	*L*a*b** color space
SVM classifier	Linear kernel, a high numeric for *C*

Table 2. Confusion matrix in binary structure for every local fruit.

Class	Matrix				Class	Matrix			
Amloki			Predicted Class		Ata			Predicted Class	
			+	-				+	-
	Actual Class	+	33	189		Actual Class	+	47	186
		-	13	5			-	2	5
Class	Matrix				Class	Matrix			
Bilombo			Predicted Class		Chalta			Predicted Class	
			+	-				+	-
	Actual Class	+	32	187		Actual Class	+	36	190
		-	11	10			-	9	5
Class	Matrix				Class	Matrix			
Orbori			Predicted class		Sapota			Predicted class	
			+	-				+	-
	Actual Class	+	27	205		Actual Class	+	25	208
		-	0	8			-	0	7

We observe from Table 4 that the accuracy level is 94.79%; that indicates the recognition rate of our expert system is high enough. The average Sensitivity rate is 82.75%; that means the recognizing rate of fruits name from the input is not so good; and for this reason, FN rate is a little bit high (17.26%), which is not so good. Also, average specificity rate is 97.07%; that means fruit recognition rate is better enough; for this reason, FP rate is too low (2.93%); which is better enough for our experiment. From our experiment, we prove that our system is working better than other existing systems for recognizing fruits.

Our experiment described for only SVMs but for evaluating the performance we can implement other two classifiers namely decision tree and Bayes net. Comparative performance of those three classifiers is shown in Table 7. Specification of the other two classifiers is shown in the Appendix section. From the all the classifier SVM perform better in terms of confusion matrices, where decision tree in the mid position and Bayes net stands in last.

In order to prove our statement more accurate, we used ROC (receiver operating characteristic) curves. Performance Visualization of all the classifier showed using the ROC curve. Another approach for performance visualization of all the classifier is AROC curve which means the area under the ROC curve. In order to model fitted well, AROC value must be equal 1. In this research ROC curve of all the classifier are shown in Fig. 6 and AUCs are shown in Table 5. From the visualization, we can see that SVM performs better than other the classifier.

Table 4. Results of metric-wise performance of SVM classifier used.

Metric	Value
Accuracy	94.79%
Sensitivity	82.75%
Specificity	97.07%
Precision	87.01%
False positive rate	2.93%
False negative rate	17.26%

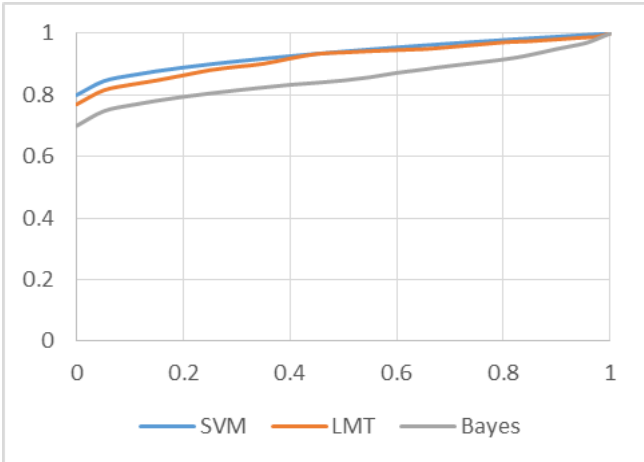


Fig. 6. The ROC curves of all three experimentally evaluated classifiers.

Table 5. Comparison of the three experimentally evaluated classifiers.

Classifier	AUC
SVMs	90.79%
Decision Tree	89.40%
Bayes Net	82.92 %

VII. COMPARATIVE ANALYSIS OF RESULTS

Comparative performance of all the work is shown in Table 6. To estimate the performance of machine vision based expert system for local fruits recognition, we have to compare with the relevant research in this context that is published recently. From the literature review, we reveal that most of the research work has some limitation and fails to illustrate the concept for classification of fruits without sufficient results and dataset. Most of them are working with very few datasets. That's why it's a challenging issue for them to measure the performance of work with relevant research. They have been perceived some works on fruits recognition for the past few years, still comparative and systematic performance evaluation on realistic hypotheses is not satisfactory. Notwithstanding such constraints, for fruit classification, we have taken the attempt to review all the paper performance relevant to our work.

Table 6. Results of the comparison of our work and others' works.

Method/Work Done	Object (s) Dealt with	Sample Size	Technique used	Segmentation Algorithm	Classification Performed	Size of Feature Set	Classifiers	Best Classifier	Accuracy
This work	Fruits (Amloki, Ata, Bilombo, Chalta, Orbori, Sapota)	240 images	*Classical Machine Learning*	*k*-means clustering	√	10	SVM	SVM	94.79%
Lak et al [7]	Apple (Fruit)	30 images	*Classical Machine Learning*	Edge detection, color and shape analyses	√	*NM*[a]	*NM*[a]	*NM*[a]	83.33%
Arivazhagan et al. [8]	Fruits (*NM*)	2635 fruits	*Classical Machine Learning*	Background subtraction	√	4	*NM*[a]	*NM*[a]	*NM*[a]
Jana et al. [9]	Fruits (*NM*)	*NM*[a]	*Classical Machine Learning*	*NM*[a]	×	*NM*[a]	SVM	*SVM*	*NM*[a]
Hossain et al. [19]	Fruit (*NM*)	*NM*[a]	Deep Learning	*NA*[b]	√	Several feature set	Deep Learning	Deep Learning	~99%
Y. Sang et al. [10]	Fruits and Plants	28000 images	*Classical Machine Learning*	*k*-means clustering	√	*NM*[a]	SVM	SVM	74.2%
Winda Astuti et al. [12]	Fruits (Cucumbers and Potatoes)	*NM*[a]	*Classical Machine Learning*	Canny Edge method	√	*NM*[a]	SVM	SVM	100%
							ANN		66.7%
Zhang and Wu [13]	18 different categories of fruits	1653 images	*Classical Machine Learning*	Otsu's Method	√	79	*k*SVM	*k*SVM	88.2%
Hussain, He, Chen [6]	15 different categories of fruits	44406 images	*Classical Machine Learning*	*NM*[a]	√	*NM*[a]	probability mechanism	probability mechanism	99%
A. Rocha et al. [14]	Fruits and Vegetables	2633 images	*Classical Machine Learning*	*k*-means clustering	√	*NM*[a]	SVM, LDA and *KNN*	*SVM*	*NM*[a]
Udamale Shivaji R. et al. [15]	Fruits (*NM*[a])	*NM*[a]	*Classical Machine Learning*	*NM*[a]	√	*NM*[a]	*NM*[a]	*NM*[a]	*NM*[a]
S. Naik and B. Patel [17]	Fruit (*NM*[a])	*NA*[b]	*Classical Machine Learning*	*NA*[b]	*NA*[b]	*NA*[b]	*NA*[b]	*NA*[b]	*NA*[b]
Raja Sekar L et al. [18]	Fruit (*NM*[a])	*NA*[b]	*Classical Machine Learning*	*NA*[b]	*NA*[b]	*NA*[b]	*NA*[b]	*NA*[b]	*NA*[b]

[a.] *NM*: Not Mentioned
[b.] *NA*: Not Applicable

In the work, it is reported that in the context of fruit recognition system SVM classifier works far better than other classifiers. The objective of the research [6] is to recognize the fruit using probability mechanism algorithm. Although they achieved good accuracy, the segmentation technique and feature set are not mentioned. Paper [7] purpose is only to detect the apple fruit but classifier is not mentioned in their work. They have used very small data size to introduce the method with low accuracy. The purpose of [8] is to recognize the fruits but classifier and accuracy are not mentioned in the work though they have used large data size. In the paper [9] is develop a system to recognize the fruit with the help of SVM but accuracy and segmentation technique is not mentioned. In the paper [10] developed an expert system for fruit and plant recognition using SVM. They have used *K*-means clustering for segmentation but accuracy level is not so good. In the work [11] applied *K*NN and SVM for Fruits (apple, strawberry, orange) recognition. They have used very small data size and they achieve several accuracies based on the different fruits. Paper [12] stated a vision-based approach for Fruits (Cucumbers and Potatoes) recognition with the help of ANN and SVM. They have achieved better accuracy for SVM. Paper [13] performed machine vision-based approach for 18 different categories of fruits using *k*SVM. In the paper [14] performed Fruits and Vegetable recognition using SVM, LDA, and *K*NN but accuracy is not mentioned. In the papers [15], [17], and [18] performed fruit recognition but accuracy and classifier are not mentioned. Paper [19] applied deep learning for fruit recognition and they have achieved good accuracy.

VIII. CONCLUSION AND FUTURE WORK

In this paper, we have performed a machine vision based expert system for recognition of fruit for retrieving our cultural heritage. We have used two feature set which is consists of ten features in total to recognize the fruits. Image processing system has been used to extract all the features. Based on the feature we have able to achieve the desired result. By analyzing the other existing works, we can say that our system works better enough. Our system accuracy level is 94.61% which is good enough. In the future, we will work with a large amount of data of the maximum number of fruits in the context of Bangladesh.

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AUTHORS' PROFILE

Md. Robel Mia has obtained his B.Sc. degree in Computer Science and Engineering (CSE) from Daffodil International University in 2019. Currently he is working as a Lecturer at the Department of CSE in Daffodil International University.

Md. Jueal Mia completed his B.Sc. (Honors) and MSc in Computer Science and Engineering from Jahangirnagar University, Savar, Dhaka-1342, Bangladesh in 2014 and 2015 respectively. Currently, he is working as a lecturer in the Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh. His research interest is on data mining, machine learning and computer vision.

Anup Majumder received his B.Sc. (Honors) and M.Sc. in Computer Science and Engineering from Jahangirnagar University, Dhaka, Bangladesh in 2014 and 2015 respectively. Previously, he worked as a lecturer in the Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh. Currently, he is working as a Lecturer in the Department of Computer Science and Engineering, Jahanginagar University, Savar, Dhaka-1342, Bangladesh. His research interest is mainly on Artificial Intelligence, Machine Learning, Expert Systems, and Data Mining.

Soummo Supriya has obtained her B.Sc. degree in Computer Science and Engineering (CSE) from Daffodil International University in 2018. Currently she is working as a Lecturer at the Department of CSE in Daffodil International University.

Md. Tarek Habib pMd. Tarek Habib is continuing his Ph.D. degree at the Department of Computer Science and Engineering in Jahangirnagar University. He obtained his M.S. degree in Computer Science and Engineering (Major in Intelligent Systems Engineering) and B.Sc. degree in Computer Science from North South University in 2009 and BRAC University in 2006, respectively. Now he is an Assistant Professor at the Department of Computer Science and Engineering in Daffodil International University. He is much fond of research. He has had a number of publications in international journals and conference proceedings. He has worked as a reviewer of a number of international journals and conferences. His main research interest is in Artificial Intelligence, especially Artificial Neural Networks, Machine Learning, Computer Vision and Natural Language Processing. He is also interested in Computer Networks and E-Commerce.