Automatic fruit classification using random forest algorithm

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Abstract*—The aim of this paper is to develop an effective classification approach based on Random Forest (RF) algorithm. Three fruits; i.e., apples, Strawberry, and oranges were analysed and several features were extracted based on the fruits' shape, colour characteristics as well as Scale Invariant Feature Transform (SIFT). A preprocessing stages using image processing to prepare the fruit images dataset to reduce their color index is presented. The fruit image features is then extracted. Finally, the fruit classification process is adopted using random forests (RF), which is a recently developed machine learning algorithm. A regular digital camera was used to acquire the images, and all manipulations were performed in a MATLAB environment. Experiments were tested and evaluated using a series of experiments with 178 fruit images. It shows that Random Forest (RF) based algorithm provides better accuracy compared to the other well know machine learning techniques such as K-Nearest Neighborhood (K-NN) and Support Vector Machine (SVM) algorithms. Moreover, the system is capable of automatically recognize the fruit name with a high degree of accuracy.

***Index Terms*—Fruit classification, Image classification, Features extraction, Scale Invariant Feature Transform (SIFT), Random Forest (RF)**

I. Introduction

Computer vision has been widely used in industries to aid in automatic and checking processes. Digital image processing plays an important role in the field of automation [1]. The important problem in computer vision and pattern recognition is the shape matching. It can be defined as the establishment of a similarity measure between shapes and its use for shape comparison. A result of recognition might also be a set of point identical between shapes. This problem has an important theoretical interesting motivation. Shape matching is intuitively accurate for humans, so there is a needed job which is not solved yet in its full generality. Shape matching applications contain image registration, object detection and recognition, and images content based retrieval [2].

Many agricultural applications used image processing to automate its duty. Detecting crop diseases is one of these applications. The crop images are analyzed to discovered the affected diseases [3]. Also, image processing are used to monitor crop to decide its harvest time [4], [5], and to recognize fruits and vegetables type [6]. Recognize and classify fruits can aid in many real life applications. For examples, it can be used as an interactive learning tool to improve learning methods for children and as an alternative for manual barcodes in a supermarket checkout system [6], [7]. It could be helpful as an assist for the plant scientists to understand the genetic and molecular mechanisms of the fruits [7]. For eye weakness people, they can use it as a tool aiding them in shopping. Therefore, automation of fruit recognition and classification process is a big gain at both agriculture and industry fields, utilizing computer vision in food products has become very wide spread [8].

This paper goal is investigating the usage of Random Forest (RF) algorithm for developing an automatic fruit classifier. The proposed classification system includes preprocessing, features extraction, and classification stages. The fruit images feature is extracted based on the fruits' shape, colour characteristics and Scale Invariant Feature Transform (SIFT). The classification is done using Random Forest (RF) algorithm. The proposed approach is evaluated using a series of experiments with 178 fruit images and compared the Random Forest (RF) results with K-Nearest Neighborhood (K-NN) and Support Vector Machine (SVM) algorithms.

The structure of this paper is as follows. Section II describes the stages of the classification proposed system. Feature extraction and classification stages will be discussed in sections III and IV. Section V introduces the results of the experimental. Finaly, the conclusion and future work is presented in section VI.

II. The Proposed Automatic Fruits Classification System

This research aims to develop an automatic fruits classification system that recognizes a fruits image name from a collection of images. Achieving this aimed is done by proposing classification system which includes the following stages:

- Preprocessing Stage: in this stage, the images are resized to 90 x 90 pixels to reduce their color index. Also, the proposed model assumes that the acquired image is in RGB format which is a real color format for an image [9].
- Feature Extraction Stage: two feature extraction methods are used in this stage. The first one extracts the shape and color features. While, the second feature extract method uses the Scale Invariant Feature Transform (SIFT).
- Classification Stage: our proposed model used the Random Forests (RF) algorithm to classify the fruit image in order to recognize its name.

More detail about feature extraction and classification stages is given in the follwoing sections.

III. Feature Extraction Stage

The aim of this stage is to extract the attributes or characteristics that describe an image. The classification accuracy are mainly depends upon feature extraction stage. So the presented work investigates using two methods for extracting images features which are shape and color features and Scale Invariant Feature Transform (SIFT).

Since, color consider as an significant feature for image representation due to the color is invariance with respect to image translation, scaling, and rotation [10]. Therefore, the first feature extraction method uses color and shape characteristics to generate the feature vector for each fruit image in the dataset. The used color moments to describe the images are color variance, color mean, color kurtosis, and color skewness [10], [11]. The shape features is described using Eccentricity, Centroid, and Euler Number features [12]. Eccentricity computes the aspect ratio of the distance of major axis to the distance of minor axis. It is calculated by minimum bounding rectangle method or principal axes method. The shape centroid defines the centroid position of image which is fixed in relative to the shape. The image Euler number defines relation between the connecting parts number and the holes number on image shape. Euler number is calculated by subtract the shape holes number from the contiguous parts number. [12].

The second method generates the feature vector uses the Scale Invariant Feature Transform (SIFT) algorithm [13]–[15]. It is an algorithm for image features extraction which is invariant to image rotation, scaling, and translation and partially invariant to affine projection and illumination changes. SIFT contains four main steps namely: scale-space extreme detection, keypoint localization, orientation assignment and keypoint descriptor [16]. The scale-space extreme detection step identifies the points of potential interest using difference-of-Gaussian function (DOG). In the keypoint localization, a model is fit to define location and scale for each candidate location. The selected Keypoints are determined based on their stability measures. In the orientation assignment step, orientations are allocated for each keypoint location according to the local image gradient directions. Then the operations are done on image data which has been converted relative to the allocated scale, orientation, and location for each feature, so providing invariance to these transformations. In the keypoint descriptors step, the local image gradients are computed for the selected scale in a certain neighborhood around the identified keypoint. These are converted to a representation to allow for important levels of local shape distortion and modify in illumination [17]. It works according to Algorithm 1.

1: Build the image Gaussian pyramid L(m, n, σ) using the following equations 1, 2, and 3.

$$G(m,n,\sigma)=\frac{1}{2\Pi\sigma^2}exp^{\frac{-(m^2+n^2)}{2\sigma^2}}, \quad (1)$$

$$L(m,n,\sigma)=G(m,n,\sigma)*I(m,n), \quad (2)$$

$$D(m,n,\sigma)=L(m,n,k\sigma)-L(m,n,\sigma), \quad (3)$$

Where σ is the scale parameter, G(m, n, σ) is Gaussian filter, I(m, n) is smoothing filter, L(m, n, σ) is Gaussian pyramid, and D(m, n, σ) is difference of Gaussian (DoG).

2: Calculate the Hessian matrix.

3: After that, calculate the determinant of the Hessian matrix as shown in the equation 4 and eliminate the weak keypoints.

$$Det(H)=I_{mm}(m,\sigma)I_{nn}(m,\sigma)-(I_{mn}(m,\sigma))^2 \quad (4)$$

4: Calculate the gradient magnitude and orientation as in equations 5 and 6.

$$\begin{aligned}Mag(m,n) \;=\; & ((I(m+1,n)-I(m-1,n))^2\\ & +(I(m,n+1)\\ & -I(m,n-1))^2)^{1/2} \quad (5)\end{aligned}$$

$$\theta(m,n)=\tan^{-1}\left(\frac{I(m,n+1)-I(m,n-1)}{I(m+1,n)-I(m-1,n)}\right) \quad (6)$$

5: Apply the sparse coding feature based on SIFT descriptors as in equations 7 and 8.

$$\min\sum_{i=1}^{S}(\|m_i-\sum_{j=1}^{Z}a_i^{(j)}\phi^{(j)}\|^2+L) \quad (7)$$

$$L=\lambda\sum_{j=1}^{Z}|a_i^{(j)}| \quad (8)$$

Where m_i is the SIFT descriptors feature, a^j is mostly zero (sparse), ϕ is the basis of sparse coding, λ is the weights vector.

Algorithm 1: SIFT Feature Extraction Algorithm

IV. Classification Stage

In the classification stage, the proposed model applies the Random Forests (RF) classifier to recognize different kinds of fruits, and comparing the Random Forest (RF) results with K-Nearest Neighborhood (K-NN), Support Vector Machine

(SVM) classifiers. The input to this stage is the fruit training dataset feature vectors with their corresponding classes, as well as the testing dataset. Where its output is the fruit class name for each image in the testing image dataset. Investigate using Random Forests (RF) is done since it consider as one of the best machine learning classification and regression techniques. It has the ability to classify large dataset with high accuracy [18], [19], [5]. It consists of a collection of tree-structured classifiers. Each tree depends on the a random vector values sampled independently and distribution for all trees in the forest [18]. Its input goes into the top of the tree, then traverses down the tree. The original data is randomly sampled, but with replacement into smaller and smaller sets. The sample class is determined using random forests trees, which are of a random number [5]. The randomizing variable determines how the cuts are performed successively when constructing the tree by selecting the node and the coordinate to divide and the position of the divided [20]. The Random Forest (RF) works as in algorithm 2.

1: Draw M_{tree} bootstrap samples from the original data
2: For each of the bootstrap samples, grow an un-pruned classification tree
3: At each internal node, randomly select n_{try} of the N predictors and determine the best split using only those predictor
4: Save tree as is, alongside those built thus far (Do not perform cost complexity pruning)
5: Forecast new data by aggregating the forecasts of the M_{tree} trees.

Algorithm 2: The Algorithm for Random Forests Classifier

V. Experimental Results

The proposed system was implemented using Matlab R2013a. It was evaluated using around 178 fruit images (Orange 46, strawberry 55, and apple 77). There was no specific benchmark data for the fruit types and varieties. So, the used dataset in these experiments has been collected with different transformations (rotation, scale change, illumination, viewpoint change, compression, and image blur) for each fruit. The dataset was divided randomly into training and testing sets. Also, these original images were used after resize to 90*90 pixels. No other preprocess are apply (like: gray scaling, cropping, histogram equalization, etc.) to measure the robustness of the algorithms for feature extraction in the comparison. Figure 1 shows some examples of training and testing datasets.

The selected fruit types are chosen to represent the similarities and differences between shape and color. In the following 3 experiments, we choose 178 images as input dataset and we run the system twice: 60% for training and 40% for testing, then 70% for training and 30% for testing. Then run KNN, SVM and RF algorithms. Moreover, we divided the fruits into the following three groups:

Fig. 1: Examples of training and testing fruit images

- **Orange and strawberry:** fruits are different in both color and shape.
- **Apple and orange:** fruits are different in color and similar in shape.
- **Apple and strawberry:** fruits are different in shape and similar in color.

Figure 2 presents the results of orange and strawberry group, which shows the accuracy, precision and recall for each fruit type when the dataset is divided into 60% training and 40% testing. We observe that strawberry image achieves high accuracy than orange image. Using shape and color as feature extraction archives the lower accuracy when classifying fruit images by KNN (71.42% orange and 72.72% strawberry) and RF (87.50% orange and 90.91% strawberry).

Extracting features based on SIFT algorithm achieves high accuracy 100% for both orange and strawberry when classifying their images by the KNN. While, using shape and color to generate images feature achieves the lower accuracy (71.42% orange and 72.72% strawberry) when using KNN classifier. When we run the system with 70% training and 30% testing, achieve high accuracy when using SIFT as feature extraction with both KNN and SVM classifiers, where RF classifier achieves 100% accuracy when extract features by shape and color (refer to Figure 3).

Similar to the above experiments, with the second and third group. Figures 4 - 7 shows the classification results for each group based on the accuracy, the precision and recall for each fruit type when the training dataset is 60% and 70% training size. For the second group, we observe that orange achieves low accuracy than apple, and the highest accuracy for recognizing apple images is achieved when using the RF classifier with SIFT as feature extraction (85%). while orange high accuracy is 65.5% when using the SVM classifier with shape and color as feature extraction. Trying to achieve better accuracy, the training set is increasing to 70%. As

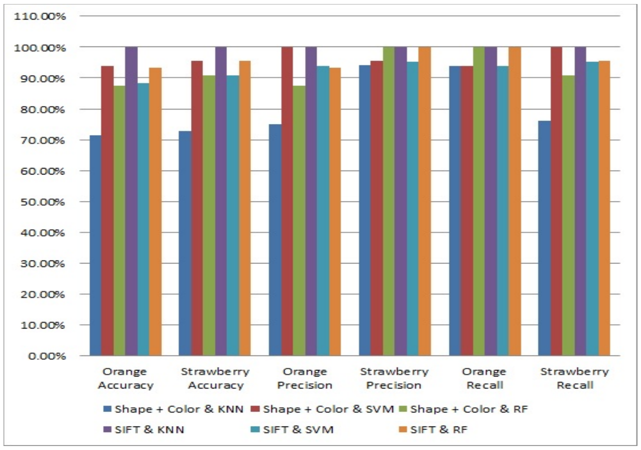

Fig. 2: Orange and Strawberry for different feature extraction and classifiers (60% training)

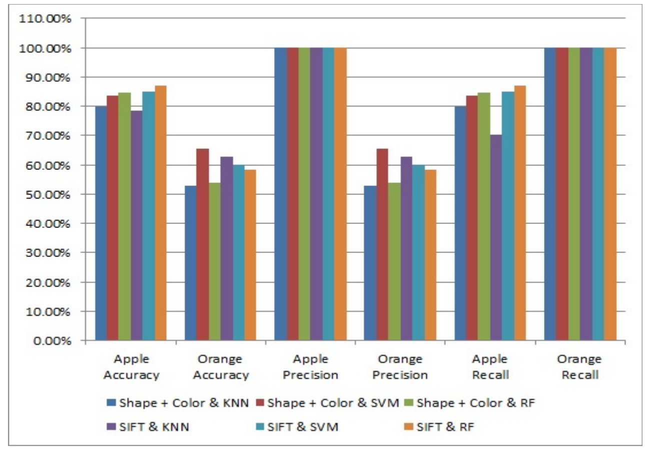

Fig. 4: Results of Apple and Orange for different feature extraction and classifiers (60% training)

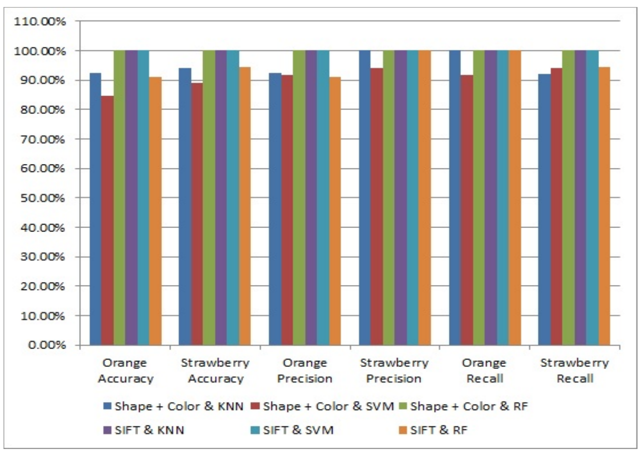

Fig. 3: Orange and Strawberry for different feature extraction and classifiers (70% training)

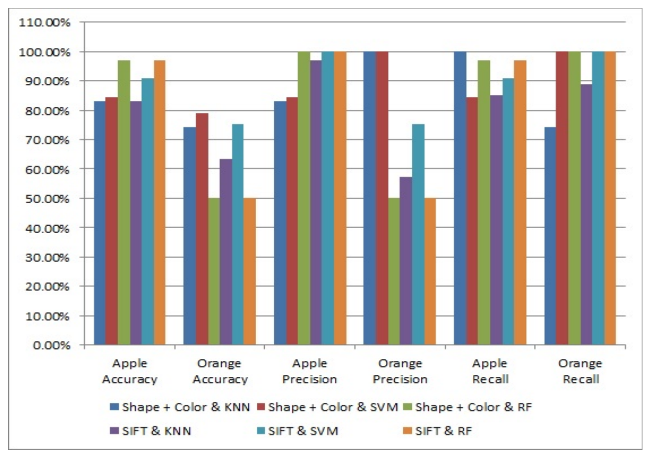

Fig. 5: Results of Apple and Orange for different feature extraction and classifiers(70% training)

shown in Figure 5, RF classifier achieve high accuracy with apple (96.97%), while it archives the low accuracy for orange (50%). Figure 6 shows that extracting features based on SIFT achieves high accuracy than using shape and color. From figure 7, we observe that the high accuracy is achieved when using RF classifier (94.74% apple, 85.71%strawberry).

VI. Conclusions and Future Work

This paper has presented a machine learning techniques for automatic fruit classification. The proposed classification system contains preprocessing, features extraction, and classification stages. In the preprocessing stage, the only process apply on fruit images is resized. The features extraction stage uses two algorithms for extracting the fruit images feature which are shape and colour algorithm and Scale Invariant Feature Transform (SIFT) algorithm. The classification is done using Random Forest (RF) algorithm. The Random Forest (RF) algorithm result is compared with K-Nearest Neighborhood (K-NN) and Support Vector Machine (SVM) algorithms.

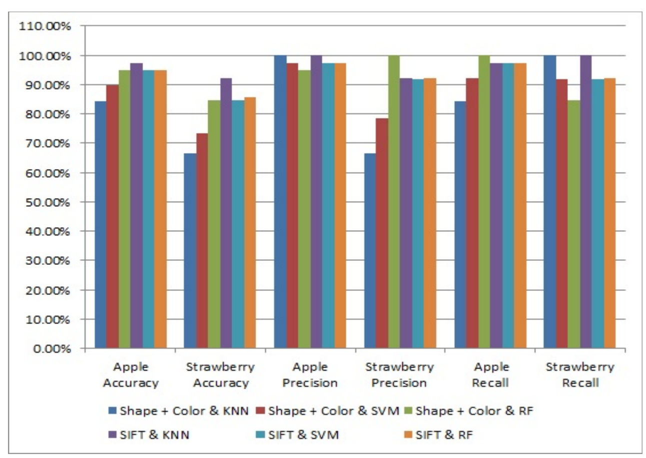

Fig. 6: Results of Apple and Strawberry for different feature extraction and classifiers (60% training)

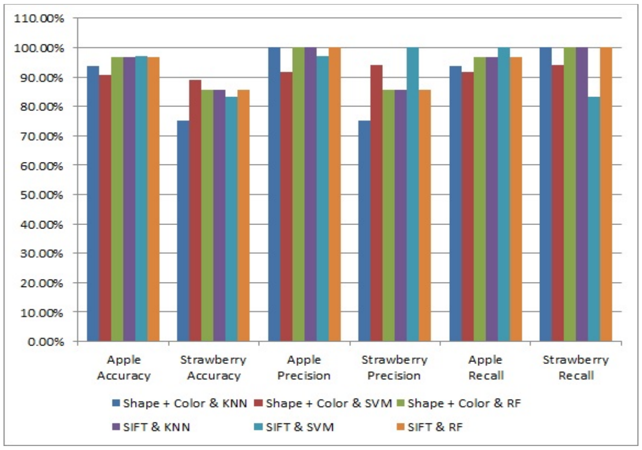

Fig. 7: Apple and Strawberry for different feature extraction and classifiers(70% training)

The distinctions degree between the fruit types is affected on the classification accuracy results. The experimental results show that the accuracy of similarities on shape group archives the lower accuracy among the three groups. For orange and strawberry group, the height accuracy is achieved (100%) with SIFT feature extraction and KNN classifier. The height accuracy achieved in the second group is for 96.97% apple (with RF classifier), and for 78.89% orange (with SVM classifier). Classify third group achieves 96.97% for apple when using with SIFT feature extraction. While strawberry high accuracy is 92.31% when using SIFT as feature extraction and KNN as classifier. In general, RF based algorithm provides better accuracy compared to the other well know machine learning techniques such as K-NN and SVM algorithms. Our future work is studying and setting the error criteria of the classifies [21].

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