Automated Flower Species Detection and Recognition from Digital Images

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Abstract
Automated flower species recognition has been studied for many years. Differences between these studies come from features which were extracted from the flower image, and the recognition algorithm that was used to recognize the flower species. A new automated system was adapted to detect the flower region from the image and recognize its species. Features based on color, texture, and shape were extracted from the interest part only, so the recognition accuracy is increased. New Dataset has been built which contains flowers from Jordan. The result showed a high recognition accuracy of our new dataset. In addition, our proposed system outperforms several methods on Oxfoed17 Dataset.

Key words:
Automated, Detection, Recognition, Digital Image processing.

1. Introduction

Nature has many different kinds of flowers, similarity in some features is found between the flowers. For example, many flowers share the red color. On the other hand, these red flowers are different from other features. Red flowers do not necessarily share the same shape. These similarities and differences highlight the difficulty of identifying each flower species automatically.
Traditional flower recognition task is done by a botanist. Many challenges are facing botanist through flower recognition task. This paper aims at providing an automated system that detects and recognizes flower species.
The importance of building automated flower recognition method stands out in many benefits such as providing fast recognition for educational purpose, as automated method accelerates the learning process. Automated flower recognition gives the people, with limited experience in flower species, the ability to recognize the species of a flower, with the advantages of saving time and effort. Flower recognition system may be extended to be used by many other fields such as in the security field for iris recognition, and for cars and plates recognition.
This paper aims also to build a flower Dataset which was not addressed in the previous data sets. Photos for Jordanian flowers were taken and used in building the Dataset. This dataset contains flowers that grow in the Jordanian habitat such as Daisy and Papaver, and the most importantly Iris Nigricans. Iris Nigricans is the national flower of Jordan. The majority of researchers focused on their regions, for example, Oxford17 dataset was collected from the researchers region, so their work fails to recognize Iris Nigricans. Including many Jordanian species in our dataset will be a new addition to the famous and the well-known flowers dataset (i.e. Oxford17, Oxford102). This is very important because it highlights species from Jordan, and shows our role in this area of research.
Pre-processing was applied to increase the segmentation performance for our dataset. The processing time is reduced through resizing the images [1]. A threshold value was selected empirically, so better segmentation was achieved. The proposed recognition task was decomposed into several binary classification tasks, based on Multiclass decomposition into binary class. One-versus-all approach was used, in which one classifier for each category was trained. Tested data passed through all training classifiers, and the class which gives the highest confidence is chosen as the class for this data [2].

Paper contributions:

- Proposing a flower recognition system, that has the advantage of a fast learning classifier.
- Building flowers dataset. This dataset includes flower species from Jordan, Including Iris Nigricans the national flower of Jordan, which was not addressed in the famous datasets. This dataset has full segmentation results, and with six types of extracted features, which will be a helpful resources for researcher in the field.
- Increasing the segmentation performance for our dataset through pre-processing.

2. Literature Review

In this section related works to the current research was classified into two categories. Their proposed systems were explained. Drawbacks of related work methods were summarized.

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2.1 Flower Image Segmentation

Earlier work on flower image segmentation was done by [3]. A new segmentation approach was introduced. Based on eliminating the color that is unusually appeared on foreground. Color dependence approach of [3] was improved by [4]. The RGB color distributions are determined by labeling foreground and background pixels in a subset of the training image. A binary segmentation was applied, based on Marcov Random Field (MRF) cost function with graph cuts optimization of [5]. In [6] two level of co-segmentation was introduced. The first level was applied in each image independently. Grabcut segmentation algorithm of [7] was used. The second level was applied on a set of images from the same species; each image was divided into super pixels, and classified into foreground and background with Support Vector Machine (SVM) classifier. In general, the related work segmentation methods does not achieve an accurate segmented foreground regions. Partial loss in flower region was produced, and undesirable parts were segmented from the background and considered as foreground region. Therefore, in the proposed system new segmentation method is deployed in a manner that keeps the flower region fully segmented.

2.2 Flower Species Recognition

Oxford17 flower dataset was introduced in [4]. Three types of features were studied independently with Nearest Neighbour classifier. The highest recognition rate for their consist viewpoints is 75%, which was achieved based on the shape feature of Scale Invariant Feature Transform (SIFT) [8]. The worst recognition rate was achieved based on Hue Saturation Value (HSV) colour feature, it is only 49%. Combing features was also studied in their approach; the results showed that shape and colour is the best for flower recognition. Texture feature of convolving the image with Maximum Response Filters (MRF8) of [9] was excluded. Recognition accuracy of this approach on the full oxford17 is 71.76% [10]. Features and testing methodology of [4] were applied by [11]. The results show that shape is the best feature while colour is as good as texture. Accuracy of combining all features was 80.49% with one-versus-one SVM, while it was 82.55% with one-versus-all SVM. Recognition accuracy of using one-versus-all SVM exceeded the recognition accuracy that was achieved by Nearest Neighbour classifier, which was used in [4]. [6] in his paper proposed an improved system for [4,12,13,14]. Combined features from Lab colour space, and various descriptors for SIFT feature were extracted from foreground only. Linear SVM that takes kernelized feature vectors was used for classification. They provide ground truth segmentation, and unsupervised learning algorithm named as Bi-Level Co-Segmentation (BiCoS). The system was tested on Oxford17 dataset, mean value of the precisions of all species was used as a measure for recognition accuracy. Recognition accuracy for BiCoS approach was 90.4%, and 91.1% for Bi-Level Co-Segmentation Multi Task (BiCoS-MT) approach, which outperforms all previous works.

In this paper a new dataset includes Jordanian flowers, which is not addressed even in the well-known dataset, will be an addition to the automated flower species.

3. Proposed System Overview

To recognize flower species, an automated system was designed, as shown in Figure 1. The internal upper box represents flower image processing. Each stage in this system is discussed through the next subsections.

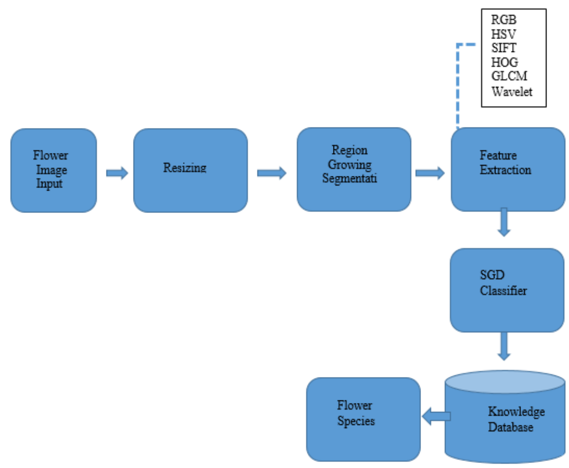


Fig 1: Block Diagram of the Proposed System

3.1 Flower Image Resizing

Image resizing was usually used in literature before image segmentation. In [1] the image data was prepared for further analysis to be used in Grab-cut segmentation, the input image was resized to its half dimension. It was mentioned that resizing will give faster processing. To get a satisfying segmentation results, it is required to find a re-sizing value to be convenient with the region growing segmentation which is deployed in the proposed system. Empirically, re-size value was experimented to achieve fast and complete segmentation with accurate foreground boundary, an optimal value of re-sizing is 350 rows, while the number of columns is calculated automatically to preserve the aspect ratio.

3.2 Region Growing Image Segmentation

The third block in Figure 1 indicates the segmentation step in the proposed system. Flower's region only is segmented from the background. Then to recognize the flower species, recognition task work only on foreground part. Active contours based on evolve curve by [15] is another region growing segmentation techniques. Curve initializes around the object, and moves toward this object boundary, even if this boundary is smoothed or disconnected. [15] based on the proposed in [16] to setting up an ideal criterion for segmentation.

Region growing segmentation implementation of [15] is deployed in the proposed system, with the pre-processing modification that was mentioned. Seeds are initially determined from rectangle mask for the image, so curve initializes around the object, and moves toward this object boundary, even if this boundary is smoothed or disconnected.

3.3 Feature Extraction

After the foreground-background segmentation step was completed; only the interest part from the image is used in the feature extraction step. Feature extraction step is shown in the fourth block in Figure 1, Different features are extracted from flower and leaf images. The list in fig 4 shows the type of features that are extracted, and stored in the knowledge database. This coming section describes the features that were used in the proposed system.

3.3.1 Color Feature

RGB is a color system consists of three components, Red, Green and Blue,[17]. Color moments can be extracted from this color space such as mean, standard deviation and skewness. Two types of color moment are extracted from each channel of RGB in the flower image, these type are Mean and Standard deviation, which is the square root of distribution variance. 1x6 color moment feature vector is formed and normalized.

HSV color histogram represents the color distribution in the image. In HSV color space, Hue, Saturation and Value refer to tint, shade and tone respectively [17]. Counts of pixels that have the same color range from all possible color is represented in the histogram. 1x18 features vector containing the quantization values for Hue, Saturation and Value channels are extracted from segmented flower image, and it is also normalized. Combined HSV and RGB color features are extracted from flower image only in the proposed system.

3.3.2 Texture Feature

Thirteen GLCM features of [18] were extracted: Energy, Sum of squares Variance, Sum average, Sum variance, Entropy, Sum entropy, Difference variance, and Difference entropy, Information measure of correlation1, Information measure of correlation2, Contrast, Correlation, and Inverse difference moment normalized which describes the texture smoothness.

Six features as an additive to the previous GLCM feature are extracted from [19]: Dissimilarity, Cluster Prominence and Cluster Shade, Homogeneity and Maximum probability. Finally, Autocorrelation.

Inverse difference normalized (INN) and two more values were extracted for describing Correlation and Homogeneity, which is calculated in a different way using dissimilarity instead of contrast. Totally, twenty two features, which represent the texture within the image are extracted and form in 1x22 Normalized vector for each flower and leaf image. By averaging four GLCM Matrices the proposed system achieved image rotation invariant.

Based on discrete 2-D wavelet transform of wavelet coefficients [20,21] wavelet features were extracted. The first output of the 2-D wavelet transform which represents the first low pass approximation for the image, it is re-entered the process again. Four iterations from 2-D wavelet transform are applied. Mean and standard deviation of the four decomposition low pass approximation coefficients are computed, and formed in 1x2 feature vector for each flower image; the feature vector is normalized and used as texture feature. Using four decomposition low pass approximation archives scale invariant. Combined features from GLCM and 2-D wavelet transform are used in the proposed system

3.3.3 Shape Feature

Scale Invariant Feature Transform (SIFT) [8] is used to extract distinctive and scale invariant key points features from the image. Key points are selected based on measures of their stability, and invariant to scale by comparing a pixel to their neighbors. Search for stable features across multiple scales is achieved by using continuous function of scale, by convolving the input image with Gaussian kernel at three different scales. Matching between images can be found by the use of SIFT features, even if the images are taken in different views, scale and rotation. In the proposed system, thirty nine features vector of SIFT key points are extracted from flower image, this achieve the scale invariant.

To extract HOG features of [22], firstly, the center of the input flower image is cropped. To ensure normalized color, RGB Gamma compression is applied, by multiplying the input image by small Gamma. Gradient is computed by filtering the image with several discrete masks, for example: centered, un-centered and Sobel mask. Based on the computed gradient, a weighted vote for an orientation-based histogram is calculated for each pixel within the cell. 60x60 cell size is chosen to capture large scale spatial information HOG. Final result comes from combining all individual vector from cells. The output vector of size 1x36 which is normalized. It encoded the local shape information from flower foreground regions. SIFT and HOG shape feature are combined, and used in the proposed system.

3.4 Recognition

Recognition task can be decomposed into several binary classification tasks based on Multiclass decomposition into binary class. One versus all approach is one from Multiclass decomposition into binary class methods, in which tested data is passed through all the trained files, and the class. This gives the highest confidence whihch is chosen as class for tested data [2].

The proposed system datasets will be extended to be larger, with more flower species, and more images per each species, therefore. A fast and effective SGD classifier is used under the Hinge loss function [23]. SGD with one-versus-all approach was used, in which one SGD is trained for each category, so it required building nineteen training binary classifiers for our new Dataset. As shown in Figure 1, after features are extracted from a tested data, it passes through all the nineteen trained files that stored in Knowledge database. The class which gives the highest confidence is chosen as class for tested data. The output for flower species will be given in the final block of system diagram as shown in Figure 1.

4. Experiments

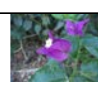
The proposed system was implemented in MATLAB R2014b, and tested on an Intel (R) Core (TM) i3-3110M CPU @ 2.40GHz, 4GB Memory, x64-based processor, Windows 8.1.

4.1 Jordanian Flower Dataset Design

Information about Jordanian flowers species was collected by reading books and visiting a local botanist. The book “Wild flowers of Jordan and Neighboring countries” [24], contains a lot of information about flower families, species and names. This book contains 488 colored images which were all photographed by the author. Some species in our dataset set were given its accurate names based on this book. Data about the traditional recognition method was also collected through visits to a botanists, who were asked about the manual recognition task challenges.

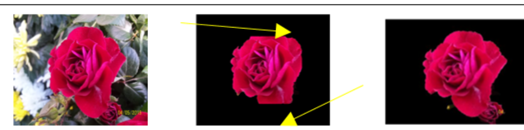
Several flower species and their leaves were photographed from wildness areas in Amman. Our dataset was built as shown in Table 1. Number of species in this dataset is nineteen. The total image in our new dataset is 513 flower images. This dataset will be extended to include more species; only the number nineteen will be updated each time.

TABLE 1: Our new Dataset

 L.Camara	 J. Azoricum	 Anchusa Italica Retz	 Bougainvillea
 Trumpet Creeper	 L. maximum	 Papaver Syriacum Boiss.	 Rosa Damascena
 P.Auriculata	 Geranium	 Alcea Digitata Boiss.	 Malava Sylvestris L.
 Poinsettia	 Marigold	 Glandularia	 Chrysanthemum
 Daisy	 Petunia	 Iris Nigricans Dinsm.	

4.2 Image Preprocessing Experiments

Preprocessing is the first step of the proposed system. Every input image resized to be 350 rows. The number of columns is calculated automatically to preserve the aspect ratio. Resizing value is selected to be convenient with region growing segmentation. Figure 2 (a) shows input from Rosa Damascena species. The result of Region growing segmentation of the same number of iteration and without resizing is shown in Figure 2 (b), the two arrows on the image show that the segmentation was not completed, while resizing the input image before segmentation gives faster and better segmented result with complete boundaries within the same iteration number of region growing segmentation, as shown in Figure 2 (c).



a. Input Image b. Without resizing c. With resizing

Fig 2: Image Resizing Effects

4.3 Thresholding Segmentation Experiments

Threshold based on histogram was applied on the Papaver flower image, which is shown in Figure 3 (a). RGB image was converted to HSV. Minimum and maximum values for each HSV channels were selected. The segmented RGB image shows the original input RGB image under the binary mask. Because of the complex background in the image, it was not segmented correctly by histogram based thresholding technique as shown in Figure 3(b). Moreover, the center of the Papaver flower in Figure 3 (b), was removed and considered as part of the background, because of thresholding segmentation is based on specific value to process the segmentation for all image pixels.

a.Input b.Histogram based c.Otsu's Method d.Green Removal

Figure 3: Threshold-Based Segmentation for Papaver Species

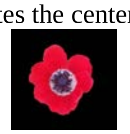
The global image thresholding by Otsu's method is also a segmentation method. It was applied on the image in Figure 3 (a). Otsu's method achieved better results than threshold based on histogram as shown in Figure 3 (c), but the center of the Papaver flower was still eliminated, same as in thresholding based on histogram. The quality of segmented image was reduced when the flower has two or more colors, in both thresholding techniques.

Based on the procedure of [4,3] that assumes flowers' region in the images to be always greenery surrounded, green removal technique was applied for image in Figure 3 (a). Threshold value for each channel in RGB image was selected. Green removal segmentation in figure 3 (d) shows unsatisfying result because the background has brown or mixture of colors.

4.4 Region Growing Segmentation Experiments

Because of the unsatisfying segmentation results of the previously discussed methods, another segmentation technique was deployed. Region growing segmentation implementation of [15] was deployed in the proposed system.

Region growing segmentation was applied for the inputs of Papaver flower in Figure 3 (a). The results are shown in Figure 4. High quality with correct boundaries were achieved for segmented flower. The center region of the flower was kept in foreground unlike the thresholding techniques that eliminates the center of the flower.



Papaver Syriacum Boiss

Figure 4: Region Growing Segmentation Results

4.5 Flower Recognition Experiments on the Proposed Dataset

Recognition task was decomposed into several binary classification tasks based on Multiclass decomposition into binary class, one-versus-all approach is used, and SGD classifier is applied with the parameters: learning rate =0.01, epochs = 4. Nineteen binary classifiers were built for training. When a new data is to be classified, it passes through all these classifiers, and the class which gives the highest confidence is chosen as class for this data. The number of images is different from a class to another. Therefore, imbalanced classes' problem is solved by applying SMOTE filter [25] on the training data. Dataset was randomly splitted into 75% training data, and 25% testing data. Recognition accuracy is averaged overall per class recognition rate.

4.6 Recognition Experiments on Oxford17 Dataset

The proposed system was applied on Oxfored17 flower Dataset, and compared with other previous work. Oxford17 dataset contains 1360 images for 17 flowers species, each class has 80 images, and these images were collected from the internet, and some of them photographed by Authors [4]. Two viewpoints from Oxford17 Dataset were considered in [4]. The first consists of viewpoint set, which is a subset of ten species, with forty image of each. In these forty images, flower region occupies a large space, and flower rotates toward the appropriated imaging angel. This makes the forty images somewhat easier than those of full set. The second data set which represents a full viewpoint of Oxfored17 Dataset, contains 1360 images for 17 flowers species. These two viewpoints were used with the testing methodology of [4].

5. Results and Discussion

5.1 Flower Recognition Results on Our new Dataset

Dataset was randomly splitted into 75% training data, and 25% testing data. SGD classifier with one-versus-all approach was used. An average of overall per class recognition rate is 92%. The measure which was used is Recall. Table 2 shows confusion matrix for recognition accuracy results. The first column in the left shows the nineteen trained files, the first row show the nineteen tested files. For each species the test file was tested against all the training files, the recognition accuracy was recorded under the species column. This column represents a clear cut values

The highest recognition accuracy rate for all tested species was achieved by testing against the species trained file. The shaded diagonal cells of Table 2 shows the recognition accuracy for each tested file against its correct species trained file. For example, highest recognition accuracy recorded for Daisy in the nineteen column of table 2 is 100%, and achieved by testing against Daisy trained file, so these tested instances were given the name of Daisy as recognition result.

Table 2: Confusion Matrix of Recognition Accuracy on our new Dataset

train / test	Rosa damascena	Marigold	Geranium	P.auriculata	L.camara	J. azoricum	Bougainvillea	Malava	Anchusa	Papaver	Glandularia	Trumpet Creeper	L. maximum	Alcea digitata	Poinsettia	Iris	Chrysanthemum	Daisy	Petunia
Rosa damascena	100%	0	0	0	0	0	0	0	0	25%	0	0	0	0	0	0	0	0	0
Marigold	0	100%	0	0	14%	0	0	0	0	0	0	0	0	0	0	0	50%	0	0
Geranium	0	0	92.30%	0	0	0	0	0	0	25%	62.50%	0	0	50%	66.70%	0	0	0	0
P.auriculata	0	0	0	85.70%	0	66%	0	0	0	0	0	0	0	0	0	0	0	50%	0
L.camara	0	20%	0	0	100%	0	0	0	0	0	25%	0	0	0	0	0	25%	0	0
J. azoricum	0	0	0	14%	0	83.30%	0	0	0	0	0	0	0	0	0	0	0	0	0
Bougainvillea	0	0	0	0	0	0	80%	0	0	0	25%	0	0	0	0	0	0	0	0
Malava	0	0	0	0	0	0	0	83.30%	0	0	0	0	0	0	0	25%	0	0	0
Anchusa	0	0	0	0	0	0	0	50%	100%	0	0	0	0	0	0	0	0	0	71.40%
Papaver	0	0	0	0	0	0	0	0	0	75%	0	0	0	0	16.70%	0	0	0	0
Glandularia	0	0	25%	0	0	0	20%	0	12.50%	0	87.50%	0	0	0	0	0	0	0	0
Trumpet	0	0	0	0	0	0	0	0	0	0	0	100%	0	0	0	0	0	0	0
L. maximum	0	0	0	0	0	0	0	0	0	0	0	0	100%	0	0	0	25%	0	0
Alcea digitata	0	0	0	0	0	0	0	0	0	0	0	0	0	100%	16.70%	0	0	0	0
Poinsettia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	83.30%	0	0	0	0
Iris	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100%	0	0	0
Chrysanthemum	0	0	0	0	0	0	0	0	0	0	0	0	62.50%	0	0	0	75%	0	0
Daisy	0	0	0	14.30%	0	50%	0	0	0	0	0	0	0	0	0	0	0	100%	0
Petunia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100%

On the other hand, testing instances from Daisy species against P. Auriculata, gave 50% that these instances are from Plumbago. Auriculata (P.Auriculata) species. Features similarities were found between both species, this leads to make Plumbago the closest species for Daisy.

For some tested species in Table 2, the closest species with their recognition accuracy ranges were extracted, and formed in Table 3. To clarify the similarities between species, flower images, with highlights points on the shared features were included in Table 3.

Table 3: Tested Flowers Species with Their Closest Species

	Tested Species	Recognition Accuracy Range Against Closest Species	Similarities
1	 Rosa	 Rosa - 100% against all 0%	Unique petals shape
4	 P.auriculata	   P.auriculata-Daisy-J. azoricum 85.7% 14.3% 14%	Color and texture similarities
6	 Petunia	  Petunia - 100% Anchusa italica 71.4%	Color similarities

Some of flower species in the dataset have unique features; they yield 100% recognition accuracy against their correct species. Flowers with unique features yield 0% when testing against all other species. This means that is impossible for the tested instances to be from any of those other species. For example, the first case in Table 3 shows that Rosa damascena has unique internal shape, the petals revolve in many layers around the flower center in unique arrangement, so tested instances of Rosa Damascena yields 0% against all other species, and 100% against Rosa Damascena species.

Smoothed petals texture and white flower color are shared between flowers in cases number four, six and eighteen of Table 2. All flower species in case ten, fourteen and fifteen shared the red and pink gradient. Some Iris Nigricans flowers in the dataset shared the light purple color with Malava.

Finally, blue color similarity is found between flowers, so testing Petunia against Anchusa gave non-zero recognition accuracy in case nineteen of Table 2. Conversely, testing Anchusa italica against Petunia column nine of Table 2 gave zero%, because Anchusa class has more images in that dataset, so it was learnt well, and better than Petunia class.

It can be concluded from both Tables 2 and Table 3 that the recognition accuracy of the tested species reduced, if the numbers of closest species increased, and their recognition accuracy is high. For example, Rosa Damascena recognition accuracy is 100% with no closest species; conversely, recognition accuracy of Chrysanthemum Indicum species is decreased to 75%, because it has three closest species, with high recognition rate for each species.

In addition, it is clear that combined shape, texture, and color features worked better than using single feature. Some species share color feature, but in the same time they don't share shape; therefore, discrimination between species will be better.

5.2 Flower Recognition Result on Oxford17 Dataset

5.2.1 Consist View Point Results

Our Proposed flower recognition system, with the testing methodology of [4] is applied. Dataset is splitted randomly into seventy five percent for training, and twenty five percent for testing. Table 4 shows numerical comparison between our own method and method of [4].

Table 4: Consist Viewpoint Comparison

Methods	Shape	Color	Texture
[4]	75.3%	49.0%	56.0%
Proposed System	41%	90.3%	57.0%

SIFT descriptor of [8] was used as shape feature in [4], while our work based on SIFT key point of [8] combined with HOG of [22] feature. Recognition accuracy based on shape achieved in [4] overcame the proposed system, because they used SIFT descriptor with parameter optimization.

Color feature of proposed system overcome the color feature of [4]. In the proposed system both RGB and HSV were used for describing the flower color, but the color feature of [4] was extracted only from HSV color space.

Recognition accuracy of proposed system based on texture is better than results achieved by [4]. Combined wavelet transform features with GLCM of [18,19,2] were extracted in the proposed. Combining textural features, increased the proposed recognition over that achieved in [4], which was described by convolving the image with MRF8 filter bank of [9].

5.2.2 Full Viewpoint Results

Same testing methodology of consist viewpoint was applied on full Oxfored17 Dataset. The numerical comparison between the proposed system and method of [4] is shown in Table 5.

Table 5: Full Viewpoint Comparison

Methods	Shape	Color	Texture
[4]	71.8%	73.7%	~56.0%
Proposed system	60.88%	89.7%	79.4%

Results of the proposed system still overcome [4] based on color and texture same as in consist viewpoint. It was noted that shape feature of the proposed performing better on the larger set, it increased around twenty percent. This is because the full dataset has more instances of similar shape. Color of proposed system is performing the best of all features, because variation in color on larger set is less than the variation in shape. Shape changed by scale, rotation and deformation. Texture of the proposed achieved significant improvement.

Combined features were used with one-versus-all SGD classifier. Dataset was randomly splitted into seventy five percent training data, and twenty five percent testing data. An average of overall per class recognition rate for the proposed system on Oxford17 Dataset is 83.52%. Table 6 shows numerical comparison between proposed systems with other previous work.

Table 6: Recognition Accuracy Comparison on Oxford17 Dataset

[11]	[4]	[12]	[6]	Proposed System
82.55%	71.76%	88.3%	90.4% BiCoS 91.1% BiCoS-MT	83.52%

6. Conclusion

Providing automated method for segmentation and recognition of flower species has many benefits to the people either in the agricultural field or in any other fields. It accelerates the learning process through automated and fast application; also it is a type of entertainment and learning with fun for the people outside the agricultural field. In addition, building our new Dataset that focus in the Arab region, show our rule in this field.

Region growing segmentation is applied with previous pre-process step, resizing the input to reduce the segmentation processing time, and increase the segmentation quality. Our method showed that some results outperform the segmentation of Oxfod17 in related works, especially in keeping the center of the flower without being segmented.

Combined features were used in this paper. Color features as RGB and HSV were extracted. The change in illumination was reduced by using HSV color space. Both GLCM and Wavelet transform as textural features, GLCM provides the system with advantage of rotation invariant, while using four scales in Wavelet transform make the proposed system invariant for different scales. HOG and SIFT as shape features provides the system with global and local shape descriptors, in addition by using SIFT key points the proposed system became more scale invariant.

While some flower share the color, they differ in shape or texture, so through this paper it was shown that combined features from color, shape and texture achieve higher recognition accuracy than using the same feature independently.

Recognition accuracy for our new Dataset is 92%. Our proposed outperforms several methods on Oxfoed17 Dataset; we achieved a class average recognition accuracy of 83.52%.

7. Future works

Nature has a verity flower species, so in the future our new Dataset will be extended to be larger, with more flower species, and more images per each species. More effective features in leaf will be studied be used in feature extraction and recognition.

The proposed system can be applied for many other type of fine grain recognition, and this work can be extend to be used in medicine, security and industry, and many other fields. Experiments will be extending on fields such as Iris and fingerprint recognition, cars recognition and plans recognition. This work can be tested also on famous Datasets such as UBIRIS for iris, flower Oxford102, and UIUC materials.

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