An Automatic Flower Classification Approach Using Machine Learning Algorithms

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***Abstract*—This work aims to develop an effective flower classification approach using machine learning algorithms. Eight flower categories were analyzed in order to extract their features. Scale Invariant Feature Transform (SIFT) and Segmentation-based Fractal Texture Analysis (SFTA) algorithms are used to extract flower features. The proposed approach consists of three phases namely: segmentation, feature extraction, and classification phases. In segmentation phase, the flower region is segmented to remove the complex background from the images dataset. Then flower image features are extracted. Finally for classification phase, the proposed approach applied Support Vector Machine (SVM) and Random Forests (RF) algorithms to classify different kinds of flowers. An experiment was carried out using the proposed approach on a dataset of 215 flower images. It shows that Support Vector Machine (SVM) based algorithm provides better accuracy compared to the Random Forests (RF) algorithm when using the SIFT as a feature extraction algorithm. While, Random Forests (RF) algorithm provides its better accuracy with SFTA. Moreover, the system is capable of automatically recognize the flower name with a high degree of accuracy.**

***Index Terms*—Flower Classification, Image Classification, Image Segmentation, Features Extraction, Scale Invariant Feature Transform (SIFT), Segmentation-based Fractal Texture Analysis (SFTA), Support Vector Machine (SVM), Random Forest (RF)**

I. Introduction

There are many flowers around the world which belong to about 250,000 named species. Most people see flowers every day, but they can not identify them. They ask specialists, browse flower books, or search the Internet through keywords searching to identify these flowers names [1]. An easy and fast way to identify flower name can be done by classifying flower images. Especially with the widely use of mobile digital cameras in all the world. Caption flower image, sending it to a flower recognition system which classifies flower image will help people in flower identification.

Flower classification systems belong to a shape matching problem, which is a fundamental problem in computer vision and pattern recognition. It defined as the establishment of a similarity measure between shapes and its use for shape comparison. The important theoretical interesting motivation for image classification comes from that shape matching is intuitively accurate for humans and need an assistant which is not solved yet in its full generality. Shape matching system includes object recognition and detection, image registration, and content based retrieval of images [2].

Therefore, the main objective of this work is to automatic classify flower image according to its features. Since flower images have a natural complex background, classification flower systems give more attention for extracting the flower region with high accuracy. After segment flower region, the flower features is extracted dependent on features like, color, shape, and texture features. Then, these extracted feature are used to train a classifier for classify flower image. So our flower classification approach proposed is designed to include these phases which are segmentation, feature extraction, and classification phases. For feature extraction phase, the proposed approach uses Scale Invariant Feature Transform (SIFT) and Segmentation-based Fractal Texture Analysis (SFTA) algorithms to extract a feature vector for each image in the dataset.

After extracting flower images feature vectors, the proposed approach classifies them using Random Forests (RF) and Support Vector Machine (SVM). Evaluating the classification approach is done using eight flower categories. The results of carrying out this evaluation demonstrate that the proposed approach is capable of automatically classify the flower name

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with a high degree of accuracy. Such flower classification system can be used in many real life applications. For examples, it can be used as an interactive educational tool to enhance learning methods for both young and adult person. For eye weakness people, it can be used as an assist tool that aiding them in shopping as mobile application.

The structure of this paper is as follows. Section 2 presents some recent research works related to flower recognition and classification. Section 3 describes the three phases of the proposed approach for classification system which are: pre-processing, feature extraction, and classification phases. The experimental results are presented in section 4. While, section 5 presents the conclusion and future work.

II. Related Work

Saitoh and Kaneko [3] proposed an automatic recognition system for wild flowers. They use both the flower and leaves image to recognize the flower name. First, the flower and leaves are segmented. Then, their features are extracted to represent the wild using a clustering method. Their recognition is achieved using a piecewise linear discriminant function [3].

Nilsback and Zisserman aim to enhance classification performance on a similar classes large dataset by extracting a combinations of features. Such combinations of features can improve classification performance on a large dataset of similar classes. These features are color, SIFT for both the foreground region and boundary, and Histogram of Gradients. Their system segments flowers images, then extracts the features combinations which are used as input to Support Vector Machine (SVM) classifier in order to classify flower image [4].

Guru and his colleagues introduce an automatic classification model for flowers using KNN classifier. First, they segment the flower using a threshold based method. Then, the textural features Gray level co-occurrence matrix and Gabor responses are extracted as features that represented the flower image. For classification phase, they train K-nearest neighbor classifier to label an unknown flower [5].

Another recognizing flower system is presented in [1]. For flower segmentation, a user selects the appropriate bounding window that holds the flower region through an interactive interface. Then, the flower is segmented from the selected windows. They extract color and shape features of the whole flower region and the pistil/stamen area to represent the flower features. Then, they recognize flower by comparing the distances between the input flower image and all flower images existing in the database to reach the most similar to the input flower image [1].

III. The Proposed Approach for Automatic Flowers Classification System

The proposed automatic flowers classification approach consists of three phases namely: segmentation, feature extraction, and classification phases.

A. Segmentation Phase

An important problem in a flower classification system is how to extract the flower region from a natural complex background with good accuracy[1]. Flower region can be segmented based on using color features, since its images consist of a large green area and flower area. The green area represents the leaves surrounding the flower and flower area represents the flower region which is characterized by its color [6].

Color segmented can be achieved using the difference/distance between two colors. In this work, the images are transformed to Lab color space. Then, a frame which includes the flower is selected by user. The Delta E is used to calculate the distance between every pixel in the selected frame and the average LAB color [7]. After that, OTSU threshold is applied on each Lab color to segmented flower. OTSU algorithm tries to find an optimal separation between classes by computing a global threshold for an image [6].

OTSU splits the pixels of an image into two classes (objects and background). Let (σ_W^2) be the within-class variance, (σ_B^2) be between-class variance, and (σ_T^2) be the total variance [8]. An optimal threshold can be defined by minimizing one of the three criterion functions in the equations 1, 2, 3.

$$\lambda = \frac{\sigma_B^2}{\sigma_W^2} \tag{1}$$

$$\eta = \frac{\sigma_B^2}{\sigma_T^2} \tag{2}$$

$$k = \frac{\sigma_W^2}{\sigma_T^2} \tag{3}$$

When using η as a criterion function, the optimal threshold t^* is calculated as follow:

$$t^* = ArgMin \eta_{t \in G} \tag{4}$$

An example for some segmented flower images is shown in figure 1.

B. Feature Extraction Phase

This phase aims to extract the best features that represent an image, since the selected features set affects on the classification accuracy. The proposed approach uses two algorithms for feature extraction, which are Scale Invariant Feature Transform (SIFT), and Segmentation-based Fractal Texture Analysis (SFTA).

1) Scale Invariant Feature Transform (SIFT): Scale Invariant Feature Transform (SIFT) is an algorithm for image features extraction which is invariant to image translation, scaling, rotation and partially invariant to illumination changes and affine projection [9], [10], [11]. SIFT contains four main steps namely: scale-space extreme detection, keypoint localization, orientation assignment and keypoint

Fig. 1. Examples of Segmented Flower Images

descriptor. Algorithm 1 represents how SIFT works to generate the interesting points for image as a feature vector for each image in the dataset.

2) Segmentation-based Fractal Texture Analysis (SFTA): Segmentation-based Fractal Texture Analysis (SFTA) is an algorithm for image texture features extraction [12]. SFTA breaks down the input image to a set of binary images from which the regions boundaries fractal dimensions are calculated to define the segmented texture patterns. So, SFTA contains two major steps: Decomposed the input grayscale image, computed the fractal dimension from its regions boundaries. Algorithm 2 describes how SFTA works to generate the feature vector for each image in the dataset.

C. Classification Phase

In the classification phase, the proposed approach applied two classifiers namely: Support Vector Machine (SVM) and Random Forests (RF) to recognize different kinds of flower. This phase inputs are the flower training dataset feature vectors with their corresponding classes and the testing

Input: images
Output: Features for each input image
For each input image

- Build the image gaussian pyramid L(x, y, σ) using the following equations 5, 6, and 7.

$$G(x,y,\sigma) = \frac{1}{2\Pi\sigma^2} exp^{\frac{-(x^2+y^2)}{2\sigma^2}}, \tag{5}$$

$$L(x,y,\sigma) = G(x,y,\sigma) * I(x,y), \tag{6}$$

$$D(x,y,\sigma) = L(x,y,k\sigma) - L(x,y,\sigma), \tag{7}$$

  Where σ is the scale parameter, $G(x,y,\sigma)$ is Gaussian filter, $I(x,y)$ is smoothing filter, $L(x,y,\sigma)$ is Gaussian pyramid, and $D(x,y,\sigma)$ is difference of Gaussian (DoG).
- Calculate the Hessian matrix.
- After that, calculate the determinant of the Hessian matrix as shown in the equation 8 and eliminate the weak keypoints.

$$Det(H) = I_{xx}(x,\sigma)I_{yy}(x,\sigma) - (I_{xy}(x,\sigma))^2 \tag{8}$$

- Calculate the gradient magnitude and orientation as in equations 9 and 10.

$$\begin{aligned} Mag(x,y) \quad = \quad & ((I(x+1,y) - I(x-1,y))^2 \\ & +(I(x,y+1) - \\ & I(x,y-1))^2)^{1/2} \end{aligned} \tag{9}$$

$$\theta(x,y) = \tan^{-1}(\frac{I(x,y+1) - I(x,y-1)}{I(x+1,y) - I(x-1,y)}). \tag{10}$$

- Finally, apply the sparse coding feature based on SIFT descriptors as in equations 11 and 12.

$$\min \sum_{i=1}^{N} (\|x_i - \sum_{j=1}^{M} a_i^{(j)} \phi^{(j)}\|^2 + L) \tag{11}$$

$$L = \lambda \sum_{j=1}^{M} |a_i^{(j)}|. \tag{12}$$

  Where x_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

Input: Grayscale image sand number of thresholds nt.
Output: Features vector V_{SFTA} for each input image
For each input image

- T $\leftarrow$ MultiLevelOtsu(I,n_t).
- $T_A \leftarrow \{\{t_i, t_{i+1}\} : t_i, t_{i+1} \in T, i \in [1..|T| - 1]\}$
- $T_B \leftarrow \{\{t_i, n_l\} : t_i \in T, i \in [1..|T|]\}$
- i $\leftarrow 0$
- For $\{\{t_l, t_u\} : \{t_l, t_u\} \in T_A \bigcup T_B\}$
  - $I_b \leftarrow TwoThresholdSegmentation(I, t_l, t_u)$
  - $\Delta(x, y) \leftarrow FindBorders(I_b)$
  - $V_{SFTA}[i] \leftarrow BoxCounting(\Delta)$
  - $V_{SFTA}[i + 1] \leftarrow MeanGrayLevel(I, I_b)$
  - $V_{SFTA}[i + 2] \leftarrow PixelCount(I_b)$
  - i $\leftarrow i + 3$
- reture V_{SFTA}

Algorithm 2: SFTA feature extraction algorithm

dataset. The output of this phase is the name of each flower image in the testing dataset.

1) Support Vector Machine (SVM): The Support Vector Machine (SVM) tries to find an optimal dividing hyperplane which effectively divides between classes for solving the problem of classification [13], [14]. SVM algorithm aims to maximize the margin around a hyperplane that divides a positive class from a negative class [14], [15], [16], [17], [18]. Consider a training dataset with n samples (x_1,y_1), (x_2, y_2), ..., (x_n,y_n). Where a feature vector x_i is in n-dimensional feature space and with labels $y_i \in \{-1, 1\}$ belonging to one of two linearly separable classes C_1 and C_2. The SVM algorithm finds an optimal hyperplane with the maximum margin between two classes by solving the optimization problem, as shown in the equations 13 and 14.

$$maximize \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j . K(x_i, x_j) \tag{13}$$

$$\sum_{i=1}^{n} \alpha_i y_i, 0 \leq \alpha_i \leq C \tag{14}$$

Where, α_i is the assigned weight to the training sample x_i. when $\alpha_i > 0$, the x_i is a support vector. A regulation parameter C is used to trade-off the training accuracy and the model complexity to achieve a superior generalization capability. K is a kernel function, which is measure the similarity between two samples.
Algorithm 3 shows how Support Vector Machine works.

Construct N binary SVM
Keypoint localization Each SVM separates one class from the rest classes
Train the i^{th} SVM with all training samples of the i^{th} class with positive labels, and training samples of other classes with negative labels

Algorithm 3: Support Vector Machine Algorithm

2) Random Forest (RF): The Random Forests (RF) 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 [19]. It creates an ensemble of decision trees. The main principle of ensemble methods is to collect weak learners together in order to build a strong learner [19], [20], [21].

The RF classifier input is go into the top of the tree, and then traverses down the tree. The original data is randomly sampled, but with replacement into smaller and smaller sets. The class of sample is determined using random forests trees, which are of an arbitrary number [21].

Let (X, Y),(X_2,Y_2) , ... (X_n,Y_n) be pairs of random variables such that X (feature vector) takes its values in R^d while Y (the label) is a binary $\{0, 1\}-$ valued random variable. The joint distribution of (X, Y) is determined by the marginal distribution μ of X (i.e., $P\{X \in A\} = \mu(A)$ for all sets $A \subset R^d$) and the a posteriori probability η: $R^d \rightarrow [0, 1]$ defined by the equation 15.

$$\eta(x) = p\{Y = 1 \mid X = x\} \tag{15}$$

The collection (X_1,Y_1),(X_2,Y_2),.(X_n,Y_n) is called the training data, and is denoted by D_n. A classifier g_n is a binary-valued function of X and D_n whose probability of error is defined by the equation 16.

$$L(g_n) = P_{(x,y),z}\{g_n(X, D_n) \neq Y\} \tag{16}$$

Where $P_{(x,y)}$ denotes probability with respect to the pair(X, Y) (i.e., conditional probability, given D_n. Random forests, introduced by Breiman, are averaged classifiers. Formally, a random forest with m trees is a classifier consisting of a collection of randomized base tree classifiers $g_n(x, Z_1), ..., g_n(x, Z_m)$. And Z_1, ..., Z_m are identically distributed random vectors, independent conditionally on X, Y, and D_n. The randomizing variable is typically used to determine how the successive cuts are performed when building the tree such as selection of the node and the coordinate to split, as well as the position of the split [22]. Algorithm 4 shows how Random Forest works.

IV. Experimental results

An experiment has been carried out to evaluate the proposed approach. The proposed system was implemented using Matlab R2013a on Windows 8.1 operation system.

A. Dataset

The proposed system was evaluated using around 215 flower images represented eight fruit categories. Figure 2 shows some samples of both training and testing datasets. The used dataset in this experiment has been taken from

1: Draw N_{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 m_{try} of the M 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: Predict new data by aggregating the predictions of the N_{tree} trees.

Algorithm 4: Random Forests Algorithm

the largest known flower dataset which includes 102 flower categories [4]. Eight flower categories are selected namely: Passion, Water lily, Rose, Tree mallow, Anthurium, Barbeton daisy, Pink-yellow dahlia, and Californian poppy. Their images have different transformations (scale change, rotation, illumination, image blur, viewpoint change, and compression) for each flower. The dataset was split randomly into two sets, one for training (70%) and other for testing (30%). The raw images were used after resize it to 330*250 pixels.

B. Evaluation Results

Since, the features extraction stage uses SIFT and SFTA algorithms and the classification stage use the SVM and RF classification algorithm, the proposed approach has been evaluated considering the following four scenarios:
Scenario 1: features extraction based on SIFT are classified using SVM
Scenario 2: features extraction based on SIFT are classified using RF
Scenario 3: features extraction based on SFTA are classified using SVM
Scenario 4: features extraction based on SFTA are classified using RF
The total dataset was divided to 70% for training and 30% for testing. The following paragraphs show the accuracy for each as scenario for each flower category.

Figure 3 shows the results of classifying the eight flower categories, which shows the accuracy for each flower categories. We observe that categories Anthurium and Barbeton daisy which are different in shape from other categories, the height accuracy is achieved (100%) with different feature extractions and classifiers. The lowest accuracy achieved 66.67% with Californian poppy when using SIFT as feature exaction and RF as classifier. Also, we notice that SFTA achieves high accuracy (77.78% to 100%) than SIFT (66.67% to 100%). From this experiment, we can say that using SIFT as feature extraction archives high accuracy when classifying flower images using SVM. While extracting features based on SFTA algorithm achieves better accuracy when classifying flower images by the FR.

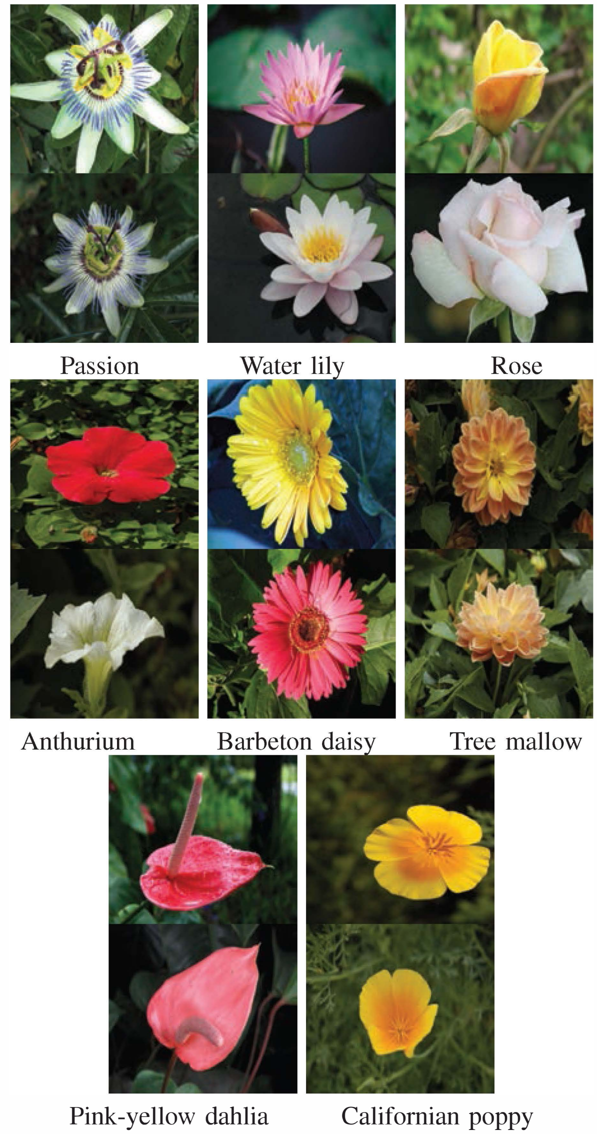

Fig. 2. Examples of training and testing flower images

V. Conclusions and Future Work

A proposed approach for flower classification is presented, it uses machine learning techniques to automatically identify flower category. The proposed approach includes three phases: segmentation, feature extraction, and classification phases. Segmentation phase aims to enhance the accuracy by separating the flower shape from the image natural background. Then, flower features is extracted using two algorithms which are Scale Invariant Feature Transform (SIFT) and Segmentation-based Fractal Texture Analysis (SFTA). Finally the classification phase can be run after the feature vectors are generated for each image. Support vector machine (SVM) and Random Forest (RF) classifiers are the used machine learning classification algorithms. the proposed approach has been done evaluated using 215 flower images

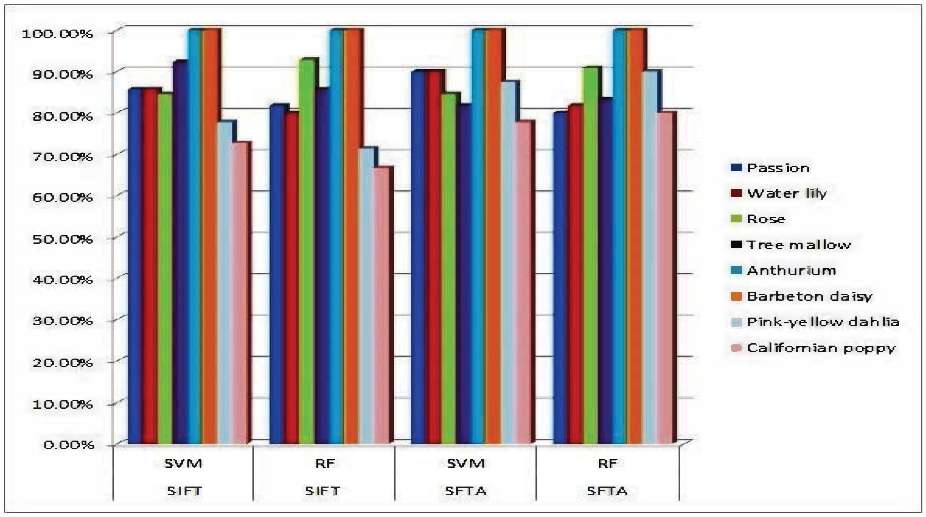

Fig. 3. Flower Classification Accurecy

for eight flowers categories.

The experimental results show that the similarities on shape categories effects on the category classification accuracy. The categories that has shape different from other categories, achieve the height accuracy is achieved (100%) with different feature extractions and classifiers. As general, we can say that Support Vector Machine (SVM) classifier provides its better accuracy using the SIFT as a feature extraction algorithm. While SFTA algorithm gives better result with Random Forests (RF) classifier. Now, we are investigating using other automatic segmentation algorithms in order to achieve height accuracy. Also, we intend to recognize more flower categories.

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