Robust Technique for Flower Classification using Image Processing based Neural Network

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Abstract:

In this paper, it is proposed to have Artificial Neural Network (ANN) for general purpose flower classification. A flower image is segmented using a semi-automated threshold based method by eliminating the background.

The proposed model is based on textural features such as Discrete Wavelet Transform (DWT) based HSI feature and colour features. The data set has samples of flower image with different classes. Also, the images of flowers are of different pose with cluttered background, under varying lighting conditions and climatic conditions. The data set has different flower images with similar appearance .The database of flower images is a mixture of images taken from World Wide Web and the images taken by us. The ANN has been trained by 50 samples to classify 5 classes of flowers and achieved classification accuracy more than 85% using colour features only.

Keywords: Artificial Neural Network, DWT, HSI, Segmentation.

Introduction:

Developing a system for classification of flowers is a difficult task because of considerable similarities among different classes. In a real environment, images of flowers are often taken in natural outdoor scenes where the lighting condition varies with the weather and time. Also, there is lot more variation in viewpoint of flower images. All these problems lead to a confusion across classes and make the task of flower classification more challenging. In addition, the background also makes the problem difficult as a flower has to be segmented automatically. Applications of classification of flowers can be found useful in floriculture, flower searching for patent analysis, etc. The floriculture industry comprises flower trade, nursery and potted plants, seed and bulb production, micro propagation, and extraction of essential oil from flowers. In such cases, automation of flower classification is essential. Since these activities are done manually and are very labor intensive, automation of the classification of flower images is a necessary task.

Hence, these tasks require automation, so as to have a computer vision system (CVS) as an alternative to this manual practice. The development of computer vision system involves acquisition of images of different types of flowers, extraction of features and design of a neural network model as classifier of agriculture/horticulture produce images. Several researchers have reported that CVS is more accurate in classification and interpretation of the images, as carried out by human beings in the real world.

Literature Review:

S. Manjunath et.al [2] has investigated the effect of texture features for the classification of flower images using probabilistic neural network as a classifier. S.M.Mukane et.al [3] has presented DWT and GLCM based feature selection for scale invariance texture image retrieval using fuzzy logic classifier. S.M.Mukane et.al [5] has presented wavelet and cooccurrence matrix based features for rotation invariant texture image retrieval using fuzzy logic classifier. Saitoh et al. [6] designed a flower classification system which extracts features from both flowers and leaves, and used a piecewise linear discrimant analysis for recognition on a dataset of 34 species each containing 20 sets of wild flowers. M. Das et al. [7] proposed an indexing method to index flower patent images using domain knowledge. Each flower image is discredited in HSV color space, and each point on the discredited HSV space is mapped to a color name in the ISCC-NBS and X Window systems in order to index the flowers. Nilsback and Zisserman [8] designed a flower classification system by extracting visual vocabularies which represent the color, shape, and texture features of flower images. Nilsback and Zisserman [9] noted that color and shape are the major features in flower classification. In this work, we investigate the suitability of texture features in designing a system for flower classification. Nilsback and Zisserman in their work [10] considered a dataset of 103 classes, each containing 40 to 250 samples. The low-level features such as color, histogram of gradient orientations, and SIFT features are used. They have achieved an accuracy of 72.8% with an SVM classifier using multiple kernels. Nilsback and Zisserman [11] proposed a two-step model to segment the flowers in color images, one to separate the foreground from background and the other to extract the petal structure of the flower. This segmentation algorithm is tolerant to changes in viewpoint and petal deformation, and the method is applicable in general for any flower class.Yoshioka et al. [12] performed a quantitative evaluation of petal colors using principal component analysis. They considered the first five principal components (PCs) of a maximum square on the petals. D.S. Guru et al [13] have proposed an algorithmic model for automatic classification of flowers using KNN classifier. In their work, Saitoh et al. [14] describe an automatic method for recognizing a blooming flower based on a photograph taken with a digital camera in a natural scene. It is based on Intelligent Scissors [15], which find the path between two points that minimizes a cost function dependent on image gradients.

Our Approach:

The proposed method has training and testing phases. In the training phase, from a given set of training images (segmented) the features are extracted and used to train the system using a Multilayer Perceptron (MLP) Neural Network.

In the testing phase, given a test image, the flower is segmented and the features are extracted. These features are queried to the Multilayer Perceptron neural network to know the flower class. The block diagram of the proposed method is given in Fig. 1.

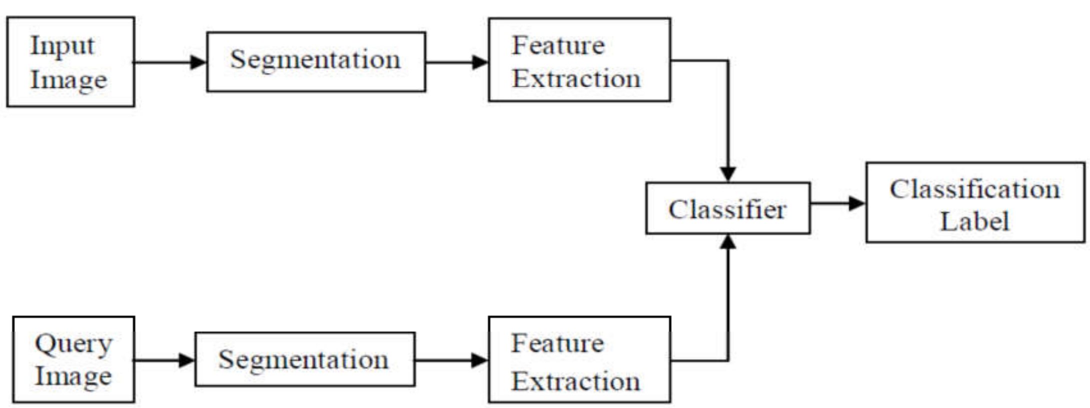

Fig 1: Block diagram of the proposed work.

The first step in flower classification is to segment the flower image by removing the unwanted background region. Flowers in images are often surrounded by greenery in the background [16]. In order to avoid matching the green background region, rather than the desired foreground region, the image has to be segmented. To segment the flower image, we use a semi-automated threshold-based segmentation algorithm. Fig. 2 shows the results of flower segmentation using the threshold-based method on a few sets of images with a cluttered background.

Fig. 2 Segmentation result (a) Input images and (b) segmented images.

Feature extraction:

Certain products are easily identified by simply color, for example, jowar and ground nut, pomegranate and mango etc. and color becomes the discriminating feature. But some have overlapping colors, for example, wheat and ground nut, mango and orange etc. When we consider the bulk samples of such products, the surface patterns vary from sample to sample. In such cases, the texture becomes ideal for recognition. Hence, we have obtained textural features of the image samples to recognize and classify the flower. The textural features namely energy and standard deviation are extracted using DWT at forth level decomposition.

DWT:

DWT Traditionally, Fourier transforms have been utilized for signal analysis & reconstruction. However, Fourier transform does not include any local information about the original signal. Therefore, Short Time Fourier Transform (STFT or Gabor transform) has been introduced, which uniformly samples the time-frequency plane. Unlike the STFT which has a constant resolution at d times and frequencies, the wavelet transform has a good time and poor frequency resolution at high frequencies, and good frequency and poor time resolution at low frequencies.

In JPEG2000, Discrete Wavelet Transform is used as a core technology to compress still images. The DWT has been introduced as a highly efficient and flexible method for sub band decomposition of signals [13]. The two dimensional DWT (2D-DWT) is nowadays established as a key operation in image processing. It is multi-resolution analysis and it decomposes images into wavelet coefficients and scaling function. In Discrete Wavelet Transform, signal energy concentrates to specific wavelet coefficients. This characteristic is useful for compressing images.

Highest level of decomposition depends upon the wavelet filter used, need of the application and features required for the classification. Using 4^{th} level of DWT decomposition, coefficients of approximate & detail Sub-bands are extracted. Based on the available wavelet coefficients, Energy (E_k) and standard deviation (σ_K) of all the sub-bands up to fourth level of decomposition are calculated.

$$E_k = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{N}|x_k(i,j)||$$

$$\sigma_k = \left[\frac{1}{N^2}\Sigma_i {}_{=1}^{N} \Sigma_j {}_{=1}^{N} \left(x_k(i,j) - \mu_k(i,j)\right)\right]^{\frac{1}{2}}$$

Where E_k is the energy & σ_k is the standard deviation for the k^{th} sub-band of dimension NxN and coefficients are X_k (i, j) & mean value is μk (i, j). For each samples of different class image, above features are computed and stored in the data base feature vector as Wavelet Statistical Features (WSF). This feature is used at the time of testing stage.

HSI features:

In our proposed algorithm, from RGB image HSI planes were separated. Then for every plane DWT is used up to 4th level of decomposition. Based on the available wavelet coefficients sum, energy and standard deviation of all the sub-bands are calculated.

Colour features:

Another feature extraction method is COLOR feature extraction. In this method RGB planes are extracted and mean, median and std. deviation of flower images are extracted.

Flower Classification:

ANN:

Artificial neural network (ANN) as a classifier has been used. An Artificial Neural Network (ANN) is an information-processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information.

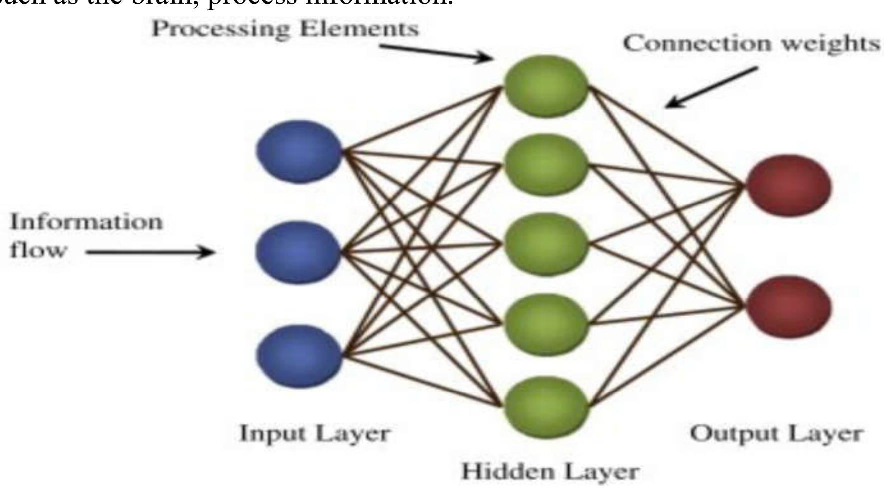

Fig. 3 The general architecture for MLP networks

The MLP and many other neural networks learn using an algorithm called backpropagation. With backpropagation, the input data is repeatedly presented to the neural network. With each presentation the output of the neural network is compared to the desired output and an error is computed. This error is then fed back (back propagated) to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output. The general architecture for MLP networks is shown in Fig.4. Performance of the above feature sets is tested with the help of a MLP classifier in terms of Success rate. Let PT be the no. of samples to be tested and out of that the system correctly classifies is PC then percentage is given as:

$$Pr=PC/PT*100$$

Algorithm 1: Classification of flower image
Step 1: Accept flower images
Step 2: Extract different texture features
Step 3: Train the MLP with extracted features
Step 4: Accept test image and perform Step 2
Step 5: Classify the flower images using MLP classifier

Experimental Results and Discussions:

In this work our own database inspite of existence of other databases has been created. Flower images from World Wide Web in addition to images from own database that can be found in and around the area. The database consists of 5 classes of flowers with 10 images of each. The images are rescaled to the size 256x256 using bicubic interpolation. In this experiment pyramid structured type of DWT is used with dB8 as a wavelet filter. Feature database is created using wavelet decomposed subbands up to forth level of decomposition. Total number of subbands up to forth level will be 16. Energy (1) and standard deviations (2) of each sub-band coefficients are calculated for each level of the samples. These features are stored in database vector.

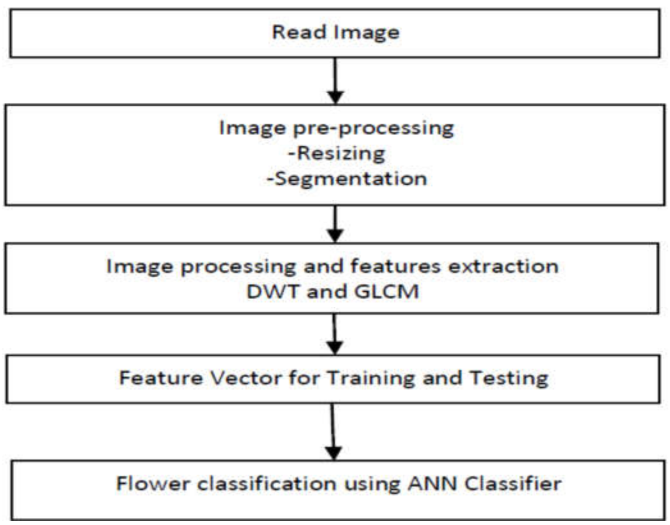

Fig. 4 Flowchart for Flower Classification

Experimentation has been conducted on databases of 50 images and 5 classes. The classification accuracy under ANN classifier has been investigated. As compared with other work we have used DWT based HSI features and colour feature.

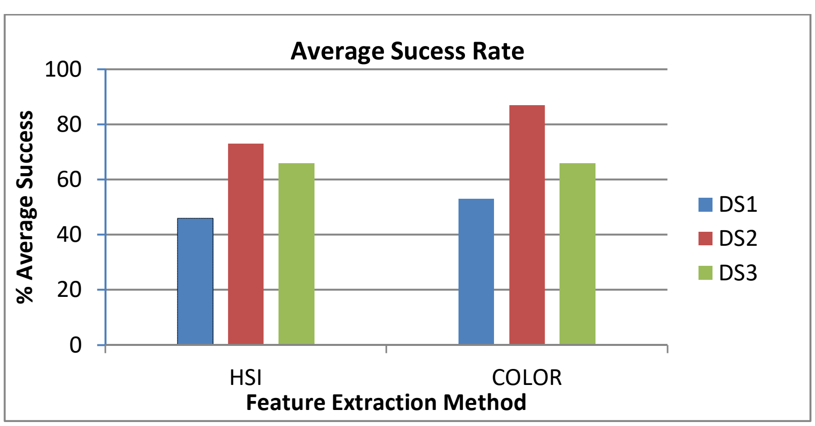

Fig. 5 Average Success Rate (%) with each feature

In this experiment classification accuracy is above 85 % using colour features and above 70 % using DWT based HSI features on small database.

Conclusion:

In this paper, it is proposed to have DWT based neural network classifier for flower classification. The neural network is trained using the backpropagation algorithm. Own database of flowers of 5 classes, each containing 10 flower images has been created. It has been found that MLP offers accuracy up to 87 % with the proposed algorithm.

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