Texture Features and KNN in Classification of Flower Images

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ABSTRACT
In this paper, we propose an algorithmic model for automatic classification of flowers using KNN classifier. The proposed algorithmic model is based on textural features such as Gray level co-occurrence matrix and Gabor responses. A flower image is segmented using a threshold based method. The data set has different flower species with similar appearance (small inter class variations) across different classes and varying appearance (large intra class variations) within a class. Also, the images of flowers are of different pose with cluttered background under varying lighting conditions and climatic conditions. The flower images were collected from World Wide Web in addition to the photographs taken up in a natural scene. Experimental Results are presented on a dataset of 1250 images consisting of 25 flower species. It is shown that relatively a good performance can be achieved, using KNN classifier algorithm. A qualitative comparative analysis of the proposed method with other well known existing flower classification methods is also presented.

General Terms
Pattern Recognition, Image Processing, Algorithms

Keywords
Flower segmentation, Gray Level Co-occurrence Matrix, Gabor Responses, Flower classification, K Nearest neighbor classifier.

1. INTRODUCTION
Developing a system for classification of flowers is a difficult task because of considerable similarities among different classes and also due to a large intra-class variation. In a real environment, images of flowers are often taken in natural outdoor scenes where the lighting condition varies with the weather and time. In addition, flowers are often more or less transparent and specula highlights can make the flower appear light or even white causing the illumination problem. Also, there is lot more variation in viewpoint, occlusions, scale 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 has become one of the important commercial trades in agriculture owing to steady increase in demand of flowers. Floriculture industry comprises of 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 very essential Further, flower recognition is used for searching patent flower images to know whether the flower image applied for patent is already present in the patent image database or not [5]. Since these activities are being done manually and it is mainly labor dependent and hence automation is necessary.

We can find a couple of works carried out in this direction. Nilsback and Zisserman [1] designed a flower classification system by extracting visual vocabularies which represent color, shape and texture features of flower images. In order to segment a flower from the background, the RGB color distribution is determined by labeling pixels as foreground and background on a set of training samples and subsequently the flower is automatically segmented using the concept of interactive graph cuts for optimal boundary and the region segmentation [2]. In order to extract color vocabulary, each flower image is mapped onto HSV color space and HSV values of each pixel of training images are clustered and treated as color vocabulary. Shift invariant feature transform (SIFT) descriptors are used to represent the shape features and responses of MR8 filter bank in different orientations are used as texture features. Also the authors use the combination of all the three visual vocabularies with different weights in order to study the effect of different features. Nilsback and Zisserman[1] considered a dataset of 17 species each containing 80 images and achieved an accuracy of 71.76 for combination of all the three features. In order to study the effect of classification accuracy on a large data set, Nilsback and Zisserman in their work [3] 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% using SVM classifier using multiple kernels. Nilsback and Zisserman [4] proposed a two step model to segment the flowers in color images, one to separate foreground and background and another model 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. Das et al., [5] proposed an indexing method to index the patent images using the domain knowledge. The flower was segmented using iterative segmentation algorithm with the domain knowledge driven feedback. In their work the image color is mapped to names using ISCC-NBS color system and X Window system. Each flower image is discretized in HSV color space and each point on the discretized HSV space is mapped to a color name in ISCC-NBS and X Window system in order to index the flowers. Yoshioka et al., [7] performed quantitative evaluation of petal colors using principal component analysis. They considered first five principal components (PC) of a maximum square on the petals. The quantitative evaluation indicates that the different PCs correspond to different color features of petals such as color depth, difference in color depth in upper and lower parts of the image etc**.** Varma and Ray [10] proposed a method for learning the trade-off between invariance and discriminative power for a given classification task. They learn the optimal, domain-specific kernel as a combination of base kernels corresponding to base features which achieve different levels of trade-off such as rotation invariance, scale invariance, affine invariance, etc. Knowledge of the trade-off can directly lead to improved classification such knowledge can also be used to perform analogous reasoning where images are retrieved on the basis of learnt invariance's rather than just image content. The classification is carried out on the basis of vocabularies of visual words of shape, color and texture descriptors. The background in each image is removed using graph cuts. Shape distances between two images are calculated as the χ^2 statistic between the normalized frequency histograms of densely sampled, vector quantized SIFT descriptors of the two images. Similarly, color distances are computed over vocabularies of HSV descriptors and texture over MR8 filter responses. An entire set of weights is learnt, spanning the full range from shape to color. Saitoh et al., [6] in their work describes an automatic method for recognizing a blooming flower based on a photograph taken with a digital camera in natural scene. They have also proposed a method for extracting flowers regions. It is based on "Intelligent Scissors" [11], which find the path between two points that minimizes a cost function dependant on image gradients. The method works under the assumption that the flower is in focus and in the centre of the photograph and that the background is out of focus. Under this assumption the cost between any two points on the flower is smaller than the cost between a point in the background and a point in the foreground. The midpoint of the image is used as the starting point to identify the flower region. This method requires no prior color information. Saitoh et al., [12] designed a flower classification system in which authors have used flower and leaves of plant. The authors have extracted features from both flower and leaves and have used piecewise linear discrimant analysis for recognition. Saitoh et al., [12] considered a dataset of 34 species each containing 20 sets of wild flowers.

Nilsback and Zisserman [1] noted that color and shape are the major features in flower classification. This is true only when the considered flower classes have less intra class variation. However, if there is a large variation within the class where the species of same types have different colors then color may not be the best suitable feature. Hence in this work we investigate the suitability of texture features in designing a system for flower classification. Flower is segmented using a threshold based method and texture features viz., Gray Level Co-occurrence Matrix(GLCM) and Gabor responses. In Gray Level Co-occurrence Matrix, feature such as contrast, energy, correlation and homogeneity are taken into account. In Gabor analysis we have extracted first three moments of each of the Gabor responses obtained for different scales and orientations. These features are used for training and classification using K-nearest neighbor classifier**.**

The organization of the paper is as follows. In section 2 the proposed method is explained with a neat block diagram along with a brief introduction to GLCM and Gabor texture analysis. The experimental results under varying database size are discussed in section 3 and the paper is concluded in section 4.

2. PROPOSED METHOD

The proposed method has training and classification phases. In training phase, from a given set of training images the texture features (GLCM / Gabor / Combination) are extracted and used to train the system using the K-nearest neighbor classifier. In classification phase a given test flower image is segmented and then the above mentioned texture features are extracted for classification. These features are queried to K-nearest neighbor classifier to label an unknown flower. The block diagram of the proposed method is given in Figure 1

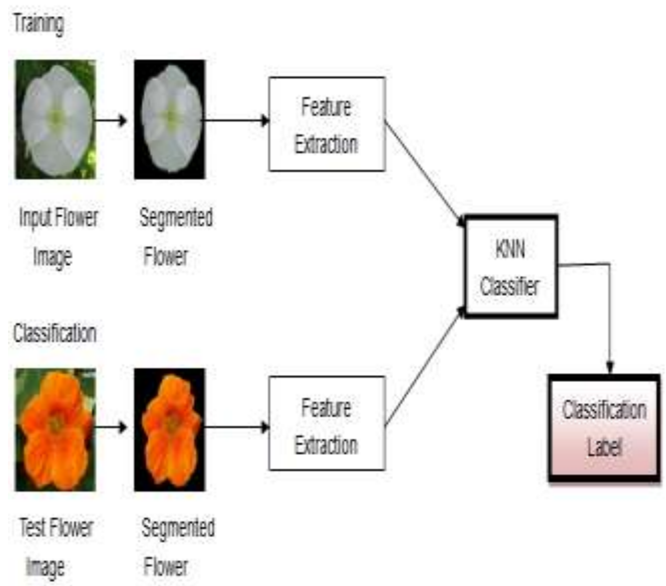

Figure 1. Block diagram of the proposed method using KNN

2.1 Flower Segmentation

The first step in flower classification is to segment the flower image. Segmentation subdivides an image into its constituent parts or objects. The level to which this subdivision is carried depends on the problem being solved. That is segmentation should stop when the objects of interest in an application have been isolated. In general, autonomous segmentation is one of the most difficult tasks in image processing. Flowers in images are often surrounded by greenery in the background. Hence, the background regions in images of two different flowers can be very similar. In order to avoid matching the green background region, rather than the desired foreground region, the image is segmented. We segment the flower image using threshold based segmentation algorithm [8]. A given image is transformed to HSV plane and intensity histogram corresponding to each channel is extracted. The histogram intensity values corresponding to two dominant regions belonging to background and flower are identified. Based on this intensity values the flower is segmented. Figure 2, shows the results of the flower segmentation using threshold based method on a few set of images with cluttered background.

2.2 Feature Extraction

As our interest is to study the statistics of texture features useful for flower classification, from a segmented flower image we propose to extract Gray Level Co-occurrence Matrix [9] and moments of Gabor responses. An introduction to GLCM and Gabor texture features are given in the flowing subsection.

2.2.1 Gray Level Co-occurrence Matrix (GLCM)

Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity at a pixel of interest. First proposed by Haralick et al., [9] in 1973, they characterize texture using a variety of quantities derived from second order image statistics. Co- occurrence texture features are extracted from an image in two steps. First, the pairwise spatial co-occurrences of pixels separated by a particular angle and distance are tabulated using a gray level co-occurrence matrix (GLCM). Second, the GLCM is used to compute a set of scalar quantities that characterize different aspects of the underlying texture. The GLCM is a tabulation of how often different combinations of gray levels co-occur in an image or image section [9]. The GLCM is a $N \times N$ square matrix, where N is the number of different gray levels in an image. An element $p(i, j, d, \theta)$ of a GLCM of an image represents the relative frequency, where *i* is the gray level of the pixel *p* at location *(x, y)*, and *j* is the gray level of a pixel located at a distance *d* from *p* in the orientation θ. While GLCMs provide a quantitative description of a spatial pattern, they are too unwieldy for practical image analysis. Haralick et al., [9] thus proposed a set of scalar quantities for summarizing the information contained in a GLCM. He originally proposed a total of 14 quantities, or features; however, typically only subsets of these are used[13]. The following five GLCM derived features are now described in Table 1 such as contrast, homogeneity, energy, entropy and correlation are extracted.

2.2.2 Gabor Filter Response

Texture analysis using filters based on Gabor functions falls into the category of frequency-based approaches. These approaches are based on the premise that texture is an image pattern containing a repetitive structure that can be effectively characterized in a frequency domain, such as the Fourier domain. One of the challenges, however, of such an approach is dealing with the tradeoff between the joint uncertainty in the space and frequency domains. Meaningful frequency based analysis cannot be localized without bound. An attractive mathematical property of Gabor functions is that they minimize the joint uncertainty in space and frequency. They achieve the optimal tradeoff between localizing the analysis in the spatial and frequency domains[13].The Gabor filter is a linear filter whose impulse response is defined by a harmonic function multiplied by a Gaussian function. Because of the multiplication-convolution property (Convolution theorem), the Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function and it is given by.

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda} + \psi\right)$$

Where $x' = x\cos\theta + y\sin\theta$ and $y' = x\sin\theta + y\cos\theta$

and, λ represents the wavelength of the cosine factor, θ represents the orientation of the normal to the parallel stripes of a Gabor function, ψ is the phase offset, σ (sigma) is the Gaussian envelope and γ is the spatial aspect ratio specifying the ellipticity of the support of the Gabor function. A filter bank of Gabor filters with various scales and rotations is created. In this work we have considered scales of 0, 2, 4, 6, 8, 10 and orientations of $0^\circ, 45^\circ, 90^\circ$ and 135°. For each obtained response image we extract first three moments as features.

Table 1. Different GLCM features

Homogeneity	$\sum_{i,j} \frac{p(i, j)}{1 + \lvert i - j \rvert}$
Entropy	$\sum_{i,j=0}^{N-1} -\ln(P_{i,j})P_{i,j}$
Contrast	$\sum_{i,j} \lvert i - j \rvert^2 p(i, j)$
Correlation	$\sum_{i,j} \frac{(i - \mu_i)(j - \mu_j)\vec{p}(i, j)}{\sigma_i \sigma_j}$
Energy	$\sum_{i,j} p(i, j)^2$

2.3 Classification

The problem of flower classification is a large and complex one, it makes sense to first try a simple method to see what performance can be achieved. We have used k-nearest neighbor approach as a classifier in this work. An object is classified by a majority vote of its neighbors, with the object being assigned to the class which is most common amongst its *k* nearest neighbors. The motivation for this classifier is that patterns which are close to each other in the feature space are likely to belong to the same pattern class. The neighbors are taken from a set of samples for which the correct classification is known. It is usual to use the Euclidean distance, though other distance measures, such as the City block, Cosine distances could be used instead. In this work we have used three different distance measures viz., Euclidean, City block and Cosine distance measure to study the effect on classification accuracy.

Figure 2. Segmentation results on few sample images (a) Input images (b) Segmented images

3. EXPERMENTATION RESULTS

3.1 Datasets

In this work we have created our own database despite of existence of other databases as these are less intra class variations or no change in view point. We collected flower images from World Wide Web in addition to taking up some photographs of flowers that can be found in and around our place. The images are taken to study the effect of the proposed method with large intra class variations. The dataset consists of 25 species of flowers with 50 images of each. The images are rescaled to the size 250×250. Fig. 3(a) shows a sample image of each 25 classes; Fig. 3(b) presents few samples of randomly selected flower classes. It is clearly understandable that there is a large intra class variations. The large intra-class variability and the small inter-class variability make this dataset very challenging.

3.2 Results

An experimentation has been conducted on databases of 15, 20, and 25 classes with varying training samples from 20 to 40 with a step of 1 per class. We study the classification accuracy under varying K using the K-nearest neighbour classifier. For experimentation we have considered three different distance measures (i) Euclidean (ii) Cosine (iii) City block distances. In order to study the effect of the size of the database, we have conducted an experiment under varying database size, 15, 20 and 25 classes. For each database size and the distance measure used the K-nearest neighbour classifier is applied with different K-values. Figure 4 shows how the k has been chosen for combined features (GLCM+Gabor) for 15 classes as an example. The best selected classification accuracies obtained for selected 'k' for all the three features and for different distance measure respectively Euclidean, Cosine, Cityblock are shown in figure 5, 6 and 7. The corresponding results are tabulated in Table 2, Table 3 and Table 4 respectively with respect to varying class size.

3.3 Comparison with pervious work

In order to corroborate the effectiveness of the proposed method with the other well known methods in the literature we have carried out a qualitative comparative analysis of the results on our data set. The comparative analysis can be seen in Table 5. We compare the performance of our method on the 17 class flower dataset which was introduced in [1]. In [1], the features are visual word histograms of color, shape and texture. The nearest neighbor classifier using a weighted distance on the three histograms has given a recognition rate of 71.76%. Using the same features, but a multiple kernel classifier, [10] achieves a recognition performance of 82.55 %, showing that this is a superior classifier. Same Process is repeated using the iterative segmentation scheme used in the paper [4]. The weights are again optimized as in [1]. This gives a recognition performance of 73.14 %. Again performance is improved by using a multiple kernel classifier, which gives a recognition performance of 83.33%. Finally, using the features computed in the paper [3] and the multiple kernel classifier leads to a performance of 88.33%. This is the best performance to date reported on the 17 class flower dataset. We compare the performance of our method with 103 flower class dataset which was introduced in [3]. In [3], contains four different features for the flowers, each describing different aspects, namely the local shape/texture, the shape of the boundary, the overall spatial distribution of petals, and the color. All the features are combined using a multiple kernel framework with a SVM classifier. The weights for each class are learnt using the method of Varma and Ray [10]. Results show that 55.1% for the best single feature to 72.8% for the combination of all the features. Although in this paper we present the results on the full 1750 image dataset consisting of 50 images for each of 25 categories. The GLCM features achieve a maximum performance of 90.13% with Euclidean distance measure and being k=12 for KNN classifier and the Gabor features achieve a performance of 79.80% with city block distance measure were k=10 and combination of GLCM and Gabor achieve the performance of 98.88% with Euclidean distance measure were k=5. The experimentation has been conducted for 20 training samples and 30 testing samples.

4. CONCLUSION

In this paper we have proposed a texture based flower classification method. In this work we have considered two different texture features viz., Gray level co-occurrence and Gabor response based features and KNN classifier for classification. Also we have created our own database of flowers of 25 classes each containing 50 flower images. To conduct the experimentation we have considered different size of database and studied the effect on classification accuracy. The experimental results have shown that the combined features outperform the individual features. The important thing to be noted in this work is that only texture features have given a good classification accuracy when compared to other results available in the literature. Study of different features viz., color, shape, and other texture features will be our future target. We also intend to study the effect of color, shape features along with the combination with texture features assigning weights to different features at querying time.

5. REFERENCES

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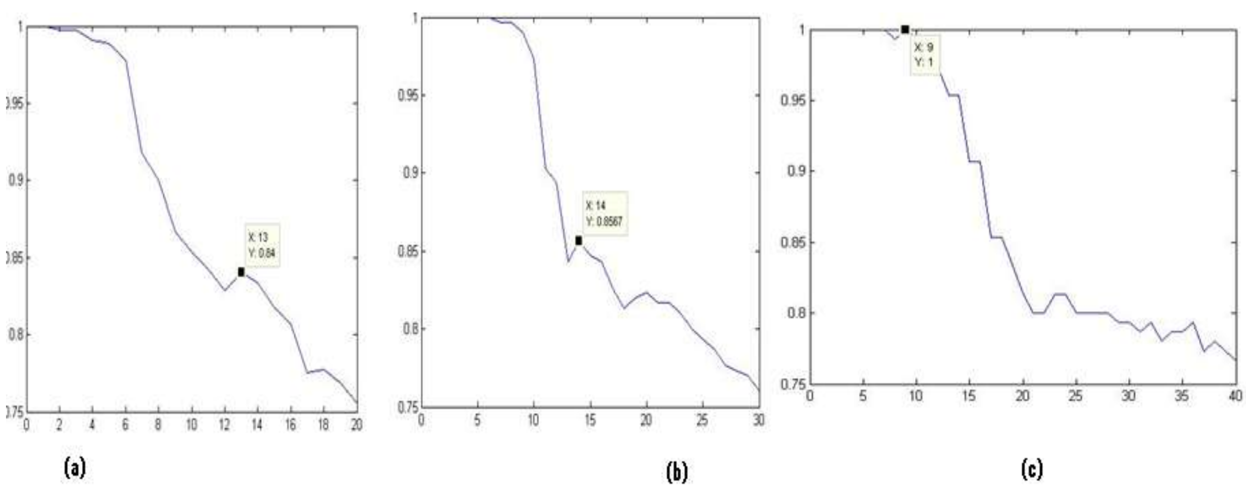

Figure 4: Classification accuracies of the proposed method with varying k

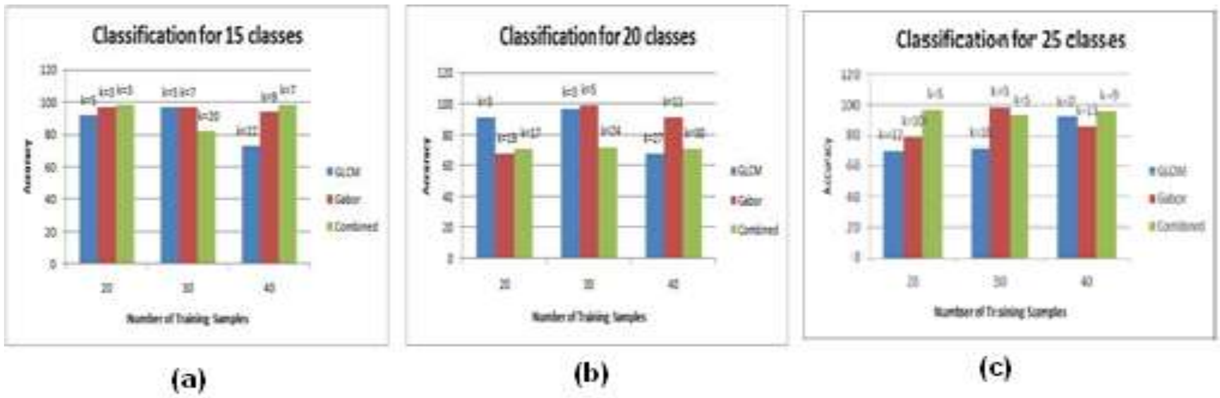

Figure. 5. Classification accuracy for different features by varying training samples using Euclidean distance (a) for 15 classes (b) for 20 classes (c) for 25 classes

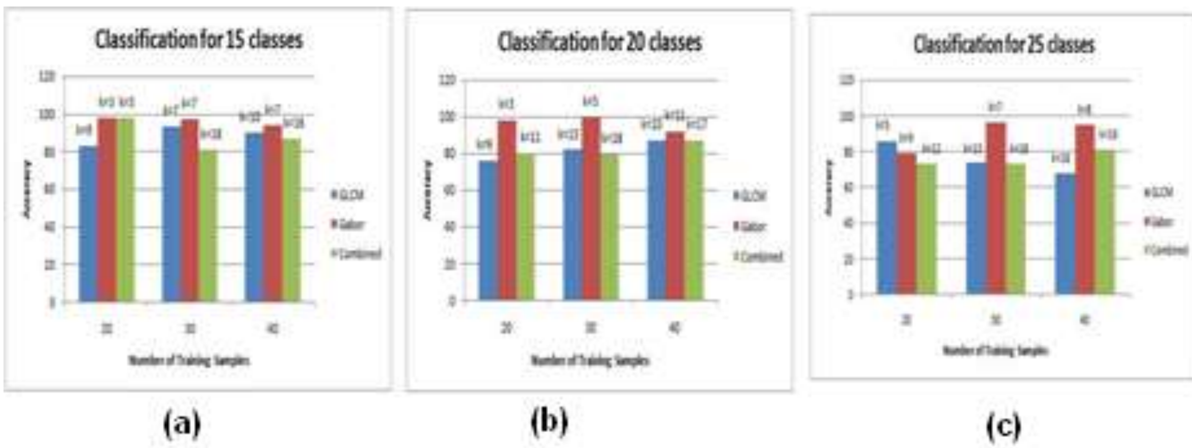

Figure. 6. Classification accuracy for different features by varying training samples using cosine distance (a) for 15 classes (b) for 20 classes (c) for 25 classes

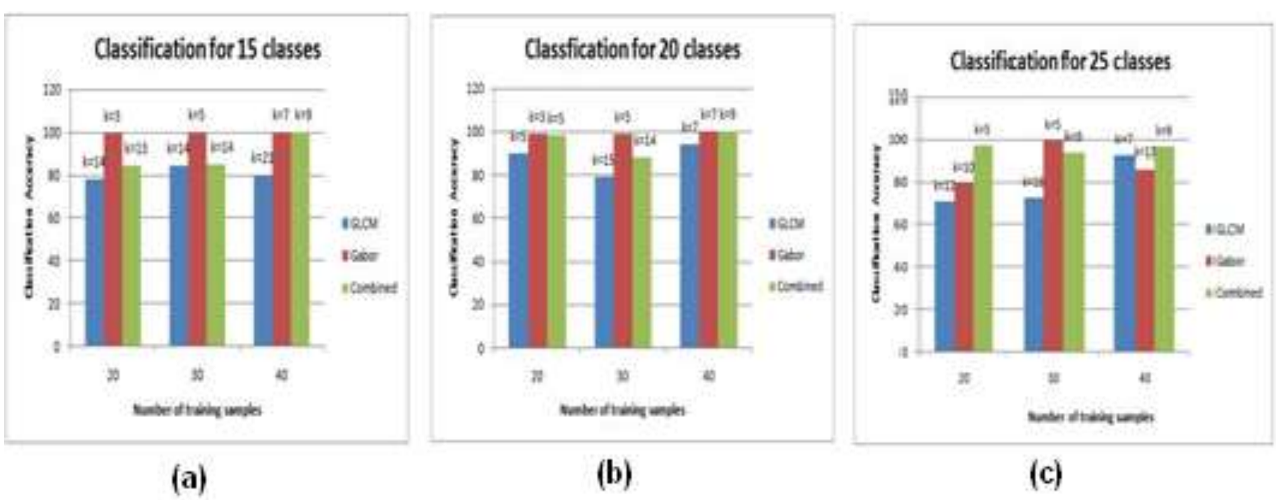

Figure. 7. Classification accuracy for different features by varying training samples using city block distance (a) for 15 classes (b) for 20 classes (c) for 25 classes

Table 2: The different distance measures for 15 classes

Training samples	Method	City block		Euclidean		Cosine	
		K	Accuracy	K	Accuracy	K	Accuracy
20	GLCM	14	76.17	05	92.44	09	80.67
	Gabor	03	99.83	03	97.78	03	98.67
	Combine	03	85.83	03	98.67	03	98.89
30	GLCM	14	81.25	05	97.00	07	93.33
	Gabor	05	99.75	07	97.00	07	97.33
	Combine	14	85.25	20	82.00	08	81.67
40	GLCM	21	79.50	22	73.33	10	90.00
	Gabor	07	100.00	09	94.00	07	94.00
	Combine	09	100.00	07	98.67	16	87.33

Table 3: The different distance measures for 20 classes

Training samples	Method	City block		Euclidean		Cosine	
		K	Accuracy	K	Accuracy	K	Accuracy
20	GLCM	05	90.17	03	91.55	09	76.83
	Gabor	03	99.83	18	68.67	03	98.33
	Combine	05	98.83	17	71.00	11	80.83
30	GLCM	15	79.25	03	97.55	13	82.25
	Gabor	05	99.75	05	99.00	05	99.75
	Combine	14	88.25	24	72.00	18	79.25
40	GLCM	07	94.50	27	68.55	10	87.55
	Gabor	07	100.00	11	91.00	11	92.00
	Combine	09	100.00	30	71.00	17	87.00

Table 4: The different distance measures for 25 classes

Training samples	Method	City block		Euclidean		Cosine	
		K	Accuracy	K	Accuracy	K	Accuracy
20	GLCM	12	70.00	**12**	**90.13**	05	86.93
	Gabor	**10**	**79.80**	10	78.88	09	79.33
	Combine	05	97.73	**05**	**98.88**	12	73.33
30	GLCM	16	72.60	**16**	**95.66**	13	74.20
	Gabor	**05**	**99.00**	05	98.44	07	96.88
	Combine	**09**	**93.40**	05	71.66	18	73.00
40	GLCM	**07**	**92.80**	07	68.88	18	68.44
	Gabor	13	86.80	13	94.88	**08**	**95.66**
	Combine	09	96.00	**09**	**97.66**	16	81.66

Table 5: Qualitative Comparison with other well known methods of flower classification

Title	Species	Size	Features	Classifiers		Accuracy in %
A Visual Vocabulary for Flower Classification [1]	17	1360	1. Color Vocabulary 2. Shape Vocabulary 3. Texture Vocabulary 4. Combined Vocabulary	Nearest Neighbor Classifier		**71.76**
Automated flower classification over a large number of classes [2]	103	8189	1. Color 2. SIFT on the foreground region 3. SIFT on the foreground boundary 4. Histogram of Gradients	Support Vector Machine		**72.8**
Learning The Discriminative Power-Invariance Trade-Off [10]	17	1360	1. Color Vocabulary 2. Shape Vocabulary 3. Texture Vocabulary 4. Combined Vocabulary	Multiple Kernel Classifier		**82.55**
Proposed Method (20 Training images per class)	25	1750	Method	Distance	K	
			GLCM	**Euclidean**	**12**	**90.13**
			Gabor	**City Block**	**10**	**79.80**
			GLCM + Gabor	**Euclidean**	**05**	**98.88**

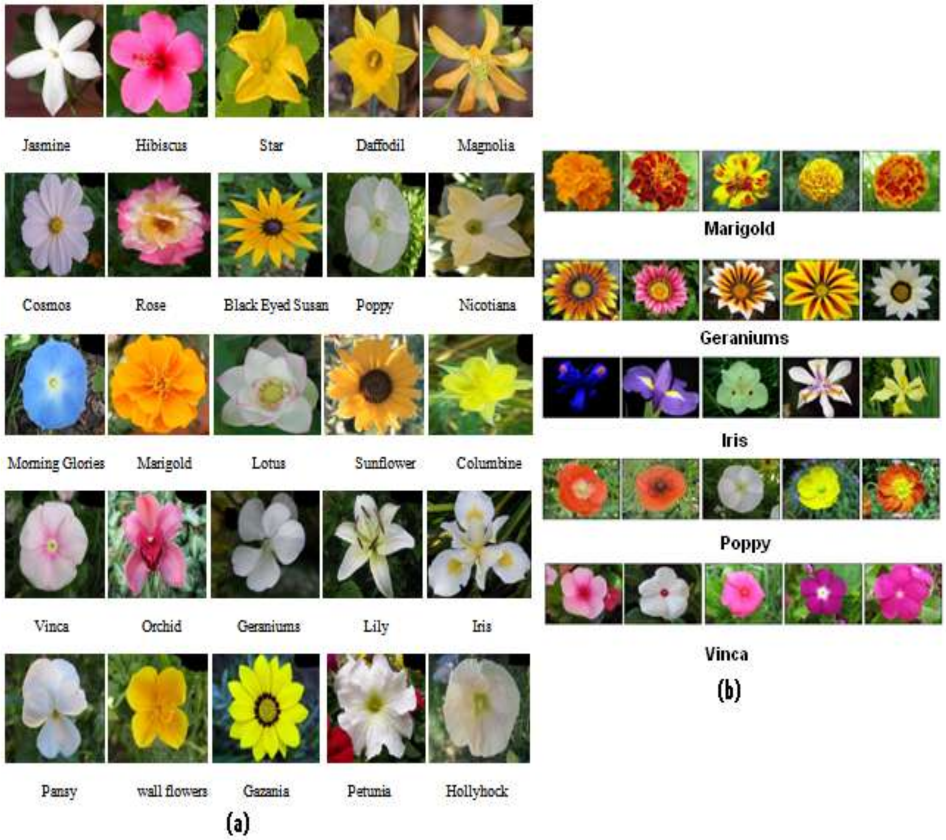

Figure 3. (a) Sample flower images of 25 flower classes. (b) Samples images of five different classes depicting large intra class variations