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Classification Framework for an flower Image Retrieval System

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Ms.S.Krishnaveni M.Sc.,M.Phil.,(Ph.D.)

Research Scholor, Mother Teresa Women's University, Kodaikanal, TamilNadu, India

Dr.A.Pethalakshmi

Associate Professor & Head, Dept. of Computer Science, M.V.M. Govt. Arts College for Women, Dindigul, Tamilnadu, India

ABSTRACT

In this paper, to analyze a new pattern classification model for classifying the quality of jasmine flower images using K-Nearest Neighbor (KNN) classifier. A flower image is segmented using a threshold based method. The data set has different jasmine flower species with similar appearance across different classes and varying appearance within a class. Also, the images of flowers are of different posing with a cluttered background under varying lighting conditions and climatic conditions. However, even when an image is sufficient, classifying a flower may still need a guidebook because with advances in digital and mobile technology it is easy to capture pictures of flowers, but it is still difficult to find out what they are. In order to know the name of a flower find more information about a flower on the web, but the link between obtaining an image of a flower and acquiring its name is missing. To assume that a training set of jasmine flower images with known class labels is available. However use an easy-to-compute low-level feature, banded color correlograms, which has been shown to be effective and efficient for content-based image retrieval.

I. INTRODUCTION

The objective of the work is to classify quality of jasmine flowers from images. The term image classification refers to the labeling of images into one of a number of predefined categories. Most of the systems generate low-level image features such as color, texture, shape, motion, and so forth, for image indexing and retrieval. This is partly because low level features (e.g., color histograms, texture patterns) can be computed automatically and efficiently. However, the semantics of images, with which users prefer most of their interaction, are seldom captured by low-level features. Currently, there is no effective method to automatically generate good semantic features of an image. One common compromise is to obtain some semantic information through manual annotations. 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.

A common approach to image classification involves addressing the following three issues: (i) how to represent an image, (ii) how to organize the data, and (iii) how to classify an image. Acquiring "nice" features and carefully modeling, the feature data are vital steps in this approach. Common features include color, texture, and shape information of an image. Some also integrate visual information and text accompanying an image.

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. 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. As flowers of different classes are more similar, developing a system to classify flower images is a very challenging task. Additionally, flower images captured in a real time, poses a number of challenges like variations in viewpoint, scale, illumination, partial occlusions, multiple instances etc. All these challenges need a very sophisticated algorithm to classify flowers. Also, the cluttered background makes the problem more difficult, to classify the flower image from the background. Moreover, the greatest challenge lies in preserving the intra-class and inter-class variabilities. The floriculture has become one of the important commercial trades in agriculture owing to steady increase in demand of flowers.

II. CLASSIFICATION

A. Image Classification

One approach to this problem is to organize the digital library in a meaningful manner using image classification. Image classification is the task of classifying images into (semantic) categories based on the available training data. This categorization of images into classes can be helpful both in semantic organizations of digital libraries and in obtaining automatic annotations of images. The classification of natural imagery is quite hard in general, for, real images from the same semantic class may have large variations and images from different semantic classes might share a common background (such as images from "clouds" and "aviation", images from "waves" and "dolphins.

Classification of flowers has majorly three stages viz., segmentation, feature extraction and classification. Before extraction of features from a flower image, the flower has to be segmented. The goal is to segment out the flower given only that the image is known to contain a flower, but no other information on the class or pose. In second step, different features are chosen to describe different properties of the flower. Some flowers are with very distinctive shapes, some have very distinctive color, some have very characteristic texture patterns, and some are characterized by a combination of these properties.

Finally extracted features are used to classify the flower. 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.

B. Objective

The major objective of this paper is to develop a novel personalized modeling framework and system to select and optimize the most significant features and the optimal number of nearest neighbors for a single input sample, corresponding to a certain problem, based on a weighted variable distance measure. The novel framework and system might provide more accurate performance and more precise personalized knowledge when compared with the global modeling and local modeling approaches.

III. RELATED WORK

Classification of flowers has majorly three stages viz., segmentation, feature extraction and classification. Before extraction of features from a flower image, the flower has to be segmented. The goal is to segment out the flower given only that the image is known to contain a flower, but no other information on the class or pose. In second step, different features are chosen to describe different properties of the flower. Some flowers are with very distinctive shapes, some have very distinctive color, some have very characteristic texture patterns, and some are characterized by a combination of these properties. Finally extracted features are used to classify the flower. 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 [2]. K-Nearest Neighbor (KNN) is one of the most popular algorithms for pattern recognition. Many researchers have found that the KNN algorithm accomplishes very good performance in their experiments on different data sets. The traditional KNN text classification algorithm has three limitations: (i) calculation complexity due to the usage of all the training samples for classification, (ii) the performance is solely dependent on the training set, and (iii) there is no weight difference between samples [1].

In pattern recognition field, KNN is one of the most important non-parameter algorithms and it is a supervised learning algorithm. The classification rules are generated by the training samples themselves without any additional data. The KNN classification algorithm predicts the test sample's category according to the K training samples which are the nearest neighbors to the test sample, and judge it to that category which has the largest category probability. In the filter model, feature selection and the classifier learning are separated in a feature subset, which means features are first selected and then the classification model is induced, based on the selected features. This type of feature selection approach is independent of any machine learning algorithms

The training process for KNN consists only of storing the feature vectors and class labels of the training samples. [2] One major problem to using this technique is the class with the more frequent training samples would dominate the prediction of the new vector, since them more likely to come up as the neighbor of the new vector due to their large number. 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.

Performance of a nearest neighbor classifier depends on the distance function and the value of the neighborhood parameter k. Euclidean metric is the most popular choice for the distance function. Of course, if the measurement variables are not of comparable units and scales, it is more meaningful to standardize the variables before using the Euclidean distance for classification. The neighborhood parameter k, which controls the volume of the neighborhood and consequently the smoothness of the density estimates, plays an important role on the performance of a nearest neighbor classifier [3]. The author 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 [4].

The author 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 [5].

The author 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 [7].

IV. 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 [6]. 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. 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.

The aim is to obtain a classifier which is discriminative enough between classes, but also is able to classify correctly all instances of the same class. It needs to be able to represent and learn that to discriminate a sunflower from a daisy, color is a useful cue but shape would be quite poor. Conversely, to differentiate a buttercup from a dandelion, shape would be much more useful, but color would not.

The author proposed a structure-based flower image recognition method. The genetic evolution algorithm with adaptive crossover and mutation operations was employed to tune the learning parameters of the Back propagation Through Structures algorithm [8]. A region based binary tree representation whose nodes correspond to the regions of the flower image and links represent the relationships among regions was constructed to represent the flower image content. Experimental results showed that the structural representation of flower images can produce a promising performance for flower image recognition in terms of generalization and noise robustness. In fact, the classification accuracy of the system depends on the selection of the feature values.

The author proposes a new representation for images. Each image is thought to consist of several blobs; each blob is coherent in color and

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texture space.2 All the blobs in the training data of 14 image categories are clustered into about 180 "canonical" blobs using Gaussian models with diagonal covariance. Each image is then assigned a score vector which measures the nearest distance from each canonical blob to the image. These score vectors are used to train a decision-tree classifier. The results of this method are compared to color histograms with the decision-tree classifier. Interestingly, the color histograms seem to perform better than blobs [9].

V. RESEARCH OVERVIEW

A. Support Vector Machine(SVM) Classifier

Review of support vector classifiers theory The way of constructing a hyperplane to get binary classifiers done that can separate members of one class from others, but most real data hardly separate because the hyperplane that can successfully separate the members of the two classes in most case does not exist. One measure to solve this problem is to map the data into a higher dimensional space, where the members of the two classes can separate by a hyperplane. However, the traditional classifier is not good at in high dimensional vector. It is extremely expensive in terms of memory and time Support Vector Machines can solve this problem. SVM avoid over fitting the data by choosing a hyperplane from the many that can separate the data. That maximizes the minimum distance from the hyperplane to the closest training point. Such a hyperplane call the maximum margin hyperplane. Another advantage of the SVM is the compact representation of the decision boundary, so the number of support vectors is small as compared to the number of points in the training set.

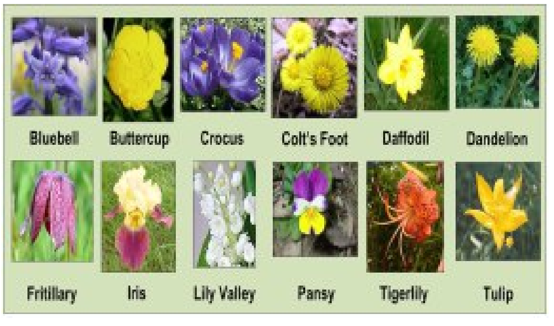

Fig: 1 Flower Categories

This data set consists of 17 species of flowers with 80 images in each category and a total of 1,360 images. All the images are in color in JPEG format and the average image size of each image is 560x560 pixels. There are species that have a very unique visual appearance, For example Fritillaries and Tigerlilies, as well as species with very similar appearance, for example Dandelions and Coltsfoot. There are large viewpoint, scale, and illumination variations. The large intra-class variability and the small inter-class variability make this data set very challenging. The flower categories are deliberately chosen to have some ambiguity on each aspect.

B. Learning and classification stage

Learning the semantics for each class through using SVM based on different features of training sample regions of each class. These binary classifiers achieve good class separation under the constraint that each region belongs to only one, or none, of the classes. After training the SVM, binary classifiers that can classify image regions based on their semantics create. In the semantic class hierarchy, all scenery regions are classified into Nature regions or Artificial regions. Since in this paper we concentrate on Nature regions, thus we further classify the Nature regions into three subclasses: Sky, Land and Water, Each one of these subclasses further divided into sub-subclasses. The Sky subclass divided into Night, Sunset, Clouds and Blue-sky. Next, the Water subclass divided into Waterfall, Blue Sea, White Wave and River. Then, the Land subclass divided into Mountain, Sand, Green ground, and Snow. The Green ground sub subclass further divided into Grass and Forest.

C. Classification

The aim is to obtain a classifier which is discriminative enough between classes, but also is able to classify correctly all instances of the same class. It needs to be able to represent and learn that to discriminate a sunflower from a daisy, color is a useful cue but shape would be quite poor. Conversely, to differentiate a buttercup from a dandelion, shape would be much more useful, but color would not. In this section first describe four features designed to represent the foreground flower regions, and then the linear.

Fig: 2 Background elimination of the flower image

The learning of different weights for different classes enables us to use an optimum feature combination for each classification. This allows us to incorporate, for example, that some classes are very similar in shape but different in color and that some classes are better distinguished by the overall shape than the internal shape and vice versa. The principal challenge now lies in the large variations within a class and the relatively few samples of images.

D. Inductive versus Transductive Reasoning Approaches

Most learning models in the area of artificial intelligence (AI) are developed and implemented, especially those employing neural fuzzy inference methods, based on either inductive inference or transductive reasoning approaches. Figure 3 graphically presents the differences between these two reasoning approaches. It can be seen that the transductive inference method is associated with both training and testing data in a problem space, while the inductive inference method has to induce a function from the training data first and then deduct the function and use it to predict the testing data.

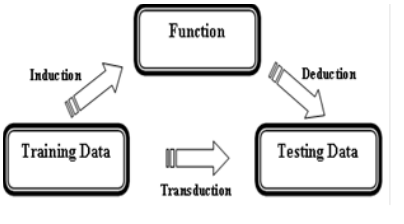

Fig: 3 Transductive Inference Model

E. Transductive Inference Method

It is defined as a method that evaluates the potential value of a model for only an individual point of the problem space by using additional information related to that single point. In contrast to the inductive inference approach, the transductive inference approach is more concerned with solving an individual given problem rather than solving a general problem.

VI. OVERVIEW OF FEATURE SELECTION METHODS

During the last few years, feature selection techniques in the machine learning field have motivated much study, and have become increasingly necessary to various bioinformatics applications especially. Nowadays, there are a growing number of applications for this technique in many different fields, such as data mining.

In general, a feature selection technique is defined as a fundamental step of the data mining process to find an optimal set of features, using certain learning algorithms from a given set of features. The primary goals of this technique are described as follows:

1. To improve classification or prediction accuracy.

2. To speed up and reduce the cost of learning stages.

3. To avoid over-fitting and improve classification or prediction model performance.

4. To reduce the dimensionality of the feature space and to indentify the relevant features to be applied for a successful classification or prediction task.

In order to efficiently and properly achieve the goals, the choice of an appropriate feature selection model, to describe a learning system and evaluate the performance of a feature subset, is regarded as an important decision in the domain of machine learning. In general, feature selection techniques are organized into two common models, depending on whether the machine learning algorithm is adopted as a part of the selection method: filter and wrapper, which are introduced in the following sections.

A. Filter Model

In the filter model, feature selection and the classifier learning are separated in a feature subset, which means features are first selected and then the classification model is induced, based on the selected features. This type of feature selection approach is independent of any machine learning algorithms. Figure 4 presents the basic structure of a simple filter model, where the feature selection process starts with a given training set characterized by the full feature set, and then various feature subsets are generated and evaluated by using the feature subset generator and evaluator. The final evaluation of a specific feature subset is accomplished by training and testing a specific classification model. Finally, ultimate classification accuracy is estimated based on the test set.

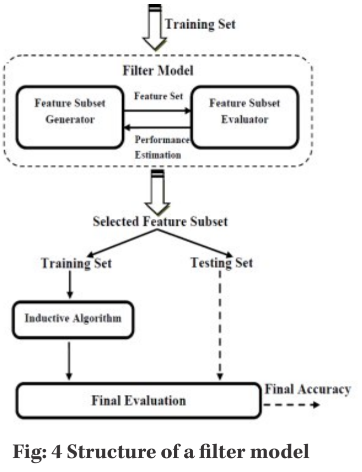

Fig: 4 Structure of a filter model

The filter model is one of the simplest and most commonly used feature selection techniques in microarray literature. The advantages of this model are that there is no machine learning process involved while feature selection occurs, and time consumption is much lower than the wrapper model. However, a major drawback of this model is that it ignores interaction with classifiers, thus classification performance is not optimal.

The principal type of filter model is the Signal-to-Noise Ratio (SNR) ranking procedure. SNR is a supervised method, which is defined as a calculated ranking number for each variable to identify how well this variable distinguishes two different classes. Moreover, it is able to efficiently reduce the dimensionality of a data set. The basic idea behind this approach is that begins with the evaluation of an individual gene and iteratively examines the informative genes in the rest of data set in terms of statistic criterion.

B. Wrapper Model

In the wrapper model, a feature subset procedure is defined, and various feature subsets are generated and evaluated using a feature subset generator and evaluator. The evaluation of a specific feature subset is accomplished by training and testing with a specific classification model. A search algorithm is then wrapped around the classification model to search the space of all feature subsets. The wrapper model is one of the simplest and most commonly used feature selection techniques in machine learning applications. In contrast to the filter model, the advantages of the wrapper model are that it has interactions with the classifier while selecting features, as well as providing more accurate performance than the filter model. However, the disadvantages of this model are that it is very computationally expensive when compared with the filter model, and the evaluation results heavily depend on the inductive algorithm.

C. Image segmentation

Image segmentation is a process of dividing an image into coherent, uncovered and significant regions. Generic, complete and to the pixel accurate unsupervised segmentation regard as it is virtually impossible. We just want to get a method to segment an image, which is satisfied with the following condition:

(1) First, the extracted regions are coherent.

(2) Segmentation should give satisfactory results on general image data without knowledge assumed.

(3) Segmentation process should be unsupervised.

In our experiment, we use hill-climbing method to segment the image, which can be satisfied with above condition.

The hill-climbing algorithm summarizes as follows:
(1) Compute the HSV color histogram of the image.

(2) Start at a non-zero bin of the color histogram and make uphill moves until reaching a peak.

(3) Choose another unclimbed bin and re-perform step 2 to find another peak. Repeat this step until all non-zero bins of the color histogram climbed.

(4) The peaks we get from above represent the first number of clusters of the input image, and, these peaks saved.

(5) In the end, neighboring pixels that have same peak put together, that is associating every pixel with one of the identified peaks. Consequently, the segments of the input image formed.

VII. IMPLEMENTATION

A. Layout of the Object

Attentive and non-attentive images have different layouts of objects.

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In an attentive image, some objects often lie at dominant locations while the others are located at less important locations. For example, for the first image shown in Fig. the flower as the main object is in the center of the image and the leaves, being the background, surrounds the flower. On the contrary, there are no dominant objects in the first image shown in Fig.5. All the objects, including the sky, the sea and the sand, have a similar priority. In summary, the overall arrangement of the objects, or the structure of the image is helpful to classify attentive and non-attentive images. Therefore, we use a tree structure scheme which organizes all the objects to represent an image.

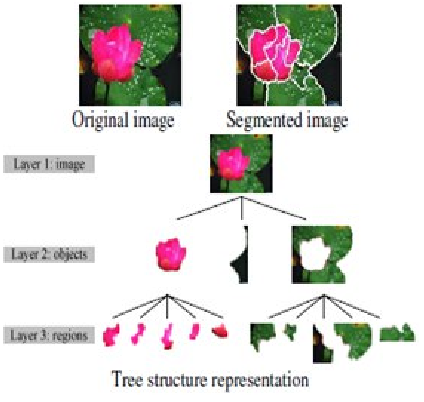

Fig: 5 Structure of a Image

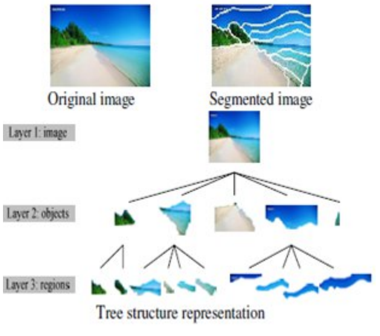

Fig: 6 Alternate Structure of a Image

Attention-driven image interpretation is applicable to both attentive and non-attentive images. The difference is that the objects extracted from the non-attentive images may not be the important ones. Based on the result of the attention-driven image interpretation, To construct a tree structure to represent the layout of an image. The tree structure has three layers: image layer, object layer and region layer. The bottom layer is the region layer, in which each node corresponds to one segmented region. The merged regions constitute the objects in the middle layer, in which each node represents one object, such as lotus, leaves, sand, sky, etc. Finally, the top layer is formed by combining all the objects into one whole image. This tree structure representation characterizes the overall arrangement of the objects and their regions.

The "direct" visual features such as color or texture cannot characterize the attentiveness of an image. Therefore, seven difference-based features f_1, f_2,..., f_7 to characterize each node in the tree structure.

f_1, f_2, f_3: relative attention values in terms of the boundary color matrix, region color matrix and texture matrix.

f_4, f_5 : normalized location of an item. F_4 and f_5 are the relative center coordination of an item.

The bottom-left corner of an image as (0, 0) and the top-right corner as (1, 1). The items near the center of an image are usually related to attentive objects while the items near the boundary of an image might be less attentive.

f_6 : normalized area of an item. Very small or very large items might not be an attentive object. The items of a reasonable size are more likely to be an important object.

f_7 : normalized length of outer-image boundary of an item.

In order to separate the attentive value into three feature components, including two color components and one texture component. The relative attention value represents the saliency between an item (object or region) and its surroundings, which are helpful for detecting attentive patterns.

$$f_7 = \frac{\text{length of outer - image boundary of the item}}{\text{length of outer boundary of the item}}$$

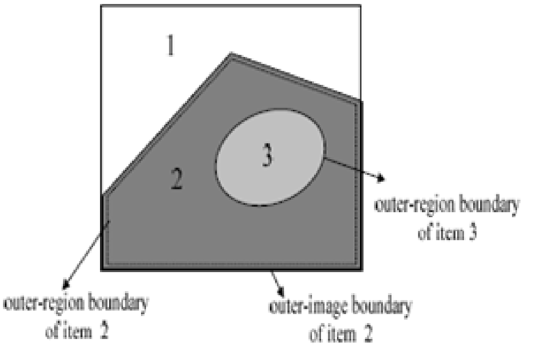

Fig: 7 Boundary Regions

The tree representation of attentive and non-attentive images is of an adaptive nature, meaning that the tree structure varies in different images. In order to classify attentive and non-attentive images, a special neural network and its training algorithm, called "Back Propagation through Structure (BPTS)" that can handle adaptive structural patterns is employed.

It is recognized that this neural network is able to generalize both the node features and the structural information encoded in the tree representation.

Table1 Classification Ratio

Number of hidden nodes	Classification rate (%)	
	On training set	On test set
5	84.6	84.4
10	85.9	82.4
15	85.6	84.9
20	86.5	84.7
25	86.5	84.4
30	86.0	83.9
35	86.8	84.8

Finally in this meta-classification module, an image is represented by an adaptive tree structure with each node carrying normalized features that characterize the object/region with visual contrasts and spatial information. Then a neural network is trained to classify an image as an "attentive" or "non-attentive" category by using the Back Propagation through Structure (BPTS) algorithm.

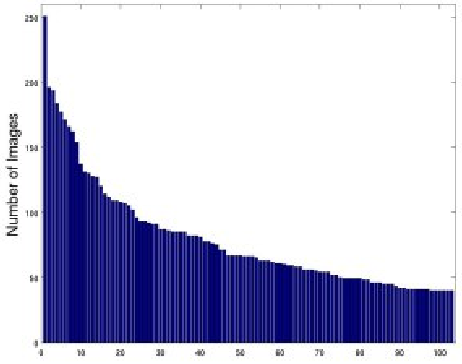

Fig 8 : The distribution of the number of images over the 103 classes.

The dataset is divided into a training set, a validation set and a test set. The training set and validation set each consist of 10 images per class (total 1030 images each). The test set consists of the remaining 6129 images (minimum 20 per class).

Conclusion

This paper was to develop a new classification modeling KNN classifier framework and system to select and optimize the most significant features and the optimal number of nearest neighbors for a single input sample, corresponding to a certain problem, based on a weighted variable distance measure. The goal of this paper was to improve classification or prediction accuracy. In jasmine image KNN classification phase a given test jasmine flower image is segmented and then the texture features are extracted for classification.

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