Linear Discriminative Analysis in Image Classification A fusing image classification algorithm is presented, which uses Bag-Of-Features model (BOF) as images' initial semantic features, and subsequently employs Fisher linear discriminative analysis (FLDA) algorithm to get its distribution in a linear optimal subspace as images' final features. Lastly images are classified by K nearest neighbour algorithm. The experimental results indicate that the image classification algorithm combining BOW and FLDA has more powerful classification performances. In order to further improve the middle-level semantic describing performance, we propose compressing the BOF distribution of images distributing loosely in high-dimensional space to a low-dimensional space by using FLDA, the images are classified in this space by KNN algorithm. Ajay Kumar Singh, ShamikTiwari& V.P. Shuklaetld[6] Wavelet based Multi Class image classification using Neural Network, A feature extraction and classification of multiclass images by using Haar wavelet transform and back propagation neural network. The wavelet features are extracted from original texture images and corresponding complementary images. The features are made up of different combinations of sub-band images, which offer better discriminating strategy for image classification and enhance the classification rate. Liping Jing Chao Zhang Michael K. Ng etld[3] SNMFCA: Supervised NMF-based Image Classification and Annotation A novel supervised nonnegative matrix factorization based framework for both image classification and annotation (SNMFCA). The framework consists of two phrases: training and prediction. In the training phrase, two supervised nonnegative matrix factorizations for image descriptors and annotation terms are combined together to identify the latent image bases, and represent the training images in the bases space. These latent bases can capture the representation of the images in terms of both descriptors and annotation terms. Based on the new representation of training images, classifiers can be learnt and built.Sancho McCann David G. Lowe etld[7] Local Naive Bayes Nearest Neighbor for Image Classification An improvement to the NBNN image classification algorithm that increases classification accuracy and improves its ability to scale to large numbers of object classes. The key observation is that only the classes represented in the local neighbourhood of a descriptor contribute significantly and reliably to their posterior probability estimates. LexiaoTian, DequanZheng, Conghui Zhu etld[8] Research on Image Classification Based on a Combination of Text and Visual Features A text-image co-occurrence data become available on the web, mining on those data is playing an increasingly important role in web applications. Utilizing description information to help image classification

III. SUPPORT VECTOR MACHINE AND RBF NETWORK:

Classification plays a big role in image classification. In this section of paper we discuss support vector machine classifier for classification purpose and radial bias network for feature optimisation of feature vector of input of classifier. The optimised feature generates a better result in compression of support vector machine classifier. SVMs are learning systems that use a hypothesis space of linear functions in a hyperspace [14], trained with a learning algorithm from optimization theory that implements a learning bias derived from statistical learning theory. The aim of Classification via SVM is to find a computationally efficient way of learning good separating hyper planes in a hyperspace, where 'good' hyper planes mean ones optimizing the generalizing bounds and by 'computationally efficient' we mean algorithms[16,19] able to deal with sample sizes of very high order. The basic problem that a SVM learns and solves is a two-category classification problem. Follow the method of Bennett's discussion (2000), suppose we have a set of l observations. Every observation can be represented by a pair $\{x_i, y_i\}$ where $x_i \in R^N$ and $y_i \in \{-1, 1\}$. That is, each observation contains an N-dimensional vector x and a class assignment y. Our aim is to find the optimal separating hyperplane; that is, the flat (N-1)-dimensional surface that best separates the data. For time being we assumed that a separating hyperplane exists, and is defined by normal vector w. On the either side of this plane we construct a pair of parallel planes such that:

$$w.x_i \geq b+1 \quad \text{for} y_i = 1$$
$$w.x_i \leq b-1 \quad \text{for} y_i = -1$$

where,$b$indicates the offset of the plane from the origin. This Often, a non-linear solution plane is required to separate data. To repeat the steps and maximize the separation between two non-linear functions can be computationally expensive [12,8]. Instead, the kernel trick is used: input data are mapped into a higher dimensional feature space via a specified kernel function. These data are linearly separable in the higher dimensional space. A method of accommodating errors and outliers in the input data was developed , and can be implemented simply by allowing an error of up to ξ in each dimension (resulting in a 'fuzzy margin') and adding a cost function C(i) to the optimization equation (Burges). We then want to minimize:

$$\frac{1}{2}\left||w|\right|^2 + C.\left(\sum \varepsilon_i\right)$$

Subject to the constraint:

$$yi(w.x_i - b) + \varepsilon_i \geq 1$$

This is substantially harder to solve than the separable case. In the Chang and Lin's LIBSVM manual, the constraints, minimization conditions and resulting decision functions are defined for each type of classification, along with algorithms to solving the required quadratic programming problems.A radial basis function (RBF) is a real-valued function whose value depends only on the distance from the origin. If a function 'h' satisfies the property $h(\mathbf{x})=h(||\mathbf{x}||)$, then it is a radial function. Their characteristic feature is that their response decreases (or increases) monotonically with distance from a central point. The distance scale, the centre, and the precise shape of the radial function are parameters of the model, all fixed if it is linear [5]. A typical radial function is the Gaussian which, in the case of a scalar input, is

$h(x) = \exp(-(x-c)^2)/r^2)$……..(1)

Its parameters are its centre c and its radius r.

A Gaussian RBF monotonically decreases with distance from the centre. In contrast, a multiquadric RBF which, in the case of scalar input monotonically increases with distance from the centre. Gaussian-like RBFs are local (give a significant response only in a neighbourhood near the centre) and are more commonly used than multiquadric-type RBFs which have a global Response. Radial functions are simply a class of functions. In principle, they could be employed in any sort of model (linear or nonlinear) and any sort of network (single-layer or multi-layer). RBF networks have traditionally been associated with radial functions in a single-layer network. In the Figure 4.4, the input layer carries the outputs of FLD function. The distance between these values and centre values are found and summed to form linear combination before the neurons of the hidden layer. These neurons are said to contain the radial basis function with exponential form. The outputs of the RBF activation function is further processed according to specific Requirements.

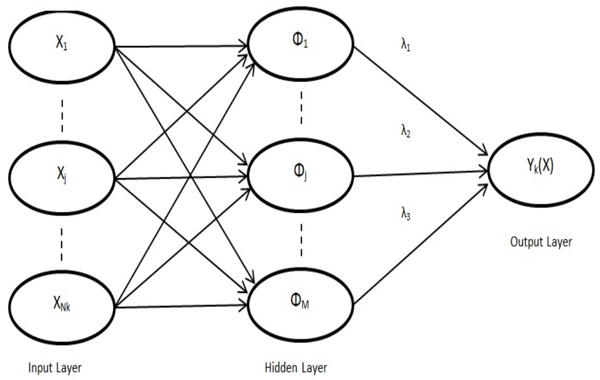

Figure 1.1.Structure of Radial Basis Function Neural Network.

In order to specify the middle layer of an RBF we have to decide the number of neurons of the layer and their kernel functions which are usually Gaussian functions. In this paper we use a Gaussian function as a kernel function. A Gaussian function is specified by its centre and width. The simplest and most general method to decide the middle layer neurons is to create a neuron for each training pattern. However the method is usually not practical since in most applications there are a large number of training patterns and the dimension of the input space is fairly large[8,9]. Therefore it is usual and practical to first cluster the training patterns to a reasonable number of groups by using a clustering algorithm such as K-means or SOFM and then to assign a neuron to each cluster. A simple way, though not always effective, is to choose a relatively small number of patterns randomly among the training patterns and create only that many neurons. A clustering algorithm is a kind of an unsupervised learning algorithm and is used when the class of each training pattern is not known. But an RBFN is a supervised learning network

IV. PROPOSED MODEL FOR IMAGE CLASSIFICATION BASED ON RBF NETWORK:

In this section we discuss the proposed model of image classification based on support vector machine and feature optimisation using radial bias network. Image feature selection process decides the performance of image classifier. We put the optimised feature sub set selection using radial bias network. The output of RBF network proceed input for support vector machine classifier. The basic idea of the proposed technique is to carry out the training process of the hidden layer of RBF neural classifiers by taking into account the class-memberships of the training samples. particularly, clusters are generated by grouping training samples belonging to the same class in order to avoid the creation of mixed clusters. Moreover, the widths of the kernel functions are selected by using a supervised procedure aimed at limiting the widths of kernels located in boundary regions between classes while maintaining, at same time, a certain overlapping inside the internal regions of each class. In the following, a detailed description of the proposed technique is provided. The complete description of model shown in figure.

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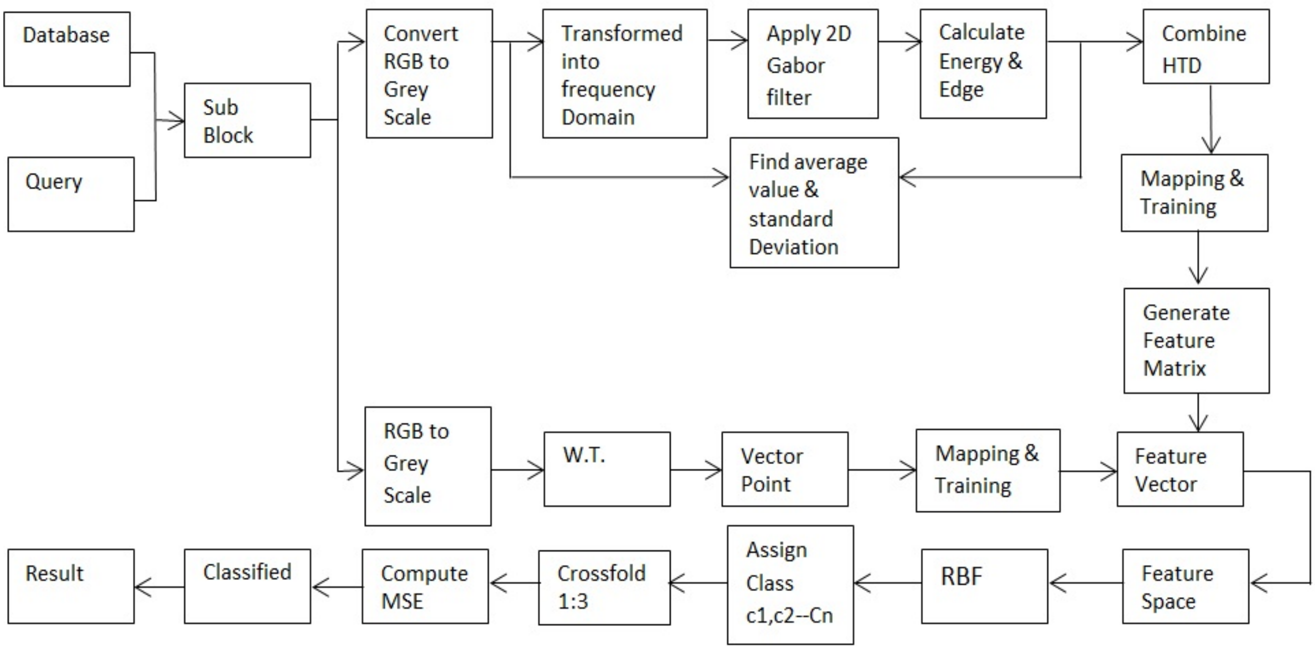

Figure 1.2 shows proposed model for image classification based on RBF network

V. IMPLEMENTATION DETAILS

In this section we implement methods for image classification using support vector machine with DAG and support vector machine with RBF network. We evaluated performance of our algorithm using a general-purpose image database containing 500 JPEG images with size of 256*256 or 256*384 pixels from COREL photo gallery. These images are divided into4 categories, and there are 100 images in each semantic category. We test the performance of; the retrieval performance is measured by precision and recall, they are defined below.

$$\text{Precision}=\frac{\text{number of relevant images retrieved}}{\text{number of images retrieved}} \quad \ldots\ldots (2)$$

$$\text{Recall}=\frac{\text{number of relevant images retrieved}}{\text{number of relevant images in database}} \quad \ldots\ldots (3)$$

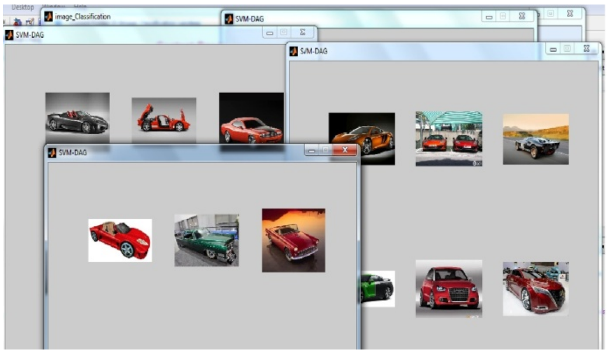

Figure 1.3 shows that the classified result of SVM-DAG method for 100 car image of 1000 database and accurate classified image is 30.

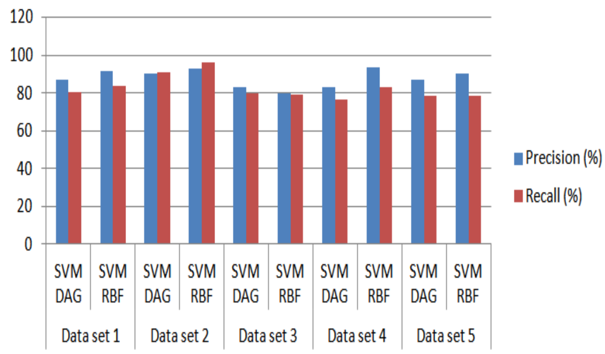

Figure 1.4 shows the comparative result analysis of SVM with DAG and RBF network. The classification performance is better than SVM-DAG.

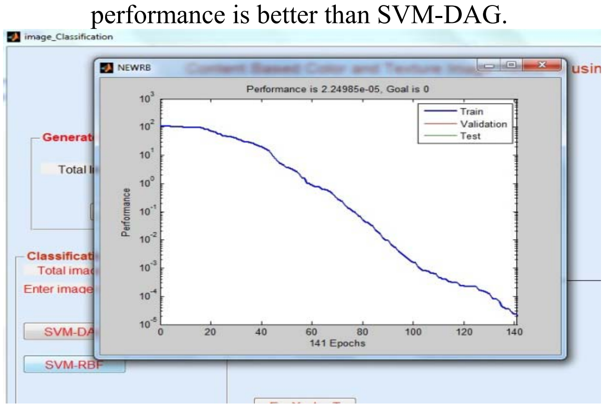

Figure 1.5 shows that the training phases of neurons for input pattern here 30 neurons are processed and 1000 epos are used for training purpose.

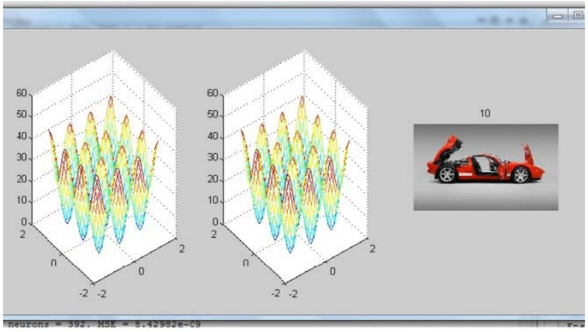

Figure 1.6 shows that the input image for classification of image dataset for generation of new pattern for cluster input vector.

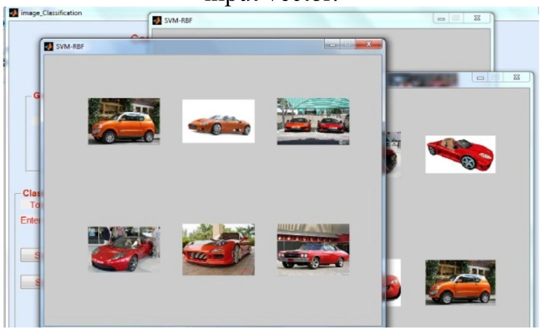

Figure 1.7 shows that the classified result of SVM-RBF method for 100 car image of 1000 database and accurate classified image is 30.

Data set	Method	Precision (%)	Recall (%)
Data set 1	SVM DAG	86.66	80.21
	SVM RBF	91.33	83.60
Data set 2	SVM DAG	90	91
	SVM RBF	93	96.06
Data set 3	SVM DAG	83.33	79.81
	SVM RBF	80	79
Data set 4	SVM DAG	83.33	76.83
	SVM RBF	93.33	83.33
Data set 5	SVM DAG	86.66	78.66
	SVM RBF	90	78.6

Figure1.8 shows the comparative result of SVM-DAG and SVM-RBF

VI. CONCLUSION AND FUTURE WORK:-

RBF-SVM reduces the semantic gap and enhances the performance of image classification. However, directly using SVM scheme has two main drawbacks. First, it treats the core point and outlier equally, although this assumption is not appropriate since all outlier share a common concept, while each core point differs in diverse concepts and Second, it does not take the unlabelled samples into account, although they are very helpful in constructing a good classifier. In this paper, we have explored unclassified region data on multi-class classification. We have designed RBF-SVM to alleviate the two drawbacks in the traditional SVM. Here RBF play a role of feature sampling technique. The sampling of the feature technique reduced the unclassified region of multi-class classification. DAG based support Vector machine perform a better classification in compression of another binary multi-class classification. DAG applied a graph portion technique for the mapping of feature data. The mapping space of feature data mapped correctly automatically improved the voting process of classification. But DAG suffered a little bit problems with mapping of space data into feature selection process. Performance of result evaluation shows that our RBF-SVM is better classifier in compression of SVM-DAG.

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