A Comparative Analysis of Feature Sets for Image Classification Using Back Propagation Neural Network

Syed A. Husain and Fouzia S. Akbar

Abstract—**The exponential growth in image data over the internet has resulted in a growing need for searching images according to our requirements. Content based image retrieval systems extract similar images from databases or the internet for facilitation of their users. A number of different feature sets and classifiers have been used by researchers for content based image retrieval. The goal of this research is to evaluate some common features sets used for classification of images and identify the best features depending upon the user requirement. Some commonly used features have been studies and a set of six feature sets have been selected for evaluation by the Back-Propagation Neural Network (BPNN). The results have been evaluated on the basis of precision and recall and it can be concluded that for natural images none of the feature sets perform well universally on all classes and the selection of optimal feature set depends on the type/class of images.**

Index Terms—**Back-propagation neural network, content based image retrieval, feature extraction, image analysis, pattern recognition.**

I. Introduction

During the last few decades, enormous progress has been done in image acquisition and storage. This progress has been yielding a large amount of multimedia data [1] including visual data. Visual information plays a vital role in every field of life. This has resulted in a huge image data bank with images that vary in resolution, noise, angle of view, illumination, in various domains and subjects. For instance, in television, tomography, robotics, photography, printing and remote sensing, etc., images of same objects contain variation in their images. Environment also affects the image contents as an image captured at evening time could be different from that taken in the morning for the same object. Hence, it is a challenge to retrieve images on the basis of their contents irrespective of their acquisition conditions. This has attracted the attention of many image mining researchers to search for algorithms that find images similar to a target image. Image Mining is the extraction of some patterns which are not explicitly found in the image, implicit knowledge and relationship between images from the large collection of images or databases [2], [3]. Images stored in the databases need to be preprocessed to improve the quality of images. Some important features are extracted from these preprocessed images. These features vary from system to system and also from images to images. For feature extraction phase, several transformations are applied. The image mining comes after the feature extraction and transformation. This process yields patterns which are later interpreted and evaluated to obtain desired knowledge [4]. A brief architecture is shown in Fig. 1.

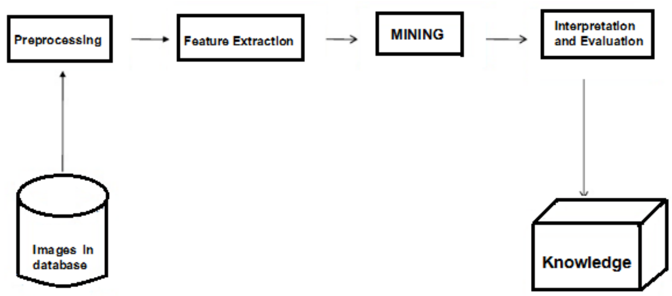

Fig. 1. Architecture of content based image mining.

II. Previous Work and Problem Identification

A lot of researchers have been targeting image mining or content based image retrieval and trying to automate the process of image analysis. Image mining can be divided into two sub-problems of feature extraction and classification. Authors have used different techniques and algorithms for feature extraction and classification to improve the accuracy and recall.

Foschi *et al*. [5] have described a method for extraction of various features and patterns from image. They used a combination of color, texture and edge features to identify Egeria densa [5]. For color feature extraction, they used average color in gray scale, RGB format and YCbCr. They evaluated the performance of all methods and found Histogram with bins method was the most accurate. The similarity measure used is given by Eq. 1. For edge feature extraction, they used the canny edge detection method with threshold as zero and combined it with stronger features like color and texture.

$$SM = \sqrt{\sum |(Mean\ of\ bins\ for\ template) - (Means\ of\ Bins\ for\ block)|} \quad (1)$$

C. Breen *et al.* [6] proposed a system that combines neural networks and ontologies in an effort to provide automatic classification of images in the sports domain. Supervised classifier has been used that performs segmentation to find the individual objects in the image. The hue value of each pixel in the segmented object has been used as input to the network. The neural network learned the shape and color of each object by adjusting its weights as it processes the training data. After successful training, the system may be used to classify test images of objects like basketballs and non-basketballs. Each concept in ontology contains a set of

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features and weights. The objects from the sample image are processed using Eq. 2 to determine if the image may be classified by a concept from the ontology. As the threshold value t is increased, the number of concepts associated with an image begins to decline as well as the number of incorrect concepts applied to the image. Therefore, recall is diminished at the expense of improving precision.

$$\sum_{i=0}^{n} Ci \;\; = \{\{\sum_{j=0}^{y} Wi,j\} \geq Ti\} \tag{2}$$

Aria *et al.* [7] have explored Back Propagation Neural Network (BPNN) for classification of remote sensing images. They have proposed Back Propagation Neural Network for classification of IRS-1D Satellite Images. Features have been extracted from the first order histogram measures [8] as shown in Eq.3 ~ 8. Classification was based on BPNN comprising a three layer network.

Mean: $$Sm = \vec{b} = \sum_{b=0}^{L-1} \mathrm{bP(b)} \tag{3}$$

S.D.: $$S_D = \sigma_b = [\sum_{b=0}^{L-1} (b - \vec{b})^2 P(b)\,]^{1/2} \tag{4}$$

Skewness: $$S_s = \frac{1}{\sigma_b^3} \sum_{b=0}^{L-1} (b - \vec{b})^3 \mathrm{P(b)} \tag{5}$$

Kurtosis: $$S_k = 1/\sigma_b^4 \sum_{b=0}^{L-1} (b - \vec{b})^4 \mathrm{P(b)} - 3 \tag{6}$$

Energy: $$S_N = \sum_{b=0}^{L-1} [P(b)\,]^2 \tag{7}$$

Entropy: $$S_E = -\sum_{b=0}^{L-1} P(b) \log_2 \mathrm{P(b)} \tag{8}$$

Stanchev *et al.* [8] proposed a method for retrieval of images by extracting the low level color, texture and shape features and then converted them into high level semantic features by using fuzzy production rules. Image segmentation has been done for color feature extraction. RGB image is converted into L*u*v* image. Twelve hues have been used as fundamental colors. There are yellow, red, blue, orange, green, purple, and six colors obtained as linear combinations of them. Five levels of luminance and three levels of saturation were identified. This result into every color being transformed into one of 180 references colors. Clustering in the 3-dimensional feature space was performed using the K-means algorithm and the image is segmented as N regions. The Quasi-Gabor filter has been explored to present the image texture features. The image is characterized with 42 values by calculating the energy for each block. It is defined by a combination of one of 6 frequencies (*f* = 1, 2, 4, 8, 16 and 32) and one of 7 orientations (*q* = 0°, 36°, 72°, 108°, 144°, 45° and 135°). They have taken the average value of the magnitude of the filtered image in each block. For shape feature extraction, the image is converting into binary. Polygonal approximation that uses straight-line, Bézier curve and B-Spline are applied resulting in the image presented as a set of straight lines, arcs and curves.

Johannes Itten model [9] has been adopted for defining fuzzy production rules that are used to translate the low level semantic features into sentences qualifying warmth degree, and contrasts among colors. Transforming the low level texture characteristics into high level semantic features such as texture of wood, rock, wall-paper, etc. is made by calculation of the low level texture characteristic of a typical set of corresponding textures and finding the "cluster center" values which are used in the fuzzy production rules. Fuzzy production rules are used for calculating similarity between the search shape and given object shape. They have combined high level color, texture and shape properties and high level semantic features defined by the expert during the image mining. Dempster-Shafer theory of evidence has been used to hold information in the structure list for the high level semantic features of images.

C. F. Tsai *et al.* [10] have classified images based upon the combination of image processing techniques and hybrid neural networks. Their approach is composed of a feature extractor, a content-based classifier, and a semantic-based classifier. Images have been divided into a number of regions from which color and texture features have extracted. The first classifier, a self-organizing map (SOM) clusters similar images based on the extracted features. Regions of the representative images of these clusters were labeled and used to train the second classifier, comprising several support vector machines (SVMs). During feature extraction, they have combined HSV color space with bi-orthogonal wavelet decompositions that include horizontal, vertical and diagonal texture information. Thus, 75 dimensional feature vectors are produced per image.

S. B. Park *et al.* [11] have introduced a method for content-based image classification using neural networks. The background removal step in the preprocessing module used region segmentation to minimize the misclassification. They have used wavelet transformation for texture feature extraction and the classifier used back-propagation algorithm. The texture features used by them are given in the Eq. 9~ Eq.15 below.

$$Contrast = \sum_{i=0}^{N-1} \sum_{j=1}^{N-1} (i-j)^2 P(i,j) \tag{9}$$

$$Diagonal\ moment = \sum_{i=0}^{N-1} \sum_{j=1}^{N-1} \sqrt{|i-j| P(i,j)/2} \tag{10}$$

$$Energy = \sum_{i=0}^{N-1} \sum_{j=1}^{N-1} P(i,j)^2 \tag{11}$$

$$Entropy = -\sum_{i=0}^{N-1} \sum_{j=1}^{N-1} P(i,j) \log\,(P(i,j) \tag{12}$$

$$Homogeneity = \sum_{i=0}^{N-1} \sum_{j=1}^{N-1} \frac{P(i,j)}{1+(i-j)^2} \tag{13}$$

$$2nd\ diagonal\ moment = \sum_{i=0}^{N-1} \sum_{j=1}^{N-1} |i-j| P(i,j)/2 \tag{14}$$

$$Uniformity = \sum_{i=0}^{N-1} \sum_{j=1}^{N-1} \frac{P(i,j)}{1+|i-j|} \tag{15}$$

where, $P\ (i,\ j)$ is the intensity value of image pixel at coordinates (i, j).

Kim *et al.* [12] proposed six descriptors for classification of images into adult or non-adult. Dominant Color, Color Structure, Edge Histogram, Color Layout, Homogeneous Texture and Region Shape, were used to extract the essential features for classification. The feature information is parsed and normalized between zero (0) and one (1) with respect to values produced by each descriptor. These normalized values are given to the back propagation neural network as input.

Zhang *et al.* [13] introduced wavelet transformation to extract texture features of images and classified them by using support vector machine. A 2-D wavelet transform decomposes an image into four sub-images. The approximated image LL has been obtained by low-pass filtering in both row and column directions. The three images LH, HL, and HH contain high frequency components. By decomposing the approximated image of each level into four sub-images iteratively, a pyramidal image tree has been acquired.

S. Sadek *et al*. [14] proposed a supervised method for color image classification based on a multilevel sigmoidal back-propagation neural network. The images were classified into five classes, i.e., “Car”, “Building”, “Mountain”, “Farm” and “Coast”. The classification is performed without any segmentation process. 2-D multilevel Haar-wavelet transform has been utilized to decompose the image. Each level of decomposition gives two categories of approximate coefficients and detailed coefficients. Nagaprasad *et al*. [15] have worked on spatial image processing for soil classification. They have used Back Propagation Network, Adaptive Resonance Theory 1 and also simplified ARTMAP algorithms for this purpose. They have attempted to support user defined processing for dynamic spatial data after extending the current spatial data mining algorithms. They have classified the soil particles into sand, salt, clay and loam.

It is evident from the above discussion that most of the research work has addressed a two class problem [5], [7], [12], on only grey scale images [6], [11], that were generally aerial or satellite images[13]-[15]. The generalized multi class color image classification has been addressed by some researchers [16], [17] but their results are not very good. The features used by image classification are varied and can be divided into color based features [9], [16], [17], shape based features [18]-[20], region based features [21], color moments [16], texture based features [22], [23], statistical features [24], DCT and DWT coefficients [13], [25]. There is no definite agreement on the selection of features for best results. The classifiers used vary from the rule and fuzzy rules based [9], support vector machines [13], [26]; ART [13], SOM [22], and vector quantization [27], [28]. The most popular and successful classifier described by many researchers has been the back propagation neural network [5], [6], [10], [12]-[14] which has been selected for evaluation of the different types of features.

III. Proposed Methodology

For each method, we have used a standard database from an online image database [15] comprising 120 colored images already classified into six classes with each class representing 20 images. Half of the images were used for training and remaining 50 images were used for testing of the neural work performance. For each method, all images were resized to a standard 240×360 pixel size. The performance of neural network trained on each method was compared on the basis of precision and recall. The precision is defined as the fraction of the retrieved images that are indeed relevant. Recall is the fraction of the relevant retrieved images versus all relevant images.

$$Precision = \frac{TP}{TP+FP} \tag{16}$$

$$Recall = \frac{TP}{TP+FN} \tag{17}$$

The back-propagation classifier consisted of an input, a hidden and an output layer as shown in Fig. 2.

Nodes of the input layer vary in each method according to the dimension of each descriptor. We have selected the 50 nodes for the hidden layer based upon experiments. Selection of fewer nodes cannot converge to the problem and having more nodes can over fit the training. Each class is representing by an output layer node.

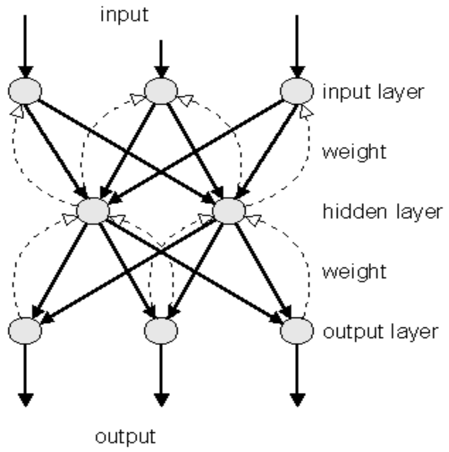

Fig. 2. Architecture of BPNN.

The following six features sets were used for training the classifier.

Gray Scale Pixel Values
Gray-Level Co-Occurrence Matrix
Hue Pixel Values
Color Histogram
Color Moments

The following learning parameters were set for the back-propagation network.

No. of epochs = n = 500
Learning goal = 0.001
Learning rate = α = 0.05
Learning Increment = lr_inc = 1.0500
Learning Decrement = lr_dec = 0.7000
Maximum Performance increment = 1.0400
Minimum Gradient = 0.0000000001
Performance function = mean squared error =

$$E_i = \frac{1}{n}\sum_{j-1}^{n}(P_{(i,j)} - T_j)^2 \tag{18}$$

IV. Results

The results obtained for each method are described in the following sections.

A. BPNN Trained on Gray Scale Pixel Values

TABLE I: Test Results for Gray Scale Pixel Values

Classes	Recognition %	Precision	Recall
Trees(Cherries)	30	0.5	0.3
River/sea	80	0.7272	0.8
Football-fields	90	0.9	0.9
Mountains	40	0.5714	0.4
Spring-flowers	80	0.7272	0.8
Yellow-stones	20	0.5	0.2
		0.6543	0.5666

In this method, normalized gray scale pixel values have been used for training for BPNN Classifier. During the testing phase, 10 test images from each class which have not been used for training were selected and the classifier results are given in Table I. It can be seen that high recognition rate was achieved for river, football-fields and spring-flowers whereas the other two classes gave low recognition rate.

B. BPNN Trained on Gray-Level Co-Occurrence Matrix

Results for the same image set using Gray-Level Co-Occurrence Matrix (GLCM) for training of the same Neural Network are shown in Table II. This method has shown better results as compared to Gray scale values in terms of precision and recall. River, Football-fields and Spring-flowers classes have shown high precision rate.

TABLE II: RESULTS FOR GLCM

Classes	**Recognition %age**	**Precision**	**Recall**
Trees(Cherries)	30	1.0	0.3
River/sea	100	1.0	1.0
Football-fields	90	0.9	0.9
Mountains	50	1.0	0.5
Spring-flowers	90	1.0	0.9
Yellow-stones	60	0.75	0.6
		0.9416	**0.7**

C. BPNN Trained on Hue Pixel Values

In this method, the hue values have been taken as the input feature for the Back-Propagation Neural Network. Color distributions in the images are very important for classification and have shown good results in the testing phase as shown in Table III.

TABLE III: RESULTS FOR HUE VALUE

Classes	Recognition %	Precision	Recall
Trees(Cherries)	80	0.8888	0.8
River/sea	60	1.0	0.6
Football-fields	100	0.909	1.0
Mountains	80	1.0	0.8
Spring-flowers	80	1.0	0.8
Yellow-stones	100	0.909	1.0
		0.9511	**0.83**

D. BPNN Trained on Color Histogram

In this method, color histogram has been used as input for training the BPNN. The results for testing phase are shown in Table IV. Color distribution in all 3 spaces; hue, saturation and value, have shown good results for all classes. Trees and spring-flowers classes have shown 100% recall. High recognition rate is also shown by river, football-fields and spring-flowers classes.

TABLE IV: RESULTS FOR COLOR HISTOGRAM

Classes	Recognition %age	Precision	Recall
Trees(Cherries)	100	0.833	1.0
River/sea	80	0.888	0.8
Football-fields	90	1.0	0.9
Mountains	90	1.0	0.9
Spring-flowers	100	1.0	1.0
Yellow-stones	70	0.777	0.7
		0.916	0.883

E. BPNN Trained on Color Moments

The color moments were used as a feature set given as input to the Back-Propagation neural network. Results of testing are given in Table V. High recognition rate was given by river and yellow-stones classes while the trees class has shown low recognition rate.

TABLE V: RESULT OF COLOR MOMENTS

Classes	**Recognition %age**	**Precision**	**Recall**
Trees(Cherries)	50	1.0	0.5
River/sea	80	1.0	0.8
Football-fields	100	1.0	1.0
Mountains	60	1.0	0.6
Spring-flowers	70	1.0	0.7
Yellow-stones	80	1.0	0.8
		1.0	**0.7333**

V. COMPARATIVE ANALYSIS OF RESULTS

The Neural Networks based on color values and texture have given better results than gray values based Neural networks because color information and relative position of pixels are considered very important in pattern recognition. The BPNN trained on color moments has shown 100% precision rate on all classes but low recall values on some classes. Football-fields class has 100% rate for both precision and recall. The low recall values for Trees and Mountains classes were 0.5 and 0.6 respectively. The Color Histogram based and Hues pixel values based BPNN gave better results on all classes. In Color Histogram method, 100% precision and recall values are shown by Spring-flowers class but for Yellow-stone class, both precision and recall rates were low i.e. 0.7. In Hue Pixel Values method, two classes Football-fields and Yellow-stones gave 0.909 and 1.0 precision and recall rates respectively. Only River/Sea class gave recall of 0.6 in Hue Pixel Values method. GLCM based neural network has also shown good results because of relative position of pixels in texture. The River/Sea class gave 100% precision and recall in this method. Football-fields class has 0.9 rates for both precision and recall. In Gray Level Pixel values, only one class i.e. Mountain has shown 0.9 precision and recall values. Remaining classes gave low performance in this method. These results are shown in Table VI.

TABLE VI: COMPARATIVE RESULTS FOR ALL 5 FEATURE SETS

	BPNN Trained on Gray Pixel Values		BPNN Trained on GLCM		BPNN Trained on Hue Pixel Values		BPNN Trained on Color Histogra m		BPNN Trained on Color Moment s	
Classes	P	R	P	R	P	R	P	R	P	R
Trees	0.5	0.3	1.0	0.3	.88	0.8	.8	1.	1	.5
River/ Sea	.73	0.8	1.0	1.0	1.0	0.6	.89	.8	1	.8
Football fields	0.9	0.9	0.9	0.9	.91	1.0	1	.9	1	1
Mountain	.57	0.4	1.0	0.5	1.0	0.8	1.	.9	1	.6
Spring flowers	.73	0.8	1.0	0.9	1.0	0.8	1.0	1.	1.	.7
Yellow stones	0.5	0.2	0.75	0.6	.91	1.0	.78	0.7	1.0	0.8
Average	.65	0.57	0.94	0.7	.95	.83	.92	.89	1.0	.73

VI. Conclusion and Future Work

It was found that various feature set are biased towards the classification of images in certain specific domains. The performance of the neural networks for multiple features sets on same database of images is varied. There is no specific set of features which gives good precision and recall on all classes. The performance deteriorates generally when natural images are used because they contain diversity in them. The color based features have achieved better performance because color information plays a vital role in pattern recognition but shown low recall. So, there exists no such feature which performs well universally on all classes and some features have biases for or against a particular class or set of classes.

This work can be enhanced by increasing the number of classes, the number of test images and the number of feature sets. The multiple features set can also be merged and used for classification.

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