Content-Based Image Retrieval System using Feed-Forward Backpropagation Neural Network

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Abstract
Extensive digitization of images, paintings, diagrams and explosion of World Wide Web (www), has made traditional keyword based search for image, an inefficient method for retrieval of required image data. Content-Based Image Retrieval (CBIR) system retrieves the similar images from a large database for a given input query image. Today, we find various methods for implementation of CBIR which uses low-level image features like color, texture and shape. In this paper, a global image properties based CBIR using a feed-forward backpropagation neural network is proposed. At first, the neural network is trained about the features of images in the database. The image features considered here are color histogram as color descriptor, GLCM (gray level co-occurrence matrix) as texture descriptor and edge histogram as edge descriptor. The training is carried out using backpropagation algorithm. This trained when presented with a query image retrieves and displays the images which are relevant and similar to query from the database. The results show a considerable improvement in terms of precision and recall of image retrieval. An average retrieval precision of about 88% and an average recall rate of about 78% is achieved using the proposed approach over SIMPLIcity project database.

Keywords
Content-Based Image Retrieval (CBIR), low-level descriptors, neural network, feed forward, back-propagation.

I. INTRODUCTION

Recent advances in science and technology has increased the use of image data in diverse areas such has entertainment, art galleries, education, fashion design, industry, medicine etc. Explosion of World Wide Web (WWW) in last decade has seen an enormous increase in the usage of digital images and the ease of access these randomly stored images in remote databases. Therefore, it is necessary to store and retrieve image data efficiently to perform assigned task and to make a decision. Developing proper tools for retrieving images from large image collections is challenging.

Text-based approach is also employed for image retrieval. In text-based approach, the images are manually annotated by text descriptors and then these descriptors are used by database management system to perform image retrieval. This technique requires vast amount of labour for manual image annotation and also there are inconsistencies between user textual queries and image annotations. To overcome the inconsistency problem, content-based approach is used. Content-Based Image Retrieval (CBIR) aims at constructing meaningful descriptors of physical attributes from images to facilitate efficient and effective retrieval.

Research activities in CBIR have progressed in 3 major directions: global image properties based, region-level feature based and relevance feedback based. Initially, developed algorithms fall under first approach and they exploit only low-level features of an image such as color, texture and shape of an object to retrieve images. They can be easily implemented and they perform well for simple images. They are not suitable for broad content image databases. Region-based approach retrieve images via image segmentation. These methods attempt to overcome the drawbacks of global feature by representing images at object level. But, the performance of these methods mainly relies on results of segmentation. Relevance feedback (RF) is an interactive process which refines the retrievals to a particular query by utilizing the user's feedback on previously retrieved results. A user defined evaluation function is necessary in this approach and also there is interaction between user and computer at each level of iteration. This approach is expensive in terms of space and time.

In this paper, a hybrid CBIR system which is a global image properties based and uses the aid of neural network for effective and efficient image retrieval is proposed. Three visual features color, texture and edge of an image are utilized in our proposed approach. A feed forward back-propagation neural network (FFBP) is used to achieve the proposed functionality. FFBP precedes both in forward and backward direction. Output computation is carried out in forward direction and error computation in backward direction. The main properties of this paper that makes it different from other CBIR are identified as follows: 1) low-level image features –color histogram from color space, along with texture and edge descriptors, are adopted in our approach. 2) search technique (training and testing) –Training is all about making FFBP NN to

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learn about the attributes and features of images in the database, so that it can make use of this knowledge about images in retrieval process when presented with query image. Back-propagation technique, which is a supervised method for learning is used for training the neural network. And testing deals with using the previously trained network in retrieving the relevant and similar images as that of query image.

2. RELATED WORKS

Focusing on literature survey, we find some most important CBIR systems [1], [2]. Some papers overview and compare the current technique in this area [3], [4]. Earliest developed CBIR adopted various color descriptors. Yoo et al. [5] prosed a signature-based color-spatial image retrieval system. A CBIR scheme based on global and local color distributions in an image is presented in [6].
Another important and essential visual feature of an image in defining its high-level semantics is texture. A novel and effective characterization of wavelet sub-bands in texture image retrieval was presented in [7]. There were some drawbacks in this paper, such as computationally expensive. To overcome this, [8] concentrated on finding good texture features for CBIR. A combined fractal parameters and collage error approach is proposed in [9], to make use of new set of statistical fractal signatures.

There are also some papers that are based on combination of texture and color features in Liapis and tziritas [10]. In this paper, two or one-dimensional histogram of the CIE Lab chromaticity coordinates are used as color features. Texture features used here are extracted using discrete wavelet frame analysis. Chun et al. [11] proposed a CBIR method based on an efficient combination of multi-resolution color and texture features. The color features used in this paper are color autocorrelograms of the hue and saturation component images in HSV color space are used. The texture features adopted include block difference of inverse probabilities and block variation of local correlation coefficient moments of the value component image.

A survey on CBIR systems based on relevance feedback approach yields [12]. This paper take into account the high-level concepts in an image. This paper introduces interactive genetic algorithm to include human-computer interaction and tries to use user's subjectivity in retrieval process using a user defined fitness function. A comparison is made between two pattern recognition using statistical and neural techniques in [13]. Finally, a neural network based approach for image processing is described in [14], which reviews more than 200 applications of neural networks in image processing and discuss the present and possible future role of neural networks, in particular feed-forward neural networks.

3. IMAGE FEATURES AND NEURAL NETWORK

This section presents a brief review of considered low-level visual features in the proposed approach and then reviews the basic concepts of the feed-forward backpropagation neural network.

A. Color Descriptor

Color is one of the important feature of an image, which depicts much of the information from the image. RGB color model do not correspond to the human way of perceiving the colors. And also RGB space do not separate the luminance component from the chrominance ones. Therefore, HSV color space is used in our approach. Each component of HSV model contributes directly to visual perception, therefore it is commonly used in image retrieval systems [15], [16]. Hue is used to distinguish colors, saturation gives a measure of the percentage of white light added to a pure color. Value indicates perceived light intensity.
The required amount of information about the image can be obtained from color distribution of pixels in an image. For this purpose, color histograms are used as color descriptors. In case of digital images, a color histogram represents the number of pixels that have colors in the image's color space, the set of all possible colors. For a given image, the procedure for calculation of color histogram is as follows: 1) Read images in database and extract RGB format pixel information from images. 2) Create normalized histograms for each of the RGB components of each image read from database. Thus, each image will have 3 histograms associated with it.

B. Texture Descriptor

Texture is another important attribute of an image and it refers to innate surface properties of an object and their relationship to the surrounding environment. For texture analysis we use a gray level co-occurrence matrix (GLCM), which is a simple and effective method for representing texture [17]. The GLCM represents the probability $p(i,j;d,\theta)$ that two pixels in an image, which are located at distance d and angle θ, have gray levels i and j. The GLCM is defined as follows:

$$p(\mathrm{i},\mathrm{j};\mathrm{d},\theta)=\#\{(\mathrm{x}_1,\mathrm{y}_1)(\mathrm{x}_2,\mathrm{y}_2)\,|\,\mathrm{g}(\mathrm{x}_1,\mathrm{y}_1)=\mathrm{i},\mathrm{g}(\mathrm{x}_2,\mathrm{y}_2)=\mathrm{j}, \\ |(\mathrm{x}_1,\mathrm{y}_1)-(\mathrm{x}_2,\mathrm{y}_2)|=\mathrm{d},\angle((\mathrm{x}_1,\mathrm{y}_2),(\mathrm{x}_2,\mathrm{y}_2))=\theta\} \quad (1)$$

where # denotes the number of occurrences inside the window, with i and j being the intensity levels of the first pixel and the second pixel at positions (x1,y1) and (x2,y2), respectively.

To simplify and reduce the computation effort, we first compute the GLCM according to one direction (i.e., θ = 0◦) with a given distance d (= 1) and calculate the entropy, which is used most frequently in the literature. Then the entropy (E) is used to capture the textural information in an image and is defined as follows:

$$E = -\sum_{i,j} c_{i,j} \log c_{i,j} \tag{2}$$

where Ci,j is the GLCM. Entropy gives a measure of complexity of the image.

C. Edge Descriptor

Edges in images constitute another important feature to represent their content. From the image perception point of view, human eyes are very sensitive to edge features of an image. Histograms are used to represent the edge features of an image. An edge histogram in the image space represents the frequency and the directionality of the brightness changes in the image. To describe edge distribution we adopt the edge histogram descriptor (EHD) [18] with a histogram based on distribution of local edges in an image. The extraction process of EHD consists of the following stages.

1) An image is divided into 4 × 4 subimages.
2) Further, each subimage is again partitioned into nonoverlapping image blocks with a small size.
3) Then categorize edges in each image block into five types: vertical, horizontal, 45° diagonal, 135° diagonal, and nondirectional edges.
4) Thus, the edge histogram for each subimage refers to the relative frequency of occurrence of the five types of edges in the corresponding subimage.
5) After examining all image blocks in the subimage, the five-bin values are normalized by the total number of blocks in the subimage. Finally, the normalized bin values are quantized for the binary representation. These normalized and quantized bins constitute the EHD.

D. Neural Networks (NN)

Neural network is a network of "neuron like" units called nodes. This neural computing technique is used in fields of classification, optimization, control theory and for solving regression problems. NN are very effective in case of classification problems where detection and recognition of target is required. NN is preferred over other techniques due to its dynamic nature. Dynamic nature is achieved by adjusting the weights according to final output and applied input data. This adjustment of weights takes place iteratively until desired output is obtained. And this weight adjustment of network is known as "learning" of neural network.

The architecture of neural network consists of a large number of nodes and interconnection of nodes. A multiple-input neuron with multiple inputs 'R' is shown in Figure 1.

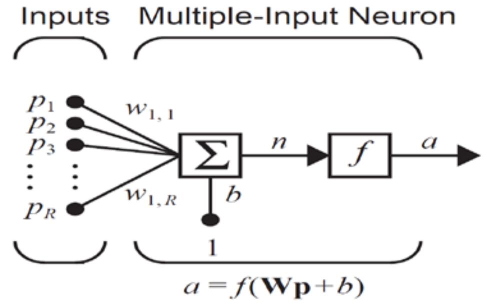


Fig. 1 Multiple-Input Neuron

The individual inputs $p_1, p_2 \dots p_R$ are each weighted by corresponding elements $w_{1,1}, w_{1,2} \dots w_{1,R}$ of the weight matrix '$\boldsymbol{W}$'. The neuron also has a bias 'b', which is summed with the weighted inputs to form the net input 'n':

$$n = w_{1,1}p_1 + w_{1,2}p_2 + \cdots + w_{1,R}p_R + b \tag{3}$$

In matrix form, this can be rewritten as,

$$n = \boldsymbol{Wp} + b \tag{4}$$

Now, the neuron output is given as,

$$a = f(\boldsymbol{Wp} + b) \tag{5}$$

The transfer function used above is a log-sigmoid transfer function. This transfer function takes the input (which may have any value between plus and minus infinity) and squashes the output in between 0 to 1 range, according to the expression:

$$y = \log sig(n) \tag{6}$$

$$y = \frac{1}{1+e^{-n}} \tag{7}$$

where 'y' is output of the function for input 'n'.

The nodes at a particular stage constitute a "layer". The first layer is called input layer and last layer is called output layer. The layers in between output and input layer are called hidden layers. As the number of hidden layers in the network increases, the performance of network increases. Each node in a network serves the purpose of summation of all its inputs. The output of a node is further applied to the next node. The simplest of all neuron is perceptron. Perceptron is a two layer structure: input layer and output layer. The output function of perceptron may be step, linear or sigmoidal. If the output function of perceptron is step then it solves classification problems, if the output function is linear then it solves regression problems. Simple perceptron or neuron is used for resolving linearly separable data. If the data is linearly non-separable then other technique such as back-propagation is used.

E. Feed Forward Back-Propagation Neural Network (FFBP NN)

FFBP NN are found to be robust technique for pattern recognition and classification. FFBP NN is a multilayer neural network, used to implement non-linear differentiable functions. The architecture of FFBP NN consists of input, hidden and output layer. FFBP precedes both in forward and backward direction. It computes output in the forward procession and computes error in the backward procession.

In the forward procession, training data is applied on the neural network through the input layer. Then data is fed to the hidden layer, the hidden layer actually performs the processing. Finally the data is applied to Output Layer; Output Layer incorporates the activation function according to which output is computed. If the function at the Output Layer is step, then it performs Classification problem. If the function at the Output Layer is linear, then it performs Regression problem.

The values computed in the forward pass are compared with desired output. The difference between the desired output and the actual output gives the error. This error is computed and propagated back towards the Hidden Layer. The gradient of the error is computed and applied on a node k in this manner:

$$e_k = desired\_output - actual\_output$$
$$e_k = d_k - y_k \quad (8)$$

where e_k error on a single output neuron k is, d_k is desired output and y_k is calculated output of neuron k. Then, gradient is calculated using equation,

$$\delta_k = \left(\frac{\delta y_k}{\delta x_k}\right) \times e_k \quad (9)$$

where x_k is the weighted sum of input values to node k.

This method of error reduction is called Gradient Decent. This method of error reduction converges to output in faster manner [9]. All of the above processing is performed in the Backward Pass of the Feed Forward Back Propagation Algorithm.

The Figure 2 shows a basic BPNN comprising of an input, hidden and output layer. where inputs applied on the input layer Xi, Hj is the hidden layer and the output of the network is Y. Error signal that is generated when the output 'Y' is compared to the target output of the training dataset comprising of the ideal classification result. The error signal moves from the output layer to the hidden layer changing the weights to adjust to the correct result once this error is minimized close to zero the weights are fixed meaning the network is trained and can be tested.

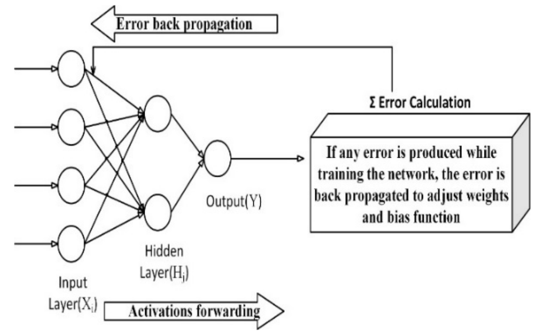


Fig. 2 Simple Back propagation Neural Network

4. PROPOSED SYSTEM

Generally there has to be user interface for communicating with the image retrieval system, which accepts query image, from the user and displays the retrieval results to him. The module responsible for implementing required image retrieval functionality is neural network and its learning method using backpropagation algorithm. At first, this network is made to learn about features of the images from database. Once trained, this network is able to retrieve the accurate and similar images efficiently on its own.

According to the aforementioned concept, we design an image retrieval system based on neural network, as shown in Figure 3. Our system operates in two phases: training and testing. Before actual training and testing are employed, we need to perform some fundamental digital image processing steps on every image we are using in the proposed system.

This means the query image and all the images present in database has to undergo some preprocessing and feature extraction: 1) Preprocessing: Some preprocessing on the image is needed in the form of color conversion and image resizing. The RGB color space image is converted into its HSV components. Variable size images are resized to $256*256$ size. 2) Feature Extraction: Statistical features of an image are evaluated with respect to color, texture and edge descriptors. The color histograms, gray level co-occurrence matrix (GLCM) for texture analysis and edge histograms.

1) Training:

The training process include creation, configuring a three-layered neural network and making it learn about the extracted color, texture and edge features of training set images. Training set include all the images from image database considered. The learning process is carried out using backpropagation algorithm, which include computing error, updating weights in order to minimize the error.

The training makes the network store the learnt knowledge in its knowledge base. This knowledge base is used in later phase in comparison and decision making tasks by network. The comparison task include comparing the features between query and training set images. And decision making task includes making decision about which two image features are most matched with respect to color, texture and edge. And finally, retrieve the top matched features' images.

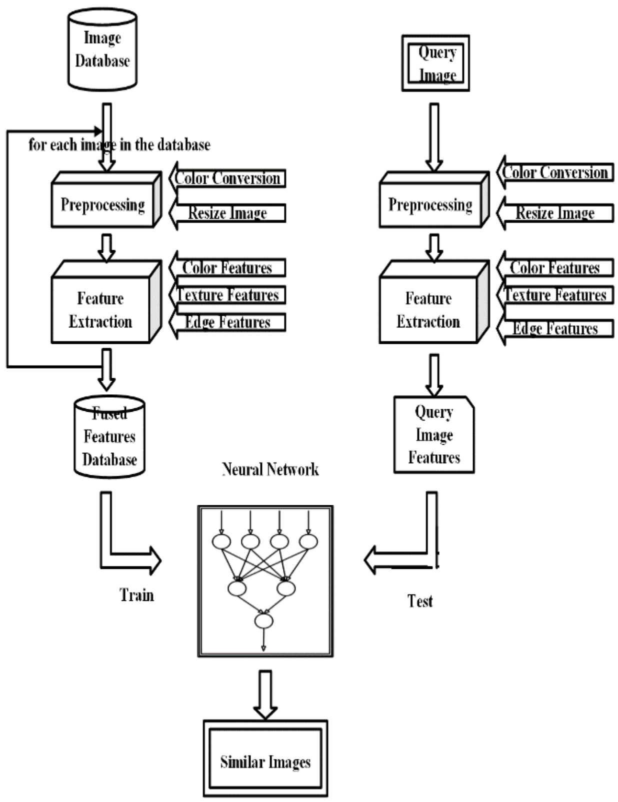


Fig. 3 General system flowchart of the proposed approach.

The backpropagation algorithm for a 3-layer network (only one hidden layer):

initialize the weights in the network (often small random values)

do

  for *each image i in the training set of database*

    O = neural-network-output(network, i)

    T = desired output for i

    calculate error (T - O) at the output units;

    calculate δ_h *for all weights from hidden layer to output layer;*

    calculate δ_i *for all weights from input layer to hidden layer;*

    update the weights to minimize error in the network;

until *some stopping criterion satisfied*

return *the network*

2) Testing:

The testing phase include the querying and retrieving task. The query image is first preprocessed and also its features are extracted. The trained network is presented with query image features. The network, acting as a classifier, selectively retrieves top matched, relevant, similar images as that of query image from the database and are presented to user. The algorithm for proposed CBIR system can be given as follows:

a) Algorithm for training phase:

setup ANN and initialize the following parameters as: number_of_layers= 3; epochs=2000; learning_rate=80%; permissible_error=0.03;

input: *network, training set*

  do

    for *each image in training set*

      extract its color features using color histogram algorithm;

      extract its edge features using edge histogram algorithm;

      extract its texture features using GLCM algorithm;

      fuse the extracted features into a single features matrix;

  until *a single feature vector matrix is built;*

  do

    train the network about class labels and feature vectors;

  until *stopping criterion epochs=2000 is satisfied*

output: *a trained neural network.*

b) Algorithm for testing phase:

input: *a query image.*

  load the input query image;

  extract its color, edge and texture features;

  load the fused features database;

  compute similarity between query image features and training set features;

output: *set of similar images if present; if not, display "No similar images found"*

The advantages of the proposed CBIR system can be given as follows:

1) Neural network based approach is efficient with respect to space and time.
2) Content-based image retrieval using neural network has high retrieval rate and recall than other approaches such as genetic algorithm.
3) Uses supervised method for learning about training set of images.

4) Scalable with respect to image database size; only thing we need to do, is to train the network about the new image features.

5. EXPERIMENTAL RESULTS

The experimental work is carried out using the database of the SIMPLIcity project covering a wide range of semantic categories from natural scenes to artificial objects for experiment. The database is partitioned into ten categories, including African people and village, beach, buildings, dinosaurs, buses, elephants, food, horses, mountains and glaciers, flowers, etc., and each category contains 100 images (Fig. 4). Partitioning of the database into semantic categories is determined by the creators and reflects the human perception of image similarity.

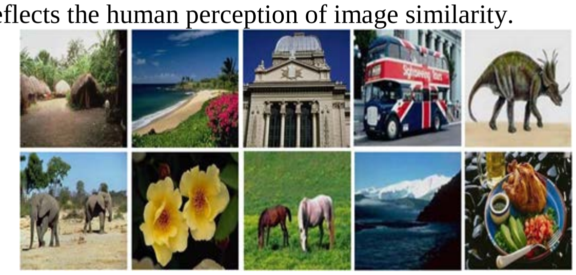


Fig. 4 Sample images of each category of the image database.

To realize the proposed system MatLab IDE is used. The GUI design environment (GUIDE) tool is used to develop the required front end GUI. The Image processing toolbox and the neural network toolbox of MatLab are used to implement the required image processing and neural network tasks.

A three layered neural network which is used as classifier, is setup and configured with parameters that are best suitable for image retrieval task. The configuration include setting the learning rate to 80%, setting the permissible error to 0.003, and selecting the "Gradient Descent Method" (backpropagation) as training algorithm. Then, the network is trained about the extracted features of all the images from the training dataset. The performance of the training process can be analysed using the performance plot, which is shown in Figure 4. The performance plot is a graph of number of epochs versus the Mean Square Error (MSE). The number of epochs we have chosen is 2000 and the MSE measures the average of the squares of the errors i.e., the difference between the two training epochs. The graph shows the best training performance at epoch number 1995.

Also, the regression plot for training process is shown in Figure 5. The regression plot gives the relationship between the input parameters (target, '0' to '1') and the output parameters given by,

$$output = (learning\_rate \times target) + bias \qquad (10)$$

In this case it is, $output = (0.8 \times target) + 0.039$

The small circles at target '0' indicate the input parameters i.e., the image features such as color, edge histogram and GLCM. The circles at target '1' indicate the output parameters i.e., image classes. The graph shows that the regression of about 87% is achieved.

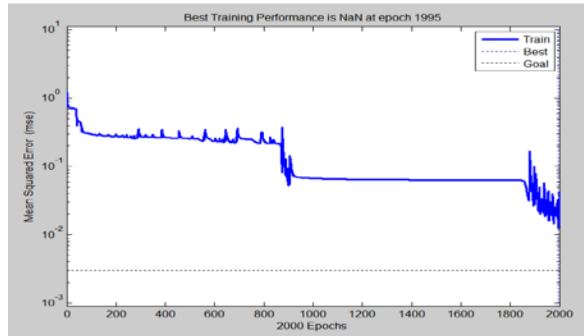


Fig. 4 Performance plot for the training process.

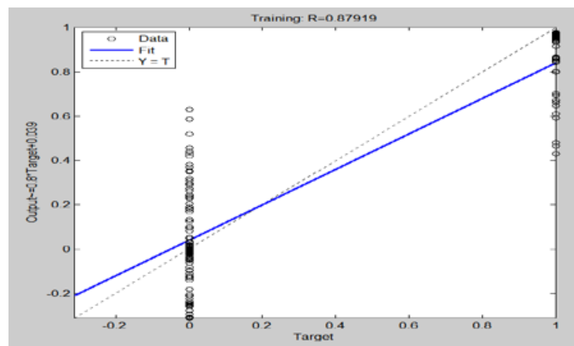
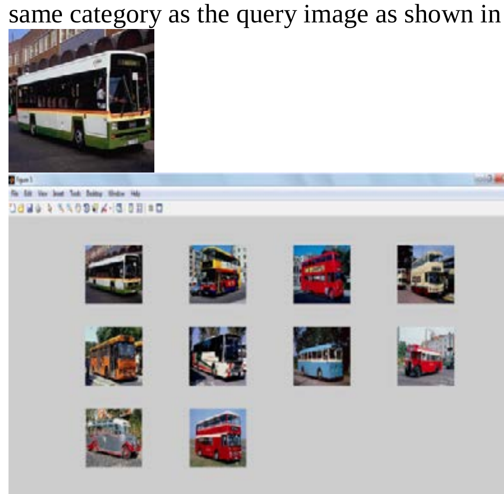


Fig. 5 Regression plot for the training process.

A given query image is feature extracted and searched for similar images. For each query image, relevant images are considered to be those and only those which belong to the same category as the query image as shown in Figure 6.



(a) (b)

Fig. 6 Retrieval process. (a) Query image. (b) Retrieved results obtained using the trained network as classifier.

Based on this concept, the retrieval precision and recall are defined as,

$$Precision = \frac{N_{A(q)}}{N_{R(q)}} \quad (11)$$

$$Recall = \frac{N_{A(q)}}{N_t} \quad (12)$$

where NA(q) is the number of relevant images similar to the query, NR(q) is the number of images retrieved by the system in response to the query, and Nt represents the total number of relevant images available in the database

The two tables given below shows the details of retrieval precision and recall values for each class of image. The TABLE I gives the precision values along with the average precision and similarly TABLE II gives recall values along with their average.

TABLE I. PRECISION VALUES FOR EACH CLASS

Category ID	Category	Precision
1	Food	0.90
2	Buildings	0.85
3	Beach	0.87
4	Elephants	0.91
5	Buses	0.89
6	Dinosaurs	0.92
7	Flowers	0.86
8	Horses	0.88
9	Mountains and glaciers	0.89
10	Africa people and village	0.87
	Average	0.88

TABLE II. RECALL VALUES FOR EACH CLASS

Category ID	Category	Recall
1	Food	0.75
2	Buildings	0.82
3	Beach	0.86
4	Elephants	0.71
5	Buses	0.77
6	Dinosaurs	0.80
7	Flowers	0.85
8	Horses	0.79
9	Mountains and glaciers	0.80
10	Africa people and village	0.70
	Average	0.78

This tabular data is plotted and shown in Figure 7 and Figure 8. As shown in figure 7, the retrieval precision for different classes vary from 85% to 92%. Therefore, the overall average precision comes to be 88%. As shown in figure 8, the recall rate for different classes vary from 70% to 86% and the overall average precision comes to be 78%.

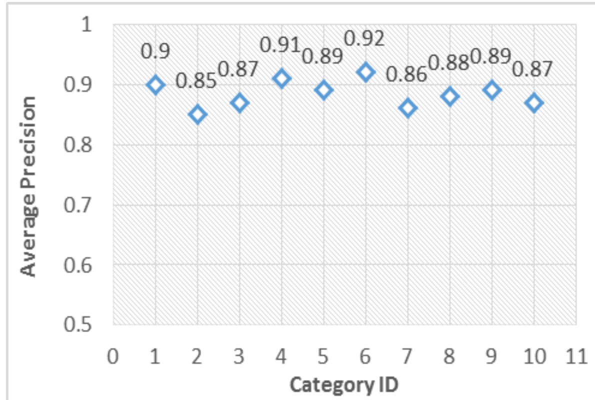


Fig. 7 Retrieval average precision of the proposed approach

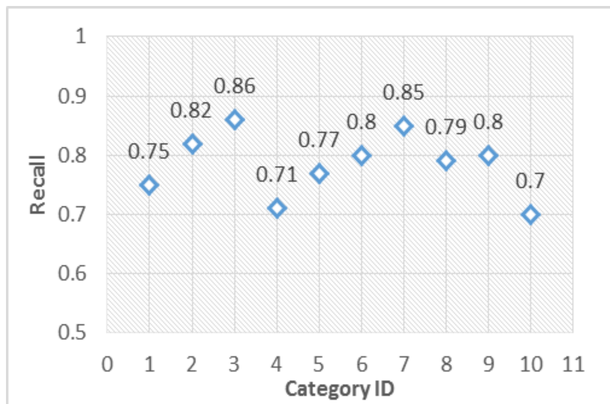


Fig. 8 Retrieval average recall of the proposed approach.

In comparison to other content-based image retrieval approaches such as those based on genetic algorithm, which is computationally heavy with respect to CPU usage and memory, the proposed approach outperforms it in terms of retrieval performance. This is because, a trained network is always fast in classifying and decision making tasks.

6. CONCLUSION

This paper has presented a CBIR system using feed-forward neural network. The color distribution histograms are used as color information of an image. Also, the entropy based on the GLCM and edge histogram are considered as texture descriptors to help characterize the images. The use of feed-forward neural network has considerably improved the recall rate and also retrieval time, due to its highly efficient and accurate classification capability. Also, the backpropagation algorithm has increased the retrieval precision due to its capability of minimizing the error during training process itself.

Experimental results of the proposed approach have shown the significant improvement in retrieval performance. A very good average retrieval precision of about 88% and average recall rate of about 78% is achieved using the proposed CBIR system. Further work include implementing the CBIR system considering more low-level image descriptors and highly efficient deep learning neural network, which might prove to be very fast and precised one.

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