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Image feature Extraction System of CBIR using neural network

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Abstract: *In Past, for our ancestors 'Imaging' is a medium through which they can expressed us some information about their life. But, as the beginning of twenty century imaging has grown rapidly in all our walks of life. Henceforth Due to digitization Volume of digital data has increases tremendously. CBIR (Content based image retrieval) is a significantly popular approach which help in retrieval of image data from large collection of storage. In this paper, we represent general-purpose CBIR system that establishes efficient combination of color, texture and shape features. In CBIR, First, The color feature of an image considered here are RGB to HSV as color descriptor, Second we used GLCM (gray level co-occurrence matrix) as texture descriptor and third edge histogram as edge descriptor. Back propagation neural network has been implemented in training the neural network. This trained network is used for similarity measure with a query image retrieves as well as display the images which are relevant to query image from database.*
Accuracy of the developed model is presented using Precision and recall of image retrieval. The outcome of the combined extracted features are compared with the isolated results. The maximum accuracy rate that reaches by using as average retrieval precision of about 92% and an average recall rate of about 89% for non linear Back propagation neural network.

Keywords: *Feature extraction, neural network, training, testing, CBIR.*

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I. Introduction

Due to rapid development in storage media, computers, image capturing devices enable to retrieve any information from the storage. But to retrieve data from these huge collections of storage has become the challenges to computer system. Using any search engine we enable to retrieve any image among the storage. Then, this search engine will retrieve many of images related to the searched. The main problem faced by user is locating his relevant image from huge amount of collection. This problem is solved by using two techniques such as text based and content based image retrieval. Content Based Image Retrieval (CBIR) is the retrieval of images based on their visual features such as color, texture, and shape [1].

After that this term has been frequently used in the process of retrieving images from huge collection of images based on the low level features such as color, shape and texture which are signature of the images.

II. Proposed Work

In our work, we combine the low-level visual features (i.e. color, texture and shape) in the proposed approach and afterword reviews the basic concepts of the feed-forward back propagation neural network to reach an appropriate level of accuracy. The proposed method is described briefly as follows:

Query Image: This is the first step in CBIR where type of image is required by user in the form of inputs. This results input in CBIR system in form of query is called query formation.
Feature Extraction: In this, the extraction methods are elaborated in order to obtain low level features of images, which resemble to be useful for image retrieval system.
Pre-processing: In this some pre-processing on image has to done in the form of image resizing and color conversion.
Image Features Database: A feature vector is extracted from each image in the database and the set of all feature vectors is organized as a database index is called feature database.
Image Database: The image database includes from WANG database which is widely used for CBIR performance evolution. The image collection that we have used in this work contains 500 images like Bus, Flowers, and Elephants etc.
Similarity measurement: For retrieving images we have used two similarity measurements, Euclidian distance and second, BPNN is a network that is trained with a training algorithm which calculates error signal by finding the difference between the training outputs from the target output.

III. Feature Extraction Method And Neural Network

Various feature extraction techniques are available for extracting image using low level features of an image like color, texture, shape etc. We have combined these low level features using feature extraction methods and feed forward back propagation neural network is used in this project in order to reach a better accuracy level for image retrieval:

3.1 *Color Descriptor:*

Color is one of the most powerful features which are visually recognized by human brain very easily and efficiently. For extracting of color features from the content of an image, we need effective color descriptor known as color space.

The RGB color space is the most widely used color space stands for Red, Green, and Blue for the digital image purposes. But, the main drawback of the RGB color space is that it is perceptually non-uniform. Hence to overcome such a drawback, different color spaces are proposed. As a color space, we choose the HSV (Hue, Saturation, and Value) space. HSV color space is more suitable since it separates the color components (HS) from the luminance component (V) and is less sensitive to illumination changes [2]. HSV describes color using more familiar comparisons such as color, vibrancy and brightness. For a given image, the process of calculation of color histogram is shown in Fig (1):

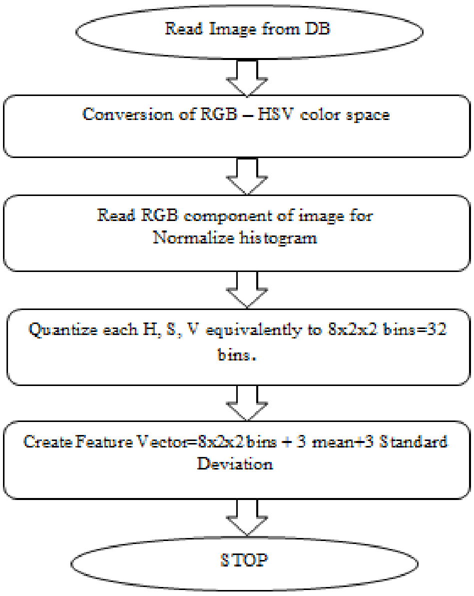

Fig (1) Flowchart for Color Feature Extraction

3.2 *Texture Descriptor:*

Texture is an important feature descriptor of an image. It refers to the distribution of gray levels and their interrelationship. For texture analysis we tend to use a grey level co-occurrence matrix (GLCM), that could be an easy and effective methodology for representing texture [17][8].In GLCM method, the pixel values are used to construct numerical structures that are associated to the texture pattern of the image. This pattern is based on the inter-relationship between one pixel and its neighbors. Statistics are divided as a first, second and higher order statistics according to number of points define the local feature.

To determine the texture features, selected statistics are applied to every GLCM by iterating through the whole matrix. The textural features are based on statistics that summarize the relative frequency distribution that describes however usually one gray tone can appear during a specified spatial relationship to another grey tone on the image. Every entry (i, j) in GLCM corresponds to the number of occurrences of the pair of gray levels i and j that are a distance d apart in the original image.

A co-occurrence matrix is a square matrix with elements corresponding to the relative frequency of occurrence of pairs of gray level of pixels separated by a certain distance d in a given direction $\theta = (0^0; 45^0; 90^0 \text{ and } 135^0)$ were implemented. Mathematically, for a given image I of size K×K, the elements of a G×G gray-level co-occurrence matrix $P(i, j / d, \theta)$ for a displacement vector d= (dx, dy) is defined as,

$$\Phi(d,\theta) = [P(i, j / d,\theta)],\ 0 < i, j \leq Ng \quad \ldots\ldots\ldots (1)$$

Where, the Ng is states as the maximum gray level.

This paper extracts some features from GLCM matrices and their formula [6][7][8][9] is mentioned in Table1.1.

Table 1.1: Features Extracted from GLCM

S.No.	Features	Formula	Description
1	Entropy	$-\sum_i \sum_j P(i,j)\log(P(i,j))$	It measures the complexity of an image.
2	Contrast	$\sum_{n=0}^{Ng-1} n^2\{\sum_{i=1}^{Ng} \sum_{j=1}^{Ng} P(i,j)\}$	It is the difference between the highest and lowest values of a contiguous set of pixels
3	Measure of smoothness	$\sum_{i=1}^{Ng} \sum_{j=1}^{Ng} P(i,j)/1+(i-j)^2$	Measures the smoothness (homogeneity) measures the gray level distribution of the image
5	Measure of uniformity	$\sum_i \sum_j P(i,j)^2$	This statistic is called as uniformity or energy. It measures the textual uniformity of pixel pair distributions.

3.3 ***Edge Descriptor:***

Edge is described as discontinuity of images. Human eyes are very sensitive in edge feature prospective. It is used to capture spatial distribution of edges in the images. Normally, to represent global feature composition of an image Histogram is used. An edge histogram in the image space represents the frequency and the directionality of the brightness changes in the image [6][7]. The edge extraction process of EHD consists the following steps is shown in Fig (2):

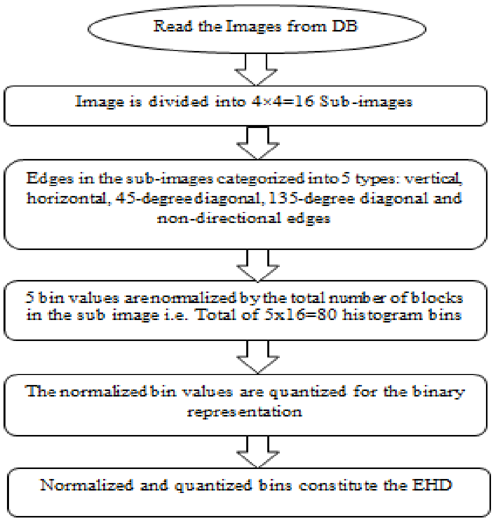

Fig (2) Flowchart for edge Feature Extraction

3.4 ***Feed Forward Back Propagation Network:***

FFBPNN is a technique used for classification and pattern recognition. FFBP NN is also known as a multilayer neural network, used to implement non-linear differentiable functions. The architecture of FFBP NN consists of 3 layers such as input, hidden and output layer. FFBP precedes both in forward as well as backward direction. It computes output in the forward procession and computes error in the backward procession. In the forward direction, training data is taken into account as input layer. Then this data is fed to the hidden layer that performs the processing. Finally it applied to output layer wherever the output of a neuron could be connected to the input of another one and therefore the last one is connected with an activation function. In this method a neural network is created.

The values computed in the forward pass are compared with desired output. The difference between the desired output and the actual output constitute as the error, which is computed and propagated back towards the Hidden Layer. The gradient of the error is computed and applied on a node k stated as:

e***k= desired output – actual output***

ek = dk – yk .... (4)

Where,

ek- error on a single output neuron k
dk -desired output
yk -calculated output of neuron k.

IV. Proposed Methodology

Generally user interface is a medium for communicating with the image retrieval system, which accepts query image from the user and displays the retrieval results. Here we tend to used hybrid approach for extracting low level features such as color, texture and edge from database. After extraction of features this module is responsible for implementing image retrieval functionality is neural network wherever back propagation algorithm implemented. According to the above concept we have design an efficient image retrieval system based on neural network shown in Fig (3). We have two phases in our proposed system: training and testing phase.All the images as well as query image present in database has to undergo pre-processing on feature extraction. According to the aforesaid concept, we tend to design an image retrieval system based on neural network and Euclidian distance, as shown in Fig (3):

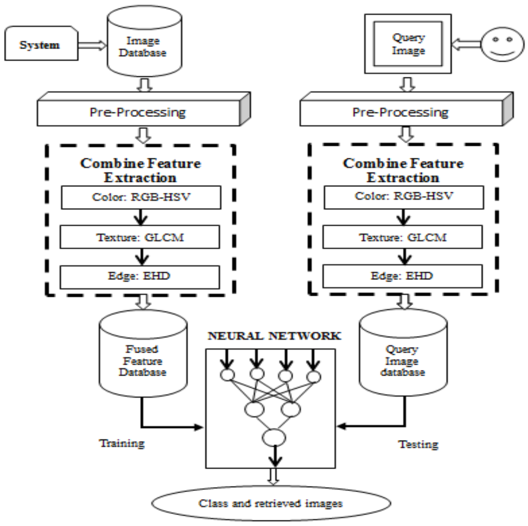

Fig (3) Block Diagram of Image retrieval system using Neural Network

Phase 1:
4.1 Training: This is three layered neural network including creation and configuration and used to learn about extracted features of training images. In our proposed system training database includes all the images from image database (50 images for each 10 classes).
Algorithm for Training phase: setup ANN and initialize the following parameters as: number_of_layers= 3; epochs=1000; learning rate=97%; 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 texture features using GLCM algorithm;
Extract its edge features using edge histogram algorithm;
Combine 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=1000 is satisfied
output: *a trained neural network.*

4.2 The back propagation algorithm for a 3-layer network (two 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 for all weights from hidden layer to output layer; Backward pass
Calculate for all weights from input layer to hidden layer; Backward pass continued
Update the weights to minimize error in the network;

Until some stopping criterion satisfied
Return the network

Table 1.2: Adjusted weights to minimize error in the network

Sr. No	*Feature Extraction*	*Number of Hidden Layers*	*Neurons in Hidden Layer*
1	*Color*	*2*	[400 35]
2	*GLCM*	*2*	[250 55]
3	*EHD*	*2*	[500 50]
4	*ALL*	*2*	[800 55]

Phase 2:
4.3 Testing: In our system the testing phase includes the querying and retrieving category of the query image. First, the query image is pre-processed. Subsequently its features are extracted using respective feature extraction methods mention in figure three. Once completing the training process, trained network is conferred with query image features.
Input: a query image.
load the input query image;
Extract its color features [38 D] using color histogram algorithm;
Extract its texture features [17 D] using GLCM algorithm;
Extract its edge features [150] using edge histogram algorithm;
load the combine features [38+17+150=205 D] of query image database;
compute similarity between query image features and training set features;
output: set of similar pictures if present;

V. Experimental Results And Analysis

The level of retrieval accuracy achieved by a system is important to establish its performance. We used database in this evolution is known as WANG database that could be a subset of the Corel database of 1000 images. This database has been considered with 10 different categories of images contained 100 images. Every category contains 50 images. By providing this dataset, image database are divided into two set as training dataset and testing dataset wherever after feature extractions the data is trained by using FFBPNN and query image is used from testing dataset.

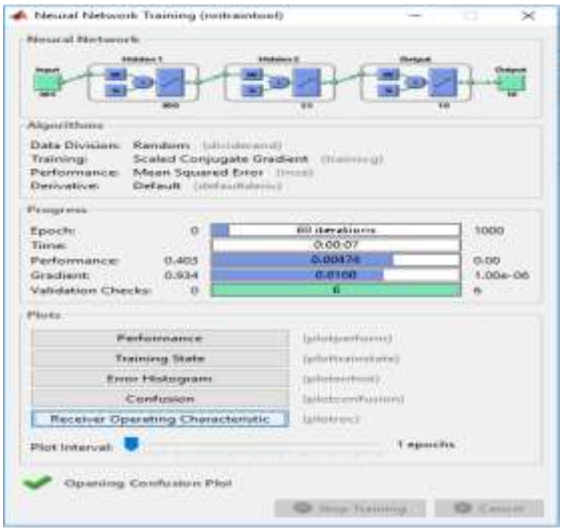

Fig (4) Training Neural Network and Performance goal met Epochs at 68 iteration.

A three layered neural network that is employed as classifier and this classifier is configured with parameters that are best suitable for image retrieval task. The configuration embody setting the learning rate to 97%, setting the permissible error to 0.003, and selecting the "Gradient Descent Method" (back propagation) as training algorithm. Then, the network is trained regarding the extracted features of all the images from the training dataset.

Performance plot= no of epochs/Mean Square Error (MSE) ……….(5)

Best validation performance is at epochs 62 is 0.0252 as shown in performance plot in Fig (5).

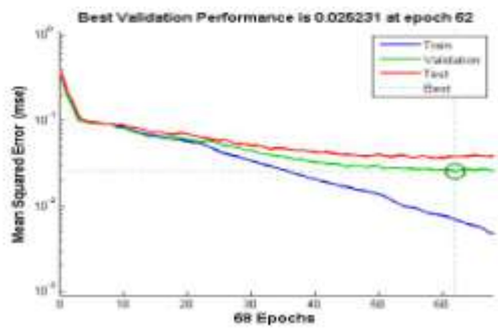

Fig (5) Best validation performance plot at 62 epoch

Gradient are individual error for each of the weights in neural network is 0.057 at epochs 62. Validation set is used to determine the performance of a neural network on patterns that are not trained during learning. The graph shows that the training regression of about 98% is achieved.

$$\boldsymbol{Output = learning\_rate \times Target + bias} \ldots\ldots\ldots\ldots\ldots (6)$$

In the proposed work, regression plot is calculated as,

Output=1×Target+0.057 at epochs 62

Precision and recall values are calculated from *confusion matrix* which is also known as error matrix and is a table that describes the performance of the classifier. The confusion matrix for the 10 image categories (i.e. African, Beach, Bus, Dinosaur etc.) is displayed below in Fig (6) providing Dinosaur as a query.

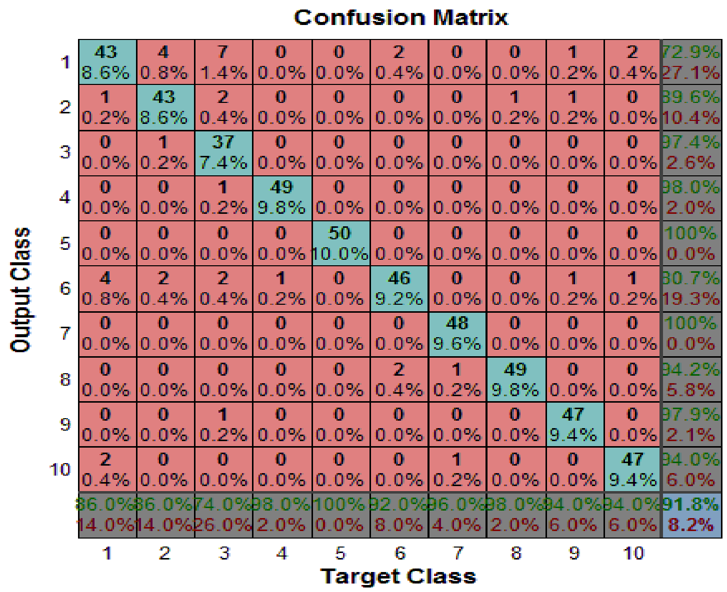

Fig (6) Plot of Confusion Matrix

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

$$\text{Precision} = \frac{\text{Number of relevant images similar to the query}}{\text{Total number of images retrieved}} \qquad \ldots\ldots\ldots\ldots\ldots \textbf{(7)}$$

$$\text{Recall} = \frac{\text{Number of relevant images similar to the query}}{\text{Total number of relevant images available in the database}} \qquad \ldots\ldots\ldots\ldots\ldots \textbf{(8)}$$

VI. Result for precision and recall value using Euclidian distance

The following tables illustrate the Precision and recall rate (%) of five images classified by Euclidian distance,

Table 1.3: Precision and recall value using Euclidian distance of query image-Beaches

Class ID	No of images in Database	No of retrieve images	No of relevant images	Precision	Recall
Beaches	50	50	27	0.54	0.54
	50	50	26	0.52	0.52
	50	50	42	0.84	0.84
	50	50	32	0.64	0.64
	50	50	25	0.50	0.50

Table 1.4: Precision and recall value using Euclidian distance of query image- Buildings & Architecture

Class ID	No of images in Database	No of retrieve images	No of relevant images	Precision	Recall
Buildings & Architecture	50	50	27	0.78	0.78
	50	50	38	0.76	0.76
	50	50	20	0.64	0.64
	50	50	32	0.66	0.66
	50	50	25	0.38	0.38

Table 1.5: Precision and recall value using Euclidian distance of query image- Buses

Class ID	No of images in Database	No of retrieve images	No of relevant images	Precision	Recall
Buses	50	50	13	0.26	0.26
	50	50	22	0.44	0.44
	50	50	20	0.40	0.40
	50	50	17	0.34	0.34
	50	50	24	0.48	0.48

Table 1.6: Precision and recall value using Euclidian distance of query image- Dinosaurs

Class ID	No of images in Database	No of retrieve images	No of relevant images	Precision	Recall
Dinosaurs	50	50	48	0.96	0.96
	50	50	48	0.96	0.96
	50	50	47	0.94	0.94
	50	50	49	0.98	0.98
	50	50	49	0.98	0.98

Table 1.7: Precision and recall value using Euclidian distance of query image- Elephants

Class ID	No of images in Database	No of retrieve images	No of relevant images	Precision	Recall
Elephants	50	50	19	0.38	0.38
	50	50	19	0.38	0.38
	50	50	22	0.44	0.44
	50	50	23	0.46	0.46
	50	50	23	0.46	0.46

VII. Results FOR precision and recall value using Feed forward back propagation neural network

The following tables illustrate the Precision and recall rate of five images classified by Feed forward back propagation neural network,

Table 1.8: Precision and recall value using BPNN of query image-Beaches

Class ID	No of images in Database	No of retrieve images	No of relevant images	Precision	Recall
Beaches	50	43	41	0.95	0.82
	50	43	41	0.95	0.82
	50	43	40	0.93	0.80
	50	43	40	0.93	0.80
	50	43	40	0.93	0.80

Table 1.9: Precision and recall value using BPNN of query image- Buildings & Architecture

Class ID	No of images in Database	No of retrieve images	No of relevant images	Precision	Recall
Buildings & Architecture	50	38	36	0.94	0.72
	50	38	36	0.94	0.72
	50	40	36	0.90	0.72
	50	40	36	0.90	0.72
	50	38	38	1	0.76

Table 1.10: Precision and recall value using BPNN of query image- Buses

Class ID	No of images in Database	No of retrieve images	No of relevant images	Precision	Recall
Buses	50	48	47	0.97	0.94
	50	48	46	0.95	0.92
	50	48	48	1	0.96
	50	48	47	0.97	0.94
	50	48	46	0.95	0.92

Table 1.11: Precision and recall value using BPNN of query image- Dinosaurs

Class ID	No of images in Database	No of retrieve images	No of relevant images	Precision	Recall
Dinosaurs	50	50	49	0.98	0.98
	50	50	49	0.98	0.98
	50	50	49	0.98	0.98
	50	50	49	0.98	0.98
	50	50	49	0.98	0.98

Table 1.12: Precision and recall value using BPNN of query image- Elephants

Class ID	No of images in Database	No of retrieve images	No of relevant images	Precision	Recall
Elephants	50	48	45	0.93	0.90
	50	48	46	0.95	0.92
	50	48	46	0.95	0.92
	50	48	46	0.95	0.92
	50	48	45	0.93	0.90

VIII. Conclusion

In conclusion, the table noticeably depicts that feature extraction is highly recognized accurately where nonlinear Feed forward back propagation neural network is used as compared to that of Euclidean distance.

This paper has depicted a CBIR system using feed-forward neural network. The color descriptor is used as color information of an image. Also, GLCM and EHD are considered as texture descriptors and edge descriptor respectively to help characterize the images.

The training images database is trained using feed forward algorithm that has considerably improved the recall rate. It also improved retrieval time, due to its highly accurate classification capability and error is computed using back propagation algorithm that enhanced the retrieval of precision rate.

Accuracy of the developed model is presented using Confusion Matrix, precision and recall rate. The outcome of the combined extracted features are compared with the isolated results. The maximum accuracy rate that reaches by using as average retrieval precision of about 92% and an average recall rate of about 89% for non linear Back propagation neural network.

From the above analysis, it is clear that the proposed system gives different accuracy level for both the Euclidean distance and neural network. The system works well with FFBPNN compared to Euclidian distance. As in some cases, the only drawback that the retrieval result contains the irrelevant images but this system is 100% accurate. The future task that can be done is to improve the accuracy rate of more efficient technique to reduce the query execution time of this CBIR system.

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