

# Image Quantification Learning Technique through Content based Image Retrieval

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**Abstract:** This paper proposes a Radial basis functionality incorporation in learning the quantification of images using Content based Image Retrieval (CBIR). The approach is trying to find out the effectiveness of Multi-Layer Perceptron (MLP) namely Radial Basis Function (RBF) through Content Based Image Retrieval. Extract the features of an image, the numeric values of each pixel is framed in to a definite input data set of image to that the neural networks MLP gives the accuracy of the prediction of that particular Image data set. This paper put forward us with new idea of neural networks structure efficiency in the accuracy of output data set which got increased by the adjustment of the weighted neurons through a Perceptron called Radial Basis Function promoting by applying k means clustering to form clusters which are parameterized with Gaussian function application. Finally compare the actual output with observed output promoting the weighted neurons adjustment for getting the actual accurate output. A new dimension, in work enhancement of neural networks technology with that of image processing.

**Keywords:** MLP, CBIR, RBFNN.

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## I. INTRODUCTION:

The effective and distinguished feature of the multilayer perceptron [1] with content based image retrieval system enables us in estimation on the previous data, for classification of various temperatures resolution to that of images. The idea behind is to classify the image variations with the outstanding feature of Radial basis function through the image processing of retrieving. The multilayer perceptron give us a new path of orientation in accuracy of prediction through the content based image retrieval [2]. In the process of retrieving images, changing from the text based retrieval to the content based retrieval [3] is very much a challenging and demanding task following with a multilayer perceptron for the accuracy in prediction of the given input image.

An overview of the research domain in 1997 is given and in [4,5], the past, present and future of image retrieval is highlighted There are several reasons why there is a need for additional, alternative image retrieval methods apart from the steadily growing rate of image production. It is important to explain these needs and to discuss possible technical and methodological improvements. Image retrieval is the process of browsing, searching and retrieving images from a large database of digital images. Advances in data storage and image acquisition technologies have enabled the creation of large image datasets. In order to deal with these data, it is necessary to develop appropriate information systems to efficiently manage these collections. It is simple to identify a

desired image from a small collection simply by browsing, but we need more effective techniques with collections containing thousands of items. Image searching is one of the most important services that need to be supported by such systems. In general, two different approaches have been applied to allow searching on image collections: one based on image textual metadata and another based on image content information. The first retrieval approach is based on attaching textual metadata to each image and uses traditional database query techniques to retrieve them by keywords [6]. However, these systems require a previous annotation of the database images, which is a very laborious and time-consuming task. Furthermore, the annotation process is usually inefficient because users, generally, do not make the annotation in a systematic way. In fact, different users tend to use different words to describe a same image characteristic. The lack of systematization in the annotation process decreases the performance of the keyword-based image search. Image retrieval systems have not kept pace with the collections they are searching. The shortcomings of these systems are due both to the image representations they use and to their methods of accessing those representations to find images. The problems of image retrieval are becoming widely recognized, and the search for solutions an increasingly active area for research and development.

In recent years, with large scale storing of images the need to have an efficient method of image searching and retrieval has increased. It can simplify many tasks in many application areas such as fingerprint identification biodiversity information systems, digital libraries, crime prevention, medicine, historical research, artificial

intelligence, military, education, web image searching. Content-Based Image Retrieval (CBIR) systems [7-9] in these systems, image processing algorithms (usually automatic) are used to extract feature vectors that represent image properties such as color, texture, and shape. In this approach, it is possible to retrieve images similar to one chosen by the user (query-by-example). There by we can overcome the disadvantages of the text based retrieval systems. The main advantages of this approach is the possibility of an automatic retrieval process, contrasting to the effort needed to annotate images. In this paper it was focused on image classification of various atmospheric conditions on the earth map/remote sensed image. Generally classification can be done with aid of various filter techniques but in order to classify the image we are using an advanced platform called Neural Networks.

Below given tht Step wise performance of CBIR and RBFNN in Quantifying the similar images.

CBIR step1: Image with Weather conditions

CBIR step2: Image segmentation

CBIR step3: Filtering techniques on segmented images

CBIR step4: Conversion of features into Input Set for an MLP

RBFNN step 5: Applying K means clustering to form the clusters for CBIR Input Set.

RBFNN step 6: Applying the Gaussian Function

RBFNN step 7: Compare actual input set and observed output set of RBFNN

RBFNN step 8: Weight Adjustment

RBFNN step 9: Output –Exact similar indexed image.

## II. PROPOSED MODEL:

CBIR activity undergone on different weather conditions image and RBF Neural Network results the predicted image accuracy: Basing on different colour content of the image the grouping is done with the clustering technique of image processing i.e K-Means clustering. The output given from grouping clusters [11] is the initial input to our effective RBFNN. The main aim is to retrieve the very desired image on comparison with query image to that of database images [12]. On applying the Gaussian function in the hidden layer of RBF network model results us the desired image [13] through iterative adjustment of weights of multilayer perceptron. Fig 1 depicts the proposed model step wise activity.

Fig 1: Proposed model

Step1: Image data base collection and Pre-processing
Step 2: Feature Extraction -CBIR
Step 3: K means clustering
Step 4: Grouping of images
Step 5: RBF neural network
Step 6: Image similarity check with quantification value

RBF-NN (RADIAL BASIS FUNCTION NEURAL NETWORKS):

RBFNNs, similarly to all Neural Networks, are associated with a set of parameters that need to be adjusted in order for the Neural Network to “learn” the correct mapping between inputs and outputs. The set of parameters of a Neural Network is directly dependent on the Neural Network’s architecture.

In particular, the RBFNN is comprised of a hidden layer and an output layer, while each layer consists of a set of nodes. The input data are presented to the RBFNN in the form of vectors[14]. Each input vector is presented to each one of the hidden layer nodes, and one response per node is obtained. The hidden layer nodes perform a non-linear operation on the input vectors. Subsequently, the responses of all hidden nodes are weighted by hidden-to-output layer weights, and are combined in order to produce an overall output. The output should ideally be equal to a desired output. The difference between the obtained and desired output is used to adjust or train the network parameters, so that the error is reduced. The network parameters consist of the hidden-to-output layer weights, and parameters associated to the hidden layer functions represented by each hidden layer node. Use of RBFN is to retrieve the desired image with the comparison with the query and the database, especially the number of input neurons number of hidden neurons. Centers  $c_i$ , width  $\sigma_i$  and weight  $w_i$  and the use of K-means clustering technique to analyze and find Clusters in the training data. The results of this group-ing are establishing prototypes of the receptive fields. The activation function in the hidden layers is Gaussian function represented by  $o(x) = \exp(-x^2)$ .

$$\text{HIDDEN LAYER: } o(x) = \exp(-(|x-c||^2) / \sigma^2)$$

$$\text{OUTPUT LAYER: } \sum o(x) W_i$$

The weights  $W_1, W_2 \dots W_n$  denotes the weights of the arcs from the hidden layers nodes to the output node. Note that the initial values of  $W_1, W_2 \dots W_n$  are adjusted so that the nodes in the hidden layer have same contribution to the

Output node . Using the hierarchical clustering algorithm we obtained a groups of similar images  $V_1, V_2$  and by using RBFN neural network with the K-means clustering algorithm, we can get a retrieved image by comparing with the query image. The retrieval image is compared against the query image. Assume for a certain set of inputs the retrieval image of the network as RI. Furthermore QI denotes the Query image given by the user. The error is estimation is determined by  $\text{Error} = \text{QI} - \text{RI}$  which is used to determine the error of nodes in the hidden layer.

In the output layer: new weight adjust =  $W_i(\text{new})$

$W_i(\text{new}) = W_i(\text{old}) \pm \alpha$

Weight difference given by the Error  $o(x)$

Where  $\delta =$  learning rate

Error =  $\text{QI} - \text{RI}$

$o(x) =$  output of Activation function in hidden layer

3: Repeat iteration until Convergence.

Here we are going to filter most of the images in the hierarchical clustering and then apply the clustered images to RBFN network, so that we can get better favored image results. Brief details on the implementation of these two clustering algorithms are presented below.

Step-wise representation of proposed model:

Step 1: Get initial input image from different conditions of image database

Step 2: Images are grouped basing on certain content features through clustering techniques

Step3: Now the images got segmented images through filtering techniques.

Step4: Segmented image values are sent as input values to RBF Neural Network model

Step5: RBFNN provides the images that are very much more similar to the input image given as the retrieved output image.

### III. ALGORITHM:

Step 1: On the Input image clustering performed

Step 2: Consider each point as its own cluster.

Step 3: Find out the most similar cluster-pairs

Step 4: Combine them to form parent cluster.

Step5: Continue the step3 to step 5 till all the point are combined into single cluster

Step 6: Now the output of above cluster is given as input to the RBFNeural Network

Step7: Enter the number of clusters as some X value as random guessing number

Step 8: this X value is the Midpoint of the cluster.

Step 9: Each Data Point finds out which center it's closest to.

Step 10: Thus each center "owns set of points".

Step 11: Each Center Finds the centro of its own points.

Step 12: Center Now moves to the New Centro

Step 13: Repeat Step 9 to Step 12 Until Terminated.

### IV. CONCLUSION:

The new dimension of content based image retrieval through RBF neural network techniques for retrieving the images, where clustered into defined groups for very fast image retrieval and allows a great searching for the most relevant images from large database. RBFNN an approach which uses K-means clustering and Gaussian function to retrieve images that are similar to initial image given to the images in database. This work can have its extension through reporting of weather forecasting accuracy rate betterment and also can enhance with Fuzzy C-means clustering technique.

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