Medical Image Retrieval System Using an Improved MLP Neural Network

G.Ravi Teja#1, G.Chaitanya#2, K.Rajesh#3

[1]*M.Tech CSE Department, K L University, India*
[2]*M.Tech CSE Department, K L University, India*
[3]*M.Tech CSE Department, K L University, India*
[1]gunti.raviteja@hotmail.com
[2]karthik.ramanareddy@hotmail.com
[3]rajesh.suresh.kundurthi@hotmail.com

Abstract—**Medical database contains huge volume of data, mostly in the form of digital medical images. Digital medical images such as X-Rays, MRI, CT is extensively used in diagnosis and planning treatment schedule. Large medical institutions produce gigabits of image data every month. For effective utilization of medical images from the archives for diagnosis, research and educational purpose, efficient image retrieval system is essential. Image retrieval systems extract features in the image to a feature vector and use similarity measures for retrieval of images. Thus the efficiency of the image retrieval system depends upon the feature selection and its classification. In this paper, a novel feature selection mechanism using Discrete Sine Transforms (DST) is proposed to implement and with Information Gain for feature reduction.**

Keyword—**Medical image retrieval; Discrete sine transform, Information gain, Neural Network, Multilayer perception.**

I. INTRODUCTION

Digital images play a vital role in diagnosis and treatment schedule planning of a disease. It provides visual information for diagnosis, progress in treatment. Image retrieval of digital medical images from archives is a challenge that is widely researched. Textual annotations of images were the basis on which images were retrieved during the early 80s. The images were retrieved using semantic queries. With the escalating volume of digital images stored, textual annotation is not feasible as manually annotating using keywords involves a huge amount of manual labor. And also with the gigabits of image data generated in present scenario, annotation of images is impossible. A system which can automatically classify images and retrieve images based on query image is required for efficient use of the archived medical data images. Earlier works in literature include use of visual features with text annotation for image retrieval Modern radiology techniques like CT, PET, MRI, X-Rays, provide essential information required for diagnose and plan treatments to the medical professionals. Thus, efficient storage and image retrieval system for utilization of the images for diagnosis, research and educational purposes are required. Image retrieval based on visual features or image based query wherein the retrieval system responds to a query image by retrieving query similar images from the archive. In this retrieval system, the images in the database are preprocessed automatically to extract features and on the basis of the features, the images are classified. The query image is similarly preprocessed to extract features and based on the similarity measures appropriate images are retrieved from the database. Figure 1 show the block diagram of an image retrieval system.

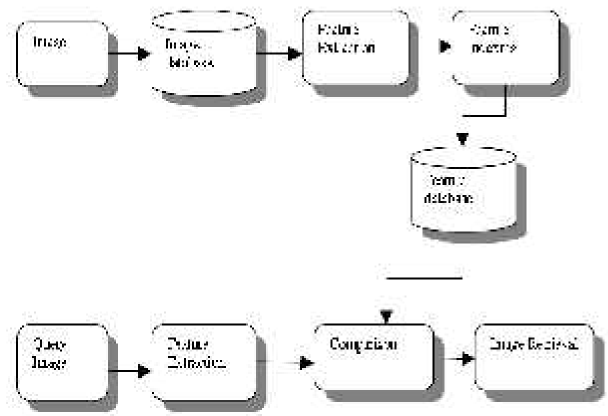

Figure 1: Block diagram of Image retrieval process

Image retrieval plays a fundamental role in handling large amount of visual information in medical applications. An effectiveness of an image retrieval system depends on:

• Multi magnitude feature vector formed using information extracted from images

• Computing distance metrics

• Identify the images in database with lowest distance metrics from the query image

Features such as texture, color, shape and spatial relationship are used for classifying images. In medical imaging, color is an effectively used feature; in fields of dermatology color is extensively used as a feature. MRI images, X-Rays are in grey scale, thus color may not be an effective feature for image retrieval. Similarity measures computed from low level image features are mainly used for image retrieval. To automatically categorize medical images, data mining techniques such as decision tree, Bayesian network, Neural networks, Support vector machines are widely used. In this paper it is proposed to extract the frequency vector from medical images sing Discrete Sine Transform (DST) and feature reduction using Information Gain (IG). The proposed Fuzzy Softmax Multilayer perceptron (SF-MLP) Neural Network is used to classify the obtained feature vectors for the given class.

This paper is organized into the following sections; section II contains related works in image retrieval. Section III briefly introduces the proposed DST, Information gain and MLP Neural Network with the proposed neural network model. Section IV gives details about the experimental setup and section V devotes on results obtained.

II. PREVIOUS RESEARCH

Rigau, et al., proposed a two-step mutual information-based algorithm for medical image segmentation. In the first step, binary space partition splits the image into relatively homogeneous regions. Second step involves clustering around the histogram bins of the partitioned image. The clustering is done by minimizing the mutual information loss of the reserved channel. The proposed algorithm preprocesses the images for multimodal image registration. Experimental results using proposed algorithm on different images show that the segmented images perform well in medical image registration using mutual information-based measures.

K. Rajkumar et al., proposed a two step medical image retrieval framework to retrieve similar images. A content based image retrieval framework based on PCA and wavelet was proposed. Wavelet filtering process is used to create a subset of images. The energy efficient wavelet decomposition is used to decompose images and corresponding energies were extracted. The retrieval system uses this subset to search for similar images. Further reduction of dimensions is obtained by applying PCA to the extracted features. Similarity matches of query image and database image was obtained using Euclidean distance. The calculated eigen vectors and the similarity measures were applied to retrieve the medical images. Due to the reduction of searching space efficiency and retrieval accuracy is improved. Experiments conducted using 200 medical images showed that the proposed method has better retrieval accuracy in terms of recall rate and precision.

Kambhatla, et al., 1997 developed local nonlinear extensions of PCA for dimension reduction. The algorithm was applied on both speech and image data. The proposed algorithm is fast to compute and provides accurate representations of the data. PCA and neural network implementations of non-linear PCA were used to compare with the proposed algorithm. Results showed that nonlinear

PCA performed better than PCA and the proposed local linear techniques perform better than neural network implementations.

Park, et al., 2003 proposed a method of image classification using neural network. In the preprocessing stage, the object region is extracted using region segmentation techniques. The images are transformed using wavelet transforms. Shape based texture features are extracted from transformed images and are used for classification of the images. The neural network was trained using back propagation learning algorithm. The training of neural network was done using 300 training data composed of 10 images from each of 30 classes. Results showed that the classification rates of 81.7% accuracy were achieved.

Su, et al., 2003 proposed a new feedback approach with progressive learning capability. The proposed approach is based on a Bayesian classifier. The positive and negative feedback are treated with different strategies. The positive examples are used for refining image retrieval results and negative images are used to modify the ranking of the retrieved images. The images are retrieved by estimating Gaussian distribution of the positive examples that represents the desired images for a given query. Bayesian network is used to re-rank the images in the database. PCA is used to update the feature subspace during the feedback process thus reducing sub-space dimensionalities. Thus the feedback process improves the retrieval process. Experimental results show that the proposed method improves the speed, memory and accuracy of the retrieval process.

III. RESEARCH METHOD

The following section briefly introduces to Discrete Sine Transform (DST), Information Gain (IG) and the Multi Layer Perceptron (MLP) Neural Network.

A. Discrete Sine Transform (DST)

The feature vector from each image was extracted using the discrete sine transform function. The pixels which are one length away from each other are selected. The algorithm pseudo is given below:

1. Compute Image size MxN

2. For each alternate value 'i' in array M and array size less than M or M+1

3. For each alternate value 'j' in array N and array size less than N or N+1

4. Compute DST (array [xi,yj])

5. Store computed value in one dimensional array

6. Repeat from step 1 till all images are computed

The discrete sine transform (DST) is a Fourier-related transform similar to the discrete Fourier transform (DFT), but using a purely real matrix.

$$S_K = p_K \sum_{n=0}^{N-1} x_n \sin\frac{\pi\left(n+\frac{1}{2}\right)(K+1)}{N} \quad K=0, 1, 2\ldots N-1$$

$$p_k = \sqrt{\frac{2-\delta_{K,0}}{N}} \qquad (1)$$

where x_n is the original vector on N real numbers. d is the Kronecker delta. DST operates on real data with odd symmetry and hence the output data are shifted by half a sample. The inverse of Discrete sine transform is given by

$$S_K^{III} = p_K \sum_{n=0}^{N-1} x_n q_n \sin\frac{\pi\left(n+\frac{1}{2}\right)\left(K+\frac{1}{2}\right)}{N} \quad K=0, 1, 2\ldots N-1$$

$$p = \sqrt{\frac{2}{N}}$$

$$q_n = \sqrt{\frac{1}{1+\delta_{n,0}}} \qquad (2)$$

Discrete sine transform is selected over Fast Fourier transform due to its simplicity and the reduced time to compute the medical image coefficients.

B. Information Gain

Information gain selects the feature vectors which are essential for the classification process. On the computed coefficient from DST, the information gain can be computed based on the class attribute. The information gain that has to be computed for an attribute X whose class attribute Y is given by the conditional entropy of Y given X, H(Y|X) is

$$I(Y; X) = H(Y) - H(Y|X)$$

The conditional entropy of Y given X is

$$H(Y|X) = -\sum_{j=1}^{j=l} P(X = x_j) H(Y|X = x_j)$$

C. Multilayer Perceptron (MLP)

Multilayer perceptron (MLP) is the most favored supervised learning network model. The neural network consists of an input layer, one or many hidden layer and an output layer. Connections between the each and every layer are typically formed by connecting each of the nodes from a given layer to all neurons in the next layer. During the training phase each connection's scalar weight is adjusted. The outputs are got from the output nodes. The feature vector says x is input at the input layer and the output represents a discriminator between its class and all of the other classes. In training, the training examples are fed and the predicted outputs are computed. The output is compared with the target output and error measured is propagated back through the network and the weights are adjusted.

The training set of size m can be represented as $T_M = \{(x_1,y_1),\ldots,(x_m,y_m)\}$ where $x_i \in R^a$ are the input vectors of dimension a and $Y_i \in R^b$ are the output vectors of dimension b and R represents the set of real numbers. Let f_X represent the function with w for the neural network. Supervised learning adjusts the weight such that:

$$F_w(X_i) = y;\ \forall\ (x_i,y_i) \in T_M$$

After the Neural network is trained with all images feature vectors, and is tested on new samples its output will be correct to a certain extent.

IV. PROPOSED FS-MLP

The proposed neural network Fuzzy Softmax Multi Layer Perceptron (FS-MLP) Neural Network improves the classification accuracy of traditional MLP Neural Network model by introducing a fuzzy hidden softmax layer. The construction of the proposed model is given in table I.

Input Neuron	50
Output Neuron	2
Number of Hidden Layer	2
Transfer function of first hidden layer	Fuzzy Softmax
Learning Rule of first hidden layer	Levenberg-Marquardt
Transfer function of second hidden layer	Sigmoid
Learning rule of second hidden layer	Levenberg-Marquardt

Table I: Parameters Used In The Proposed Fs-Mlp

The activation function in a neural network controls the amplitude of the output such that the range of output is between 0 and 1 or -1 to 1. Mathematically the interval activity of the neuron can be shown to be:

$$V_k = \sum_{j=1}^{p} w_{kj} x_j$$

Where xi is the input and wjk is the weights. The output of the neuron, y_k would therefore be the outcome of some activation function on the value of v_k . The most common type of activation used to construct the neural network is the sigmoid function.

A sigmoid activation function uses the sigmoid function to determine its activation. The Sigmoid function is given as:

$$f(x) = \frac{1}{1+e^{-x}}$$

This function can range between 0 and 1, but it is also sometimes useful to use the -1 to 1 range. An example of the sigmoid function is the hyperbolic tangent function where the range is -1 to 1.

$$\ddot{}\ (V) = \tanh\left(\frac{V}{2}\right) = \frac{1-\exp(-V)}{1+\exp(-V)}$$

The softmax activation function,(Bridle, 1990), applied to the network outputs ensures that the outputs conform to the mathematical requirements of multivariate classification probabilities. So if the classification problem has C categories, or classes, then each class is modeled by one of the network outputs. If Zi is the weighted sum of products between its weights and inputs for the i-th output, i.e.,

$Z_i=\sum_j w_{ji} y_{ji}$

Then

$Softmax_i=\frac{e^{Z_i}}{\sum_{j=1}^{C} e^{Z_i}}$

The softmax activation function ensures that all outputs conform to the requirements for multivariate probabilities. That is,

0<softmaxi<1, for all i=1, 2… C and

$$\sum_{i=1}^{C} softmax_i = 1$$

A pattern is assigned to the i-th classification when Softmax is the largest among all C classes. The poor convergence rate of Error Back propagation algorithm (EBP) in neural network has been a major concern; many efforts have been made to speed up the algorithm. Though various approaches have been tried in literature, with very little improvement. Second order approaches like Newton's method; conjugate gradient's or Levenberg-Marquardt (LM) optimization techniques achieve significant improvement on realization performance. LM is the most efficient in achieving realization accuracy. It combines the speed of Newton algorithm and the stability of the steepest descent method. The major disadvantages of the LM are the memory requirement to operate large Jacobians and the necessity of inverting large matrices.

For the LM algorithm, the performance index to be optimized is defined as

$$F(w) = \sum_{P=1}^{P} \left[\sum_{k=1}^{K} (dkp - okp)^2 \right]$$

where $w = [w_1\ w_2\ \dots\ w_N]^T$ consists of all the weights of the network, dkp is the desired value of the K^{th} output and the P^{th} pattern, okp is the actual value of the the k^{th} output and the p^{th} pattern, N is the number of weights, P is number of patterns, and K is the number of the network outputs. The above equation can be rewritten as

$$F(w) = E^T E$$

Where $E = [e_{11} \dots e_{K1}\ e_{12} \dots e_{K2} \dots e_{1P} \dots e_{KP}]^T$

$e_{kp}=d_{kp}-o_{kp}, k=1,...,K$

p=1... P

Where E is the cumulative error vector for all patterns. The Jacobian matrix 'J' is defined as and the weights are calculated using

$$J = \begin{bmatrix} \frac{\partial e_{11}}{\partial w_1} & \frac{\partial e_{11}}{\partial w_2} & \cdots & \frac{\partial e_{11}}{\partial w_N} \\ \frac{\partial e_{12}}{\partial w_1} & \frac{\partial e_{12}}{\partial w_2} & \cdots & \frac{\partial e_{12}}{\partial w_N} \\ \vdots & \vdots & & \vdots \\ \frac{\partial e_{K1}}{\partial w_1} & \frac{\partial e_{K1}}{\partial w_2} & \cdots & \frac{\partial e_{K1}}{\partial w_N} \\ \vdots & \vdots & & \vdots \\ \frac{\partial e_{1P}}{\partial w_1} & \frac{\partial e_{1P}}{\partial w_2} & \cdots & \frac{\partial e_{1P}}{\partial w_N} \\ \frac{\partial e_{2P}}{\partial w_1} & \frac{\partial e_{2P}}{\partial w_2} & \cdots & \frac{\partial e_{2P}}{\partial w_N} \\ \vdots & \vdots & & \vdots \\ \frac{\partial e_{KP}}{\partial w_1} & \frac{\partial e_{KP}}{\partial w_2} & \cdots & \frac{\partial e_{KP}}{\partial w_N} \end{bmatrix}$$

$$W_{t+1}=W_t-(J^T_t J_t+ \mu_t I)^{-1} J^T_t E_t$$

Where I is the identity unit matrix, μ is a learning parameter and J is Jacobian of m output errors with respect to n weights of the neural network. For $\mu = 0$ it becomes the Gauss-Newton method. For very large μ the LM algorithm becomes the steepest decent or the EBP algorithm. The μ parameter is automatically adjusted at each iteration in order to secure convergence. The LM algorithm requires computation of the Jacobian J matrix at each iteration step and the inversion of $J^T J$ square matrix, the dimension of which is N X N.

V. RESULTS

50 medical images were used in the experimental setup containing four class labels. The top 40 relevant attributes were selected using information gain. Figure 2 shows some of the MRI images used in this work.

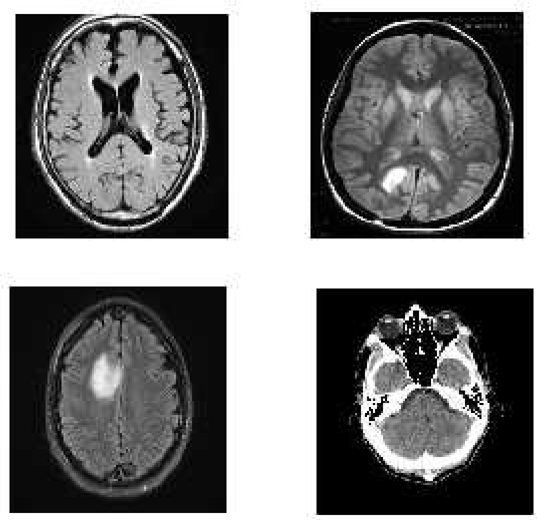

Figure 2: Sample images used in this work.

The results obtained from regular MLP Neural Network and the proposed FS-MLP Neural Network is shown in figure 3.

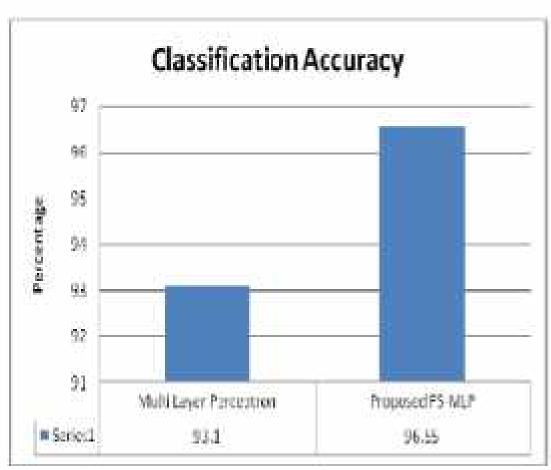

Figure 3: Classification accuracy measured in percentage.

VI. SUMMARY AND CONCLUSION

In this paper it was proposed to extract features using Discrete Sine Transform (DST) and select the top 50 attributes based on class attribute using information gain. The extracted features were trained with the existing MLP Neural network classifier and compared with the proposed FS-MLP neural network. The classification accuracy of the proposed method improved by a percentage of 3.45. Using less number of features in the proposed method decreases the overall processing time for a given query.

References

[1] N. S. Chang, and K. S. Fu, "Query by pictorial example," IEEE Trans. on Software Engineering, Vol.6, No.6, pp. 519-524, Nov.1980.

[2] S. K. Chang, C. W. Yan, D. C. Dimitroff, and T. Arndt, "An intelligent image database system,"IEEE Trans. on Software Engineering, Vol.14, No.5, pp. 681-688, May 1988.

[3] J. Dowe, "Content-based retrieval in multimedia imaging," In Proc. SPIE Storage and Retrieval forImage and Video Database, 1993.

[4] C. Faloutsos et al, "Efficient and effective querying by image content," Journal of intelligent information systems, Vol.3, pp.231-262, 1994.

[5] Sonali Bhadoria and C.G. Dethe, "Study of Medical Image Retrieval System" 2010 International Conference on Data Storage and Data Engineering, pg 192-6.

[6] H. M¨uller, N. Michoux, D. Bandon, and A. Geissbuhler. A review of contentbased image retrieval systems in medical applications-clinical benefits and future directions. In International Journal of Medical Informatics, volume 73, pages 1–23, 2004.

[7] T. Lehmann, M. G¨uld, C. Thies, B. Fischer, K. Spitzer, D. Keysers, H. Ney, M. Kohnen, H. Schubert, and B. Wein. Content-based image retrieval in medical applications.

[8] Y. Cheng, R. Swamisai, S. E. Umbaugh, R. H. Moss, W.V. W. V. Stoecker, S. Teegala, and S. K. Srinivasan. Skin lesion classication using relative color features. In Skin

[9] C.-Y. Lin, J.-X.Yin, X. Gao, J.-Y.Chen, and P.Qin, “Asemantic modelling approach formedical image semantic retrieval using hybrid Bayesian networks,” in Proc. 6th Int. Conf. Intell. Syst. Des. Appl. (ISDA), 2006, pp. 482–487.

[10] Rigau J, Feixas M, Sbert M, et al. Medical image segmentation based on mutual information maximization. In Proc of MICCAI 2004 (Saint-Malo). Berlin: Springer-Verlag, 2004. 135－142.

[11] K. Rajakumar, K. Rajakumar, “An Integrated Approach for Medical Image Retrieval Using PCA and Energy Efficient Wavelet Transform”, European Journal of Scientific Research ISSN 1450-216X Vol.51 No.3 (2011), pp.340-348.

[12] Nandakishore Kambhatla, Todd K. Leen, “Dimension Reduction by Local Principal Component Analysis”. Neural computation, October 1, 1997, Vol. 9, No. 7, Pages 1493-1516.