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Medical Image Classification Using Genetic Optimized Elman Network

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Abstract: Problem statement: Advancements in the internet and digital images have resulted in a huge database of images. Most of the current search engines found in the web depends only on images that can be retrieved using metadata, which generates a lot of unwanted results in the results got. Content-Based Image Retrieval (CBIR) system is the utilization of computer vision techniques in the predicament of image retrieval. In other words, it is used for searching and retrieving of the right digital image among a huge database using query image. CBIR finds extensive applications in the field of medicine as it helps medical professionals in diagnosis and plan treatment. **Approach:** Various methods have been proposed for CBIR using the image's low level features like histogram, color, texture and shape. Similarly various classification algorithms like Naïve Bayes classifier, Support Vector Machine, Decision tree induction algorithms and Neural Network based classifiers have been studied extensively. In this study it is proposed to extract global features using Hilbert Transform (HT), select features based on the correlation of the extracted vectors with respect to the class label and propose a enhanced Elman Neural Network Genetic Algorithm Optimized Elman (GAOE) Neural Network. **Results and Conclusion:** The proposed method for feature extraction and the classification algorithm was tested on a dataset consisting of 180 medical images. The classification accuracy of 92.22% was obtained in the proposed method.

Key words: Medical image retrieval, neural network, classification, hilbert transform, information gain

INTRODUCTION

Content-Based Image Retrieval (CBIR) also known as Content-Based Visual Information Retrieval (CBVIR) and Query by Image Content (QBIC) is the utilization of computer vision techniques in the predicament of image retrieval (Chang *et al*., 1988). In other words it is used to solve the problem of searching for the right digital image among a huge database (Aigrain *et al*., 1996; Ardizzone and Cascia, 1997). This method has been an area of research which has drawn a lot of interest for the past decade. Advancements in the internet and digital images have resulted in an even huger database of pictures. It is of vital need to be able to search for the desired images in an easier way for the maximum utilization of the database.

"Content-based" implies that searching via this method will actually examine the definite contents of the image rather than just analyze the "metadata" such as tags or keywords affiliated with the image. The content may refer to the color or shapes present in the image or any information that can be extracted from the picture. This method of content based image retrieval is highly efficient and more appropriate because most of the current search engines found in the web depend only on images that can be retrieved using metadata, which generates a lot of unwanted results in the results got (Beigi *et al*., 1998). Hence, a method that can filter pictures based on the content (like color, shape) would catalog the images better and also reduce the possibility of garbage in the result and provide more accurate results. There is a common shared demand among individuals of various domains to find certain images; some of them being medical professionals, architects, reporters, publishers, design engineers and so on. Even though the requirements of the desired image may differ greatly, it would be advantageous to categorize the queries for image into three planes:

- Basic features: color, shape
- Logical features: identity of the objects present
- Abstract features: significance of the scene in the image

Currently the efficiency of CBIR is stunted because of the fact that it worked only at the lowest level effectively. Studies in literature show that compounding the base level features, i.e., color and shapes along with

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text tags can help override these problems. But, it has not yet been perfected in terms of the way in which these characteristics can be best merged for higher levels of retrieval. Despite the different limitations, CBIR is a rapidly developing technological process with lots of potential for further improvement, which should be employed wherever possible and wherever appropriate.

In this study it is proposed to extract feature vectors globally using the Hilbert Transform, select the relevant features using correlation among the attributes and propose a novel classification algorithm Genetic Algorithm Optimized Elman (GAOE) Neural network.

Park *et al*. (2004) proposed a content based image automatic classification of object images using neural network. The image is segmented to extract the object region and texture features of the object region were extracted. The background is removed to improve the object classification. The image is normalized. Wavelet transforms are applied for the extract features and the classification was done using 49 values of features extracted. The neural network classifier was created using the learning pattern of the texture feature. Experimental results showed that classification accuracy rate achieved with removal of background was higher. 300 training data and 300 test data was used, showed a classification accuracy rate of 81.7 and 76.7%.

Sadek *et al*. (2008) proposed a new architecture for CBIR using Splines Neural Network based Image Retrieval (SNNIR). The efficiency of traditional neural networks is limited due to the assumption of linear relationship among features and the difficulty of representing high level concepts in low level features. The proposed neural network is based on an adaptive model called splines neural network. The splines neural network facilitates the system to determine nonlinear relationship between different features in images which betters the comparison accuracy. Results of the proposed system show that it is more effective and efficient to retrieve visual-similar images for a set of images with same conception can be retrieved.

Williams and Peng (1990) proposed a novel variant of RNN learning algorithm. The proposed algorithm shapes the behavior of RNN as it runs and also executes efficiently on serial machines. The proposed learning algorithm is for temporal supervised learning tasks wherein the examples used specify the desired behavior in form of input and desired output trajectories. The proposed algorithm had five important properties:

- It's an on-line algorithm, which is used to train the network while it runs
- General purpose algorithm which can be used for all types of RNN
- Trains the networks to perform arbitrary time-varying behaviors
- Can be implemented on serial machines
- Experimentally proven to be as efficient as other learning algorithms of RNN with the added advantage of combining all the attractive features of algorithms in use

Iakovidis *et al*. (2009) proposed a novel scheme for Content Based Image Retrieval (CBIR) for medical images. The proposed method was formalized according to the patterns for next generation database systems (PANDA) framework for pattern representation and management. The low level features extracted from the medical images were clustered in the feature space to form higher level, semantically meaningful patterns. Expectation-maximization algorithm was used to automatically determine the number of clusters. The similarity between the clusters was estimated as a function of the similarity of both their structures and the measure of components. Experiments showed that the proposed scheme can be efficiently applied for medical image retrieval from large database.

MATERIALS AND METHODS

Neural networks are based on the model of neuron; the perceptron is simple mathematical representation of the neuron. The feed-forward neural network is a network of perceptrons with the connecting links are characterized by weights. Mathematically a neuron is given by:

$$y = \varphi\left(\sum_{j=1}^{n} w_j x_j + b\right)$$

$$w_1, \ldots\ldots, w_n$$

$$x_1, \ldots, x_n$$

where, are input signals, are weights of the neuron, φ is the activation function, b is the bias and y is the output signal.

Typical output from neural network are represented as closed unit interval [0, 1] or [-1,1]. The feed forward neural network consists of input layer, one or more hidden layer and an output layer. Recurrent Neural Networks (RNN) are a special type of neural network used to generate temporal outputs of nonlinear systems (Elman, 1990) and can simulate any time series.

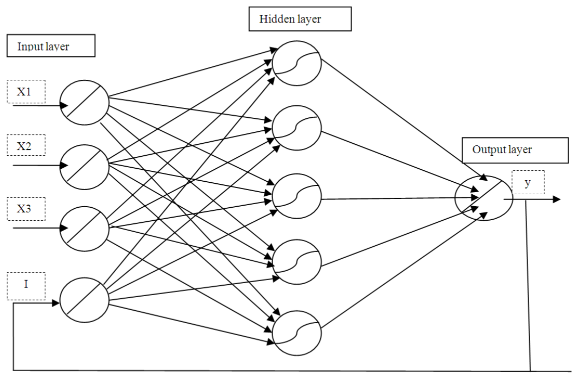

Fig. 1: The basic architecture of Elman network

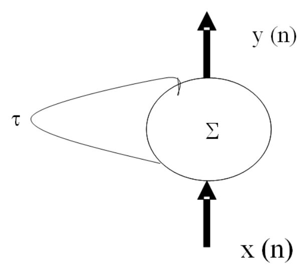

Fig. 2: The context unit in RNN

Elman networks are commonly used RNN. Figure 1 show a general architecture of Elman network with one hidden layer.

Activation functions in neural networks define how an output is given by a neuron for the inputs fed into it. The activation functions are continuous and differentiable. The sigmoidal function is the most widely used activation function; it ranges from 0-1. When the output range is required to be -1 to 1, the hyperbolic tangent function or tanh function is used. The tanh is given as follows:

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

The context unit used in the RNN is shown in Fig. 2. It is obtained by summing the past values and multiplying the summation with a scalar value.

The conjugate gradient algorithm iterates in the selection of search directions that are non-interfering, so that the successive minimization, along that direction does not undo any progress of the minimization previously done. The current gradient of the search direction is orthogonal to the previous search directions, thus the error surface has the steepest descent.

Fast Fourier transforms (Bracewell, 1995) are mathematical algorithms which compute the DFT faster.

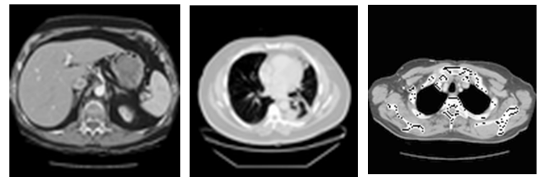

Fig. 3: Images used in the investigation

Table 1: Parameters used in the proposed model

Input Neuron	56
Output Neuron	3
Context Unit Time	0.8
Number of Hidden Layer	1
Number of Neurons in hidden layer	4
Transfer function of hidden layer	GA - Tanh
Learning Rule of hidden layer	Conjugate Gradient
Number of iterations	500

The fast Fourier transforms use the kernel and shift rule of the DFT to reduce the number of computations. The Hilbert transform of a function f (x) is given by:

$$F(t) = \frac{1}{\pi}\int_{-\infty}^{+\infty}\frac{f(x)}{t-x}d(x)$$

$$F(t) = \frac{1}{\pi t}.f(t)$$

Since the integral is evaluated using the Cauchy principal value the above equation can be written as the convolution.

Using the convolution theorem of Fourier transform we can evaluate the above equation as the product of f (x) with -i×sgn (x).

Where:

$$\mathrm{sgn}(x) = \begin{cases} -1 & \text{for} \quad x<0 \\ 0 & \text{for} \quad x=0 \\ 1 & \text{for} \quad x=1 \end{cases}$$

Genetic Algorithm based optimization is introduced hidden layer of the Elman network and the proposed architecture of the Genetic Algorithm Optimized Elman (GAOE) Neural Network is shown in Table 1.

Sample medical images used in the experimental setup are shown in Fig. 3.

RESULTS AND DISCUSSION

A total of 180 images with three different classes were used in this work. Using Information Gain for data reduction, the classification accuracy obtained from the proposed algorithm is benchmarked with other algorithms found in literature.

Table 2: Classification accuracy

Method	Classification accuracy (%)
Random forest	78.89
CART	86.11
MLP-NN	86.11
Proposed NN	92.22

Table 3: TP and FP rate

	Random Forest	CART	MLP -NN	Proposed NN
TP rate Class a	0.85	0.783	0.833	0.90
TP rate Class b	0.83	0.733	0.820	0.85
TP rate Class c	0.90	0.850	0.930	0.87
FP rate Class a	0.04	0.080	0.060	0.02
FP rate Class b	0.10	0.120	0.090	0.03
FP rate Class c	0.07	0.130	0.060	0.03

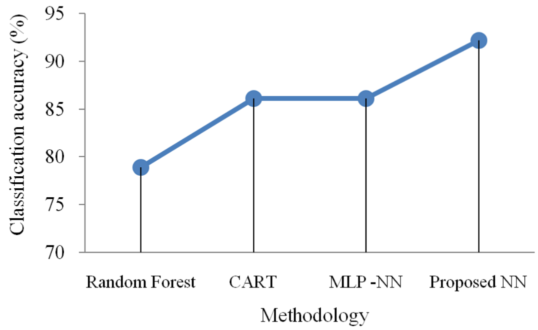

Fig. 4: The classification accuracy of various classifiers

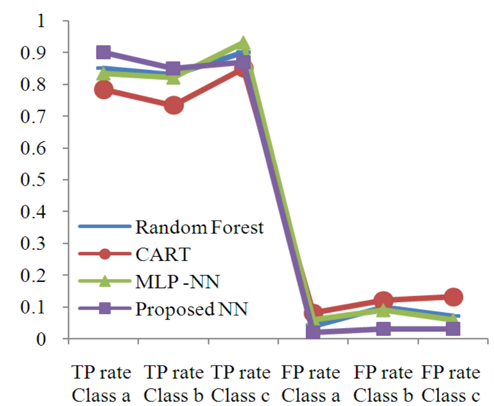

Fig. 5: The plot of TP and FP

Table 2 lists the classification accuracy; Table 3 lists the true positive and true negative rate with respect to each class. Figure 4 and 5 shows the classification accuracy and plot of TP-FP rate respectively.

From Fig. 4 it is seen that the proposed method for image classification is able to achieve better accuracies compared to other algorithms. It is also seen that the classification accuracy improves by 6.11% compared to Multi Layer Perceptron Neural Network (MLP-NN).

CONCLUSION

In this study it was proposed to implement a novel Neural Network algorithm to improve the classification accuracy in medical image retrieval. Features were extracted using the fast Hilbert transform and important features were extracted using Information Gain (IG). The proposed Neural Network (NN) algorithm optimized the Elman network by introducing a hidden layer comprising Genetic Algorithm with Tanh activation function. Results obtained show that the classification accuracy improves by 6.11% compared to Multi Layer Perceptron Neural Network and over 13.33% when compared against an ensemble of decision tree algorithms.

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