Glaucomatous Image Classification Using Wavelet Based Energy Signatures And Neural Networks

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***Abstract*— Glaucomatous image classification can be efficiently performed using the texture features of an image. These texture features are accurately obtained using the energy distributed over the different wavelet sub bands. The various wavelet filters used in this paper are daubechies (db3), symlet3 (sym3) and bi-orthogonal (bio3.3, bio3.5, bio3.7) filters. In this paper, we propose a novel technique to extract the energy signatures obtained using 2-D Discrete Wavelet Transform (DWT) and these coefficients are subjected to feature selection scheme. Sequential Forward Feature selection algorithm is used to select the best features. The selected features are fed to Feed Forward Back Propagation Neural Network classifier. The classifier is used to predict the status of the person. Experimental analysis has been done to calculate the accuracy of prediction.**

***Keywords*—Approximation coefficient, clinical decision support system, cup to disc ratio, diagonal decomposition, horizontal decomposition, multifocal electroretinograph, optic nerve head ,sequential feature selection, two dimensional discrete wavelet transform.**

I. INTRODUCTION

Glaucoma is the second leading cause of blindness worldwide. Glaucoma is caused due to the increase in intraocular pressure of the eye. The intraocular pressure increases due to malfunction or malformation of the drainage system of the eye. The anterior chamber of the eye is the small space in the front portion of the eye. A clear liquid flow in-and-out of the chamber and this fluid is called aqueous humor. The fluid, aqueous humor nourishes and bathes nearby tissues. The intraocular pressure of the eye is maintained by the aqueous humor. The pressure within the eye is maintained by producing a small amount of aqueous humor while an equal amount flows out of the eye through a microscopic drainage system called trabecular meshwork. Glaucoma is mainly caused due to increase in intraocular pressure. Increased intraocular pressure results from either increased production or decreased drainage of aqueous humor. The increased intraocular pressure within the eye damages the optic nerve through which retina sends light to the brain where they are recognized as images and makes vision possible. Hence elevated intraocular pressure is considered a major risk factor for Glaucoma.

The prevalence of Glaucoma in worldwide is increasing rapidly .This is due in part to the rapidly aging population. Blindness due to Glaucoma greatly impacts the independence of many people who are part of this aging population. A prevalent model estimates that at the current time, there are about 60 million people worldwide with Glaucoma. Thus Glaucoma has become the second leading cause of blindness worldwide. Thus it becomes necessary to detect Glaucoma earlier and can provide better treatment.

In this paper we are proposing a novel method to detect Glaucoma at an early stage by differentiating Glaucoma affected retinal images from normal retinal images by extracting the energy signatures from the provided dataset using Two dimensional discrete wavelet transform and subject them to classification process. In this paper, we propose the use of 3 different wavelet filters such as daubechies, symlets and biorthogonal on a set of fundus images by employing 2-D DWT. The texture features using wavelet transforms in image processing are often employed to overcome the generalization of features. We calculate the averages of the detailed horizontal and vertical coefficients and wavelet energy signatures obtained by wavelet decomposition. The extracted features are subjected to feature selection procedure to determine the combination of relevant features to maximize the class similarity. SFS algorithm is implemented to select the best decorrelated features for Neural Network.

II. RELATED WORKS

Efforts are made for several years to detect or diagnosis the disease, glaucoma, so that the sufferings caused by the disease can be reduced or even fully cured. The optical coherence tomography [1] and multifocal electro retinograph (mfERG) [2] are prominent methods employed in order to analyze functional abnormalities of the eye especially glaucoma. The mfERG gives detailed topographical information of each zone and can therefore detect small-area local lesions in the retina and even in its central region (fovea). The discrete wavelet transform (DWT) [3] analyses mfERG signals and detect glaucoma. In ophthalmology, CDSS [4] [5] are used efficiently to create a decision support system that identifies disease pathology in human eyes. In CDSS, both structural and texture features of images are extracted. The extracted structural features mainly include disk area, rim area, cup to disc ratio and topographical features. Automatic glaucoma diagnosis can be done by calculating cup to disc ratio (6). The CDR (Cup-to-Disc Ratio) is defined as the ratio of the vertical cup height divided by the vertical disc height. A CDR value that is greater than 0.65 indicates high glaucoma risk. The glaucoma diagnosis can be improved by the enhancement of optic cup to disc ratio[7].The enhancement is done such that the least square fitting is used to determine boundary of cup and disc. The glaucoma progression can be identified from textural features using a method called POD[8]. Glaucoma often damages the optic nerve head (ONH) and ONH changes occur prior to visual field loss. Thus, digital image analysis is a promising choice for detecting the onset and/or progression of glaucoma by using the method of proper orthogonal decomposition (POD). A baseline topography subspace was constructed for each eye to describe the structure of the ONH of the eye at a reference/baseline condition using POD. Any glaucomatous changes in the ONH of the eye present during a follow-up exam were estimated by comparing the follow-up ONH topography with its baseline topography subspace representation. The texture features and higher order spectra [9][10] can also be used for glaucomatous image classification. The wavelet decomposition is used for feature extraction and the classification is done using support vector machine, sequential minimal optimization, naive Bayesian, and random-forest classifiers.

III. DATASET

The retinal images used for this study were collected from the the Kasturba Medical College, Manipal, India(CASNET).The doctors in the ophthalmology department of the hospital manually curated the images based on the quality and usability of samples. All the images are stored in lossless JPEG format. The dataset contains 30 fundus images. The 30 fundus images consist of 15 normal and 15 glaucomatous images collected from 20 to 70 year-old subjects. The fundus camera, a microscope, and a light source are used to acquire the retinal images to diagnose diseases. Fig 1(a) and (b) presents typical normal and glaucoma fundus images, respectively.

Figure 1(a). Normal Retinal Image

Figure1 (b).Glaucomatous Image

IV. METHODOLOGY

The retinal images in the dataset are subjected to standard histogram equalization. The histogram equalization will assign the intensity values of pixels in the input image, so that the output image has a uniform distribution of intensities. The histogram equalization will increase the dynamic range of the histogram of an image. The following detailed procedure was then employed in order to classify glaucomatous image. The detailed procedure is shown in fig 2.

A. *Image Decomposition*

The wavelet features of an image are obtained by undergoing wavelet decomposition. Here the wavelet decomposition is done by using 2-D discrete wavelet transform which captures both spatial and frequency information's of a signal. DWT analyses the image by decomposing the given image into coarse approximation and detail information. The coarse approximation is done by low pass filtering and detail information via high pass filtering. Consider the image is represented as m*n matrix[10], it is subjected to four decomposition directions corresponding to 0 degree (horizontal, cH), 45 degree (diagonal, cD), 90 degree (vertical, cV) and 135 degree (diagonal, cD). Each element of the matrix represents the gray-scale intensity of one pixel of the image thereby resulting in four coefficient matrices. The first level of decomposition results in four coefficient matrices, namely, A1, Dh1, Dv1, and Dd1.

B. *Feature Extraction*

The 2-D DWT [10] is used in order to extract the energy signatures. The DWT is applied to three different filters namely daubechies (db3), symlets (sym3) and biorthogonal (bio3.3, bio3.5, bio3.7). With the help of these filters, we obtain the wavelet coefficients. Since the number of elements in these matrices is high, and we only need a single number as a representative feature, we employ averaging methods to determine such single valued features. The definitions of the three features that were determined using the DWT coefficients are in order. Equations (1) and (2) determine the averages of the corresponding intensity values, whereas (3) is an averaging of the energy of the intensity values. Thus wavelet coefficients which are subjected to average and energy calculation results in feature extraction.

$$Average\ Dh1 = \frac{1}{p \times q} \sum_{x=\{p\}} \sum_{y=\{q\}} |Dh1(x,y)| \quad (1)$$

$$Average\ Dv1 = \frac{1}{p \times q} \sum_{x=\{p\}} \sum_{y=\{q\}} |Dv1(x,y)| \quad (2)$$

$$Energy = \frac{1}{p^2 \times q^2} \sum_{x=\{p\}} \sum_{y=\{q\}} |Dv1(x,y)^2| \quad (3)$$

C. *Feature Selection*

The importance of feature selection is that it chooses a subset of input variables by eliminating features with little or no predictive information. Feature selection (also known as subset selection) is a process wherein subsets of the features available from the data are selected for application of a learning algorithm. The best subset contains the least number of dimensions that most contribute to accuracy and discard the remaining, unimportant dimensions. This is an important stage of preprocessing and is one way to avoid the curse of dimensionality. The purpose of feature selection algorithm is to identify relevant features according to a definition of relevance. Sequential Forward Selection is the feature selection algorithm used here. Sequential Forward Selection is the simplest greedy search algorithm. In sequential forward selection algorithm, we start with no variables and add them one by one, at each step adding the one that decreases the error the most, until any further addition does not significantly decrease the error. Sequential forward selection algorithm performs best when the optimal subset contains small number of features. When the search is near the empty set, a large number of states can be potentially evaluated. Towards the full set, the region examined by SFS is narrower since most of the features have already been selected.

D. Dataset Classification

The Classification stage in this paper is done using Soft Computing approach. The algorithm used is Neural Network Classifier. This Classifier here uses a feed forward back propagation procedure to train and test the image. Neural Networks are among the more used methodologies for classification and patterns recognition. Neural networks are members of a family of computational architectures which are inspired by biological brains. Such architectures are mainly called "connectionist systems", and they are composed of interconnected and interacting components called nodes or neurons.

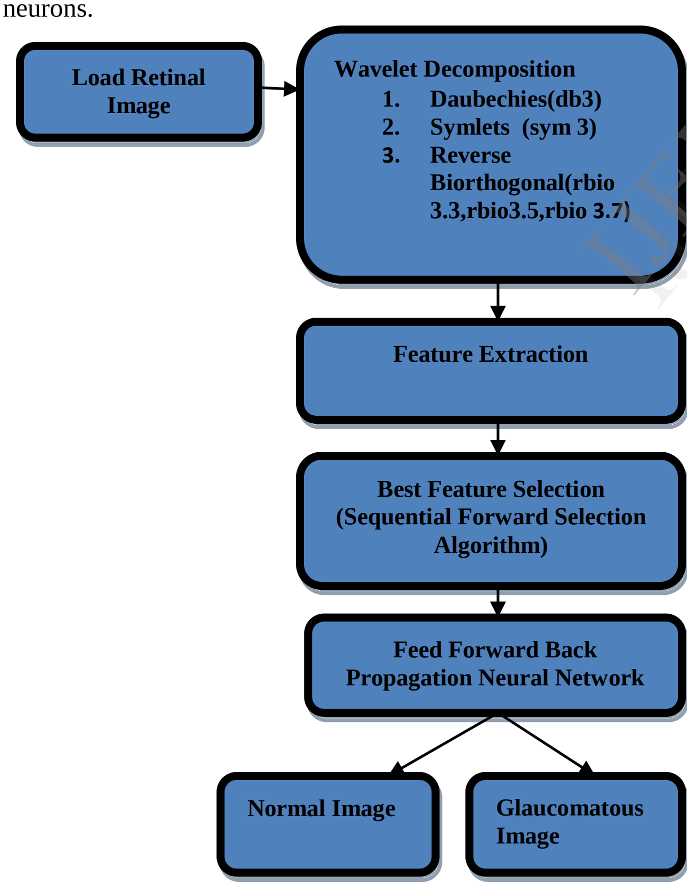

Figure 2.Block Diagram of the detailed procedure

In this paper, the classifier mainly performs two functions such as training the classifier and neural network prediction. A two-layer feed-forward network, with sigmoid hidden and output neurons which can classify vectors arbitrarily well, with enough neurons in its hidden layer is used here for classification. Firstly we perform training of this classifier and the neural network prediction is done

a) Training the classifier

The feature vector matrix is formed by calculating feature values from all the images. The sequential feature selection calculated feature selected matrix is used to train the neural network. The functionality of a neural network is determined by the combination of the topology (number of layers, number of units per layer, and the interconnection pattern between the layers) and the weights of the connections within the network. The topology is commonly held fixed, and the weights are determined by a certain training algorithm. The process of adjusting the weights to make the network learn the relationship between the inputs and targets is called learning, or training. Here we use supervised learning. The network is trained by providing it with inputs and desired outputs (target values). These input-output pairs are provided by an external teacher, or by the system containing the network. The difference between the real outputs and the desired outputs is used by the algorithm to adapt the weights in the network. It is often posed as a function approximation problem where the given training data consist of pairs of input patterns x, and corresponding target t, the goal is to find a function f(x) that matches the desired response for each training input. A two layered feed-forward network is used here. There is an input layer, an output layer, and a hidden layer between the input and the output layer. Each unit receives its inputs directly from the previous layer (except for input units) and sends its output directly to units in the next layer (except for output units).. Every unit only acts as an input to the immediate next layer. Obviously, this class of networks is easier to analyze theoretically than other general topologies because their outputs can be represented with explicit functions of the inputs and the weights. The algorithm is called back-propagation, because it propagates the errors backward through the network. Most units in neural network transform their net inputs by using a scalar-to-scalar function called an activation function, yielding a value called the unit's activation. Except possibly for output units, the activation value is fed to one or more other units. Activation functions with a bounded range are often called squashing functions. The activation function used here is sigmoid function. This function is especially advantageous for use in neural networks trained by back-propagation; because it is easy to differentiate, and thus can dramatically reduce the computation burden for training. It applies to applications whose desired output values are between 0 and 1.

b) Neural Network Prediction

After the training process is done, the neural network predicts or differentiates between the normal and glaucoma affected images. Thus the dataset containing 30 images are classified to normal and glaucoma effected image.

V. SOFTWARE REQUIREMENT AND DESCRIPTION

The operating system used is Windows XP and the tool used is Matlab of version 7.9. MATLAB is a high-level technical computing language and interactive environment for algorithm development, data visualization, data analysis, and numerical computation. Matlab is a data analysis and visualization tool which has been designed with powerful support for matrices and matrix operations. As well as this, Matlab has excellent graphics capabilities, and its own powerful programming language. One of the reasons that Matlab has become such an important tool is through the use of sets of Matlab programs designed to support a particular task.

VI. RESULTS AND DISCUSSIONS

The program code is generated using Matlab and the result is analyzed. The output is such that it classifies the dataset into normal and glaucomatous images .The dataset classification is done using neural network. Supervised Learning is done in classification .The training is done by using the labeled details imported from the Clinical Decision Support System (CASNET/glaucoma). After learning of network, testing and validation is done. Thus the neural network classifies normal and glaucoma image. The performance of Neural network is shown in Fig (6.1).

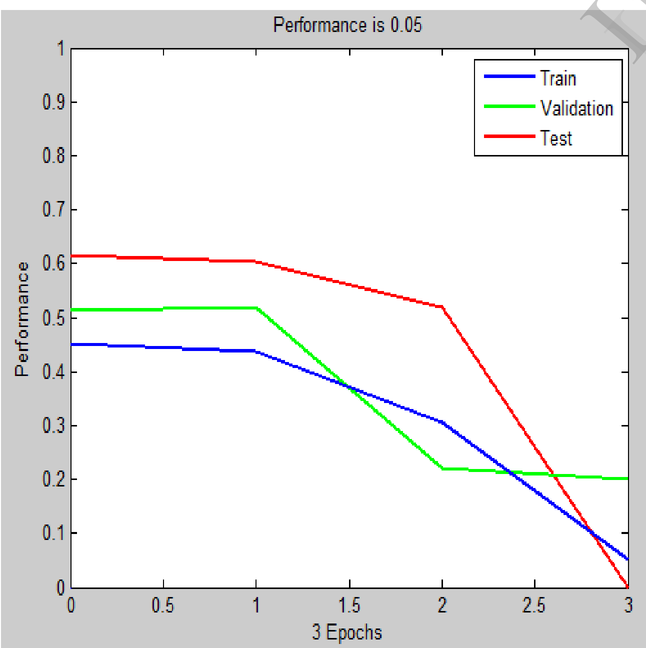

Figure. 6.1. Performance graph of Neural Network

A confusion matrix is plotted. The confusion matrix is shown in Fig (6.2). A confusion matrix is an array showing relationships between true and predicted classes. Entries on the diagonal of the matrix, in blue, give the overall accuracy. The entries in green gives correct classification. The entries of the diagonal, in red, count the misclassifications. The entries in the gray give class accuracy. Thus by analyzing the confusion matrix, the overall accuracy is given as 100%. The entries in the green show the correct classification that is 15 retinal images are normal while other 15 are glaucoma affected images in the dataset.

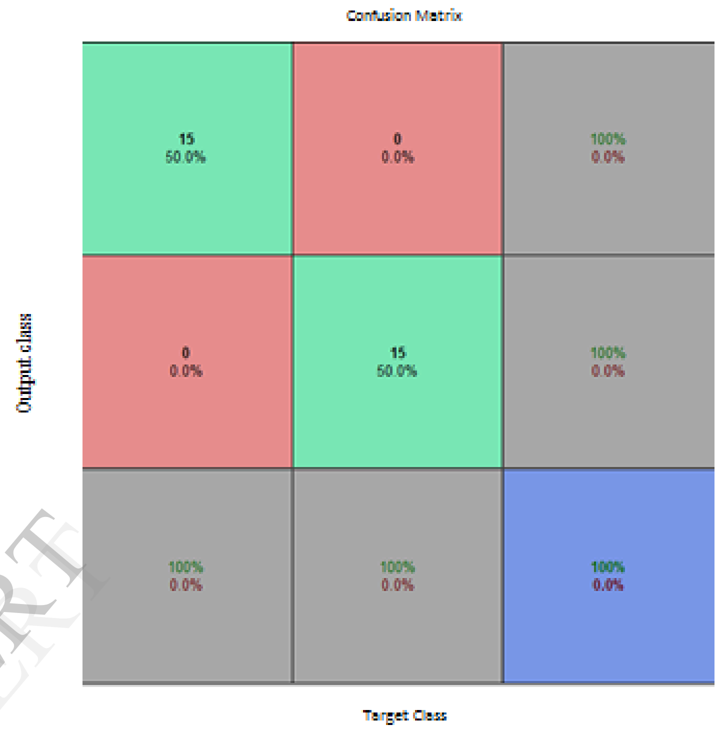

Figure 6.2 Confusion matrix of neural network

VII. CONCLUSION

This paper demonstrates the feature extraction process using three wavelet filters. The daubechies, symlets and bi-orthogonal are the wavelet filters used. The wavelet coefficients obtained are then subjected to average and energy calculation resulting in feature extraction. The sequential feature selection algorithm is then used for selecting the most appropriate features for classification. The classification is done using Neural networks which provides higher accuracy. We can conclude that the energy obtained from the detailed coefficients can be used to distinguish between normal and glaucomatous images with very high accuracy.

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