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Early Stage Glaucoma Screening and Segmentation using FFNN

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***Abstract*— Glaucoma is an ocular disorder resulting in optic nerve damage or loss to the field of vision, in many patients caused by a clinically characterized pressure buildup in regards to the fluid of the eye i.e. intraocular pressure-associated optic neuropathy. Optic nerve damage and visual field damage caused by glaucoma are essentially progressive and irreversible. Hence if the condition is detected early enough, it is possible to arrest the development or slow the progression with medical and surgical means. In this paper wavelet texture features are extracted using daubechies, symlets and reverse biorthogonal wavelet filters. Extracted energy signatures are given to the neural networks and hence discriminate between normal and glaucomatous images. Finally segmentation methods based on optimal thresholding by clustering are used to exactly spot the region of disease.**

Keywords*— Glaucoma, Goldmann equation, IOP, wavelet transform, feed forward neural network, delta rule, segmentation, thresholding

I. INTRODUCTION

Glaucoma is medically defined as a heterogeneous group of disease in which damage to the optic nerve is usually caused by raised ocular pressure which is normally associated with increased fluid (aqueous humour) pressure in the eye (above 21mmHg). It has been called the "silent thief of sight" because the loss of vision often occurs gradually over a long period of time, and symptoms only occur when the disease is quite advanced. As the revitalization of the degenerated optic nerve fibers is not viable, if detected early enough, it is possible to arrest the development or slow the progression with medical and surgical means.

This disorder can be roughly divided into two categories as shown in Fig 1: open angle and closed angle (angle closure) where the angle refers to the area between the iris and cornea, through which fluid must flow to escape via the trabecular meshwork, an area of tissue in the eye located around the base of the cornea. Open-angle, chronic glaucoma is caused by the slow clogging of the drainage canals and has a wide and open angle. It progress at a slower rate and patients may not notice they have lost vision until the disease is significant.

Closed angle is caused by sudden rise in intraocular pressure (IOP) and is painful; visual loss can progress quickly, but the discomfort often leads patients to seek medical attention before permanent damage occurs. Its symptoms include red eyes, headache and nauseous, intense eye pain, dilated pupils, see rainbows around lights at night, or have blurred vision. These signs may last for hours or until IOP is reduced. With each narrow-angle glaucoma attack, part of peripheral vision is lost. Primary open-angle glaucoma reports for 90% cases. Secondary glaucoma may be caused by an eye injury, inflammation, certain drugs such as steroids, condition that severely restrict blood flow to the eye such as severe diabetic retinopathy, central retinal vein occlusion and advanced cases of cataract.

The factors affecting IOP and increased chances of glaucoma includes age, sex, race/ethnic background, heredity, diurnal & seasonal variation, blood pressure, obesity, drugs, posture, exercise, neural, hormone, etc.

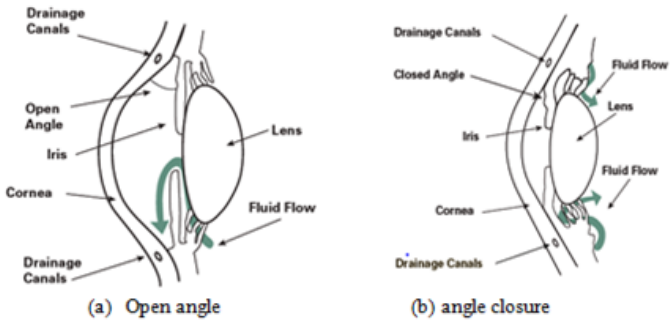

Fig 1: Types of Glaucoma

The IOP of the eye is determined by the balance between the amount of aqueous humor produced and discharged. Goldman equation, is used in cell membrane physiology to determine the reversal potential across a cell's membrane, taking into account all of the ions that are permeant through that membrane. The equation states:

$$Po = (F/C) + Pv \qquad (1)$$

where, Po is the IOP, F is the rate of aqueous formation, C is the facility of outflow and Pv is the episcleral venous pressure. An association between increased IOP and the loss of sight in glaucoma has been determined since 19th century.

In this paper the detection and segmentation of glaucoma is achieved in an accurate and efficient way. Wavelet transform combined with feed forward neural networks is used for the early stage glaucoma screening and later segmentation is done using optimal thresholding by clustering to exactly spot this ocular disease location. This method is completely depending on the textural features i.e.; structural independence of the fundus images and hence early stage detection of glaucoma can be made known with great efficiency.

II. Related Works

Early detections of glaucoma typically relied only on the examination of structural damage to the optic nerve combined with measurements of visual function. Because clinical examination of the optic nerve head (ONH) and retinal nerve fiber layer (RNFL) is subjective and therefore prone to variability, recent studies are made on objective methods to aid in the diagnosis of glaucoma. Techniques such as confocal scanning laser ophthalmoscopy, scanning laser polarimetry, optical coherence tomography is subjective ONH evaluation and selective perimetry techniques provides earlier detection of visual field deficits which is the basic structural and functional analysis of glaucoma detection. Structural features include disk area and diameter, rim area, cup area and diameter, cup-to-disk ratio and RNFL loss and functional analysis verifies the percentage of vision loss, blurredness, etc.

The second and progressively developing method of glaucoma detection is the Automated Clinical Decision Support Systems (CDSSs) which includes the methods such as proper orthogonal decomposition, mfERG wavelet analysis and diagnosis using texture and higher order spectra. In CDSS, structural/textural features are extracted from the digital fundus images and this automated analysis provides faster and accurate glaucoma detection systems. In POD, pixel-level information is used to gauge significant structural feature changes across samples that are location or region specific and changes are got by comparing topographic measurements from locations with decreases in retinal height from baseline within the optic disc margin. Another method uses a combination of texture and higher order spectra (HOS) features in which HOS derives amplitude and phase information while texture provide measures such as smoothness, coarseness, and regularity.

The extraction of textural features proposed in this paper does not rely on structural changes and hence determines glaucoma at its initial stages. The system automatically classifies normal and diseased eye images based on the distribution of average and energy texture features obtained from three wavelet families. The following chapters contain a detailed description of the proposed method, dataset used, performance evaluation, experimental result and finally the conclusion.

III. Proposed Method

A. Screening of Diseased Retinal Image

Energy distribution and average features over the wavelet sub bands is used here to compute the texture features from the digital retinal images. It can be used for image features independent in size and is often characterized by frequency domain properties. DWT is used to extract features and analyze discontinuities and abrupt changes contained in signals. In this method, each level of transformation provides an analysis of the source image at a different resolution, resulting in its independent approximation and detailed coefficients. Thus this system automatically classify normal and diseased eye images based on the distribution of average and energy texture features obtained from three wavelet families with enhanced specificity and sensitivity.

Features are extracted from three wavelet filters on a set of glaucomatous and normal images by employing the standard 2-D-DWT. This system proposes to use three well-known wavelet filters, Daubechies (db3), Symlets (sym3), and Reverse Biorthogonal (rbio3.3, rbio3.5, and rbio3.7) filters. The averages of the detailed horizontal and vertical coefficients and wavelet energy signature from the detailed vertical coefficients of all wavelet filters are then calculated for feature extraction. The fourteen extracted features are then trained to the neural network system during training phase and then using these trained values test image can be classified to normal or glaucomatous in the testing phase.

a. Image Attributes

The retinal images used for this paper are obtained from publically available DRIVE and STARE database. All the images were taken with a resolution of 512 x 512 pixels and stored in lossless JPEG format. The dataset contains 30 digital fundus images: 15 normal and 15 glaucomatous images from 20 to 70 year-old subjects. Fundus camera, a microscope, and a light source were used to acquire the retinal images to diagnose the diseases. The resulting retinal image shows the optic nerve, fovea, and the blood vessels. Fig. 2 (a) and (b) represents typical glaucoma and normal fundus images, respectively.

(a) Glaucoma (b) Normal

Fig 2: Retinal images

The images in the dataset are first subjected to standard histogram equalization which is an image enhancement procedure and it is used in order to assign the intensity values of pixels in the input image, such that the output contained a uniform distribution of intensities. Also it increases the dynamic range of the histogram of an image.

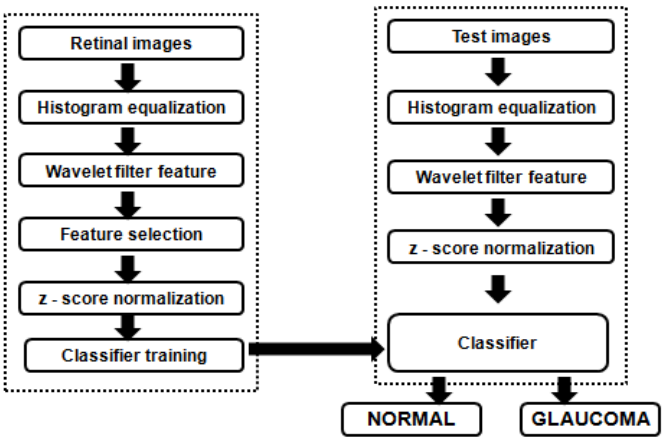

Fig 3: Block diagram

Assuming that different texture patterns have different distribution in the space-frequency domain, the energy and average feature values are extracted from the images using db3, sym3 and rbio3.3, 3.5 and 3.7 wavelet filters families which is then subjected to feature selection and normalization for the detection purpose. Fig 3 represents the basic block diagram for the flow of above mentioned methodology.

b. Discrete Wavelet Transform

DWT captures both spatial and frequency information of a signal. It analyzes the image by decomposing it into a coarse approximation via low-pass filtering and into detail information via high-pass filtering. Let each image be represented as a p x q gray-scale matrix I [i, j], where each element of the matrix represents the gray scale intensity of one pixel of the image. Each non border pixel has eight adjacent neighbouring pixel intensities. These eight neighbours are used to traverse the matrix. The resultant 2-D DWT coefficients are the same irrespective of whether the matrix is traversed right-to-left or left-to-right. Hence, it is sufficient that we consider four decomposition directions corresponding to 0◦ (horizontal, Dh), 45◦ (diagonal, Dd), 90◦ (vertical, Dv), and 135◦ (diagonal, Dd) orientations. The decomposition structure for one level is illustrated in Fig. 4 shown below. In this figure, I is the image, g[n] and h[n] are the low-pass and high-pass filters, respectively, and A is the approximation coefficient. The four coefficient matrices, A1, Dh1, Dv1, and Dd1 obtained from first level of decomposition has large number of elements, and as there is only the need of a single number representative feature, averaging methods are used to determine the single valued features.

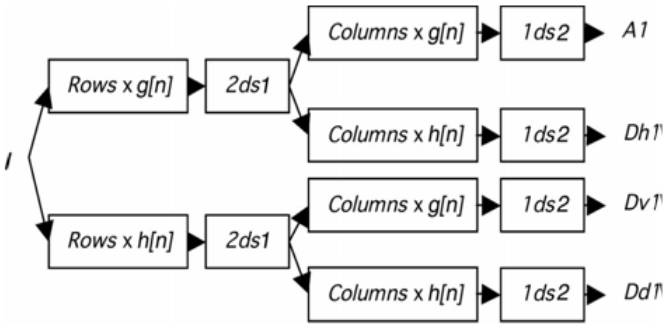

Fig 4: One level decomposition structure

The definitions of features that were determined using the DWT coefficients are in order given below. The first two equations determine the averages of the corresponding intensity values, whereas the third is an averaging of the energy of the intensity values.

$$Average\ Dh1 = \frac{1}{p\,x\,q}\sum_{x=\{p\}}\sum_{y=\{q\}}|Dh1(x,y)| \qquad (2)$$

$$Average\ Dv1 = \frac{1}{p\,x\,q}\sum_{x=\{p\}}\sum_{y=\{q\}}|Dv1(x,y)| \qquad (3)$$

$$Energy = \frac{1}{p^2 x\, q^2}\sum_{x=\{p\}}\sum_{y=\{q\}}(Dv1(x,y))^2 \qquad (4)$$

c. Pre-Processing of Features

Among all the features that could be extracted using three wavelet families, only 14 features of the Normal and Glaucomatous image samples is being used. The features that exhibited p values < 0.0001 were chosen for analysis where, the p value is a statistical measure that helps to determine whether or not their hypotheses are correct.

d. Normalization of Features

Each of the 14 features will be then subjected to z-score normalization. In the process of z-score normalization, a sample (vector) consisting of 14 features is converted to zero mean and unit variance. The new value using mean and standard deviation of the input vector are computed as follows:

$$y_{new} = \frac{y_{old} - mean}{std} \qquad (5)$$

e. Feed-Forward Back Propagation Neural Network

Neural-network method is found to be a useful alternative to statistical techniques such as those which involve regression analysis or probability density estimation and today neural networks are an established tool in the field of pattern recognition. It is defined as a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs and is modeled after the neuronal structure of human brain. A neural network is specified by the following components: neuron model - information processing unit of the NN determined by the choice of activation function, an architecture - set of neurons and links connecting neurons and learning algorithm used for training the NN by modifying the weights in order to model a particular learning task correctly on the training examples. The most widely preferred multi layered feed forward back propagation network is used here, shown in Fig 5, is featured by the links that extend in only one direction and the learning algorithm is based on gradient descent method.

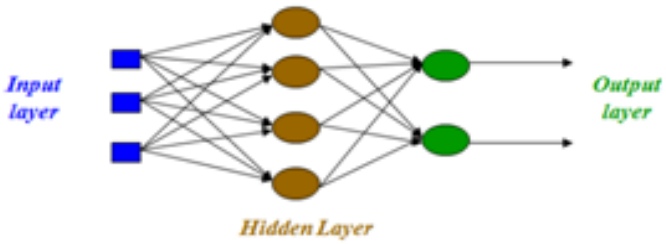

Fig 5: multi layered feed forward network structure

Feed-forward neural network (FFNN) consists of cascaded squashed linear functions. The inputs feed into a layer of hidden units, which can feed into layers of more hidden units, which eventually feed into the output layer. Each of the hidden units is a squashed linear function of its inputs.Neural networks of this type can have as inputs any real numbers, and they have a real number as output. The basic idea of delta rule learning algorithm in FFNN is to use gradient descent to search the space of possible weight vector to find the weights that best fit the training examples. This rule is important because it provides the basis for the backpropagration algorithm, which can learn networks with many interconnected units. The delta training rule considers the task of training an unthresholded perceptron, that is a linear unit, for which the output o is given by:

$$o = w_0 + w_1x_1 + \cdots + w_nx_n \quad (6)$$

When a training set of input patterns is given to the network, it computes its output pattern and if there is an error or a difference between actual and desired output patterns the weights are adjusted to reduce this error. In a back-propagation neural network, the learning algorithm has two phases. First, a training input pattern is presented to the network input layer. The network propagates the input pattern from layer to layer until the output pattern is generated by the output layer. If this pattern is different from the desired output, an error is calculated and then propagated backwards through the network from the output layer to the input layer. The weights are modified as the error is propagated.

Except during training, there are no backward links in this network. Weight values (also known as biases) are associated with each vector and node in the network, and these values constrain how input data are related to output data. Thus the weight vectors is determined by the iterative flow of training data through the network i.e., weight values are established during a training phase in which the network learns how to identify particular classes by their typical input data characteristics. The delta rule of back propagation algorithm computes the derivative of difference between target activation and obtained activation to drive learning. The activation function in this case is a linear sigmoid function, in which the output is given by:

$$y = \frac{1}{(1 + e^{-x})} \quad (7)$$

where, x is the network inputs. The effects of error in the output nodes are propagated backward through the network after each training case and the system adjusts weights of NN in order to minimize total mean squared error calculated using delta rule. Once the system is optimized with trained features, the test images can be given so that the detection of glaucoma and normal retinal images can be achieved with best results. Input features are categorized as 0 and 1. In addition to robustness to noise, neural networks also provide more speed of operation and accuracy than the traditional classifiers like Support Vector Machine (SVM), Sequential Minimal Optimization (SMO), Random Forest and Naive Bayes.

B. Segmentation of Diseased Retinal Image

Segmentation of the diseased retinal image is achieved by optimal thresholding by clustering means. Here a clip-level (or a threshold value) is used to turn a gray-scale image into a binary image. Initially a threshold value T is obtained as, T = (maximum value of image brightness + minimum value of image brightness)/2. Using T, segmentation of image to two cluster i.e.; two sets of pixels as B (all values less than T) and N (all pixel values greater than T) is obtained; Calculating the average value of B and N separately as mean ub and un, the new threshold is obtained as , T= (ub+un)/2. Repeating the above steps up to iterative conditions where T stabilizes i.e. adjacent values of T has very small difference; we obtain optimal thresholding. After segmentation, edge detection using Sobel operator is used to extract the contours of the segmented object and thus we get the necessary region from the retinal image. This intensity based thresholding method uses green channel of the fundus image for segmentation as it posses more amount retinal disorder information. Thus by using the above explained segmentation method the exact region of retinal image where glaucoma is affected can be spotted.

IV. Experimental Results

The proposed method of glaucoma detection was tested on a publically available DRIVE and STARE database. 30 images, of which 15 normal and 15 glaucomatous where used as the database. The 14 wavelet features were extracted from each retinal image (1 x 14 matrix) and thus for the whole data set a 30 x 14 feature matrix was formed where each row corresponds to each image input and the 14 columns represents the features extracted for each case. Fig 6 and 7 given below represents each case of a glaucomatous and normal retinal image and the 14 features values extracted from it using the specified wavelet filters.

Feature	db3	sym3	rbio 3.3	rbio 3.5	rbio 3.7
avghl	-4.8523e-017	-4.8523e-017	1.0588e-021	7.6201e-006	-1.7739e-005
engCV	2.3546e-033	2.3546e-033	2.0179e-043	2.3102e-012	8.6400e-013
engCD			7.7726e-077	8.2265e-014	4.1225e-011
engCH					3.1468e-010

Fig 6: A Glaucoma image case and its extracted features

Feature	db3	Sym3	rbio 3.3	rbio 3.5	rbio 3.7
avghl	3.0004e-005	3.0004e-005	1.0122e-004	-1.0692e-004	5.0420e-005
engCV	7.2884e-010	7.2884e-010	1.7608e-009	1.1320e-007	4.0341e-008
engCD			1.1386e-009	1.5488e-007	1.2341e-007
engCH					2.5422e-009

Fig 7: A Normal image case and its extracted features

This input vectors is then fed to the neural network system of 120 hidden layers and target matrix defined as an identity matrix of size 30 to exactly classify the normal and diseased retinal image. Fig 8 represents the network structure created for the implementation of the proposed method.

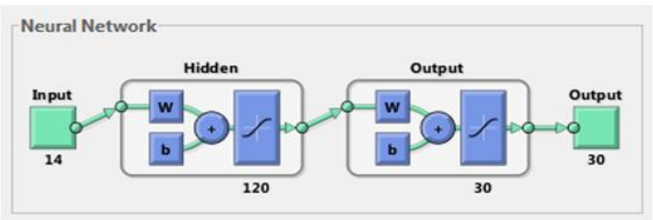

Fig 8: Network structure obtained during implementation

Thus soon after the network training phase, the test images are given whose features are extracted by undergoing the same procedures and then the obtained test values are compared with the trained set of feature values to obtain the classifications. Once a retinal image is categorized as the diseased case, a message displays Glaucoma Detection and then segmentation is done to locate the exact disease location. Else if the image is normal then it displays the corresponding message and then no further segmentation is required. These results are depicted in Fig 9 and 10 shown below.

Fig 9: Glaucoma image results

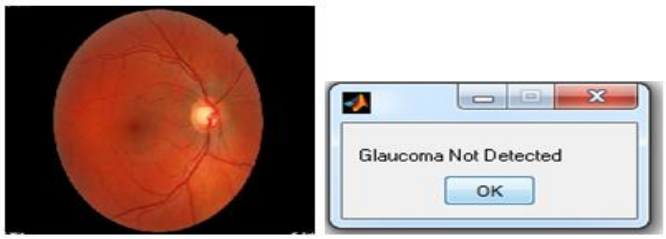

Fig 10: Normal image results

In order to analyze the system performance 4 parameters Sensitivity (TPR), Specificity (SPC), Positive Predictive Accuracy (PPV) and Accuracy (ACC) was calculated with respect to the four conditions true positive (TP-correctly identified), true negative (TN-correctly rejected), false positive (FP-incorrectly identified) and false negative (FN-incorrectly rejected) where positive (P) and negative (N) corresponds to glaucoma and normal case respectively.

The test outcome can be positive or negative corresponding to the identification or rejection of patterns respectively. The equations for calculating these parameters are given below:

$$TPR = TP/P = TP/(TP + FN) \quad (8)$$

$$SPC = TN/N = TN/(FP + TN) \quad (9)$$

$$PPV = TP/(TP + FP) \quad (10)$$

$$ACC = (TP + TN)/(P + N) \quad (11)$$

Sensitivity measures the proportion of actual positives which are correctly identified and Specificity measures the proportion of negatives which are correctly identified. A perfect predictor would be described as 100% sensitive and 100% specific; however, theoretically any predictor will possess a minimum error bound.For this neural network system we obtained the four conditions as:

- TP=15
- FP=0
- TN=14
- FN=1

Hence using the above equations we get the performance parameters as:

- Sensitivity = 93.7500 %
- Specificity = 100 %
- Positive Predictive Accuracy = 100 %
- Accuracy = 96.6667%

TABLE I. COMPARISON OF NEURAL NETWORK PERFORMANCE TOTRADITIONAL CLASSIFIERS

	TP	FP	TN	FN	No. of misclassifications	Accuracy
SVM	13	2	13	2	4	86.67
SMO	13	2	12	3	5	86.01
Random Forest	10	5	13	2	7	76.98
Naïve Bayes	13	2	11	4	6	80.00
Neural Network	15	0	14	1	1	96.67

Thus the success rate is about 96%. On comparing these estimations with the traditional classifiers outputs such as that for Support Vector Machine (SVM), Sequential Minimal Optimization (SMO), Random Forest and Naive Bayes, we observed that the minimum number of misclassifications and hence the best classification accuracy is obtained for the proposed neural network system. The results are tabulated in Table I. So are the results obtained for the glaucoma screening and segmentation technique using FFNN system.

V. CONCLUSION

Computer aided diagnosis for ocular diseases like glaucoma provides an automated detection process. They not only alleviate the increasing burden on the clinicians by providing automatic and objective diagnosis with valuable insights, but also offer early detection and easy access for patients. Fewer resources are then required to diagnose the disease conditions. Wavelet transforms are efficient tools for feature extraction and is successfully used in biomedical image processing. In this proposed method, a wavelet-based texture feature set made up of the energy and averages of wavelet coefficients is used as the feature values. A feed forward back propagation neural network system is then employed to automatically detect whether glaucoma is present or not. This automated detection method is rapid, easy to operate, non-invasive, inexpensive, has no structural and image size dependence and thus enables early stage detection of the disease with improved accuracy. Further

segmentation by thresholding is applied to locate the exact point of glaucoma affected in the retinal image and also to determine the disease severity.

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REFERENCES

[1] Wavelet – Based Energy Features for Glaucomatous Image Classification, Sumeet Dua, U. Rajendra Acharya, Pradeep Chowriappa and S.Vinitha Sree, *IEEE TRANSACTIONS on Information Technology In Biomedicine, Vol. 16, No: 1, January 2012.*

[2] Diagnostic Tools for Glaucoma Detection and Management, Pooja Sharma, Pamela A. Sample PhD, Linda M. Zangwill PhD, and Joel S. Schuman MD, *Survey Of Ophthalmology, Vol. 53, November 2008.*

[3] Clinical Evaluation of the Proper Orthogonal Decomposition Framework for Detecting Glaucomatous Changes in Human Subjects, Robert N. Weinreb, Gianmarco Vizzeri, Luciana M. Alencar, *Ophthalmology & Visual Science, Vol. 51, January 2010.*

[4] Glaucoma detection by wavelet-based analysis of the global flash multifocal electroretinogram, J.M. Miguel-Jimeneza, L. Boquete, *ELSEVIER, Medical Engineering & Physics, February 2010*.

[5] Automated Diagnosis of Glaucoma Using Texture and Higher Order Spectra Features, Xian Du, Chua Kuang Chua, *IEEE TRANSACTIONS on Information Technology In Biomedicine, Vol. 15, No. 3, May 2011*

[6] Wavelet Feature Selection for image classification, Ke Haung, Selin Aviyente, *IEEE TRANSACTIONS on Image Processing, VOL 17, NO:9, September 2008*.

[7] Text categorization with SVM: learning with many relevant features, T. Joachims, *ECML-98*

[8] Classification and Regression by Random Forest, Andy Liaw and Matthew Weiner, *ISSN 1609-3631, Vol 2/3, December 2002*

[9] Neural Networks for pattern recognition, Christopher M Bishop, *Dept of Computer Science and Applied Mathematics, Aston University, UK*.

[10] Neural Networks and pattern recognition, Anna Bartkowiak, *Institute of computer science, University of Wroclaw, 2004*.

[11] Survey of Retinal Image Segmentation and Registration, Mai S. Mabrouk, Nahed H. Solouma and Yasser M.Kadah.

[12] Survey over image thresholding techniques and quantitative performance evaluation, Mehmet Sezgin and Bulent Sankur, *Journal of Electronic Imaging 13(1), January 2004*.