International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)
Volume 3 Issue 5, May 2014

Non-Invasive Diagnosis of Eye Diseases using Image Segmentation and Neural Networks

L.Parvathavarthiny, S.Batmavady

Abstract -**Diagnosing retinal diseases is a recent technological advancement in eye care. It enables the optometrist to capture a digital image of the retina, blood vessels and optic nerve located at the back of eyes. Retinal blood vessel segmentation plays an important role in diagnosing the pathologies. The conventional methods use the Ensemble classifier of Bagged and Boosted decision tree of segmentation to detect the abnormalities of retina. In the latest literature, segmentation of retinal image is carried out using Gabor filter. In the proposed work, Log-Gabor filter is used which overcomes the disadvantages of Gabor filter. The different types of Artificial Neural Network (ANN) such as cascade feedforward NN, Radial Basis Function NN (RBFNN) were chosen for analyzing the retinal images and to predict the eye diseases. The collected database is trained by Neural Network (NN) and compared with new test images for diagnosis. This prediction model gives better accuracy and sensitivity than the existing ones.**

Index Terms – **Artificial Neural Networks, cascade feedforward NN, Gabor filter, Gradient Orientation Analysis, Log-Gabor filter, Morphological transformation, Radial Basis Function NN, Retinal blood vessels, Segmentation.**

I. INTRODUCTION

Retinal, or fundus, photography is used to document the health of the eye and in the diagnosis of certain eye conditions. The high powered lenses of the fundus camera focus on the structures of the back of the eye allowing images of the optic nerve, macular, retina and the blood vessels to be taken. The morphological characteristics of retinal blood vessels themselves have been associated with cardiovascular and coronary disease in adult life [1]. Some of the diseases such as retinopathy, cataract, glaucoma,etc, can be detected by using efficient segmentation and training of neural network. A neural network is an artificial representation of human brain that tries to simulate its learning process [2].The existing method uses segmentation of blood vessels by using an ensemble classifier of boosted and bagged decision trees. The feature vector is mainly based on gradient orientation analysis (GOA), Morphological transformation with linear structuring element and the Gabor filter response encode information to successfully handle both normal and pathological retinas with bright and dark lesions simultaneously. The classifier based on the boot strapped and boosted decision trees are a classic ensemble classifier which has been widely used in many application areas of image analysis [3] and [4]. Artificial neural networks (ANNs) are a family of massively parallel architectures that are capable of learning and generalizing from examples and experience to produce meaningful solutions to problems even when input data contain errors and are incomplete [10]. This NN is used to predict the diagnosis of eye diseases.

L. Parvathavarthiny, student is with Dept. of Electronics and Communication Engineering, Pondicherry Engineering College, Pillaichavady, Puducherry.
S. Batmavady, Professor is with Dept. of Electronics and Communication Engineering, Pondicherry Engineering College, Pillaichavady, Puducherry.

II. METHODOLOGY

A Orientation Analysis of a Gradient Vector Field -The blood vessels are localized by analyzing the orientation of the gradient vector field. The unit gradient vectors of the image are highly discontinuous along the bilaterally symmetrical regions. Therefore, the blood vessels are localized by finding the discontinuities in the gradient orientation. The feature extraction depends on the orientation of the gradient vector field and not on its magnitude; therefore, it is robust against low contrast and non uniform illumination [5].

The gradient vectors for the image I(x,y) are approximated by the first-order derivative operators in the horizontal (k_x) and vertical (k_y) directions

$$g_x(x,y)=I(x,y)*k_x \quad \text{-----} \quad (1)$$
$$g_y(x,y)=I(x,y)*k_y$$

The gradient vectors g_x (x,y)and g_y (x,y)are normalized by dividing with their magnitude to compute the unit gradient vectors $u_x(x,y)$ and $u_y(x,y)$:

$$u_x(x,y)=gx(x,y)/\sqrt{gx(x,y)^2+gy(x,y)^2}$$
$$u_y(x,y)=gy(x,y)/\sqrt{gx(x,y)^2+gy(x,y)^2} \quad \text{--} \ (2)$$

The discontinuity magnitude in the gradient orientation D(x,y) is expressed in terms of the first derivatives of unit vectors as

$$D(x,y)=d_{xx}^2(x,y)+d_{xy}^2(x,y)+d_{yx}^2(x,y)+d_{yy}^2(x,y)$$

D(x,y) contains the gradient orientation analysis map of enhanced blood vessels.

where

$$d_{xx}^2(x,y)=u_x(x,y)*k_x$$
$$d_{xy}^2(x,y)=u_x(x,y)*k_y \quad \text{-----} \ (3)$$
$$d_{yx}^2(x,y)=u_y(x,y)*k_x$$
$$d_{yy}^2(x,y)=u_y(x,y)*k_y$$

ISSN: 2278 – 1323

B Morphological Transformation - The morphological opening using a linear structuring element oriented at a particular angle will eradicate a vessel or part of it when the structuring element cannot be contained within the vessel [9].This happens when the vessel and the structuring element have orthogonal directions and the structuring element is longer than the vessel width

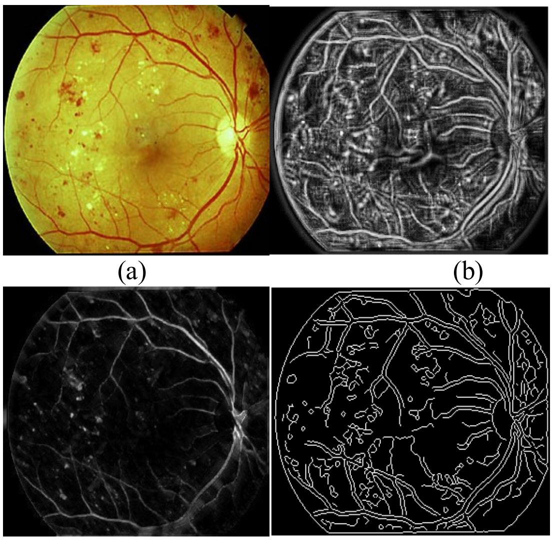
$$Is_{th} = \sum_{\theta \epsilon A} I_{th}^{\theta} \qquad \text{-------- (4)}$$

The morphological tap-hat transform is shown in fig. Where I_{th}^{θ} is the tap-hat transformed image, I is the image to be processed and θ is the angular rotation of the structural element.

C Gabor Filter response - A Gabor filter is a linear filter and has been broadly used for multi-scale and multidirectional edge detection. The Gabor filter can be fine-tuned to particular frequencies and directions, and therefore acts as a low-level feature extractor and background noise suppressor. These Gabor filter has design consideration [8]. The impulse response of a Gabor filter kernel is defined by the product of a Gaussian kernel and a complex sinusoid. It can be expressed as

$$g(x,y)= \exp\{-0.5(\frac{x'^2+\gamma y'^2}{2\sigma^2})\}\exp\{2\pi\frac{x'}{\lambda}+\varphi \qquad \text{------ (5)}$$

Where the wavelength of the sinusoidal factor is, θ is the orientation, φ is the phase offset, σ is the Gaussian envelope, λ is the special aspect ratio. The prime factor is represented as $x' = x\cos\theta + y\sin\theta$ and $y' = -x\sin\theta + y\cos\theta$. The maximum filter response over the angle θ, spanning [0, π] in steps of π/18, is computed for each pixel in the image at different scales ($\sigma = \{2,3,4,5\}$).The Gabor filter response to the inverted green channel of the colored retinal image is obtained by a 2-D convolution operator and is computed in the frequency domain [6] and [7]. This Gabor filter used for segmenting the edges.



(a) (b) (c) (d)

Fig.2.1 segmented outputs. (a) Input image of Diabetic Retinopathy. (b) Edge highlighted by gradient orientation analysis. (c) Morphological transformation. (d) Gabor Filter response.

D Log-Gabor Filter response - In proposed work the process of GOA and morphological transformation is carried out as the existing method and instead of Gabor filter response here Log-Gabor filter is used. An alternative to the Gabor function is the log-Gabor function proposed by Field. There are two important characteristics in the Log-Gabor filter. Firstly the Log-Gabor filter function always has zero DC components which contribute to improve the contrast ridges and edges of images. Secondly, the Log-Gabor function has an extended tail at the high frequency end which allows it to encode images more efficiently than the ordinary Gabor function. The Log-Gabor filters are defined in the log-polar coordinates of the Fourier domain as Gaussians shifted from the origin is obtained by the equation:

$$G_{(s,t)}(\rho,\theta)= \exp\left(\frac{-1}{2}\left(\frac{\rho-\rho s}{\sigma\rho}\right)^2\right)\exp\left(\frac{-1}{2}\left(\frac{\theta-\theta(s,t)}{\sigma\theta}\right)^2\right)$$

With $\rho s = \log_2(n)-s$

$$\theta(s,t) = \begin{cases} \frac{\pi}{nt}t & \text{if s is odd} \\ \frac{\pi}{nt}(t+0.5) & \text{if s is even} \end{cases} \qquad \text{----------(6)}$$

$$(\sigma\rho, \sigma\theta) = 0.996\left(\sqrt{\frac{2}{3}}, \frac{1}{\sqrt{2}}\frac{\pi}{nt}\right)$$

Where (ρ, θ) are the log-polar coordinates, n_t and n_s are the number of orientation and scales of multi-resolutions scheme, $\sigma\rho, \sigma\theta$ are the bandwidths in ρ and θ common for all filters.

III ARTIFICIAL NEURAL NETWORK

The simplest definition of a neural network, more properly referred to as an Artificial Neural Network (ANN), which is provided by the inventor of one of the first neurocomputers.

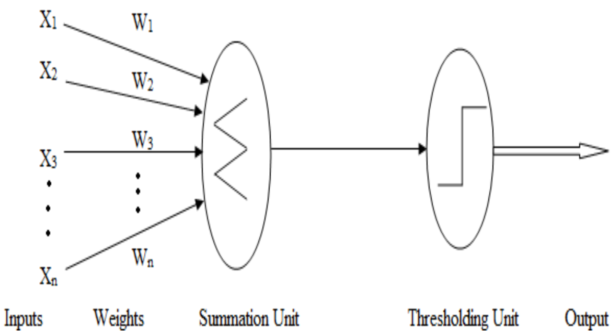


Fig 3.1 Simple model of an artificial neuron

Here $x_1,x_2,x_3,\ldots x_n$ are the n inputs to the artificial neuron and $w_1,w_2, w_3,\ldots.w_n$ are the weights attached to the input links. Recollecting that a biological neuron receives all inputs through the dendrites, sums them and produces an output if the sum is greater than a threshold value[11].

(A) Cascade Feedforward Neural Network

Cascade feedforward back propagation model shown in Fig.3.2 is similar to feedforward networks, but include a weight connection from the input to each layer and from each layer to the successive layers. While two-layer feed forward networks can potentially learn virtually any input output relationship, feedforward networks with more layers might learn complex relationships more quickly. Cascade forward back propagation ANN model is similar to feed forward back propagation neural network in using the back propagation algorithm for weights updating, but the main symptom of this network is that each layer of neurons related to all previous layer of neurons.

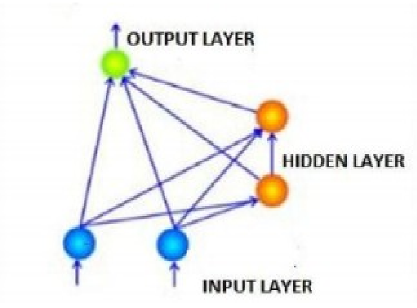


Fig 3.2 Cascade Forward Back propagation Network

Fig 3.2 shows a three-layer network which has connections from layer 1 to layer 2, layer 2 to layer 3, and layer 1 to layer 3.The three-layer network also has connections from the input to all three layers. The additional connections might improve the speed at which the network learns the desired relationship[12].

(B) Radial Basis Function Neural Network

RBFN is an alternative to the more widely used Multi Layer Preceptor (MLP) network and is less computer time consuming for network training. Radial basis function emerged as a variant of Artificial Neural Network. This network may require more neurons than standard feedforward back propagation networks, but often they can be designed in a fraction of the time it takes to train standard feed-forward networks. They work best when many training vectors are available. However, their roots are embedded in much older pattern recognition techniques as for the example potential function, clustering, functional approximation, interpolation and mixture model.

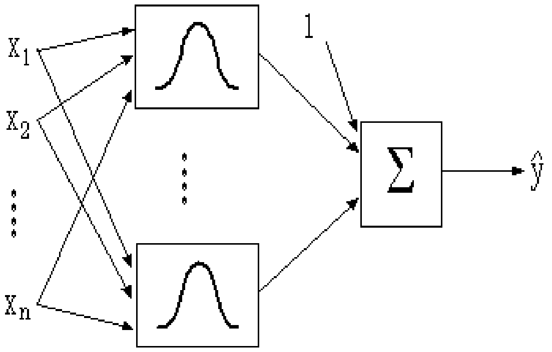


Fig 3.3 RBF network with one output

Fig.3.3 illustrates an RBF network with inputs $X_1, X_2 \ldots\ldots\ldots\ldots X_n$ and output Y_k. The arrow in the figure represents parameters flow in the network. At the input of each neuron, the distance between the neuron center and the input vector is calculated. The output of the neuron is then formed by applying the basis function to this distance. The RBF network output is formed by a weighted sum of the neuron outputs. The RBF expansion for hidden layer and a Gaussian RBF is represented by

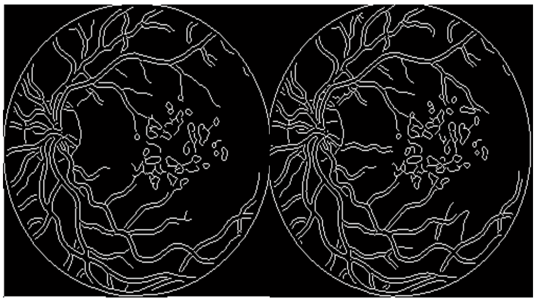
$$Y_k(X) = \sum_{i=1}^{H} W_{ki} \exp\left(-\frac{||X-X_i||^2}{\sigma_i^2}\right) \text{ ----- (7)}$$

IV RESULTS

The retinal images are enhanced by Gradient orientation analysis and followed by morphological transformation and then segmented using Log-Gabor filter. And performance of Gabor and Log-Gabor filter response is compared.

(a) (b)

Fig 4.1 Comparison of Gabor and Log-Gabor filter response of the disease retinal detachment. (a) Gabor filter response (b) Log-Gabor filter response.



(a) (b)

Fig 4.2 Comparison of Gabor and Log-Gabor filter response of the disease Age related Macular Degeneration (AMD). (a) Gabor filter response (b)Log-Gabor filter response.

Likewise normal and abnormal retinal images are filtered using Log-Gabor filter response and trained to neural networks.

Early prediction of retinal diseases is performed by using cascade feedforward NN, RBFNN and pattern recognition NN. Number of layers used is 2. Total images collected are 21 and randomly chosen 17 images are used to train these neural network with corresponding targets such as retinal disease is present or not (either 1 or 0). Check the performances of these networks by giving test images (remaining 4). Regression plot and ROC performance of Neural Networks is obtained and Pattern recognition NN gives more accuracy than the other NN. Accuracy can be calculated by

ISSN: 2278 – 1323

Accuracy = (TN + TP)/ (TN+TP+FN+FP) Where TP=True Positive, TN= True Negative, FP=False Positive, FN=False Negative

Regression is a statistical measure that attempts to determine the strength of the relationship between one dependent variable and a series of other changing variables. Fig 3.3 shows the regression plot for cascade feedforward NN and Radial Basis Function NN.

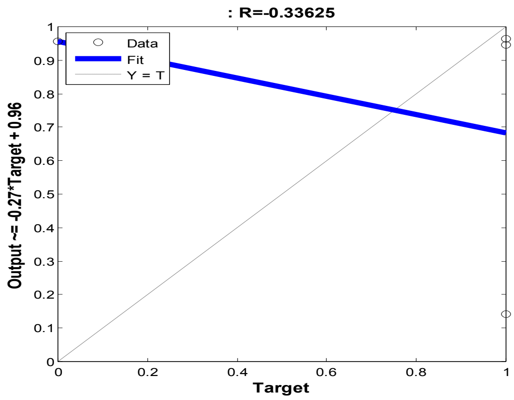


Fig 4.3 (a) regression plot for Cascade feedforward NN

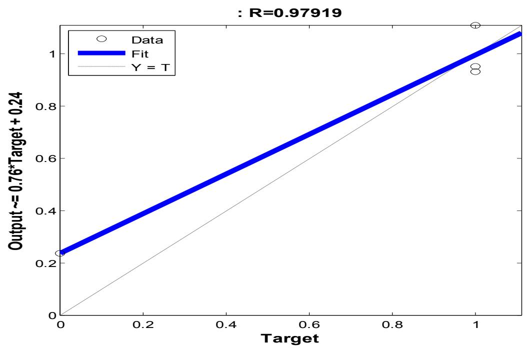


Fig 4.3 (b) regression plot for Radial Basis Function NN

Receiver Operating Characteristic (ROC) curve is an excellent way to compare diagnostic tests. The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test. The closer the curve comes to the 45-degree diagonal of the ROC space, the less accurate the test. The colored lines in each axis represent the ROC curves. The ROC curve is a plot of the true positive rate (sensitivity) versus the false positive rate (1 - specificity) as the threshold is varied. A perfect test would show points in the upper-left corner, with 100% sensitivity and 100% specificity. For this problem, the network performs very well. Fig 3.4 shows the ROC curve for cascade feedforward NN and Radial Basis Function NN of retinal diseases diagnosis.

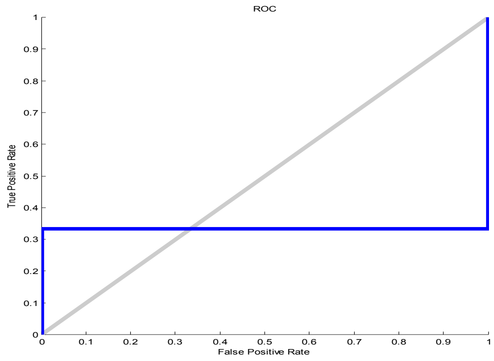


Fig 4.4 (a) ROC curve for Cascade feedforward NN

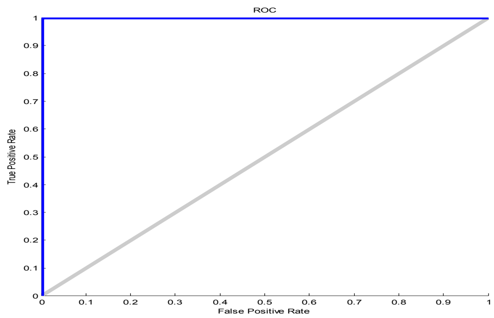


Fig 4.4 (b) ROC curve for Radial Basis Function NN

Table I
Comparison table for different types of Neural Network.

NN n/w type	CFNN	RBFN
No. Neurons	7	21
Computation time	1.36min	21sec
MSE	9.67e-5	1.1e-4
Regression	-0.33	0.97
Accuracy	50	100

IV CONCLUSION

Medical diagnosis of retinal diseases takes long course of time and initially similar kind of treatment is carried out between all types of fever affected patients by keeping them for few days' observation. This leads to loss of vision and more medical expenditure for prediction itself. From the retinal images of the region present lesions can be predicted. This project work is proposed to automatically perform prediction of eye diseases from the retinal images. In this thesis, it is proposed to model a non-invasive method to identify the diagnosis of eye diseases using retinal image. The sample images are enhanced by Gradient Orientation Analysis, morphological transformation and then segmented the edges of region using the Log-Gabor filter response.

The Log-Gabor filter is used for segmenting the edges of the blood vessels and lesions which overcomes the disadvantages of Gabor filter. Gabor filter have DC components so it perform non-uniform coverage of edge segmentation, whereas Log-Gabor filter has no DC component and it perform accurate edge segmentation of blood vessels and lesions. From the obtained results, it is easy to identify where the diseases are located accurately. So this proposed method can be used for early detection of retinal diseases like diabetics, hypertension, glaucoma, etc,

The outputs of segmented images are used to train the artificial neural networks. The different types of Artificial Neural Network (ANN) such as cascade feed forward NN, Radial Basis Function Neural Network (RBFNN) was chosen for analyzing the retinal images and to predict the eye diseases. The collected database are trained on cascade feed forward NN, Radial Basis Function Neural Network (RBFNN) with actual diagnosis results and verified with new test images. This gives better accuracy and sensitivity than the existing models.

REFERENCES

[1] C. G. Owen, A. R. Rudnicka, C. M. Nightingale, R. Mullen, S. A. Barman, N. Sattar, D. G. Cook, and P. H. Whincup, "Retinal arteriolar tortuosity and cardiovascular risk factors in a multi-ethnic population study of 10- year-old children; The child heart and health study in England (CHASE)," *Arterioscl., Throm., Vasc. Biol.*, Jun. 2011.

[2] D. Marin, A. Aquino, M. E. Gegundez-Arias *et al.*, "A New Supervised Method for Blood Vessel Segmentation in Retinal Images by Using Gray-Level and Moment Invariants-Based Features," *Medical Imaging, IEEE Transactions on,* vol. 30, no. 1, pp. 146-158, 2011.

[3] Muhammad M. Fraz, P. Remagnino, A. Hoppe, B. Uyyanonvara, Alicja R. Rudnicka, Christopher G. Owen, and Sarah A. Barman., "An Ensemble Classification-Based Approach Applied to Retinal Blood Vessel Segmentation", *IEEE Transactions on Biomedical Engineering*, vol. 59, no. 9, September 2012.

[4] R. Polikar, "Ensemble based systems in decision making," *IEEE Circuits syst. Magaz,* vol. 6, no. 3, pp. 21–45, Sep. 2006.

[5] D. Onkaew, R. Turior, B. Uyyanonvara, and T. Kondo, "Automatic extraction of retinal vessels based on gradient orientation analysis," in *Proc. 8th Int. Joint Conf. Comput.Sci.Software Eng.*, pp. 102–107, 2011.

[6]E. Ricci and R. Perfetti, "Retinal blood vessel segmentation using line operators and support vector classification", *Medical Imaging, IEEE Transactions on*, vol. 26, no. 10, pp. 1357–1365, Oct. 2007.

[7]Joni-KristianKamarainen, Ville Kyrki, HeikkiKälviäinen, "Invariance Properties of Gabor Filter-Based Features-Overview and Applications" *IEEE Transactions on Image prosessing*, vol. 15, no. 5, May 2006.

[8] DanianZheng, Yannan Zhao, Jiaxin Wang, "Features extraction using a Gabor Filter family", 6th IASTED International Conference on Signal and Image Processing, vol.9, no. 14, August 2004.

[9]Ana Maria Mendonça, and AurélioCampilho,"Segmentation of Retinal Blood Vessels by Combining the Detection of Centerlines and Morphological Reconstruction"*IEEE transactions on medical imaging*, vol. 25, no. 9, September 2006.

[10]K.Saminathan , M.Chithra Devi , T.Chakravarthy , " Pair of Iris Recognition for Personal Identification UsingArtificial Neural Networks", International Journal of Computer Science Issues, Vol. 9, Issue 1, No 3, January 2012.

[11] Rahib H.Abiyev, Koray Altunkaya, "Personal Iris Recognition Using Neural Network", International Journal of Security and its Applications, Vol. 2, no. 2, April, 2008.

[12] Dheeraj S. Badde, Anil k. Gupta, Vinayak K. Patki, "Cascade and Feed Forward Back propagation Artificial Neural Network Models for Prediction of Compressive Strength of Ready Mix Concrete", IOSR Journal of Mechanical and Civil Engineering (IOSR-JMCE), ISSN: 2278-1684, pp. 01-06, 2010.

L.Parvathavarthiny received her B.Tech degree in Electronics and Communication Engineering at Christ college of Engineering and technology, Pondicherry, India in the year, 2012. She is currently persuing his M.Tech degree in Wireless Communication at Pondicherry Engineering College, Puducherry, India. Her area of interest includes Image processing and Neural Networks.

Dr.S.Batmavady is working as Professor in the department of ECE at Pondicherry Engg. College, Puducherry. She has published quite a good number of papers in reputed conferences and journals. Her areas of interest include Image Processing , Signal Processing and Soft Computing.

ISSN: 2278 – 1323