ANN Glaucoma Detection using Cup-to-Disk Ratio and Neuroretinal Rim

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ABSTRACT
Glaucoma is a disease in which the intraocular pressure is very high, causing the optic disc to become cupped with eventual everlasting impairment of vision. It is the second leading cause of permanent blindness. It cannot be cured, but its progression can be slowed down by treatment in early stage. Therefore, detecting glaucoma in time is crucial. In this paper glaucoma is classified by extracting two features using retinal fundus images. (i) Cup to Disc Ratio (CDR). (ii) Ratio of Neuroretinal Rim in inferior, superior, temporal and nasal quadrants that is to say ISNT quadrants. Glaucoma frequently damages superior and inferior fibers before temporal and nasal optic nerve fibers and which start decreasing the superior and inferior rims areas and change the order of ISNT rule. Hence, the detection of rim areas in four directions can assist the correct verification of ISNT rule and then improve the correct diagnosis of glaucoma at early stages. In the end, feed forward back propagation neural network is used for classification based on the above two features. The tool used to accomplish the objective is MATLAB R2013a. The average accuracy of the system is around 96%. The method does not rely on trained glaucoma specialists or specialized and costly OCT/HRT machines. Several fundus retinal images containing normal and glaucoma were applied to the proposed method for demonstration.

Keywords
Glaucoma, Fundus Image, Cup to Disk Ratio, Neuroretinal Rim, ISNT rule, Artificial Neural Network.

1. INTRODUCTION
Glaucoma is a chronic and irreversible Neurodegenerative eye condition in which the nerve that connects the eye to the brain (optic nerve) is progressively damaged. According to World Health organization [1], glaucoma is the second leading cause of blindness; after cataracts. Glaucoma, however, presents perhaps an even greater public health challenge than cataracts because the blindness it causes is irreversible. Patients with early glaucoma do not usually have any visual signs or symptoms. Progression of the disease leads to loss of vision, which occurs gradually over a long period of time. As the symptoms only occur when the disease is quite advanced, glaucoma is called the “silent thief of sight”. In Southern India, studies have shown a prevalence of glaucoma of 2.6% and 90% of these cases have never been diagnosed before, compared to about 50% previously undiagnosed when similar studies are done in Europe [1].

Early detection and prevention is the only way to avoid total loss of vision. In healthy eyes, there is normal balance between the fluids, one that is produced in the eye, and the second that leaves the eye through eye’s drainage system [2]. This balance of fluids keeps Inter Ocular Pressure (IOP) within the eye constant but in glaucoma, the balance of fluids produced within the eye is not maintained properly which in turn causes an increase in IOP, resulting in the damage of optic nerve.

The diagnostic criteria for glaucoma include 1)intraocular pressure measurement, 2)optic nerve head evaluation, 3)retinal nerve fiber layer and 4)visual field defect. . Optic nerve head assessment in fundus images is more promising and advanced. The observation of optic nerve head, cup to disc ratio (CDR) and neural rim configuration are important for early detecting glaucoma in clinical practice. Due to increase in IOP, the cup size begins to increase which consequently increases the CDR. As the cup size increases it also affects the Neuroretinal Rim (NRR) [2]. NRR is the region located between the edge of the disc and the physiological cup. In the presence of glaucoma, area ratio covered by NRR in superior and inferior region becomes thin as compared to area covered by NRR in nasal and temporal region. The digital fundus image of a normal eye and glaucoma tic disc and inferior, superior, nasal and temporal (ISNT quadrants) are illustrated in Figure 1.

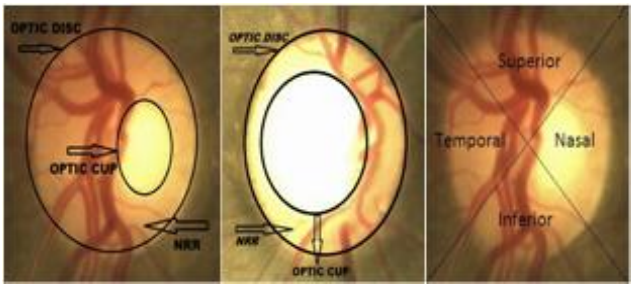


Figure 1: Normal Disc, Glaucoma tic Disc, ISNT Quadrants

Optic nerve assessment is thus able to detect glaucoma early and is currently performed by a trained glaucoma specialist, or using specialized expensive equipment such as the OCT (Optical coherence tomography) and HRT (Heidelberg Retinal Tomography) systems [17]. However, optic disc assessment by an ophthalmologist is subjective and the availability of OCT/HRT is limited because of the cost involved.

The 2D fundus digital image is taken by a fundus camera,which photographs the retinal surface of the eye. In comparison with OCT/HRT machines, the fundus camera is easier to operate, less costly, and is able to assess multiple eye conditions [17]. Many researchers have utilized the fundus images to automatically analyze the optic disc structures.

2. LITERATURE REVIEW
Many studies have been conducted to improve computer based decision support algorithms for early diagnosis of glaucoma by extracting optic disc and cup to calculate CDR ratio. Fauzia Khan et al [2] used Morphological techniques to extract two major features for detection of glaucoma i.e. CDR,

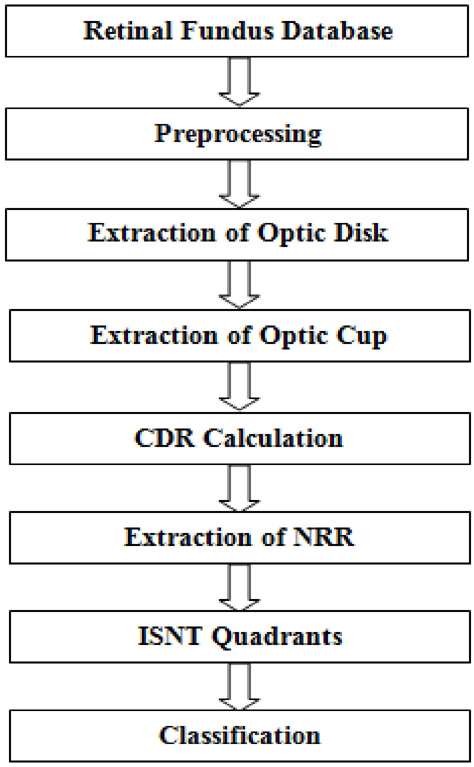
Area ratio of NRR in ISNT quadrants. The proposed method achieves an average accuracy of 94% having an average computational cost of 1.42 seconds. Kavitha et al [3] estimated the cup to disc ratio by extracting disc using component analysis method, manual threshold analysis and region of interest (ROI) based segmentation. For extraction of cup component analysis method was used. Babu et al [4] has implemented Hill Climbing Algorithm for the extraction of optic disc whereas for optic Cup extraction Fuzzy C-Mean clustering. The algorithm was able to detect glaucoma with an accuracy of 90%. A.Murthi and M.Madheswaran [5] used a fused approach based on multimodalities including level set segmentation, convex hull and ellipse fitting boundary is proposed. Chih-Yin Ho et al [6] proposed an automatic detection system which contains two major phases: the first phase performs a series modules of digital fundus retinal image analysis including vessel detection, vessel inpainting, cup to disc ratio calculation, and neuro-retinal rim for ISNT rule; the second phase determines the abnormal status of retinal blood vessels from different aspect of view. Yang et al [7] extracted the optic disc using HRT images for the assessment of glaucoma in an eye. They proposed Multi-scale region and boundary hybrid snake method to extract the optic disc. Li et al [8] proposed a modified active shape model (ASM) for shape detection of optic disc boundary. N.M.Tanet et al [9] proposed a probabilistic mixture model for optic cup segmentation. It is assumed that the pixel intensities within the optic disc can be modeled to a mixture model. Expectation maximization (EM) is used to solve the optimization problem for Gaussian Mixture Model (GMM). The results from evaluations show an improvement of 8.1% in cup area overlap and 14.1% in relative area difference from the ARGALI cup segmentation. Yuji Hatanaka et al [10] proposed a method to measure the cup-to-disc ratio using a vertical profile on the optic disc. The AUC of 0.947 was achieved with this method. Fengshou Yin et al [11] proposed an automatic method of segmenting OD and optic cup based on a statistical model technique (active shape model). Edge detection and the Hough Transform are combined with a statistical deformable model to extract the OD boundary. The method is further extended to obtain the cup boundary on a vessel-removed OD image. The system was tested on a dataset of 325 images. It has a mean absolute CDR error of 0.10, which outperforms existing methods. Sandra Morales et al [12] proposed a method for the extraction of the optic disc contour is mainly based on mathematical morphology along with principal component analysis (PCA). It makes use of different operations such as generalized distance function (GDF), a variant of the watershed transformation, the stochastic watershed, and geodesic transformations.

Thus, this paper proposes an intuitive, efficient and objective method for calculating CDR, NRR area and ISNT quadrants area. The proposed method is quite easy and it is better than other as automatically classifies digital fundus images into either normal or glaucomatous types by using artificial neural network, in order to facilitate ophthalmologists and public health care clinics. This paper is divided into sections out of which Section 3 the proposed methodology, in Section 4 Artificial Neural Network and its training and testing part is explained and in the last Section 5 the result is concluded.

3. PROPOSED METHODOLOGY

To identify glaucoma, two features are required to be extracted by Mean Threshold, Morphological method in order to evaluate CDR and to find NRR ratio in ISNT quadrants. For CDR evaluation, optic disc and cup is required and to find NRR ratio in ISNT quadrants, NRR itself is required.

3.1 Flowchart



3.1.1 Retinal Image Database

To develop the algorithm for automatic detection of glaucoma, the first essential step was to obtain the effective database and for that purpose 90 retinal images were collected in total from various online databases. In which, 30 images from High Resolution Fundus image database[20] and 20 from optic-disc.org [21] database images and rest all from other different online databases including DROINS [22].

3.1.2 Image Preprocessing

In color retinal images, Optic disc appears to be the brightest part having pink or light orange color and is considered to be Region of Interest (ROI). ROI is the region around the optic disc that must first be delineated, as the optic disc generally occupies less than 5% of the pixels in a typical retinal fundus image. While the disc and cup extraction can be performed on the entire image, localizing the ROI would help to reduce the computational cost as well as improve segmentation accuracy. The ROI from all images is crop down and is resized to 256×256 as shown in Figure 2.

Figure 2: Original Image Resized

3.1.3 Extraction of Optic Disc and Cup

To suspect glaucoma, evaluation of CDR is one of the key elements, which is calculated by the extraction of optic disc and cup. Firstly, the original colored fundus image was cropped and resized. In next step, blood vessels are removed from the image. For this morphological operation such as the dilation, erosion, is performed as defined in equation (1) and (2). Dilation causes objects to grow in size by adding pixels to the boundaries of the object in the input image. Image is dilated by using the structuring element "DISK". This dilation results in filling all internal gaps and lighting blood vessels but increasing the size of optic disc which will affect the CDR. For this after dilation the image is being eroded by same structuring element and size. Erosion is done to contrast the boundary of the object. The result of this operation has a smooth image without any blood vessels.

The dilation of A by B is defined by:

$$A \oplus B = \bigcup_{b \in B} A_b \quad --- (1)$$

The erosion of A by B is defined by:

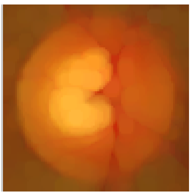
$$A \Theta B = \bigcup_{b \in B} A_{-b} \quad --- (2)$$

Where A: binary image

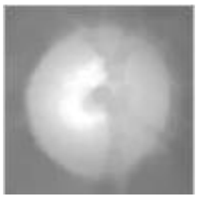
B: Structuring element

After that, a number of images were analyzed and it was concluded that optic disc has a better contrast in V plane extract from HSV image. After calculating the mean value of the V plane image; this value was set as threshold for converting it to binary image. The unwanted objects obtained in resultant binary image were labeled and removed by applying another morphological operation which removes from a binary image all connected components (objects) that have fewer than some pixels value. This helps in removing all the unwanted objects except the optic disc.

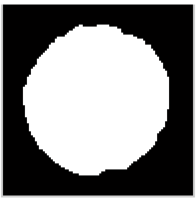
Further the Gaussian filter is applied to the resultant image to smoothen the boundaries of the images as shown in Figure 3.



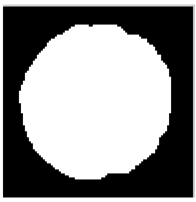
(a) Morphological operations



(b) V plane image



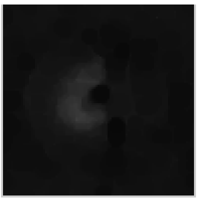
(c) Binary Image



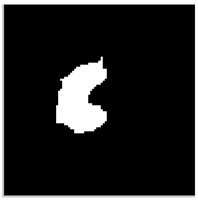
(d) Gaussian filtered image

Figure 3: Extraction of optic disk

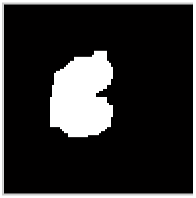
For the extraction of cup, green plane is extracted from the eroded image; the cup has much brighter contrast as compared to other regions of fundus image. In next step, green plane is converted into gray scale image by using global threshold which chooses the threshold to minimize the intraclass variance of the black and white pixels. After extracting the binary optic cup morphological operation i.e. for removal of small objects is applied same as optic disk but with less pixel value as cup size is small. To smoothen the boundaries of optic cup, Gaussian filter is applied to the resultant binary image of the optic cup as shown in Figure 4.



(a) Green plane image



(b) Gray Image



(c) Gaussian filtered image

Figure 4: Extraction of optic cup

3.1.4 CDR Calculation

The area is calculated by counting the number of white pixels after that, the area of cup is divided by the area of disc to calculate CDR.

$$CDR = \frac{Cup\ \ Area}{Disk\ \ Area} \quad --- (3)$$

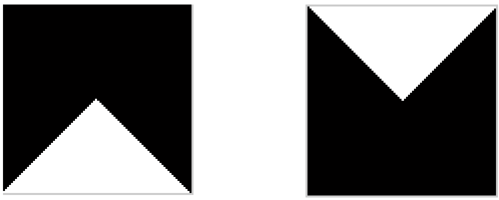
3.1.5 Extraction of Neuroretinal Rim

Extraction of NRR is another feature used for the detection of glaucoma. Loss of axons in Glaucoma is reflected as abnormalities of the neuroretinal rim. Identification of the neuroretinal rim width in all sectors of the optic disc is of fundamental importance for detection of diffuse and localized rim loss in glaucoma. The rim width is calculated using ISNT rule.

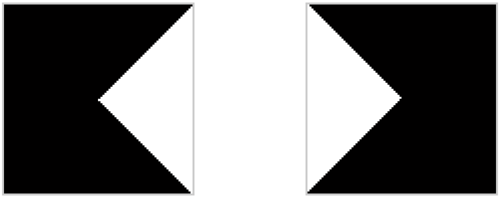
3.1.6 ISNT calculation

Rim area is measured in the ISNT quadrants. Usually the rim area thickness must be more in the superior and inferior region when compared to the temporal and nasal region. To obtain the thickness in all the four quadrants, a binary image of the neuroretinal rim is taken and then cropped as in Figure 4. A mask of the cropped image size is used to filter one quadrant. Then the mask is rotated 90º to obtain the other quadrant areas. Figure 5 shows the mask used for identifying rim area in the ISNT side of optic disc.

Figure 4: NRR Image



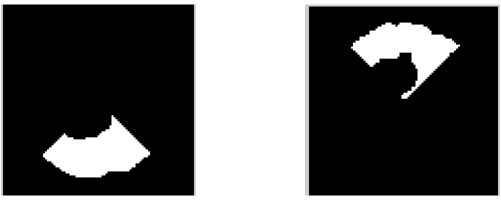
(a) **(b)**



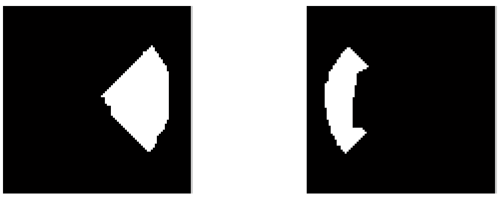
(c) **(d)**

Figure 5: Mask used for detecting the Rim area in (a)inferior quadrant; (b)superior quadrant; (c) nasal quadrant; (d) temporal quadrant of the optic disc

This neuroretinal rim configuration gives rise to a cup shape that is either round or horizontally oval. Neuroretinal rim area is calculated by subtracting the area of the optic cup from area of optic disc. Figure 6 shows area covered by NRR in ISNT Quadrants. The area covered by white pixels is counted for the evaluating the ISNT Ratio.



(a) I quadrant **(b) S quadrant**



(c) N quadrant **(d) T quadrant**

Figure 6: Rim area of ISNT quadrants of the optic disc

3.1.7 Classification

Classification has been done on bases of two features i.e. CDR and NRR ratio in ISNT quadrants. Disc which is normal has CDR less than 0.5 and it obeys the ISNT rule i.e. the sum of the area in inferior and superior region is more than nasal and temporal region whereas the glaucoma tic disc violates ISNT rule and has CD ratio greater than 0.5. After that, images are feed into the neural network is which classify them on the basis of above features.

4. ARTIFICIAL NEURON NETWORK

An artificial neuron network (ANN) is a computational model based on the structure and functions of biological neural networks. These are generally presented as systems of interconnected "neurons" which can compute values from inputs, and are capable of machine learning. ANN is also called as neural network [23].

A Neural Network is a massively parallel distributed processor made up of simple processing units which have natural propensity for storing experiential knowledge and making it available for use. Its working is similar to brain in two ways. First, Knowledge is acquired by the Network from its surroundings through a learning process. Second,

Interneuron link strength is used to store acquired knowledge [23].

The word network in 'artificial neural network' refers to the inter–connections between the neurons in the different layers of each system. Figure 7 shows a neural network.

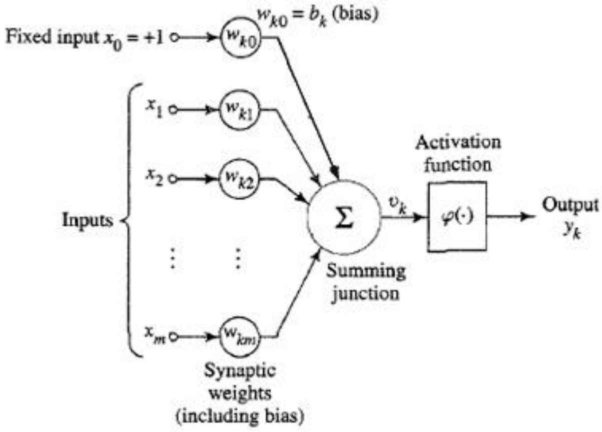


Figure 7: A Neuron

Linear Combination Uk, Uk = ∑wkj *xj

Induced Local Field Vk, Vk = Uk + bk,

Activation function define the value of output Yk,Yk = ϕ (Vk)

4.1 Feed Forward Back Propagation Neural Network Algorithm

Backpropagation is a common method of training artificial neural networks used in conjunction with an optimization method such as gradient descent. It is a generalization of the delta rule to multi-layered feed forward networks. The method calculates the gradient of a loss function with respects to all the weights in the network [19]. A loss function or cost function is a function that maps an event or values of one or more variables onto a real number intuitively representing some "cost" associated with the event. The gradient is fed to the optimization method which in turn uses it to update the weights, in an attempt to minimize the loss function.

Step 1: - Weight Initialization: -

Set all weights and Node threshold to some small random values.

Step 2: - Calculation of activation: -

Input Unit: - The Activation Level of the input unit is determined by the instances presented to the Network.

Hidden unit and Output unit: - The Activation Level Oj of Hidden unit and Output Unit are determined by:

Oj = F [∑ wji*Oi – θj]

Where wji - weight from input Oi to unit j,

θ j - Node threshold at unit j,

F - Activation Function.

Step 3: - Weight Training: -

a. Start at output unit and work backward to the hidden layer recursively adjust the weight by

$$w_{ji}(t+1) = w_{ji}(t) + \Delta w_{ji}$$

b. The weight change is computed by

$$\Delta w_{ji} = \eta \delta_j O_i$$

Where η = learning rate,

δ_j = error gradient

The error gradient is given as follows at Output Unit

$$\delta_j = O_j (1 - O_j)(T_j - O_j)$$

And for Hidden Unit

$$\delta_j = O_j (1 - O_j) \sum \delta_k w_{kj}$$

Where T_j = Target Value,

O_j = Actual Output Value,

δ_k = Error Gradient at unit k to which a connection point at unit j.

Step 4: - Repeat Iterations until convergence.

4.2 Simulation

In the proposed method, a multi-layered feed forward neural network which consists of input layer, at least one hidden layer and output layer is used. The hidden layer and output layer nodes adjust the weights value depending on the error in classification. [25] The network will be trained by scaled gradient conjugate backpropogation forward direction, but the error is back propagated and weights are update to reduce the error. The database consists of 90 images out of which 45 are normal and 45 glaucomatous. The Activation function used is sigmoid activation function. In this case, a 5*90 input, 20 hidden layer and 1 output layer is taken. The 5 features are CDR ratio and the four quadrants of ISNT rule. Neural network pattern reorganization technique is used for finding the accuracy of training, validation and testing. Database is dividing into a three set: 50% images for training, 25% images for validation and 25% images for testing. Training samples are presented to the network during training and the network is adjusted according to its error. Validation samples are used to measure network generalization, and are used to halt training when generalization stops improving. Testing samples have no effect on training and so provide an independent measure of network performance during and after training.

The below figures 8, 9, 10, 11 show the performance of the system through confusion matrix in Training, testing, and validation phases.

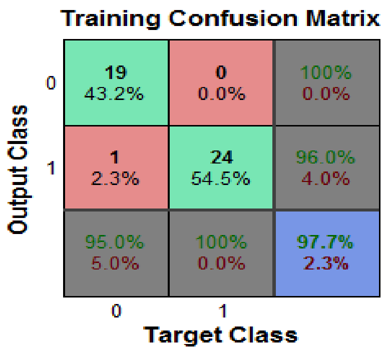


Figure 8 : Training Confusion Matrix

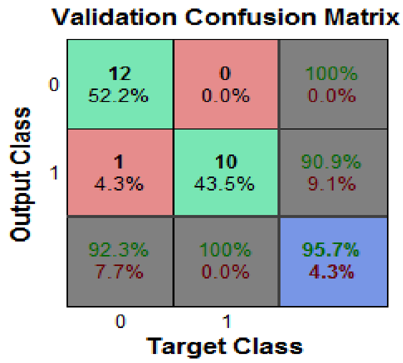


Figure 9: Validation Confusion Matrix

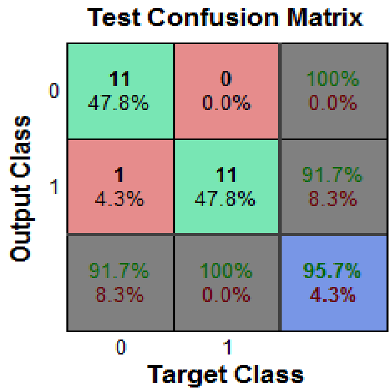


Figure 10: Testing Confusion Matrix

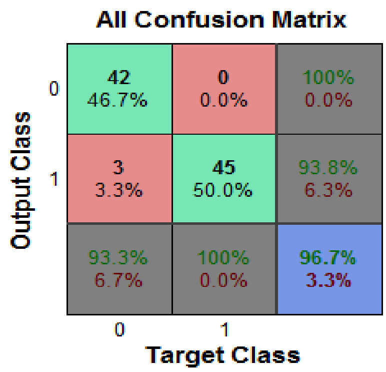


Figure 11: All Confusion Matrix

These Figures shows that the system average accuracy is 96.7%. The below Figure 12, 13 shows the performance plot and the error plot of the system in Training, testing, and validation phases.

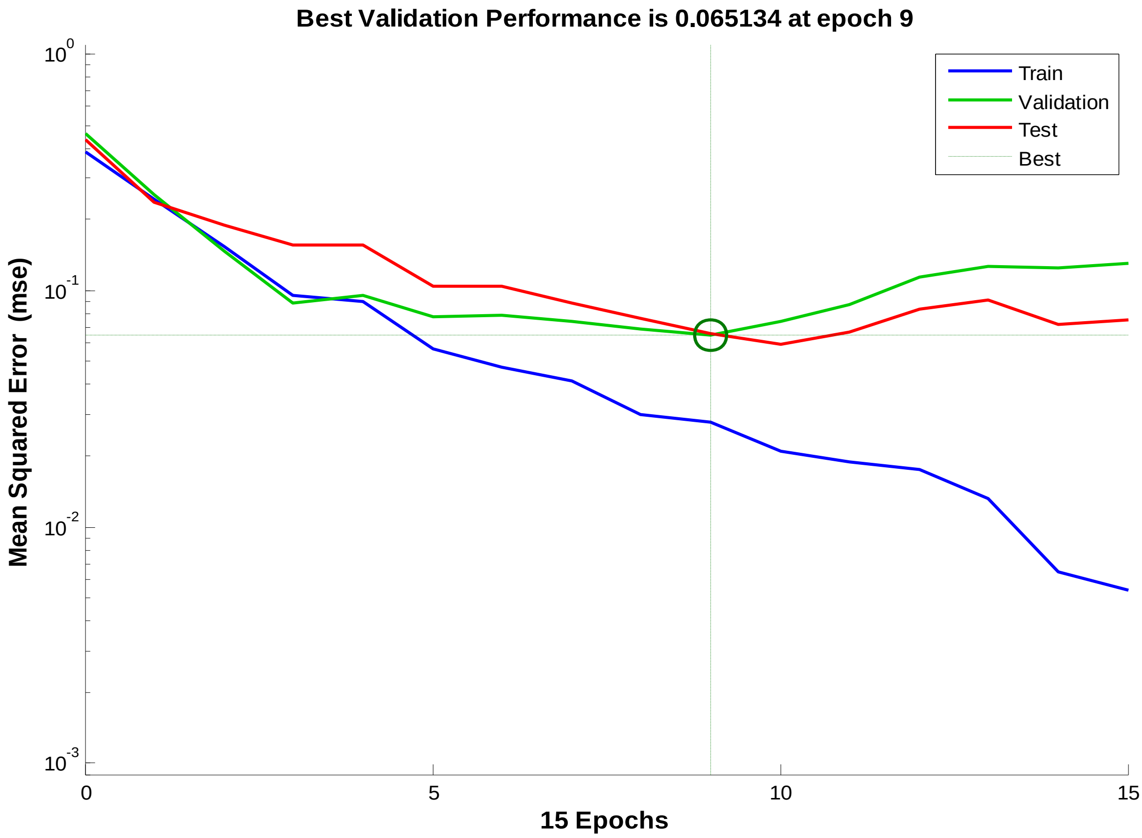


Figure 12: Performance Plot of the neural network

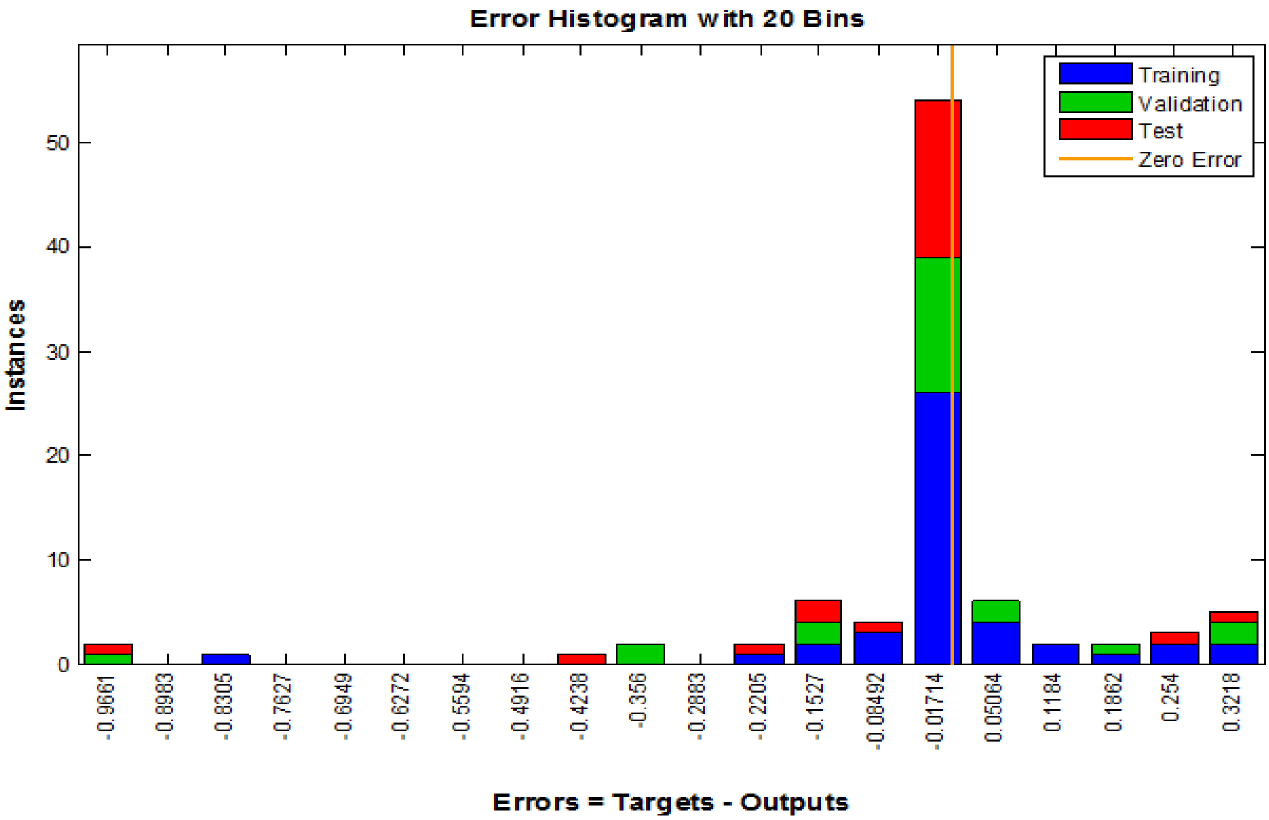


Figure 13: Error Plot of the neural network

5. CONCLUSION

In this paper, an automatic glaucoma detection system using two features i.e. CDR calculation and ISNT rule analysis, which facilitates early diagnosis of glaucoma and follow-up evaluation is disscused. The novel method uses morphological techniques to extract the two features. To determine the performance of our approach, 90 retinal images were processed and their CDR and ISNT quadrants were computed. The method achieves an average accuracy of 94% to 96% which is better than the previous approach mentioned in [2] as firstly the classification is done manually and the accuracy mentioned in there is 94%. Whereas here the accuracy achieved is 96.7%. Even though the performance is still far from perfect, the result is subjective, consistent and fast. It does not rely on trained glaucoma specialists or specialized and costly OCT/HRT machines. The good performance of this approach leads to a large scale clinical evaluation and will be able to report large clinical findings in the future.

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