



Implementation of FPGA in Detecting Glaucoma using Neural Networks

M.Shahana¹ | S.Vengatesh Kumar¹ | N.Hemakumari² | M.L.Syed Ali¹

¹Assistant Professor, Department of ECE, Mohamed Sathak Engineering College, Tamilnadu, India

³Associate Professor, Department of ECE, Mohamed Sathak Engineering College, Tamilnadu, India

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ABSTRACT

Glaucoma is an eye disease caused by increased Intra Ocular Pressure, resulting in damaged optic nerves. This paper proposes detecting glaucoma disease using artificial neural networks as a classifier. Features like optic cup area, optic disk area, and neuro-retinal rim area are used. FPGA implementation offers adaptability and parallel architecture of neurons, making it a better choice than DSP or ASIC. Matlab R2015a software extracts features, and the neural network is implemented on a Spartan 3a FPGA kit

KEYWORDS: FPGA implementation, ROI, optic disk area, artificial neural networks.

1. INTRODUCTION

The human eye is crucial for detecting eye diseases such as glaucoma, cataract, macular degeneration, and diabetic retinopathy. Glaucoma is a silent eye disease that affects the optic nerve, leading to thinning and drying, resulting in irreversible visual loss. It affects anyone, regardless of age or population, and early diagnosis is the best way to prevent it. Glaucoma is best treated with eye drops or tablets to reduce pressure inside the eye. This study aims to detect glaucoma using FPGA hardware and an artificial neural network as a classifier. However, there is no lifetime prevention for glaucoma, and treatment is best achieved through eye drops or tablets.

1.1 Glaucoma

Glaucoma affects approximately 45 million people globally, with 79 million expected to suffer by 2020. The optic nerve, responsible for transmitting eye data to the brain, is damaged in glaucoma, leading to vision loss. The main cause of this damage is increased Intra Ocular Pressure (IOP), which causes the eye to constantly deliver aqueous humor, a liquid that should flow out of the eye. In glaucoma, the eye's liquid pressure increases due to the inability to properly drain aqueous humor, causing damage to the optic nerve fibre. This damage can be detected using Optical Coherence Tomography (OCT) and Heidelberg Retina Tomography (HRT), but the cost of glaucoma diagnosis is high Colour

Fundus Image (CFI) technique is widely used to analyse glaucoma and other visual diseases.

1.2 Glaucoma Effects

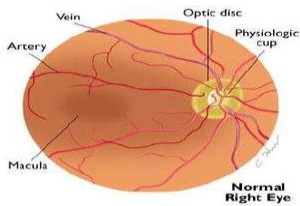


fig A: normal fundus image

Fig A shows the fundus image of a normal eye taken from a fundus camera. The bigger circular area is the optic disk area and the smaller circular area within the optic disk is the optic cup area. The difference between the optic disk and the optic cup area is called the Neuro-Retinal Rim (NRR).

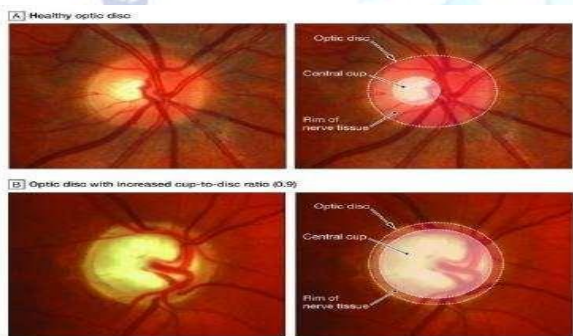


fig b: (b) Healthy optic disk (c) Unhealthy optic disk

Glaucoma disease is identified by changes in the optic disk area, with healthy eyes having a small optic cup size compared to the optic disk. However, glaucoma causes an increase in the optic cup size and the optic cup to optic disk ratio.

2. Methodology

The proposed glaucoma detection system involves pre-processing the input fundus image for noise removal, feature extraction, and classification using neural networks, which includes removing features like optic disk area, cup area, and neuro retinal rim area.

2.1 Fundus Retinal Images

The proposed method was tested using 30 fundus images from the HRF image database, including 15 healthy and 15 glaucoma images, in jpeg format with a resolution of 3504x2336 pixels, as shown in fig-d

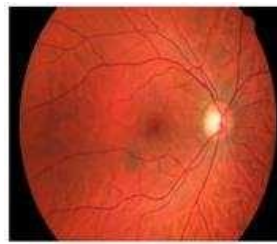


fig d : Input fundus image

2.2 Image Pre-processing

The pre-processing process aims to improve the image by enhancing certain elements or removing unwanted noise. The input images are high resolution, so they are resized to 875x563 pixels. The image is converted to a HSV color map using the rgb2hsv (N) command. The optic disk is highlighted by removing red color and unwanted pixels. The region of interest (ROI) is marked to reduce processing time and initialize the temporary boundary of the optic disk. The ROI is defined by marking the centre and drawing a rectangle around it. The region of interest is then cropped from the original image

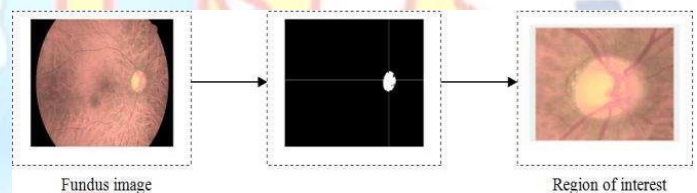


fig e : Image pre-processing

2.3 Feature extraction

2.3.1 Optic Disk Extraction

Feature extraction from the pre-processed image is done using the segmentation technique called multi-thresholding. It partitions an image into similar regions based on thresholding values, with the main part being determining the threshold value. For example, an 8-bit resolution image has a threshold value between 0 and 255. After determining these values, every pixel in that region is assigned a fixed value. When multiple threshold values are established in the same image, higher and lower limits are set for each region. For example, to segment the optic disk, the threshold value is set as follows:

$I_{disk}(x,y) = 255$ if $a(x,y) > TD$ and 0 otherwise. Where T_c is the threshold value for optic cup extraction.

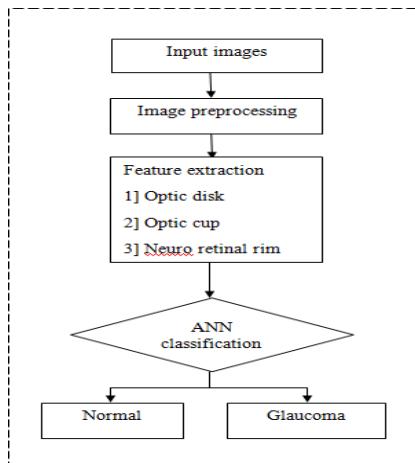


fig c : Methodology of the proposed system

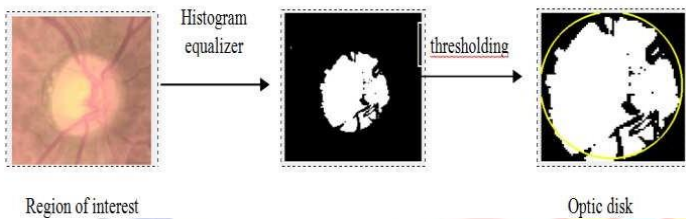


fig f : Optic disk extraction

2.3.2 Optic Cup Extraction

The optic cup extraction is a technique similar to optic disk extraction, using thresholding to segment the optic cup. The threshold value TC is set higher than TD to account for the brighter optic cup area, as shown in the code: $I_{cup}(x,y) = 255$ if $a(x,y) > T_c$ and 0 otherwise.

Where T_c is the threshold value for optic cup extraction..

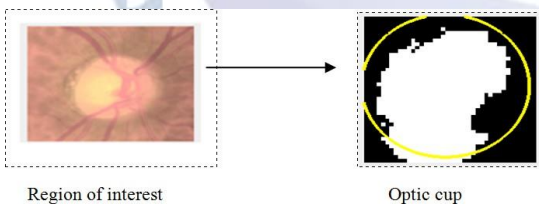


Fig g: Optic cup extraction

2.3.3 Neuro Retinal Rim Extraction

The neuro retinal rim area is the area between the optic cup and optic disk areas, calculated by subtracting the cup area from the disk area. The optic cup to disk ratio (CDR) and neuro retinal rim area are calculated by subtracting the optic disk area from the optic cup area.



fig h: NRR extraction

$$\text{Cup to disk ratio} = [\text{cup area}] / [\text{disk area}]$$

$$\text{Neuro retinal rim area} = [\text{optic disk area} - \text{optic cup area}]$$

2.4 Artificial neural networks

Neural networks can be implemented using analog or digital systems, with digital implementation being more common due to its higher precision, repeatability, lower noise sensitivity, testability, adaptability, and compatibility with various preprocessors. Digital neural network hardware can be classified as FPGA-implementation, DSP-implementation, or ASIC-implementation. DSP implementation lacks parallel architecture and re-configurability, while ASIC-based implementation lacks re-configurability. FPGA implementation offers both adaptability and parallel architecture of neurons, making it a better choice for neural networks.

A neural network is a set of connected neurons with weights associated with each interconnection. It can learn by changing the weights of connections based on inputs. The network has three layers: input, hidden, and output. A single hidden layer can solve most problems, while multiple layers can be used depending on the complexity of the problem.

2.4.1 Feed Forward Propagation

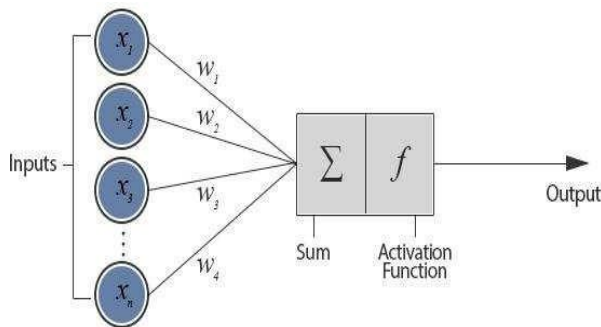
Neural networks use two algorithms: feed-forward and back propagation. Feed-forward algorithms calculate the output sum by summarizing weights and inputs to neurons. The activation function is applied to the output sum, and weights are randomly set for the first feed-forward iteration. A neural network cannot be based solely on feed-forward or back propagation algorithms.

fig d shows the structure of a neuron. The circle represents the neuron which has $x_1, x_2, x_3, \dots, x_n$ inputs and $w_1, w_2, w_3, \dots, w_n$ are the weights on the connections respectively.

The output of a neuron is given by the equation

$$y = f(p) \quad (1) \text{ and the value of } p \text{ is given}$$

Where x_i is the i th input of the network and w_i is the weight on the i th connection. The function $f(p)$ is called the activation function of the neuron.



There are three types of activation functions namely Linear, Log-sigmoid and Tan-sigmoid functions as shown below

Linear function,
$$f(x) = x$$

Sigmoid-function,
$$f(x) = \frac{1}{1 + e^{-x}}$$

Tan-sigmoid function,
$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

2.4.2 BackPropagation

Back propagation involves calculating the error between actual and desired output, adjusting weights to reduce the error. Similar to feed forward calculations, back propagation calculations are applied at each level but executed in reverse order, from output to input layer.

Let's first consider the output layer and hidden layer. First the error is calculated at the output by subtracting the actual output from the desired output

$$\text{error} = \text{desired} - \text{actual}$$

Change in the output sum is calculated by taking the product of derivation of activation function and the error. We will call this as the delta output sum.

$$\text{Delta output sum} = S'(\text{output sum}) * (\text{error})$$

Where $S'(\text{output sum})$ is the derivation of activation function applied to the output sum.

The change in the nets corresponding to output neurons is calculated by dividing the delta output sum by the hidden layer results.

$$\text{Delta weights} = (\text{delta output sum}) / (\text{hidden layer results})$$

Change in the hidden layer sum is denoted by delta hidden sum and is calculated by following equation.

$$\text{Delta hidden sum} = [\text{delta output sum} / \text{hidden-to-output weights}] * [S'(\text{hidden sum})]$$

Now the change in the weights between the input and hidden layer is calculated as follows

$$\text{Delta weights} = \text{delta hidden sum} / \text{input data}$$

The back propagation process is completed by applying a feed forward and repeating the process thousands of times for more accurate results.

3.RESULTS

The methodology was tested on high resolution fundus (HRF) database images, with results for glaucoma images and healthy images shown in tables-1 and table-1 respectively

Table-1: Glaucoma eye results

File name	Cup area	Disk area	Rim area	Cup/ Disk ratio	prediction
01_g	804.248	3019.071	2214.823	0.266	Glaucoma
02_g	1256.637	3019.071	1762.433	0.416	Glaucoma
03_g	1385.442	3959.192	2573.75	0.35	Glaucoma
04_g	1194.591	4185.387	2990.796	0.285	Glaucoma
05_g	1520.531	4656.626	3136.095	0.327	Glaucoma
06_g	1194.591	4185.387	2990.796	0.285	Glaucoma
07_g	1134.115	4071.504	2937.389	0.279	Glaucoma

Table-2: Healthy eye results

File name	Cup area	Disk area	Rim area	Cup/ Disk ratio	Prediction
01_h	1075.21	5026.548	3951.338	0.214	Healthy
02_h	907.92	3739.281	2831.36	0.243	Healthy
03_h	0	4185.387	4185.387	0	Unknown
04_h	530.929	3848.451	3317.522	0.138	Healthy
05_h	962.113	4901.67	3939.557	0.196	Healthy
06_h	855.299	4185.387	3330.088	0.204	Healthy
07_h	346.361	4901.67	4555.309	0.071	Healthy

The extracted disk area, cup area and neuro retinal rim area are fed to the artificial neural network. The performance of ROC is as shown below.

3.1 Receiver Operating Characteristic curve (ROC)

The system's performance was evaluated using 30 fundus images from the HRF image database. The training phase used 16 images (8 healthy and 8 glaucoma), while testing phase used 14 images (seven glaucoma eye images and seven healthy). The system predicted glaucoma-affected results for all glaucoma images and healthy eye results for 6 out of 7 healthy images.

Therefore, accuracy can be given as,

$$\text{Accuracy} = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} * 100$$

here,

T_p = true positive = glaucoma image being identified as glaucoma image = 7

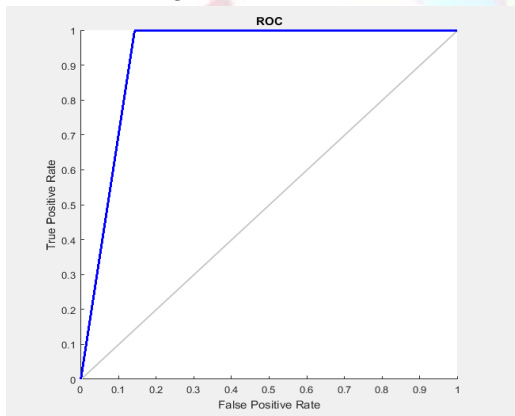
T_n = true negative = healthy image being identified as healthy image = 6

F_p = false positive = glaucoma image being identified as healthy image = 1

F_n = false negative = healthy image being identified as glaucoma image = 0

Therefore,
accuracy = $13 / 14 = 92.85 \%$

We obtained the accuracy of 92.85 %. The ROC graph is shown in fig-.



4. CONCLUSION

The proposed system aims to efficiently detect glaucoma in early stages without relying on trained specialists or expensive HRT/OCT machines. It extracts three features from a digital fundus image: optic disk, optic cup, and neuro-retinal rim. Artificial neural networks classify the disease, and thresholding approaches are used for segmentation. The system's performance was evaluated using 30 retinal images, with an accuracy of 92%. The system can be improved by

using the same camera settings for fundus images and using advanced segmentation techniques. Further accuracy can be achieved by adjusting camera settings and segmentation techniques.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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