

Optic Cup Detection for Diagnosing Glaucoma using Neural Network

I. Mary Surgin Sanju^{1*}, R. Kavitha Jaba Malar²

¹Student, Department of Computer Science, St. John's College Arts and Science, Ammandivilai, India

²Associate Professor, Department of Computer Science, St. John's College Arts and Science, Ammandivilai, India

Abstract: Glaucoma is an important cause of vision failure in human being. In early stage, people cannot realize that they have reached the glaucoma stage. There will be no indication like pain or immediate loss of vision. Checking the top of optic nerve called cup-to-disc ratio is very important for diagnosing glaucoma. Images are acquired by fundus camera. The cup segmentation techniques are used to isolate the needed parts of the retinal image and to calculate the disc ratio. This research proposes an intelligent image processing method to detect glaucoma to help the ophthalmologist in screening glaucoma. The proposed approach is based on the segmentation of optic disk and the optic cup. Hough Transform is used to calculate the radius of the cup. The vertical cup to disk ratio is used for identification of glaucoma symptoms in the fundus image. The results of the proposed method indicate that the approach is effective in glaucoma detection with better accuracy over existing works.

Keywords: Extraction, nerve, vision

1. Introduction

Glaucoma is a variety of eye disorder occurring due to the damage of optic nerve. Here the eye pressure causes the damaging of delicate nerve fibers of the optic nerve. When a huge nerve fibers are damaged, blind spots found in the field of vision. Once nerve damage and visual loss occur, it is permanent. Most people don't notice these blind areas until much of the optic nerve damage has already occurred. It is a leading cause of blindness in older people. Early detection and treatment by the ophthalmologist are the keys to preventing optic nerve damage and vision loss from glaucoma. The exact causes of optic nerve damages from the glaucoma are not yet predicted. The high eye pressure leads to glaucoma, many people can also has glaucoma with "normal" eye pressure. Chronic open-angle glaucoma is the most common form of glaucoma. The "open" drainage angle of the eye can become blocked leading to gradual increased eye pressure. If this increased pressure results in optic nerve damage, it is known as chronic open-angle glaucoma. Optic disk is brighter than any part of the retina image and is normally circular in shape. It is also the entry and exist point for nerves entering and leaving the retina to and from the brain. Near to the centre of the retina is an oval shape object called macula. The fovea is near the centre of the macula and it contains packed cone cells. Due to high

amount of light sensitive cells, the fovea is responsible for the most accurate vision. The retina is a multi-layered sensory tissue that lines the back of the eye. It contains millions of photoreceptors that capture light rays and convert them into electrical impulses. These impulses travel along the optic nerve to the brain where they are turned into images.

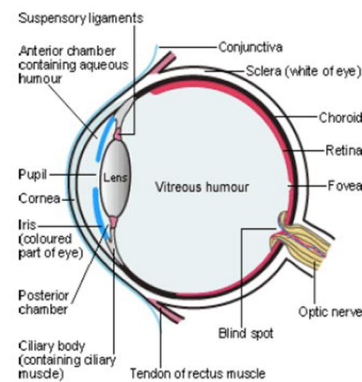


Fig. 1. Structure of the eye

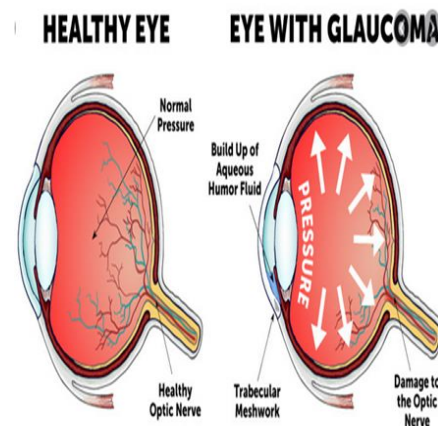


Fig. 2. Normal and Abnormal eye

The optic nerve damage and vision loss usually occurs so gradually and painlessly. Angle-closure glaucoma results when the drainage angle of the eye narrows and becomes completely blocked. In the eye, the iris may close off the drainage angle

*Corresponding author: sanjuisac04@gmail.com

and cause a dangerously high eye pressure. When the drainage angle of the eye suddenly becomes completely blocked, pressure builds up rapidly, and this is called acute angle-closure glaucoma. The symptoms include severe eye pain, blurred vision, and headache, rainbow haloes around lights, nausea and vomiting. Unless an ophthalmologist treats acute angle-closure glaucoma quickly, blindness can result. When the drainage angle of the eye gradually becomes completely blocked, pressure builds up gradually, and this is called chronic angle-closure glaucoma. This form of glaucoma occurs more frequently in people of African and Asian ancestry, and in certain eye conditions.

2. Literature Survey

Huang (2003) developed a novel approach to diagnose diabetes based on the fractal characteristics of retinal images. The influence of the image resolution upon the fractal dimension is explored. They found that a low-resolution image cannot yield an accurate fractal dimension. Therefore, an approach for examining the lower bound of image resolution is also proposed. As for the classification of diagnosis results, four different approaches are compared to achieve higher accuracy. Tang developed (2016) a localizing micro aneurysms in Fundus Images through Singular Spectrum Analysis. The approach proposed in the evaluated system has great potential when used in an automated diabetic retinopathy screening tool or for large scale eye epidemiology studies. Bob Zhang (2014) developed Detecting Diabetes Mellitus and Non-Proliferative Diabetic Retinopathy using Tongue Color, Texture, and Geometry Features. In this study, a non-invasive approach to classify Healthy/DM and NPDR/DM-sans NPDR samples using three groups of features extracted from tongue images was proposed. Shailesh Kumar (2018) developed Diabetic Retinopathy Detection by Extracting Area and Number of Micro aneurysm from Color Fundus Image. There are two features namely; number and area of MA have been determined. Initially, pre-processing techniques like green channel extraction, histogram equalization and morphological process have been used. For detection of micro aneurysms, principal component analysis (PCA), contrast limited adaptive histogram equalization (CLAHE), morphological process, averaging filtering have been used. Gonzalez (2017) presented automated detection of diabetic retinopathy using SVM. A computer assisted diagnosis based on the digital processing of retinal images in order to help people detecting diabetic retinopathy in advance.

3. Proposed Methodology

The digital colour retinal images required for the detection of Diabetic Retinopathy are provided by the BejanSingh Eye Hospital, Nagercoil, TamilNadu. Total 15 glaucoma images were collected for this experimentation. A specialist manually marked optic disc, blood vessel, damage area, exudates and micro aneurysm in the retinal image. The digital images are processed and saved on the hard drive of a Windows based computer with a resolution of 512 x 512 pixels in 24 bit TIFF format. The user can browse for the image files in his or her

local drives then select a particular image and display it on the picture box at runtime. Fundus imaging generally affected by non-uniform illumination due to several factors such as the narrow lens in the completely dilated pupil, variation in light reflection and diffusion, noise, low contrast, differences in retinal pigmentation and differences in cameras, limitations of the instrument as the ring-shaped model illumination pattern and imaging related to variation in illumination axes of the eye with respect to optical axes.

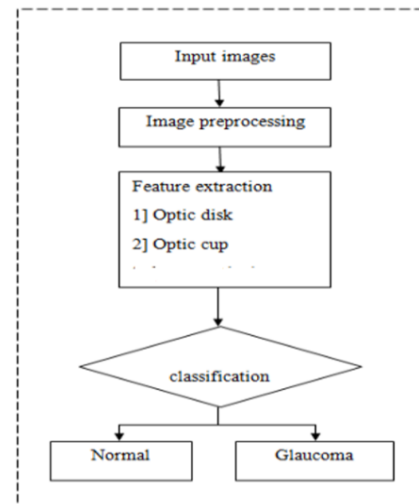


Fig. 3. Proposed Architecture

The optic disc may suffer from a reduction of brightness. Thus, the exudates or similar lesions in such regions are not distinguishable from the background color near the disc. The retinal image quality has a great impact on the features of retinal lesions, especially exudates. Given each f in the initial image and a small $M \times M$ running window w , then the image is filtered to produce the new image pixel $f(i, j)$

$$f(i,j) = 255 \left(\frac{[\Psi_w(f) - \Psi_w(f_{min})]}{[\Psi_w(f_{max}) - \Psi_w(f)_{min}]} \right)$$

$$\Psi_w(f) = \left(1 + \exp \left(\frac{\langle f \rangle_w - f(i,j)}{\sigma} \right) \right)$$

And f_{max} and f_{min} are the maximum and minimum intensity values in the whole image, while $\langle f \rangle_w$ and σ_w indicate the local window mean and standard deviation which are defined as

$$\langle f \rangle_w = 1 / M^2 \sum_{(l,j) \in w(k,l)} f(i,j)$$

Where, (k, l) represents the location of each pixel within window w . The size of window M should be chosen to be large enough to contain a statistically representative distribution of the local variations of pixels. Optic cup is detected using a region of interest based segmentation and the bounding rectangle enclosing the region of interest is set as 1.5 times the

disc width parameter. The detection of the optic cup exactly is used to calculate the neuro-retinal rim area present between the disc and cup. The optic cup and disc areas usually differ in color known as pallor. Once the segmentation process is over, the feature extraction process is carried out. From the optical disk, we extract area, perimeter, entropy, maximum intensity, minimum intensity and Cup-to-Disc Ratio (CDR). Similarly, optic cup also has the same features. The total number of pixels that lie in the corresponding segment is called as area. If we calculate the area for optic disc means, we choose an OD image and if we calculate the area for optic cup means, we select only OC image. The input image is feature extracted and this feature vector is afforded as the input to the neural network in the training phase. We align afforded random weights to the node at primarily. Then, the output found from the NN is equated to the original and error is computed. Then, weights are varied applying LMA so as to minimize the error. This process is carried out for a large number of images so as to yield a stable system having weights aligned in the nodes. The retinal images of both the normal person as well as a abnormal person are afforded as input by this phase.

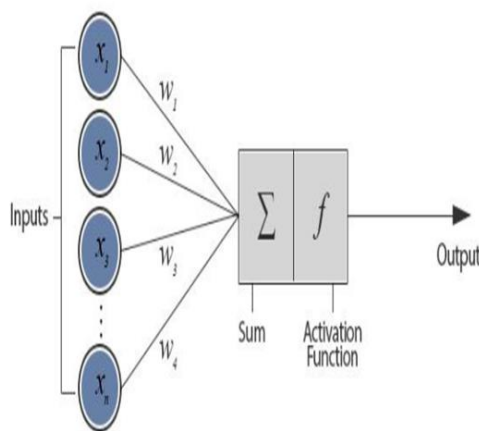


Fig. 4. Neuron structure

There can be ‘n’ inputs to a neuron and there is a weight associated with each interconnection between neurons. The neural network can learn by changing the weights of the connections based on the inputs to the neurons. The neural network has three layers namely input layer, hidden layer and output layer. Based on the complexity of the problem there can be a single hidden layer or multiple hidden layers. But a single hidden layer will be enough to solve most of the problems. The activation function is applied to the output sum to get the output. For the first feed forward iteration the weights are set randomly. First the error is calculated at the output by subtracting the actual output from the desired output error = desired –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. Delta weights = (delta output sum) / (hidden layer results). Change in the hidden layer sum is denoted by delta hidden sum and is calculated by following equation. Delta hidden sum = [delta output sum / hidden-to-output weights] * [S'(hidden sum)]

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

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

4. Result and Discussion

We have used the Neural Network technique which is considered as the best technique to classify images and detect OD and OC for identify whether the eye is infected by Glaucoma disease or not. The process for detecting Glaucoma disease starts by selecting the eye image and then eye image is given as input to the system and then after processing image on an algorithm we get result whether the eye is infected by Glaucoma or not. The proposed system can be used by the doctor, lab assistant or any other person who can handle the computerized system because this system is very much user-friendly. After testing all images we obtained result (Confusion Matrix) as given below.

Table 1
Confusion Matrix

	Predicted as Normal Image	Predicted as Infected by Glaucoma	Total
Normal Images	TN=48	FP= 2	50
Glaucoma Images	FN=1	TP=49	50
	49	51	100

TN=True Negative; FP=False Positive; FN=False Negative; TP=True Positive

5. Conclusion

The system is very useful to detect glaucoma efficiently so that the disease can be diagnosed in the early stages. The system does not depend on trained glaucoma specialist and expensive HRT/OCT machines. In this project the glaucoma detection is done by extracting three features i.e. optic disk, optic cup and neuro-retinal rim from a digital fundus image. The artificial neural network is used as a classifier to identify the disease. The thresholding approach is used for optic disk and optic cup segmentation. The system gave 0.9607 and 0.98 value of precision and recall respectively. In future, we will try to increase the accuracy of system by using different technologies.

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