Abstract — The retina is the only tissue in human body from which the information of blood vessel can be unswervingly obtained. The information of retinal vessel plays an important role in the diagnosis and treatment of various diseases such as glaucoma, age-related macular degeneration, degenerative myopia, diabetic retinopathy etc. The morphology of the retinal blood vessel and the optic disk is an important structural indicator for assessing the presence and severity of retinal diseases such as diabetic retinopathy, hypertension, glaucoma, hemorrhages, vein occlusion, and neovascularization. However, to assess the diameter and tortuosity of the retinal blood vessel or the shape of the optic disk, manual planimetry has commonly been used by ophthalmologists, which is generally time consuming and prone to human error, especially when the vessel structures are complicated or a large number of images are acquired to be labeled by hand. Therefore, a reliable automated method for retinal blood vessel and optic disk segmentation, which preserves various vessel and optic disk characteristics, is attractive in computer-aided diagnosis. However here implement a new competent method for the detection diseases using the retinal fundus image. In this anticipated work first step is the extraction of retinal vascular tree using graph cut technique. The blood vessel information is then use to calculate approximately the position of optic disc. These results are given to an ANN classifier for the detection and classification of diseases. By robotically identify the disease from normal images, the workload and its costs will be reduced.

Keywords — Fundus Images, optic disc, Diabetic Retinopathy, Hypertension, Glaucoma, ANN.

I. INTRODUCTION

CSCC will do the final formatting of your paper. If your paper is intended for a conference, please observe the conference page limits. Retinal image analysis is one of the crucial topics in medical image processing. During the last few centuries, people are trying to extract the various features like blood vessels, optic disc, macula, fovea are automatically from retinal image. [1]. The Fundus Image Analysis system described in this paper is developed to assist ophthalmologist’s diagnosis by providing second opinion and also functions as an automatic tool for the mass screening of diabetic retinopathy. Color fundus images are used by ophthalmologists to study eye diseases like Diabetic Retinopathy(DR), Age related Macular Degeneration (AMD) hypertension, glaucoma, vein occlusion and Retinopathy of pre-maturity (ROP). Extraction of the normal features like optic disc, fovea, blood vessels and abnormal features like exudates, cotton wool spots, Microaneurysms (MA) and hemorrhages from color fundus images are used in fundus image analysis system for comprehensive analysis and grading of Diabetic Retinopathy (DR) [2].

For the diagnosis of complete diseases, assessment of retinal blood vessel is significant. It offer a lot information conversely for easy recognition of exudates or microaneurysms [3]. Diabetic retinopathy is cause by mutually the forms of diabetes i.e. diabetes mellitus and diabetes insipidus. It is a extremely asymptomatic disease in the premature stages and it could lead to lasting vision loss if untreated for long time. The problem here is the patients may not know about it until it reaches advanced stages. Once it reach advanced stages vision loss become unavoidable [4].

Here we using graph cut technique for blood vessel segmentation. we have implemented a preprocessing method, which consists of an efficient adaptive histogram equalization and robust distance transform. This operation improves the robustness and the accuracy of the graph cut algorithm.[5] The optic disc segmentation starts by defining the location of the optic disc. This method used the convergence features of vessels into the optic disc to calculate approximately its location. The disc area is then segmented using two different automated methods (MRF image reconstruction and compensation factor). Both methods use the convergence feature of the vessels to identify the position of the disc. [6].

The purpose of image classification scheme is to assign each input to one of the diseases pattern classes. It is the process of assigning a label to each unknown input image. In this work, the artificial neural network approach namely, Back propagation network (BPNs) is used to classify the images The back propagation algorithm is used in layered feed-forward ANNs. This means that the synthetic neurons are rearranged in layer and drive their signal “forward”, and then the errors are propagated backwards. The system receives input by neurons in the input layer, and the output of the system is given by the neurons on an output layer.[7] Glaucoma is a term describing a group of ocular (eye) disorders that result in optic nerve damage, often associated with increased fluid pressure in the eye (intraocular pressure)(IOP). The disorders can be roughly divided into two main categories, "open-angle" and "closed-angle glaucoma. [9]

Vision is the most advanced human sense. So images play the most important role in human perception. The human eye is nearly in the shape of a sphere. Its average diameter is approximately 20 mm. The eye is made up of three coats,
enclose three apparent structures. The outermost layer is composed of the cornea and sclera. [10]
The morphology of the retinal blood vessel and the optic disk is an important structural indicator for assessing the presence and severity of retinal diseases such as diabetic retinopathy, hypertension, glaucoma, hemorrhages, vein occlusion, and neovascularization. However, to assess the diameter and tortuosity of the retinal blood vessel or the shape of the optic disk, manual planimetry has commonly been used by ophthalmologists, which is generally time consuming and prone to human error, especially when the vessel structures are complicated or a large number of images are acquired to be labeled by hand. Therefore, a reliable computerized method for retinal blood vessel and optic disk segmentation, which preserves various vessel and optic disk characteristics, is attractive in automatic diagnosis. [11]

Blood vessels can be seen as thin elongated structures in the retina, with variation in width and length. In order to segment the blood vessel from the fundus retinal image, we have implemented a preprocessing technique, which consists of an effective adaptive histogram equalization and robust distance transform. This operation improves the robustness and the accuracy of the graph cut algorithm. [12]

II. METHODOLOGY

The proposed method is made up of four fundamental parts. Basic system level block diagram is shown below:

![Fig 1: Basic blocks](image)

A. Blood Vessel Segmentation

Blood vessels can be seen as thin elongated structure in the retina, with variation in width and length. In order to fragment the blood vessel from the fundus retinal image, we have implemented a preprocessing technique, which consists of an efficient adaptive histogram equalization and robust distance transform. This action improves the robustness and the accuracy of the graph cut algorithm. Fig. 2 shows the illustration of the vessel segmentation algorithm. [6]

**Fig. 2. Vessel segmentation algorithm.**

The graph cut is an energy-based object segmentation approach. The method is characterized by an optimization process designed to reduce the power generated from a given image data. This power defines the relationship between neighborhood pixel elements in an image. The graph cut method is used in our detection because it allows the amalgamation of prior knowledge into the graph formulation in order to guide the model and find the optimal segmentation. [6]

To concentrate on the beyond mentioned trouble, the segmentation of blood vessels using the graph cut need a special graph formulation. One of the method used to deal with the shrinking bias problem is to require an extra connectivity prior, where the user marks the restraint connectivity [8]. In order to attain full automatic segmentation, we used the method presented in [9], which overcomes the “shrinking bias” by adding the mechanism of vectors flux into the production of the graph.

B. Graph Construction for Vessel Segmentation

The graph cut is an energy-based object segmentation approach. The technique is characterized by an optimization operation designed to minimize the energy generated from a given image data. This energy defines the relationship between neighborhood pixel elements in an image. A graph \( G(v, E) \) is defined as a set of nodes (pixels) \( v \) and a set of undirected edges \( E \) that connect these neighboring nodes. The graph included two special nodes, a foreground (Fg) terminal (source \( S \)) and a Bg terminal (sink \( T \)). \( E \) includes two types of undirected edges: neighborhood links (n-links) and terminal links (t-links). Each pixel \( p \in P \) (a set of pixels) in the graph presents two t-links \( \{p, S\} \) and \( \{p, T\} \) connecting it to each terminal , while a pair of neighboring pixels \( \{p, q\} \in \mathbb{N} \) (number of pixel neighbors) is connected by an n-link [13]. Thus,

\[
e = N \bigcup_{p \in P} \{(p, S), (p, T)\}, v = P \cup \{S, T\} \tag{1}
\]

The graph cut technique is used in our segmentation because it allows the incorporation of prior knowledge into the graph formulation in order to guide the model and find the optimal segmentation. Let us assume \( A = (A_1, A_2, \ldots, A_P) \) is a binary vector set of labels assigned to each pixel in the image,
where Ap indicate assignments to pixels p in P. Therefore, each assignment Ap is either in the Fg or Bg. Thus, the segmentation is obtained by the binary vector A and the constraints imposed on the regional and boundary proprieties of vector A are derived by the energy formulation of the graph defined as

\[
E(A) = \lambda \cdot R(A) + B(A) \quad \text{(2)}
\]

Where the positive coefficient \( \lambda \) indicates the relative importance of the Regional term (likelihoods of Fg and Bg) RA against the boundary term (Relationship between neighborhood pixels) BA. The regional or the likelihood of the Fg and Bg is given by

\[
R(A) = \sum_{p \in F} R_p(A_p) \quad \text{(3)}
\]

During the minimization of the graph energy formulation in (2) to segment thin objects like blood vessels, the second term (boundary term) in (2) has a tendency to follow short edges known as “the shrinking bias” [14]. This crisis cause a important dilapidation of the routine of the graph cut algorithm on thin elongated structures like the blood vessels.[6]

C. Optic Disc Segmentation

The optic disc segmentation starts by defining the position of the optic disc. This method used the convergence feature of vessels into the optic disc to view its location.

D. Optic Disk Location

The double image of vessels segmented is used to find the location of the optic disk. The process iteratively traces toward the centroid of the optic disk. The vessel image is prune via a morphological open method to eliminate thin vessels and keep the main arcade. The centroid of the arcade is calculated using the following formulation:

\[
C_x = \frac{\sum_{i=1}^{K} x_i}{K}, \quad C_y = \frac{\sum_{i=1}^{K} y_i}{K} \quad \text{(4)}
\]

Given the gray scale intensity of a retinal image, we select 1% of the brightest region. The algorithm detect the brightest region through the most number of pixels to establish the location of the optic disk with respect to the centroid point (right, left, up, or down). The algorithm adjusts the centroid point iteratively until it reaches the vessel convergence point or the center of the main arcade (center of the optic disk) by reducing the distance from one centroid point to next one in the direction of the brightest region, and correcting the central position inside the arcade accordingly.[6]

In contrast to the MRF image reconstruction, we have incorporated the blood vessels into the graph cut formulation by introduce a compensation factor V ad. This feature is consequent using former information of the blood vessel. The power function of the graph cut algorithm usually comprises boundary and regional terms. The boundary term defined is used to assign weights on the edges (n-links) to measure the similarity between neighboring pixels with respect to the pixel proprieties (intensity, texture, and color). Therefore, pixels with similar intensities have a strong connection. The regional term in (3) is derived to define the likelihood of the pixel belonging to the Bg or the Fg by assigning weights on the edges (t-link) between the image pixels and the two terminals Bg and Fg seeds. In order to incorporate the blood vessels into the graph cut formulation, we derived the t-link as follows:

\[
S_{\text{link}} = \begin{cases} 
-\ln P_r(I_p \setminus F_g \text{seeds}) & \text{if } p \neq \text{vessel} \\
-\ln P_r(I_p \setminus F_g \text{seeds}) + V_{\text{ad}} & \text{if } p = \text{vessel} 
\end{cases} \quad \text{(5)}
\]

\[
T_{\text{link}} = \begin{cases} 
-\ln P_r(I_p \setminus B_g \text{seeds}) & \text{if } p \neq \text{vessel} \\
-\ln P_r(I_p \setminus B_g \text{seeds}) & \text{if } p = \text{vessel} 
\end{cases} \quad \text{(6)}
\]

Where p is the pixel in the image, Fg seeds is the intensity distribution of the Fg seeds, Bgseeds represents the intensity distribution of the Bg seeds, and V ad is the compensation factor given as

\[
V_{\text{ad}} = \max_{p \in \text{vessel}} \{- \ln P_r(I_p \setminus B_g \text{seeds})\} \quad \text{(7)}
\]

The intensity distribution of the blood vessel pixels in the region around the optic disk makes them more likely to...
belong to Bg pixels than the Fg (or the optic disk pixels). Therefore, the vessels inside the disk have weak connections with neighboring pixels making them likely to be segmented by the graph cut as Bg.

**E. Diseases Classification**

Extracted blood vessels and optic disc information’s are given to ANN classifier for the detection and categorization of diseases. The function of image categorization scheme is to assign each input to one of sample classes. It is the method of assigning a label to each unknown input image. In this work, the artificial neural network approach namely, Back propagation network (BPNs) is used to classify the images. The back propagation algorithm is used in layered feed-forward ANNs. This means that the artificial neurons are organized in layers and send their signals “forward”, and then the errors are propagated backwards. The network receives input by neurons in the input layer, and the output of the system is given by the neurons on an output level.

Here, back propagation algorithm is applied for learning the samples, Tan-sigmoid (tansig) and log-sigmoid (logsig) functions are applied in hidden layer and output layer respectively, Levenberg-Marquardt optimization (trainlm) is used for adjusting the weights as training methodology. For training process, firstly altered features are extracted block by block in one image. When we use a new image for classification, only those selected features are extracted and the trained classifier is used to classify the abnormality in the image.

Diabetic retinopathy is cause by mutually the forms of diabetes i.e. diabetes mellitus and diabetes insipidus. It is an extremely asymptomatic disease in the premature stages and it could lead to lasting vision loss if untreated for long time. The problem here is the patients may not know about it until it reaches advanced stages. Once it reach advanced stages vision loss become unavoidable [4]. As diabetic retinopathy is the third major cause of blindness particularly in India, there is an immediate requirement to develop efficient diagnosis method.

**III. RESULT AND DISCUSSION**

For the vessel segmentation method, we tested our algorithm on two public datasets, DRIVE and STARE with a total of 60 images. The optic disc segmentation algorithm was tested on DRIVE and DIARETDB1 consisting of 129 images in total. The performances of both methods are tested against number of alternative methods. The DRIVE consists of 40 digital images which were captured from a Canon CR5 non mydriatic 3CCD camera at 45° FOV. The images have a size of 768 × 54 pixels. The dataset includes masks to separate the FOV from the rest of the image. Figs. 4 and 5 show the segmented images and the manually labeled images for the DRIVE and the STARE datasets, respectively.

The entire work done by with the help of MATLAB. Experiment shows that the outcome the scheme is comparable with others when applied on standard data set (images). This is clear in the simulation output shown in Figure 8.1 to figure 8.4.
Fig 7 Results of Glaucoma

Fig 6 shows the processing steps for the detection of Diabetic retinopathy. Input image is converted into green channel image for noise reduction. Blood vessels are segmented by the graph cut technique. MRF and compensation factor method gives the optic disc. Further processing via ANN gives the affected disease. Fig 7 shows the processing steps for the detection of Glaucoma.

IV. CONCLUSION

In this paper we have presented blood vessels and optic disk segmentation in retinal images by integrating the mechanism of flux, MRF image reconstruction, and compensation factor into the graph cut method.

In the second stage information’s extracted from blood vessels and optic disc are given to an ANN classifier and find whether the image is infected or normal, finally classify the diseases. This proposed methodology can be utilized in hospitals to detect diseases occurring on the eyes by doctors easily. Future scope of this project is to detect many eye diseases thus making mankind to be benefitted in large extent to be free from eye diseases leading to blindness with higher efficiency. From the results and its slotted out puts, clearly identify whole concepts about the whole work.

V. REFERENCES