SEGMENTATION OF BLOOD VESSEL AND OPTIC DISK IN RETINAL IMAGES AND DISEASE DETECTION THROUGH CLASSIFICATION

Susan George[1], Dr.R.A Jaikumar[2], Abhilash S Vasu[3]
[1]PG Scholar, Dept. of ECE, SHM Engineering College, Kollam, Kerala, India
[2]Professor, Ponjesly College of Engineering, Nagercoil, Tamilnadu
[3]Asst.Professor, Dept. of ECE, SHM Engineering College, Kollam, Kerala, India

ABSTRACT
Retinal image analysis is increasingly prominent as a non-intrusive diagnosis method in modern ophthalmology. In this paper, we present a novel method to segment blood vessels and optic disc in the fundus retinal images and their classification for disease detection. The method could be used to support non-intrusive diagnosis in modern ophthalmology since the morphology of the blood vessel and the optic disc is an important indicator for diseases like diabetic retinopathy, glaucoma and hypertension. Our method takes as first step the extraction of the retina vascular tree using the graph cut technique. The blood vessel information is then used to estimate the location of the optic disc. The optic disc segmentation is performed by the expectation maximization method which segments the optic disc by removing vessels from the optic disc region using prior local intensity knowledge of the vessels. The proposed method is tested on DRIVE datasets. Diseases on eye detected through the classification method. The paper presents use of muiti-SVM as classifier for the disease detection on eye. The results and comparison with alternative methods show that our method achieved exceptional performance in segmenting the blood vessel and optic disc.
Keywords: EM algorithm, graph cut method, Maxflow algorithm, morphological operation, segmentation.

I. INTRODUCTION

The segmentation of retinal image structures has been of great interest because it could be used as a non-intrusive diagnosis in modern ophthalmology. The morphology of the retinal blood vessel and the optic disc is an important structural indicator for assessing the presence and severity of retinal diseases such as diabetic retinopathy, hypertension, glaucoma, haemorrhages, vein occlusion and neo-vascularisation. However to assess the diameter and tortuosity of retinal blood vessel or the shape of the optic disc, manual planimetry has commonly been used by ophthalmologist, which is generally time consuming and prone with human error, especially when the vessel structure are complicated or a large number of images are acquired to be labelled by hand. Therefore, a reliable automated method for retinal blood vessel and optic disc segmentation, which preserves various vessel and optic disc characteristics is attractive in computer aided-diagnosis. The human eye is usually an important place connected with the skin in which the vascular situation is usually right observed. Retina may be the neural section of the eyes and in addition to fovea and also optic disc, this leading to one of the main highlights of a retinal fundus image. Presently, there is an increasing interest for establishing automatic systems that screens a huge number of people for vision threatening diseases like Diabetic Retinopathy, Glaucoma and Hypertension to provide an automated detection of the disease. DR is a chronic disease which nowadays constitutes the primary cause of blindness in people of working age in the developed world. The DR is a micro vascular complication of diabetes, causing abnormalities in the retina and in the worst case blindness. About 10,000 diabetic people worldwide lose the vision each year. There is evidence that retinopathy begins its development at least 7 years before the clinical diagnosis of type 2 diabetes. If the diabetic retinopathy is not detected and the patient does not receive appropriated treatment it is very likely that glaucoma will be followed. The term of glaucoma refers to a group of diseases characterized by optic neuropathy. These are characterized by structural change and functional deficit (measured by visual field change). Intraocular pressure is used to diagnose glaucoma patients when is not possible visualize the optic nerve and the visual fields cannot be measured. However, even when intraocular pressure is an important risk factor for glaucoma, it is not part of the definition. Hypertension (HT), is known as high blood pressure or arterial hypertension. HT is rarely accompanied by any symptoms and its identification is usually through screening, or when seeking healthcare for an unrelated problem. Some with high blood pressure report headaches . Different efforts have worked for the prevention of the blind condition due to a retinopathy, glaucoma. The analysis of retinal images represents a non-invasive process to perform the diagnosis and control of patients. Interactive and automatic systems for the analysis of retinal images have been designed. Early models are based on supervised systems. These systems have probed their efficiently in different methods. Unfortunately supervised systems require of high processing time and hand labeled image as part of the training process. Due to the systems have been training using images with specific characteristics the system comprises its performance to image with similar features. The state of the art on retinal image analysis has the need of unsupervised systems that perform the analysis of retinal images without human supervision or interaction. The optic disc (OD) is usually more important compared to any kind of part of the retina and it is normally spherical in shape.

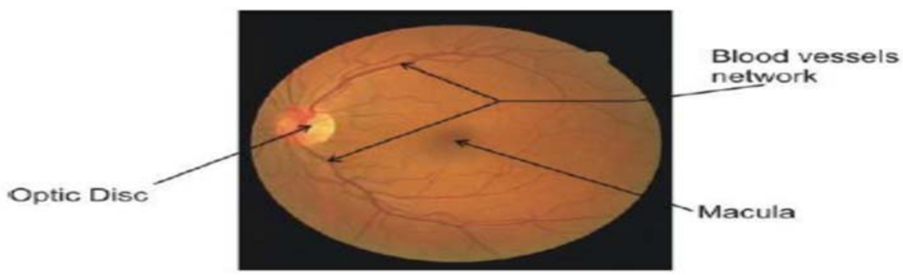

Fig 1: Retina structures: blood vessels, optic disc and macula.

II. RELATED WORKS

Blood vessel is visible while thin elongated constructions in the retina, with variance wide along with length in which converge in the optic disc. An accurate segmentation of the blood vessels is the first step to extract features and fundamental information to create a diagnosis, evaluate treatments progress and keep control of diseases. Segmentation of our blood vessel with retinal images makes it possible for early on diagnosis. Automating this technique offers several benefits which include reducing subjectivity along with eradicating some sort of careful tiresome process. Guide book diagnosis along with evaluation of the retinal photos is a time consuming along with unreliable process and since the amount of photos increases the study gets quite challenging. As a result it's important to use automatic algorithms regarding evaluation of images. OD(Optic Disc) segmentation comes with a great medical importance in aiding various other retina impression evaluation tasks including vessel monitoring, fovea localization, acceptance of still left along with correct sight last but not least impression registration.Various scientific studies had been performed for the segmentation of bloodstream along with optic disk normally, nonetheless just few these had been related in order to retinal bloodstream.

i.MATCHED FILTERS

Matched filters were being according to a new link measure between the predicted design sought intended for and also the referenced signal. The idea according to directional 2D harmonized filtration. To further improve retinal vasculature 2D matched harmonized filtration kernel has been designed to convolve using the initial fundus picture. The kernel has been rotated and balanced into often nine as well as a dozen orientations to adjust to into blood vessels regarding a variety of layouts. Many kernel forms are actually researched. Many methods were being additionally planned to spot true blood vessels.

ii. **TRACKING METHODS**

This tracking methods get a steady our blood vessel fragment beginning a point granted sometimes physically as well as instantly according to certain local information. These methods generally look at to get the route which best suits a vessels report model. Sobel edge sensors, gradient operators along with matched filters have been applied to find the vessels along with border. Though these types of methods have been perplexed by our blood vessels bifurcations along with crossings, they might deliver precise sizes of our blood vessels tortuosity along with widths.

iii. **MORPHOLOGICAL PROCESSING**

In order to part the actual bloodstream within a retinal image statistical morphology can be utilized since the vessels had been the actual behaviour that shows morphological properties these kinds of seeing that connectivity, linearity as well as curvature connected with wrecks different efficiently on the crest collection. Although history behavior furthermore suit such a morphological outline. As a way to discriminate bloodstream coming from different similar set ups, cross curvature evolution as well as linear selection.

III. METHODOLOGY

A. BLOOD VESSEL SEGMENTATION

Blood vessel visible as elongated constructions within the retina, along with variance wide and size. As a way to portion the blood vessel in the fundus retinal impression, it has applied the preprocessing technique, which usually consists of an effective adaptive histogram equalization and strong length convert. This particular procedure increases the robustness and the accuracy and reliability on the graph cut technique. Fig.3.1 shows the illustration of the vessel segmentation algorithm.

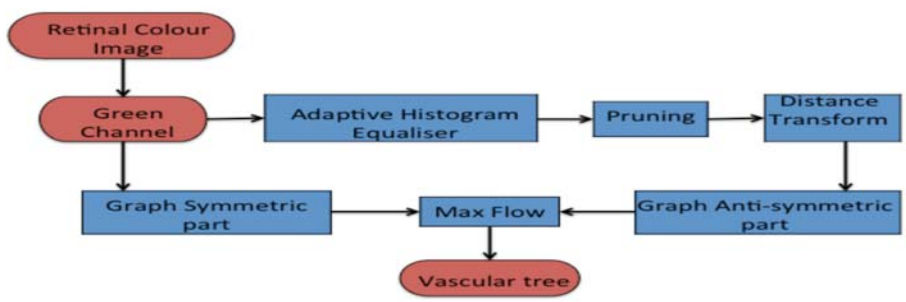

Fig2.Vessel segmentation algorithm

i. **Preprocessing**

Apply a contrast enhancement process to the green channel image. The intensity of the image is inverted, and the illumination is balanced. The resulting image is further enhanced by adaptive histogram equalizer, given by:

$$I_{Enhanced} = \left(\sum_{p' \in R(p)} s(I(p) - I(p'))/h^2\right).M \quad (1)$$

Where I is the green channel of the fundus retinal color image, p denotes a pixel, and p′ is the neighborhood pixel around p. p′∈ R(p) is the square window neighborhood with length h.s(d) = 1if d > 0, and s(d) = 0 otherwise with d = s (I (p) − I (p′)). M = 255 value of the maximum intensity in the image. r is a parameter to control the level of enhancement. Increasing the value of r would also increase the contrast between vessel pixels and the Bg as seen in Fig.3.2. The experimental values of the window length was set to h = 81 and r = 6. A binary morphological open process is applied to prune the enhanced image, which remove all the unwanted pixels in Fig.3.2(d). This method also reduces the false positive, since the enhanced image will be used to construct the graph for segmentationThe distance transform algorithm is used to create distance map image which calculate the direction and the magnitude of the vessel gradient, Fig. 3.2(e) and (f) shows the distance map of the entire image and a sample vessel with arrows representing the direction of the gradients, respectively. From the sample vessel image, we can find the center line with the brightest pixels,which are progressively reduced in intensity in the direction of the edges (image gradients). The arrows in Fig. 3.2(f) are referred to as vector field, which are used to construct the graph in the next sections.

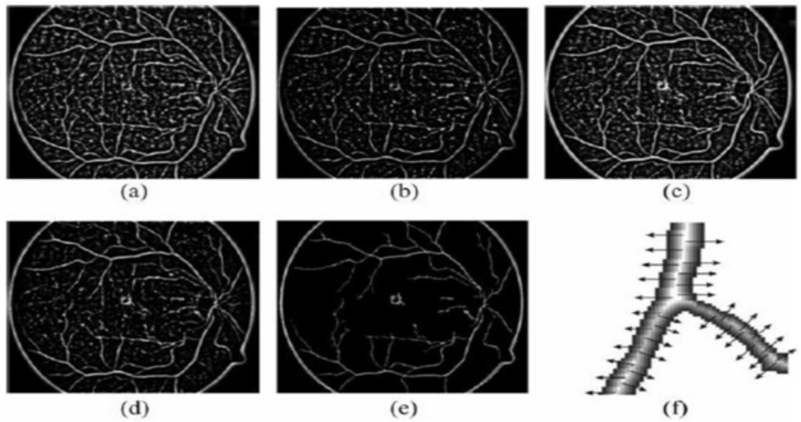

Fig.3.Preprocessing. (a) $h = 45, r = 3$, (b) $h = 45, r = 6$, (c) $h = 81, r = 3$, (d) $h = 81, r = 6$, (e) distance map, and (f) sample of a vessel with arrows indicating the vessel gradients.

ii. **Graph Construction for Vessel Segmentation**

The graph cut is usually an energy-based object segmentation method. The actual method is seen as a good optimisation procedure meant to limit the energy generated from provided picture information. This particular energy identifies the connection among area pixel components in the picture. A graph G (ν, ϵ) is defined as a set of nodes (pixels) ν and a set of undirected edges ϵ that connect these neighboring nodes. The graph included two special nodes; a foreground (Fg) terminal (source S) and a background (Bg) terminal (sink T). ϵ includes two types of undirected edges:

Edge	**Weight**	**For**
{p,q}	*B{p,q}*	*{p,q}∈N*
{p,S}(Fg)	*λ.R_p(Fg)* *K* *0*	*p∈P* *p∈F* *p∈B*
{p,T}(Bg)		*p∈P* *p∈F* *p∈B*

Table.1Weight of the edges in the graph

neighborhood links (n-links) and d terminal links (t-links). Each pixel p ∈ 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} ∈ N (number of pixel neighbors) is connected by an n-link.Thus

$$\epsilon = N \cup_{p \epsilon P}\{\{p,S\},\{p,T\}, v = P \cup \{S,T\}\} \quad (2)$$

An edge e ∈ ϵ is assigned a weight (cost)We>0.A cut is defined by a subset of edges C ∈ ϵ,where G (c) = ν, ϵ\C〉 separating the graph into Fg. The max-flow algorithm is used to cut the graph and find the optimal segmentation. Table 1 assigns weight to the edges ϵ in the graph, where:

$$K=1+ \max_{p\epsilon P}\sum_{\{p,q\}} B_{p,q} \quad (3)$$

and F and B represent the subsets of pixels selected as the Fg and Bg, respectively. Thus, F⊂P and B⊂ P such that FUB=null set. Bp,q defines the discontinuity between neighboring pixels, and its value is large when the pixel intensities. λ> 0 is a constant coefficient, which will define in the energy formulation of the graph. 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=(A1, Ap. . .AP) is a binary vector set of labels assigned to each pixel p 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 :

$$E(A)=\lambda .\ R(A) + B(A) \quad (4)$$

where the positive coefficient λ 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:

$$R(A)=\sum_{p\in P} R_p(A_p) \quad (5)$$

Rp(Ap) specifies the assignment of pixel p to either the Fg or the Bg. Bp,q defines the discontinuity between neighboring pixels, and its value is large when the pixel intensities Ip and Iq are similar and close to zero when they are different. The value of Bp,q is also affected by the Euclidean distance dist(p,q) between pixels p and q.

B. **OPTIC DISC SEGMENTATION**

The optic disc segmentation starts by defining the location of the optic disc. This process used the convergence feature of vessels into the optic disk to estimate its location. The disk area segmented using two different automated methods (Expectation maximization method and morphological operation).Both methods use the convergence feature of the vessels to identify the position of the disk.

i. **Expectation and Maximization Method**

Expectation–maximization (EM) algorithm is an iterative method for finding maximum likelihood or maximum a posteriori (MAP) estimates of parameters , where the model depends on unobserved latent variables. The EM iteration alternates between performing an expectation (E) step, which creates a function for the expectation of the log-likelihood evaluated using the current estimate for the parameters, and maximization (M) step, which computes parameters maximizing the expected log-likelihood found on the *E* step. These parameter-estimates are then used to determine the distribution of the latent variables in the next E step.

Given a statistical model which generates a set X of observed data, a set of unobserved latent data or missing values Z, and a vector of unknown parameters ɵ , along with a likelihood function , the maximum likelihood estimate (MLE) of the unknown parameters is determined by the marginal likelihood of the observed data:

$$L(\theta;X,Z)=p(X,Z|\theta) \quad (8)$$

$$L(\theta;X)=p(X|\theta)=\sum_{Z} P(X,Z|\theta) \quad (9)$$

However, this quantity is often intractable (e.g. if Z is a sequence of events, so that the number of values grows exponentially with the sequence length, making the exact calculation of the sum extremely difficult). The EM algorithm seeks to find the MLE of the marginal likelihood by iteratively applying the following two steps: Expectation step (E step): Calculate the expected value of the log likelihood function, with respect to the conditional distribution of Z given X under the current estimate of the parameters ɵ(t):

$$Q(\theta|\theta^{(t)})=E_{Z|X,\theta^{(t)}}[\log L(\theta,X,Z)] \quad (10)$$

Maximization step (M step): Find the parameter that maximizes this quantity:

$$\theta^{(t+1)}=\arg\max_{\theta} Q(\theta|\theta^{(t)}) \quad (11)$$

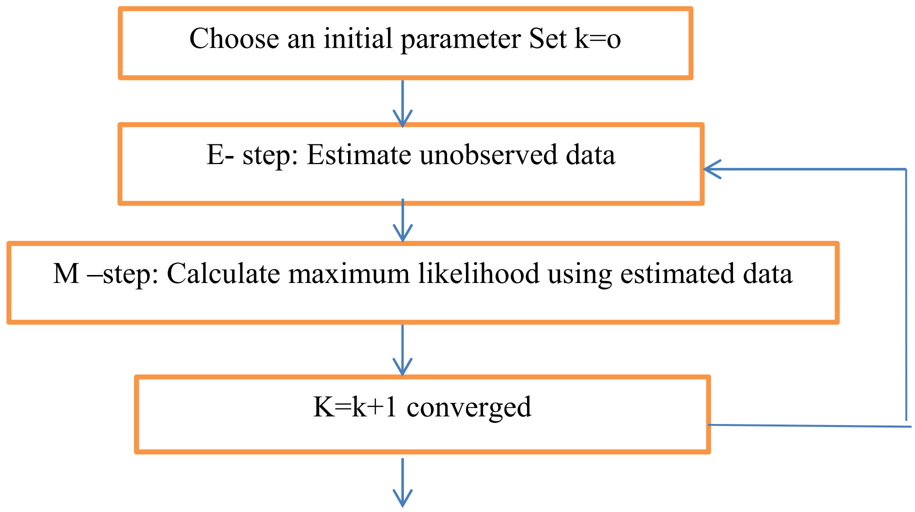

Fig4 :An overview of the EM algorithm.

The motivation is as follows. If know the value of the parameters θ , I can usually find the value of the latent variables Z by maximizing the log-likelihood over all possible values of Z , either simply by iterating over Z or through an algorithm such as the Viterbi algorithm for hidden Markov models. Conversely, if know the value of the latent variables Z ,find an estimate of the parameters ɵ fairly easily, typically by simply grouping the observed data points according to the value of the associated latent variable and averaging the values, or some function of the values, of the points in each group. This suggests an iterative algorithm, in the case where both ɵ and Z are unknown:

- First, initialize the parameters ɵ to some random values.
- Compute the best value Z for given these parameter values.
- Then, use the just-computed values of Z to compute a better estimate for the parameters θ . Parameters associated with a particular value of Z will use only those data points whose associated latent variable has that value.
- Iterate steps 2 and 3 until convergence.

ii. **Morphological Operation**

Binary images may perhaps include many defects. Particularly, the binary regions produced by uncomplicated thresholding are usually distorted by means of sound along with surface Morphological picture finalizing pursues our aims regarding taking away these types of defects by means of human resources with the kind along with structure in the picture. Most of these tactics could be lengthy to grayscale images. Morphological picture processing is an accumulation of non-linear operations relevant to the design or maybe morphology regarding features within the picture. Morphological operations rely just around the comparative placing our order regarding pixel values, not really on their statistical values, along with therefore are especially suitable for our finalizing regarding binary images. Morphological operations may also be placed on greyscale images so that the gentle exchange functions are usually unknown and therefore the complete pixel values are usually regarding no or maybe modest attention. Morphological technique probe a graphic that has a small shape or maybe template known as a structuring element. The particular structuring element is put by any means probable destinations in the picture and it's compared with our corresponding area regarding pixels. Many operations examination if these components “fit" within the area, and some examination regardless of whether the item "hits" or maybe intersects our area. A morphological function over a binary picture creates a new binary picture that the pixel includes a non zero value provided that our examination is productive at that position in the input picture. The structuring element is a small binary picture, a small matrix regarding pixels, each and every that has a value regarding zero or maybe one: The particular matrix dimensions identify the size of our structuring element. The particular design regarding ones along with zeros specifies they shape of your structuring element. An origin of our structuring element is usually

considered one of its pixels, while usually the origins could be exterior our structuring element. One common process should be to have got odd dimensions in the structuring matrix and also the origins understood to be our centre in the matrix Structuring aspects participate in morphological picture finalizing exactly the same role while convolution kernels in linear picture selection. When a structuring element is positioned inside a binary picture, every one of its pixels is usually from the corresponding pixel in the area under the structuring element. The structuring element is said to fit the image if, for each of its pixels set to 1, the corresponding image pixel is also 1. Similarly, a structuring element is said to hit, or intersect, an image if, at least for one of its pixels set to 1 the corresponding image pixel is also 1. Zero-valued pixels of the structuring element are ignored, i.e. indicate points where the corresponding image value is irrelevant.
Fundamental operations : Erosion and dilation

Erosion with small square structuring elements shrinks an image by stripping away a layer of pixels from both the inner and outer boundaries of regions. The holes and gaps between different regions become larger, and small details are eliminated.Larger structuring elements have a more pronounced effect, the result of erosion with a large structuring element being similar to the result obtained by iterated erosion using a smaller structuring element of the same shape. If s1 and s2 are a pair of structuring elements identical in shape, with s2twice the size of s1.

Erosion removes small-scale details from a binary image but simultaneously reduces the size of regions of interest, too. By subtracting the eroded image from the original image, boundaries of each region can be found: b = f− (f ɵ s) where f is an image of the regions, s is a 3×3 structuring element, and b is an image of the region boundaries. The dilation of an image f by a structuring element s produces a new binary image g with ones in all locations (x,y) of a structuring element's origin at which that structuring elements hits the input image f, i.e. g(x,y) = 1 if s hits f and 0 otherwise, repeating for all pixel coordinates (x,y). Dilation has the opposite effect to erosion. It adds a layer of pixels to both the inner and outer boundaries of regions. Results of dilation or erosion are influenced both by the size and shape of a structuring element. Dilation and erosion are dual operations in that they have opposite effects.

C. FEATURE EXTRACTION

Feature extraction can be seen as a special kind of data reduction of which the goal is to find a subset of informative variables based on image data. Since image data are by nature very high dimensional, feature extraction is often a necessary step for segmentation to be successful. Feature extraction is also a means for simplifying segmentation problem.
Several types of features are available among which the textural features are found to be more suitable to medical images. Apart from textural features, they can also be extracted from the anatomical structures of the retinal image. The extracted features should provide the characteristics of the input type to the classifier by condensing the description of the relevant properties of the image into a feature space of specific dimension (n). The pixels of the gray level image are transformed into a feature vector X=[x1, x2….xn] where each xi is a unique feature and n is the dimension of the feature vector.

i. Textural features

The textural features are feature set used in this work. Since the abnormality was widely spread in the image, the textural orientation of each class is different, which aid in better classification accuracy. Features based on gray level co-occurrence matrix (GLCM) were used in this work.

ii. Features Based On Gray Level Co-Occurrence Matrix

The image properties related to second-order statistics is estimated by the GLCM. Several researchers suggested the use of gray level co-occurrence matrices (GLCM) which have become one of the most well-known and widely used texture features. GLCM $\{P\ (d,\ \theta)\ (i,\ j)\}$ represents the probability of occurrence of a pair of gray-levels (i, j) separated by a given distance d at angle θ. The commonly used unit pixel distances and the angles are 0°, 45°, 90° and 135°.The features such as contrast, inverse difference moment, correlation, variance, cluster shade, cluster prominence and Homogeneity are calculated using GLCM.

D. CLASSIFICATION

These features are selected for reducing noise and enhancing the result of classifier accuracy. In this work, segmentation is done on retinal images to separate the blood vessels since these are the best indicators of the presence of DR. The features given to the classifier include the areas of these segmented structures and textural features obtained from GLCM. The SVM classifier classifies the input image as normal (not affected by DR) or DR images based on the training done by giving the sample features. SVM was first introduced by Vapnik. SVM have shown good performance in data classification. Its success depends on the tuning of several parameters which affect the generalization error. During the early stages classification was limited to only two data classes (binary classification). However, further research developed an SVM that can classify data into more than two classes. There are two options for implementing the multi-class SVM, by combining several binary SVM or combining all of the data which consists of several classes into a form of solving optimization problems. However, the second approach of optimization problem to be solved is much more complicated. This study used a multi-class SVM classification machine which uses a one-against all method.

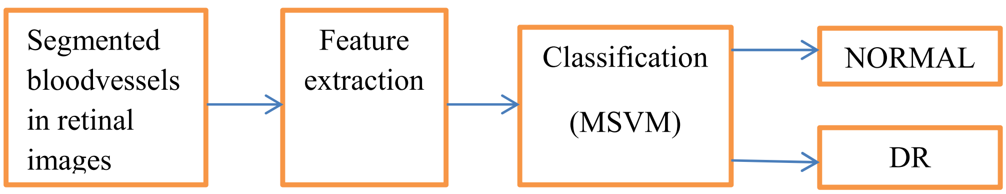

Fig 5 : Methodology for disease detection in retinal images

IV. RESULTS AND ANALYSIS

For the blood vessel and optic disc segmentation method, we tested our algorithm on DRIVE datasets and the corresponding results obtained. Blood vessel segmented output used for the disease detection through the classification procedure.

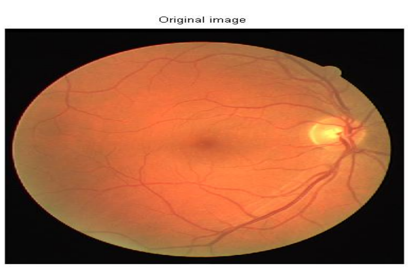

Fig 6. Original image

Figure 6 shows the original image from the DRIVE datasets which undergoes for the technique of preprocessing where the green channels of the retinal images are enhanced through contrast enhancement process. The preprocessing technique consists of an effective adaptive histogram equalization and a robust distance transform which improves the accuracy. The preprocessed output is shown in figure 7

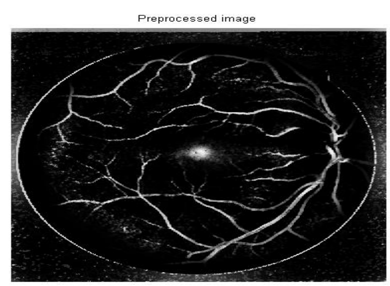

Figure 7. Preprocessed image

The graph cut technique – an energy based object segmentation method used in the enhanced image to obtain the blood vessel segmented output of retinal image, shown in figure 8

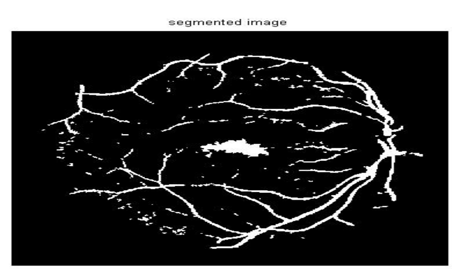

Fig 8. Blood vessel segmentation

The blood vessel segmented image undergoes the Expectation Maximization [EM] method to obtain the optical disc segmented output image, shown in figure 9

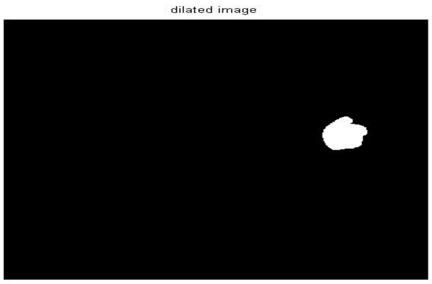

Fig 9 Optic disc segmentation

Features extracted from the segmented blood vessels of the retinal images and are fed to the MSVM classifier for training. The classifier differentiated the disease affected retinal images and the normal ones as shown below.

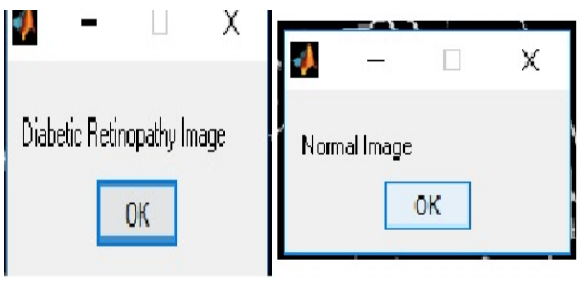

Fig.10 Classification of segmented images

Classifier	Accuracy	Sensitivity	Specificity
SVM	80%	40%	66%

Table.2 Performance analysis of classifier

I. CONCLUSION

It presented a novel technique intended for arteries along with optic computer segmentation within the fundus from the retinal photographs, the process could be utilized to help nonintrusive diagnosis within modern day ophthalmology because morphology from the blood vessel along with the optic disc is an significant signal intended for diseases similar to diabetic retinopathy, glaucoma, along with hypertension. The method takes seeing that primary step the actual removal from the retina vascular tree when using the graph cut technique. This blood vessel information will be then utilized to calculate the placement from the optic disc. In order to segment the actual blood vessel within the EM algorithm along with morphological preprocessing in to the graph cut approach. The task in addition entails comparison development, adaptive histogram equalization, binary opening, along with distance convert intended for preprocessing..EM algorithm is an iterative method for finding maximum likelihood or maximum a posteriori(MAP) estimates of parameters , where the model depends on unobserved variables. The Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. This pursues the goals of removing these imperfections in segmented image using EM algorithm. This method provides more accuracy and less time consuming. In this work, the SVM classifier is trained through supervised learning for the features extracted to classify the retinal images. The retinal images used in this work are obtained from the publicly available DRIVE databases. The developed system will provide a second opinion to the ophthalmologist to do accurate diagnosis.

REFERENCES

1. K. Fritzsche, A. Can, H. Shen, C. Tsai, J. Turner, H. Tanenbuam,C. Stewart, B. Roysam, J.Suri, and S. Laxminarayan, “Automated model based segmentation, tracing and analysis of retinal vasculature from digital fundus images,” in State-of-The-Art Angiography, Applications and Plaque Imaging Using MR, CT, Ultrasound and X-rays.BocaRaton,FL, USA: CRC Press, 2003, pp. 225-298.
2. A. Hoover, V. Kouznetsova, and M. Goldbaum, “Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response,” IEEETrans.Med.Imag.,vol.19,no.3,pp.203-210,Mar.2000.
3. A. M. Mendonca and A. Campilho, “Segmentation of retinal blood vessels by combining the detection of centerlines and morphological reconstruction,” IEEE Trans. Med. Imag., vol. 25,no.9,pp.1200-1213,Sep.2006
4. J. Soares, J. Leandro, R. Cesar, H. Jelinek, and M. Cree, “Retinal vessel segmentation using the 2-D gabor

wavelet and supervised classification,"IEEE Trans. Med. Imag., vol. 25, no. 9,pp.1214-1222,Sep.2006.

5. J. Staal, M. D. Abramoff, M. Niemeijer, M. A. Viergever, and B. van Ginneken, "Ridge-based vessel segmentation in color images of the retina,"IEEE Trans. Med. Imag., vol. 23, no. 4, pp.501-509,Apr.2004.
6. "Digital Image Processing" by Rafael C. Gonzalez and Richard E. Woods
7. "Image Processing, Analysis and Machine Vision" by Milan Sonka, Vaclav Hlavac and Roger Boyle
8. "Fundamentals of Digital Image Processing" by Anil K. Jain
9. "Digital Image Processing: PIKS Scientific Inside" by William K. Pratt
10. "Digital Image Processing" by JayaramanS
11. https://www.ndeed.org/EducationResources/CommunityCollege/Radiography/AdvancedTechniques/Real_Time_Radiography/ImageProcessingTechniques.htm
12. https://www.rroij.com/open-access/an-overview-on-image-processing-techniques.php?aid=47175
13. https://en.wikipedia.org/wiki/Image_processing
14. https://sisu.ut.ee/imageprocessing/book/1
15. https://arxiv.org/abs/astro-ph/0412138