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Automatic Detection of Optic Disc using Structural Learning

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Abstract — **An automatic detection of optic disc (OD) abnormality in a fundus image plays an important role developing a computer aided system for eye diseases. An optic disc is located in a complex area of an eye surrounded by blood vessels. It is more challenging task to exactly detect optic disc area. In this paper structured learning to detect optic disc area has been discussed. A classifier model has been trained based technique on structured learning to obtain edge map of OD. Thresholding is performed on the edge map to obtain binary image of edge map. Finally circle hough transform technique is performed to mark boundary area of OD.**

INTRODUCTION

There are many causes of visual impairment and blindness but major of them are diabetic retinopathy, glaucoma, hypertension and macular degeneration. These eye diseases can occur in the retina and all of these diseases can be detected through a direct and regular ophthalmologic examination. Many factors, such as growth in population, aging, are causing to the increase of the patients with these diseases, which make the number of Ophthalmologists needed for evaluation by direct examination becomes a limiting factor. As a result, an automated computer aided diagnosis system is needed which can significantly reduce the burden on the ophthalmologists and may helpful for accurate results is desired.

Detection of Optic Disc (OD) is a complex task as it is an area within retina surrounded by blood vessels. It is a challenging task to extract exact optic disc escaping blood vessels. The ratio of the size of the OD to size of the optic cup is considered for glaucoma diagnosis. More the cup-to-disc ratio may lead to fundus which is more suspicious of glaucoma. Detecting OD automatically is challenging due to there are many variations with respect to OD's shape, size and color.

Although there are many difficulties in OD detection, it plays an important role, which has attracted extensive attention from medical professionals and researchers. OD detection is often a key step for the detection of other anatomical structures For example, the OD location helps to prevent false positive detection of exudates incurred by diabetic retinopathy, since both OD and exudates are formed by bright regions in the fundus image [1].

The traditional method for detection of OD uses traditional edge detector, such as Prewitt edge detector, to capture the edge information. By using traditional methods, there is more noise that may be in terms of blood vessel around optic disc or may be in terms of color and shape of OD. For different the traditional edge operators, using different channels as input may lead to different results, which makes choosing which channels as input is a critical decision. In some cases, the green channel or the red channel of the original fundus image is used and in some cases, a combination of the red channel and green channel is used. However, due to the variability of the fundus image, any individual method does not guarantee an optimal result. So an automated OD detection system for eye diseases is needed for accurate results.

I. Literature Survey

Zhun Fan, IEEE, Yibiao Rongb, Xinye Caic, Jiewei Lua, Wenji Lia, Huibiao Lina and Xinjian Chenb [1], in 2017 proposed method of optic disc detection through paper "Optic Disk Detection in Fundus Image Based on Structured Learning". They suggested an algorithm for OD detection based on structured learning. A classifier model is trained on the basis of structured learning. They proved that the proposed method is very useful with the state-of-the-art methods and is a reliable tool for the segmentation of OD.

Hanan S. Alghamdi King Abdulaziz University, Jeddah, Saudi Arabia Hongying Lilian Tang University of Surrey, Guildford, United Kingdom Saad A. WaheebKing Faisal Specialist Hospital, Jeddah, Saudi Arabia TundePetoNational Institute for Health Research Biomedical Research Centre at Moor fields Eye Hospital NHS FoundationTrust [2] in 2016 presented their method through paper "Automatic Optic Disc Abnormality Detection in Fundus Images: A Deep Learning Approach" in which they proposed an complete supervised model for OD abnormality detection. The most informative features of the OD are learned directly from retinal images and are adapted to the data set at hand.

B. Vinoth Kumar, P. Swathika, M. PradhibaSelvarani , S. Karpagam [3] proposed their work in 2015 through paper "Detection of anatomical structures in optical fundus images "in which they proposed a method to implement an computerized system for the automatic detection of major anatomical structures in digital fundus images such as blood vessels, Optic Disc (OD) and macula. Blood vessel capturing provides a tracing of the retinal vessel of the eye, from which a reference frame may be obtained, that can simplify the process of locating other fundus objects. They proposed method to describe and figure out a machine learning-based, automated system to detect exudates in digital color fundus photographs, for early diagnosis of diabetic diseases.

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Morales et al. [4], in 2013 has categorized these methods into three types, such as template based methods, deformable model based methods and morphology based methods. In the template based methods, it extracts the candidate regions of the OD by thresholding. The Hough transform is then performed to highlight the candidates as circles and the region with the highest average intensity is selected as the OD.

A. Aquino, M. E. Geg´undez-Arias, and D. Mar´ın [5] 2010 adopted Prewitt edge detector to obtain OD boundary candidates and circle Hough transform is employed to finish the final OD boundary segmentation.

Welfer et al.[6], in 2010 suggested a flexible method for detection OD by segmenting OD using adaptive morphological technique.

H. Li and O. Chutatape [7], in 2004 adopted the principal component analysis (PCA) method to detect the OD region, and the borderline of OD is detected by a modified active shape model.

A. Osareh, M. Mirmehdi, B. Thomas, and R. Markham [8], in 2002 employed deformable model based methods, in which colour mathematical morphology is used to remove the blood vessels and provide a consistent OD region for the snake to lock onto.

Walter et al. [9], in 2002 used the morphology based methods, in which extracted the OD using watershed transformation with the assumption that the OD represents a high intensity region. The gray image achieved by PCA is selected as the input. The Stochastic Watershed is employed to extract the watershed regions then region discrimination is performed to select the pixels which belong to the OD based on the average intensity of the region.

Lalonde et al. [10], in 2001 employed the canny edge detector to extract the edge of OD and then Hausdorff-based template matching is applied to fit the OD boundary by a circle.

II. EXISTING SOLUTIONS & PROBLEMS

The traditional method employs edge detector, such as Prewitt edge detector or Canny edge detector etc., to extract the edge information. When the edge operator is applied to detect the OD edge, blood vessel edges are detected besides OD edge. As the blood vessels on the fundus image are very thick, it can be considered as major obstacle to detect exact OD shape. The traditional method which uses edge detector for optic disc detection does not give proper and accurate results. All the traditional methods are unsupervised methods which are based on some assumptions like Optic Disc area is a bright region etc. Based on only assumptions, it will not give accurate edges of OD which defines shape of the OD.

In addition, for the traditional edge operator, using different channels as input may lead to different results, which makes choosing which channels as input is a critical decision. In some cases, the green channel or the red channel of the original fundus image is used and in some cases, a combination of the red channel and green channel is used. However, due to the variability of the fundus image, any individual method does not guarantee an optimal result.

Figure 1 shows the disadvantages of the traditional edge operator. It can be observed that when the Prewitt edge detector is performed on the green channel, only vascular edges are detected, which is shown in Fig. 1(d). Besides, Fig. 1(d) and Fig. 1(e) illustrate that using different channels as input leads to different results [1].

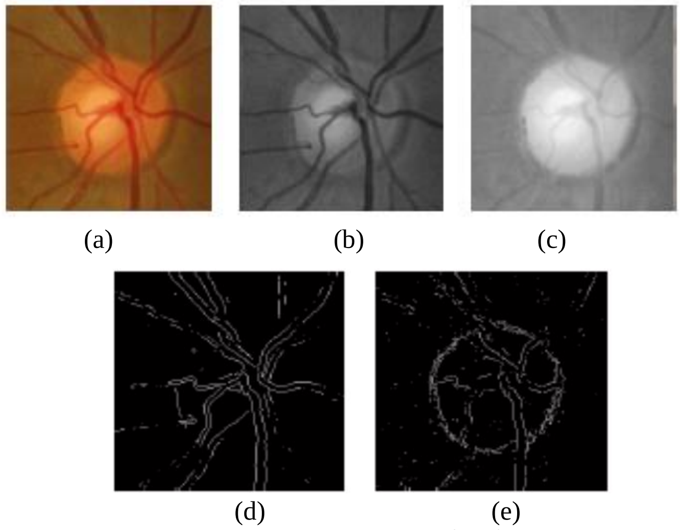

Figure 1. a) Fundus Image b) The green channel of the fundus image c) Red channel of the fundus image d) Edges obtained by applying prewitt operator on the green channel e) Edges obtained by applying prewitt operator on the red channel

As seen from results for traditional methods, there is need of proper detection of the OD edges to detect its abnormality. The proposed method is to solve all the problems with respect to traditional method.

III. PROPOSED SOLUTION

The proposed method employs structured learning for OD detection and is considered to be a supervised method to prevent making assumptions. The proposed method uses the edge data of the fundus image for detection of the OD.

The structured learning is a supervised method and it can train the edge detector to get the interested edge information, like the information related to OD edge. In the proposed method the original fundus image is given as input image for the edge detector to be trained. As it considers original fundus image as it is, it solves the problem of which channels of the original image should be chosen for edge detection. The Random Forest is taken as an edge detector for structured learning, which automatically selects an advantageous set of features from the original fundus image including all three (green, red and blue) channels, so that the resulting detector can capture the edge most properly. Random forests or random decision forests work by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.

a. System Block Diagram

The block diagram for OD segmentation is shown in Figure 2 [1]. Firstly cropping of OD region from fundus image is carried out which has the highest intensity. For cropping, the correlation filter can be used which employs a Laplacian of Gaussian template to find out the key elements of OD structure to detect a point located in the OD. A 300 ×

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300 cropped sub image which includes the OD is then cropped based on the detected point. In the training stage, structured learning is used to train the model. In the test stage, given a test image, a model is trained to achieve the edge map of the OD. To find out exact shape of the edge map of the OD, it is necessary to convert it to a binary image, therefore, thresholding is performed on the edge map. At the end, to encircle the boundary of OD Circle Hough transform is applied.

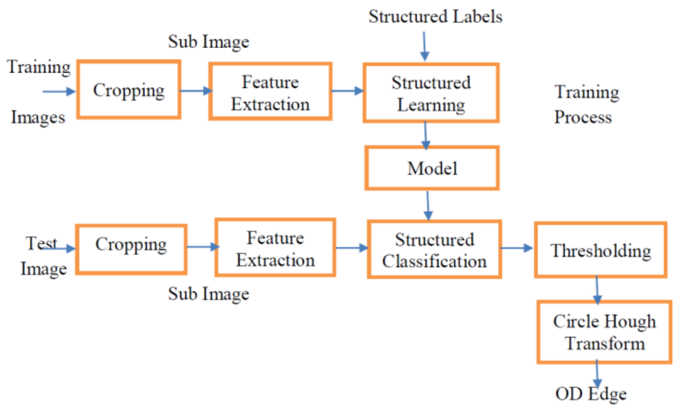


Figure 2: Block Diagram of the Proposed System

Features may include edge information with respect to OD region, Intensity of OD region, Depth of the Image etc. Sliding Window is a window with default size 32x32 which moves across the fundus image and with respect to the patch obtained, the trained structured forest makes a prediction for each window to achieve the OD edge map.

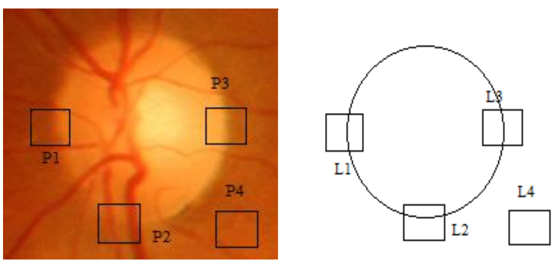
IV. METHODOLOGY

Methodology of Implementation includes following steps:

a. Obtaining Edge Map by Structured Learning
b. OD Edge Detection
c. Features to be extracted
d. Thresholding
e. Circle hough transform

a. Obtaining Edge Map by Structured Learning:

Structured learning or structured prediction is a supervised machine learning technique that involves predicting structured objects instead of scalar discrete or real values. This technique represents the problem of learning a mapping where the input or output space may be arbitrarily complex representations, such as strings, sequences, graphs, object pose, bounding boxes etc. Similar to commonly used supervised learning techniques, structured prediction function are typically trained by means of observed data in which the ground truth is used to adjust model parameters.



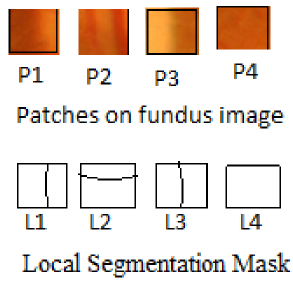


Figure 3: The OD boundary is consisted of local structures; these structures are usually characterized by arcs. Since the output space of the structured learning can be arbitrarily complex representing, the problem of OD edge detection can be formulated as predicting local segmentation masks given fundus image patches.

The OD edges in local patches are highly interdependent. They mostly contain patterns like arc. As given in examples in Figure 7, Patches P1, P2, contains OD edge and P4 is the patch without OD edge. L1, L2, L3 and L4 are respective local segmentation masks. As the output space of the structured learning can be arbitrarily complex representations, the problem of OD edge detection using structured learning can be formulated as predicting local segmentation masks given input image patches. Precisely, given a patch on the fundus image as input like patch P1, the desired output of the trained model is a local segmentation mask like L1 in figure 3.

b. OD Edge Detection:

To obtain edge map of OD region, Structured Support Vector Machine (S-SVM) toolbox is employed. To detect the OD edge, proposed method uses structured forests. Firstly patch is cropped from the fundus image. A feature vector is then extracted to represent the patch so that the trained random forest can recognize the pattern in the patch. The random forest consists of different trees and the output of each tree is considered to be a local segmentation of the OD edge. The final output of the random forest is averaged over the local segmentation on each tree. A sliding window with default size 32x32 moves over the fundus image and the trained structured forest makes a prediction for each window to achieve the OD edge map [1].

c. Extraction of features:

The process of feature extraction for each patch includes 13 channels, including 3 colors, 2 magnitude and 8 orientation channels, are generated first. A patch of 32 X 32 is cropped from each channel and downsampled by a factor of 2, resulting in 32 X 32 X 13/4 = 3328 candidate features. And further the pair-wise features are extracted for the patch. Consequently, the patch is downsampled to a resolution of 5X5. Sampling all candidate pairs and computing their differences yield an additional $C^2_{5X5} = 300$ candidate features for each patch in each channel. Thus the total number of features obtained for each patch is 13 X 300 + 3328 = 7228.

d. Thresholding:

For a grayscale image I, a binary image BW can be created using thresholding method. The thresholding method

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checks for intensity at each pixel for a defined level T and replaces pixel in an image with a black pixel if the intensity I(x; y) is less than some fixed value T, or a white pixel if the image intensity is greater than that value.

This can be defined as:

$$BW(x; y) = 1 \text{ if } I(x; y) > T$$
$$= 0 \text{ others}$$

e. Circle Hough Transform:

Circle Hough transform is a method used to find the circle patterns in the image. The procedure of Circle Hough transform can be defined as

$$(cx; cy; r) = CHT(I_{BW}; r_{min}; r_{max})$$

where I_{BW} is a binary image and $(r_{min}; r_{max})$ is the search range of the radius. (cx; cy) and r are respectively the center position and radius obtained by circle Hough transform.

V. RESULTS

Blocks implemented:

a. Cropping:

i. Collection of Fundus Image databases:

Fundus images from various databases collected like databases DRION, High definition databases which includes high definition fundus images from which optic disc area needed to be cropped further.

ii. Cropping of Optic disc from fundus image:

To crop the sub images which include the OD from the fundus images first which can be done by locating the OD. Proposed method employs the correlation filter [10] which uses a Laplacian of Gaussian template to match the key elements of OD structure to detect a point located in the OD. A 300 x 300 sub image which includes the OD is then cropped based on the detected point and subsequent operations are performed on the sub images.

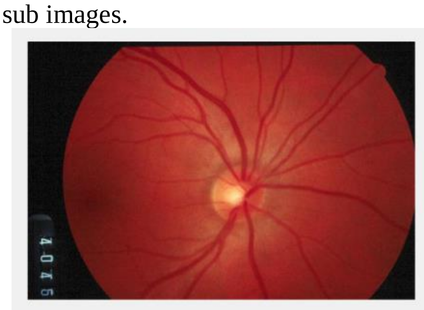


Figure 4: Fundus Image

Figure 3 shows the original fundus image from which optic disc area need to be cropped.

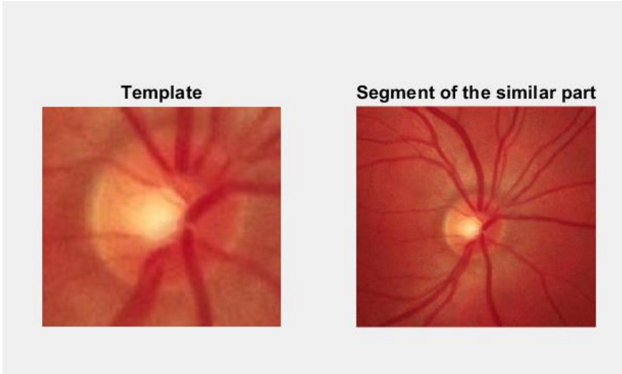


Figure 5: Locating Optic disc area

By using template matching concept, correlational filter which employs laplacian of Gaussian template is used to match the key elements of OD region. Figure 4 shows result of correlation between template and fundus image by showing segment of the similar part.

c.

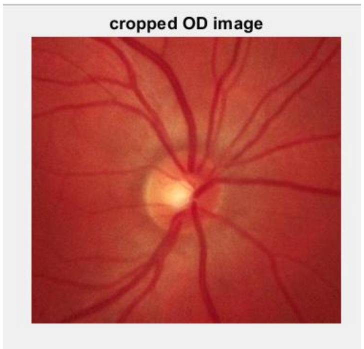
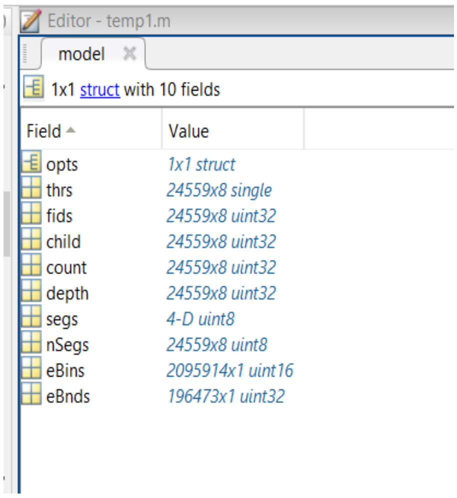


Figure 6: Cropped OD region

According to correlation concept, segment of fundus image which is matching with template image is cropped as shown in Figure 5.

b. Feature Extraction:

a. Firstly OD region needs to be extracted which is bright region amongst fundus image.
b. Edges with respect to OD region needs to be extracted.
c. Extracted features of cropped OD region.



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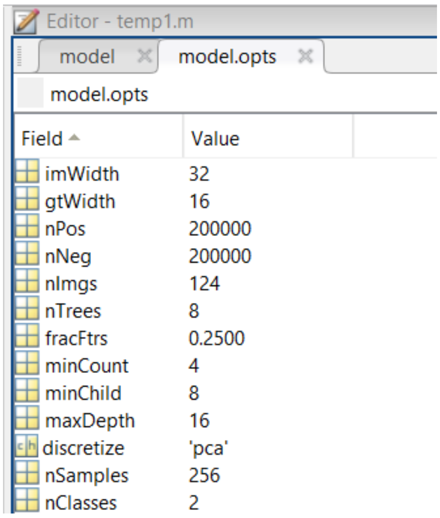

Field	Value
imWidth	32
gtWidth	16
nPos	200000
nNeg	200000
nImgs	124
nTrees	8
fracFtrs	0.2500
minCount	4
minChild	8
maxDepth	16
discretize	'pca'
nSamples	256
nClasses	2

Figure 7: Features Extracted

Setting for model is done by loading model and setting standardized values for them.

Definitions Features extracted:

Tree: A tree is a data structure made up of nodes or vertices and edges without having any cycle. The tree with no nodes is called the null or empty tree. A tree that is not empty consists of a root node and potentially many levels of additional nodes that form a hierarchy.

Maximum depth of tree: In a tree data structure, the total number of edges from root node to a particular node is called as depth of that node. In a tree, the total number of edges from root node to a leaf node in the longest path is said to be Depth of the tree.

Local Patches: The OD edges in local patches are highly interdependent. They often contain well-known patterns, such as arc. They can be used to train the forest.

c. Implementing Structured Learning:

After feature extraction it is needed to install Support Vector Machine (SVM) structured learning toolbox for classification and learning data. It is a machine learning technique which learns structure from data.

Structured learning is the subfield of machine learning concerned with computer programs that learn to map inputs to arbitrarily complex outputs. This stands in contrast to the simpler approaches of classification, where input data (instances) are mapped to "atomic" labels, i.e. symbols without any internal structure, and regression, where inputs are mapped to scalar numbers or vectors.

A Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating hyperplane. In other words, given labeled training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples. In two dimentional space this hyperplane is a line dividing a plane in two parts where in each class lay in either side.

Support Vector Machine which can classify two data sets with a hyperplane in between them is as shown below:

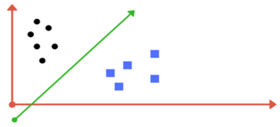

Figure 8: Typical response of SVM

Consider the problem of separating the set of training vectors belonging to two separate
classes,

$$D = \{(x^1, y^1), \ldots, (x^l, y^l),\ x \in R^n,\ y \in \{-1, 1\}\},$$

with a hyperplane, $(w, x) + b = 0$.

The set of vectors is said to be optimally separated by the hyperplane if it is separated without error and the distance between the closest vector to the hyperplane is maximal. where the parameters w, b are constrained by,

$$\text{Min} \,|(w, x_i)+b| = 1$$

Nearest data points with respect to hyperplane is said to be support vectors.

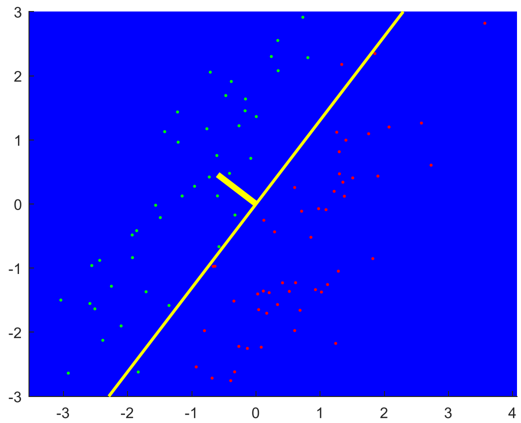

Figure 9: Output after executing SVM learning program

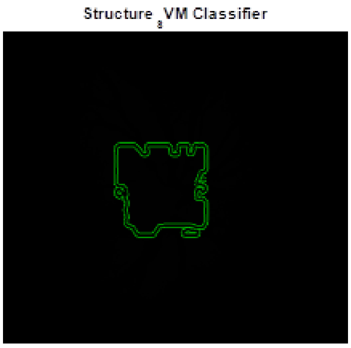

Figure 10: Creating Mask using SVM classifier

Firstly using SVM classifier, it is needed to create mask of the OD image which will be the approximate shape of the OD. Further processing will be on the mask not directly on the OD image.

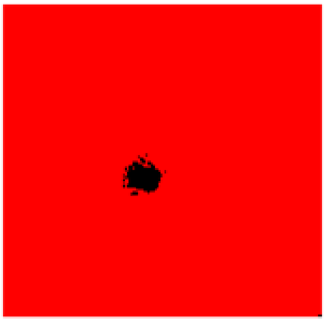

Figure 11: Finding the color difference

To find out the exact edges of the OD it needed to find out the color difference.

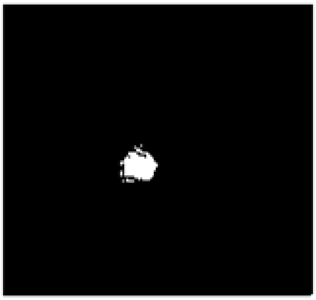

Figure 12: After applying thresholding

After applying the thresholding, color difference image will be converted to the binary image i.e. black and white image.

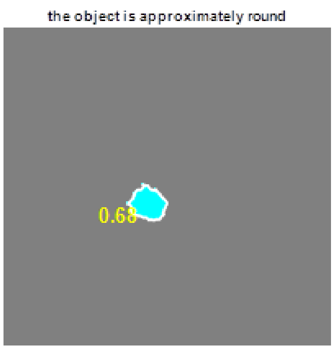

Figure 13: Finding circularity of the OD

Now to detect the abnormality of the OD it is needed to find the circularity of the OD shape obtained. Normally circularity below 0.65 will be considered as abnormal OD and circularity above 0.65 will be considered as normal OD.

Figure 14: After applying Circle Hough Transform

To highlight the OD area, Circle Hough Transform is used.

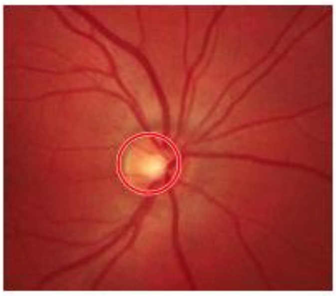

Figure 15: Imposing Circle Hough Transform on OD image

Finally imposing the circle hough transform on the original OD image.

VI. CONCLUSION

It can be concluded from above experimentation that optic disc detection by using structured learning gives clear and accurate shape of optic disc as compared to traditional edge operators. As the proposed method is supervised method it provides exact shape of the OD as compared to traditional edge operators.

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