International Conference on Communication and Signal Processing, July 28 - 30, 2020, India

Glaucoma Detection from Retinal Fundus Images

Rahul Krishnan, Varun Sekhar, Sidharth J, Gautham S and Gopakumar G

Abstract—**Glaucoma is an optic nerve disease that damages the optic nerves and can cause blindness if it remains untreated. CDR (Cup-to-Disc Diameter Ratio) is one of the factors with which we can determine the presence of Glaucoma. The detection is carried out using an existing pipeline in which segmentation of optic disc and cup is carried out first followed by CDR calculation based on which a prediction is made. A threshold-based algorithm was used for segmenting the Optic Disc. For the cup region, a modified region growing algorithm was applied. The segmentations were followed by infilling blood vessels and morphological operations. The CDR value calculated from the segmented images was fed to an SVM model to classify. Cup segmentation is a challenging and hard problem. There are many algorithms that tackle the same. The proposed method approaches this challenge with a novel method for segmenting the optic cup. The results show that the proposed approach could accurately predict the presence of Glaucoma with less computational requirements.**

Index Terms—**Optic disc Segmentation, Optic cup Segmentation, Image processing, Glaucoma detection, SVM Classifier, Region growing**

I. Introduction

GLAUCOMA is an eye disease that damages your eye's optic nerves, which can worsen over time. The optic nerves inside your eye can be damaged by increased pressure, called as the intra-ocular pressure. This can even result in permanent vision loss if the damage worsens. Most people with glaucoma have no early symptoms or pain. Glaucoma is accompanied by optic nerve cupping in the optic nerve head. Optic disc or the optic nerve head is the point of exit for ganglion cell axons leaving the eye. It contains a central bright region called the Optic Cup and the peripheral region surrounding it called the Neuroretinal Rim. Optic cupping is a phenomenon in which the nerve fibers begin to die because of the increased intra-ocular pressure in the eye along with a possible loss of blood flow to the optic nerve. As a result, the support structure for the optic cup is destroyed and hence the cup becomes larger. Optic nerve cupping progresses as the cup enlarges in comparison to the optic disc. Developing an automated method to screen eye fundus images can play a very important role in the prevention of glaucoma.

Rahul Krishnan, Varun Sekhar, Sidharth J, Gautham S and Gopakumar G are with the Department of Computer Science and Engineering, Amrita Vishwa Vidyapeetham, Amritapuri, India (e-mail: rahul.krishnan27@gmail.com v4run1998@gmail.com jsidharth52@gmail.com gauthamsathyan@gmail.com gopakumarg@am.amrita.edu).

978-1-7281-4988-2/20/$31.00 ©2020 IEEE

A classifier model can be used as a pre-screening tool by ophthalmologists to classify a set of eyes as normal or glaucomatous. The classification is carried out by calculating the CDR (Cup-to-disc Diameter Ratio), where the ratio of the diameters of the optic disc and cup are taken. A classifier can be trained to classify an eye fundus image as glaucomatous based on CDR value. This tool can benefit the patients by making the examinations cheaper and faster, and the doctors by reducing the effort needed to be put by them.

The proposed method follows an image segmentation-based approach which demands less computational power while having the advantage of not requiring a large amount of training data and being computationally efficient.

This paper is organized such that, Section II will present the literature review, followed by the proposed method in Section III. Section IV will list the experimental results obtained, followed by the conclusion in section V.

II. Literature Review

Glaucoma can be characterized by the change in structure of the optic nerve due to the enlargement of the optic cup, thus glaucoma prediction/classification is in a way aims to characterize the cup and disc regions. There are different ways to address this kind of prediction problem. Either, we can look for hand engineering features on regions of interest[1] or can directly feed the images to a deep learning networks to take decision[2][3][4]. Some of the existing methods for segmenting the disc and cup are by the use of deep learning-based approaches[5][6] to form an ensemble neural network[7] which uses modified versions of convolutional neural networks such as M-Net[8] or U-Net[3]. Another implementation with the use of an altered version of U-Net provides an improved accuracy score with the lesser time needed for prediction[4]. These methods, however, need a large amount of training data that may not be readily available and would require large amounts of GPU memory to train while taking longer prediction time. The other main classification method is by the use of image processing techniques such as active contours[9] or Hough transforms[10] or by using Otsu segmentation to perform the segmentation of optic disc and cup[1] from the image. These methods can give good accuracy scores with the added advantage of not requiring much training data as compared to deep learning models[11].

III. FRAMEWORK

A. Dataset

The images used for experimentation are from the Drishti-GS[12][13] dataset provided by IIIT, Hyderabad. It contains a total of 101 images, 50 training images, and 51 testing images. Each image is of the dimension 2049 X 1760. The ground truth of each image is comprised of 3 fields viz. average boundaries for optic disc and cup derived from the manually marked images, a soft map image of optic disc and cup formed by fusing together the manually marked segmentations as shown in Fig. 1, and CDR values as measured by 4 eye experts.

B. Proposed Method

A flowchart for the proposed method is shown in Fig. 2. Given a retinal fundus image, the red channel is extracted followed by subtraction of mean and standard deviation. The red channel is extracted since the optic disc can be distinguished from a background in the red channel. A thresholding operation is then performed to obtain the segmented optic disc. The segmentation of the optic cup is performed using a region growing based approach. Following the segmentation, the diameters of the segmented optic disc and optic cup are measured using ellipse fitting and the CDR value is calculated. The CDR value is then passed on to a linear classifier for prediction.

1) Optic disc segmentation: The retinal fundus image is preprocessed for optic disc segmentation by extracting the red channel from the RGB image since the optic disc is distinguishable from the background in the red channel as shown in Fig.3a. This is followed by subtracting the mean and standard deviation from the image as shown in Fig.3b so as to further highlight the optic disc. The threshold for segmentation is calculated using Otsu's method[14], which is then applied to the preprocessed image. Then, the blood vessels in the optic disc as shown in Fig. 4b are found out by applying a threshold which is computed by the local mean intensity[15] in the neighborhood of each pixel with a sensitivity value of 0.7. The value 0.7 was calculated empirically. The vessel image is obtained after taking the complement of the resulting image. The complement is taken since the resulting image will be that of regions excluding the vessel and other dark regions. An ellipse is fitted using the Least-Squares criterion on the binary image in order to create a mask. This mask is then applied to the blood vessel image in order to obtain the vessels lying inside the optic disc. Both the resulting vessel image and the binary image are merged together by performing an OR operation. A sequence of morphological closing and opening operations using a disc shaped structuring element are performed on the resulting image in order to obtain the segmented optic disc. A sample segmented image which achieved a dice score of 0.93 is shown in Fig. 4a.

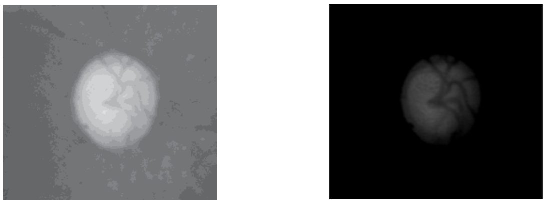
(a) Retinal Image (b) Disc softmap image (c) Cup softmap image

Fig. 1. Retinal image with ground truth

2) Optic Cup segmentation: For segmenting optic cup, after observing a number of images it was found out that the optic cup is distinguishable in the green channel of the retinal fundus image as shown in Fig. 5a. Hence, the retinal fundus image is preprocessed by extracting the green channel followed by a contrast adjustment. Contrast adjustment was done by saturating the top 1% and bottom 1% of the pixel values. The boundary pixels of the optic disc are identified from the segmented disc object. The standard deviation of the boundary pixel intensities is calculated. Then a few random pixels are selected from the boundary pixels and are set as seed points. The number of seed points was taken as 10 after experimentation with different values. For each seed point, a region growing algorithm[16] is applied and are merged together. The algorithm works by comparing pixels in the neighborhood of the seed point and the pixel is appended to the seed point if their intensity difference is below a pre-calculated threshold. The process stops when the difference between the mean intensity of the grown region and the neighboring pixel becomes larger than the threshold. The standard deviation calculated earlier is set as the threshold so that all the pixels belonging to optic disc excluding those pixels which belong to optic cup are added to region grown object. The initial segmented optic cup object as shown in Fig. 5b is obtained by taking the difference of the segmented optic disc object and grown region. Morphological opening and closing operations using a disc shaped structuring element is then performed on the resulting image. This is followed by fitting an ellipse using Least-Squares criterion[17] in order to obtain a mask. This mask is applied to the blood vessel image in order to obtain the vessels lying inside the optic cup. Both the resulting vessel image and the initial segmented cup object are merged together by performing an OR operation. A sample segmented image is shown in Fig. 5c.

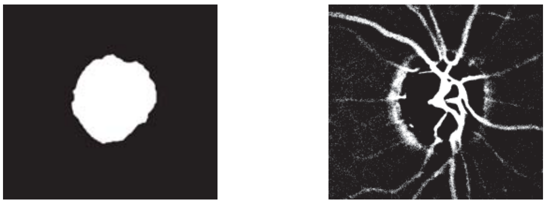
3) CDR measurement and prediction: For estimating the diameter of the segmented objects, an ellipse fitting based approach[17] is followed. The best fit ellipse for optic disc and optic cup is found and the length of its major axis is taken as the diameter of the respective object [18]. For predicting

Fig. 2. Flowchart



(a) R Channel image (b) Preprocessed Image

Fig. 3. Preprocessing results from optic disc segmentation



(a) Segmented disc (b) Optic Vessel

Fig. 4. Results from optic disc segmentation

the presence of Glaucoma an SVM model with an RBF kernel is used. The model was trained using ground truth of 50 images from the Drishti-GS dataset. The model is trained with the input as the ground truth CDR values and the target as the diagnosis of the corresponding retinal image. This model is then used to predict the presence of Glaucoma in a retinal fundus image after estimating the CDR value of the segmented optic disc and optic cup [19-21].

IV. Results And Discussion

The proposed method was evaluated using Dristhi-GS dataset[12][13]. The results of optic disc and optic cup segmentation are shown in Fig. 4a and Fig. 5c. The metric used for measuring the accuracy of the segmentation is Dice score and IOU measure. Both these measures are used to assess the performance of an image segmentation method. The Dice score and IOU measure are calculated as shown in Eq. 1 and Eq. 2 respectively.

$$Dice\ score = (2 * n(X \cap Y))/(n(X) + n(Y)) \quad (1)$$

$$IOU = (n(X \cap Y))/(n(X \cup Y)) \quad (2)$$

Where X, Y are the two images to be compared.
n(A) is the number of pixels in image A.
$X \cap Y$ gives the intersection of images X and Y
$X \cup Y$ gives the union of images X and Y

The results of the segmentation are reported in Table I. IOU metric mostly focuses on the poor classifications on each of the single instances. Dice metric measures the average performance, whereas the IOU metric measures something closer to worst case performance. The ground truth contains CDR values of each retina as manually measured by 4 ophthalmologists. The CDR values measured by using the

TABLE I
SEGMENTATION RESULTS

Segmentation	Dice score	IOU
Optic disc	0.94 ±0.02	0.89 ±0.04
Optic cup	0.75 ±0.16	0.69 ±0.19

(a) Green channel Image (b) Initial result (c) Segmented cup

Fig. 5. Intermediate results from optic cup segmentation

proposed method was evaluated against the ground truth by using root mean squared error (RMSE). RMSE was used since it gives how much the values vary around our predictions. The RMSE measured is reported in Table II.

The prediction accuracy was evaluated using F1 score. F1 score is given by the harmonic mean of precision and recall. The result achieved by the SVM model is 86%. Cup segmentation is a challenging and hard problem. There are many algorithms which tackle the same.

The proposed method approaches this challenge with a novel method for segmenting the optic cup by using region growing technique in a fast and efficient manner achieving a Dice score of 0.75 ± 0.16 with an overall prediction performance of 86% for classification is reported in Table III.

TABLE II
CDR ESTIMATION ERROR

CDR as measured by	Mean squared error
Expert 1	0.231
Expert 2	0.180
Expert 3	0.244
Expert 4	0.240

TABLE III
PREDICTION PERFORMANCE COMPARISON

Method	Result
Proposed method	86%
[18] K.Dutta et al.	83%
[19] G.C. Bedke et al.	71%
[20] Y.Gao et al.	85%

V. Conclusion

The proposed method was able to solve optic disc and optic cup segmentation with a Dice score of 0.92 ± 0.02 and 0.75 ± 0.16 respectively. The CDR value was measured with an RMSE of 0.224. The prediction using a linear classifier was able to achieve an F1 score of 86%. Since the segmentation followed an image processing approach, it would be relatively faster than a solution following a deep learning-based approach while having the added advantage of not requiring a large amount of training data and being computationally efficient. We plan to further improve the optic cup segmentation algorithm so as to achieve much better results. We plan to run the algorithm on different datasets in order to identify the weak points of this algorithm, which can be further analyzed to improve the efficiency and accuracy of prediction. This program can be used for automatic diagnosis of glaucoma in screening programs.

REFERENCES

[1] D, Naga V, Kanchana. (2019). Recognition of glaucoma using Otsu segmentation method. International Journal of Research in Pharmaceutical Sciences. 10. 1988-1996. 10.26452/ijrps.v10i3.1407.

[2] Gopakumar G., Sai Subrahmanyam G.R.K. (2019) Deep Learning Applications to Cytopathology: A Study on the Detection of Malaria and on the Classification of Leukemia Cell-Lines. In: Balas V., Roy S., Sharma D., Samui P. (eds) Handbook of Deep Learning Applications. Smart Innovation, Systems and Technologies, vol 136. Springer, Cham

[3] Ronneberger O., Fischer P., Brox T. (2015) U-Net: Convolutional Networks for Biomedical Image Segmentation. In: Navab N., Hornegger J., Wells W., Frangi A. (eds) Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. MICCAI 2015. Lecture Notes in Computer Science, vol 9351. Springer, Cham

[4] Sevastopolsky, A. Optic disc and cup segmentation methods for glaucoma detection with modification of U-Net convolutional neural network. Pattern Recognit. Image Anal. 27, 618–624 (2017). https://doi.org/10.1134/S1054661817030269

[5] Yin, Pengshuai, Guanghui Xu, Jingwen Wang, Yuguang Yan, Hua-qing, Min, Qingyao Wu and Mingkui Tan. "Optic Disc and Cup Segmentation using Ensemble Deep Neural Networks." (2018).

[6] M. Sushil, Suguna, G., Lavanya, R., and M. Devi, N., Amrita University, "Performance comparison of pre-trained deep neural networks for automated glaucoma detection", Lecture Notes in Computational Vision and Biomechanics, vol. 30, pp. 631-637, 2019.

[7] Dietterich T.G. (2000) Ensemble Methods in Machine Learning. In: Multiple Classifier Systems. MCS 2000. Lecture Notes in Computer Science, vol 1857. Springer, Berlin, Heidelberg

[8] R. Mehta and J. Sivaswamy," M-net: A Convolutional Neural Network for deep brain structure segmentation," 2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017), Melbourne, VIC, 2017, pp. 437-440. doi: 10.1109/ISBI.2017.7950555

[9] Kass, D. 1988. Snakes: Active contour models. International Journal of Computer Vision, 1(4), p.321–331.

[10] Richard O. Duda and Peter E. Hart. 1972. Use of the Hough transformation to detect lines and curves in pictures. Commun. ACM 15, 1 (January 1972), 11–15. DOI:https://doi.org/10.1145/361237.361242

[11] G. D. Joshi, J. Sivaswamy and S. R. Krishnadas," Optic Disk and Cup Segmentation from Monocular Color Reti- nal Images for Glaucoma Assessment," in IEEE Transactions on Medical Imaging, vol. 30, no. 6, pp. 1192-1205, June 2011

[12] Sivaswamy, Jayanthi Krishnadas, Subbaiah Chakravarty, Arunava Joshi, Gopal Ujjwal. (2015). A comprehensive retinal image dataset for the assessment of glaucoma from the optic nerve head analysis. JSM Biomed Imaging Data Pap. 2.

[13] J. Sivaswamy, S. R. Krishnadas, G. Datt Joshi, M. Jain and A. U. Syed Tabish," Drishti-GS: Retinal image dataset for optic nerve head (ONH) segmentation," 2014 IEEE 11th International Symposium on Biomedical Imaging (ISBI), Beijing, 2014, pp. 53-56.

[14] N. Otsu," A Threshold Selection Method from Gray- Level Histograms," in IEEE Transactions on Systems, Man, and Cybernetics, vol. 9, no. 1, pp. 62-66, Jan. 1979.

[15] Bradley, Derek Roth, Gerhard. (2007). Adaptive Thresh- olding using the Integral Image. J. Graphics Tools. 12. 13-21.

[16] Dirk-Jan Kroon (2019). Region Growing , MATLAB Central File Exchange. Retrieved 29/12/2019. (https://www.mathworks.com/matlabcentral/fileexchange/19084-region-growing)

[17] Ohad Gal (2019). fit ellipse , MATLAB Central File Exchange. Retrieved December 29, 2019. (https://www.mathworks.com/matlabcentral/fileexchange/3215-fit_ ellipse)

[18] Dutta, Kaushik Mukherjee, Rishav Kundu, Shamik Biswas, Tanmay Sen, Anindya. (2018). Automatic Evaluation and Predictive Analysis of Optic Nerve Head for the Detection of Glaucoma. 1-7.

[19] Kanchana.R, Rajalakshmi.J, Mukesh.M.S, Nagarajan.V (FEB 2014), "Evolution of multi sensor image fusion using decimated biorthogonal wavelet transform and undecimated non-orthogonal wavelet transform", Int J of Electronic Communications Engineering Advanced Research, Vol.2, SP-1, Feb.2014, pp. 72-75

[20] G. C. Bedke, R. R. Manza, D. D. Patil and Y. M. Rajput," Secondary glaucoma diagnosis technique using retinal nerve fiber layer arteries," 2015 Int Conf on Pervasive Computing (ICPC), Pune, 2015, pp. 1-4.

[21] Gao, Yuan Yu, Xiaosheng Wu, Chengdong Zhou, Wei Wang, Xiaonan Chu, Hao. (2019). Accurate and Efficient Segmentation of Optic Disc and Optic Cup in Retinal Images Integrating Multi-View Information. IEEE Access. PP. 1-1.