# A Survey on Detection and Segmentation of Optic Disc in Retinal Images

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**Abstract -** *Optic disc detection in retinal images is a trivial step in the process of diabetic retinopathy and glaucoma detection. Thus, it plays an important role in automatic retinal screening systems. Segmentation is also considered as one of the methods to locate the position of optic disc in optic images. Multiple methodologies have been developed for optic disc detection and disc diameter calculation, few of these literatures are discussed in this paper. These methods include conventional approaches using machine learning algorithms as well as deep learning-based object detection and segmentation approaches.*

***Key Words***: Optic Disc, Object Detection, Segmentation, Deep Learning, CNN.

## 1. INTRODUCTION

Optic disc (OD), also known as the optic nerve head is a small blind spot in the eye which acts as an exit point for the ganglion cell axons leaving the eye. It plays a very important role in diabetic retinopathy and glaucoma detection. There are multiple methodologies which can help to find out the various anomalies in the optic disc size which can further help us in detection of the above- mentioned diseases.

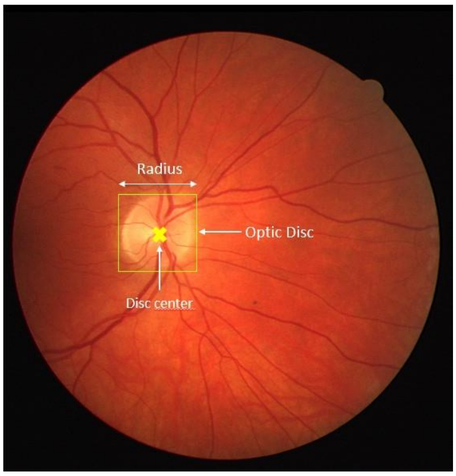


**Fig -1**: Retinal fundus image from DRIVE dataset

Numerous methodologies can be utilized to measure the optical disc size. Every method has certain advantages and disadvantages which affect their further implementations and the research objectives.

Optic discs have an average dimension of 1.76mm horizontally by 1.92mm vertically. But the normal optic disc size can vary by racial group. Research conducted by the Baltimore eye survey studied the topological characteristics of the optic disc in 3,387 people and found the mean optic disc area to be 2.94 mm2 in African Americans compared with 2.63 mm2 in whites, as obtained by planimetry[17]. The African Descent and Glaucoma Evaluation Study (ADAGES) found a mean disc area of 2.06 mm2 in African Americans compared with

1.77 mm2 in whites using confocal scanning laser ophthalmoscopy measurements [9]. The mean disc area in Caucasians ranges between 1.73 $mm^2$ to 2.63 $mm^2$, [10][11][12][13][14][15][16][17][18]. Similarly in Hispanics the disc area ranges from 2.46 $mm^2$ to 2.67 $mm^2$,[16] and for Asians it is between 2.47 $mm^2$ to 3.22 $mm^2$[15].

### *1.1. Need for optic disc detection:*

It is observed that eye diseases are increasing at a rapid rate. Dealing with such situations using traditional means creates a lot of complexities. As a result often there is stress seen in the medical field, to ease their work we developed a cost lucrative computerized automatic idiosyncratic system that can provide aid to our teams of medical experts in preliminary stages of diagnosis, resulting in economizing time and reducing their strain and efforts on the needless examination and inspection of people who are healthy. Glaucoma is an eye disease which damages the optic nerve and can lead to blindness if left untreated. It is currently the main cause of irreversible vision loss and is caused by high intraocular pressure pushing against optic nerve in the eye Progression of the disease can lead to 'pale disc' and disc hemorrhage. Angle- closure glaucoma and open-angle glaucoma are the two common glaucoma types and present different warning signs. Angle-closure glaucoma causes very noticeable symptoms, for example, blurred vision, severe eye pain, sudden sight loss, light halos and more. On the other hand, open-angle glaucoma slowly progresses and shows no symptoms, until peripheral vision is lost thus it is called "the sneak thief of sight". Therefore, regular eye examination once per year is essential and recommended for early glaucoma screening, particularly for people, over 40 years old, as the number of patients increases sharply with age and for people with early warning signs. The Optic disc detection is the fundamental step in computer- aided disease diagnosis. Reliable Optic Disc detection is a necessary step in the diagnosis of various retinal diseases such as diabetic retinopathy and glaucoma. Therefore, the optic disc is an important anatomical feature in the retinal images, and its detection is a prerequisite for developing automatic screening systems.

### *1.2. Classical methods used for detection:*

Classical methods to diagnose eye problems are trusted but are time consuming but they are accurate. They need specialised machines and instruments to perform and they aren't come cheap. So, there is an entry barrier for spending money. Because of this, classical methods are becoming very expensive to afford for patients worldwide. This is the main motive to work on inventing new techniques for eye disease detection. Which will be cheaper and accurate.

Some classical methods are as follows:

- Glaucoma Suspect
- Narrow-Angle Suspects
- DR Suspects
- Macular Degeneration Suspects

### *1.3. Benefits of different methodologies:*

There is a need for different methodologies for optic disc detection which can help in increasing the accuracy for OD detection which can further help in the pipeline of the disease detection process. Also, different approaches have their own set of advantages and disadvantages and thus the selection of the method depends upon the research objective or the application. Another important aspect is the computational power usage. These impacts and decides the usage of the methodology because the given pipeline or the application developed from these methods have to run on a range of devices, which can highly vary in their computing power. Also reducing the compute power usage of the method can help to mass produce and reduce the complexity of the instruments. This all can also help in reducing the manufacturing costs of the devices and thus helps to reach different types of population i.e. urban to rural areas.

### *1.4. Deep learning contributions:*

There are various methods of optic disc detection which are been introduced in the deep learning domain. Since the traditional segmentation techniques are usually difficult to achieve good performance especially in illness cases, some machine learning based approaches have been explored .However comparing to the latest developed deep neural networks (DNN) based methods, the performance of these conventional machine learning approaches mostly relies on the hand crafted features,thus the performance is expected to be further improved by introducing DNN methods to learn more discriminative features automatically .

Recently DNN based segmentation approaches like M-Net is shown to outperform segmentation and conventional machine learning based methods. However, like most of the existing approaches, this work is still a two-step approach. It performs coarse boundary detection first and then applies an ellipse fitting to generate a smooth ellipse shape boundary.

Deep Object Detection Networks.

With the resurgence of deep learning, computer vision community has significantly improved object detection results over a short period of time. Modern object detection systems can mainly be divided into two groups: one-stage detectors and two-stage detectors. OverFeat [1] was one of the pioneered modern one-stage object detectors based on deep networks. More recent works like RetinaNet [2], have demonstrated their promising results. Generally, these approaches are applied over regularly sampled candidate object locations across an image. In contrast, two-stage detectors are based on a proposal- driven mechanism, where a classifier is applied to a sparse set of candidate object locations. Following the R-CNN work [6], recent progress on two-stage detectors have focused on processing all regions with only one shared feature map, and on eliminating explicit region proposal methods by directly predicting the bounding boxes.

Various extensions to this framework have been presented, e.g., Faster R-CNN [3], and Mask-R-CNN [4].

## 2. Literature Survey

| Year | Author and Title | Aim | Methodologies, Algorithms, Technologies | Result / Accuracy | Conclusion |
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| 2019 | Optic Disc and Cup Segmentation Based on Deep Learning | Segmentation of OD and OC from the fundus images | Utilizes Fully Convolutional Network, Hough Circle Transform Algo for OD detection.<br><br>The main contributions of this papers are as follows:<br>1.Proposed a fully automatic method that can recognize and cut the fundus image to obtain an image of the area containing the optic disc.<br>2. To improve the segmentation performance, proposed a new pre-processing method. | Dataset: REFUGE, Custom dataset<br><br>IoU: 0.92<br>Dice: 0.95 | Proposed method outperforms most of state-of-the-art methods for simultaneous segmentation of the OD and OC. Pre-processing method helps to find more hidden information from fundus images. |
| March 2020 | Automatic optic nerve head localization and cup- to-disc ratio detection using state-of-the-art deep-learning architectures[21] | Compares the performance of various deep-learning architectures for detecting the optic nerve head and vertical cup- to-disc ratio in fundus images. Three different architectures are compared: YOLO V3, ResNet, and DenseNet. | Compares the deep-learning architectures regarding their processing time, localization accuracy, and classification accuracy. The target object is the optic nerve head (ONH), which is the most prominent feature in fundus images, and the performance for classifying its vertical cup-to- disc ratio (VCDR), which is a widely accepted index for the assessment of | Training Dataset: 1959 images<br>Test Dataset: 204 images<br><br>Readings:<br>Low resolution (224 x 224):<br><br>DenseNet:<br>IoU: 80.0%, mAP: 5099.51%, VCDR: 0.065<br><br>ResNet:<br>VCDR - 0.062<br>YOLO v3: VCDR(MAE) - 0.069 | DenseNet has the best performance in this study. At a resolution of 224 × 224, its mean detection time was<br>394 ms, and its localization and classification accuracy are 80% and 0.065, respectively (mean IoU and MAE of the VCDR prediction, respectively). As the input image resolution increased, the overall performances (localization, classification, and diagnostic performance) all improved, and the difference among the architectures became |

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| | | | glaucoma diagnosis. Optic nerve head (ONH) and determine its vertical cup-to-disc ratio (VCDR) Compares the predicted IoU, MAE, VCDR and mAP with the ground truth values | High resolution (832 x 832):<br><br>DenseNet:<br>IoU - 80.7%, VCDR - 0.048<br><br>ResNet:<br>IoU - 77.2%, VCDR - 0.062<br><br>YOLO v3:<br>IoU - 81.5%, VCDR - 0.053 | practically insignificant. |
| Oct 2018 | UOLO - automatic object detection and segmentation in biomedical images[22] | Proposed UOLO, a novel framework for the simultaneous detection and segmentation of structures of interest in medical images. UOLO consists of an object segmentation module in which intermediate abstract representations are processed and used as input for object detection. | For image segmentation, Deep Fully Convolutional network achieves the highest performance on a variety of images and problems. For object detection, DNN are used for feature extractions. Proposed a new architecture UOLO, a combination of FCNN (U-Net) for object/image segmentation and DNN (Yolo v2) for Object detection. | Datasets and Results:<br><br>Messidor:<br>OD seg: IoU - 0.88, Dice - 0.93<br>OD det: IoU: 0.111, S1R - 99.74<br><br>IDRID:<br>OD seg: IoU - 0.88, Dice - 0.93<br>OD det: IoU: 0.095, S1R - 99.79<br>DRIVE<br>Used for testing | A network that performs joint detection and segmentation of objects of interest in medical images by using the abstract representations learned by U-Net. UOLO can detect objects from a different class for which segmentation ground- truth is available. This network can be trained with relatively few images with segmentation ground- truth and still maintain a high performance. |

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| 2019 | OPTIC DISC SEGMENTATION USING CASCADED MULTIRESOLUTION CONVOLUTIONAL NEURAL NETWORKS[23] | Segmentation of OD from fundus images. | Introduces a prior CNN called the P- Net, which is arranged in cascade with the Fine-Net (previous work), to generate a more accurate optic disc segmentation map. The P-Net generates a low-resolution (256 × 256) segmentation map which is then further upscaled along with the input image and is fed to the Fine- Net, which yields a high-resolution segmentation map (1024 × 1024). | Messidor: Dice: 0.96 Jaccard: 0.93<br><br>Drishti-GS: Dice:0.97 Jaccard:0.94<br><br>Drions-DB Dice:0.96 Jaccard:0.93 | Quantifies the benefits of generating a prior segmentation map by an increase in Dice and Jaccard coefficients. This paper validates the proposed framework on three publicly available datasets and shows that similar results are achieved on all three datasets indicating robustness and generalization capability. The proposed framework facilitates the objective of fast and early detection of retinal diseases by providing robust OD segmentation without any manual (specialist) intervention. |

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| 2017 | Optic Disc Detection Using Vessel Characteristics and Disc Features[24] | Uses disc features and vessel features to detect the optic disc | Uses two main approaches to detect the optic disc:<br>1. Parabola fitting to the segmented vascular structure. Uses K-means clustering to get the best three clusters considering all the three points in the intersection.<br>2. Circular template-based Intensity matching. | The proposed algorithm is evaluated on six datasets.<br>(1.) DRIVE:100<br>(2.) DRIONS:100<br>(3.) STARE:100<br>(4.) DIARETDB:99.2<br>(5.) DIARETDB1:100<br>(6.)MESSIDOR:99.42 | Constructed a feature set of vessel densities along with maximum intensity windows along horizontal and vertical dimension. There might be a case where a particular region fails for a feature set, but it will surely work for another feature set. Thus, these feature sets contain all the characteristics of OD region and hence gives best possible performance in all conditions. |
| 2018 | Optic disc segmentation from retinal fundus Images via Deep object Detection Networks.[25] | Uses retinal fundus Images for optic disc segmentation. | Uses Faster R- CNN as the object detector, this method achieves state-of-the-art OD segmentation results on ORIGA dataset, outperforming existing methods in this field. | Methods Used on Orignma Dataset: MCV 87.1<br>ASM 88.7<br>EHT 89.7<br>MDM 89.2<br>SP+ASM 90.5<br>SDM [ 91.1<br>U-Net 88.5<br>M-Net 92.9 | In this paper, the optic disc segmentation problem is been redefined as an object detection problem, and then proposes a new pipeline to segment OD from retinal fundus images using Faster R-CNN as the object detector. |

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| 2018 | An automated region-of-interest Segmentation for Optic Disc Extraction.[26] | Optic disc segmentation for the retinal fundus images. | Uses the<br>techniques such as Fuzzy c-means and Hough Transform.<br>Fuzzy. Here the c-means binarization technique is used as pre-processing for the Hough transform algorithm. Hough transform then detects the optic disc. | Methods Used On the Dataset:<br>ORIGA :96%<br>DRIVE:100%<br>DRISHTI-GS:100%<br>DiaRetDB1:78.38% | In this paper we present an automated for the Region— Interest segmentation of optic disc detection in retinal images.<br>Their segmentation technique reduces the processing area required for optic disc segmentation techniques leading to notable performance enhancement and reducing the amount of the required enhancement and reducing the amount of the required computational cost for each retinal image. |

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| 2019 | An Automated method of Optic Disc Detection from Retinal Fundus Images.[27] | Localisation of optic disc and segmentation of its boundary. | Used techniques in this is Fuzzy C Means clustering and ellipse fitting. The fuzzy C means is used to perform the segmentation fo OD from ROI and using ellipse<br><br>fitting the boundary points are drawn. | The proposed method is used on the following datasets with their accuracy ratios respectively:<br><br>DIARETDB1:88.08%<br>DRIONS-DB:90.67%<br>MESSIDOR:90.00% | A method to detect OD based on Fuzzy C Means clustering and ellipse fitting is proposed in this paper. Morphological operations are performed on fundus image to remove the gaps within OD region for correct segmentation. A brightest portion of the V component in HSV converted image is used to localize the OD and 250×250 size Region of Interest (ROI) matrix is extracted. The Fuzzy C Means (FCM) clustering is used to perform the segmentation of OD from ROI. |

## 3. CONCLUSIONS

In this literature survey various methodologies for locating optic disc in retinal images are discussed. Here we have studied recent literature which utilizes different machine learning and deep learning techniques. Deep learning-based object detection algorithms have been proved reliable and provide state-of-the-art results. The architecture of these algorithms can be further modified to obtain optimized processing speed and computational power usage for set of objects. These improvements can influence and accelerate the implementation of these methods in real-world application and screening systems.

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