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A Study on Current Optic Disc Detection Methods

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ABSTRACT

Optic Disc (OD) detection is a main pre-processing step in many algorithms designed for automatic extraction of retinal anatomical structures and lesions. The optic disc localization will help to differentiate the disc from other features of the retina. Its detection is a the primary step for the identifying normal and pathological features and for detecting diseases like Diabetic retinopathy and glaucoma. Reliable and efficient OD localization is significant tasks in ophthalmic-image processing. The main objective of this paper is to study current Optic Disc detection methods and techniques. We have provided a brief description of each technique. The current challenges and limitation relevant to the detection of optic disc detection were highlighted.

Keywords: Optic Disc Detection, Ophthalmic image processing

1. INTRODUCTION

One of the main parts of the human eye is optic disc (OD). Light received by the human eye, is carried through the optic nerve to the brain. Ganglion cell axons leave the eye from the optic disc. Due to the absence of rods or cones, optic disc corresponds to a small physiological blind spot in each eye. At this point, light sensitive rods are absent, which results in a break in the field of vision. The Fig.1 shows different parts of the human eye. In a normal human eye 1 to 1.2 million neurons were carried by the optic disc from the eye to the brain. The OD appears as an oval shape, and it is brighter than neighboring as shown in Fig.2

The change in shape and size of optic disc results in ophthalmic diseases like glaucoma, diabetic retinopathy, and hypertension, etc. These diseases result in visual impairment in early stage and in a later

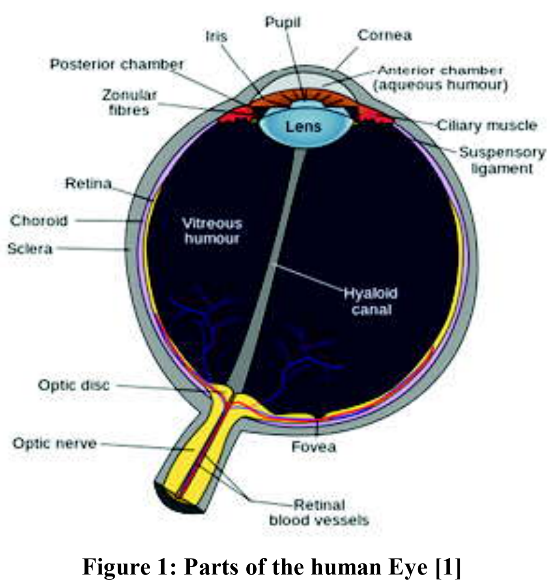

Figure 1: Parts of the human Eye [1]

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stage, blindness. The few causes these problems are aging, obesity, etc. Early diagnosis and proper treatment are needed to avoid visual impairment and blindness [3].

OD segmentation is one of the main subproblems in ophthalmic-image processing. This is the main step in classifying other fundus structures [4]. The optic disc has a bright yellowish color with a whitish central cupping. From this cupping the central retinal artery and vein pass. Location of OD can be used for vessel tracking and for registering changes within the OD region. OD localizing is essential for identification of some diagnostic marks for hypertensive retinopathy. OD detection also useful in the diagnosis of glaucoma.

Optic disc detection is a fundamental step for the diagnosis of other normal and pathological features. For instance, in macula recognition, optic disc position plays an important role. The performance of diabetic maculopathy lesion detection can be improved by masking the false positive OD region. In glaucoma detection, the measurement of varying OD to cup diameter ratio is used. Vessel tracking methods start from the optic disc. For registration of multimodal or temporal image, OD acts as the main feature. In this paper, we are addressing current optic disc detection techniques. We provide a brief description of each optic disc detection technique, highlighting its techniques and performance metrics. The paper is organized into four sections. In Section II we describe brief introduction about the retinal image processing which includes Fundus photography, retina dataset, and performance metrics of OD segmentation. In Section III, discusses the various optic disc segmentation methods and in Section IV gives an insight about the limitations and challenges.

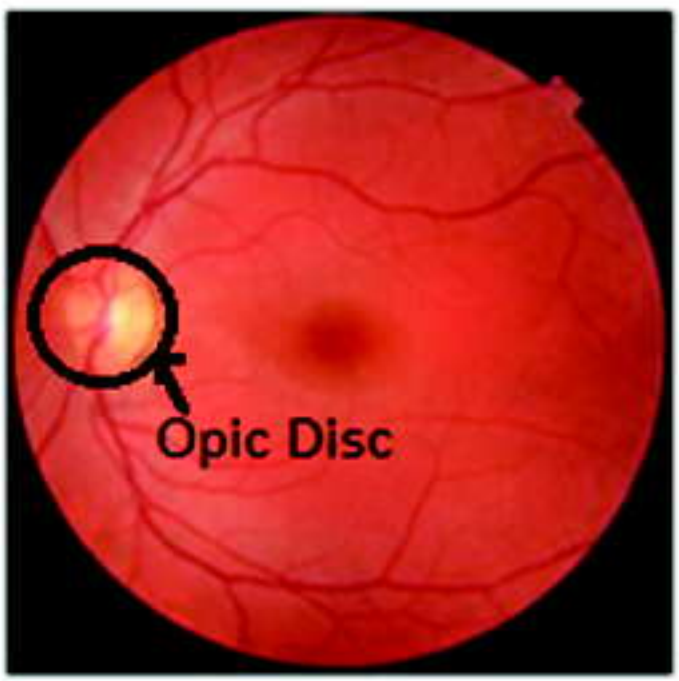

Figure 2: Digital fundus image of the human eye [2]

2. RETINAL IMAGE PROCESSING

2.1. Fundus photography

In this photos are taken off the back of eyes. In fundus photography, particular fundus cameras with an intricate microscope attached are used. The optic disc, central and peripheral retina, and macula are structures that can be visualized on a fundus photo. Fundus photography can be executed with specialized dyes, or colored filters [5]. There are three main modes of examination 1. Color, where the retina is illuminated by white light and examined in full-color 2.Red free fundus photography uses a filter so as to observe superficial lesions and other abnormalities within the retina and surrounding tissue 3. In

Angiography a fluorescent dye is injected into the blood stream for recording vascular flow within the retina and surrounding [6].

2.2. Publicly Available Retinal Image Datasets

Most of the retinal optic disc segmentation methodologies presented in this survey are tested on various publicly available datasets, for example, DRIVE, STARE, MESSIDOR, and INSPIRE. In this section, we provide a brief summary of some retinal datasets.

DRIVE Dataset. The Digital Retinal Images for Vessel Extraction (DRIVE) dataset [7] consists of 40 color fundus images. The images were acquired from a diabetic retinopathy research program in the Netherlands. Seven images of the dataset have pathology. The Canon CR5 non-mydriatic 3CCD camera is used for capturing the images. It a 45-degree field of view (FOV). Each image was captured using 8 bits per color plane at 768 by 584 pixels. The field of vision is circular with a diameter of nearly 540 pixels. For this database, the images have been cropped near the field of vision. In total there are 40 images, 20 tests and 20 training images.

STARE Dataset. The Structured Analysis of Retina (STARE) dataset [8] is funded by the US National Institutes of Health. The project has 400 fundus images. Each image is the diagnosis. The blood vessels are annotated in 40 images. The Optic nerve head (ONH) is localized in 80 images. A Top Con TRV-50 fundus camera with a 35p field of view was used to capture the images.

MESSIDOR Dataset. MESSIDOR [9] contains 1200 images in two sets; the images were captured in three ophthalmological departments by a research program sponsored by the French Ministries of Research and Defense. Two diagnoses are provided by the medical experts for each image, retinopathy grade, and risk of macular edema. A color video 3CCD camera on a Topcon TRC NW6 nonmydriatic retinography with a 45p field of view was used to capture the images. The images are saved in uncompressed TIFF format.

DIARETDB0 Dataset. The Standard Diabetic Retinopathy Database Calibration level 0 DIARETDB0 [10] consists of 130 color fundus images, 20 normal and 110 with signs of diabetic retinopathy, acquired from the Kuopio University Hospital in Finland. The images were captured by a digital fundus camera with 50p field of view.

DIARETDB1 Dataset. The diabetic retinopathy database and evaluation protocol DIARETDB1 [11] consists of 89 color fundus images acquired from the Kuopio University Hospital in Finland. The dataset consists of 84 images with diabetic retinopathy and 4 normal images. The images were captured by a digital fundus camera with 50p field of view. Four experts annotated the microaneurysms, hemorrhages, and hard and soft exudates.

INSPIRE Dataset. INSPIRE is a Iowa Normative Set for Processing Images of the retina [12]. INSPIRE-AVR consists of 40 color images of the vessels and optic disc and an arterio-venous ratio reference standard. The reference standard is the average of the assessment of two experts using IVAN (a semi-automated computer program developed by the University of Wisconsin, Madison,WI, USA) on the images.

DRIONS-DB. Digital Retinal Images for Optic Nerve Segmentation Database. This is a public database for benchmarking ONH segmentation from digital retinal images. The database consists of 110 color digital retinal images belonging to the Ophthalmology Service at Miguel Servet Hospital, Saragossa (Spain). The color analogical fundus camera is nearly centered on the Optic nerve head to get the images. The images were stored in slide format. The images were digitized using an HP-PhotoSmart-S20 high-resolution scanner, RGB format, resolution 600x400 and 8 bits/pixel.

Local Dataset. Many papers used local dataset along with the standard datasets available. Table 1 provides a summary of the datasets discussed here.

2.3. Process of optic disc detection

The process for optic disc detection is commonly divided into four steps. First, is the preprocessing stage, here noise removal, color space conversion etc. tasks are performed on input image so as to make image ready for processing. Second is processing stage in this, steps are carried out for optic disc detection. The third is optic disc detection, here post processing for ex, the morphological operation is performed if required to exactly detect optic disc. In fourth step result analysis is done by using performance measure (discussed in next section).

2.4. Performance Metrics

The outcome of optic disc segmentation process is divided into the three distinctive areas, 1) the true positive (TP) area representing the overlapping area between the manually marked (ground truth) and automatically marked areas, 2) the false negative (FN) area where a pixel is categarize only in the manually marked area, and 3) the false positive (FP) area where the pixel is classified only in the automatically segmented area. A higher sensitivity value implies a higher validity of results [13].

$$\textit{Specificity (SP)} = TN/TN + FP \tag{1}$$

$$\textit{Sensitivity (SN)} = TP/TP + FN \tag{2}$$

$$\textit{Accuracy (ACC)} = TP + TN/TP + FP + FN + TN \tag{3}$$

Sensitivity Eq.2. is the probability of an abnormal class to be identified as abnormal. Specificity Eq.1. is the probability of a normal class to be identified as normal. Accuracy Eq.3. represents the ability or quality of the performance.

3. OPTIC DISC DETECTION METHODS

The Optic Disc detection techniques are discussed below. We demonstrated the methodology by creating a flowchart for each technique. Kittipol Wisaeng [14], proposed an algorithm for OD segmentation. The system description is depicted in the flowchart shown in figure 3. where histogram specification is applied after normalizing the color of the retinal images. The contrast enhancement is done between the OD and the retina background to increase the likelihood of optic disc detection. A median filtering is applied to the intensity band. Finally, original retinal image (RGB space) is transformed to LUV color space. After transformation, a morphology methods and Otsu's algorithms is used. The morphological closing operation is applied on intensity channel of gray scale image. This is required to eliminate blood vessels and to create a constant optic disc region. Global image threshold is carried out using Otsu's method. The result of retinal image is binarized with thresholding. The accuracy result reported, is of 91.35% for STARE dataset and with an accuracy of 97.61% for the local dataset.

Table 1
Summary of fundus retinal images datasets

Dataset Name	*Camera used*	*FOA(Field Of View)*	*No. of images*	*Country*
DRIVE [7]	Canon CR5 non-mydriatic 3CCD	45p	40	Netherlands
STARE [8]	Top Con TRV-50	35p	400	U.S.
MESSIDOR [9]	Top Con TRC NW6 3CCD	45p	1200	France
DIARETDB0 [10]	Digtal Fundus Camera	50p	130	Finland
DIARETDB0 [11]	Digtal Fundus Camera	50p	89	Finland
DRIONS-DB []	Colour analogical fundus camera	-	110	Spain
INSPIRE [12]	-	-	40	U.S.A

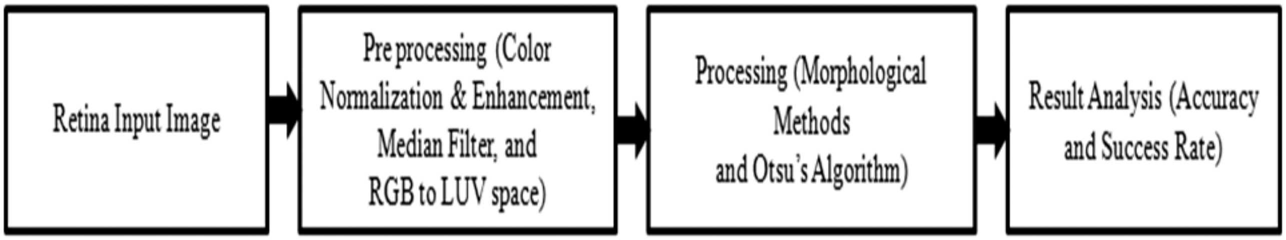

Figure 3: Flowchart for algorithm in [14]

Noor Elaiza Abdul Khalid [15] proposed a method for OD and optic cup (OC) segmentation as shown in Figure 4. The region of interest ROI (OD and OC) cropping and color channel analysis is carried out. Then, fundus images are used to determine the min, mean and max values for the color channel analysis. The fundus images are filtered using the green channel due to its good contrast than another color channel. Dilation and erosion morphological operation are used to erase the blood vessel inside the OD and smooth the intensity profiles around the center of the optic disc. Fuzzy c-Means (FCM) used due to its accuracy in segmentation in the presence of intensity in homogeneities and can directly substitute into current methodologies that required hard segmentation, soft segmentations, gain field estimates, or in homogeneity corrected images. In this algorithm, membership is assigned based on the distance between the cluster center and the pixel. If a pixel is near to cluster center, then it's membership is higher. Reported accuracy here is 93.70%.

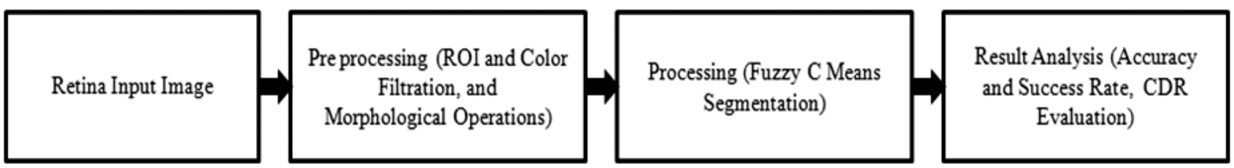

Figure 4: Flowchart for algorithm in [15]

Nilima K and Amudha J [16], investigate the use of computational saliency model for OD detection in retinal images. Flowchart of the system is shown in figure 5. The dataset used here is a subset of the STARE Project's dataset [8]. The subset used consists of eighty-one retinal images. Computational bottom-up saliency model Itti and Koch (IK) [17] is used. This IK model performs well for the focused attention stage of visual attention and predicting human fixation points. IK model computes saliency map using a set of basic image features at multiple scales. The morphological opening operator is performed on the original image as a pre-processing step. This is required before using IK model for computing saliency map. In the second step, saliency map is computed using IK model on the images obtained in a pre-processing step. Binary segmentation performed. A threshold is applied to saliency map. This thresholding is based on Otsu's algorithm. This paper addresses the relevance of saliency models in detecting Optic disc. The major advantage of the work is its indication of using computational models for detecting the OD in retinal images. Success rate reported is 72.83%.

Arif Muntasa [18], propose a hybrid method for the optic disc detection in the retinal image. The procedure depicted in Figure 6. Blood vessels are filtered from retinal images using homomorphic and median filtering. Canny detection algorithm used for edge detection since it is an optimal edge detection

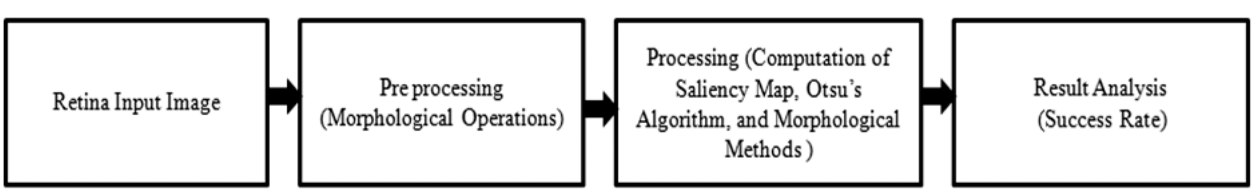

Figure 5: Flowchart for algorithm in [16]

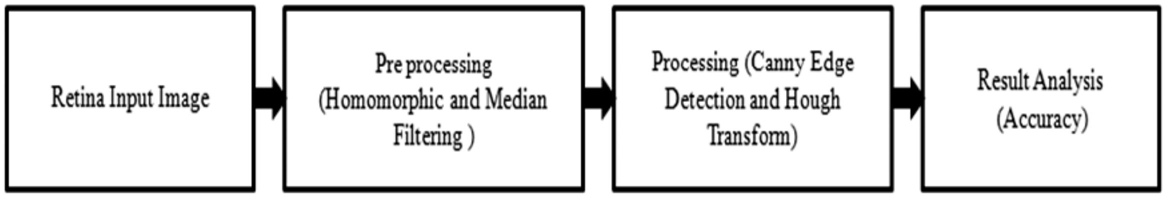

Figure 6: Flowchart for algorithm in [18]

algorithm [19]. To find circular shape in the image, the edge of the retinal image were extracted. Optic disc detection is carried out using Hough transform. Forty retinal images from INSPIRE dataset [12] are used for the experiment in this research. The balanced accuracy reported for this detection process is 81.6018%.

G. G. Rajput [20], presents an method for identification of optic disc in fundus retinal images as shown in figure 7. The candidate OD regions were identified using mathematical morphology operations. After this center and circular optic disc boundary is identified using the circular model. In the output image region, minima are represented by white pixels. A structuring element of size 50 in morphological operation is used to remove irrelevant regions. This method was evaluated on a public database, MESSIDOR. An average overlapping between the "true" OD region is compared with the one segmented by aforementioned OD segmentation approach is 99.47% with success rate of 93%.

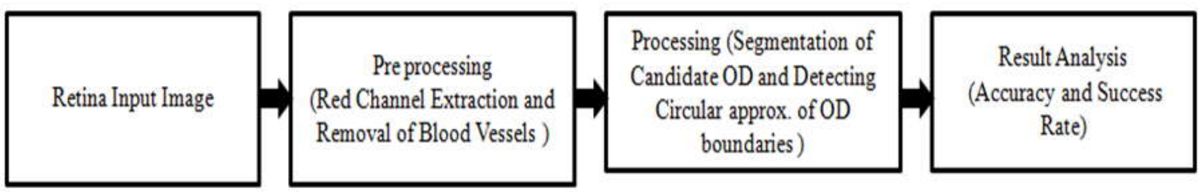

Figure 7: Flowchart for algorithm in [20]

Manish [21], proposed a procedure for detection of optic disc in fundus images as shown in Figure 8. A KL divergence matching technique and vessel detection is used. OD is selected after reducing the effect of noise. This image is named as a template image. For training 10 images are used. These template's images used to get optic disc images. Histogram of these template's images is calculated. Then it is used for histogram matching. The algorithm proposed here was tested on 60 images from DRIVE data set and 20 images from STARE database. For histogram matching, KL divergence is used. KL divergence [22] method is used to calculate the distance between the template and moving histogram. This algorithm gives 100% accuracy for DRIVE database and 90% accuracy for STARE database.

Niluthpol [23], proposes an algorithm to automatically detect OD and blood vessel of retinal image as shown in fig.9. Steps include, preprocessing is carried out by Global Thresholding. A global threshold is determined by using Otsu method [24]. Most of the bright pixels are in the OD, for a normal image. Morphological operations are used to obtain complete OD region. The features used for extraction are, area, the ratio of the major axis and a minor axis, the length of the major axis and minor axis are used. Blob test is used to obtain these features; with this Compactness, features are extracted. This sub-image of OD is taken from the blue plane of the image. Small noises removal is done with a median filter. Then a sub-

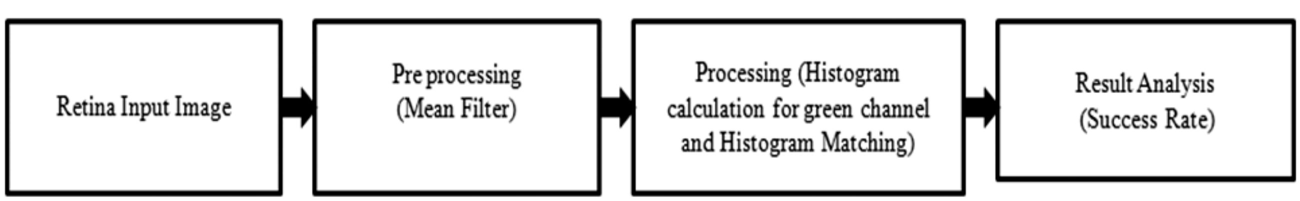

Figure 8: Flowchart for algorithm in [21]

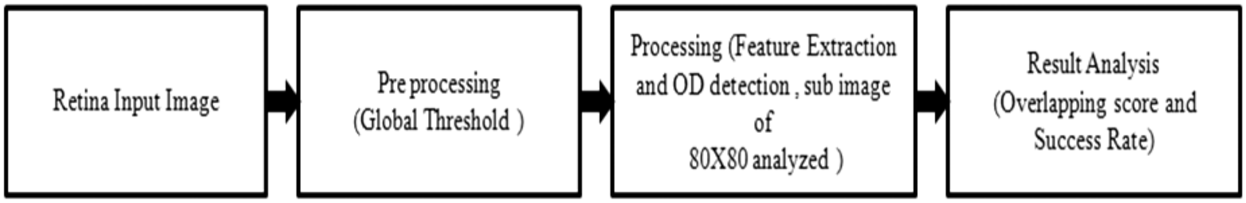

Figure 9: Flowchart for algorithm in [23]

image is divided into smaller non-overlapping blocks and is analyzed. The mean pixel area is calculated. The image is changed to binary image with the white region is those regions that have an area more than the mean and the other regions are converted into the black. The bounding box is used for calculation of the center and radius of the circle. Here the DRIVE [7] and STARE [8] datasets are used. Performance is measured using the degree of overlap between the true OD. Here the calculated degree greater than 0.75, is considered as successfully identified. 100% accuracy is reported, for well captured images.

Snehal [4], presents optic disc detection using Principal Component Analysis (PCA), Mathematical Morphology and Circular Hough Transform. The flowchart is shown in fig.10. Here MESSIDOR [9] database is used. RGB image converted to a grayscale image. PCA is used which helps to identify patterns in data. These identified patterns than can be used for reducing its dimensions. In this method, 3 principal components of the image were calculated. To remove blood Vessels, mathematical morphology operations were used. Closing operation is used for filling vassals. The Circular patterns are detected using circular hough transform. Set of images from MESSIDOR databases were used in this paper. This method able to segment OD properly for a subset of images. All OD segmentation methods discussed above are summarized in Table 2.

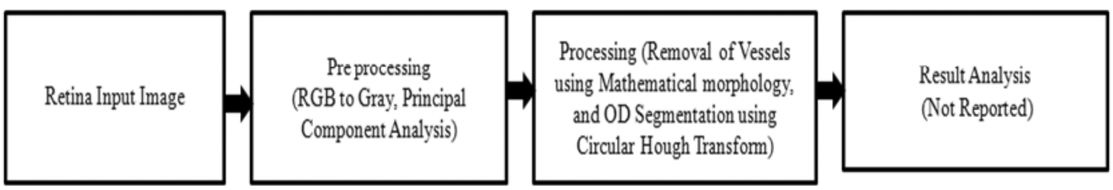

Figure 10: Flowchart for algorithm in [4]

Dehghani and colleagues [25] proposed a novel technique that uses histogram matching for localizing the OD and its center in the presence of pathological regions as shown in figure 11. Four retinal images from the DRIVE data set were used to create three histograms from the color image components (red, blue, and green) as a template. Noise from the image is reduced using an average filter. The next step included extracting the OD for each retinal image using a window with a usual size of the OD. Then a template was created by obtaining a histogram for each color component for each OD and calculating the mean of the aforementioned histograms. To reduce the effect of pathological regions with high intensity, the histograms with the intensity of lower than 200 were used. The correlation between the histograms of each channel was calculated in order to gain the similarity of two histograms. Finally, thresholding was applied to the correlation function to localize the center of the OD. The methodology was applied on three datasets: 40 images from DRIVE, 273 images from a local dataset, and 81 images from STARE. The success rates were 100%, 98.9%, and 91.36% for the datasets, respectively.

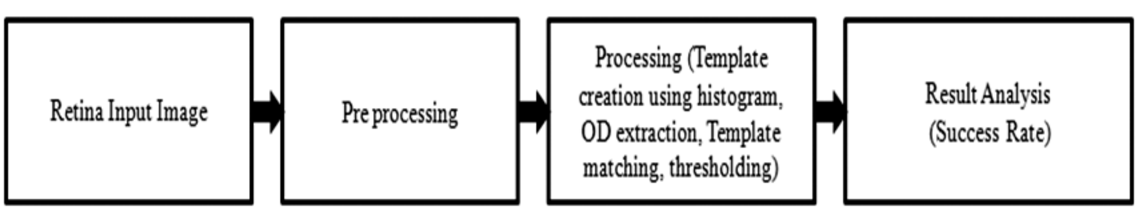

Figure 11: Flowchart for algorithm in [25]

Fraga et al. [26] presented a methodology for the OD segmentation containing different stages as shown in figure 12. In order to decrease the contrast variability and increase the process reliability, the retinal image was normalized by means of the retinex algorithm [27]. Two different techniques were used to localize the optic disc: (1) analyzing the convergence of the vessels [28] to detect the circular bright shapes and (2) detecting the brightest circular area based on a fuzzy Hough transform [29]. After detecting the OD, the segmentation techniques were conducted using the region of interest specified by a difference in Gaussian filter. The vessel tree boundaries were segmented by Canny filter to compute the edges. The vessels edges from the Canny output were suppressed using the vessel tree segmentation. Finally, the histogram information was included to measure the accuracy of segmentation. The methodology was evaluated on 120 images from the VARIA dataset. The method achieved 100% of OD localization for both fuzzy convergence and Hough transform. Using brute force search, the segmentation success rates were 92.23% and 93.36% for the fuzzy convergence and the Hough transform, respectively.

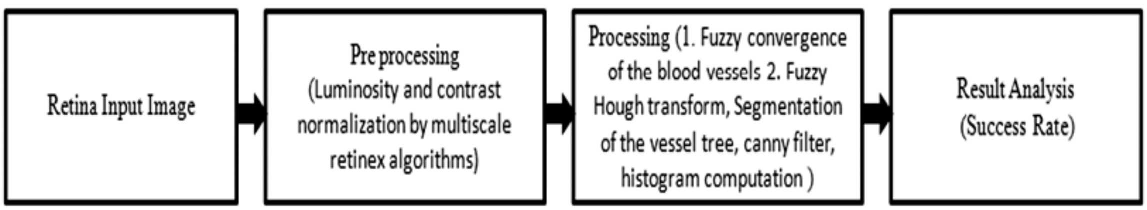

Figure 12: Flowchart for algorithm in [26]

Tjandrasa and colleagues [30] applied the Hough transform as an initial level set for the active contours for optic disc segmentation as shown in figure 13. The OD segmentation steps start by converting the image to a grayscale image and then implementing the image preprocessing (image enhancement). Therefore, homomorphic filtering is applied to reduce the effect of uneven illumination. Homomorphic filtering has two stages: (1) applying a Gaussian low pass filter, (2) obtaining the filtered edge by performing dilation. The blood vessels are removed in the next step to make the segmentation process easy. The threshold is applied to detect the low pixel values in the image and followed by applying the median filter to blur the blood vessels. The next step in OD segmentation is detecting a circle which matched the location of OD by performing a Hough transform. Subsequent to this, an active contour model is used to obtain the OD boundaries that are as close to the original OD boundaries as possible. The active contour model is applied with a special processing termed Selective Binary and Gaussian Filtering Regularized Level Set (SBGFRLS) [31]. The algorithm achieved 75.56% of accuracy using 30 images from DRIVE dataset.

Deepali Godse [32] proposed an method to identify an optic disc and its center in fundus retinal images. The flowchart is shown in figure 14. Thresholding is used to find out candidate regions. Density criterion is applied to find out OD region. The technique has been developed and tested on standard databases like Diaretdb0 (130 images), Diaretdb1 (89 images), Drive (40 images) and local database (194 images). It is able to identify optic disc and its center in 98.45% of all tested cases.

Ana Maria Mendonc et. Al [33] uses blood vessel network and intensity data to locate the OD as shown in figure 15. The entropy of vascular directions is used to quantify vessel orientation about an image point.

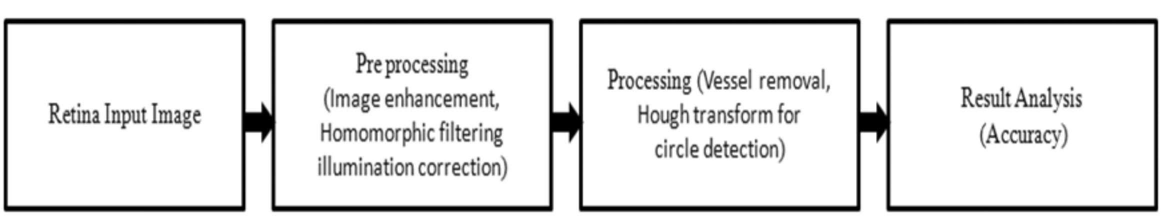

Figure 13: Flowchart for algorithm in [30]

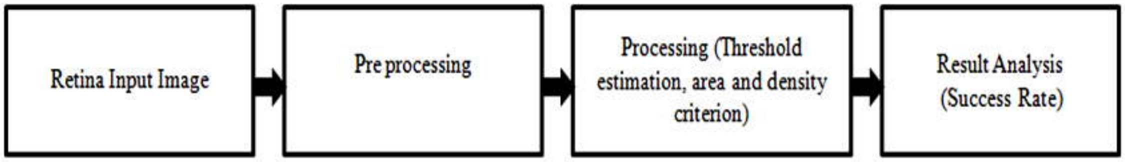

Figure 14: Flowchart for algorithm in [32]

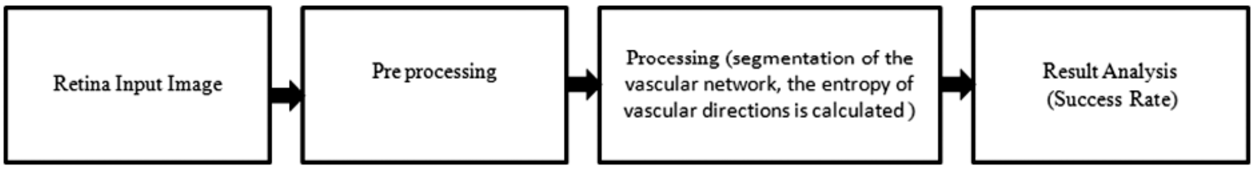

Figure 15: Flowchart for algorithm in [33]

To compute the occurrence and the diversity of vessel orientations around a point, the entropy of vascular directions is used. A map for entropy of vascular directions is computed, after the segmentation of the vascular network. The intensity map showing the Euclidean distance is calculated. The red and green channels of the RGB fundus retinal image is used for distance calculation. The OD candidate regions were generated from this map by considering only pixels with the largest distance. The place where the maximum value of entropy present is the initial OD candidate region. This method was able to identify OD in 1357 out of the 1361 images of the four data sets.

Shijian Lu, [34] proposed technique, the flow chart shown in figure 16. It uses the circular bright format, usually identified with optic disc. Because the optic disc is circular and brighter region, then the surroundings. Its intensity constantly darker as distance from optic disc increases. A line operator is used to get this circular brightness format. The line operator calculates, brightness variations along the multiple lines. To detect the optic disc a specific pattern of the orientation of the line segment with the minimum/maximum variation is used. All these methods are summarized in Table 1 below.

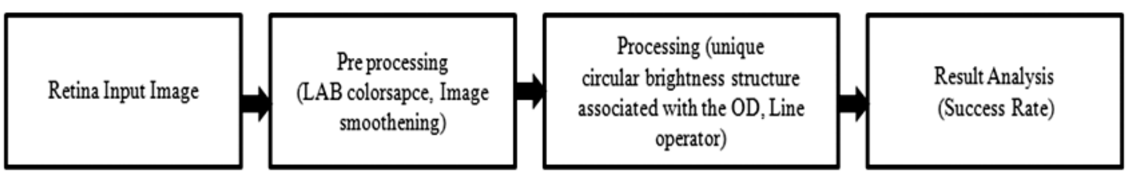

Figure 16: Flowchart for algorithm in [34]

Table 2
Optic Disc detection methods

Authors	*Year*	*Image processing technique*	*Performance metrics*	*Dataset Number ofimages*	*Result*
Kittipol Wisaeng	2014	Morphology method and Otsu’s method	Success rate	STARE 81local dataset 42	91.35% 97.61%
Noor Elaiza Abdul Khalid et.al.	2014	Erosion and Dilation with Fuzzy c-Means (FCM)	Accuracy	27High-resolution fundus images	93.70 %
Nilima Kulkarni, Amudha J	2014	Saliency Model and morphology Operations, Otsu’s method	Success rate	STARE 81	72.83%

(*contd...Table 2*)

Authors	*Year*	*Image processing technique*	*Performance metrics*	*Dataset Number ofimages*	*Result*
Arif Muntasa et.al.	2015	Homomorphic and median filtering andHough transform	Balanced accuracy	INSPIRE 40	81.6018%
G.G. Rajput et. Al.	2015	Mathematical morphology	Overlapping score Success rate	MESSIDOR 100	99.47% 93%
Manish et. al.	2015	Histogram Matching	Success rate	DRIVE 40 STARE 20	100% 90%
Niluthpol et. al.	2014	Morphological,Edge Detection and Feature Extraction	Success rate	DRIVE 40 STARE 81	100% 91.3%
Snehal et. al.	2014	PCA, Mathematical Morphology and Circular Hough T.	-	MESSIDOR(subset)	-
Deepali et al.	2013	Thresholding, area estimation Hough transform	Success rate	DirectDB0 130 DirectDB1 89 Drive 40 Local	96.12% 96.12% 100 % 100%
Dehghani et Al.	2012	Histogram matching	Success rate	DRIVE 40 STARE 81 Local 237	100% 91% 98.9%
Fraga et al.	2012	Fuzzy convergence and hough transform	Success rate Accuracy	VARIA 120	100% 93.36%
Tjandrasa et al.	2012	Hough transform and active contours	Accuracy	DRIVE 30	75.56%
Ana Maria Mendonc et. al.	2013	Entropy of vascular directions and search for maximal values of entropy	Success rate	DRIVE 40 STARE 81 MESSIDOR 1200	100% 98.8% 99.8%
Shijian Lu et. al.	2011	Line operator, circular brightness structure	Success rate	DIARETDB0 130 DIARETDB1 89 DRIVE 40 STARE 81	96.3%

4. CONCLUSION

We have provided a focus on current Optic Disc detection techniques. The preprocessing step used in most of the algorithms is necessary to enhance the optic disc region and thereby improving results. Almost all the discussed algorithms above are based on the image processing techniques. Also, most of the current methods have been tested on a limited number of datasets such as DRIVE and STARE. The algorithms performed differently depending on the datasets of images. Some approaches used a small data set, while some used large data sets to train and test the algorithm. Many methods were tested only on normal retinal images. Most of the OD detection methods were based on the circular Hough transform. The retinal images used to evaluate OD detection methods mostly have been taken from adults. The retinas of infants, babies, and children have different morphological characteristics than that of adults, and this difference must be considered. The evaluation metrics haven't been addressed completely in all of these methods. Many papers used local datasets for method evaluation. Therefore, the corresponding methods cannot be compared with other methods those using standard data sets. Similarly, ground truths given by experts vary according to the level of expertise.

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