Review Paper

A Review on the optic disc and optic cup segmentation and classification approaches over retinal fundus images for detection of glaucoma

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Abstract

Glaucoma is one of the leading severe retinal disease which damages the optic nerve head on the retinal part of the eye irreversibly. Once the person is diagnosed with glaucoma, it cannot be treated entirely, but it can be controlled. If glaucoma is not diagnosed in time, it will lead to vision loss by damaging the Optic Nerve Head. The glaucoma detection is performed based on the optic disc and optic cup parameters on the retinal part of the eye. In the existing system, many image processing and machine learning techniques used for the segmentation and classification of optic disc and optic cup. To improve the precision of diagnosis, the existing techniques used need an improvement. This article helps readers with more information about the existing methods applied for the diagnosis of glaucoma, it also lists the research gaps and technical challenges to improve the accuracy of segmentation and classification methods.

Keywords Intraocular pressure (IOP) · Optic disc (OD) · Optic cup (OC) · Optic nerve head (ONH) · Convolutional neural network (CNN)

1 Introduction

Medical imaging is a process of creating images of internal parts of the human body for medical diagnosis. The internal structure of the body can be easily visualized with medical images. Many recordings and measurement techniques are used to produce images. Computer vision techniques and medical analysis concepts are designed to provide medical image data. It is extended to all fields of medical science, especially to Ophthalmology.

Ophthalmology [1] is a medical branch in which it deals with diagnosis and treatment of eye disorder. There are many retinal diseases, such as glaucoma, diabetic retinopathy, cataracts, etc. From the past 15 years, various techniques for the automatic detection of glaucoma are developed but these methods need an improvement.

1.1 Retinal fundus images

The human eye is an essential organ in the human body in which allows vision. The human eye is capable to differentiate more than 10 million colors, enables depth perception. It is composed of two segments, namely the anterior segment and the posterior segment. The anterior segment consists of iris, cornea, and lens. The posterior segments composed of retina, vitreous, choroid, and sclera. The area where the connection between sclera and cornea is the limbus. The central part of the eye is called the pupil and which is surrounded by a pigmented circular area called iris. Figure 1 [2] shows the anatomical structure of the human eye.

The fundus camera is used to capture the retinal images, and these images are called fundus images. These images help doctors to quickly diagnose most varieties of

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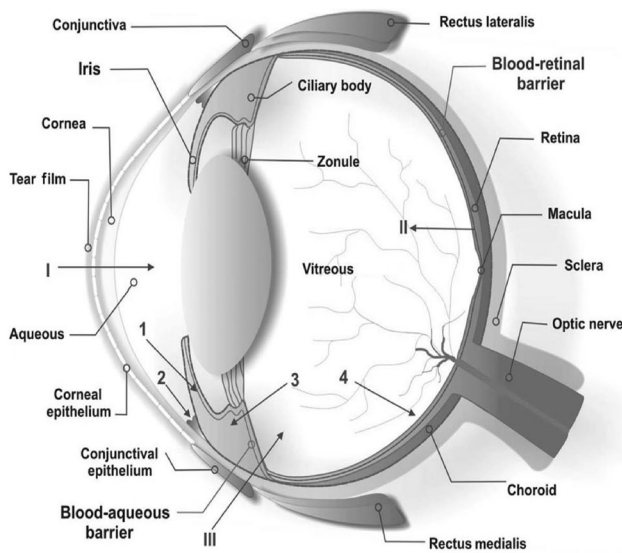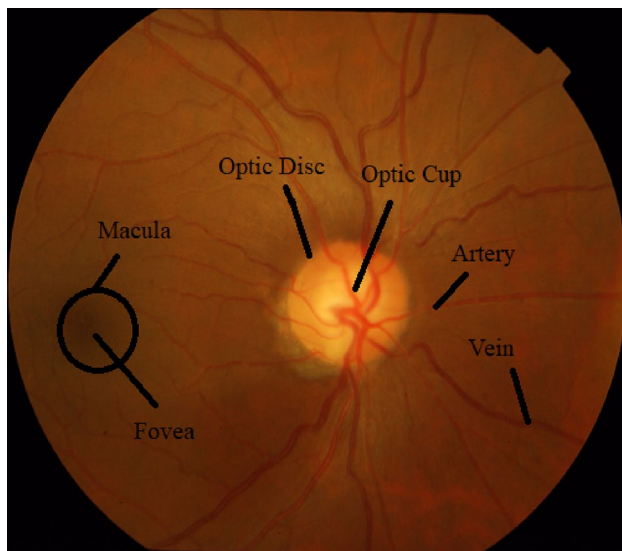
Fig. 1 Structure of the human eye

Fig. 2 Structure of retina

eye diseases which occur on the retina. The various eye diseases like glaucoma, maculopathy, retinopathy, etc. can be easily measured. Figure 2 represents the Structure of Retina and its main components. There are different retinal features like an optic disc, optic cup, fovea, macula, exudates, etc. These features vary from person to person. Mainly glaucoma will be identified by measuring the retinal part of optic disc and optic cup.

Optic disc [3, 4] is the bright yellow part of the retina containing more neurons. The shape slightly looks like circular, but it varies from person to person. It is also named as blind spot because it does not provide the color-attiring photoreceptors such as rods and cones. Optic Cup is the

bright central part of the optic disc and which is an essential parameter for detecting glaucoma. Compared to the optic disc, the optic cup is smaller in size. For a healthy patient, the optic cup shape is one-third of the optic disc. If the size of the optic cup increases than the standard size, it leads to glaucoma.

The macula is the central part of the retina. Which is approximately yellow, and the size is 5.5 mm. It receives images and light signals. The macula is a very delicate region in which many photoreceptor cells used to get color and subtle details. Due to degeneration, infection, vascular trauma, and inflammatory problems, the macula may get affected. The fovea is the central part of the macula, and it does not contain any blood vessels. It is a minimal area, and the diameter is approximately 1.5 mm. The fovea helps to give a central vision for the human eye, which is dark brown or red, and it is the dark part of the retina. Exudates are one of the features of the retina, which forms due to the leakage of the arteries and veins. It is a bright patch form of the retina, and the appearance is yellow-white.

1.2 Main contribution of this paper

There are many survey papers till date, which gives information about the optic disc and optic cup segmentation and classification techniques used for the diagnosis of glaucoma. But in most of the existing survey papers, we get the information about image processing techniques applied for both segmentation and classification approaches, and also there are only a few survey papers that are particular about the optic disc, optic cup segmentation and classification process. In the current system, there is an automatic and early detection of glaucoma to make the system faster. Hence, in recent years most of the researchers applying machine learning and deep learning techniques to make the decision-making system. In this paper, all the existing till date published articles including both image processing and deep learning techniques applied for fundus image segmentation and classification methodologies are collected from multiple resources. This article helps to compare the image processing and deep learning technique by performance metrics. Hence, this paper promotes the researcher to improve performance.

The paper contains eight sections. Section 2 describes detail description and various types of glaucoma. Section 3 contains the information about various publicly available database, Sect. 4 describes different types of parameters used to detect the OD and OC, Sect. 5 contains the related works to find disc and cup, Sect. 6 describes the performance metrics used for checking the performance of the method applied, Sect. 7 describes the research gaps that

are identified after the survey and final section concludes the findings.

2 A brief overview of glaucoma

Glaucoma is a significant eye disease that occurs on the retina of the eye, and it is the second-largest eye disease in the world which causes blindness. The optic nerve connects to the brain and it helps to scan the images from the eye. The glaucoma damages to these optic nerves. If glaucoma is not detected in the early stage, it leads to vision loss. The regular eye check-up is the only precautionary measure to avoid glaucoma. Mainly glaucoma occurs due to the Intraocular Pressure (IOP) [5, 6] on the eye. Intraocular pressure is the high pressure on the eye; due to this, more fluid is produced on the eye, leading to the blockage on the eye's channel. Due to this, the optic nerve gets damaged and it gives rise to glaucoma.

Some standard tests like Tonometry, Ophthalmoscopy, Perimetry, Pachymetry, etc., are used for glaucoma detection. The pressure that occurs within the eye is diagnosed by conducting tonometry, and the device is called a tonometer. If the value is more than 21 mm Hg, it will be classified as glaucoma. In Ophthalmoscopy, the doctors detect any damage to the Color and Shape of the optic nerve. Perimetry helps to find the range of pressure inside the eye. Based on the cornea's thickness, the shape and color of the optic nerve is detected by the Pachymetry test.

Mainly glaucoma is classified into three types (1) Open Angle Glaucoma (2) Closed Angle Glaucoma and (3) Normal-tension Glaucoma.

2.1 Open angle glaucoma

It is a major and most common type of glaucoma. In this case, there are no early symptoms or early warning signs. During the initial stages, it isn't easy to identify. The people who are suffering from open-angle glaucoma will feel normal in the beginning stages. Once they lose the vision, the doctors will come to know that the person is suffering from glaucoma. Out of all glaucoma cases, 90% of cases suffering from this type of glaucoma.

In the case of open-angle glaucoma, the produced eye fluid will not be drained clearly in the drainage canals. The liquid will be slowly blocked and resulting in slow fluid flow through the drainage canals. Due to this, the intraocular pressure on the eye increases, causing the optic nerve to get damaged. In this case, a wide-angle will be developed between the cornea and iris. If the blockage occurs beyond or somewhere inside the drainage canals, it will
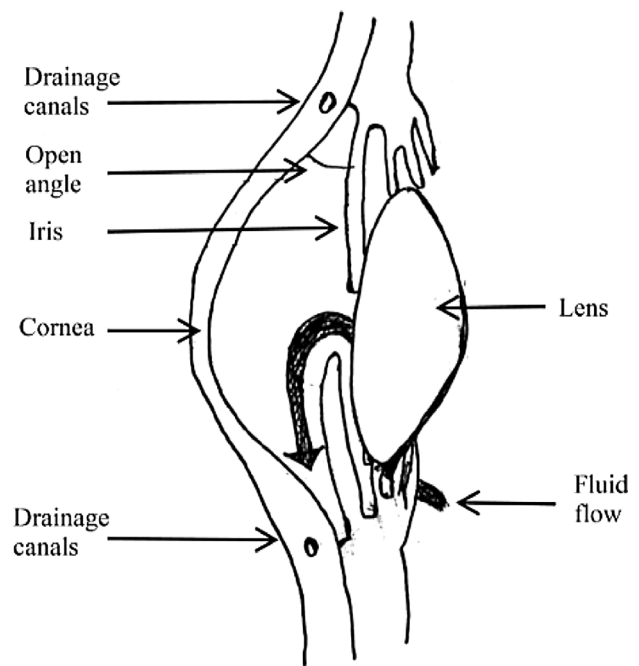

Fig. 3 Open-angle glaucoma

lead to open-angle glaucoma. Figure 3 [7] shows the complete architecture of open-angle glaucoma.

2.2 Closed-angle glaucoma or acute angle glaucoma

Closed-angle glaucoma is one of the types of glaucoma. The symptoms of closed-angle glaucoma are nausea, headache, eye pain, and vision will get blurred. The generated eye fluid will not get adequately drained in the drainage canals. Due to this, intraocular pressure occurs and causes the optic disc to get damage. The narrow-angle form between iris and cornea. If the blockage occurs at the entrance of the drainage, canals lead to closed-angle glaucoma. Figure 4 [7] shows the complete architecture of closed-angle glaucoma.

2.3 Normal-tension glaucoma

It is also called low-tension glaucoma [8]. In this case, the optic nerve gets affected even though there is no much pressure on the eye. The average pressure on the human eye is in the range between 12–22 mm Hg. The people having normal eye pressure also sometimes suffer from glaucoma. Mainly it occurs due to family history. They were treated by decreasing the pressure on the eye as low as possible using laser treatment, medications, and by some surgery.
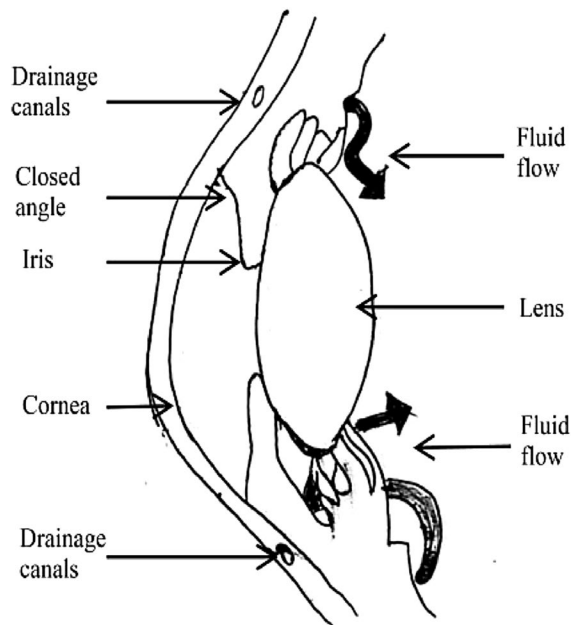
Fig. 4 Closed-angle glaucoma

3 Retinal image acquisition

In the retinal imaging technique [9], the two-dimensional images converted into three-dimensional retinal tissues. These images are useful for diagnosing and managing several eye diseases. Capturing the rear image of the eye is called the fundus. Hence it is named a fundus camera. The detailed visualization of the eye can be easily obtained by using a fundus camera [10]. The fundus cameras are readily available in most of the eye care centres and hospitals. Some of the eye's main components that can easily visualized from the fundus camera are optic disc, fovea, exudates retina, and macula.

3.1 Publicly available dataset

Some of the publicly available datasets used to detect glaucoma are discussed below,

3.1.1 DRIVE dataset

DRIVE (Digital Retinal Images for Vessel Extraction) [11] database was acquired from the diabetic retinopathy research program in the Netherlands and consist of nearly 40 images. Out of 40 images, 7 of them are having pathology, and remaining are normal images. The images automatically divided into two groups with 20 images for testing purposes and the other 20 images for training

purposes. Those images captured using a canon CR5 non-mydriatic 3eco camera with a 45-degree field of view to get high clarity fundus images.

3.1.2 MESSIDOR dataset

MESSIDOR Dataset [12] consists of two sets of images containing 1200 images. One set used for retinopathy grade, and another set is for the risk of macular edema. French Ministers of research and defence capture the images by ophthalmological department. The captured images stored in the TIFF format. The nonmydriatic retinopathy with a 45-degree field of view is used to capture the images.

3.1.3 ORIGA dataset

ORIGA [13] dataset mainly used for Glaucoma analysis and research purposes. This dataset consists of 650 images. Out of 650 images, 160 images were glaucomatous, and 482 were non-glaucomatous images.

3.1.4 REFUGE dataset

The REFUGE [14] dataset is a part of the Retinal Fundus Glaucoma Challenge (REFUGE), which is in conjunction with MICCAI 2018. This dataset contains 1200 fundus images, and it is the current largest publicly available fundus image database. Here, the ground truth segmented images and the fundus images clinical values are also available in the database.

3.1.5 DRISHTI-GS dataset

The DRISHTI-GS [15] dataset consists of 101 fundus images, including 50 training images and 51 testing images. The images include OD and OC masks with their CDR values. This dataset is collected by joint association of Arvind Eye hospital located in Mumbai and researchers of IIIT Allahabad. It consists of all age group images and is useful only for research purposes.

4 Parameter analysis

The image classification methods help to differentiate the images from glaucoma and healthy images based on some parameters. Some of the parameter metrics are CDR, ISNT rule, DDLS (Disk Damage Likelihood Scale), GRI (Glaucoma Risk Index), etc.

4.1 CDR

Finding horizontal, vertical, and area ratio between the cup to disk is called CDR (Cup to Disk Ratio) [16]. If the ratio is less than or equal to 0.3, then it is considered as healthy eye. Once the ratio increases by more than 0.3, then it is treated as an abnormal eye. Based on CDR value, we can quickly identify whether the person is having glaucoma or not. HCDR (Horizontal Cup to Disk Ratio) is used to calculate the horizontal ratio and calculated using the below Eq. (1).

$$H_{CDR} = H_{CUP} / H_{DISK} \tag{1}$$

H_{CUP}, H_{DISK} is the horizontal length of the optic cup and optic cup respectively.

To calculate the vertical ratio, VCDR (Vertical Cup to Disk Ratio) is used and Eq. (2) gives the formula to calculate V_{CDR},

$$V_{CDR} = V_{CUP} / V_{DISK} \tag{2}$$

V_{CUP}, V_{DISK} is the vertical length of the cup and disk respectively.

To calculate Area, ACDR (A rea of Cup to Disk Ratio) is used with the Eq. (3).

$$A_{CDR} = A_{CUP} / A_{DISK} \tag{3}$$

A_{CUP} is an Area of the optic cup. A_{DISK} is an Area of the optic disk.

4.2 ISNT rule

The inner layer of the optic disk contains neuroretinal rim. The rim consists regions of inferior, superior, temporal, and nasal. All these regions are ordered based on the ISNT rule. The below-mentioned order is the standard ISNT rule form for the normal eye.

$$I > S > N > T$$

here I is inferior, S is superior, N is nasal, and T is temporal.

4.3 DDLS (Disk damage likelihood scale)

The scale which measures the disk damage likelihood is called DDLS [2], and also it calculates the severity of the disease.

$$DDLS = MinRim_{width} / DD \tag{4}$$

here DD is the Disk Diameter, $MinRim_{width}$ is the minimum width of rim and is calculated using the Eq. (4).

4.4 GRI (Glaucoma risk index)

Using various Principal Components, GRI is Calculated. Based on the range of PCA (Principal Component Analysis), eye can be classified as normal or abnormal. The principal component PC1 to PC5 is calculated. Equation (5) used to calculate the GRI value.

$$\begin{aligned} GRI = {} & 6.8375 - 1.1325\,(PC1) + 1.6500\,(PC2) \\ & + 2.7225\,(PC3) + 0.6750\,(PC4) + 0.6650\,(PC5) \end{aligned} \tag{5}$$

If the GRI range is (8.68 ± 1.67), then the eye is treated as a healthy eye and if the GRI range is (4.84 ± 2.08), then the eye is treated as the abnormal eye.

5 Literature survey

In recent years, medical imaging is growing very fast for medical diagnostics by using digital imaging systems. Many techniques like image processing, machine learning, deep learning, etc., are applied to identify glaucoma. The glaucoma is mainly identified on ONH (optic nerve head). So, to detect ONH many localization and segmentation methods are used. After the localization of optic nerve head, locating the boundary of optic disc and optic cup is the challenging task here. In the existing system, many methods were applied, but to increase the parameters like accuracy, sensitivity, and specificity, new methods has to be identified. As glaucoma leads to vision loss in severe cases, detection in the early stages is the key to avoid vision loss.

The literature survey on various segmentation and classification approaches over retinal fundus images are discussed in the below Tables 1 and 2 respectively. Table 3 explains the Literature survey based on some of the performance metrics.

By comparing all the segmentation approaches from Table 1, it is clear that all the above captured methods have both advantages and disadvantages. The Level set-based approach [36, 37] is mainly used for handling sharp corners and it is an efficient and versatile approach. It is a very time-consuming method and it results in under segmentation or over-segmentation. The threshold-based approach [38, 39] is fast and simple. This method does not give good results with a flat and broad range of pixels. The clustering-based approach [40] is easy to eliminate noise and works well with differentiating homogeneous and heterogeneous regions. According to the survey, the segmentation of images with a clustering-based approach is better than other approaches.

The KNN is very effective for a large number of training data, but the computation cost is very high. It is not a parametric methodology for data arrangement. The information

Table 1 Summary of various segmentation approaches for the detection of optic disc and optic cup

Reference	Method	Performance measure	Performance value	Database used	Remarks
Rangaraj [17]	Gabor filters, phase portraits, FROC analysis	Detection rate	100%	DRIVE	–
Juan Carrillo [18]	ISNT rule	Success rate	88.5%	Attention centre of glaucoma in bucaramanga	Residual noise after the segmentation
Jagadeesh Kumar [19]	Support vector, clustering kernel density estimation, cluster overlapping system	Success rate	97.25%	DIARETDB1	SVM based machine intelligence grounded on quadratic normalization
Sharanagouda Nawaldgi [20]	Pearson-R coefficients and euclidean distance/CDR	Accuracy	97%	ORIGA	CDR, NRR thickness, ML thickness, and ISNT rule are calculated
Shishir Maheshwari [21]	Bit-plane slicing, Local binary pattern, Support vector machine, decision level fusion	Sensitivity Specificity Accuracy	98.83% 96.64% 99.30%	Local dataset	Performance classification based on all three RGB channels
Sonali [22]	Contrast limited adaptive histogram equalization (CLAHE)	–	–	Drishti-GS1	Histogram equalization is applied separately for all three channels
Cheng et al. [23]	Clustering-based approach for both segmentation of optic disc and optic cup	Accuracy	90.00%	MESSIDOR	Over segmentation or under segmentation of OD and OC
Sarkar et al. [24]	Threshold-based approach for both segmentation of OD and OC	Accuracy	83.168%	RIM-ONE	The testing will be done on similar set of images
Noor et al. [25]	Thresholding for both segmentation of optic disc and optic cup	Accuracy	70.9%	DRIVE	There is less accuracy in the segmentation of optic disc and optic cup
Mishkin Khunger et al. [26]	LBP for feature extraction, Daugman's calculation for iris recognition	Sensitivity Specificity Accuracy	96% 96% 96%	MESSIDOR	Automated Detection using Histogram Features (ADHF) and Automated Detection using Structural and Non-structural features (ADSN)
Huazhu Fu et al. [27]	Disc-aware ensemble network (DENet)-combination of residual network (ResNet) and segmentation guided network	AUC B-Accuracy Sensitivity Specificity AUC B-Accuracy Sensitivity Specificity	0.9183 0.8429 0.8478 0.8380 0.8173 0.7495 0.7876 0.7115	SCES Dataset SINDI Dataset	This proposed method helps for glaucoma screening by collecting contextual information of the OD
Yanwu Xu et al. [28]	Disc segmentation-active shape model, normalization of segmented disc-reconstruction based method	AUC Sensitivity Specificity AUC Sensitivity Specificity	0.823 58.0% 85% 0.860 73.9% 85%	ORIGA SCES	Codebook generation technique
Xu Sun et al. [29]	Deep object detection network	Overlapping error E (disc) Overlapping error E (cup)	0.069 0.213	ORIGA	The join localization and segmentation are proposed in a single method

Table 1 (continued)

Reference	Method	Performance measure	Performance value	Database used	Remarks
Niharika Thakur et al. [30]	Level set based adaptively regularized Kernel-based intuitionistic Fuzzy C means (LARKIFCM)	Accuracy Dice similarity Accuracy Dice similarity	0.15 0.91 0.16 0.90	RIM ONE DRISHTI-GS	The method consumes less time and gives more accurate result
Sevastopolsky [31]	Modified U-net	IOU Dice IOU Dice	0.69 0.82 0.75 0.85	RIM-ONE v.3, DRISHTI-GS	Simple framework and Simple implementationConsumes less prediction time
Mamta Juneja et al. [32]	Deep learning GNET (glaucoma network)-an enhanced model of UNet	Dice metric IOC	0.93 0.88	DRISHTI-GS	Separate individual Unet models for OC and OD segmentation helps to get more accurate results
Jongwoo Kim et al. [33]	FCN (Fully connected network)	Sensitivity Specificity Accuracy	0.9798 0.9910 0.9881	RIGA dataset,	Compared with the results of multi-class FCN and the binary class FCN
Shuang Yu et al. [34]	Modified U-net from Resnet-34	Disc dice Disc Jacc Cup dice	97.38% 94.92% 88.77%	MESSIDOR RIGA	Used minimum epochs and achieved good performance
Baidaa Al-Bander et al. [35]	Fully convolutional densenet	Accuracy(OD) Accuracy(OC)	0.9989 0.9985	Five publicly available database	Results with high-quality segmentation

comprises of k models. In SVM, the searching capability is very high. But the disadvantage is, it is very inefficient for binary image classification. It is a supervised learning technique of data analysis and an administered learning technique for information investigation. In Naïve Bayes classification, images are trained quickly, but it assumes that the extracted features are independent. It is a straight forward classifier, in which it is dependent on Bayes' hypothesis. Random forest works well with broad number dataset classification, but it is not best fit for the dataset that contains noise. In ANN, less time is required for training model with training the data but the computation cost is high. ANN is a computational model, dependent on the working of neurons in the organic cerebrum with an enormous gathering of straightforward unit associations called axons. Its associations convey actuation signals with shifting quality. If the approaching sign is solid, neurons get enacted and travel to another associated neuron. Hence, the SVM classifier is the most commonly used classifier in which it gives maximum accuracy compared to all classification approaches. However, every method has its advantages and disadvantages, but improved methods need to be proposed for the detection of the optic disc and optic cups to diagnose glaucoma.

We have many segmentation approaches for the detection of the optic disc and optic cup. In a Level set-based approach, it tracks interfaces of moving articles by taking care of the issue of bend and surfaces in an understood way by utilizing advancing shape. It utilizes the idea of sign capacity whose zero compares to a unique curve. Active contour modeling based approach depicts the layout of the limit by limiting the energy-dependent on forces which apply weight toward shapes of the item and inner powers that oppose the deformation. Active shape demonstrating based approach iteratively disfigures to recognize the state of the article in the new picture. Here, the state of the model is obliged by the distribution of focuses on the object. It utilizes Mahalanobis separation dependent on standard deviation and intends to search for solid edges in the picture. The clustering-based approach is an iterative methodology of collecting a bunch of objects having comparable conduct lie on one gathering while lying on another gathering which dependent on likenesses. It depends on the estimation of the functioning of density, the total number of clusters, threshold get formed, and distance function. A hybrid approach is used for the segmentation of an object, which is the combination of many segmentation approaches. To extract the ROI (Region of Interest), this technique will be mainly used.

In the existing systems, there is a manual detection process, in that it requires manual input from the ophthalmologist to proceed for the diagnosis of glaucoma. This process requires more time; also, there is no quality in recognition. Hence, it's essential to develop a faster and

Table 2 Summary of various classification approaches

Reference	Method	Performance measure	Performance value	Database used	Remarks
Xiangyu Chen [16]	Deep convolutional neural network	AUC	0.88	ORIGASCES	–
Rangaraj [17]	Gabor filters, phase portraits, FROC analysis	Detection rate	100%	DRIVE	
Sarkar et al. [24]	Threshold-based approach for both segmentation of OD and OC	Accuracy	94.00%	RIM-ONE	The testing will be done on a similar set of images
Guangzhou An [41]	CNN architecture	AUC	0.963	DIARETDB1	Individual five subordinate classification models of CNN were trained
Anum A. Salam [42]	SVM technique local binary pattern (LBP), gabor wavelet transform	Sensitivity Specificity Accuracy	100% 87% 100%	DIARETDB1	Analysing structural changes in the retina using CDR, ISNT ratio, NRR ratio, vertical and horizontal cup height
Miguel Raimundo [43]	SVM	Specificity	100%	ORIGA	High sensitivity functional tests for early diagnosis of glaucoma by exploiting visual pathways with a small degree of redundancy
BASIT [44]	Marker-controlled watershed transform	Sensitivity Specificity Accuracy	99.21% 76.22% 98.92%	DRIVE, Shifa, CHASE_DB1, and DIARETDB1	Many morphological operations are used in the pre-processing step
Raghavendra [45]	Artificial neural network, support vector machine, KNN-classification	Sensitivity Specificity Accuracy	98.00% 98.30% 98.13%	Kasturba medical college dataset	The training time is depend on the learning rate
Prasad [46]	Morphological hough transform algorithm (MHTA), naive Bayes classifier, K-nearest neighbour	Sensitivity Specificity Accuracy	86.41% 78% 78.19%	High-Resolution Fundus (HRF) database	
Shilpa Sameer Kanse [47]	SVM classifier, thresholding-based techniques, KNN-classifier, NB classifier, ANN classifier, adaboost classifier, and random forest classifier	Accuracy	96%	DIARETDB1	Due to some physiological changes in the patients, the set threshold value is not adequate. Because of this, handling intensity variations of the cup region is difficult
Manal Al Ghamdi [48]	Semi-supervised method	Sensitivity Specificity Accuracy	91.7% 93.3% 92.4%	RIM-ONE database	Compared to the random selection method the classification is higher in self-learning method
Anindita Septiarini [49]	Correlation feature selection (CFS) method. classification: KNN algorithm	Sensitivity Specificity Accuracy	95.12% 95.35% 95.2%	Dataset collected from 2 hospitals in Yogyaka	The proposed method failed to detect the color gap between the optic cup and optic disc

Table 2 (continued)

Reference	Method	Performance measure	Performance value	Database used	Remarks
Lili Xu [50]	Adaptive local thresholding (blood vessel extraction), SVM (classification)	Sensitivity Accuracy	85.56% 93.36%	DRIVE	Images are converted into binary image for better blood vessel extraction
Yuki Hagiwara [51]	Long short-term memory (LSTM), CNN, glaucoma risk index	Sensitivity Specificity Accuracy	98.00% 98.30% 94.10%	Local dataset	Hand-crafted extraction and selection of features are needed
Vinoth Kumar [52]	Classical differentiation evolution method, memetic differential evolution method	Optimization accuracy	100%	DIARETDB1	Performance analysis by statistical hypothesis test
Huazhu Fu [53]	U-net deep network, CNN	Accuracy	89.8%	ORIGA	Glaucoma screening performances by both ORIGA and SCES datasets
Radim KOLÁŘ [54]	Fractal dimension (FD), support vector machine (SVM)				Fractal coefficients are used for the detection of glaucoma
Bock [55]	Frequency doubling technology (FDT), standard automated perimetry (SAP) principal component analysis (PCA), SVM	Sensitivity Specificity Accuracy	89.67% 93.00% 93.00%	Erlangen glaucoma registry (EGR)	Feature extraction based on the pixel intensity value
Rajendra Acharya [56]	Linear discriminant analysis (LDA), ANN,	Not specified	RIM-ONE	Higher-order spectral information used for feature extraction	
Dua et al. [57]	DWT, for feature ranking chi-square, gain ratio, info gain, relief is used	Accuracy	83.168%	Local database	Three wavelet filters are used for feature ranking and feature selection methods
Mookiah et al. [58]	DWT, HOS, RT SVM (Polynomial 2) glaucoma risk index for image classification	Sensitivity Specificity Accuracy	86.67% 93.33% 93.33%	Kasturba medical college, Manipal, India	With the use of integrated GRI, the glaucoma is differentiated as glaucoma or not
Issac et al. [59]	The adaptive threshold is used for segmentation, morphological features for feature extraction, SVM for classification	Sensitivity Specificity Accuracy	94.11% 100% 90.00%	RIM-ONE	Classification performance is improved compared to the other classification method
Singh et al. [60]	Brightest pixel intensity for segmentation, DWT for feature extraction, SVM for classification	Sensitivity Specificity Accuracy	94.75% 100% 90.91%	Not specified	Improved classification method
Wong et al. [61]	Level set approach, SVM for classification	Intra-observer variability Inter-observer variability	86.5% 95.2%	Not specified	CDR evaluation is increased
Chrástek et al. [62]	Active contour modelling LDA (classifier)	LDA classifier estimated error	27.75%	159 images (Local dataset)	Classification performance is improved

Table 2 (continued)

Reference	Method	Performance measure	Performance value	Database used	Remarks
Dutta et al. [63]	Thresholding, ISNT rule, SVM and ANN	Accuracy	90.00%	Local dataset of 250 images	All the features extracted are not used for classification
Megha et al. [64]	Horizontal cup to disc ratio (HCDR) Vertical cup to disc ratio (VCDR), KNN for classification	Sensitivity Specificity Accuracy	86.00% 84.00% 99.00%	RIM-ONE	Segmentation and classification are improved
Tan et.al [65]	Superpixel approach, SVM	AUC (Area undercover)	0.95	ORIGA	The cost of computation is increased
Xu et al. [66]	Histogram features for feature extraction, SVM for classification	Area difference	31.50%	ORIGA	The localization of the optic cup is improved
Noronha et al. [67]	Higher-order spectrum cumulant features for feature extraction, SVM and Naive Bayes for classification	Sensitivity Specificity Accuracy	100% 92% 92.65%	Local dataset of 277 images	The classification of images needs to be improved by adding more number of features
Rao et al. [68]	Discrete wavelet transform, CDR, ANN, naive Bayes	Accuracy-NB classifier Accuracy-ANN	89.96% 97.6%	The local database of 300 images	An improved method of classification
Prasad [69]	Naïve Bayes classifier hybrid classifier (naïve Bayes + KNN)	Sensitivity Specificity Accuracy	84.16 40 75.4	HRF (high-resolution fundus)	Texture, shape and intensity features are extracted
Jos_e Ignacio Orlando [70]	Convolutional neural networks (CNNs)	AUC	0.78	Drishti-GS1	off-the-shelf CNNs are used for the detection of glaucoma
Abbas [71]	Deep invariant features and deep neural network	Sensitivity Specificity Accuracy	84.50% 98.01% 99%	DRION-DB	Compare to CNN and SVM; this is a better classification method
Andres Diaz-Pinto et al. [72]	Deep convolutional generative adversarial networks (DCGAN)-semi supervised learning method	Specificity Sensitivity AUC F-score	0.7986 0.8290 0.9017 0.8429	one private and 14 public databases and 1 private database (86,926 images)	This method can be worked as CAD for glaucoma diagnosis
Jose Ignacio Orlando et.al [73]	UNET architecture	Sensitivity Specificity Accuracy	0.85 0.91 0.90	REFUGE (1200 images)	Combination of multiple models helps to increase the individual performance
Vismay Agrawal et al. [74]	CNN (segmentation) densenet201 and resnet18(classification)	Specificity Sensitivity ROC	0.75 0.85 0.856	REFUGE (400 images) DRISHTI-GS1(101 images)	Using two models for image classification helps to increase performance
Muhammad Naseer Bajwa et al. [75]	RCNN (regions with convolutional neural network)-localization	AUC Sensitivity	0.868 0.71	7 publicly available database for image localization and ORIGA for classification	Two-stage methods for localization and classification more help for glaucoma screening

Table 2 (continued)

Reference	Method	Performance measure	Performance value	Database used	Remarks
Feng Li et al. [76]	Deep Residual Neural Network	Accuracy Sensitivity Specificity AUC	0.941 0.957 0.929 0.992	Shanghai Zhongshan Hospital database	More helpful for large scale dataset screening of fundus images

automatic system. The machine learning and deep learning techniques help in all the computer vision tasks, especially in the medical field. This deep learning technique also plays a major role in the segmentation and classification of images. In the existing papers, the researcher applied different types of architecture using deep learning techniques and achieved good results. This technique helps the system to train and test a large number of images in a limited amount of time. It helps to extract the hierarchical information from the images and to distinguish from glaucoma and non-glaucomatous images.

The understandings of the existing system methods applied for the detection of glaucoma discussed below,

- Compared to image processing techniques, machine learning and deep learning techniques give good accuracy for the detection of glaucoma.
- The survey suggests that Pre-Processing is an essential initial step to be concentrated.
- The optic disc is more visible on the green channel of the RGB image. In the green channel, the image background and the blood vessels will be easily differentiated. It helps for the removal of blood vessels in the detection of optic disc.
- Finding optic disc and central bright pixel of optic disc are used for the detection of the optic cup.
- Identifying morphological technique for detecting the optic disc and optic cup boundary to calculate cup-to-disc ratio.

6 Performance metrics

The performance of the methodologies applied for the detection of optic disc and optic cup can be estimated by using some parameters. The few metrics used for the performance analysis is discussed below,

6.1 CDR acceptability

The CDR acceptability is the difference between the CDR which is calculated manually and the clinical CDR. If the difference between the two is less than 0.2, then it is normal; otherwise, it is abnormal. The CDR acceptability measured by using below Eq. (6),

$$CDRacc = CDRclinical - CDRcal \leq 0.2 \qquad (6)$$

Table 3 Literature survey based on some of the performance metrics

Cheng et al. [23]	Clustering-based approach for both segmentation of optic disc and optic cup	Mean CDR error	0.107	MESSIDOR	Over segmentation or under segmentation of OD and OC
Xu et al. [66]	Histogram features for feature extraction, SVM for classification	The relative absolute area difference	31.5%	ORIGA	The localization of the optic cup is improved
Liu et al. [77]	Level set approach (optic disc segmentation)	Avg. CDR acceptability	97%	Local dataset of 73 images	Manual inputs are decreased during segmentation
Mahapatra et al. [78]	Random forest for classification	Correlation	0.85	DRISHTI-GS	The classification accuracy is more

6.2 Mean error

The closeness between the observed outcome and the actual result is called a mean error. If the mean error increases, the performance decreases.

6.3 Standard deviation

The difference between the cluster of objects and the mean error is the standard deviation. If the mean error increases, then the performance decreases.

6.4 F-score

F-score is the metric used to measure the accuracy in which the value is between 0–1. If the resultant value close to 1, then it gives better performance.

6.5 Correlation coefficient

The correlation coefficient is used to find the relationship between the direction and strength of two variables that are in the range of 0–1.

6.6 Sensitivity, specificity and accuracy

Based on the diagnostic examinations, the test will be analysed on the view of accuracy, sensitivity, and specificity [17] characteristics. The test which is used for the detection of positive infection is sensitivity. How likely the patients without sickness will be effectively eliminated with the help of specificity. The correctness of the test is measured by accuracy. The below mentioned Eqs. (7), (8), (9) gives the formula to calculate Accuracy, Specificity, and Sensitivity respectively.

$$Accuracy = (TN + TP)/(TN + TP + FN + FP) \qquad (7)$$

$$Specificity = TN/(TN + FP) \qquad (8)$$

$$Sensitivity = TP/(TP + FN) \qquad (9)$$

TN = True Negative FN = False Negative TP = True Positive FP = False Positive

7 Research gap

The retinal image analysis is a very difficult task because of its structural feature variations of the patient. According to the survey, the diagnosis of glaucoma is based on the proper detection of the optic cup and optic disc. The difficulties faced during the detection of glaucoma is listed below,

a   Over segmentation or under segmentation occurs due to the low contrast of an image and invisible borders between the optic cup and disc.
b   The presence of peripapillary atrophy and blood vessels on the retina decreases the performance of the segmentation. Hence, the pre-processing of an image is a very important step to remove the blood vessels and to avoid the peripapillary region on the retina as a disc region. So, by applying many filters and improved morphological approaches during pre-processing will help to segment the optic region easily.
c   Comparatively the features of OD and many other parts of the retina are same. Because of the entire brightness and the lesion around the OD, it is very difficult to locate. Hence extracting more features helps to increase the performance in the detection of OD.
d   Increasing the number of datasets for image classification will decrease the performance of the model. Hence, improving the classification approaches helps to classify the normal and glaucoma image.

8 Findings

- The usage of more filters and morphological operations to remove blood vessels during image pre-processing may lead to the problem during the segmentation process.
- The red channel is more suitable for its clear appearance during optic disc segmentation as compared to the other channels.
- The green channel is more suitable for optic cup segmentation due to its high contrast in the channel compared to other channels.

9 Conclusion

The paper includes many segmentation and classification methodologies applied till date for the diagnosis of glaucoma. Here we summarise many challenges that have to be taken for consideration to overcome the problems of segmentation and classification techniques. In the existing papers, the researchers considered many features for classification purposes. To increase the classification performance, still more features can be extracted. The main challenge is to avoid under segmentation or over-segmentation of optic disc and cup boundary due to the presence of more number of blood vessels on this part. This problem can be overcome by segmenting the disc on the red channel due to the highest inequality between the disc and non-disc region and many challenges in optic disc segmentation due to the presence of blood vessels can also be avoided by applying morphological operations in the pre-processing stage. Compared to the segmentation of optic disc, the optic cup segmentation is very tedious due to its interlink with many surrounding tissues and blood vessels. Hence, due to the less visibility of blood vessels in the green channel, the optic cup segmentation can be done on this channel. From the study of the existing technique, it shows that the deep learning techniques applied during the segmentation and classification of fundus images give more accurate result compared to image processing techniques. But, it shows that the techniques applied can be improved for getting more accuracy in locating the boundary of the optic disc and the optic cup. Finally, the paper concludes that the improvement in the segmentation and classification approaches helps for the early diagnosis of glaucoma.

Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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