Retinal Fundus Image for Glaucoma Detection: A Review and Study

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Abstract: Glaucoma is one of the severe visual diseases that lead to damage the eyes irreversibly by affecting the optic nerve fibers and astrocytes. Consequently, the early detection of glaucoma plays a virtual role in the medical field. The literature presents various techniques for the early detection of glaucoma. Among the various techniques, retinal image-based detection plays a major role as it comes under noninvasive methods of detection. While detecting glaucoma disorder using retinal images, various medical features of the eyes, such as retinal nerve fiber layer, cup-to-disc ratio, apex point, optic disc, and optic nerve head, and image features, such as Haralick texture, higher-order spectra, and wavelet energy, are used. In this paper, a review and study were conducted for the different techniques of glaucoma detection using retinal fundus images. Accordingly, 45 research papers were reviewed and the analysis was provided based on the extracted features, classification accuracy, and the usage of different data sets, such as DIARETDB1 data set, MESSIDOR data set, IPN data set, ZEISS data set, local data set, and real data set. Finally, we present the various research issues and solutions that can be useful for the researchers to accomplish further research on glaucoma detection.

Keywords: Classification, cup-to-disc ratio, glaucoma, Haralick texture, retinal image.

1 Introduction

The World Health Organization reports that the second leading cause of blindness is glaucoma; it has affected 60 million individuals in 2010 [43] and it will affect about 70.6 million cases of blindness in 2020 [24]. Glaucoma is one of the soundless thieves of spectacle. Hence, the timely detection of glaucoma plays a virtual role for intercepting irretrievable damages in eyes. Especially, for aged humans, the visual disorder of glaucoma leads to permanent blindness. Consequently, this irretrievable disorder of glaucoma is significantly detected in early stages [57]. Several types of glaucoma can be represented as follows: (i) open-angle glaucoma, (ii) angle-closure glaucoma, (iii) normal tension glaucoma, and (iv) congenital glaucoma [23]. Moreover, before performing the glaucoma diagnosis, there are important factors that should be checked, such as tonometry, ophthalmoscopy, perimetry, gonioscopy, and pachymetry. Then, the diagnosis of the glaucoma is performed based on the medical record of the patient’s intraocular pressure (IOP), visual field loss tests, and physical evaluation of optic nerve head (ONH) via ophthalmoscopy [9]. The testing of glaucoma can be conducted through digital fundus camera, optical coherence tomograph (OCT), IOP measurement, ONH evaluation, retinal nerve fiber layer (RNFL), and visual field defect [23].

Due to the malfunction of the drainage structure of the eyes, IOP is increased rapidly. Then, the pressure of fluid in the eyes increases constantly; thus, it damages the optic nerve of the eyes [36] and causes permanent vision loss [1], which leads to the irretrievable disorder of glaucoma. Moreover, due to the damaged RNFL, the thickness of the RNFL is decreased, which is also one of the main causes of glaucoma disorder [3]. In addition, several possible ways lead to glaucoma disorder, such as ONH, nerve fiber layer, structural changes, and the functional stoppage of the visual field concurrently [33].
1.1 Glaucoma Detection Using Retinal Image

This section presents the details about retinal fundus image, in which the thickness of the RNFL [7] is used to diagnose glaucoma. Glaucoma detection using the retinal image is one of the important noninvasive techniques in the medical area [46], which includes healthy and nonhealthy retinas for ophthalmologists [42]. The major advantage of retinal fundus images is that, in most clinical environments, retinal fundus images can be obtained easily. Then, extricating the information from the digital image analysis is used to find the ocular diseases of glaucoma [51].

Figure 1 shows the general architecture of the glaucoma detection process using retinal fundus image. The steps involved in glaucoma detection can be described as follows: (i) Read the input image; (ii) Pre-process the input image based on the process of sampling, region of interest (ROI) extraction, and channel selection; (iii) Segment input image, such as retinal vessel-based segmentation, optic disc detection, and segmentation; (iv) Identify the region of analysis using segmentation; (v) Extract the texture feature and feature selection; and (vi) Classify the input image using different classifiers, such as support vector machine (SVM), artificial neural network (ANN), $k$-nearest neighbor (KNN), and naive Bayes (NB) classifiers.

2 Retinal Fundus Image for Glaucoma Detection: A Review and Study

This section presents the investigation of different classifiers, such as SVM classifier, thresholding-based techniques, KNN classifier, NB classifier, ANN classifier, AdaBoost classifier, and random forest classifier, which are available for glaucoma detection and diagnosis.

2.1 SVM Classifier-Based Technique

This section shows the review of the SVM classifier-based technique, which is used in the process of glaucoma detection. Agarwal et al. [3] have developed an approach using cup-to-disc ratio (CDR) and rim-to-disc ratio to identify glaucoma in retinal fundus images. Then, they have proposed another one important technique, called adaptive threshold-based method, which have been independent of noise and quality of the image. In addition to, they have considered rim-to-disc ratio, which has been combined with CDR to detect glaucoma that gives more reliability. Furthermore, the same SVM-based classification technique was used for glaucoma detection using fundus image, which has been described by Narasimhan et al. [35]. They have extracted the blood vessels using local entropy thresholding technique, which have been presented inside the optic disc. Then, they have considered two features to detect glaucoma, such as CDR and inferior superior nasal temporal (ISNT) ratio. After computing the features automatically, the classification can be done using various classifiers such as SVM, KNN, and NB classifier. Then, the maximum classification can be done using the SVM classifier with 95% accuracy.
Hussain and Holambe [23] dealt with the SVM classifier, which has been used in the eye fundus images to detect and classify glaucoma. They have proposed computerized aid diagnosis system, which has been used to find the malformation present in fundus images. Then, the proposed computerized aid diagnosis system was used to check glaucoma disorder progression. The major goal of this paper was used to detect glaucoma automatically, with the help of different parameters of fundus image measurement between glaucoma patients and normal patients. Then, the glaucoma diagnosis using the features of higher-order spectra (HOS) and discrete wavelet transform (DWT) based on the data mining technique was developed by Mookiah et al. [57]. After extracting the features, statistical analysis can be done based on the independent sample t-test. Then, the results of these extracted features were given to the SVM classifier with different mathematical expressions, such as linear, polynomial order 1, 2, 3, and radial basis function (RBF), to choose the best kernel function. Mookiah et al. have used the SVM classifier with the second polynomial order of kernel function, which have been used to detect glaucoma disorder in early stages with an accuracy of 95%.

Moreover, the evaluation of glaucoma using the optic disc and optic cup segmentation from digital fundus images was developed by Mittapalli and Kande [32]. They have evaluated glaucoma disorder using the optic cup properties based on the structural and grey level. In this work, they have used 59 retinal images to detect glaucoma. Based the specific results of both optic cup and optic disc parameters, the assessment of glaucoma disorder was calculated with an F-score of 89% using the SVM classifier. Bock et al. [9] have developed an automated glaucoma detection system, which has been widely used in digital color fundus images. They have proposed a probabilistic two-stage classification, which has been used to extract the competitive, reliable, and probabilistic glaucoma risk index (GRI) from the images of the low-cost digital color fundus camera. Finally, they have compared the GRI performance to medical relevant glaucoma parameters using the SVM classifier with 88% accuracy.

Kotowski et al. [28] have focused on imaging modalities of the optic nerve and RNFL, in which they have discussed the imaging capabilities pertinent for the diagnosis of glaucoma. Here, the imaging process was possible to mistakenly recognize the glaucoma and its progression; therefore, a combination of the structural and functional measures was based on clinical management decisions. Finally, they have done the classification of glaucoma diagnosis using the SVM classifier and achieved an accuracy of 88%. Furthermore, Kavitha et al. [26] have examined the early detection of glaucoma using CDR in retinal images. The extraction of optic disc was done automatically. Then, they have proposed the segmentation process based on the component analysis and ROI, which has been used for the detection of the optic disc. In addition, they have proposed a model of active contours, which have been used to accurately plot the boundary using the SVM classifier.

Also, the same aforementioned type of the SVM classifier was used for glaucoma detection using retina image analysis [10]. They have used the data screening approach for large-scale screening. For the detection of glaucoma, they have taken the mixture of healthy and glaucomatous eyes of 200 real images. Finally, the performance of the system was compared to the human medical experts in detecting glaucoma through retina fundus images using the SVM classifier. Then, the superpixel classification-based optic disc and optic cup segmentation for glaucoma screening were developed by Cheng et al. [11]. They have performed the evaluation using MESSIDOR database, which contains 650 images. Then, the skilled professionals marked the optic disc and optic cup boundaries physically. Then, the Library for SVM (LibSVM)-based classification was used to find glaucoma detection.

Septiarini and Harjoko [47] have used an online type of features to detect glaucoma disorder effectively. They have performed the feature extraction technique in retinal fundus images based on two groups of feature types, such as morphological and nonmorphological types. Here, the type of feature extraction technique was determined by the grouping-based methodology. Finally, they have concluded that the detection of glaucoma with the morphological features achieved 95% accuracy with the SVM-based classifier. Then, the segmentation of blood vessels and optic disc in retinal images has been developed by Salazar-Gonzalez et al. [45]. They have used the graph cut technique to extract the tree of the retina vascular. Then, the location of the optic disc was estimated by the information of the blood vessels. Here, the segmentation of optic disc was performed based on the two different methods, such as the Markov random field (MRF) image reconstruction method and the compensation factor method.
Acharya et al. [2] have proposed a decision support system for the detection of glaucoma disorder using Gabor transform. They have used a mixture of features, such as mean, variance, skewness, and energy, which have been extracted from digital fundus images. After extracting the features, the dimensionality was reduced using principal component analysis. Then, various ranking methods were proposed, such as Bhattacharyya space algorithm, $t$-test, Wilcoxon test, receiver operating curve and entropy, to make the features in ranking order. Finally, they have concluded that the $t$-test-based ranking method provided better performance. The efficient detection of the optic cup from the intra-image learning method was proposed by Xu et al. [53]. They have presented a superpixel-based learning framework for intra-image learning, which has been based on the retinal structure priors. They have used the optic cup feature for the identification of glaucoma. Here, the classification was performed based on the SVM classifier, in which the classification could not be based on the prelabeled training samples.

Xu et al. [52] have proposed a superpixel classification for the efficient localization of optic cup in digital fundus images. In this work, they have performed the testing process using the clinical database of ORIGA-light, in which they have analyzed 325 images. Finally, the classification was performed based on the SVM classifier with an accuracy of 90%. Mishra et al. [31] have proposed the active contours method, which has been used to determine the pathological process of glaucoma. Here, the method was applied on 25 color fundus images. Finally, the method was used to classify all the glaucoma disease images using the SVM classifier.

### 2.2 Thresholding-Based Techniques

The classifier technique related to the threshold-based techniques is reviewed in this section. Ho et al. [21] have proposed a system for an automatic fundus image analysis for the clinical diagnosis of glaucoma using threshold-based classification. Here, the developed automatic detection system has two phases. (i) First, the automatic digital fundus retinal image analysis was done based on various measurements, such as vessel detection, CDR calculation, and neuroretinal rim for ISNT rule. (ii) Second, the irregular status of retinal blood vessels from patients, which have been lead to glaucoma such as vascular thickening, vessel hemorrhage, occlusion of retinal vascular, and abnormal angiogenesis. Finally, they have demonstrated their system with a number of clinical fundus retinal images that contain information of both normal and glaucoma images. Zhang et al. [57] have proposed a method named as ARGALI (Automatic CDR Measurement System for Glaucoma Detection and Analysis), in which glaucoma detection was performed based on the localization of optic disc ROI. Here, the proposed threshold-based technique finds the ROI for 96% of the images from the 1564 retinal images.

Kumar et al. [29] have designed an active contours technique for the automatic detection of glaucoma, in which the ultrasound (US) images of the eye were used to detect glaucoma-affected patients. Then, using live US images, the efficient angle was calculated using the proposed algorithm, which has been used to determine the exact location of the apex point of the anterior chamber region. Hence, the speckle noise problem was eliminated for glaucoma detection with effective segmentation. The diagnosis of glaucoma on fundus images using vertical CDR measurement was developed by Hatanaka et al. [19]. They have used Canny edge detection filter to detect the edge of the optic disc. Then, they have erased the image blood vessels from the image. After this initial adjustment, they have collected 20 profiles, which have been obtained from the center of the optic disc on blue channel of the color image in the vertical direction. After that, the thresholding technique was used to determine the edge of the cup area on the vertical profile to calculate the CDR. Finally, they have achieved an accuracy of 96% using 25 glaucoma images from the 79 images for glaucoma diagnosis.

dela Fuente-Arriaga et al. [13] have presented a methodology for glaucoma detection based on the measurement of vascular bundle displacements of blood vessels within the optic disc in human retinal images. Here, the proposed method was used to determine the position of the centroids of the ISNT and nasal vascular bundle segmented zones, where the dislocation of centroid position was determined using the chessboard distance metric. Out of the 67 images, the proposed method plays successful detection in 62 images.
Pachiyappan et al. [41] have described a system using fundus and OCT images for the automated diagnosis of diabetic retinopathy and glaucoma. Here, they have used RNFL thickness to detect glaucoma disorder in early stage, which was extracted from the OCT images of the patient. Then, the proposed algorithm of active contours-based deformable snake algorithm was used to estimate the RNFL thickness with anterior and posterior boundaries segmentation. Here, the proposed method found the optical disc detection with an accuracy of 97.75%.

Chiranjeevi and Telagarapu [12] have developed an algorithm, in which the efficient angle calculation was done to find the precise position of the apex point of the anterior chamber region. Here, they have considered 100 images, where they have identified 97% of the clinical parameter features correctly. Then, the major difficulty they have faced while measuring clinical parameters includes speckle noise, delineation of the weak edge, poor resolution, and poor contrast, which are present in the US images. Finally, the proposed method was used to reduce the various difficulties that have been presented in the clinical parameters with 97% accuracy. Besides, the detection of glaucoma using RNFL arteries have been developed by Bedke et al. [7]. They have used two functions for glaucoma detection, such as median filter and HAAR wavelet transform. Moreover, they have used Drishti-GS and HRF data set, which contains 101 glaucomatous images for glaucoma analysis. Then, they have calculated the area and diameter from extracted RNFL arteries. Here, they have used the thresholding-based classification with 71.28% accuracy.

Agarwal et al. [4] have proposed automatic glaucoma detection in fundus images using the adaptive threshold-based technique. The authors have described an important diagnostic tool for the detection of glaucoma, which has been mainly used to analyze the computer-aided fundus images. Here, they have used various features, such as mean and standard deviation, which can be extracted from histogram-based images. Then, the correlation between both features of mean and standard deviation was used to segment the optic disc and optic cup parameters with 90% accuracy of glaucoma screening. Then, the diagnosis of glaucoma on retinal fundus images using the automatic measurement of CDR was proposed by Poshtyar et al. [42]. Here, the proposed method of CDR measurement was computationally more efficient, in which the area determination of CDR measurement was used to diagnose glaucoma in retinal fundus images with 92% accuracy.

Ahmad et al. [5] have proposed an image processing technique of retinal fundus images to detect glaucoma. Here, they have used the features in two-fold, such as CDR and the ratio of the neuroretinal rim in ISNT quadrants. Then, they have implemented the proposed techniques on 80 retinal images and the classification was done based on the SVM classifier with 0.8141 s as the average computational time and an accuracy of 97.5%. The detection of glaucoma using retinal fundus images was described by Khan et al. [27]. Here, they have used two features, such as CDR and the ratio of the neuroretinal rim in ISNT quadrants, which have been extracted from morphological techniques. They have implemented the proposed method on 50 retinal images and achieved 94% accuracy with a computational time of 1.42 s.

Murthi and Madheswaran [34] have presented a glaucoma detection technique based on multimodalities, which have been used to evaluate the neuroretinal optic cup with various methods such as labeling, convex hull, and ellipse fitting methods. They have processed the retinal images with their CDR values; the results show the diagnosis of glaucoma with 70% accuracy. Dutta et al. [16] have addressed an automated image processing approach for the detection of glaucoma, in which their proposed approach was based on the segmentation of superpixels from fundus color retinal images. Further, they have calculated the radius of optic disc and optic cup using Hough transform. In addition, the vertical CDR parameter was used to identify the symptoms of glaucoma in the fundus image. Then, they have proposed effective glaucoma detection by segmenting the superpixels from fundus color retinal images with a better accuracy of 90%.

Glaucoma detection using CDR in color fundus images was examined by Naz and Rao [38]. For that, they have performed the preprocessing method of anisotropic filtering, in which the visual impact of reproduction errors can be reduced. Here, they have extracted the automatic disc using three techniques, such as edge detection, optimal thresholding, and manual threshold analysis. For detecting the optical cup, the proposed level set method was developed by Naz and Rao [38], which was used to screen the diagnosis of glaucoma in an early stage. Joshi et al. [25] have proposed the optic disc and cup segmentation method from monocular
color retinal images for glaucoma assessment. Here, they have considered each point of interest in multidimensional feature space. After selecting the feature space, the local image information around this space was integrated, which has been used to provide robustness around the optic disc region. Moreover, they have proposed a cup segmentation method, in which the segmentation process mainly depends on the anatomical evidence. Then, the calculated segmentation shows the reliability in managing the different geometric and photometric changes using the threshold-based technique with 97% accuracy.

Then, the neuroretinal optic cup detection in glaucoma diagnosis was proposed by Zhang et al. [58], in which the accuracy of the neuroretinal cup detection was improved using the boundary estimation method based on the multimodality fusion approach. Here, they have taken 71 retina fundus images, which have been segmented manually. Finally, they have found that their developed method accurately detects the optical cup height of 69 neuroretinal images with 97.2% accuracy. Besides, Aquino et al. [6] have derived the template-based methodology for segmenting the optic disc from digital retinal images. To obtain circular optic disc boundary estimation, the derived methodology used the techniques of both morphological and edge detection. Here, the circular Hough transform (CHT) was used to extract the features, in which the pixel was situated inside the optic disc as initial information. Due to this reason, they have proposed another one important voting-type algorithm, which has been based on the location methodology on the massive digital retinal database. Finally, the threshold-based technique was used to detect optic disc boundary using the MESSIDOR data set with 97% accuracy.

### 2.3 ANN Classifier-Based Techniques

Zhang et al. [55] have examined the minimum redundancy maximum relevance (mRMR)-based feature selection for automatic glaucoma diagnosis. Here, they have used the features such as retinal image and eye screening data, which were collected from the heterogeneous data sources. Then, using the measurement score regression, the optimal feature set was derived automatically and the performance curve was plotted. The proposed mRMR-based feature selection considers one fourth of the original features. Then, the classification was carried out based on the ANN classifier with better accuracy and $F$-score.

Singh et al. [49] have proposed an automatic diagnosis of glaucoma using image processing-based methods. Here, they have extracted the wavelet features of the segmented optic disc from fundus image. Then, the classification of glaucoma image was measured based on the five classifiers, such as SVM, KNN, NB, random forest, and ANN classifiers. Finally, they have concluded that the better feature selection and evolutionary attribute selection can be performed by ANN classifiers with 94.7% accuracy. The diagnosis of glaucoma can be performed based on digital fundus images, which have been described by Nayak et al. [37]. Here, they have extracted the features from various features, such as CDR, optic disc center distance, and the area of the blood vessels. Then, they have used ANN classifier to classify the normal and glaucoma images with an accuracy of 86%.

### 2.4 NB Classifier-Based Techniques

Based on the HOS cumulants features, Noronha et al. [39] have proposed an automated glaucoma diagnosis system. Here, they have extracted the features of HOS cumulants from radon transform (RT). Then, the results of RT were applied over digital fundus images. Here, the classification was done in three ways, such as normal, mild glaucoma, and moderate/severe glaucoma. Noronha et al. have used NB classifier-based techniques for digital fundus image classification with 92.65% accuracy.

Based on the combination of probability models and ensembles of individual algorithms, the detection of the optic disc in fundus images was developed by Harangi and Hajdu [18]. However, they have proposed the modified algorithm, in which more than one candidate was presented for every member algorithm. Here, the optic disc position and nodes of the candidates can be found based on the maximum weighted clique and spatial weighted graph methods with 98.46% accuracy.
2.5 Random Forest Classifier-Based Technique

This section presents the random forest classifier-based technique for glaucoma detection. Based on the features of texture and HOS, Acharya et al. [1] have proposed the automated diagnosis of glaucoma from digital fundus images. Here, they have used the supervised classification based on the four different types of classifiers, such as SVM, sequential minimal optimization, NB, and random forest classifiers. Then, they have performed the classification after selecting the features and Z-score normalization. Finally, they have concluded that the classification and identification of glaucoma images using the random forest classifier had 91% accuracy.

In the study of Hoover and Goldbaum [22], the fuzzy convergence of the blood vessels was used to locate the optic nerve in retinal images. Then, they have considered the wavelet transform-based features for glaucoma detection. In their method, they have performed the testing based on the healthy retinas and diseased retinas, which was used to detect the confusion and confusing manifestations with 89% accuracy.

2.6 Other Classifiers for Glaucoma Detection

This section presents glaucoma detection based on the various classifiers such as Fisher linear discriminant classifier, two-layer fuzzy classifier, KNN classifier, and AdaBoost classifier. Belghith et al. [8] have developed the glaucoma progression detection method using Heidelberg retinal tomograph (HRT) images. Here, they have proposed a graphical model of MRF to handle the spatial pixel dependency. Moreover, they have implemented the algorithm of variational expectation maximization (VEM) for speculating the topographic ONH changes in glaucoma detection framework. Finally, the two-layer fuzzy classifier was used to classify the HRT images with an accuracy of 88%.

Zhang et al. [56] have proposed an automatic glaucoma diagnosis based on the feature selection methodology of mRMR. Here, they have obtained the feature sets of an optimal candidate from the data of clinical screening and retinal fundus image. Once the feature selection was completed, they have classified retinal fundus images based on the AdaBoost classifiers with 85% accuracy. Simonthomas et al. [48] have addressed a method for glaucoma detection based on the image processing method. Here, they have used the features of Haralick texture, which can be extracted from digital fundus images. In glaucoma detection, they have performed the classification based on the KNN classifier, which was used to identify the glaucoma images with 98% accuracy.

During the progress of glaucoma disorder, Xu et al. [54] have investigated the sequential relationship between the ONH surface depression and RNFL thinning. Then, they have used the measuring techniques based on two methods such as confocal scanning laser ophthalmoscopy (CSLO) and spectral-domain OCT (SD-OCT). Here, the classification was performed using Fisher’s linear discriminant classifier with an accuracy of 94%.

3 Analysis and Discussion

This section shows the analysis of glaucoma disorder detection based on the literature taken for reviewing, in which we have considered various factors for analysis, such as feature extraction-based analysis, data set utilization, and the objective of glaucoma detection.

(a) Analysis Based on Feature Extraction: In this section, Table 1 shows the feature extraction analysis based on the image features such as texture, Haralick texture features, HOS, wavelet energy features, mean, variance, skewness, kurtosis, pixel, orientation and density, and residual image intensity. Accordingly, the wavelet energy features have been examined in Refs. [22, 26, 32, 33, 55] and HOS features were used in Refs. [1, 26, 33, 39]. In addition, another one important feature of ONH was used to perform better glaucoma detection, which has been used in Refs. [54, 58].
Moreover, Table 2 shows the survey of medical features based on the feature extraction analysis such as CDR, vessel, apex point, optic disc, optic disc morphology, neuroretinal rim, ONH, and optic disc hemorrhage or disc pallor. Optic disc pallor defines an abnormal coloration of the optic disc as visualized by a fundoscopic examination. Consequently, the medical features of CDR were used in Refs. [3–5, 11, 16, 21, 27, 31, 35, 38, 42, 47, 52, 57], which have been given more reliability in glaucoma determination. Moreover, in Refs. [12, 29], they have considered apex point as a medical feature to detect the disorder of glaucoma. Then, the RNFLs of medical features extraction were described in Ref. [7], which has been used to predict the glaucomatous images with more accuracy.

(b) Analysis Based on the Data Set Used: Figure 2 shows the bar graph based on different types of data sets such as real data set, M-VEP data set, IPN data set, SCES data set, GRI data set [17], ORIGA data set, local data set, ZEISS data set, DIARETDB1 data set [14], ORIGA-light clinical data set [40], DRIVE data set

Table 1: Analysis Based on Image Features.

<table>
<thead>
<tr>
<th>Features</th>
<th>Works</th>
</tr>
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<tbody>
<tr>
<td>Texture</td>
<td>[1, 10]</td>
</tr>
<tr>
<td>Haralick texture features</td>
<td>[48]</td>
</tr>
<tr>
<td>HOS</td>
<td>[1, 26, 33, 39]</td>
</tr>
<tr>
<td>Wavelet energy features</td>
<td>[22, 26, 32, 33, 49]</td>
</tr>
<tr>
<td>Mean, variance, skewness,</td>
<td>[2]</td>
</tr>
<tr>
<td>and kurtosis</td>
<td></td>
</tr>
<tr>
<td>Pixel, orientation, and</td>
<td>[10, 18, 37, 54, 58]</td>
</tr>
<tr>
<td>density</td>
<td></td>
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<tr>
<td>Residual image intensity</td>
<td>[8]</td>
</tr>
</tbody>
</table>

Table 2: Analysis Based on Medical Features.

<table>
<thead>
<tr>
<th>Features</th>
<th>Works</th>
</tr>
</thead>
<tbody>
<tr>
<td>RNFL</td>
<td>[7]</td>
</tr>
<tr>
<td>CDR</td>
<td>[3–5, 11, 16, 21, 27, 31, 35, 38, 42, 47, 52, 57]</td>
</tr>
<tr>
<td>Vessel</td>
<td>[21]</td>
</tr>
<tr>
<td>Apex point</td>
<td>[12, 29]</td>
</tr>
<tr>
<td>Optic disc</td>
<td>[9, 13, 19, 23, 28, 34, 53]</td>
</tr>
<tr>
<td>Optic disc hemorrhage</td>
<td>[28]</td>
</tr>
<tr>
<td>Optic disc morphology</td>
<td>[6, 45]</td>
</tr>
<tr>
<td>Neuroretinal rim</td>
<td>[5, 21, 23, 34, 57]</td>
</tr>
<tr>
<td>ONH</td>
<td>[54, 58]</td>
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Figure 2: Bar Chart Based on the Data Set Used.
[15], STARE data set [50], RIMONE data set [44], MESSIDOR data set [30], HRF data set [20], and DEMD data set. In Figure 2, we can analyze the different data set usages for the reviewed papers. Accordingly, the number of papers, such as Refs. [3, 12, 13, 19, 21, 26, 29, 48, 49, 55, 58], specifies the real data set for glaucoma detection. Then, the works are done in [32] based on the two data sets, such as RIMONE data set and DIARETDB1 data set. Moreover, the data sets of SCES, ZEISS, and IPN are effectively included in Refs. [2, 13, 23], respectively. Finally, we concluded that most number of papers have used real data set for the detection of glaucoma.

(c) Analysis Based on Accuracy: In this section, Table 3 shows the analysis of literature papers based on the classification accuracy. Here, the reviewed papers are categorized in five ways based on the accuracy values, such as below 80% accuracy, above 95% accuracy, and the ranges of accuracy between 80% and 85%, between 85% and 90%, and between 90% and 95%. Here, the four reviewed papers such as Refs. [5, 12, 41, 48] have obtained more than 95% accuracy. From Table 3, we can understand that nine reviewed papers have achieved an accuracy between 90% and 95%.

(d) Analysis Based on Objective: This section shows the objective analysis of reviewed papers using a pie chart, which is shown in Figure 3. Here, the pie chart can be plotted based on the various objectives such as glaucoma detection, glaucoma stages classification, vertical CDR measurement, blood vessels segmentation, optic disc boundary detection, optic cup detection, and ONH deformation. From the above reviewed 45 papers, we concluded that 26 papers reached the objective of glaucoma detection. Then, four papers such as Refs. [25, 52, 53, 58] reached the objective of optic cup detection. Moreover, the objective of optic disc boundary detection was performed in Refs. [6, 21, 28, 45]. Then, the vertical CDR measurement [19, 34] and optic cup detection [25, 32] were performed in two papers of each. Finally, we can understand that most researchers did the work based on the objective of glaucoma detection compared to other types of objectives such as blood vessel segmentation and optic disc boundary detection.

(e) Analysis Based on Imaging Technologies: This section discusses the different imaging technologies used for glaucoma detection. From the research study, it is revealed that four major imaging modalities are applied for image processing-based glaucoma detection. Accordingly, fundus, HRT, OCT, and US images are applied for glaucoma detection. Figure 4 shows the pie chart based on the

Table 3: Analysis Based on Simulation.

<table>
<thead>
<tr>
<th>Accuracy level</th>
<th>Works</th>
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<tbody>
<tr>
<td>Below 80%</td>
<td>[7, 21]</td>
</tr>
<tr>
<td>80–85%</td>
<td>[55, 56]</td>
</tr>
<tr>
<td>85–90%</td>
<td>[1, 3, 8–10, 16, 29, 31, 37, 38, 52]</td>
</tr>
<tr>
<td>90–95%</td>
<td>[2, 11, 13, 27, 33, 35, 39, 47, 49]</td>
</tr>
<tr>
<td>Above 95%</td>
<td>[5, 12, 41, 48]</td>
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</table>

Figure 3: Pie Chart Based on Objective.
frequency of the research works that are based on imaging modalities. Accordingly, fundus imaging was actively applied for glaucoma detection. For example, 39 research works used fundus images for glaucoma diagnosis. On the contrary, two research works are used the other modalities, such as HRT, OCT, and US.

Table 4 shows the effectiveness of the imaging technologies for glaucoma detection. Here, the maximum accuracy of 98.46% is reached by the fundus imaging-based research work. The average accuracy of the fundus imaging is 90%. The average accuracy of the HRT, OCT, and US imaging modalities are 91%, 97.75%, and 94%, respectively. The bold values given in Table 4 indicates the better performance.

4 Gaps and Issues

Based on the literature review conducted, we identify some of the important challenges that require a more advanced procedure to handle it. Some of the challenges are listed here.

One of the important medical features used in the literature to find the presence of glaucoma is CDR. Usually, the ophthalmologists determine the cup and disc areas and diagnose glaucoma using a vertical CDR. However, the determination of the cup area is very difficult. Again, the automatic calculation of optic cup boundary is challenging due to the interweavement of blood vessels with the surrounding tissues around the cup [58].

The broad range of CDR makes it difficult to identify early changes of ONH, and different ethnic groups possess various features in ONH structures. Hence, it is still important to develop various detection techniques to assist clinicians to diagnose glaucoma at early stages.

For the detection of glaucoma based on features, some work uses the thresholding operation. However, fixed a thresholding is also not adequate to handle large-intensity variations in the cup region that arise due to physiological differences across patients. The energy minimization-based deformable models are not appropriate for this problem due to the absence of edge- or region-based information associated with the cup region to derive energy functional [25].

Another one important indicator for glaucoma is blood vessels. Commonly, the blood vessel segments may be modeled by line segments. The problem of finding the convergence of the vessel network may then be

<table>
<thead>
<tr>
<th>Table 4: Analysis Based on Diagnostic Prediction Using Imaging Technologies.</th>
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<tbody>
<tr>
<td><strong>Average accuracy (%)</strong></td>
</tr>
<tr>
<td>Fundus</td>
</tr>
<tr>
<td>HRT</td>
</tr>
<tr>
<td>OCT</td>
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<tr>
<td>US image</td>
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The bold values given in Table 4 indicates the better performance.
modeled as a line intersection problem. Identifying the intersection of a number of lines (a convergence) is a fundamental geometric problem, with applications ranging from astronomy to engineering, such as model fitting and prediction [22].

In some of the methods of glaucoma detection, features are extracted from the whole fundus image or a subimage containing an optic disc. The features from the image portions outside the optic disc do not carry any significant information about glaucoma and are redundant and may also adversely affect the automatic classification [49].

The mostly used classifier called SVM performs classification by constructing an $N$-dimensional hyperplane that optimally separates the data into two categories. SVMs view the classification problem as a quadratic optimization problem. However, it is very sensitive to outliers in the training samples and it requires a long time to train the huge amount of data from large databases.

Another one important classifier called KNN classifier needs all available data. This may lead to considerable overhead too if the training data set is large. Also, it finds difficulty in deciding on an optimal $k$-value. Again, the noisy or mislabeled data directly influence the classification of new instances.

5 Discussion

For glaucoma detection, blood vessel segmentation is an important step to be done. Although many promising techniques and algorithms have been developed, there is still room for improvement in blood vessel segmentation methodologies. The development of techniques, which work for images acquired from different imaging equipment under different environmental conditions, is also an open area for research in vessel segmentation algorithms. We have seen that the choice of classification method influences both accuracy and efficiency. Several classification methods for the prediction of the glaucoma disease have been proposed, while large numbers of optimization algorithms have been investigated. The question remains how best to select and implement the classification methods. Some certain options are more promising than others, but the optimal choice also depends on the interaction between the various aspects of the implementation.

To expand the utility of glaucoma detection algorithms for healthcare, there is a need to create larger data sets with available ground truths, which include the labeling of vessels, other anatomical structures, and classification. The collection of large databases with different kinds of images available online for the research purpose will open a new era in this automatic glaucoma detection. Furthermore, the development of research software applications, which integrate various computer-assisted retinal image analysis algorithms, such as CDR estimation, vessel extraction, feature extraction, and classification, is a new research direction. Commonly, most of the glaucoma detection methodologies are evaluated on the retinal images of adults. The morphological characteristics of retinal images of premature infants, babies, and children are very different from that of the adult retina. Therefore, the analysis of the retinal images of premature infants, babies, and children will be a good research direction for the researchers in this field.

Over the past decade, a lot of understanding has been gained about automatic glaucoma detection. It is not an easy procedure to understand: the underlying process of how the features influence the learning theories is difficult to envisage. How it influences the relation between images and learning models is even more mystifying. For instance, better results with statistical features have been reported for glaucoma detection from the fundus images. Furthermore, it may turn out that fundus images are not the optimal image technologies for images of thin structures. Therefore, what we have learned from past research is that recent image technologies, such as HRT, OCT, and US images, are a useful adaptation of automatic glaucoma detection. From the continuing interest in glaucoma detection, it can be deduced that image processing-based methods will not be abandoned in the near future. It is already a successful method for many applications and it can undoubtedly be adapted and extended to aid in many more problems.
6 Conclusion

This paper presents the collective survey of different techniques used for automated glaucoma detection using various features. The main intention of this study was to study and review glaucoma detection techniques based on retinal images. Here, we have taken 45 research papers based on glaucoma detection and analyzed the papers based on three factors. The first one is feature extraction using medical features, such as CDR, apex point, neuroretinal rim, and ONH, and image features, such as wavelet energy and Haralick texture. Second, the techniques were categorized based on the classification accuracy achieved by the various classifiers, such as SVM, KNN, NB, and AdaBoost classifier, based on the threshold technique and random forest classifier. Finally, we have performed the analysis using different data sets, such as VEP data set, IPN data set, SCES data set, GRI data set, ORIGA data set, local data set, ZEISS data set, DIARETDB1, and ORIGA-light data set. Finally, we present the various research issues and solutions that can be useful for the researchers to accomplish further research on glaucoma detection. Based on the analysis, we concluded that more number of researchers have used the classification based on the threshold-based technique and SVM classifier.

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