A REVIEW ON DETECTION OF ABNORMALITY IN DIABETIC RETINOPATHY

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Abstract: This paper provides the literature survey about detection of diabetic retinopathy (DR) in retina fundus image. This review consists of segmentation of blood vessels and classification of DR. The objective of this paper is to provide the relevant literature in the digital image processing for the detection and classification of DR. It gives the information about various algorithm employed in DR.

Keywords: Diabetic Retinopathy, Microaneurysms, Haemorrhages, exudates and blood vessel segmentation

1. Microaneurysms and Haemorrhage Detection

In the year of 1995, the detection of Microaneurysms (MAs) in diabetic retinopathy was proposed by Timothy Spencer et al., [1] where the retina images were captured through digitized fluorescein angiograms. The system used several preprocessing stages to obtain the candidate MAs. The bilinear top-hat transformation and matching filter was employed to predict the initial segmentation of retina images. The binary images of the candidate MAs were obtained thorough thresholding process. Finally, a novel region growing algorithm was used to analysis the size, shape characteristics of the MA region. The results were reveals through Receiver Operating Characteristic (ROC) curve.

In the year of 2000, a screening method for diabetic retinopathy was proposed by Bernhard et al., [2]. The screening method comprises of preprocesing, shape estimation, feature extraction and classification. In preprocessing, mean and median filter was used to remove the noises from the retina image. The shape and size of the MA region was estimated using region growing algorithm where mean filtered image was used. The statistical features of mean, major axis variance, minor axis variance and min circle were predicted from candidate region of diabetic retinopathy and form the feature vector. The obtained features were fed into three types of classifiers are Bayes classifier, classifier using Mahalanobis distance and k-NN classifier on 134 images. The result shows that Mahalanobis classifier provides better results in screening of diabetic retinopathy.

In the year 2005, a local adaptive algorithm for the detection of Microaneurysms in digital fundus image was developed by Ke Huang and Michelle Yan [3]. First, the total image was divided into several sub-regions using local adaptive thresholding algorithm where each region was affected by large amount of artifacts. To overcome this problem low pass with Gaussian filter was employed each region. The background non uniform illumination was eliminated by shading effect. The morphological operation of top-hat filter was introduced in shade and enhanced retina image was to obtain the valid MA region. The simultaneously optic disc and retinal blood vessels were segmented.

A differentiate between the normal fundus and abnormal fundus image using computer-aided screening method was implemented by Apichart et al [4]. The computer aided screening method comprises of preprocesing, blood vessel segmentation and matching algorithm. First, local contrast enhancement technique was applied on retinal image to minimize the non-uniform retinal image. Second, optic disc and fovea was identified by local variation of retina image and matching correlation. The Blood vessels were segmented using multilayer perceptron neural network. The exudates were recognized using recursive region growing algorithm. The haemorrhages were identified using color and template matching algorithm. The results show the sensitivity of 74.8%, specificity of 82.7%, and positive predictive value of 69.56%.

In the year of 2007, the causes of vision loss and clinical evaluation of diabetic retinopathy (DR) and diabetic macular edema (DME) were outlined by Jaime et al [5]. In this outline, they approach that patient with high vision loss were affected by diabetes mellitus. Both DME and DR were produced from the immoderate level of blood glucose on vessels and it damages the micro vascular. The development of DR was reduced by intensive glycemic and blood pressure control. The vision loss from proliferative DR and DME was reduced by laser photocoagulation method. So, overall outline of patient with diabetes and vision loss was present.

An automatic detection of haemorrhages and microaneurysms in the retinal image was proposed by María García et al. [6]. In this approach first normalizes the contrast and luminosity of the retinal image. They used 29 features based on color and shape of the candidate region. The relevant features were selected from 29 features using logistic regression. There are four types of classifier such as multilayer perceptron (MLP), radial basis function (RBF), support vector machine (SVM) and a combination of these three NNs using a majority voting (MV) schema were used. The selective features were fed into these classifier to classify the candidate region was normal or abnormal. The performance of this approach was evaluated on 115 images where 50 set of training image and 50 set of testing image. They reported their success rate on 100% of sensitivity, 56% of specificity, and 83.08% of accuracy.

The Automatic Detection of Microaneurysms and Haemorrhages in Digital Fundus was investigated by Giri Babu Kande et al. [7]. The matching filter was used to improve the red lesions in the retina image against background. The red lesions were distinguished from background retina image based on relative entropy-based thresholding technique. The enhanced vasculature was suppressed by morphological method of top-hat transformation technique. Finally, SVM classifier was applied to distinguish the candidate red lesions from other segments in the retina image. The performance of this approach was evaluated on 98 retinal images where 20 images for training and 69 images for testing. They report their performance of 100% of sensitivity and 91% of specificity.

Dupas et al., proposed an algorithm for the detection of microaneurysms, hemorrhage and grading the diabetic retinopathy [8]. First, the green channel of retina image was extracted from color fundus image. In preprocessing, filters the retina image and normalize the non-uniform contrast of the retina image. The closing operator in mathematical morphology was used to fill the black holes in the retina image. The black hot-top process of difference between the closing operator and contrast normalization technique was extracting the black component against the background of the retina image. The microaneurysms was identified by automatic threshold technique and then finally kNN classifier classifies the candidate region was mild, moderate and severe based on the grading level of DR. They reported a success rate of 72.8% of sensitivity and 72.7% of specificity.

In the year of 2011, a method for the detection of haemorrhages from the fundus image was presented by Jang et al. [9]. In this approach, RGB space was converted into HIS color space. In preprocessing, the non-uniform illumination was corrected by Gaussian algorithm. The CLAHE algorithm was applied for contrast enhancement of the retina image. The Temple matching technique with normalized cross-correlation method was employed to extract the various shapes of the hemorrhage candidate. The exact shape of the hemorrhage was predicted using adaptive seed region growing segmentation (ASRGS) algorithm. Finally, statistical tool of compactness, area and aspect ratio was used to detect the hemorrhage candidate region form the retina image. The result of this approach reveals the success rate of 85% of sensitivity.

In the year of 2012, a survey on detection of hemorrhage in fundus retina images was given by Parisut et al. [10]. In this survey they provide the various process of hemorrhage detection. They provide review on morphological approach, neural network, and region growing method for detection of hemorrhage. They report about the performance metrics where pixel based, lesion based and image based approaches were used.

An automatic detection of Microaneurysms in fluorescein angiography fundus image was proposed by Meysam et al. [11]. The optic nerve head was detected by applying random transform and masking image. The tap-hot transform and averaging filter was applied on retinal image to remove the noise and background image. The preprocessed image was divided into sub-image and applies random transform (RT) technique for each image for the detection and segmentation of vascular tree. Followed by segmentation, appropriate thresholding technique was employed to extract the Microaneurysms candidate region form the retina image. The result of this approach was evaluated on three databases and provides a success rate of 94% of sensitivity and 75% of specificity.

In the year of 2013, detection of Microaneurysms in retina image was presented by Niladri et al. to reduce the blindness [12]. The CLAHE method was applied on green channel of the retina image for contrast enhancement. The smoothing of the retina image was obtained by apply median filter on contrast enhanced image. The mathematical operation image opening, closing and filling operation was taken for the removal of bright lesions and finally obtains the Microaneurysms candidate region.

A hybrid classifier of m-Mediods was proposed by UsmanAkram et al in the year of 2014, based on modeling approach and combines it with a Gaussian Mixture Model was used to detect or classify microaneurysms and non-microaneurysms in retinal fundus image using color and shape features. Their method was evaluated on DRIVE, STARE, DIARETDB and MESSIDOR database. This method obtained an accuracy of 98.12% [13].

An automatic detection of microaneurysms in retinal fundus image was proposed in the year of 2015 by Tamilarasi and Duraiswamy [14]. During preprocessing bottom-hot filtering and gamma correction was

performed on green channel of the retina image for enhancement. The optic disc was segmented and removed using Circular Hough Transform (CHT) and blood vessels were removed using matching filter. The multiscale Gaussian kernel was used for extraction of microstructure features from the retina image. Finally, Markov Chain Monte Carlo method was used as classifier to distinguish between microaneurysms and non-microaneurysms. Their method was evaluated on DIARETDB0 and DIARETDB1 database and obtained a sensitivity of 7.86% and specificity of 98.33%.

Roberto et al. proposed six step algorithms for the detection of microaneurysms [15]. In preprocessing stage reduction of non-uniform illumination and normalization of retina image was taken. The bottom-hat transform was applied on normalized image to leave the reddish region. The segmentation of blood vessel, MA and other reddish region from background were obtained through binarized the image of interest. The blood vessel was removed from region of interest using hit-or-miss transform applied on the binary image. The Shape based and random transform features were distinguishing the MA from other lesion using hierarchical system classifier. Their method was evaluated on 189 retina image and obtained a sensitivity of 92.32% and specificity of 93.87%.

In the year of 2016, a microaneurysms detection method based on Markov Random Field (MRF) was implemented by Razieh et al. [16]. During preprocessing stage, top-hat morphological transformation was employed on green channel image and contrast stretching was applied on result of top-hat morphological transformation output to increase the contrast between the background and retinal features. The background of the retinal image was obtained by applying mean filter on retinal image. The subtraction between mean filter and top-hat morphological transformation output provides non-noise retina image. The matching filter and Gaussian function was used to segment the blood vessels from the retina image. The Markov Random Filed was used to extract the candidate microaneurysms from the retina image. The SVM based classifier was used to classify the lesions into MA and non-MA using 23 features from shape, intensity and Gaussian distribution. Their performance was evaluated on DIAREDB1 database and obtained average sensitivity for different false positive per image.

In the year of 2017, Malihe Javidi et al. present a detection system for microaneurysms and vessel extraction using training and testing phases [17]. In training phase of the vessel extraction discriminative dictionary learning (DDL) was used for vessel segmentation whereas in testing phase Gaussian Mixture Model was applied to generate the vessel map based on threshold. The binary vessel map of the vessel and non-vessel patches were fed into Fisher discrimination dictionary learning classifier to detect or classify vessel and non-vessel. In the case of microaneurysms detection, discriminative dictionary learning extracts the candidate region and fed into classifier to detect MA candidate region. Their performance was evaluated on DRIVE and STARE database and obtained a sensitivity of 72.01%, specificity of 97.02% and accuracy of 94.50% for DRIVE database, 77.80% of sensitivity, 96.53% of specificity, 95.17% of accuracy for STARE database for vessel segmentation. The microaneurysms were evaluated at various false positive points using free-response receiver operating characteristic (FROC) curves. Table 1 provides the sensitivity and specificity of microaneurysms and haemorrhages detection.

Table 1: Comparison of sensitivity and specificity of automated microaneurysms and haemorrhages detection

Authors	Sensitivity	Specificity	database	Methods
Wang et al., 2000 [18]	-	-	54 fundus image	Bayesian statistical classifier
Kahai et al., 2004 [19]	100	63	143 images	Decision support system
Neubauer et al.,2005 [20]	93	100	184 color fundus image	Retinal thickness layer
Singalavanija et al.,2006 [21]	75	83	900 fundus images	Combination of image processing techniques with neural network
Estabridis et al.,2007 [22]	-	-	High resolution image database	Adaptive threshold method
Abramoff et al.,2008 [23]	84	64	-	Machine learning method
Nayak et al.,2008 [24]	90	100	140 color fundus image	Combined method of morphological processing technique and texture analysis method
Vujosevic et al. 2009 [25]	82	92	55 color fundus image	Detected by Statistical method
Agurto et al.,2011 [26]	98	85	Rist and UTHSCSA database	Amplitude-modulation frequency-modulation
Hassan et al., 2012 [27]	89.4	63.9	324 images from various database	Normalization, filtering, morphological techniques and threshold method
Enrique et al., 2015 [28]	-	-	Above 1000 images from various database	Image processing techniques
Rahim et al., 2016 [29]	86.79	100	900 color fundus images	Fuzzy image processing

2. EXUDATE DETETION IN DIABETIC RETINOAPTHY:

In the year of 2003, Osareh and his coworkers implemented an automatic method for identification of retinal exudates in digital color images [30]. The system comprises of preprocessing, segmentation and classification. In preprocessing stage, first RGB color image was converted into HSI color space where contrast enhancement was employed on Hue color space. Second, segmentation process was followed by preprocessing where fuzzy-c-mean algorithm was applied on enhanced retina image to segment the excaudate region from. Finally, artificial neural network (ANN) classifier was used to classify the segmented region into exudates and non-exudates. The result reveals that system achieves sensitivity of 95% and specificity of 88.9%.

The neural network approach was developed by Gerald Schaefer and Edmond Leung used to detect the exudates in the retina image [31]. Here, windowing technique was used to extract the parts of the retina image where histogram equalization and principle component analysis (PCA) method was applied. The key of the histogram equalization and histogram specification was equalizing the intensity of the retina image. The key of the PCA method was to dimensionality reduction, the raw features are reduced. The feature vector from the sliding window technique was fed into neural network to classify the whether the area was exudates or non-exudates. The results were performed on 17 images where 10 images were taken for training purpose and 7 images were taken for testing purpose.

In the year of 2008, Clara I. Sanchez et al. was proposed an automatic system to detect the hard exudates from the retina image [32]. The system composed of preprocessing, feature extraction, classification and post processing. The color normalization and contrast enhancement of the retina image was obtained by the conversion of RGB color space to HIS colors pace where three parameters were used based on characteristics of retina image. The features were extracted from the HIS color space based on the color information of the retina image using within-class and between-class scatter matrix method. The obtained features were given into Fisher's linear discriminant analysis method to classify the retina image was exudates on non-hardexudates. In post processing stage, apart from exudates other pathologies of DR was present and detected by morphological preprocesing method. The performance was evaluated using 58 retinal images and it obtains 88% sensitivity.

Akara Sopharak et al. used Fuzzy C-Means (FCM) clustering method to detect the exudates from low contrast digital images [33]. First, RGB color space was converted into Hue, saturation and Intensity HIS color space. Second, the intensity band was applied to median filter operation to reduce the noise in the retina image. Third, contrast-limited adaptive histogram equalization method was fed into noise removal image for contrast enhancement. Four different types of features were extracted from the contrast image are intensity value, standard deviation of intensity, hue and edge pixels. The obtained four features were given into FCM clustering to cluster the exudates from the retina image. They reported a success rate of 87.2% of sensitivity, 99.2% of specificity respectively. The result of FCM clustering and morphological approach was compared with FCM clustering.

An automatic detection of hard exudates in retina images was proposed by Maria Garcia et al. in the year of 2009 [34]. First, normalize the contrast and luminosity of the retina image. Second, exudates are segmented from the retina image using combination of global and adaptive thresholding technique. Third, 24 statistical features were extracted from the segmented candidate exudates region. From the 24 features, relevant features were selected using logistic regression method. Finally, the selective features were fed into input to the radial basis function (RBF) neural network classifier to classify the retina image as exudates on non-exudates. They report their evaluation on 117 retina image and obtain 100% of sensitivity, 70.4% of specificity and 88.1% of accuracy.

The same author, Maria Garcia et al. continued their work in comparison of three types of neural network classifiers such as multilayer perceptron (MLP), radial basis function (RBF) and support vector machine (SVM). They reported their results of 91.04% of accuracy, 77.78% of specificity and 100% of sensitivity using SVM classifier compared to other two neural network classifier. So, in this study they presented SVM classifier provides better results compared to MLP and RBF classifier for the detection of exudates [35].

Clara and their coauthors proposed an automatic method for the detection of hard exudates from the retina image [36]. First, normalize the contrast and luminosity of the retina image was based on statistical method of mean and standard deviation of pixels. The overall improvement of the contrast between the lesions and background retina image was improved by within-class and between-class scatter matrix method. The separation between the lesions and background retina was obtained by mixture model and dynamic threshold technique. The differentiation between the hard exudates and other pathologies of DR was based on edge detection method in post processing technique. The performance was evaluated on 80 retinal images and reported their success rate of 100% of sensitivity and 90% of specificity.

In the year of 2010, the early detection of exudates and haemorraghes in diabetic retinopathy was presented by Michael et al. [37]. First, the red lesions in DR are detected using pixel feature classification. Second, cluster the candidate pixel and extract the features from each cluster candidate. In this study, k-nearest neighbour (kNN) classifier was used to classify candidate region of exudates and haemorraghes into normal or abnormal.

JayaKumari and Maruthi proposed a detection of exudates based on preprocessing, segmentation, feature extraction and classification [38]. In preprocessing, contrast adaptive histogram equalization was applied on original retina image to increase the contrast. In segmentation, contextual clustering algorithm was operated on contrast retina image to segment the exudates from the retina image. In feature stage, statistical features of the candidate region are standard deviation, mean, intensity; edge strength and compactness were extracted. The above features were fed into Echo State Neural Network (ESNN) classifier to distinguish between exudates and non-exudates. Their performance was evaluated on 35 retina images and obtained a sensitivity of 93% and specificity of 100%.

In the year of 2012, segmentation based technique for the detection of exudates from fundus image was proposed by Atul Kumar et al. [39]. In this approach they applied various stages of preprocessing, image boundary tracing, image segmentation and finally classification. In preprocesing stage; color space conversion, image normalization, adaptive median filtering and adaptive histogram equalization was applied. In image boundary tracing stage; edge detection & zero padding, adaptive threshold & centroid, optic disc localization and vessel extraction. In image segmentation, morphological operation and matching filter was used. In feature extraction; combined two-Dimensional Principal Component Analysis (2DPCA) was used to extract the lesion features. Finally, SVM classifier was used to classify the exudates into soft exudates, subretinal exudates, and hard exudates. They reported a success rate of sensitivity of 97.1% and specificity of 98.3%.

In the year of 2012, detection of exudates in color fundus image was developed by Doaa Youssef and Nahed [40]. In this approach, first correct the problem of non-uniform illumination and presence of noise. It was corrected by apply median filter to green channel of the retina image for the removal of noise. The contrast enhancement of the retina image was corrected by apply top-hat morphological operation. It was obtained by the subtraction top-hat opening and top-hat closing result. The optic disc was detected by Hough transform and canny edge detector, first Hough transform detect the circular objects in the digital images and canny detect the candidate pixels in the obtained circle. The blood vessel tree was extracted by morphological dilation and

erosion process. Finally, exudates were detected by iterative process. The approach reveals the success rate of sensitivity of 80% and specificity of 100%.

An automatic identification of exudates on STARE database was designed by Haniza et al. [41]. In this approach, first extract the green channel image from original color fundus image. The averaging filter was act as filter on green channel image to remove the noise. The averaging filter image was fed into Fuzzy C Means (FCM) clustering to divide the original image into 5 categories or clusters where 3 groups for blood vessel, healthy background retina, and low intensity exudates while other 2 groups for high intensity exudates. Here they interest in extraction of last two groups and omit the other groups from FCM output. The prewitt operation of edge detection was applied on last two groups to identify the edges of exudates. The binary image of the exudates was predicted by Otsu thresholding method. Finally, inverse matrix was employed to segments the exudates and retinal background from the retina image. The system reveals the segmentation results of 97.8% of sensitivity, 99% of specificity.

In the year of 2012, Harangi and his coauthors implement an automatic detection of exudates from color fundus image [42]. The detection system comprises of preprocessing, segmentation, feature extraction and classification. In preprocesing stage, green channel was extracted from the retain image and apply contrast contrast-limited adaptive histogram equalization to this channel for normalize the retina image. The border of the Exudate candidate region was extracted by active contour model and the result was binary image. The statistical features were derived from the binary boundary of the candidate Exudate region. Finally, Naïve Bayes classifier was employed for classification of candidate region was Exudate or non-Exudate. The result reveals their performance as 75% of sensitivity on 89 retina images.

A detection of exudates and complete system for maculopathy detection from patient vision loss was given by Anam Tariq et al. [43]. The mean and variance based segmentation was used for background estimation and noise was detected by the ratio of hue and intensity channel of the retina image. The morphological closing operator was applied on preprocesing image to remove the blood vessel from the retina image. The adaptive contrast enhancement was used to normalize the contrast of the retina image. The Gabor filter was employed on contrast enhanced image for different orientation of retina image to get enhanced bright image. The adaptive threshold technique was fed into Gabor filter enhance image to create binary map. Finally detect the optic disc based on averaging and Hough transform technique. The macula was detected based on the distance from optic disc and enhanced blood vessel. The statistical features were extracted from the candidate region and given to Gaussian Mixture Model classifier to classify the candidate lesion was exudates or non-exudates. This method was tested on MESSIDOR and STARE database and provide sensitivity of 94.25%, specificity of 99.2% and accuracy of 97.83%.

In the year of 2014, an automatic Exudate detection method using basic image processing techniques was developed by Diptoneel Kayal and Sreeparna Banerjee [44]. Initially, median filter was applied on gray channel image to compute the smoothing of the retina image. Next, image subtraction was applied between smoothing image and original image to extract the region with high brightness. The dynamic thresholding was used to compute or detect the exudates from retina image. Their detection performance was evaluated on DIARETDB0, DIARETDB1 database and provides a sensitivity of 97.25% and specificity of 96.85%.

In the same year, Usman Akram and his coauthors developed an automated detection of exudates and macula using hybrid classifier [45]. The automated detection system consists of two phases; first phase for detection of exudates; second phase for detection of macula. Initially, morphological closing operation was evolved in exudates detection for smoothing the fundus image. The contrast bright lesions of the retina were improved by applying CLAHE method. Further enhance the bright lesions by Gabor kernel function. Finally, adaptive threshold was employed on output of Gabor kernel image for detection of exudates candidate region. The features were extracted using statistical features of green channel and HSV color space. The hybrid classifier Gaussian mixture model and support vector machine was used to detect to detect exudates and non-exudates. In macula detection, contrast enhancement, binary map by low adaptive threshold was used. The features were extracted from the mean intensity of the green channel, area of the macula region, optic disc coordination, Normalized cross correlation for binary map, boundary pixel intensity for each region. The obtained feature vectors are fed into GMM classifier for clinically significant macular edema (CSMA) and non-CSMA. Their method was evaluated on MESSIDOR and HEIMED database and obtained a sensitivity of 97.3%, specificity of 95.9% and accuracy of 96.8%.

Mahendran et al. have proposed an exudates detection method using retinal fundus image in 2014 [46]. During preprocessing, gray scale image was subjected to median filtering process for efficient noise reduction in retina fundus image. Further, CLAHE was employed on median filter output and optic disc and blood vessels were removed using canny edge detector and morphological closing operator. The Gray Level Co-occurrence Matrix (GLCM) was employed as feature extractor from candidate region. These features were fed into PNN classifier to classify into normal, moderate NPDR and severe NPDR. Their performance was evaluated on DRIVE and MESSIDOR databases.

In the year of 2013, segmentation of exudates from retina image using statistical atlas based method was developed by Sharib Ali et al. [47]. Their performance was evaluated on HEI-MED database and provides a result on FROC curve

In the year of 2014, an automatic detection of exudates using contextual and textural features was proposed by Xiwei Zhang et al. [48]. Initially, preprocessing was performed on retina image for noise removal and detects the reflection zone. The morphological opening and closing with hexagonal structuring element was used to remove dark structure such as vessel and dark lesions of the retina image. The bright features of the retina image were removed by adaptive template method. The candidate exudates were extracted by two segmentation methods are mean filter and morphological top-hat algorithm. The mean filter was used for the extraction of large exudates candidate while morphological top-hat algorithm was used for small exudates region extraction. The random forest was used as a classifier to classify the candidate lesion into exudates and non-exudates based on contextual and texture features. Their performance was evaluated on three database are Messidor, DiaRetDB1 and HEI-MED. Their method shows a detection of AUC of ROC curve of 0.95% of DiaRetDB1 database, 0.93% of Messidor database and 0.94% of HEI-MED database.

An automatic detection of bright lesions of exudates and drusen in retinal fundus image was presented by Désiré Sidibé et al. [49]. In this method sparse coding technique with SVM algorithm was used for classification of bright lesions using color features, SIFT features, HOG (Histogram of oriented gradients) features and LBP (Local binary patterns) features. Their performance was evaluated on 828 images and obtained a sensitivity and specificity of 96.50% and 97.70% for normal class; 99.10% and 100% for the drusen class and 97.40% and 98.20% for the exudates class.

In the year of 2015, Elaheh Imani and Hamid-Reza proposed a retinal Exudate segmentation in retinal fundus image [50]. Initially, MCA algorithm was performed on retinal image to separate the vessel from lesion with appropriate direction. The dynamic thresholding and mathematical morphological operator was applied on lesions for the detection of exudates. Their method was evaluated on three public available dataset are DiaretDB, HEI-MED and e-ophtha dataset and obtained an accuracy of 96.1%, 94.8% and 93.7%.

An automated system for the detection of exudates and macula candidate region from retinal fundus image was implemented by Sarni Suhaila Rahim et al. [51]. During preprocessing, fuzzy filtering was performed on green channel to improve the quality of the retina image. Next, fuzzy histogram equalization method was applied on well quality image to improve the contrast of the retina image. The Circular Hough Transform was used to localized and detect the optic disc in retina image. The morphological operation was used to extract the blood vessels from retina image. The six different statistical features were extracted from the candidate region of exudates and macula. Finally, SVM, Naïve Bayes and k-NN classifier was used to classify the exudates and non-exudates based on extracted six features. Their performance was evaluated on DIARETDB0, DIARETDB1, MESSIDOR, DRIVE, STARE, REVIEW and ROC database. Their method provides an accuracy of 93% for kNN, 93% for RBF SVM and 75% for Naïve Bayes classifier.

An automatic detection of bright lesion in retina fundus image was proposed by Ratna Bhargavi et al. [52]. The bilateral filter was employed on contrast green histogram equalization image to remove the unwanted noise. The optic disc was removed by morphological operation of image dilation followed by vessels were extracted using Hessian matrix. The candidate region of bright lesions was detected using subtraction between optic disc and vessel extraction image. The texture features were extracted from the candidate region and fed into SVM classifier for distinguish between exudates and non-exudates. Their performance was evaluated on DIARETDB1 and MESSIDOR database and obtained an accuracy of 96.66%.

In the year of 2016, Karthika and Shenbagavalli proposed a morphological method of opening, closing, dilation, erosion and gradient for the detection of exudates in retinal fundus image. Their performance was evaluated using entropy, kurtosis, standard deviation, mean and average value of the candidate region of the exudates [53].

3. Blood Vessel Segmentation:

This Section Covers the Review on Blood Vessel Segmentation

Table 2: Blood vessel segmentation

Author name with year	Methods	Images/database
Akita and Kuga, 1982 [54]	Supervised method was used for retinal segmentation	.
Chaudhuri et al., 1989 [55]	Matching filter was used for retinal segmentation	Fundus images are taken from a TOPCON TRV-50 fundus camera at 35" field of view
Nekovei and Ying, 1995 [56]	Supervised method was used for retinal segmentation	25 images
Tolias and Panas, 1998 [57]	Unsupervised method was performed for retinal segmentation	------
Martinez-Perez et al., 1999 [58]	Multi scale method was used.	-------
Hoover et al., 2000 [59]	Matching filter was used.	20 images are used
Simo and de Ves, 2001 [60]	Model based approach was performed.	4 images taken form database (Canon CF-60U and Nikon NFC 50 fundus cameras)
Zana and Klein, 2001[61]	Mathematical morphology method was used.	200 angiographies images
Gang et al., 2002 [62]	Matching filter was used to separate the retinal vasculature.	48 color fundus images
Xiaoyi and Mojon et al., 2003 [63]	verification-based multithreshold probing method was used	20 retinal images
Niemeijer et al., 2004 [64]	Supervised method was performed for vessel segmentation	DRIVE database
Ayala et al., 2005 [65]	Mathematical morphology method was used.	20 color ocular fundus images
Sofka and Stewart., 2006 [66]	Multi-scale approach was used.	STARE and DRIVE databases
Salem et al., 2007 [67]	Unsupervised method was performed	STARE dataset
Narasimha-Iyer et al., 2007 [68]	Vessel profile based method was used	------
Espona et al., 2007 [69]	Vessel deformable based method was used	DRIVE database
Yang et al., 2008 [70]	Mathematical morphology method was performed	(Hoover database) 20 retinal images
Yao and Chen, 2009 [71]	Matching filter and pulse coupled neural network (PCNN)	(Hoover database) 20 retinal images
Xu and Luo, 2009 [72]	Supervised method	50 retinal images from Beijing Tongren Hospital.
Ng et al., 2010 [73]	Maximum likelihood estimator and Gaussian-profiled valley	STARE database
Lam et al., 2010 [74]	Vessel profile based method	STARE and DRIVE database
Sun et al., 2011 [75]	Mathematical morphology method with fuzzy filter	Images are taken from thirty series of cineangiography from seven patients, each containing 50–100 angiogram
Miri and Mahloojifar, 2011 [76]	Mathematical morphology method	Drive database
Fraz et al., 2012 [77]	Mathematical morphology method	DRIVE and STARE database
Bankhead et al., 2012 [78]	Wavelets model-based approach	DRIVE and REVIEW database
Nguyen et al., 2013 [79]	Multi-scale line detectors	DRIVE, STARE, and REVIEW datasets

Yin et al., 2014 [80]	Hessian Matrix and Binarisation of Threshold Entropy	DRIVE and REVIEW database
Azzopardia et al., 2015 [81]	Bar-selective Combination of Shifted Filter Responses	DRIVE, STARE and CHASE_DB1 database
Roychowdhury et al., 2015 [82]	Morphological operator with Gaussian mixture model	DRIVE, STARE and CHASE_DB1 database
Liskowski and Krawiec, 2016 [83]	Supervised segmentation method	DRIVE, STARE, and CHASE database
Soomro et al., 2016 [84]	Local Normalisation with Discrete Normalised Laplacian of Gaussian Detector	STARE database

4. Conclusion:

A survey of several methods for automatic detection of DR in digital color fundus image is presented in this chapter. This chapter provides the existing method related to DR lesion detection method of microaneurysms & exudates, retinal blood vessel segmentation. The goal of this paper is to learn about the several algorithms for DR detection, analyze the method and develop an algorithm for DR detection.

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