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A Survey on Feature Extraction Methods in Retinal Fundus Images for Diabetic Retinopathy

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Abstract— The uniqueness of retinal microvasculature is that it is the only part of human circulation that can be directly visualised non-invasively in vivo and readily photographed. Developments in fundus image processing over the past 20 years includes advancement being made towards developing automated detection for conditions, such as diabetic retinopathy, age-related macular degeneration and retinopathy of prematurity. Features of retinal blood vessels, microaneurysms, exudates and the hemorrhages are extracted to detect the Diabetic Retinopathy (DR) in the early stages. Diabetic Retinopathy results fluid leaks from retinal blood vessels leading to vision loss. Microaneurysms appear as small circular dark spots on the surface of the retina. The appearance of red and yellow lesions on retina is exudates and hemorrhages. Image processing algorithms can be used to reduce the workload of ophthalmologist and play a vital role in quality assurance tasks. Feature extraction is the first step in developing these automated algorithms for detecting retinal pathologies. Here we review numerous early studies that used for automatic detection of these features. Most of the literature has differences in the method used to evaluate their algorithms or the dataset used, which makes it difficult to compare any two algorithms together. Our study reveals that even though a large number of feature extraction technique are available there is still scope for more accurate algorithms which will work with High Resolution Fundus (HRF) images also.

Keywords— Diabetic retinopathy, Exudates, Hemorrhages, Micro aneurysms

I. INTRODUCTION

The disorders related to retina like Diabetic Retinopathy (DR), Age-related Macular Degeneration (AMD) and Glucoma etc can cause visual impairments. These disorders can be diagnosed by the ophthalmologists with the help of the digital image processing. The retinal fundus images of the patients are procured by capturing the fundus images of the eye with a digital fundus camera. It provides important data about retina and various systematic and non systematic diseases. Fundus image analysis is a non invasive method and automatic methods to avoid traditional manual grading [1].

The fast progression of diabetes is one of the main challenges in current health care. The number of people affected with the disease continues to grow at an alarming rate. If not treated early, diabetes leads to severe complications like macro and micro vascular changes which results in heart disease, renal problems and diabetic retinopathy (DR). If DR is not detected and treated early increased blood glucose level in diabetic patients will rupture the small blood vessels called capillaries in the eye. Due to this blood leaks into the retina of the eye there by causing damage to retina which leads to permanent vision loss. In order to avoid increased screening time and human error, there is a need for efficient and accurate automated algorithms to detect and classify DR and other retinal pathologies.

So far the most effective treatment for DR can be administrated only at the first stages of the disease. Therefore early detection through regular screening is important. To lower the cost of such screening digital image capturing technique must be used, because this technology enables us to employ state-of-art image processing techniques which automate the detection of abnormalities in retinal images. The retinal fundus image shown in figure1 includes anatomical structures and lesions of DR.

(a) Anatomical structures of retina

- Optic Disc: The optic disc represents the beginning of the optic nerve and is the point where the axons of retinal ganglion cells come together.

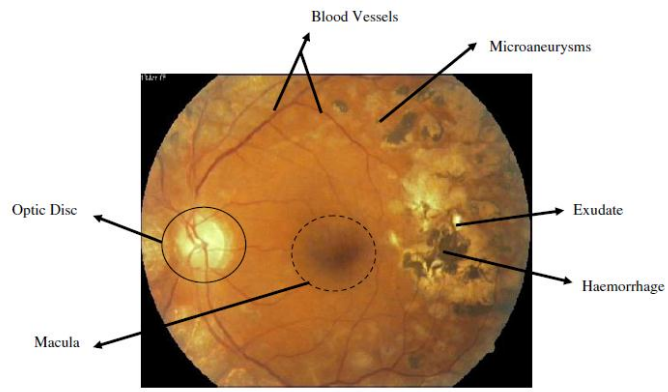


Figure 1: Color fundus image with exudates, hemorrhages, microaneurysms, fovea and optic disc.

- Fovea: The depression in the retina that contains only cones and provides accurate vision.
- Macula: Area in the middle of the retina that allows seeing object with great detail.
- Blood vessel: Thin, elongated piecewise linear Structures in the retina and they have limited curvature.

(b) Lesions of DR

- Exudates: Due to damages of blood vessels of retina lipid leak out of the blood vessels forming exudates which are a major indicator of DR.
- Heammorrhages: Smallest spots of blood that break into the retina.
- Microaneurysms (MAs): These are enlarged aneurismal retina vessels that show up as red dots in retina. This is caused due to the occlusion of vessel capillary and frequent leak of fluids.

This paper reviews automated detection systems for DR. This review is organized as follows: Section I contains the introduction of DR and details of retinal fundus images. Different detection methods for the extraction of micro-aneurysms, exudates and hemorrhages are discuss in section II .These features are used for the automatic detection of DR. In the automatic detection of DR stages section we reviewed different automated detection systems which have been reported in scientific literature. The last section of this paper presents conclusions and outlines further work.

II. DETECTION METHODS OF LESIONS

This paper deals with the recent feature based techniques that exploit the visual characteristics of the objects. Therefore, we have divided the approaches of retinal object segmentation, according to the features involved. The papers are categorised according to the image processing methodologies and algorithms used. The following sections describe exudates, haemorrhages and microaneurysms detection techniques. These detection techniques yield most of the features which are used in automated DR detection systems. Each segmentation method category is introduced, discussed and the papers of this category are summarized. The performance measures used by the algorithms and the method used for feature extraction are tabulated at the end of each section.

II.1. Microaneurysm Detection Methods

Microaneurysm is a small swelling that forms in the wall of tiny blood vessels. These small swellings may break and allow blood to leak into nearby tissue. People with diabetes may get microaneurysms in the retina, the light-sensitive area at the back of the eye. MAs appear as small circular dark spots on the surface of the retina. The detection of MAs is still an issue. Several recent works focus on this problem and detection methods are based on mathematical morphology, ,supervised classification, pixel classification, template-based ,thresholding based method, region growing based method and unsupervised methods.

II.1.1.Mathematical Morphology based methods

One of the earliest proposed techniques for microaneurysm detection described in [2] use fluorescein angiograms. A combination of bilinear top-hat transformation and matched filtering are employed to provide an initial segmentation of the images. Thresholding this processed image provides a binary image containing candidate microaneurysms. A novel region-growing algorithm fully delineates each marked object and subsequent analysis of the size, shape, and energy characteristics of each candidate results in the final segmentation of microaneurysms. Paper [3] used method discussed in [2] to multiple longitudinal florescence images in order to detect the microaneurysm turnover that is the appearance or disappearance of microaneurysm objects over time. The microaneurysm detector achieved a sensitivity of 82% for a rule based classifier.

Method described in [4] investigates a set of optimally adjusted morphological operators to detect microaneurysms from non-dilated pupil and low-contrast retinal images. For this purpose, the pre-processing of retinal image was performed using mathematical morphology and a shade-corrected algorithm was employed for vessel detection. Thresholding and exudates reconstruction were employed for exudates removal. The extended minima transform and local thresholding were applied to the pre-processed image for microaneurysms detection. Finally these detected microaneurysms were compared with the ground truth of the specialists. The sensitivity and specificity are rated as 81.66% and 99.99%, respectively.

Akram *et.al* in [5] extracted all the possible candidate microaneurysms regions using feature vector. Feature vector was formulated based on certain properties like shape based features, grey level features, colour features and statistical features and are used for classifying microaneurysms and non microaneurysms. Candidate region extraction was performed to improve the contrast of dark regions using mathematical morphology, contrast normalisation and filter banks. A hybrid classifier combining Gaussian Mixture Model (GMM) and Support Vector Machine (SVM) was used to improve the accuracy of the classification. The proposed method achieved 98.6% sensitivity, 97.2% specificity and 98.4% accuracy on Messidor database.

II.1.2 Supervised methods

Most of the currently available supervised methods [6],[8] divide MAs detection into two consequent stages: candidate extraction and classification. Usually, the first step of candidate extraction is image pre-processing to reduce noise and to improve contrast. After pre-processing, image segmentation is used to extract as much regions as possible that probably corresponds to MAs. In the second step, the resulting candidates are labelled as true or false ones using a supervised learning based method. This classification requires a training set to establish the boundaries of the classes. The training set consists of pairs of feature vectors and class labels. Feature vectors are ordered sets of certain property values, mostly geometrical or colour descriptors that may help to distinguish MAs from other objects.

II.1.3.Pixel classification based method

Red lesions which are larger than the linear structuring element cannot be detected using candidate extraction technique. In [6] a pixel classification based method is used to overcome this limitation. It is a supervised method. So it needs to be trained using sample pixels. Pixel based classification can detect larger candidate objects and reduces the number of spurious candidate objects on the vessels by integrating a vessel segmentation technique with red lesion detection. For candidate classification KNN classifier is used. This candidate extraction method achieves a sensitivity of 89% and specificity of 96%.

A double-ring filter was used in [7] to detect the initial microaneurysm candidates. The filter used the property that MAs are dark circular regions within a brighter region to detect the MA candidates. It consists of an inner ring and an outer ring. A given pixel is considered to be a MA pixel if the average intensity of the inner ring is smaller than the average intensity of the outer ring. After the initial candidates are detected classification is performed using 12 extracted features and an Artificial Neural Network (ANN). Sensitivity obtained by this method was only 65%.

II.1.4.Template based method

Another supervised method to detect MAs described in [8] used template-matching based algorithm along with wavelet transform. Microaneurysms are detected by locally matching a lesion template in sub bands of wavelet transformed images and searched for the best adapted wavelet within the lifting scheme framework. The optimization process is based on a genetic algorithm followed by Powell's direction set descent. Microaneurysms were detected with a sensitivity of 89.62% and a positive predictive value of 89.50% for colour images. Limitations of this method are that a few MAs are not detected because they are too close to big vessels or clustered and some haemorrhages are detected as MAs.

II.2.5.Thresholding based method

A hierarchical approach based on Multiscale Correlation Filtering (MSCF) and dynamic thresholding is proposed in [9]. It consists of a coarse level and a fine level. The approach was evaluated using the public retinal image database provided on the ROC competition website. The selection of scales in the first level is vital to the success of succeeding steps. Sigma values have to be chosen such that the kernel can match lesions of various sizes always producing a high correlation coefficient. Only five scales are used. Gaussian masks of different sizes are utilized to find the correlation of coefficients with the original image.

II.1.6. Region based method

Recursive region growing segmentation algorithm combined with moat operator is used in [10] to detect microaneurysms automatically. The sensitivity and specificity are reported as 77.5% and 88.7%, respectively. Method described in [11] shows how image contrast normalisation can improve the ability to differentiate microaneurysms and other dots on in the retinal images. Watershed transform was applied to obtain better contrast normalisation. Dots within the blood vessels are handled using local vessel detection technique. Prior to this, pre-processing was done with candidate region growing and candidate evaluation techniques. Watershed retinal region growing technique was also employed. KNN classifier was used for the classification of images based on the features. The sensitivity and specificity are given as 85.4% and 83.1%, respectively.

In [12] a method bases on region growing algorithms is used for microaneurysm detection and a tree ensemble classifier is used for MA classification. It uses an extensive set of 70 features in order to perform the classification. MA candidate detection and MA candidate classification are performed for extraction of microaneurysms. Region growing operation is performed in order to enhance the shapes of the detected MA candidates. The set of initial candidates are used as input. The procedure involves iteratively growing along the 8-connected pixels from the minimum intensity pixel of the candidate until a stopping condition is reached. Stopping condition used here is a maxima point of the energy function. The energy function is defined as the average value of the gradients around the boundary of the grown region. All the parameters at this stage have been kept the same except the maximum grown size.

II.1.7. Unsupervised methods

In [13] the microaneurysms are detected from the colour fundus images by applying the pre-processing techniques in order to remove the optic disc and blood vessels using morphological operations. The pre-processed image was then used for feature extraction and these features were used for the purpose of classification. The classifiers used are support vector machine, Meta-cognitive Neural Network (McNN) and Self-adaptive Resource Allocation Network (SRAN). In this study, the McNN classifier produces a sensitivity of 100% and specificity of 90.90%, whereas the SRAN and SVM classifiers produce sensitivity and specificity of 100% and 83.33% and 93.33% and 100%, respectively. This clearly indicates that the McNN classifier achieves better classification performance with reduced misclassification rate.

An unsupervised method that does not require any training or classification steps has been demonstrated in [14]. This is a promising method for MA detection when compared with other supervised methods. This technique discriminates between vessels and MAs by using a 1D scanline at different directions for each pixel. While a MA will have local minima in all directions of the rotated scanline, a vessel will have only one minima when the scanline is perpendicular to the vessel. A probability map is produced at each pixel by using this property and then simple thresholding is applied to produce the final set of candidates.

Method proposed by Subbuthai and Muguganand in [15] for the detection of retina lesions consists of pre-processing, extraction of candidate region, formation of feature vector and classification. A total of 24 features are proposed in this paper which contain shape, colour, gray and texture based properties of lesions. Three types of classifiers such as SVM, KNN and ELM are used to compare and find the suitable classifier for given selected features for MAs detection in the retina images. The proposed framework is evaluated using 259 retinal images collected from publicly available DIARETDBO, DIARETB1 and DRIVE databases. The results of ELM classifier show better performance of MAs detection.

A summary of microaneurysm detection algorithms presented in this literature is listed in Table 1. For each method the table describes algorithms used and the reported performance for each method. Figure 2 shows the performance of different microaneurysm detection methods.

II.2.Exudates

Exudates are formed due to the accumulation of lipids and proteins in the retina. They are bright, reflective, white or yellow coloured lesions. They show increased vessel permeability and associated risk of retinal edema. Although, not sight threatening, they are a marker of fluid accumulation in the retina. However, if exudates appear close to the macula centre they can cause vision loss. Mostly, they are seen together with microaneurysms. These microaneurysms indicate an increased leakage, and the classical lesion is a circular ring of exudates with several microaneurysms at its centre [16].

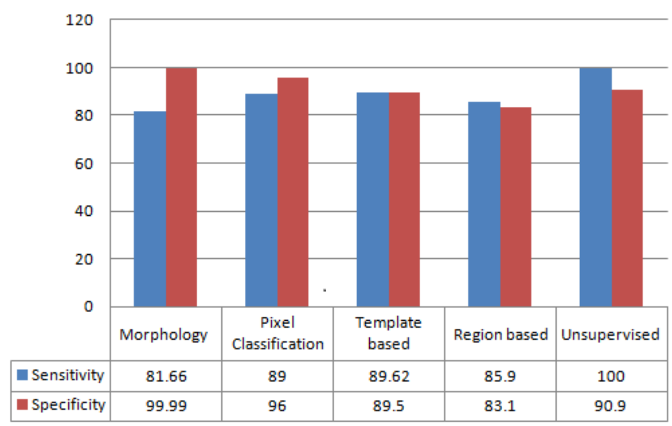


Figure2. Plot for performance in terms of sensitivity and specificity from reported microaneurysm methods.

Manual detection of exudates is expensive since it requires trained ophthalmologists. Automatic exudates detection enables laser therapy to be performed to prevent or delay visual loss and may be used to encourage improvement in the diabetic retinopathy control. Considerable amount of research work is done in exudates detection. Several techniques have been proposed in the literature to detect exudates from fundus images. Most of the image segmentation approaches for exudates detection can be grouped as: global and adaptive thresholding, region growing, clustering, morphology and classification. [17]

II.2.1.Thresholding

Thresholding is the simplest method for exudates extraction. In [18] histogram based multilevel thresholding was used to extract the brighter region on 8 bit gray level images. Median filtering used for blood vessel segmentation and convergent point of the blood vessels were found using least square regression technique. This convergent point is used to determine the OD among the brighter regions extracted by thresholding the retinal image. Brighter regions other than the OD are marked as exudates. Areas of ground truth regions of optic disc and exudates are marked manually. The accuracy and sensitivity of exudates detection were 62.69 % and 87.43%, respectively and algorithm achieved an accuracy of 81.24% and sensitivity of 90.11% for detection of optic disc. Low accuracy for exudates detection is the main drawback of this method.

A combination of global and adaptive thresholding is presented in [19] for exudates segmentation on colour images. Here each image was normalized and a group of features were extracted from image regions and the subset which best discriminate between exudates and retinal background was selected by means of logistic regression (LR). A radial basis function (RBF) neural network is introduced to detect exudates in retinal images. Both lesions based (pixel resolution) and image based criterion discussed. Using a lesion-based criterion, a sensitivity of 92.1% and a positive predictive value of 86.4% were achieved. With an image based criterion, a sensitivity of 100%, specificity of 70.4% and accuracy of 88.1% were obtained. The performance of this method is limited in images with a few dim exudates.

Maximum entropy thresholding is used in [20] for exudates extraction. Contrast-Limited Adaptive Histogram Equalization (CLAHE) was applied to the green component in order to improve the contrast in the pre-processing stage. Then optic disc boundary is determined and eliminated after applying blob boundary measurement and morphological reconstruction. Accuracy of 93% and 89% were obtained for detection of OD and exudates respectively. This method does not require any training sets which require large amounts of data and take more time to be processed.

Another simple threshoding technique, histogram based thresholding, was used in [21]. Optic disc is located and detected using histogram matching and exudates were detected by transforming into binary images based on histogram based thresholding technique. Pre-processed retinal image is split into two equal parts around its central axis. The histogram of each part is computed and the difference of two histograms is computed. To select the threshold value, the resultant difference histogram instead of the image is supplied as the input to Otsu thresholding. The accuracy rate of 99%, 90%, and 89% were obtained for DRIVE, DIARECTDB1 and local dataset respectively. A colour space approach was proposed in [22] where the object of interest area is used as exudates colour references for retinal segmentation. The experiment is carried out using image fundus with exudates according to some reference of threshold values. Sensitivity of 96.87% and specificity of 78% were achieved by this method. The accuracy of the system is 95.54%. The drawback of this approach is the misinterpretation in segmentation process between exudates and optic disc in retinal fundus images.

II.2.2.Region growing

In [23] a recursive region growing technique is used to identify exudates in grey level images on 10 X 10 windows and by selecting a threshold value manually. In this paper images pre-processed using adaptive, local, contrast enhancement and optic disc were located by identifying the area with the highest variation in intensity of adjacent pixels. Blood vessels were identified by means of a multilayer perception neural network, for which the inputs were derived from a principal component analysis (PCA) of the image and edge detection of the intensity. The obtained sensitivity and specificity for the detection of exudates were 80.21% and 70.66% respectively. A combination of region growing with edge detection was used in [24]. PCA based model is used to localize optic disk in the candidate regions and the boundary of optic disk is extracted by a modified active shape model (ASM) method. By using LUV colour space, object colour difference image was obtained using mean squared Weiner filtering for noise removal followed by a canny edge detector for finding optimum threshold. The improvement on region growing method on LUV colour space was employed in the study of Li *et.al* [24]. The sensitivity and specificity of exudates detection were 100% and 71%, respectively. By this approach, computational issues are limited by exploiting edge detection to limit the size of regions.

In region growing and thresholding approaches, the problem of cotton wool spots classification from exudates candidates was not taken into consideration. Therefore, two main criteria have introduced for improvement of exudates detection diagnostic accuracy, i.e. lesion based and image based. In image-based criteria, the main aim is to take a decision on the basis of presence or absence of exudates candidates anywhere in the image region and to check whether the given image has any signs of DR predominantly. The image-based criteria have measured system accuracy in terms of percentage of tested normal and abnormal images to the total number of images. Number of exudates detection along with the border detection in proper manner gives very good results [25].

II.2.3 Clustering

The fuzzy clustering is a clustering algorithm where each point may have various degrees of membership. Fuzzy means clustering is most commonly used method in the exudates detection. A modified version of fuzzy-c-means clustering is applied by Dunn *et al*. [26] and improvement to it was given by Bezdek *et al* [27].

Local contrast enhancement, colour normalization and fuzzy C-Means clustering followed by neural network classification is performed in [28] to distinguish between two disjoint classes as exudates or non exudates. It achieved 93.0% sensitivity and 94.1% specificity for exudates classification. The less accuracy results because of uneven illumination but improved detection accuracy is possible with LUV colour space. Candidate fuzzy C-means clustering and the neural network were applied to the colour retinal images in which segmentation relies on histogram shape [29]. Sensitivity and specificity of exudates segmentation were 96.0% and 94.6% respectively. Exudate identification process takes 3 minute for processing each image on an average.

In [30] morphological operations and fuzzy-C means (FCM) clustering was used for detection of blood vessel and exudates in retinal images. The number of pixels affected with exudates and blood vessel extraction are found using morphological operation. By taking the brightest pixels a mask is created to eliminate optic disc and it is detected using Circular Hough Transform. Blood vessels were detected using morphological operations followed by connected component analysis. Then the exudates are determined using FCM and 8 clusters of images were formed. These exudates clusters are selected and isolated to determine the final exudates images. The sensitivity, specificity and accuracy obtained are 91.1%, 97.95% and 97.67% respectively.

II.2.4.Morphology

Mathematical morphology operators are performed in [31] to obtain the exudates after blood vessels and optic disc are removed. Morphological reconstruction techniques are used to determine contours of gray level variations of the image. Morphological filtering techniques and the watershed transformation used for optic disc detection. Using a small image database sensitivity of 92.8% and a predictive value of 92.4% are obtained in [31]. In [32] closing and reconstruction operators together with thresholding are used to remove the optic disk and blood vessels. Since the exudates pixels have high contrast to its surrounding pixels, their contour is highlighted in the standard local deviation image. Thus they were differentiated according to the local variation. The sensitivity and specificity for exudates detection is 80% and 99.5%, respectively. The performance of this algorithm is worse for low contrast exudates detection.

In [33] the lightness L of the perceptually uniform LUV colour space is enhanced via a top-hat by opening operator followed by the top hat by closing operator. Since exudates are brighter than background region, a reconstruction by dilation is performed on the regional minimal image to estimate the background region. Then subtracting the background regions from the enhanced image and performing the H-maximal transformation, the exudates candidates are obtained by a thresholding operator. Finally, a reconstruction operation is performed on the candidate regions to improve the detection accuracy. However, they ignored the local structure information of the exudates regions. The reflection from various components of the retinal tissue is erroneously regarded as exudates regions.

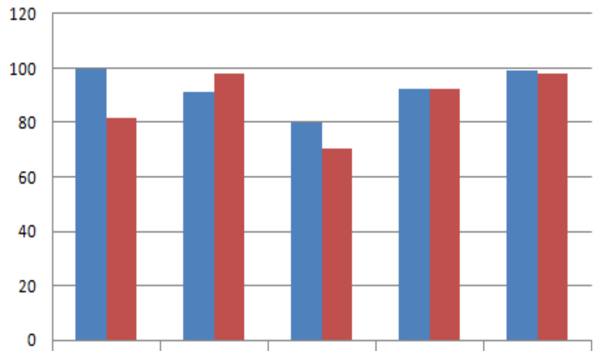
II.2.5 Classification

A similar approach of region growing is applied in the study of Gardner et al [34], with the use of back propagation neural network. The neural network was trained with the masked fashion of input data to classify known outputs of exudates squares. This was performed on image level basis instead of pixel-based classification. Statistical classifiers such as multilayer perceptron, support vector machine and radial basis function require training the images for the detection of hard exudates [19]. In the study proposed in [17], a simple minimum-distance discriminator Bayesian classifier was composed based on its colour characteristics to detect the exudates. Decision support system and grading of DR diagnosis have provided with the use of naive Bayes classification in [35].

The authors of [36] presented a comparative study of exudates classification using SVM and NN. SVM demonstrated improved accuracy with respect to others. A similar NN based approach has also proposed by Hunter *et .al* in [37]. Here a hierarchical feature selection based method was applied. The characterization of exudates candidates based on the combination of wavelength statistical features and grey level co-occurrence features by applying SVM classifier was proposed in [38]. A method composed of feature extraction, template matching and enhanced minimum distance discriminant classifier is proposed in [39] for the extraction of exudates candidates. In the method described in [40] Ada Boost classifier is utilized to distinguish bright and red retinopathy lesions based on feature rates generated for top thirty features from a set of seventy eight features.

Supervise approaches in [29] have attempted to detect exudates. SVM and MLPNN have analysed and compared. Based on histogram shape a local dynamic thresholding was used. Machine learning supervised based approach was proposed by Niemeijer et al in [41].In [42] a combined approach of circular Hough transform and Convolutional Neural Network (CNN) algorithms proposed for detecting exudates. This method is trained separately and tested in three different datasets and achieved 100%, 98.41%, sensitivity and specificity in the DiaretDB0 data set, 99.2%, 97.97% sensitivity and specificity in the DiaretDB1 dataset and 100%, 98.44% sensitivity and specificity in the DrimDB data set.

A summary of exudates detection algorithms presented in this literature is listed in Table 2. For each method the table describes algorithms used and the reported performance for each method. Figure 3 shows the performance of different exudates detection methods.



	Thresholding	Clustering	Region Growing	Morphology	Classification
Sensitivity	100	91.1	80.21	92.6	99.2
Specificity	81.5	97.95	70.66	92.4	97.97

Figure3. Plot for performance in terms of sensitivity and specificity from reported microaneurysm methods.

II.3.Hemorrhages

The irregular and dark red shapes of blood dots in a retinal fundus image are an indication of the presence of haemorrhages. Haemorrhages are caused by the leakage of blood vessels and affect vision in the eye. Blot and dot are the two types of haemorrhages found in retinal fundus images. Blots haemorrhages contain a larger area than dot haemorrhages. The blot or dot haemorrhages are occurred in the retina image as irregular shape. The work described in [44] presents a system to recognise normal and abnormal images by extracting features and feeding it into a statistical classifier for pattern recognition. Pre-processing is done to differentiate the dark abnormalities from the bright abnormalities. Then region growingalgorithm is used to estimate the shape of the abnormality. This paper compares performance of three classifier such as Bayesian, Mahalanobis, and KNN classifier. Among them mahalanobis classifier has given the best result. This method achieves sensitivity of 83% in case of haemorrhage detection.

A fully automated computer algorithm to detect exudates, haemorrhages and microaneurysms (HMA) is proposed in [10]. Here a new algorithm, named as Moat Operator, is used to optimize the segmentation of haemorrhages and microaneurysms. The sensitivity and specificity values achieved are 77.5% and f 88.7% respectively. The problem with this method is that it fails to identify haemorrhages adjacent to blood vessels.

The computerized screening system developed in [23] to classify the normal and abnormal of retinal images used matching correlation to sharpen the red lesions from its background. Thresholding method is used for classifying HMA from non HMA. But due to colour similarity, blood vessels were classified into same group as HMA. The sensitivity and specificity for screening of diabetic retinopathy were 80.21% and 70.66% respectively.

An image processing method for the detection of both haemorrhages and microaneurysms has been demonstrated in [46]. A gold standard reference is defined by classifying each patient as having or not having diabetic retinopathy. A single-lesion visual grading comprising meticulous outlining of all single lesions in all photographs is build independently and used to develop the automated red lesion detection system. Their algorithm demonstrated a specificity of 71.4% and a sensitivity of 96.7%. The robust detection of red lesions in digital colour fundus photographs is a critical step in the development of automated screening systems for diabetic retinopathy [47]. A hybrid approach of mathematical Morphology and pixel classification is presented for the detection of lesions. Their method achieved a sensitivity of 100% at a specificity of 87% in detecting the red lesions.

The method described in [45] uses a bottom-up and top-down strategies to cope with difficulties in lesions detection, such as in homogeneous illumination. After the application of appropriate strategy, they used local contrast enhancement, fuzzy C means clustering and hierarchical support vector machine to classify bright non lesion areas, exudates and cotton wool spots. The approach described in [16] for haemorrhage detection consists of two parts. These are detection of normal blood vessels and detection of blood vessels with haemorrhages. Then the two images were subtracted to obtain haemorrhages. Overall sensitivity, specificity and accuracy of the system are 82%, 86% and 85.9% respectively.

Table 1: Comparison of different methods for Microaneurysm candidate

Authors	Year	Methods	SN	SP
Spencer et al[2]	1996	Morphological operator, Gaussian Filter	49	-
Cree et al[3]	1997	Matched filter, Region based	82	-
Sinthanayothin et al[10]	2002	Recursive region growing, moat operator	77.5	88.7
Niemeijer et al[6]	2005	Gaussian filter pixel classification	89	96
Fleming et al[11]	2006	Watershed retinal region growing	85.4	83.1
Quellec et al[8]	2008	Template matching, Wavelet transform	89.62	89.5
Mizutani et al[7]	2009	Double ring filter, Neural network	47	-
Zhang et al [9]	2010	Multiscale correlation filtering	71.3	-
Lazar et al[14]	2011	Local minimal operation	88.5	99.7
Sopharak et al[4]	2013	Extended minima, Bayesian classifier	86	99
Akram et al[5]	2013	Mathematical morphology	94	90
Bala et al[13]	2014	Unsupervised classifier	100	90.9
Habib et al[12]	2017	Region based	-	-
Subbuthai et al[15]	2017	Unsupervised classifier	-	-

Table 2: Comparison of different methods for Exudate candidate

Authors	Year	Methods	SN	SP	Acc
Philips et al[43]	1993	Noise removal thresholding	87	-	-
Gardner et al[34]	1996	Pre-processing with edge detection filter	93.1	93.1	
Ege et al[44]	1999	Template matching, Region growing, thresholding	-	-	87
Wang et al[17]	2000	Brightness adjustment, colour characteristics	100	75.7	75.2
Hunter et al [37]	2000	Hierarchical feature selection	-	-	91
Sinthanayothin[10]	2002	Moat Operator, RRGS(n=30)	88.5	99.7	88.8
Osareh et al[36]	2002	Normalization, enhancement, FCM	93.4	82.7	90.1
Walter et al[31]	2002	Morphology, Thresholding (Lesion based) (n=30)	92.8	92.4	-
Walter et al[31]	2002	Morphology, Thresholding (Image based) (n=30)	100	88.6	-
Zhang et al[45]	2004	Improved FCM (n=30)	97	96	-
Kavitha et al[18]	2005	Multilevel thresholding (n=10)	100	-	-
Lee et al[24]	2006	Normalization and pattern recognition(n=430)	-	-	92.3
Garcia et al[19]	2009	Global and adaptive thresholding, logistic regression	100	81.5	92.5
Princye[30]	2013	FCM clustering	91.1	97.95	97.67
Sreng et al[20]	2013	Maximum entropy Thresholding	-	-	89
welfer et al[33]	2013	Morphological operator	-	-	-
Roy et al [40]	2014	Ada boost classifier	-	-	-
Win et al[21]	2016	Histogram based thresholding	-	-	90
Susetianingtias et al[22]	2016	Colour space approach	96.87	78	95.54

III.CONCLUSION

A wide variety of approaches has presented for automatic detection of retinal features but not have a clear separation among feature types. A generalization of individual results is difficult as these reported systems are highly optimized with respective analyzed retinal images. Generally, most retinal images have characterized by being low contrast and infested with image artifacts which hunter further analysis of automatic detection and segmentation of microaneurysms, exudates and haemorrhages. The characteristics features suggested in various approaches have required exploiting in eliminating the false positive region in feature detection. Cost effective treatment in terms of effective alternatives for ocular therapies and automated system for accurate segmentation of pathologies on the retina is the major concern of improvement towards DR diagnosis. Reliable and accurate automated system to diagnose each DR grading stage through proper segmentation and counting of these features and effective drug concentration to be maintained at the site of actions over the particular period of time is required to achieve desired pharmacological response. The ultimate aim of the clinical studies with the concern of both the above aspect is drastically increasing all over the world day by day.

REFERENCES

[1] O. Faust, R. Acharya, E. Y.-K. Ng, K.-H. Ng, and J. S. Suri, "*Algorithms for the automated detection of diabetic retinopathy using digital fundus images: a review*", Journal of medical systems, vol. 36, no. 1, pp. 145–157, 2012.

[2] T. Spencer, J . A .Olson, K. C. McHardy, P. F. Sharp, and J. V. Forrester, "*An image processing strategy for the segmentation and quantification of microaneurysms in fluorescein angiograms of the ocular fundus*," Computers and biomedical research, vol. 29, no. 4, pp. 284–302, 1996.

[3] M. J. Cree, J. A. Olson, K. C. McHardy, P. F.Sharp, and J. V. Forrester, "*A fully automated comparative microaneurysm digital detection system*," Eye, vol. 11, no. 5, p. 622, 1997.

[4] A. Sopharak, B. Uyyanonvara, and S. Barman, "*Simple hybrid method for fine microaneurysm detection from non-dilated diabetic retinopathy retinal images,"* Computerized Medical Imaging and Graphics, vol. 37, no. 5-6, pp. 394–402, 2013.

[5] M. U. Akram, S. Khalid, and S. A. Khan, "*Identification and classification of microaneurysms for early detection of diabetic retinopathy,"* Pattern Recognition, vol. 46, no.1, pp. 107–116,2013.

[6] M.Niemeijer, B. Van Ginneken, J. Staal, M. S. A. Suttorp-Schulten, and M. D. Abramoff, "*Automatic detection of red lesions in digital color fundus photographs*," IEEE Transactions on Medical Imaging, vol. 24, no. 5, pp. 584–592, May 2005.

[7] A. Mizutani, C. Muramatsu, Y. Hatanaka, S. Suemori, T. Hara, and H. Fujita, "*Automated microaneurysm detection method based on double ring filter in retinal fundus images*," in Medical Imaging 2009: Computer-Aided Diagnosis, vol. 7260. International Society for Optics and Photonics, 2009, p. 72601N.

[8] G. Quellec, M. Lamard, P. M. Josselin, G. Cazuguel, B. Cochener, and C. Roux, "*Optimal wavelet transform for the detectionof microaneurysms in retina photographs*." IEEE Transactions on Medical Imaging, vol. 27, no. 9, pp. 1230–41, 2008.

[9] B. Zhang, X. Wu, J. You, Q. Li, and F. Karray, "*Detection of microaneurysms using multiscale correlation coefficients,"* Pattern Recognition, vol. 43, no. 6, pp. 2237–2248, 2010.

[10] C. Sinthanayothin, J. F. Boyce, T. H. Williamson, H. L. Cook, E. Mensah, S. Lal, and D. Usher, "*Automated detection of diabetic retinopathy on digital fundus images*," Diabetic medicine, vol. 19, no. 2, pp. 105–112, 2002.

[11] A. D. Fleming, S. Philip, K. A. Goatman, J. A.Olson, and P. F. Sharp, "*Automated microaneurysm detection using local contrast normalization and local vessel detection,"* IEEE transactions on medical imaging, vol. 25, no. 9, pp.1223–1232, 2006.

[12] M. Habib, R. Welikala, A. Hoppe, C. Owen, A.Rudnicka, and S. Barman, "*Detection of microaneurysms in retinal images using an ensemble classifier*," Informatics in Medicine Unlocked, vol. 9, pp. 44–57, 2017.

[13] M. P. Bala and S. Vijayachitra, "*Early detection and classification of microaneurysms in retinal fundus images using sequential learning methods*," International Journal of Biomedical Engineering and Technology, vol. 15, no. 2, pp. 128– 143, 2014.

[14] I. Lazar and A. Hajdu, "*Microaneurysm detection in retinal images using a rotating cross section based model,"* in Biomedical Imaging: From Nano to Macro, 2011 IEEE International Symposium on. IEEE, 2011, pp. 1405–1409.

[15] P. Subbuthai and S. Muruganand, "*Roc curve analysis for automatic detection of microaneurysms in the retinal fundus image*," International Journal of ChemTech Research, vol. 10, no. 13, pp. 190–194, 2017.

[16] U. R. Acharya, C. M. Lim, E. Y. K. Ng, C. Chee, and T. Tamura, "*Computer-based detection of diabetes retinopathy stages using digital fundus images*," Proceedings of the institution of mechanical engineers, part H: journal of engineering in medicine, vol. 223, no. 5, pp. 545–553, 2009.

[17] H. Wang, W. Hsu, K. G. Goh, and M. L. Lee,"*An effective approach to detect lesions in colour retinal images*," in Computer Vision and Pattern Recognition, 2000. Proceedings. IEEE Conference on, vol. 2. IEEE, 2000, pp. 181–186.

[18] D. Kavitha and S. S. Devi, "*Automatic detection of optic disc and exudates in retinal images*," in Intelligent Sensing and Information Processing, 2005. Proceedings of 2005 International Conference on. IEEE, 2005, pp. 501–506.

[19] M. Garcia, C. I. S´anchez, J. Poza, M. I. L´opez, and R. Hornero, "*Detection of hard exudates in retinal images using a radial basis function classifier*," Annals of biomedical engineering, vol. 37, no. 7, pp. 1448–1463, 2009.

[20] S. Sreng, J.-i Takada, N. Maneerat, D. Isarakorn, R. Varakulsiripunth, B. Pasaya, and M R. Panjaphongse, "*Feature extraction from retinal fundus image for early detection of diabetic retinopathy*," in Humanitarian Technology Conference (R10-HTC), 2013 IEEE Region 10.IEEE, 2013, pp. 63–66.

[21] K. Y. Win and S. Choomchuay, "*Automated detection of exudates using histogram analysis for digital retinal images,*" in Intelligent Signal Processing and Communication Systems (ISPACS),2016 International Symposium on. IEEE, 2016, pp. 1–6.

[22] D. T. Susetianingtias and S. Madenda, "*An approach to exudates detection using color reference segmentation in retinal fundus image,"* International Journal of Computer Applications, vol. 146, no. 2, 2016.

[23] C. Sinthanayothin, V. Kongbunkiat, S. Phoo jaruenchanachai, and A. Singalavanija, "*Automated screening system for diabetic retinopathy,"* in Image and Signal Processing and Analysis, 2003. ISPA 2003. Proceedings of the 3rd International Symposium on, vol. 2.IEEE, 2003,pp. 915–920.

[24] H. Li and O. Chutatape, "*Automated feature extraction in colour retinal images by a model based approach*," IEEE Transactions on biomedical engineering, vol. 51, no.2,pp.246–254,2004.
[25] S. Joshi and P. Karule, "*A review on exudates detection methods for diabetic retinopathy*," Biomedicine & Pharmacotherapy, vol. 97, pp. 1454–1460, 2018.
[26] J. C. Dunn, "*A fuzzy relative of the isodata process and its use in detecting compact well separated clusters*," 1973.
[27] J. C. Bezdek, J. Keller, R. Krisnapuram, and N. Pal, Fuzzy models and algorithms for pattern recognition and image processing. Springer Science & Business Media, 1999, vol. 4.
[28] A.Osareh, M. Mirmehdi, B. Thomas, and R. Markham, "*Automated identification of diabetic retinal exudates in digital colour images*," British Journal of Ophthalmology, vol. 87,no. 10, pp. 1220–1223, 2003.
[29] A. Osareh, B. Shadgar, and R. Markham, "*A computational-intelligence-based approach for detection of exudates in diabetic retinopathy images*," IEEE Transactions on Information Technology in Biomedicine, vol. 13, no. 4, pp. 535–545, 2009.
[30] P. H. Princye and V. Vijayakumari, "*Detection of exudates and feature extraction of retinal images using fuzzy clustering method,*" Computational Intelligence and Information Technology, 2013.
[31] T. Walter, J.-C. Klein, P. Massin, and A. Erginay, "*A contribution of image processing to the diagnosis of diabetic retinopathy detection of exudates in color fundus images of the human retina*," IEEE transactions on medical imaging, vol. 21, no. 10, pp. 1236–1243, 2002.
[32] A. Sopharak, B. Uyyanonvara, S. Barman, and T. H. Williamson, "*Automatic detection of diabetic retinopathy exudates from non dilated retinal images using mathematical morphology methods*," Computerized medical imaging and graphics, vol. 32, no. 8, pp. 720–727, 2008.
[33] D. Welfer, J. Scharcanski, and D. R. Marinho, "*A morphologic two-stage approach for automated optic disk detection in color eye fundus images,*" Pattern Recognition Letters, vol. 34, no. 5, pp. 476–485, 2013.
[34] G. Gardner, D. Keating, T. H. Williamson, and A. T. Elliott, "*Automatic detection of diabetic retinopathy using an artificial neural network: a screening tool*." British journal of Ophthalmology, vol. 80, no. 11, pp. 940–944, 1996.
[35] S. K. Mitra, T.-W. Lee, and M. Goldbaum, "*A Bayesian network based sequential inference for diagnosis of diseases from retinal images*," Pattern recognition letters, vol. 26, no. 4, pp. 459–470, 2005.
[36] A. Osareh, M. Mirmehdi, B. Thomas, and R. Markham, "*Comparative exudate classification using support vector machines and neural networks*," in International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, 2002, pp. 413–420.
[37] A. Hunter, J. Lowell, J. Owens, L. Kennedy, and D. Steele, "*Quantification of diabetic retinopathy using neural networks and sensitivity analysis*," in Artificial Neural Networks in Medicine and Biology. Springer, 2000, pp. 81–86.
[38] L. Xu and S. Luo, "*Support vector machine based method for identifying hard exudates in retinal images*," in Information, Computing and Telecommunication, 2009. YC-ICT'09.IEEE Youth Conference on. IEEE, 2009, pp. 138–141.
[39] V. V. Kumari and N. SuriyaNarayanan, "*Diabetic retinopathy-early detection using image processing techniques*," International Journal on Computer Science and Engineering, vol. 2, no. 02, pp. 357–361, 2010.
[40] S. Roychowdhury, D. D. Koozekanani, and K. K.Parhi, "*Dream: diabetic retinopathy analysis using machine learning*," IEEE journal of biomedical and health informatics, vol. 18, no. 5, pp. 1717–1728, 2014.
[41] M. Niemeijer, B. van Ginneken, S. R. Russell, M. S. Suttorp-Schulten, and M. D. Abramoff, "*Automated detection and differentiation of drusen, exudates, and cotton-wool spots in digital colour fundus photographs for diabetic retinopathy diagnosis*," Investigative ophthalmology & visual science, vol. 48, no. 5, pp. 2260–2267, 2007.
[42] K. Adem, "*Exudate detection for diabetic retinopathy with circular hough transformation and convolutional neural networks,*" Expert Systems with Applications, vol. 114, pp.289–295, 2018.
[43] R. Phillips, J. Forrester, and P. Sharp, "*Automated detection and quantification of retinal exudates*," Graefe's archive for clinical and experimental ophthalmology, vol. 231, no. 2, pp. 90–94,1993.
[44] E. B, H. O, L. O, M. K, J. B, K. D, and C. DA, "*Screening for diabetic retinopathy using computer based image analysis and statistical classification*."Comput.Meth. Programs Biomed. vol. 62, p. 165, 2000.
[45] X. Zhang and O. Chutatape, "*Top-down and bottom-up strategies in lesion detection of background diabetic retinopathy*," in Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on, vol. 2. IEEE, 2005, pp. 422–428.
[46] M. Larsen, J. Godt, N. Larsen, H Lund Andersen, A. K. Sjolie, E. Agardh, H. Kalm, M. Grunkin, and D. R. Owens, "*Automated detection of fundus photographic red lesions in diabetic retinopathy*," Investigative ophthalmology & visual science, vol. 44, no. 2, pp. 761–766, 2003.
[47] M. Niemeijer, B. Van Ginneken, J. Staal, M. S. Suttorp-Schulten, and M. D. Abramoff, "*Automatic detection of red lesions in digital colour fundus photographs*," IEEE Transactions on medical imaging, vol. 24, no. 5, pp. 584–592, 2005.

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