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An Overview of Deep Learning Methods for Exudate Detection in Diabetic Retinopathy

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Abstract: - Background: This comprehensive review aims to provide a thorough overview of exudate detection techniques with a focus on their application in diagnosing diabetic retinopathy(DR) early.

Main body of the abstract: This review employs a systematic analysis of peer-reviewed articles, investigating the utilization of deep learning techniques in exudate detection. These techniques encompass convolutional neural networks, fuzzy c-means clustering, neural networks, and more. The precise detection and quantification of exudates are pivotal in monitoring the progression of DR, as they serve as crucial indicators for assessing the risk factors associated with vision-threatening complications. Conventional methods are prone to erroneous clinical decisions due to factors like observer fatigue and subjectivity during interpretation. Consequently, an increasing number of deep learning-based approaches have emerged to address these limitations.

Short conclusion: The techniques for detecting diabetic retinopathy exudates demonstrate considerable promise in terms of accuracy and efficiency. Nonetheless, further research is imperative to develop more robust and reliable methods, facilitating early diagnosis and timely intervention in cases of DR.

Keywords: Diabetic Retinopathy, Exudate detection, Deep learning techniques, Bright lesions, Fundus images, Optic disc.

Background

Diabetic retinopathy is a form of ocular disease brought on by high blood sugar and high blood pressure, which can harm the retina's blood vessels and cause blindness. Every person with diabetes is at risk of DR, which affects one-third of those with the disease (Fig. 1)[1,2]. For ophthalmologists, accurately evaluating DR takes time, and it can be quite difficult for new ophthalmology professionals and clinicians. Therefore, there are huge potential advantages to establishing an automated diagnostic method for DR.

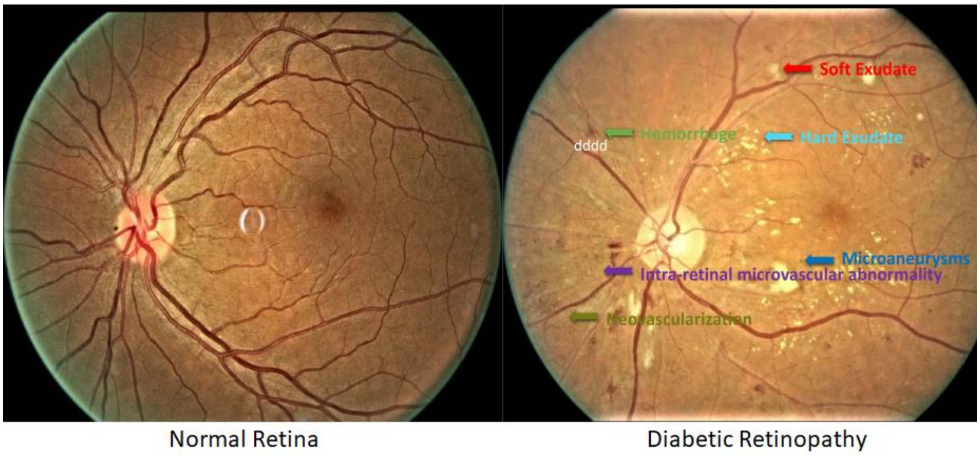

Fig. 1. D retinal illustration. The normal retina is depicted on the left, and the DR-4 retina is shown on the right.

1. Main text

This study's main goal is to assess the early alterations related to diabetes by image segmenting bright lesions, or exudates. Removal of the optic disc has been suggested before the automated exudates identification procedure since optic disc and exudates both display comparable colour, contrast, and brightness. The various techniques aim to reduce incorrect positive results in order to identify only authentic exudate candidates.

1.1. Clinical studies

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The diabetes duration is one of the huge risk factors in order to create DR. The two phases of DR pertaining to the diabetes clinical profile are non-proliferative and proliferative. In its first stage, retinal edoema and the depositions of lipoprotein exudates in the retinal tissue are caused by fluid leakage and excessive internal bleeding as a result of retinal capillary loss. Natural remedies are crucial to preventing these DR progressions, and antioxidants hold significant promise in this regard. As the first line of defence against more metabolic problems as DR progresses, water-soluble antioxidants, lipid-soluble antioxidants, and certain enzymes, including vitamins C, E, A, D, K+CU, Zinc, Selenium, and the carotenoids lutein, zeaxanthin, and astaxanthin, are helpful. The main factor in minimising diabetes complications is the consumption of antioxidants via food and dietary supplements. Surgery or laser photocoagulation are additional DR therapy options in addition to this antioxidant strategy, but future advancements in the treatment of this illness are still necessary.

2. Prominent characteristics of exudates

Exudates appear in three different forms:

- stiff exudates.
- encircled exudate plaques.
- soft exudates.

Stiff exudates are seen such as vivid yellow areas in the retina's outer or inner layers. Exudate plaques, which vary in size, show a diffused build-up of lipoprotein. Exudates that are fluffy or soft seem white and are often paler yellow in colour and lay on a shallower level within the delicate retina. A type of lesion found in the fundus that is caused by excess lipids that may be seen through retinal imaging is called an exudate. Exudates have a variety of patterns, sizes, contrasts, and forms, and their colours range from white to yellow. Exudates are the brilliant lesions with the highest intensity value and reasonably clear borders(Fig. 2.).

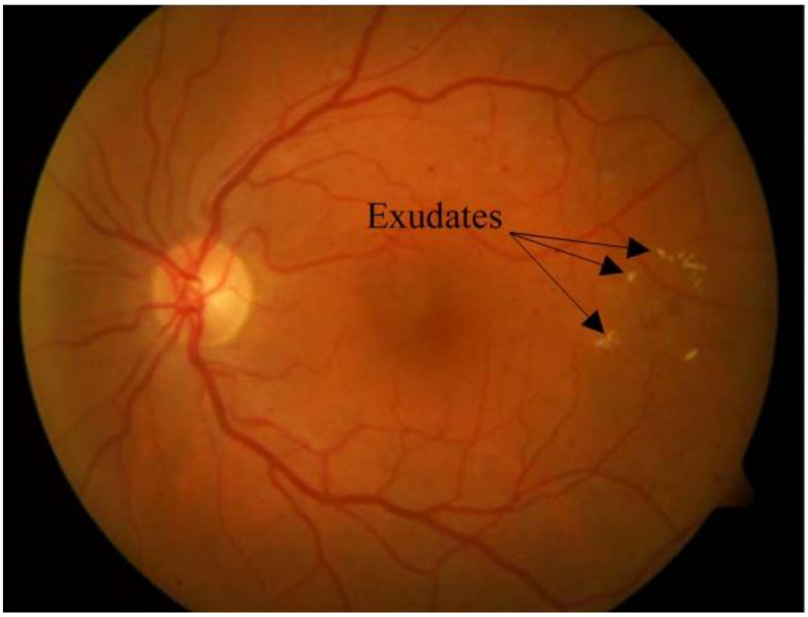

Fig. 2. An illustration of a typical retinal exudate.

3. Terminology and relevant studies

Most image segmentation methods for exudates identification fall into one of many categories, such distinctive feature approach, as mixture modeling, edges and border detection, global and adaptive thresholding, region growth, clustering, morphology, etc.

3.1. Thresholding

Among the most straightforward approaches for extracting exudates is grey level thresholding-based[1]. A layered thresholding was performed using the histogram employed for exudates segmentation. Adaptive intensity thresholding, recursive region expansion, and median filtering were combined in an approach for exudates extraction. Artificial neural networks were utilised to identify and categorise exudates using exudate candidate feature inputs[2]. A region-growing technique is utilised to find exudates after thresholding image intensity, to distinguish between light and dark lesions. The Mahalanobis classifier performs better than Bayesian and K-Nearest Neighbor classifiers. In, a straightforward grey level thresholding-based exudates segmentation approach was put forward[3].

Exudate segmentation was accomplished in five successive phases. To begin with, the green component of the histogram was modelled in order to create an upgraded picture, which was then statistically modelled using a mixture model before being dynamically thresholded. The optic disc underwent additional automated localization and masking processing. The sharp border of hard exudates was finally detected utilising postprocessing that included morphological procedure and Kirsch's technique for characterising edge strength[4]. The shade correction approach was used by Ward et al.[5] to pre-process colour fundus pictures before thresholding was used to separate the exudates from the background based on their high brightness. A method utilised in[6] segments exudates using a combination of a local threshold with a global or adaptive threshold analysis. The threshold was chosen automatically for the research[7], but any image-based accuracy required personal selection of the region of interest. This method's drawback is that it makes it possible to see falsely brilliant lesions like cotton wool spots. To differentiate between hard and soft exudates, several experiments were done to thresholding of colour histograms, binarization, non-linear diffusion segmentation based on mathematical morphology, and CIELab colour space conversion[8].

3.2. Region growing

To locate exudates, [9] used a region-based growing segmentation in a recursive fashion technique. Depending on the user chosen threshold value, Sinthanayothin [10] presented a recursive area expanding approach to find EXs on 10x10-inch windows with greyscale images. In work of Li [11], the computation of object colour difference picture was achieved noise suppression, edge detection, and an enhanced region-expanding approach on the Luv colour space using mean-squared Weiner filtering (Fig. 3).

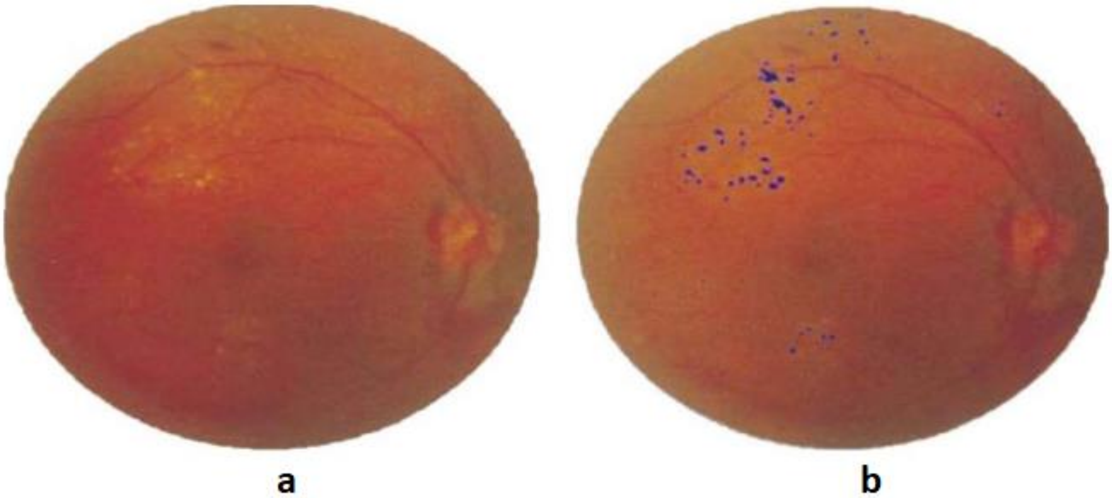

Fig.3. (a) Original picture[18] (b) Exudates found in growing area[18]

By using edge detection to restrict region size, this method limits computational issues. Previous approaches did not deal with the difficulty of distinguishing cotton wool patches from potential exudates. Therefore, criteria based on lesions and images have been introduced to enhance the diagnostic precision in detecting exudates. Each exudate lesion is treated as a separate connected region with the ability to contain one or more pixels under the lesion-based criterion[12]. There are various exudate regions that can be separated out of every atypical retinal picture. There will be a database of exudate regions produced to take into account a collection of images of the retina and using the proper segmentation methodology[13]. The specificity and sensitivity of the lesions can be determined by conducting a comparison of obtained data with a sketch of exudates according to an ophthalmologist[14]. However, diagnosis does not depend on the quantity of exudates. An algorithm exhibits good statistics but subpar performance if it can locate all exudates but not the borders correctly[15].

In reality, the lesion-based accuracy may be evaluated using patches with more than 10x10 pixels, or at the pixel level (pixel resolution)[16]. A pixel-based sharpness metric will offer greater accuracy compared to its patch-based equivalent., notwithstanding the difficulty of producing an exact pixel-based ground truth[17]. In actuality, exudate pixels could only half cover a region. Therefore, when performance is not assessed based on pixel resolution, the impact of misclassification mistakes for specific patches should be considered[18,19].

The goal of criteria based on images is to determine whether any evidence of DR in a particular image, primarily based on the identification of potential exudate sources inside the imaging area. The criteria based on images have determined the efficiency of the system as a result of dividing all of the pictures by the ratio of normal to aberrant images under test. The amount of exudates detected is adequate for diagnostic purposes, but accurate border detection also exhibits acceptable statistics.

3.3. Clustering

The retinal pictures in colour were clustered using fuzzy C-means clustering(FCC) and the neural network(NN), whose segmentation is based on histogram shape (Fig. 4), for the extraction of exudates[20]. Osareh et al. [21] applied pre-processing and segmentation techniques to boost the local contrast of retinal pictures, colour normalisation, and FCC to differentiate between two categories of exudates and non-exudates. This method produces less precision when there is uneven light, but the Luv color space makes for higher detecting accuracy.

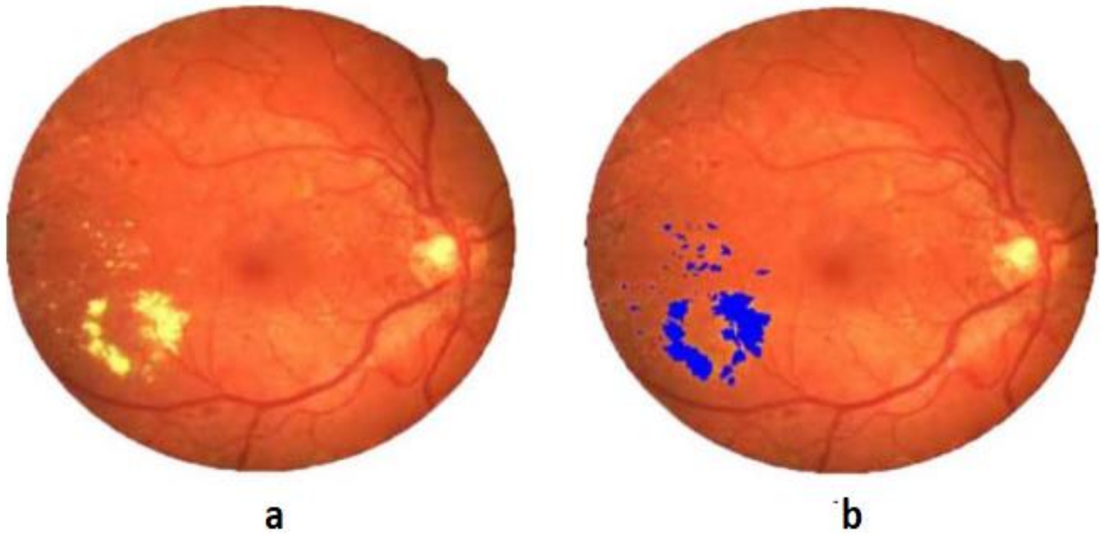

Fig. 4. (a) Orignal picture[20] (b) Cluster analysis of exudates[20]

The primary flaw with these techniques is that it is difficult to determine the exact lesion level. Other yellowish lesions like cotton-wool patches have also been misclassified as a result of color characteristics criterion.

It was suggested in [22] to calculate a map that shows the difference in intensity using median filtering, real-time grouping to identify lesions, and then leveraging expertise in the field of major, primary, and secondary arteries to improve the accuracy of exudate recognition. A variant of FCC was employed by Dunn et al. [23], that was further refined by Bezdek et al. [24].

Fuzzy c-means clustering to find exudate outlines and a statically classifier technique were presented by Sopharak et al. [25]. Geometry and cytological data were used in the literature for the analytical approach-based diagnosis of DR [26]. Red lesions are frequently detected using multiscale methods, which are used as characteristics in classification methods to locate exudates [27, 28].

Strategies based on working from the ground up with three stages are utilized in order to differentiate between cotton wool patches and exudates when detecting brilliant lesions. An improved version of C-means fuzzy sectioning, which is performed in two stages on the Luv colour space, is utilised in the pretreatment module [29] that incorporates local contrast enhancement as well. Later, a hierarchical support vector machine (AVM) based categorization module was implemented.

Table 1 : Comparative analysis of different exudate detection methods.

Sr. No.	Author	Method	Classifier	Sensitivity	Specificity	Accuracy
1.	Kavitha and Devi [1]	Thresholding at several levels	_	100	_	_
2.	Usher et al. [2]	Moat operator and relative rotation graphs	_	95.1	46.3	_
3.	Ege et al [3]	Thresholding image intensity	_	99	_	_
4.	Philips et al. [6]	Noise cancellation thresholding	_	87	_	_
5.	Kavitha and Duraiswamy [8]	Histogram thresholding in colour	_	89	99.1	99.1
6.	Ege et al. [14]	Template matching and renormalization group thresholding	lesion-based	_	_	87
7.	Osareh et al. [20]	Genetic algorithm-based feature selection and FCC (image based)	Numerous layers of neural network	96	94.6	_
8.	Osareh et al. [20]	Genetic algorithm-based feature selection and FCC(lesion based)	Numerous layers of neural network	93.5	92.1	_
9.	Osareh et al. [21]	FCC and Enhancement	Neural network	93	94.1	_
10.	Wynne et al. [22]	Understanding of the specific placements of retinal blood vessels FCC increases contrast	_	100	74	_
11.	Hann et al. [26]	Geometrical and mathematical techniques	_	88.6	98.4	_
12.	Zhang and Chutatape [28]	Improved FCC	AVM	97	96	_
13.	Jayakumari and Santhharam [29]	In-context grouping	Fuzzy Art neural network	93.4	80	_
14.	Grisan and Ruggeri [30]	Graph of k-nearest neighbours	_	91.1	95.4	_

15.	Giancardo et al. [31]	Normalization, Thresholding, texture statistical features	Fisher's linear discriminant	100	100	_
16.	Sreng [32]	Entropy thresholding for maximum	_	_	_	89
17.	Azar and Balas [33]	Thresholding	Minimal separation	95	_	_
18.	Win and Choomchuay [34]	Thresholding using a histogram	_	_	_	90
19.	Sinthanayothin et al. [35]	Moat operator and recursive region growing segmentation	_	88.5	99.7	88.8
20.	Ravivarma et al. [36]	Hyperbolic median filter and FCC	AVM	_	_	98
21.	Asha and . Karpagavalli [37]	A feature set for FCC	Extreme learning machine	100	87	90
22.	Sopharak et al. [38]	Operator morphology fine-tuned to perfection	_	73	87	79
23.	Walter et al. [40]	Thresholding morphology (image based)	_	100	88.6	_
24.	Walter et al. [40]	Thresholding morphology (lesion based)	_	92.8	92.4	_

25.	Fleming et al. [41]	Algorithm for multi-scale morphology	_	95	84.6	_
26.	Dupas et al. [42]	Thresholding morphology	_	92.8	92.4	_
27.	Sopharak et al. [43]	Contrast enhancement and FCC	Nearest neighbour	87.3	99.2	99.1
28.	Manoj et al. [44]	Morphology	_	95	94	_
29.	A Singh et al. [45]	Morphology and threshold for intensity	_	92	_	_
30.	Biyani and Patre [46]	Morphology and K means clustering	_	88.3	99.3	_
31.	Ghaffar and Uyyanonvara [47]	Morphological compact tree	_	_	_	78.7
32.	Shilpa and Nagabhushan [48]	Ensemble morphological approach	_	100	89.6	96.9
33.	Nayak et al. [49]	Morphology and thresholding	Artifical neural network	95	100	_
34.	Nugroho et al. [50]	Thresholding, morphology, and filtering	_	90	99	99

35.	Gardner et al. [51]	Edge detection filtering during preprocessing	Neural network	93.1	93.1	_
36.	Garcia et al. [52]	Logistic regression, with both global and adaptive thresholding (lesion-based criterion)	Radial basis function neural network	88.5	77.4	_
37.	Garcia et al. [52]	Logistic regression, with both global and adaptive thresholding (lesion-based criterion)	Multi layer perceptron	88.1	80.7	_
38.	Garcia et al. [52]	Logistic regression, with both global and adaptive thresholding (lesion-based criterion)	AVM	87.6	83.5	_
39.	Garcia et al. [52]	Logistic regression, with both global and adaptive thresholding (image-based criterion)	Radial basis function neural network	100	92.6	97.1
40.	Garcia et al. [52]	Logistic regression, with both global and adaptive thresholding (image-based criterion)	Multi layer perceptron	100	81.5	92.5
41.	Garcia et al. [52]	Logistic regression, with both global and adaptive thresholding (image-based criterion)	AVM	100	77.8	91
42.	Wang et al. [53]	Colour properties and brightness control	Bayesian	100	75.7	75.2
43.	Mitra et al. [54]	Manifestation set	Simple bayes	_	_	86
44.	Osareh et al. [55]	Normalization, improvement and FCC	Neural network-scaled conjugate gradient	93.4	82.7	90.1

45.	Osareh et al. [55]	Normalization, improvement and FCC	Back propagation neural network	89	89.8	89.6
46.	Osareh et al. [55]	Normalization, improvement and FCC	K-nearest neighbors algorithm	80.2	93.1	87.1
47.	Osareh et al. [55]	FCC	AVM	90.7	92.4	95.5
48.	Hunter et al. [56]	Hierarchical feature selection	Neural network	_	_	91
49.	Hunter et al. [56]	Kirsch method, region expansion, and edge detection	_	100	71	_
50.	Xu and Luo [57]	Transforms of stationary wavelets and a co-occurrence matrix of grey levels	AVM	88	80	84
51.	Sohini and Dara [59]	Algorithm with minimum intensity and maximal strength	Hierarchical	74.2	98	_
52.	Niemeijer et al. [61]	Lesion probability map	_	95.5	86	_
53.	Sopharak et al. [62]	Mathematical morphology + FCC	_	87.3	99.2	99.1
54.	Sopharak et al. [62]	Procedures and a list of features	AVM	92.3	98.5	98.4

55.	Sopharak et al. [62]	Naive bayesian feature set (Mahalanobis))	Closest neighbour	90.4	96.7	96.6
56.	Sopharak et al. [62]	Support vector machines feature set (Mahalanobis)	Closest neighbour	91.1	97.4	97.3
57.	Lin et al. [63]	Graph of the K nearest neighbours	_	91.1	95.4	_
58.	Gerald and Leung [64]	Principal components analysis and normalization	Neural network	94.7	94.2	_
59.	Prentasic and Loncaric [65]	Process and potential feature pool	Neural network	77	_	_
60.	Xiao et al. [66]	Characteristics for identifying edges, shapes, statistics, and phases (lesion)	AVM	84.6	94.4	_
61.	Xiao et al. [66]	Characteristics for identifying edges, shapes, statistics, and phases (image)	AVM	97.3	90	93.7
62.	Ruba and Ramalakshmi [67]	Characteristics of a matrix of gabor and grey levels	AVM	78.6	86.4	82
63.	Agurto et al. [70]	Multiple-scale thresholding for optimal amplitude	Modified least squares	100	73	96
64.	Reza and Eswaran [74]	Marker-controlled watershed transformation and preprocessing.	_	95	_	_

65.	Massey et al. [75]	Method based on a level set and simple feature set	_	96.9	98.9	98.87
66.	Esmaeili et al. [76]	Level set and the curlet transform	_	98.4	90.1	_
67.	Kayal and Sreeparna [77]	Standardized picture cuts for segmentation	_	97.1	96.1	_
68.	Lalonde et al. [78]	RetsoftPlus software	_	100	87	_
69.	Lee et al. [79]	Alignment and identification of patterns	_	_	_	92.3
70.	Lee et al. [79]	Modeling a mixture with a moving threshold (lesion based criteria)	_	90.2	96.8	_
71	Lee et al. [79]	Modeling a mixture with a moving threshold (Image based criteria)	_	100	90	_
72	Bodapati et al. [81]	Baseline with dual attention		72.23		86.22
73	Oulhadj et al.[82]	Capsule network and Inception		72.23		86.54
74	Han et al. [83]	CWN				86.12
75	He et al. [84]	DenseNet-121 with CABNet				78.98
76	Guo et al. et al. [85]	AABNet		58.77		77.15
77	Wang et al. [86]	DeepMT-DR		83.1		83.60

3.4. Morphology

The maximum variance and the region expanding segmentation approach were utilised in the work of [38] (Fig. 5) to get the exudates and the centre of the optic disc, respectively. Using mathematical morphological approaches, Walter et al. [40] automated system to identify exudates in colour fundus pictures. For the removal of luminous regions such as the retinal disc and exudates, the similar method of morphological procedures has been suggested in [39]. By using a morphology-based technique so as to extract candidates, complicated segmenting contours actively, and a region-wise classifier to cut down on erroneous exudates candidates, Harangi et al. [72] presented three step solutions.

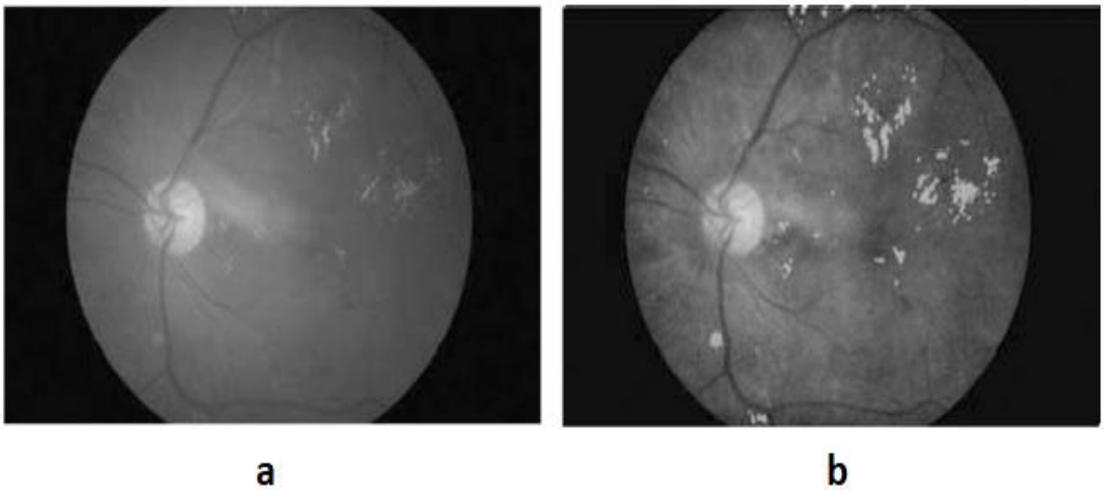

Fig. 5. (a) Orignal picture[38] (b) Detection by morphology exudates [38]

3.5. Classification

To categorise known outputs of exudate squares, a neural network was trained with filtered data and back propagation, as in a study by Gardner et al. [51]. Instead of using pixel-based categorization, this was done at the image level. Training the pictures is necessary to recognise hard exudates (Fig. 6) for statistical classifiers as the AVM, radial basis function, and multilayer perceptron (MLP) [52]. It was built employing lesion and image-based parameters on 117 pictures. Based on its colour properties, a straightforward Bayesian classifier with a minimum distance discriminator was created in the study of [53] to identify the exudates. The grading of DR diagnoses and the application of simple Bayes classification for decision assistance systems were described in [54]. The author [55] compared the performance of AVM and NN in classifying exudates. AVM showed increased accuracy compared to others. Hunter et al. [56] have also proposed a similar NN based strategy. In the cited literature, a method based on selecting features in a hierarchical structure was employed. The study [57] provided a method for categorising possible exudates by utilising a mixture of statistical information about wavelengths and grey-level co-occurrence characteristics. A approach consists by means of enhanced minimum distance discriminant classifier, feature extraction, and template matching to extract exudate candidates from 50 photos [58]. An Ada Boost classifier [59] has been used to distinguish between white and red retinopathy lesion were identified using feature rates derived from the top 30 features selected from a set of 78 features. To find exudates, supervise techniques [60] have been used. We analysed and contrasted AVM and MLP NN. Based on the shape of the histogram, local dynamic thresholding was implemented. Niemeijer et al. [61] proposed the utilisation of AVM.

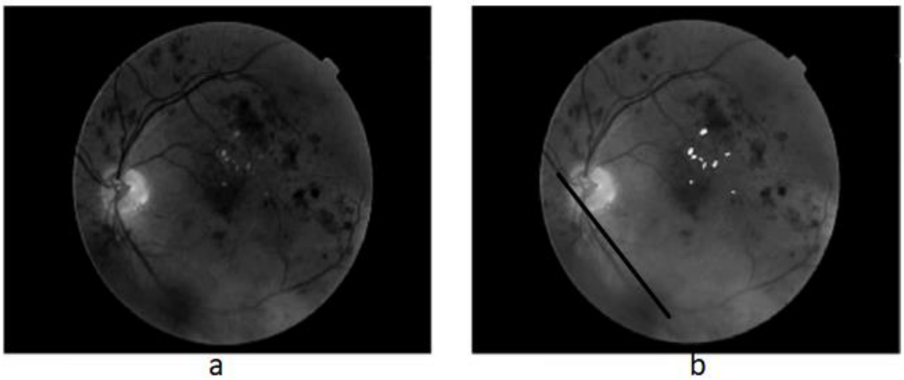

Fig. 6. (a) Orignal picture[52] (b) Detection outcome from exudates classification[52].

3.6. Others

One relatively new technique is the AM-FM (amplitude modulation-frequency modulation) representation at multiscale [68,69]. Initially, the AM-FM method was utilised on the image's green channel, and then IA was extracted by using the best threshold for looking for potential lesions. Based on parameters including RGB space, texture, and form that were gathered from each candidate, a partial least squares approach has been employed to identify exudates candidates (Fig. 7) [70]. For exudate detection in retinal pictures, to improve accuracy beyond that of thresholding, we used minimal distance discriminate as our classification function by measuring the distance between each pixel and the centre of each class [71]. Candidates for exudate boundaries were initially identified utilising a two-step process, and both types of lesions were then distinguished using colour, shape, and position properties. In [72], researchers combined edge and brightness information to detect exudates and quantify the extent of diabetic retinopathy. But the difficulty of differentiation diversity among lesion types has not been adequately addressed by these approaches. It was suggested to use a top-down method to rank the disease's severity by assessing the macular region's symmetry [73]. The suggested method, which is use the H-minimum (fixed threshold) idea [74], distinguishes between luminous lesions like cotton wool and hard exudates patches by using markers derived from an pre-processing method with moderate filtering used for modifying gradient images and segmenting watersheds using boundary tracing.

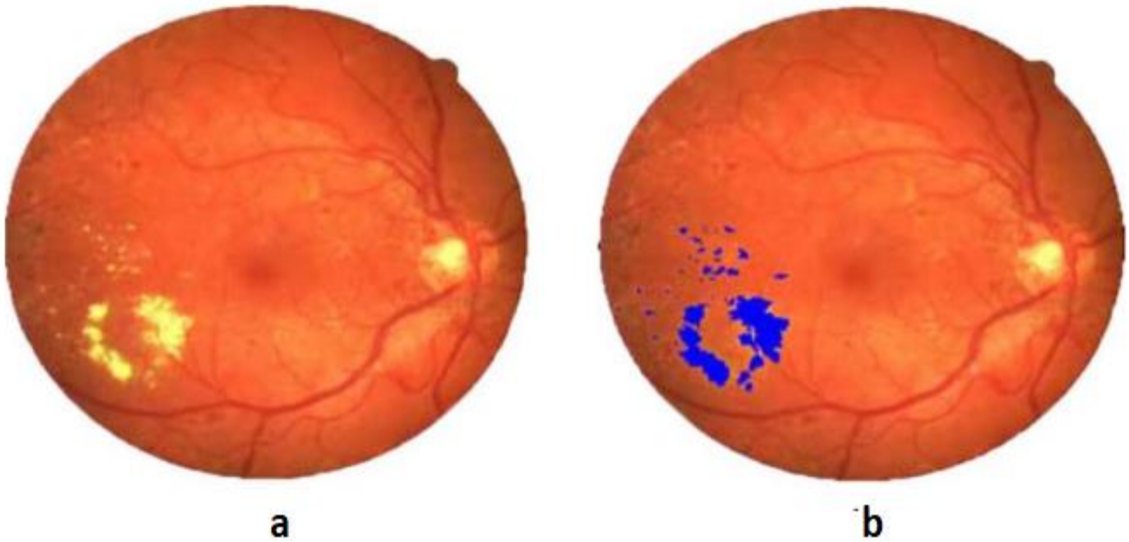

Fig. 7. (a) Orignal picture[70] (b) Detection data is released by an AM-FM algorithm.[70].

4. Detection and segmentation of exudates

Various, thresholding techniques and a mixture of classifiers have been the foundation of the strategies utilized to remove the exudates. Due to considerations affecting spatial light variance, applying straightforward thresholding directly to colour fundus pictures is difficult. Most methods require improving the photo's contrast or adjusting their colour before using thresholding to get around this issue. For exudate training and classification, powerful computing is needed. Many algorithms for classifying in sequence are also necessary for the mixture of classifiers approach.

Exudate detection using a mathematical morphological approach has a low accuracy downside but a greater sensitivity rate. The computing time of the region-based segmentation approach has limitations, but it is highly sensitive to the evaluation of exudate detection. On the one hand, however, the accuracy of blood vessel-based segmentation techniques decreases in the existence of noise while delivering a greater rate of detecting exudates. In contrast, the accuracy of techniques that use reliable segmentation of the optical disc sees a slight improvement in the rate but becomes affected by the effect of noise. The robust segmentation of the optical disc techniques has a higher accuracy rate. Still, it is impacted by noise, whereas the segmentation based on blood vessel techniques has a lower accuracy rate but gives a higher detection rate for exudates. A high level of accuracy in detecting exudates is achieved with minimal computational effort when using the adaptive median thresholding strategy; however, noise impacts are a problem for it. Similar approaches based on clustering offer advantages in that noise contents are greatly reduced, but they may not be as accurate in locating exudates. Some researchers used area growth approaches to find exudates, which may have led to under or over-segmentation and required a lot of time. The comparison of several exudates detection techniques is shown in Table 1.

5. Conclusions

Many strategies have been presented for automatic exudate detection, but there is no clear distinction between the different forms of exudates. It is challenging to generalize from specific outcomes because these systems have been well-optimized, and their corresponding retinal pictures have been well examined. Most retinal images are typically poor images in contrast and rife with abnormalities; this calls for extra analysis to detect and segment exudate automatically. To get rid of the location where exudates are detected incorrectly, it necessitates the leveraging characteristics and features offered in various aspects . The main area for progress in DR diagnosis is economical options for eye treatments. An automated approach for effectively removing light disorders that manifest on the retinal surface are two examples of low-priced medical care.It is necessary to maintain an effective drug concentration at the location where the designated amount is to obtain the optimal pharmacological response over time. This can be done using effective automated methods for counting the number of lesions after they have been extracted whenever a DR grade is assigned to provide an accurate diagnosis. Efficiency is the primary concern of clinical trials with where these problems may be detected and treated using automated grading methods, and how this efficiency can be increased for this diabetic condition to develop less rapidly that threatens vision along to fight this condition permanently that is growing at an alarming rate over the globe.

List of abbreviations

Support Vector Machine – AVM

Neural Network – NN

Multi Layer Perceptron – MLP

Amplitude modulation-Frequency modulation – AM-FM

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