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Performance analysis of automated lesion detection of diabetic retinopathy using morphological operation

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Abstract

Diabetic retinopathy is one of the most common complications of diabetes. Hemorrhages, micro-aneurysms, exudates are one of the earlier signs of diabetic retinopathy. This paper proposes an algorithm of matched filter with morphological operation for the detection of lesions in the fundus retinal image. Contrast limited adaptive histogram equalization method is used for the extraction of vessels. The noise is removed from the images using matched filter. After enhancement, the thresholding is applied for vessel extraction. The threshold of the image is done by the iterative self-organizing data analysis technique algorithm method. After removal of optic disk and the blood vessels from the retinal image, the morphology method is used to easily identify different types of lesions. The diabetic retinopathy images were collected from DIARETDB1; the morphology operation method is analyzed using the metrics of sensitivity, specificity and accuracy. The proposed method's detection accuracy value for the recognition of micro-aneurysms, exudates and hemorrhages was 98.43%, 98.06% and 98.68% compared with the results of the differential evolution algorithm. Detection of lesion such as micro-aneurysms, hemorrhages and exudates was possible. When compared with the differential evolution algorithm, morphological method achieved good accuracy for the detection of diabetic retinopathy.

Keywords Diabetic retinopathy · Hemorrhages · Micro-aneurysms · Exudates · Matched filter · Fundus retinal image

1 Introduction

Eye illnesses influence a huge number of human creatures which are expected to extend within the close future. Legitimate discovery and treatment of eye maladies anticipate visual misfortune in more than 50% of patients. Retinal images have been illustrated to be exceptionally effective apparatuses for malady determination. For occurrence, restorative specialists utilize ophthalmology photographs taken from the retina in arrange to analyze eye and systemic diseases [1]. Eye disease such as diabetic retinopathy (DR) and age-related macular degeneration (AMD) shows themselves on the retina. They are recognizable by examination of retinal images and may be treatable on the off chance that is identified at an early stage. Diabetic retinopathy is an eye malady that harms the retina. Presently, a day's 80% of diabetic patients are influenced by DR. It can be treatable when the malady is found at the early stage. The organize of the DR is classified into two as shown in Fig. 1. They are non-proliferative DR and proliferative DR. NPDR is the early organize of the disease [2]. The hemorrhages, micro-aneurysms, exudates, cotton wool spots are the early organize side effects of non-proliferative DR. The proliferative DR is the extreme organize of the infection. In proliferative DR, the modern vessel is shaped interior the retina. Within the dim injuries, small micro-aneurysms and hemorrhages are set and exudates are known as the shinning injury within the non-proliferative diabetic retinopathy. A micro-aneurysm may be within the side of a blood vessel.

Noise individuals with diabetes, influenced by DR, have the beginning organize of the indications of smaller micro-aneurysms that are now and then found within the retina of the eye. Smaller micro-aneurysms are the little ruddy dabs that show on the retinal image [3]. A hemorrhage is the next stage of DR within the retinal fundus image. Be that as it may, a few retinal hemorrhages can cause extreme impedance of vision.

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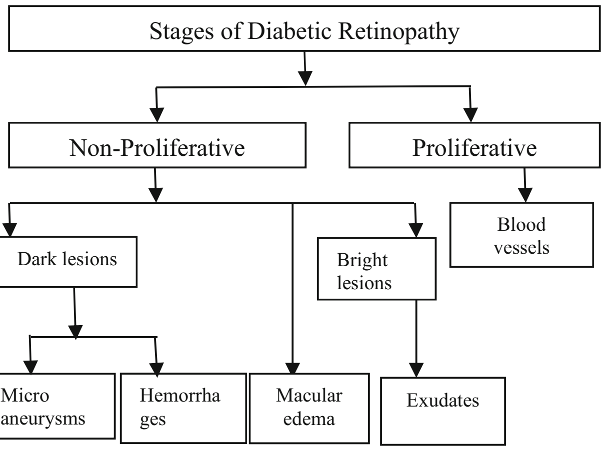

Fig. 1 Stages of diabetic retinopathy

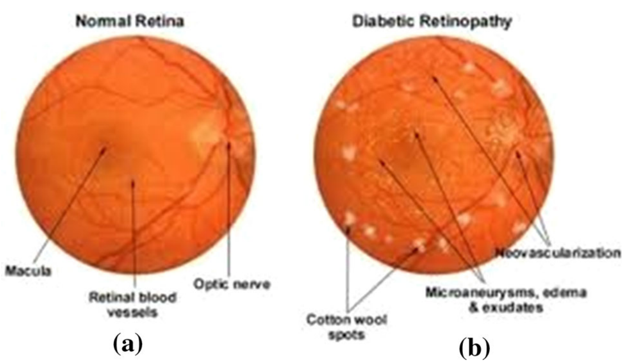

Fig. 2 **a** Normal retinal fundus image, **b** retinal fundus image

Hemorrhages are the yellow specks on the retinal lesion. Exudates are classified as delicate exudates and hard exudates. They are the blood spillages within the vessel's interior the retina. This spillage may lead to vision misfortune. Exudates are the serious organize of lesion for diabetic retinopathy determination. The cotton wool spots are, moreover, known as the shinning lesion [4]. Within the proliferative arrange, the modern vessel was shaped interior the retina. This vessel arrangement pieces the vision of the eye. So, the vision isn't clear for the patients. This is often the serious stage of diabetic retinopathy, and it leads to visual impairment. Figure 2 shows the difference between the normal retinal image and the DR-affected retinal image. The DR-affected patients do not see the clear view. The background of the vision is to be blurred and not to be seen by the patients. This could be curable only at the early stage.

Concurring to the WHO, the All India Ophthalmological Society (AIOS), in 2014, took an activity to identify the nearness of diabetic retinopathy among patients with diabetes in eye clinics over India. The west and south zones, and over half had diabetes more than 5 a long time. A cross-sectional test of subjects matured 50 a long time, and more seasoned was chosen employing a cluster-examining strategy from Palakkad locale of Kerala State.

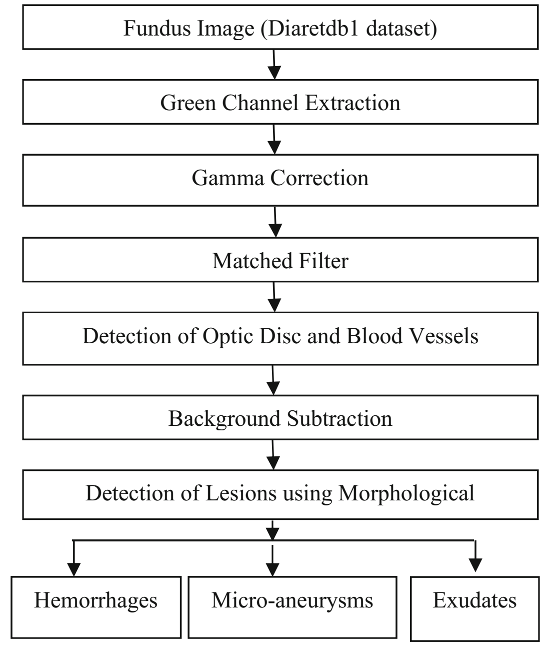

Fig. 3 Flow diagram of proposed method

2 Proposed method

This work proposes an algorithm of matched filter with morphological operation for the detection of different types of lesions in the fundus retinal image.

Figure 3 shows flow diagram of proposed method. The diabetic retinopathy retinal image was taken from the DIARETDB1 dataset, and the image should be enhanced for the clear view of the image that is easy to detect of lesions from the fundus image. After enhancement, the lesions were detected and classified using the matched filter with the morphological operation and classified the lesions depending upon the area [5].

2.1 Green channel extraction

The green channel is isolated from the RGB retinal image. Since the green channel of the color retinal image for the most part shows a tall differentiate between the vessels and the foundation, the vessel extraction is to be simple. After getting green channel, the glow upgrade is connected for redressing the uneven luminance [2].

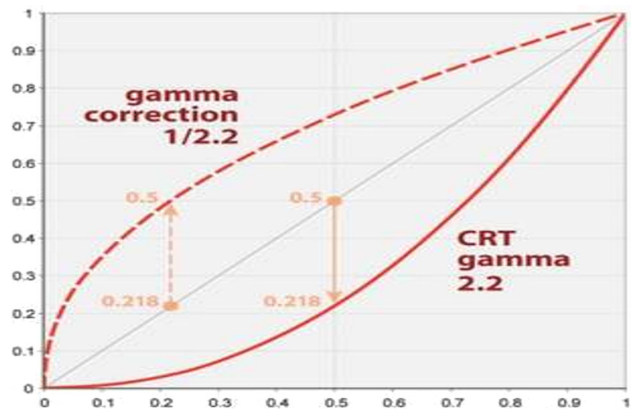

Fig. 4 Transformation curve for a gamma correction

2.2 Gamma correction

The gamma correction is applied for the green channel image for luminosity enhancement [6]. Due to uneven luminance in the image, the details or the features in a retinal image are not clearly shown for the detection of lesions. The luminance of an image makes as even by using the gamma correction technique after channel extraction [7].

Figure 4 shows the change bend for gamma redress. Gamma adjustment may be a nonlinear operation that's utilized to encode and translate luminance of an image in video or still image frameworks. Shifting the sum of gamma adjustment changes not as it were the brightness, but too the ratios of ruddy to green to blue [8] power-law expression,

$$V_{\text{out}} = A V_{\text{in}}^{\gamma} \tag{1}$$

where

The non-negative real input value V_{in} is raised to the power γ and multiplied by the constant A, to get the output value V_{out}. In the common case of $A = 1$, inputs and outputs are typically in the range 0–1. A gamma esteem $\gamma < 1$ is some of the time called an encoding gamma, and the method of encoding [9] with this compressive power-law nonlinearity is called gamma compression; alternately, a gamma esteem $\gamma > 1$ is called a interpreting gamma, and the application of the broad power-law nonlinearity is called gamma extension. The yield of the gamma adjustment is the improved image for giving the superior execution on the discovery of lesions.

2.3 Matched filter

The basic utilization of a coordinated channel in flag handling is the maximization of the signal-to-noise proportion within the nearness of additive stochastic clamor, or more particularly white Gaussian commotion. This could be gotten by connecting a known signal, or format, with an obscure flag to identify the nearness of the layout within the obscure signal [10]; the gamma adjusted image is given as input for the matched filter. This moves forward the SNR value for discovery of injuries in retinal fundus image.

$$y[n] = \sum_{k=-\infty}^{\infty} [n-k]x[k] \tag{2}$$

The FFT function [11] is connected for the gamma adjusted image. After applying FFT, the image is changed into recurrence space work. The advancement of flag to commotion proportion leads to increase the exactness of location of injuries. In a number of candidates such as movement and stereo correspondence and target location, it is regularly required to explore for known objects or structures within the watched images. This matched filter includes characterizing layouts that closely speak to the objects of intrigued to be identified and localized [12]. A facilitate is found at the zone at the zones where the cross-correlation peaks and the amplitudes of the peaks surpass a chosen constrain. Since the cross-correlation operation is related to the convolution, the total operation can be carried out inside the spatial space utilizing spatial filtering with the illustration or formats; hence, the term is called "matched filter." Let us assume that a target template is denoted by $t(m, n)$, $m, n \in W$ with W being the region of support of the template. Then, this format is spatially moved by (k, l) and cross-correlated with the first image to yield [13].

$$C[k,l] = \sum_{m}\sum_{n} x[m,n]T[m-k,n-l] \tag{3}$$

where $c(k, l)$ is the cross-correlation at the spatial location k,l.

2.4 Detection of blood vessels

The filtered image is given as input for the detection and removal of blood vessels in the retinal image. Figure 5 shows the flow diagram for detection of vessels. The principle component analysis (PCA) is applied for the filtered image. PCA is an orthogonal change utilized to change over a set of perceptions of conceivably connected factors into a set of values of directly uncorrelated factors called vital components. PCA is numerically characterized as an orthogonal direct change that changes the information to a unused facilitate framework such that the most noteworthy change by a few projection of the information comes to lie on the primary arrange, the moment most noteworthy change on the moment arrange, and so on. Calculate examination ordinarily joins more space particular suspicions around the fundamental structure and understands eigenvectors of a somewhat distinctive matrix.

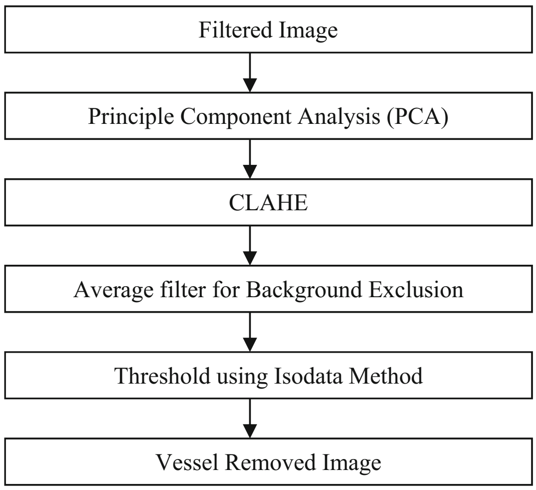

Fig. 5 Flow diagram for detection of vessels

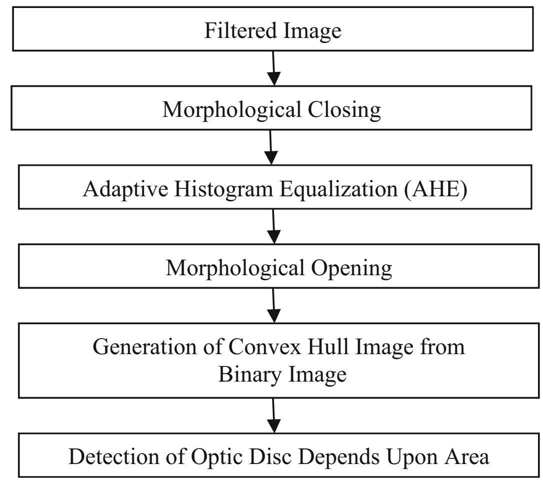

Fig. 6 Flow diagram for detection of optic disk

This PCA component is utilized for getting an uncorrelated factors called guideline components for the extraction of blood vessels within the fundus retinal picture. The uncorrelated factors are improved by utilizing CLAHE. CLAHE is the differentiated restricted versatile histogram equalization. This CLAHE strategy is utilized for the differentiate improvement for way better extraction of vessels. CLAHE is advancement on AHE. AHE encompasses a disadvantage of over increasing commotion. CLAHE limits the intensification by clipping the histogram at a predefined esteem some time recently computing the CDF. Contrast limited AHE (CLAHE) varies from conventional versatile histogram equalization with its differentiate restricting. The differentiate constraining strategy has got to be connected for each neighborhood from which a change work is determined. Here, like in AHE the change work is straightforwardly corresponding to the cdf of pixels values neighborhood. After CLAHE is connected, the picture is to be upgraded on differentiate. The upgraded picture is connected as input for the normal channel. The normal channel is the common linear smoothening algorithm. After upgraded, the thresholding is connected for vessel extraction. The edge of the image is done by the ISODATA strategy. ISODATA is the iterative self-organizing information investigation method algorithm. Cluster centers are haphazardly set, and pixels are doled out based on the most limited separate to center strategy. The standard deviation inside each cluster and the separate between cluster centers are calculated z. Clusters are part in case one or more standard deviation is more noteworthy than the user-defined edge z. Clusters are combined in the event that the removal between them is less than the user-defined threshold.

The refinements are

- Clusters that have as well few individuals are disposed of. Clusters that have as well numerous individuals are separated into two modern cluster groups.
- Clusters that are as well expansive are separated into two unused cluster bunches. On the off chance that two cluster centers are as well near together, they are consolidated. The vessels are extricated by this method and expelled by foundation prohibition.

2.5 Detection of optic disk

Figure 6 shows flow diagrams for detection of optic disk removal. A morphological operation on a double image makes a modern twofold image in which the pixel includes a nonzero value as it were if the test is fruitful at that area within the input twofold image. In scientific morphology, opening is the expansion of the disintegration of a set A by an organizing component B; in morphological opening, disintegration operation expels objects that are littler than organizing component B and widening operation re-establishes the shape of remaining objects. Closing is opening performed in switch. It is characterized basically as an expansion taken after by a disintegration utilizing the same organizing component for both operations. See the segments on disintegration and widening for points of interest of the person steps. The closing administrator, hence, requires two inputs: an image to be closed and an organizing elements.

Gray-level closing comprises clearly of a gray-level widening taken after by a gray-level disintegration. Closing is the double of opening, i.e., closing the closer view pixels with a specific organizing component is proportionate to closing the foundation with the same component. To identify the optic plate to begin with the morphology, closing operation is connected on the sifted picture an improved by AHE. After upgrading, the morphological closing operation

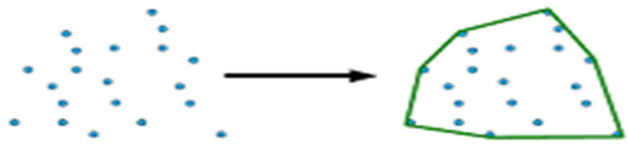

Fig. 7 Convex hull transform

is discovered out for discovery based on concentrated value. After morphological operation, the double image is changed into arched frame image for expulsion of little zones and distinguishes the tall concentrated ranges on retinal image for location of optic disk. The arched frame of a twofold image is the set of pixels included within the littlest arched polygon that surrounds all white pixels within the input.

A raised polygon could be a straightforward polygon without any self-intersection in which any line fragment between two focuses on the edges ever goes exterior the polygon. After getting of curved body image, the optic plate was recognized depending upon the region. The littlest region within the picture pixels is to be dismissed by utilizing the foundation evacuation approach. The little locales are established by utilizing the list esteem of pixels at that point the optic plate was extricated by the locale property of region. After discovery of OD of a retinal image, it is extricated by foundation avoidance strategy. Figure 7 shows the curved frame transform.

2.6 Background subtraction

Foundation subtraction, moreover, known as frontal area location, could be a strategy within the areas of image handling and computer vision wherein an image's closer view is extricated for assist handling. By and large, an image's districts of intrigued are objects (people, cars, content etc.) in its closer view. After the arrangement of picture pre-processing (which may incorporate image denoising, post-handling like morphology, etc.), question localization is required which may make utilize of this technique. Foundation subtraction may be a broadly utilized approach for recognizing moving objects in recordings from inactive cameras. The basis within the approach is that of identifying the moving objects from the distinction between the current frame and a reference outline, regularly called "foundation image," or "foundation show." Foundation subtraction is generally done on the off chance that the image in address could be a portion of a video stream.

Figure 8 shows foundation subtraction is by and large based on an inactive foundation theory which is regularly not appropriate in genuine situations. With indoor scenes, reflections or enlivened pictures on screens lead to foundation changes. Especially, due to wind, rain or brightening changes brought by climate, inactive foundations strategies

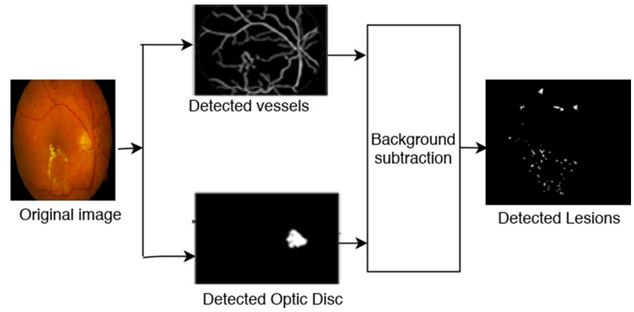

Fig. 8 Background subtraction

have challenges with open air scenes. Here utilizing basic math calculations, we will section out the objects basically by utilizing image subtraction strategy of computer vision meaning for each pixels in $I(t)$, take the pixel esteem signified by $P[I(t)]$ and subtract it with the comparing pixels at the same position on the foundation picture indicated as $P[B]$. In scientific condition, it is composed as

$$P[F(t)] = P[I(t)] - P[B] \tag{4}$$

2.7 Detection of lesions

After expulsion of optic circle and the blood vessels from the retinal image, the morphology strategy is connected for simple found out of the detection of lesion. This lesion is recognized by utilizing the escalated esteem, and amplified minima change is connected after morphology [14]. Amplified minima change is the territorial minima of the H-minima transform [15]. Territorial minima are associated components of pixels with a consistent escalated esteem, and whose outside boundary pixels all have a better esteem. By utilizing this boundary, the lesions are to be detected. Extended minima change is the territorial minima of the H-minima transform [16]. Territorial minima are associated components of pixels with a consistent concentrated esteem, and whose external boundary pixels all have the next esteem. H-minima may be a nonnegative scalar. By default, extended min employs 8 connected neighborhoods for 2-D images and 26 connected neighborhoods for 3-D images [17].

Figure 9 shows the stream graph for discovery of lesions. After discovery, the lesion is classified as miniaturized microaneurysms, hemorrhages and exudates by utilizing the extend of the range of a specific lesion [18, 19]. The range is to be less than 100 at that point the lesion is to be miniaturized scale aneurysms and range is between the extend of 100 and 500; at that point it is to be considered as hemorrhages [20]. The range is to be more noteworthy at that point 500; at that point the recognized lesion may be considered as exudates

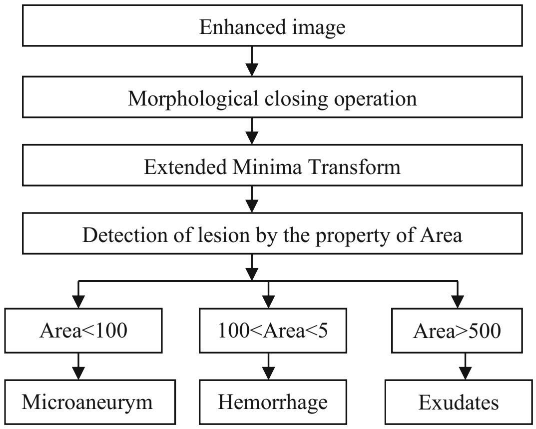

Fig. 9 Flow diagram for detection of lesions

in our proposed strategy. The seriousness of the disease is found by the no. of injuries within the fundus image [21].

3 Results and discussion

3.1 Performance metrics

The detected lesions are evaluated by using the performance metrics of sensitivity, specificity and accuracy.

(i) Sensitivity.

Sensitivity refers to the test's ability to correctly detect DR patients and their stage of DR. We should calculate the proportion of true positive, false negative in all evaluated cases.

Mathematically, this can be expressed as

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5}$$

(ii) Specificity.

Specificity relates to the test's capacity to accurately dismiss healthy DR patients without a condition.

Mathematically, this can be expressed as

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{6}$$

(iii) Accuracy.

The accuracy of a test is its capacity to distinguish the persistent and sound cases accurately. To appraise the accuracy of a test, we ought to calculate the extent of true positive, true negative, false positive, false negative in all assessed cases.

Mathematically, this can be stated as:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{7}$$

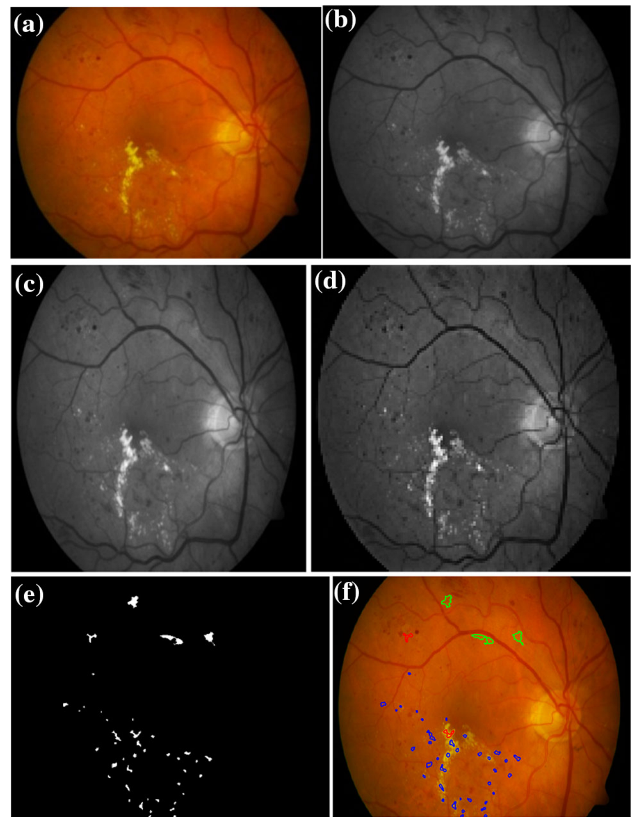

Fig. 10 **a** Original image, **b** Green channel. **c** Gamma correction, **d** Filtered image. **e** Detected lesions, **f** overlapped lesions

3.2 Result of lesion detection

The fundus image is taken from the DIARETDB1 dataset and upgraded utilizing gamma redress. After that, the blood vessels and the optic plate are expelled by foundation subtraction. The lesion is recognized utilizing morphological operation after applying foundation subtraction. The identified lesions are as takes after.

Figure 10(a) shows the red, green, blue retinal fundus image. This image is taken as input for the encouraging handling. The RGB image is spitted into R, G and B channels. Within the three channels, the green channel is taken as input for the improvement in preparation. (b) shows the green channel image. This image clearly shows the vessels and the foundation image, usually used to extricate the lesion from the foundation of the image that's more valuable for the ophthalmologist to conclude the organize of the diabetic retinopathy effortlessly.

The green channel image is utilized for upgrading. The radiance was improved utilizing gamma adjustment. Figure 10(c) shows the gamma-rectified image. After gamma adjustment, the image was shifted utilizing coordinated channel. Figure 10(d) shows the shifted image. This image is the upgraded image of the fundus image. The lesion is recognized

Table 1 Comparison of various results

Dark/red lesion (Mas) detection						
S.No	Method	Dataset	Highlights	Sensitivity	Specificity	Accuracy
1.	Kar et al. [1] (for MAs)	DIARETDB1, MESSIDOR	Curvelet, differential evolution algorithm	95.23	95.12	97.23
2	Akram et al. [9] (for MA)	DIARETDB, MESSIDOR	Hybrid classifier (GMM and m-mediods)	98.07	96.17	97.43
3.	Figueiredo et al. [20] (for MAs)	DIARETDB, MESSIDOR	Anisotropic wavelet bands, cartoon texture Decomposition	93.45	88.92	94.68
4	Xu et al. [4] (for MAs)	Grampian diabetes database, UK	SVM classifier model, pathological risk factors	93	94	–
5	Proposed method (for MAs)	DIARETDB1, MESSIDOR	Morphological operation, matched filter, PCA, ISODATA, convex hull transform	98.97	97.17	98.43

Table 2 Comparison of various results

Dark/red lesion (Hems) Detection						
No	Method	Dataset	Highlights	Sensitivity	Specificity	Accuracy
1.	Kar et al. [1] (for HEMs)	DIARETDB, MESSIDOR	Curvelet, differential evolution algorithm	97.83	98.36	98.12
2.	Akram et al. [9] (for both MA and HEM)	DIARETDB, MESSIDOR	Hybrid classifier (GMM and m-mediods)	98.07	96.17	97.43
3.	Figueiredo et al. [20] (for HEMs)	DIARETDB, MESSIDOR	Anisotropic wavelet bands, cartoon texture Decomposition	86.34	90.19	95.12
4.	Xu et al. [4] (for HEMs)	Grampian diabetes database, UK	SVM classifier model, pathological risk factors	–	–	–
5.	Proposed method (for HEMs)	DIARETDB1	Morphological operation, matched filter, PCA, ISODATA, convex hull transform	98.82	96.14	98.06

utilizing morphological operation. The lesion is recognized on the nuts and bolts of concentrated data of the fundus image. The tall escalated image is isolated from the fundus image. The isolated lesion is classified as hemorrhages, smaller-scale aneurysms and exudates depending on the range of the lesions. After the location of lesion that's covered with a unique image that appears the clear, see lesions that display within the retina. The clear see makes a difference the ophthalmologist to determination the disease. The lesions are signified with distinctive colors to classify the lesion for knowing the organize of the malady. The blue color denotes micro-aneurysms, red color denotes the hemorrhages, and green color denotes the exudates present in the retinal fundus image. The morphological operation method classifies the lesions by using these lesions by using the area of the lesions.

Figure 10(e) shows the detected lesions used our proposed method for detecting lesions for diagnosis diabetic retinopathy. Figure 10(f) shows the overlapped lesions on an original retinal image with good performance metrics.

3.3 Performance measure

Performance of the morphological operation method is evaluated using the metrics of specificity, sensitivity and accuracy as follows. The morphological Operation method is compared with the differential evolution as shown in Table 1 Tables 2 and 3.

As per the suggestion given by the reviewer, Xu et al. [4] only detected micro-aneurysms lesion using SVM method. They achieved 93% sensitivity and 94% specificity. In our proposed method, we have explained about different lesions and also improve the 98.97% sensitivity, 97.17% specificity and 98.43%.

The lesion-level performance of the morphological operation method is compared with some differential evolution methods and is presented in Tables I, II and Table III for the

Table 3 Comparison of various results

Bright lesion (Exs) detection

S. no	Method	Dataset	Highlights	Sensitivity	Specificity	Accuracy
1	Kar et al. [1]	DIARETDB1, MESSIDOR	Curvelet, differential evolution algorithm	97.81	98.18	98.32
2.	Akram et al. [9]	DIARETDB, MESSIDOR	Hybrid classifier (GMM and m-mediods)	97.39	98.02	97.56
3	Figueiredo et al. [21]	DIARETDB, MESSIDOR	Anisotropic wavelet bands, Cartoon texture decomposition	89.81	97.47	98.12
4.	Xu et al. [4] (for EXs)	Grampian diabetes database, UK	SVM classifier model, pathological risk factors	–	–	–
5.	Proposed method	DIARETDB1	Morphological operation, matched filter, PCA, ISODATA, convex hull transform	99.03	98.37	98.68

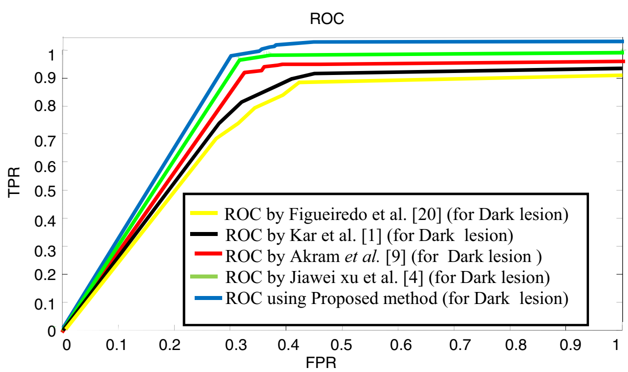

Fig. 11 ROC curve for dark lesion detection (MAs)

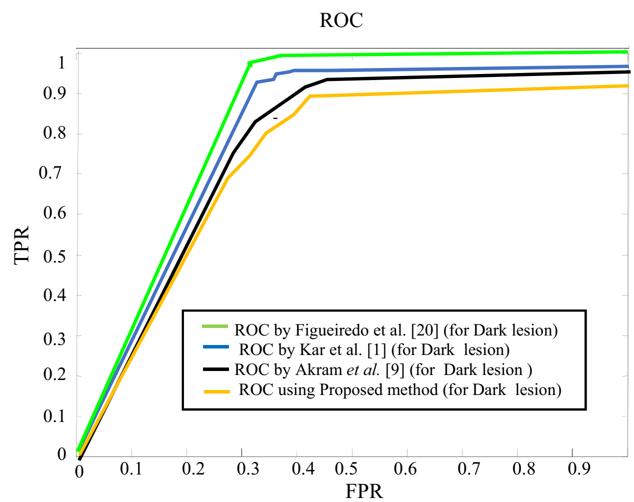

Fig. 12 ROC curve for dark lesion detection (EXs)

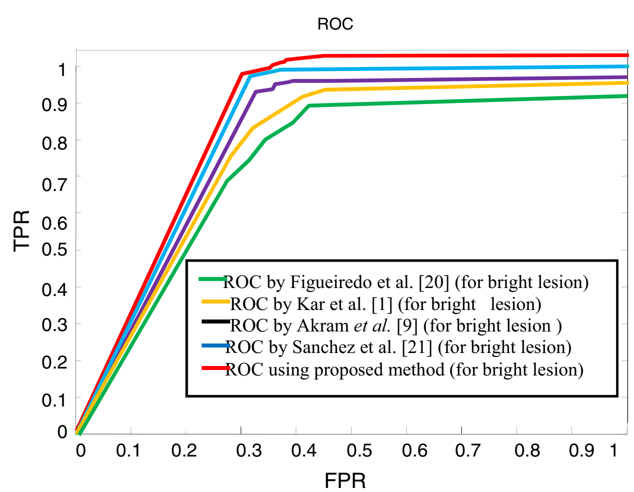

Fig. 13 ROC curve for bright lesion detection (HEMs)

dark/red and the bright lesions, respectively. The other methods' results are shown on the basis of the results reported in their respective works. An important point needs mentioning that despite all the existing methods reported in Tables 1, 2 and 3 do not use the same databases, and their inclusion is just for the sake of comparison. The proposed method detection accuracy value for the recognition of micro-aneurysms, exudates and hemorrhages was 98.43%, 98.06%, and 98.68% compared with the results of the differential evolution algorithm. Performance comparison for the dark and bright lesion detection shows that the morphological operation method outperforms the existing techniques [1, 4, 9, 20, 21]. However, compared to [1] the proposed method has a scope of improvement by 1.41% and 1.03% for the Sen and Acc values, respectively. Factual execution of the proposed framework is analyzed utilizing receiver operating characteristics (ROC) curve, which is the plot between True Positive Rate (TPR = Sensitivity) versus False Positive Rate (FPR = 1-Specificity). Based on lesion-level assessment, ROC curves for the dark/red and the bright lesion location are delineated in Figs. 11, 12 and 13.

3.4 Run time

Within the proposed strategy, the complete program takes the time for running 17.523 s. This progresses the time effectiveness for concluding the malady and the time was spared for ophthalmologist. The existing strategy takes more to determine the infection of DR. Within the existing strategy, the OD & vessel extraction takes more than 10 min and the entire handle takes up to 12 min for determination the disease.

4 Conclusion

This work proposes an algorithm of matched filter with morphological operation for the detection of different types of lesions in the fundus retinal image. When compared, this method is the best method for differential evaluation method. After removal of optic plate and the blood vessels from the retinal image, the morphology strategy is applied simply to found out the lesions. The diabetic retinopathy images were collected from DIARETDB1 database. The fundus image lesion detection of the morphology operation method is analyzed using the metrics of sensitivity, specificity and accuracy. In detection of lesion such as micro-aneurysms, it achieves 97.43% accuracy that is 0.02% more accurate when compared with differential evolution. In the detection of hemorrhages, it achieves 98.06% accuracy, that is, the morphological operation method achieves 1.07% more accurate than the differential evolution. In the detection of exudates, it achieves 98.68% accuracy, respectively, using DIARETDB1 dataset on the proposed method that is matched filter with the morphological method for detecting the lesions. When compared with the differential evolution algorithm, it achieved morphological method good accuracy for the detection of diabetic retinopathy. The computational time of matched filter with morphological operation is 19.82 s. This is less compared to differential evolution algorithm (12 min).

References

1. Kar, S.S., Maity, S.P.: Automatic detection of retinal lesions for screening of diabetic retinopathy. IEEE Trans. Biomed. Eng. **65**(3), 608–618 (2017)
2. Biyani, R.S., Patre, B.M.: Algorithms for red lesion detection in Diabetic Retinopathy: a review. Biomed. Pharmacother. **107**, 681–688 (2018)
3. Zhou, W., Wu, C., Yi, Y., Du, W.: Automatic detection of exudates in digital color fundus images using superpixel multi-feature classification. IEEE Access **5**, 17077–17088 (2017)
4. Xu, J., Zhang, X., Chen, H., Li, J., Zhang, J., Shao, L., Wang, G.: Automatic analysis of microaneurysms turnover to diagnose the progression of diabetic retinopathy. IEEE Access **6**, 9632–9642 (2018)
5. Deepak, K.S., Sivaswamy, J.: Automatic assessment of macular edema from color retinal images. IEEE Trans. Med. Imag. **31**(3), 766–776 (2011)
6. Mansour, R.F.: Evolutionary computing enriched computer-aided diagnosis system for diabetic retinopathy: a survey. IEEE Rev. Biomed. Eng. **10**, 334–349 (2017)
7. Pires, R., Avila, S., Jelinek, H.F., Wainer, J., Valle, E., Rocha, A.: Beyond lesion-based diabetic retinopathy: a direct approach for referral. IEEE Trans. Inf. Technol. Biomed. **21**(1), 193–200 (2015)
8. Dashtbozorg, B., Zhang, J., Huang, F., Ter Haar Romeny, B.M.: Retinal microaneurysms detection using local convergence index features. IEEE Trans. Image Process. **27**(7), 3300–3315 (2018)
9. Akram, M.U., Khalid, S., Tariq, A., Khan, S.A., Azam, F.: Detection and classification of retinal lesions for grading of diabetic retinopathy. Comput. Biol. Med. **45**, 161–171 (2017)
10. Raju, M., Sangramsing, K., Suvarnsing, B., Jaypalsing, K.: Automated detection of microaneurysm, hard exudates, and cotton wool spots in retinal fundus images. IOSR J. Comput. Eng. **17**(6), 152–156 (2015). **e-ISSN: 2278-0661**
11. Zhou, L., Zhao, Y., Yang, J., Yu, Q., Xu, X.: Deep multiple instance learning for automatic detection of diabetic retinopathy in retinal images. IET Image Process **12**(4), 563–571 (2017)
12. Roychowdhury, S., Koozekanani, D.D., Parhi, K.K.: DREAM: diabetic retinopathy analysis using machine learning. IEEE Trans. Inf. Technol. Biomed. **18**(5), 1717–1728 (2013)
13. Salazar-Gonzalez, A., Kaba, D., Li, Y., Liu, X.: Segmentation of the blood vessels and optic disk in retinal images. IEEE Trans. Inf. Technol. Biomed. **18**(6), 1874–1886 (2015)
14. Roychowdhury, S., Koozekanani, D.D., Kuchinka, S.N., Parhi, K.K.: Optic disc boundary and vessel origin segmentation of fundus images. IEEE Trans. Inf. Technol. Biomed. **20**(6), 1562–1574 (2015)
15. Morales, S., Engan, K., Naranjo, V., Colomer, A.: Retinal disease screening through local binary patterns. IEEE Trans. Inf. Technol. Biomed. **21**(1), 184–192 (2015)
16. Seoud, L., Hurtut, T., Chelbi, J., Cheriet, F., Langlois, J.P.: Red lesion detection using dynamic shape features for diabetic retinopathy screening. IEEE Trans. Med. Imaging **35**(4), 1116–1126 (2016)
17. Wang, S., Tang, H.L., Hu, Y., Sanei, S., Saleh, G.M., Peto, T.: Localizing microaneurysms in fundus images through singular spectrum analysis. IEEE Trans. Biomed. Eng. **64**(5), 990–1002 (2016)
18. Annunziata, R., Garzelli, A., Ballerini, L., Mecocci, A., Trucco, E.: Leveraging multiscale hessian-based enhancement with a novel exudate inpainting technique for retinal vessel segmentation. IEEE Trans. Inf. Technol. Biomed. **20**(4), 1129–1138 (2017)
19. Yu, S., Xiao, D., Kanagasingam, Y.: Machine learning based automatic neovascularization detection on optic disc region. IEEE Trans. Inf. Technol. Biomed. **22**(3), 886–894 (2017)
20. Figueiredo, I.N., Kumar, S., Oliveira, C.M., Ramos, J.D., Engquist, B.: Automated lesion detectors in retinal fundus images. Comput. Biol. Med. **66**, 47–65 (2017)
21. Sánchez, C.I., Hornero, R., López, M.I., Aboy, M., Poza, J., Abásolo, D.: A novel automatic image processing algorithm for detection of hard exudates based on retinal image analysis. Med. Eng. Phys. **30**(3), 350–357 (2018)