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Improved retinal fundus image quality with hybrid image filter and enhanced contrast limited adaptive histogram equalization

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***Abstract*---**Retinal fundus image preprocessing has contributed extensively to medical image analysis and retrieval of appropriate images. The acquired retinal images are usually messy and come from different sources. They need to be standardized and cleaned up. Retinal image preprocessing enables the improvement of retinal image quality and enhances the image features that are required for processing. The success of the retinal image diagnosis for early prediction of Diabetic Retinopathy (DR) depends on the reliability of preprocessing. The automatic preprocessing of color retinal fundus images without affecting the image quality is still challenging. Retinal images often have issues such as low contrast intensity, uneven light intensity, blurring, noise disturbances, sensor system that lack of focus, low contrast, irregular shapes with high variability, object movement, ill-defined boundaries, heterogeneous pixel intensities and the annotation of medical images to support diagnosis. In this work, issues such as noisy/ill in defined boundaries, uneven light intensity, low contrast, and blurring of images in the retinal fundus images are addressed with the proposed method. The results of the proposed method are reliable, contrast enhanced, edge preserved preprocessed images for given color input images. The performance of retinal image preprocessing is evaluated using metrics such as MSE, PSNR, SSIM, and UQI.

***Keywords*---**Diabetic Retinopathy, Enhanced CLAHE, Hybrid image filter, Image Enhancement, Retinal fundus images.

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Introduction

Eye is an essential organ in human vision. Diabetic retinopathy is a diabetes complication that affects human eyes. It is caused by damage to the blood vessels of the light-sensitive tissue at the back of the eye (retina). Diabetic retinopathy typically presents with no symptoms during the early stages.(Tsiknakis et al. 2021). The condition is often at an advanced stage when symptoms become noticeable. Blindness due to diabetic retinopathy (DR) is usually preventable with routine checks and effective management of the underlying diabetes. Symptoms include blurred vision, difficulty seeing colors, floaters, and even total loss of vision. People with diabetes should have their vision checked at least once annually to rule out DR(Wan et al. 2021).

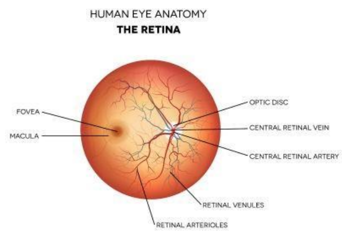
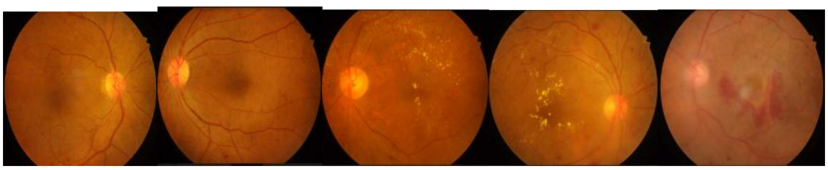


Fig. 1: Human Eye

Most of the people who are having prediabetes, gestational diabetes, uncontrolled blood pressure, high cholesterol, high blood sugar, and pregnancy must go for routine check-up for early prediction of diabetic retinopathy. Leaving retinal illness among diabetic's patients without giving treatment at the earlier stage may cause blindness in several cases. The retinal fundus image with the lesion is given below. Figure 2 depicts the retinal images representing various stages of diabetic retinopathy.



(a) (b) (c) (d) (e)

Fig. 2: represents the various stages of diabetic retinopathy.(a) No DR, (b) mild NPDR, (c) moderate NPDR, (d) Severe NPDR, (e) Proliferative DR

In today's medical world, retinal fundus images are widely used in clinical diagnoses to detect retinal disorders. Retinal fundus image is a medical image acquired through fundus photography using a fundus camera. Retinal images often have issues such as low contrast intensity, uneven light intensity, blurring, noise disturbances, sensor system that lack of focus, low contrast, irregular shapes with high variability, object movement, ill-defined boundaries, heterogeneous pixel intensities and the annotation of medical images to support diagnosis[4]. So it is essential to preprocess the image so that it is an improvement of the image data that restrain averse distortions or enhance some image features that are important for further processing. In this work, the key issues that are addressed include noisy/ill defined boundaries, uneven light intensities, low contrast and blurring of images in the retinal fundus images. In-order to address the above issues, the proposed algorithm (IP-HEC) for improving the retinal image enhancement technique with hybrid filter and enhanced CLAHE is used for preprocessing.

The paper follows a chronological structure. The Methods and methodology carried out in the field of color retinal image preprocessing are discussed in Section II. The Experimental Results with its performance measures are discussed in Section III. The conclusions for future research directions are explained in Section IV.

Methods

Diabetic Retinopathy (DR) is a retinal disease caused by diabetes mellitus (DM). It causes blindness globally if not treated intime. Thus early prediction and necessary treatments are needed to delay or avoid vision deterioration and vision loss.(Tsiknakis et al. 2021; Wan et al. 2021). To diagnose the disease, capturing retinal fundus images using a variety of cameras, under various environmental conditions that induce noise to the final retinal image. Retinal image preprocessing is needed to enhance the fundus images and avoid heterogeneity.

Methodology

The main aim of the retinal image preprocessing is to improve the retinal image quality with hybrid filters to denoise the image and applying enhanced Contrast Limited Adaptive Histogram Equalization on the denoised image for better image quality. The results are compared with different enhancement techniques of images. Performance evaluation of the preprocessed image is done using various metrics such as PSNR, MSE, SSIM, and UQI.

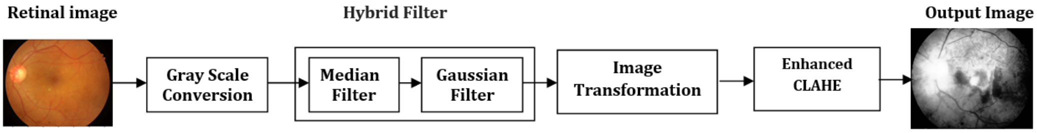


Fig. 3: Proposed method architecture

Gray Scale Conversion

As the initial step of image preprocessing, RGB images are converted into gray scale images (Sheet et al., 2022) . This is because in many objects, color is not necessary to recognize and interpret an image. Grayscale can be good enough for recognizing certain objects. Because color images contain more information than black and white images, they can add unnecessary complexity and take up more space in memory. Converting a color retinal image into grayscale reduces the number of pixels that need to be processed. A gray scale image is an image with a single sample pixel value having only intensity information. Gray scale conversion involves the mapping of multiple color channels(R,G,B) to a single gray scale value in terms of a weighted sum. The formula for gray scale conversion based on luminance properties is given below.

$$. G= 0.2989 * R + 0.5870 * G + 0.1140*B,$$

where,

R, G, B represents the Red, Green, and Blue color of the pixel, respectively. Coefficients of R, G, B represent the human perception of the color.

Hybrid Filter

Hybrid filter combines Gaussian filter and median filter. The Gray scale image is added with a Gaussian filter and the resultant image is applied with a median filter. The output of the median filter will be denoised and edge smoothened image. Let us discuss the filters used within hybrid filters.

a. Gaussian Filter: Gaussian filter(Sugimoto et al. 2020)] is used to remove noise in an image. It is a linear filter with a weighting value for each member. It is a low pass filter that removes the high frequency component from the image. This filter uses Gaussian Distribution Function to blur or smoothen the image. The degree of smoothing in the Gaussian filter is determined by its standard deviation. It works with 'weighted average'; more weight is given to the image's central pixel and lesser weight to its neighboring pixels. The Gaussian filter is represented as a two-dimensional array at[x, y].

$$G\ (x, y) = \frac{1}{2\pi\sigma^2}\, e^{-\frac{x^2+y^2}{2\sigma^2}}$$

where,
G (x, y) represents an element of the Gauss matrix at position [x, y].
σ denotes a standard deviation or sigma.
x, y represents the size of the Gauss matrix which places the points x to + x, and the middle points are at x = 0 and y = 0.

b. Median Filter: Median filter(Mohan et al. 2021) is a non-linear filter used to remove noise from an image or signal. Noise reduction is one of the typical preprocessing steps that enhances the edge detection in an image. Median filter works by a window that slides along the image, and the median intensity value of the pixels within the window becomes the output intensity of the pixel being processed. The median value of an image is calculated by sorting all pixel values from the surrounding neighborhood in numerical order and then replacing the pixel being considered with the middle pixel value.
Median filter formula is represented as:

$$I'(x, y) = \text{median}\ \{l(x+i, y+j) \mid (I, j) \in R\}$$

Where,
R is the moving region.

Image Transformation

The transform function, T(r), compresses the input levels below and above the threshold into a narrow range of darker levels (lower pixel count) and brighter levels (higher pixel count) and thereby improves contrast. Apply Image Transformation on the output of hybrid filter, that reduces the lightness level of gray images and improves contrast

Image transformation formula is represented as:

$$I_t = 255.0 * (blur/255.0)**2$$

Histogram Equalization

Histogram Equalization is a computer image processing technique used to improve contrast in images. It accomplishes this by effectively spreading out the most frequent intensity values, i.e. stretching out the intensity range of the image. Applying Histogram Equalization function on the transformed images

H_n = histogram (n); // Generate Histogram of the image.
cdf = imhist.cumsum()//Apply cumulative distribution on the image histogram
cdf = imhist.max()*cdf/cdf.max()// Normalize.

Enhanced CLAHE:

Contrast Limited Adaptive Histogram Equalization (Alwazzan et al. 2021) is used on retinal images to enhance the contrast in an image and improve prediction accuracy. The CLAHE clipped the histogram at a predefined clipping value to avoid excessive contrast enhancement that results in processed images with artifacts [20]. Improper contrast enhancement leads to poor manifestation in vanishing regions, typically the vein parts. The issue can be solved by applying enhanced CLAHE. CLAHE is created and the Clip Limit value varies from 0.002 – 0.005. Apply CLAHE on the image histogram. The proposed model greatly improved the image contrast. Increased contrast can be selected as the slope of the function that has a relationship in the increase, the input value, and the desired input image. The slope of the function can also be improved in contrast enhancement controls.

Algorithm

The algorithm for the proposed method of preprocessing is given below..
// Input : RGB retinal image - IRGB
//**Output :** Enhanced Image - I_{col}.

1. Read the Retinal Fundus Image for Preprocessing
2. Transform input images into Gray Scale image.
3. Apply hybrid filter for removing noises and preserves the edges
4. Add enhanced Contrast Limited adaptive Histogram Equalization on the output image from Hybrid filter.
   4.1 Make Look-up Table(LUT) for the given retinal image.
   4.2 Generate Histogram for the image

4.3 Perform clipping Histogram based on the clip limit.
4.4 Perform mapping Histogram
4.5 Interpolation of the Image is to be performed
5. Covert the gray image into RGB image.
6. Finally preprocessed image is given as output.

The outcome of the proposed method is an improved retinal image quality with hybrid filter and Enhanced CLAHE.

Experimental Results and Discussion

The proposed algorithm CLAHE has been tested over a quantity of 516 images using a 500 GB hard disk system with a 4 GB RAM, and various metrics have been evaluated from the tested results. The retinal images, gathered from the IDRiD (Indian Diabetic Retinopathy Image Dataset dataset). IDRiD dataset (Wan et al. 2021) consists of diabetic retinopathy lesions and normal retinal images with pixel level annotations.

Table 1
Attributes considered for the experimental setup

Attributes	Features
Total no. of retinal images tested	516
Image Category :	
0 – Normal	168
1 – Mild NPDR	25
2 – Moderate NPDR	168
3 – Severe NPDR	93
4 – Proliferative DR	62
Image Type	jpeg
Image Dimensions	varying

Experimental Results

The proposed method has been tested on various classes of retinal images such as normal images, mild NPDR, moderate NPDR, Severe NPDR and Proliferative DR images. Figure 4. represents the comparisons of retinal images sets on the proposed IE-HFEC method.

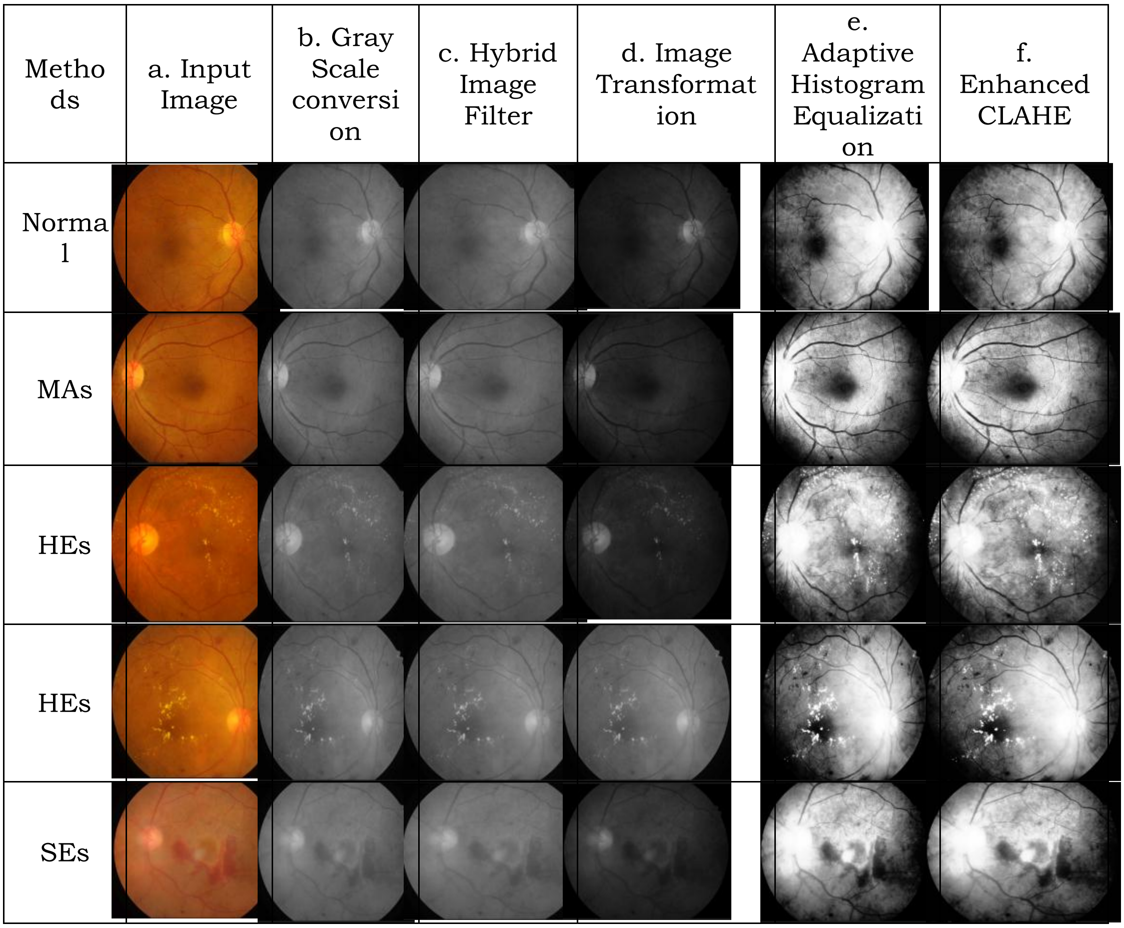


Fig. 4: A comparison of the retinal image sets on the proposed IE-HFEC method

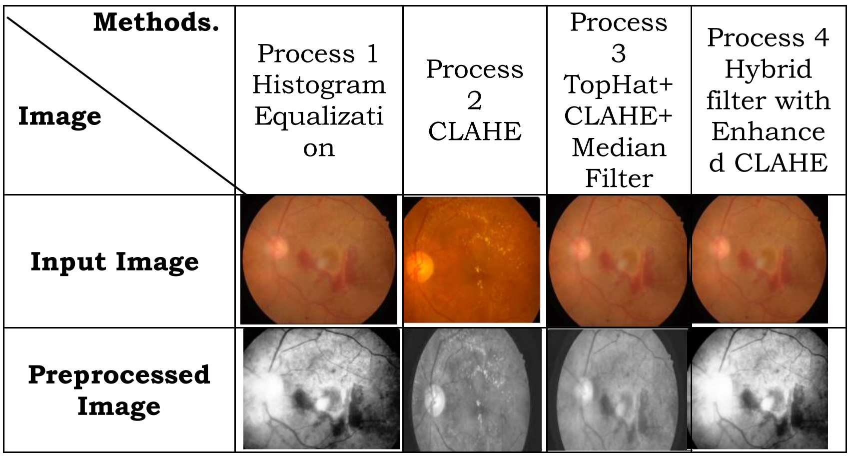


Fig. 5: Result comparison on different Image enhancement methods

Parameters for Performance Analysis

The metrics used for evaluating the performance measures of preprocessed retinal images are MSE, PSNR, SSIM and UQI. The metrics used for evaluating the algorithm's efficiency are as follows:

Mean Square Error (MSE)(**Mohan et al. 2021**) is an average of squared error between the original and preprocessed image. The error is the difference between original and the processed image. It is a full reference metric and the MSE value closer to zero is the better result. When MSE value decreases, then error rate also decreases with increase in image quality.

$$\mathrm{MSE} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[g(i,j)-f(i,j)]^2$$

Where M,N represents the number of rows and columns in the input image, 'g' represents the noise image and 'f' represents the filtered image.

Peak Signal to Noise Ratio (PSNR)(**Mohan et al. 2021**) is the most commonly used image quality assessment technique to measure the quality of reconstruction of lossy image compression codecs. Here the signal refers to the original data and noise represents the error yielded by the compression or distortion. It calculates the difference between the original image and the preprocessed image[17]. The PSNR is usually computed in decibel form. In image quality degradation, the PSNR value ranges from 30 to 50 dB for a 8-bit data representation and from 60 to 80 dB for a 16 bit data, Better Quality of image is obtained with higher PSNR value. PSNR equation is represented as

$$\mathrm{PSNR} = 10\log_{10}(\mathrm{peakval}^2) / \mathrm{MSE},$$

where,
peakval (Peak Value) denotes the maximum possible pixel value of the image data. peakval=255 for an 8-bit image. MSE denotes the Mean Square Error value.

Structural Similarity Index (SSIM)(**Sara et al. 2019**) is a perceptual metric that quantifies the image quality degradation caused by processing such as data compression or by losses in data transmission. It is a measuring tool , used in image quality assessment that needs two images - a reference image and a processed image, for the same image capture., SSIM value is calculated based on three attributes, i.e., luminance, contrast, and structure, to better suit the workings of the human visual system.
Structural Similarity Index Method(SSIM) can be expressed as:

$$SSIM(x, y) = [l(x, y)]^{\alpha} \cdot [c(x, y)]^{\beta} \cdot [s(x, y)]^{\gamma}$$

where,
l denotes the luminance that compares the brightness between two images,
c denotes the contrast, used to differ the ranges between the brightest and darkest portion of the original and processed image.
s denotes the structure that compares the local luminance pattern between two images to calculate the similarity of the images.

α, β, γ are positive constants.
Again, the luminance, contrast and structure of an image can be expressed separately as:

$$l(x,y)=\frac{2\mu_x\mu_y+C_1}{\mu_x^2+\mu_y^2+C_1},\quad c(x,y)=\frac{2\sigma_x\sigma_y+C_2}{\sigma_x^2+\sigma_y^2+C_2},\quad s(x,y)=\frac{\sigma_{xy}+C_3}{\sigma_x\sigma_y+C_3}$$

where μ_x and μ_y are the local means, σ_x and σ_y are the standard deviation and σ_{xy} is the cross-covariance for images x and y sequentially. If α = β = γ = 1, then the index is simplified as the following form using equations

$$\mathrm{SSIM}(x,y)=\frac{(2\mu_x\mu_y+C_1)(2\sigma_x\sigma_y+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)}$$

The Structural Similarity Index (SSIM) values range between 0 to 1, 1 means it perfectly matches the reconstructed image with the original one.

Universal Quality Index(UQI)(Sara et al. 2019) evaluates the image quality using the loss of correlation, luminance distortion, and contrast distortion. UQI measure is computed by comparing the Riesz-transform features at key locations between the processed image and its original image. UQI is a predecessor of SSIM, UQI can be expressed as :

$$Q=\frac{4\sigma_{xy}\,\bar{x}\,\bar{y}}{(\sigma_x^2+\sigma_y^2)\,[(\bar{x})^2+(\bar{y})^2]}$$

The performance of the proposed IE-HFC method is measured using metrics such as peak-to-Signal Ratio, Mean Squared Error, Structural Similarity Index and Universal Image Quality. Results are tabulated below for the 20 retinal images inclusive of all classes of images.

Table 2
PSNR, MSE, SSIM and UQI Values for the proposed IE-HFEC method

Image Name	MSE	PSNR	SSIM	UQI
Image0001	76.21	29.37	0.59	0.51
Image0002	73.2	29.21	0.64	0.56
Image0003	73.54	29.34	0.61	0.46
Image0004	73.31	29.31	0.59	0.46
Image0005	75.92	29.21	0.58	0.59
Image0006	75.21	29.35	0.56	0.43
Image0007	75.96	29.29	0.62	0.52
Image0008	74.22	29.48	0.51	0.43
Image0009	76.15	29.46	0.55	0.38
Image0010	74.44	29.41	0.52	0.43
Image0011	76.08	29.31	0.47	0.38
Image0012	73.04	29.49	0.5	0.31
Image0013	77.85	29.31	0.57	0.47

Image0014	75.42	29.48	0.64	0.46
Image0015	76.48	29.47	0.56	0.47
Image0016	75.11	29.31	0.48	0.42
Image0017	77.84	29.32	0.65	0.52
Image0018	75.61	29.36	0.53	0.46
Image0019	75.74	29.32	0.59	0.48
Image0020	73.24	29.42	0.55	0.42
Average	75.23	29.36	0.57	0.46

Table 3
Performance measures for the proposed IE-HFEC method

Classes Metrics	0-Normal (No DR)	1-Mild NPDR	2-Moderate NPDR	3-Severe NPDR	4-PDR
PSNR	29.31	29.33	29.42	29.39	29.36
MSE	74.07	75.33	74.93	76.22	75.61
SSIM	0.61	0.57	0.51	0.56	0.58
UQI	0.50	0.49	0.38	0.46	0.47

Table 4
Comparison with Other Color Image Enhancement Methods such as Histogram Equalization, CLAHE, TopHat+CLAHE+Median Filter, Hybrid Filter with Enhanced CLAHE

Methods	PSNR	MSE	SSIM	UQI
Histogram Equalization	29.56	75.22	0.57	0.46
CLAHE	27.78	108.08	0.12	0.40
TopHat,CLAHE,Median Filter	26.72	100.15	0.43	0.41
Hybrid Filter, Enhanced CLAHE	29.29	76.36	0.55	0.44

Table 5a.
A comparative performance measures (PSNR,MSE) for the IE-HFEC and other methods

Metrics / Image Sets	PSNR				MSE			
	P1	P2	P3	P4	P1	P2	P3	P4
Normal	29.31	27.72	28.10	29.33	74.07	109.75	100.65	75.87
MAs	29.33	27.65	28.18	29.34	75.33	111.00	98.84	75.64
HEs	29.42	28.26	28.28	29.34	74.93	96.00	96.61	75.65
SEs	29.39	27.57	27.99	29.18	76.22	113.00	103.15	77.55
PDR	29.36	27.74	28.05	29.25	75.61	109.00	101.67	77.09

Table 5b.
A comparative performance measures (SSIM,UQI) for the IE-HFEC and other methods

Metrics / Image Sets	SSIM				UQI			
	P1	P2	P3	P4	P1	P2	P3	P4
Normal	0.61	0.14	0.43	0.53	0.50	0.40	0.41	0.41
MAs	0.57	0.16	0.43	0.58	0.49	0.46	0.44	0.51
HEs	0.51	0.16	0.37	0.57	0.38	0.30	0.34	0.43
SEs	0.56	0.18	0.44	0.53	0.46	0.34	0.42	0.41
PDR	0.58	0.16	0.47	0.57	0.47	0.49	0.45	0.47

It is, therefore, concluded from the above results that, in all cases, the Process 4 (IE-HFEC) is found to be better than the Process 1, Process 2 & Process 3 for all types of images in terms of better PSNR value, reduced MSE value and improved SSIM and UQI values.
During the experiment, it was observed that

- The IE-HFEC methods works well with different classes of retinal images such as normal images, mild NPDR, moderate NPDR, Severe NPDR and Proliferative DR images.
- The Enhanced images are greatly helpful for making segmentation of lesions (MAs, HEs, EXs, SEs, Cotton Wool) better. Thus, in the next phase, image segmentation and classification will be carried out on the preprocessed retinal images for early DR prediction.

Conclusion

Diabetic retinal fundus images are difficult to detect during the early stages as with the progress in time, DR may cause vision loss in our patient. In this work, the retinal fundus images are preprocessed using different image enhancement methods and the results are analyzed by comparing it over four parameters such as MSE, PSNR, SSIM and UQI in improving the 516 retinal fundus images. It was observed that the hybrid filter with enhanced CLAHE improves the quality of retinal fundus images during preprocessing by producing a lower MSE value and has a higher PSNR value compared to other processes except the SSIM and UQI value which is better for Gaussian filter.

Data Availability

The data sets used and analyzed during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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