



## **Enhancement of the Retinal Images Based on Wavelet Fusion Technique Using Adaptive Histogram Equalization Method**

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**Abstract:** Colour retinal image enhancement plays an important role in eye diseases and classification techniques. Optical coherence tomography devices are used to take images, which often suffer from a lack of lighting and contrast. In this study, a new algorithm for improving colour retinal images was suggested. The suggested algorithm was developed on the basis of improving the lighting (L) based on (Lab) colour space while preserving the colour information (a and b). The lighting enhancement included the wavelet fusion between the original lighting component and the improved component twice using contrast-limited adaptive histogram equalisation (CLAHE). Data containing 40 image forms (driver rental images dataset) were used, and the proposed method of improvement was compared with several other methods, such as principal component analysis using reflection model (PCAURM), luminosity and contrast adjustment (LCA), fuzzy logic by stretch membership function (FLSMF), CLAHE, contrast enhancement approach (CEA) and modified color histogram equalization (MCHE). The collected results showed that the proposed method obtained excellent quality rates in terms of natural image quality evaluator (4.680), entropy (6.985), contrast enhancement measurement (0.569) and structural similarity index (0.963).

**Keywords:** CLAHE, Driver data, (Lab) color space, Enhancement of the retinal wavelet fusion.

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### **1. Introduction**

The main characteristic of images is contrast, which is effectively important in the human visual perception of image quality. An objective method based on local correction of quality is adopted using an adaptive representation of the local correction structure where any image patch is analyzed into its average intensity, signal strength, and components of the signal structure afterward, it is very important in improving images, which plays an important role in many applications [1 - 4]. There are many previous studies that dealt with the topic of improving medical images, especially retinal images with low light and contrast.

Perceptual distortions are evaluated in different ways, this study was carried out by Shiqi Wang et al [5] The ability to produce a local variance quality map is an advantage of this method over previous variance quality models, and it is used for variance enhancement algorithms. The correction-dependent

variance quality index (PCQI) method provides accurate predictions about human perception of variance changes.

Diagnosing diabetic retinopathy is based on retinal images. The main objects of retinal images are exudates, retinal vessels, and low-contrast microvascular disease. This study was conducted by Yeddu Aruna Suhasini Devi and Manjunatha Chari Kamsali [6], spatial collaborative contrast enhancement (SCCE) has been proposed where it uses the interrelationship and spatial spread of gray levels over the retinal image and enhances the contrast. The experimental results of SCCE improve the contrast of retinal images in a better way than several existing methods including normal torsion and CLAHE.

It is necessary for clinicians to make an accurate diagnosis is the image quality of the color retina. Therefore, a dispersion image-forming model was proposed to improve the color images of the retina, which was suggested by Li Xiong et al [7]. The backlight and transmission map was estimated by two

parameters of this model. A method that combines Mahalanobis distance discrimination and global spatial, entropy-based contrast enhancement is suggested which extracts foreground pixels. It extracts background and foreground in the high and low-intensity region respectively and can perform well in blur images with little intensity range. E. D. Pisano et al [8] introduced a study depending CLAHE by restructuring the histogram of the image, it prevents the problem of over-reinforcement by restructuring as mentioned earlier by arrangement and the height should not exceed the segment limit. Because the histograms of different regions have different values, it is very complicated to set the clip's border for illumination unevenly, to overcome the limitations of the histogram equalization HE. The technique used to improve the medical image and improve its contrast is the histogram equation, and the traditional histogram equation has bad results in improving the image, this study was proposed by Wei-Yen Hsu and Ching-Yao Chou [9] to improve the retinal images using MCHE, This algorithm gives good contrast enhancement but does not return good color information. When images contain bright and dark areas, this method was suggested by Bhupendra Gupta and Tarun Kumar Agarwal [10] suggested and CEA whereby an approach is designed to improve contrast without affecting details in bright areas in dark images with irregular lighting, This technique preserves the original data, but does not provide a good improvement in brightness and contrast. Hazim G. Daway et al [11] suggested Three types of medical images were improved from x-ray and magnetic resonance images, wherein the few bands using FLSMF increased the dynamic range of the red, green and blue compounds in the medical images, unevenness or limited representation in the color gamut negatively affects the clarity of the image, This algorithm gave a good contrast improvement, but sometimes it made a chromatic error due to the direct processing of the red, green and blue compounds. Ju Ping et al [12] suggested a method to improve the lightness of images by combining Young-Helmholtz (YH) transformation with the adaptive equation of the density number matrix. This study was done to enhance contrast in the detail and remove noise in the images by using the adaptive histogram equalization method. The image after enhancement can be displayed in the red, green, and blue (RGB) color space by inverse Y-H transformation with the same saturation and hue.

M. Zhou, et al,[13] introduced an algorithm depending on LCA used to enhance the retinal image depending on the luminosity and contrast tuning of the retinal color image using the luminance

acquisition matrix and the gamma correction of the value channel in the HSV color space (hue, saturation, and value), to improve the R, G, and B channels (red, green and blue), on straight. This algorithm provided a good improvement to the retinal images somewhat . Another method proposed by Neha Singh and Ashish Kumar Bhandar, [14] is a low-light image enhancement (LIME) method when depending on PCAURM, the luminance coefficient of the V component is calculated by the multi-band theory concept. Based on the reflection model and multi-band principle, the proposed algorithm works with dark images adaptively, stretching the RGB color input image starting to correct any kind of color distortion, and then converting it to the HSV color space, Relying on Fechner's principle which adaptively regulates parameters of enhancement function and PCA framing based on image merging approach to extract relevant features from these two images. In this study, we will go to improve retinal Images based on modifying CLAHE by wavelet fusion technique using lab color, the distinguishes this algorithm is the preservation of the color information (ab) and the improvement of the lightness (L), which reduces color distortion due to enhancement, and at the same time it increases the contrast and detail values and with little distortion due to the use of fusion technology.

## 2. Suggested method

In this study, the retinal images are enhanced depending on the CLAHE with the introduction of the technique of fusion of the original lighting component in (lab) space and the improved component of the same space while preserving the color information (ab).

### 2.1 Enhancement lightness component-based lab

The image is converted from RGB space to Lab space according to the following equations [15]:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.41 & 0.35 & 0.18 \\ 0.21 & 0.71 & 0.07 \\ 0.01 & 0.11 & 0.95 \end{bmatrix} \cdot \begin{bmatrix} r'(x, y) \\ g'(x, y) \\ b'(x, y) \end{bmatrix} \quad (1)$$

$$f(r) = \begin{cases} \sqrt[3]{r} & \text{for } r > q, \\ 7.787r + \frac{16}{116} & \text{for } \leq q. \end{cases} \quad (2)$$

$$L = \begin{cases} 116 \left(\frac{Y}{Y^n}\right)^{\frac{1}{3}} - 16 & \frac{Y}{Y^n} > q \\ 903.3 \left(\frac{Y}{Y^n}\right) & \frac{Y}{Y^n} \leq q \end{cases} \quad (3)$$

$$a = 500 \left( f \left( \frac{x}{x^n} \right) - f \left( \frac{y}{y^n} \right) \right) \quad (4)$$

$$b = 200 \left( f \left( \frac{y}{y^n} \right) - f \left( \frac{z}{z^n} \right) \right) \quad (5)$$

(q = 0.008856), It is preferable that the values of L are stretched ( 0,1 ) be according to the relationship:

$$L_n = \frac{L - \min(L)}{\max(L) - \min(L)} \quad (6)$$

$L_n$  is a regular lighting channel that has been enhanced with CLAHE. There are two steps to the CLAHE method. The first step is divide the image into several regions that will not overlap each other and are almost equal in size. Second, it calculates the histogram equalization for each region depending on  $\gamma$  is obtained by [16]:

$$\gamma = \frac{mn}{f} \left( 1 + \frac{\alpha}{100} (S_{max} - 1) \right) \quad (7)$$

where  $\gamma$  is the clip limit,  $m \times n$  is the number of pixels in each region,  $f$  is the number of grayscales,  $\alpha$  is a clip factor (0 – 100), and  $S_{max}$  is the maximum allowable slope. From Eq. (10), if  $\alpha = 0$ , . However,  $S_{max}$  should be set to four for still images. In this study, two successive improvements to the spacecraft were performed using CLAHE

## 2.2 The wavelets fusion

Wavelet decompositions between the lightness enhancement by CLAHE and the original lightness component in the lab color space.

In this method, the representation of any random function is like a superposition of wavelets and this is exactly the basic idea of the wavelet transform, since wavelets are functions generated by function  $\Psi$  by dilations. It is preferable to reconstruct the original function from its waveform decomposition, as well as to perform decomposition and rebuild a hypothetical function for practical purposes. Where equations representing filtering were used, where two types of filters were used, which is a high-pass filter  $g$  and a low-pass filter  $h$ , where the function was presented in the form of samples. The coarse function approximations can be calculated iteratively when fusion the sound reduction process with the filtering process because it is related to the orthogonal wavelet bases, to ensure re-construction preparation, the following conditions must be followed [17]:

$$\check{g}_n = (-1)^n h_{1-n} \quad (8)$$

$$g_n = (-1)^n \check{h}_{1-n} \quad (9)$$

$$\sum_n h_n \check{h}_{n+2k} = \delta_{k,0}. \quad (10)$$

Let  $h_n = 2^{1/2} \int \phi(t-n)\phi(2t)dt$  and  $g_l = (-1)^l h_{j-l}$   $h = low - pass filter$  and  $= high - pass filter$  .  $\Psi = a$  single prototype filter function and  $\phi = a$  scaling function.

Also, the relationship between filters, wave functions, and scales must be documented with the following equations [17]:

$$\phi(t) = \sum_n h_n \phi(2t - n) \quad (11)$$

$$\check{\phi}(t) = \sum_n \check{h}_n \check{\phi}(2t - n) \quad (12)$$

$$\Psi(t) = \sum_n g_n \phi(2t - n) \quad (13)$$

$$\check{\Psi}(t) = \sum_n \check{g}_n \check{\phi}(2t - n) \quad (14)$$

When performing the practical method, the two rectangular-shaped images are processed in the vertical direction, i.e. vertically. Then the sampling process is carried out downward along each column. After one stage of processing, one image is converted into a focus level of accuracy (M-1) into 4 sub-images, a level image with lower resolution, secondly an image with a horizontal orientation, thirdly an image with a vertical orientation, and finally an image with a diagonal orientation. These sub-images correspond to the low- low, low- high, high- low, and high -high bands. Then the application is repeated continuously on the outputs of the low-low band, and the noise is reduced until it reaches the desired level.

## 2.3 Reverse transformation

Relying on the inverse transformation from lab space to RGB space, according to the following [18]:

$$L_{ne} = L_{ne} \times 100 \quad (15)$$

$$X = X_n \begin{cases} \left( \frac{L}{166} + \frac{a}{500} + \frac{16}{166} \right)^3 & \text{if } L > d, \\ \frac{1}{7.787} \left( \frac{L}{116} + \frac{a}{500} \right) & \text{if } L \leq d, \end{cases} \quad (16)$$

$$Y = Y_n \begin{cases} \left( \frac{L}{116} + \frac{16}{166} \right)^3 & \text{if } L > h, \\ \frac{1}{7.787} \frac{L}{116} & \text{if } L \leq h \end{cases} \quad (17)$$

$$z = z_n \begin{cases} \left( \frac{L}{116} - \frac{b}{200} + \frac{16}{116} \right)^3 & \text{if } L > d, \\ \frac{1}{7.787} \left( \frac{L}{116} - \frac{b}{200} \right) & \text{if } L \leq d, \end{cases} \quad (18)$$

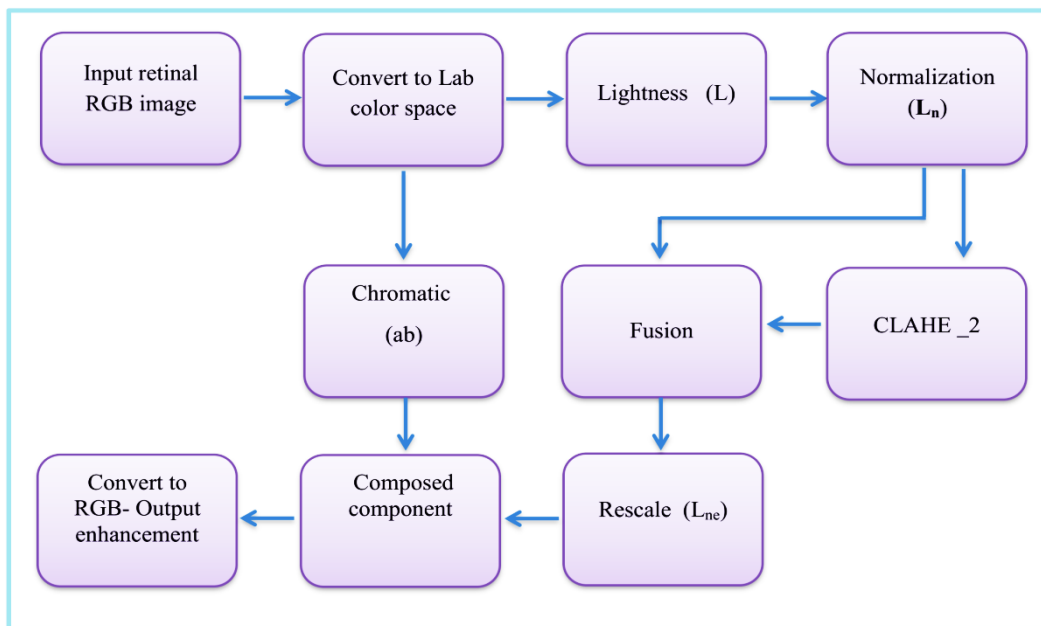


Figure. 1 A Scheme of the proposed method

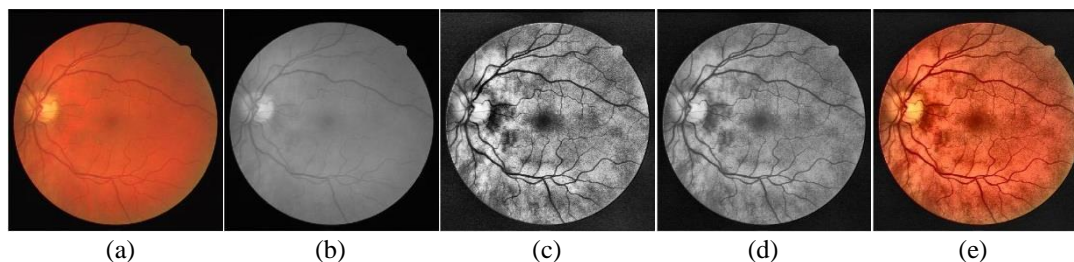


Figure. 2 The most important stages of improvement of the proposed method in: (a) original image, (b) lighting component, (c) lighting enhancement CLAHE, (d) image fusion between (b) and (c), (e) final enhancement after reverse transform

where  $d = 7.9996$ . Fig. 1 shows a detailed diagram of the proposed method, Fig. 2, shows with pictorial examples the most important stages of improvement with the technology of fusion of the original and improved lighting component.

### 3. Quality assessment

To find out the efficiency of improvement, reference and non-reference quality measures were used. It is preferable when improving the use of non-reference quality measures such as entropy, contrast enhancement measurement, and natural image quality evaluator but reference measures such as SSIM were used to determine the extent to which the original data was preserved as much as possible.

The structural similarity index (SSIM), measures the similarity between the original and processing by [19]:

$$SSIM = \frac{(2\mu_x \mu_y + a_1)(2\sigma_{xy} + a_2)}{(\mu_x^2 + \mu_y^2 + a_1)(\sigma_x^2 + \sigma_y^2 + a_2)} \quad (19)$$

The  $\mu_x, \sigma_x$ , and  $\mu_y, \sigma_y$  being the mean intensity and standard deviation set of intensity with size  $x$  (original) and image  $y$  (processed) respectively, while  $\sigma_{xy}$  denote their cross-correlation.  $a_1$  and  $a_2$  are small constants.

The entropy scale is determined by the maximum amount of information in the image that is given by [20]:

$$E = -\sum_i p(i) \log(p(i)) \quad (20)$$

where  $p(i)$  is the histogram of the lightness component.

The contrast enhancement measurement (CEM), this non-reference scale measures detail and contrast in images that is given by [21]:

$$C_{local} = \frac{max-min}{max+min} \quad (21)$$

where  $max$  and  $min$  represent respectively the maximum and minimum lightness values, within

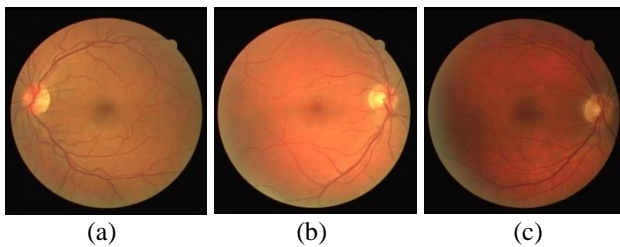


Figure. 3 The original images respectively selected from the driver retinal data: (a) label 1, (b) label 18, and (c) label 30

Table 1. Average of quality enhanced retinal images

Method	SSIM	NIQE	CEM	EN
<b>Sug.</b>	<b>0.963</b>	<b>4.680</b>	<b>0.569</b>	<b>6.985</b>
PCAURM[14]	0.951	4.791	0.482	4.792
MCHE[9]	0.925	5.166	0.508	<u>5.627</u>
LCA[13]	0.841	5.037	0.429	5.369
FLSMF[11]	0.890	5.573	<u>0.561</u>	5.475
CLAHE[8]	0.835	<u>4.717</u>	0.401	5.616
CEA[10]	<b>0.982</b>	4.908	0.402	4.835

$N \times N$ . in this research we used  $N = 50$ .

The natural image quality evaluator (NIQE), is a non-reference scale that measures the amount of color detail in an image, the lower its value, the higher the color information, this scale is mathematically based on statistical features and the multivariate gaussian model (MVG). The properties of each part of the image are calculated after it is divided into several regions with constant size. The ranges for the best patch sizes are  $32 \times 32$  to  $160 \times 160$  [1]. Thus, the digital image quality,  $d$ , is the distance between the quality consideration feature model and the MVG model using [22] :

$$d = \sqrt{((R_1 - R_2)^T \left(\frac{S1 + S2}{2}\right)^{-1} (R_1 - R_2))} \tag{22}$$

Where  $R_1$ , and  $R_2$  are the mean vectors and  $S1 + S2$  covariance matrices of the natural MVG model and the MVG of the distorted image, respectively.

#### 4. Result and discussion

In this paper, a new algorithm for enhancing retinal images was suggested. All algorithms were programmed using the Matlab (r2020a) by i7 RAM 12 GB and proses 2.7 GHz. Driver retinal data [23] was used in this study. We chose three images (a, b and c) with the label (1, 18 and 30) subjective quality,

as shown in Fig. 3. These data included 40 TIF-type images ( $565 \times 584$  size). Retinal images were enhanced using different methods, such as PCAURM, MCHE, LCA, FLSMF, CLAHE, CEA and Suggested (Sug.) algorithm. To determine the efficiency of enhancing these images, several quality measures, such as NIQE, EN, CEM and SSIM, were used. Table 1 shows the average of the quality assessment for the retinal images (including 40 images) under enhancement by a different method. We noted that the best value (NIQE, EN and CEM) was obtained with the proposed method, as for the reference scale SSIM, the highest value was obtained with CEA, followed by the proposed method, which indicated the success of the proposed method in enhancing and preserving the original data as much as possible. For the Tables (2, 3 and 4), we noticed the same behaviour of the quality standards, as reflected in the selected image. Figs. 4, 5 and 7 are illustrations (Images\_1, Images\_18 and Images\_30) that have been improved using various methods. Through visual observation, we noted the success of the proposed method in obtaining the best improvement in terms of increasing brightness and contrast, followed by the methods CLAHE and MCHE. In Fig. 7, the enlarged part of an improved image shows that with the Sug method, more colour information was obtained, and the number of details was increased. Moreover, the Sug method resulted in the highest increase in the value of illumination, followed by CLAHE. The histogram in Fig. 6 for the images\_18 showed that the best wide distribution ranges for the red, green and blue channels were for the Sug. algorithm, followed by CLAHE and MCHE. In the future, the proposed algorithm can be used and developed to improve color microscopy images captured at irregular lightness levels.

#### 5. Conclusion

This study aimed to enhance the retinal images with low contrast and irregular lighting by adopting a new algorithm. The suggested method was compared with the algorithms PCAURM, MCHE, LCA, FLSMF, CLAHE and CEA by using quality measurement using SSIM, ENTROPY, NIQE and CEM. By analysing the results, we concluded that the suggested algorithm succeeded in enhancing retinal images and led to better results compared with other methods. It had the best values for the average for SSIM (0.963), entropy (6.985), NIQE (4.680) and CEM (0.569) depending on driver retinal data.

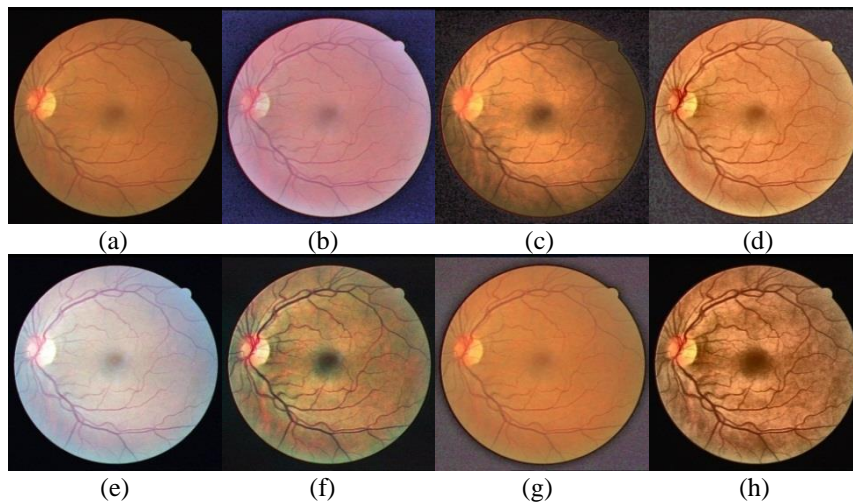


Figure. 4 Images-1 enhanced using several methods: (a) Original, (b) PCAURM, (c) MCHE, (d) LCA, (e) FLSMF, (f) CLAHE, (g) CEA, and (h) Sug

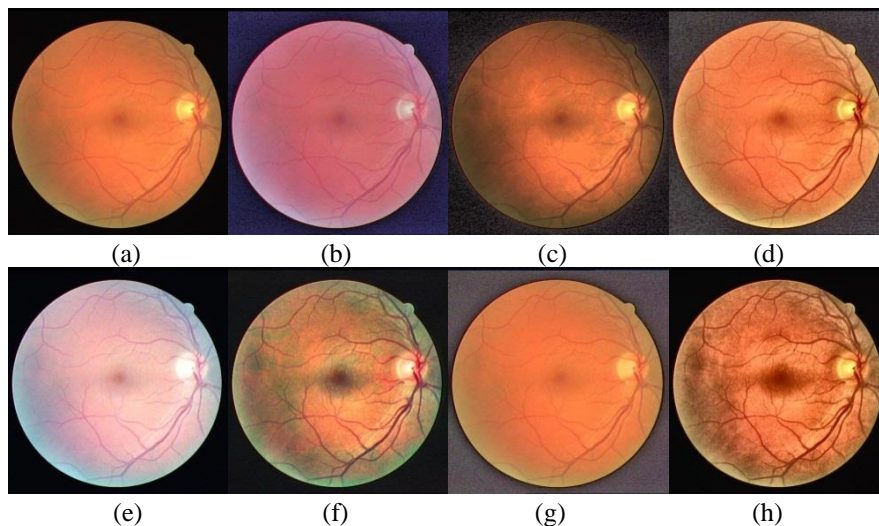


Figure. 5 Images-18 enhanced using several methods: (a) Original, (b) PCAURM, (c) MCHE, (d) LCA, (e) FLSMF, (f) CLAHE, (g) CEA, and (h) Sug

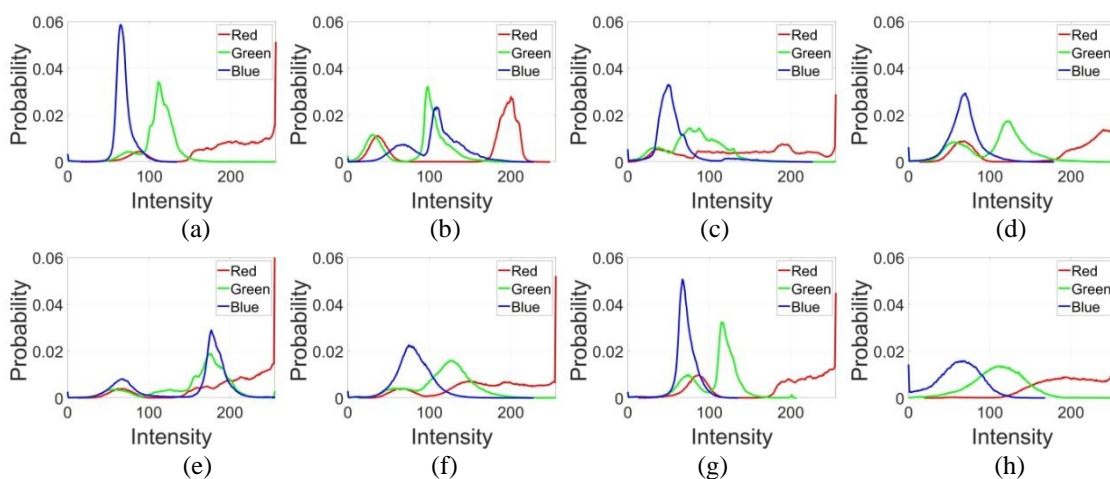


Figure. 6 The histogram of: (a) Original Images-18 enhanced using several methods, (b) PCAURM, (c) MCHE, (d) LCA, (e) FLSMF, (f) CLAHE, (g) CEA, and (h) Sug

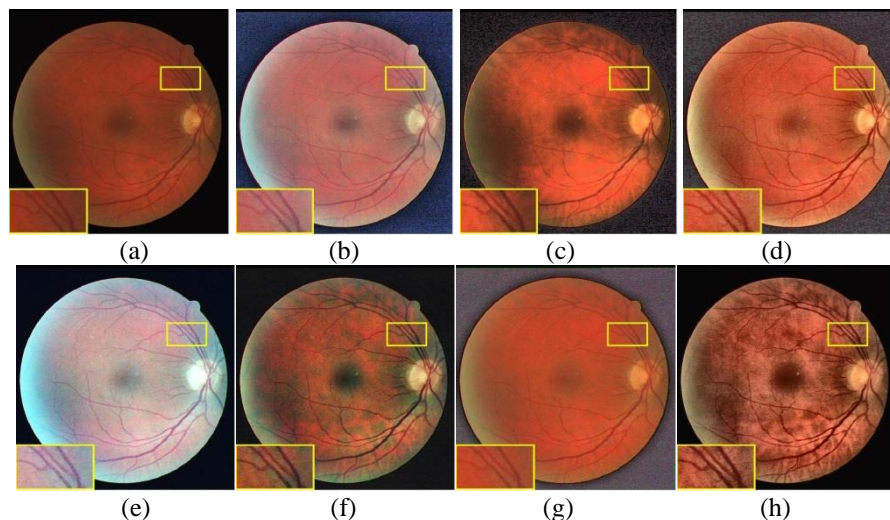


Figure 7. Images-30 enhanced using several methods: (a) Original, (b) PCAURM, (c) MCHE, (d) LCA, (e) FLSMF, (f) CLAHE, (g) CEA, and (h) Sug. (including an enlarged part)

Table 2. Quality metrics for enhanced image\_1.

Method	SSIM	NIQE	CEM	EN
<b>Sug.</b>	<u>0.953</u>	<b>4.578</b>	<b>0.606</b>	<b>7.057</b>
PCAURM[14]	0.945	4.945	0.406	4.810
MCHE[9]	0.907	5.193	0.508	<u>5.767</u>
LCA[13]	0.826	5.328	0.510	5.378
FLSMF[11]	0.903	4.894	0.427	5.362
CLAHE[8]	0.814	5.695	<u>0.581</u>	5.567
CEA[10]	<b>0.983</b>	<u>4.798</u>	0.406	4.744

Table 3. Quality metrics for enhanced image\_18

Method	SSIM	NIQE	CEM	EN
<b>Sug.</b>	0.971	<b>4.411</b>	<b>0.535</b>	<b>7.032</b>
PCAURM[14]	<u>0.974</u>	4.595	0.387	4.765
MCHE[9]	0.927	4.709	0.462	<u>5.652</u>
LCA[13]	0.868	4.863	0.482	5.364
FLSMF[11]	0.943	4.666	0.403	5.294
CLAHE[8]	0.837	5.314	<u>0.534</u>	5.632
CEA[10]	<b>0.987</b>	<u>4.453</u>	0.385	4.680

Table 4. Quality metrics for enhanced image\_30

Method	SSIM	NIQE	CEM	EN
<b>Sug.</b>	<u>0.944</u>	<b>5.325</b>	<b>0.617</b>	<b>6.903</b>
PCAURM[14]	0.849	5.752	0.438	5.136
MCHE[9]	0.906	5.608	0.502	5.465
LCA[13]	0.782	6.098	0.527	<u>5.484</u>
FLSMF[11]	0.723	6.092	0.461	5.413
CLAHE[8]	0.833	6.576	<u>0.590</u>	5.444
CEA[10]	<b>0.955</b>	<u>5.433</u>	0.417	4.632

### Conflicts of interest

The authors declare no conflict of interest.

### Author contributions

Hazim G. Daway has contributed to the design and implementation of the research by using Matlab Emtinan Mohammed Jawad and Haidar J. Mohamad have supervised the written paper and providing the necessary data. All authors approved the final version.

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