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Comparison of the Fundus Image Enhancement Techniques for diagnosis Diabetic Retinopathy

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Abstract
In order to diagnose diabetic retinopathy, this paper compares various fundus image enhancing approaches. Pre-processing is necessary for medical images since they often have noise, poor contrast, and uneven illumination. Numerous methods based on the spatial domain have been developed for image enhancement. Nevertheless, these techniques typically fail to yield appropriate results for uneven lighting and a broad range of low-contract. The selection of the best enhancement approach that may greatly increase the early diagnosis the diabetic retinopathy. This research compares the pre-processing of fundus images for diagnosis Diabetic Retinopathy using histogram equalization, adaptive histogram equalization, Contrast Limited Adaptive Histogram Equalization and exposure based sub-image histogram equalization approaches. The histogram, entropy, SNR, absolute mean brightness error and peak signal-to-noise ratio of fundus images are examined using Python in order to fairly evaluate these techniques.

Keywords: Diabetic retinopathy, Fundus image, Microaneurysms, Histogram equalization

I. Introduction

The primary cause of blindness is diabetic retinopathy (DR) [1]. According to a World Health Organization report, by the year 2030, over 347 million individuals would have diabetes. Diabetic retinopathy (DR) is a retinal abnormality that has become more common in diabetic patients in recent years. If they have had diabetes for more than 15 years, those 30 years of age or older have a 78% risk of developing DR. If a person is under 30 and has had diabetes for the same amount of time, this percentage rises to 97% [2]. Adults in working age are so impacted by DR. This report encourages DR screening at an early stage.

Stroke, diabetic neuropathy, cardiovascular disease, diabetic nephropathy, and diabetic retinopathy are among the systemic consequences associated with diabetes mellitus. Retinopathy is the term for retinal damage. DR develops as a result of chronic diabetes mellitus, which causes blood vessels to become clogged, leaky, and grow randomly. DR doesn't exhibit any visual disturbance until it reaches the advanced phase. Therefore, early eye screening for DR is crucial.

DR is divided into two stages such as proliferative diabetic retinopathy (PDR) and non-proliferative diabetic retinopathy (NPDR), respectively. Microaneurysms, hemorrhages, hard exudates, cotton-wool spots, aberrant new vasculature, venous bends, dilations, and segmentations are characteristics that are used to diagnose DR [3]. The earliest obvious indication of DR is represented by the tiny red dots on the retina, known as microaneurysms. Therefore, the first line of prevention against DR is early diagnosis of microaneurysms. The traditional methods to diagnosis diabetic retinopathy include Visual acuity tests, pupil dilation, fundus fluorescein angiography (FFA), fundus photography or ophthalmoscopy, optical coherence tomography and digital retinal screening.

It is extremely challenging to prevent and diagnose DR in early stages, especially in rural and isolated places where there is a severe lack of ophthalmologists and eye care facilities. This issue can be resolved by employing fundus pictures for automatic DR detection. With automated DR detection algorithms, a large number of diabetic patients can be screened, and those who are suspected may be referred to eye specialists for additional diagnosis. Diagnostic features are extracted from fundus images using digital image processing for automatic DR detection. Other imaging modalities such as FFA and OCT are more expensive and have additional adverse effects.

Researchers have proposed a number of techniques to use digital image processing on fundus images in order to identify DR. Every technique needs an image that has been pre-processed. Fundus image preprocessing is done to highlight the features of fundus images. Enhancement is required because fundus images suffer from noise, poor contrast, and uneven illumination. The main obstacles to detecting red lesions are the presence of white lesions in the retina (exudates) and the segmentation of microaneurysms in low contrast areas. Since microaneurysms typically have a diameter of less than 125 micrometers, it might be challenging to identify them due to their small size and background intensity change [4].

Rest of the paper has been structured as follows: Section II describes various enhancement techniques for pre-processing of acquired fundus image, section III gives performance evaluation for pre-processing technique and section IV provides overall conclusion and result of the paper.

II. Image Enhancement techniques for diagnosis the Diabetic Retinopathy

Researchers are continuously fascinated with medical image enhancement techniques. Image enhancement improves additional information in spite of the low brightness and restores the graphical quality of the medial image. These enhancing techniques fall into two categories: spatial domain and transform domain [5]. In spatial domain approaches, operations such as picture augmentation are carried out directly on the image's pixel level. The second category entails picture transformation in the frequency domain.

A. Histogram Enhancement

HE is the most popular contrast enhancement method Because it is comfortable and easy to use. To improve the overall contrast of the provided image, HE flattens density scattering and expands the gray level range. This method has made use of the transformation of the gray levels of the provided image to its enhanced image level cumulative distribution function (CDF). Because of intensity saturation and obnoxious artifacts, HE has the disadvantage of shifting the image's mean brightness to the middle of the dynamic range.

B. Adaptive histogram equalization (ADHE)

Image contrast is advanced via ADHE [6, 7]. It is a method for processing images on a computer. Because it is adaptive, it calculates multiple picture histograms and uses them to reallocate the image's intensity values. Therefore, ADHE is more suited for enhancing edge enhancement and regional contrast in each area of the image. Nonetheless, it has a strong tendency to over-amplify the noise in areas of the image that are quite homogeneous. Contrast limited adaptive histogram equalization has solved this issue.

C. Contrast Limited adaptive histogram equalization (CLAHE)

Because it restricts the contrast, CLAHE is different from regular AHE. This characteristic also applies to global HE, which is the source of CLAHE. It is mostly used to improve retinal images with low contrast. For CLAHE, each neighbourhood pixel has a transformation function that is derived using a contrast-limited method. The primary reason CLAHE was created was to stop the noise that ADHE produces from being amplified excessively.

D. Exposure based Sub-Image Histogram Equalization (ESIHE)[8]

The instruments for controlling the level of augmentation cannot be produced by any of the aforementioned methods. A novel approach based on histogram clipping [9]–[11] provides a way to regulate the pace of augmentation while maintaining brightness. These methods control the histogram's extreme value by clipping the value that exceeds the designated threshold. These strategies offer a distinctive method for figuring out the clipping threshold. The issue of contrast enhancement may be addressed by alternative methods, however low exposer enhancement is still not as well studied. ESIHE maintains both enhancement rate control and entropy, and it is best effective on low disclosure gray fundus images. Entropy expansion and over-enhancement control for under-exposed fundus images are two goals that ESIHE achieves.

III. Performance measurement of the enhancement techniques

Histogram, entropy, absolute mean brightness error, SNR, and PSNR are considered as the performance metrics for various image enhancement techniques.

A. Histogram

A histogram shows the relative frequency of occurrence of various gray levels in an image. Histograms with a wide range of gray levels and a smooth surface are essential for high-quality images.

B. Entropy

The average information content is called Entropy and used to gauge the quality of an image. An image's information richness increases with its entropy value.

$$\text{ENT} = -\sum_{l=0}^{l-1} \text{I(l)} * \log\ \text{I(l)} \quad \ldots\ldots (1)$$

C. Signal to Noise ratio

Consider r (x, y) be the original image and t (x, y) is enhanced image. The noise estimation in enhanced fundus image is analysed by Signal to noise ratio.

$$\text{SNR} = 10\ \log_{10}\left[\frac{\sum_{0}^{\eta x-1}\sum_{0}^{\eta y-1} r[(x,y)]^2}{\frac{1}{\eta x \eta y}\sum_{0}^{\eta x-1}\sum_{0}^{\eta y-1} r[(x,y)-t(x,y)]^2}\right] \quad \ldots\ldots (2)$$

D. Absolute mean brightness error (AMBE)

How much brightness is maintained in the enhanced fundus image is the goal of the AMBE calculation. It is the overall difference between the mean of the improved fundus image and the original gray fundus image.

$$\text{AMBE} = [E(X)-E(Y)] \quad \ldots\ldots (3)$$

Here, X is input image and Y enhanced image and E(.) represent mean.

The fundus image's enhanced intensity conservation is specified by AMBE. Excessive brightness change is the distortion that it mostly detects.

E. Peak signal-to-noise ratio (PSNR)

For PSNR calculation first mean square error (MSE) is calculated as-

$$\text{MSE} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[X(i,j)-Y(i,j)]^2}{M \times N} \quad \ldots\ldots (4)$$

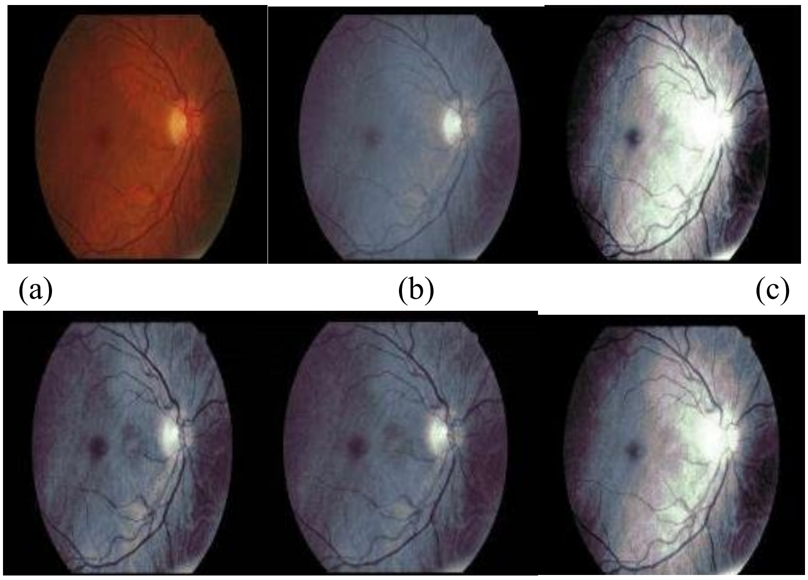
The root mean square error (RMSE) is calculated from root of MSE then PSNR as-

$$\text{SNR} = 20 \times \log_{10}\left[\frac{\max(Y(i,j))}{\text{RMSE}}\right] \quad \text{……………………………………………………………..…… (5)}$$

Here, X (i, j) is input image having M by N pixels, Y (i, j) is enhanced image. Greater the PSNR better will be contrast of enhanced image

It is conceivable to examine the visual quality from figure 1. The HE produces a brighter image, while the ADHE and CLAHE procedures improve images with intermediate brightness. However, the HE technique sharpens the image's low intensity content. It has been noted that ESIHE has superior visual quality and motion exposure compared to others.

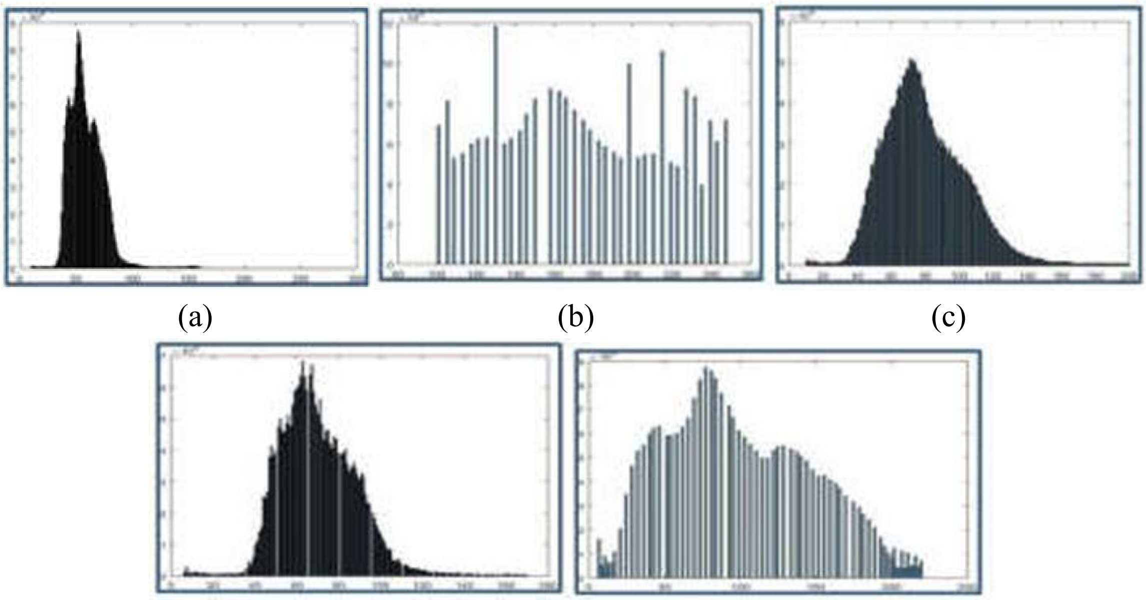
Figure: 1 Enhanced fundus image: (a) color (b) gray (c) HE (d) ADHE (e) CLAHE (f) ESIHE



(a) (b) (c)

(d) (e) (f)

Figure: 2 Histogram of enhanced fundus images (a) gray (b) HE (c) ADHE (d) CLAHE (e) ESIHE



(a) (b) (c)

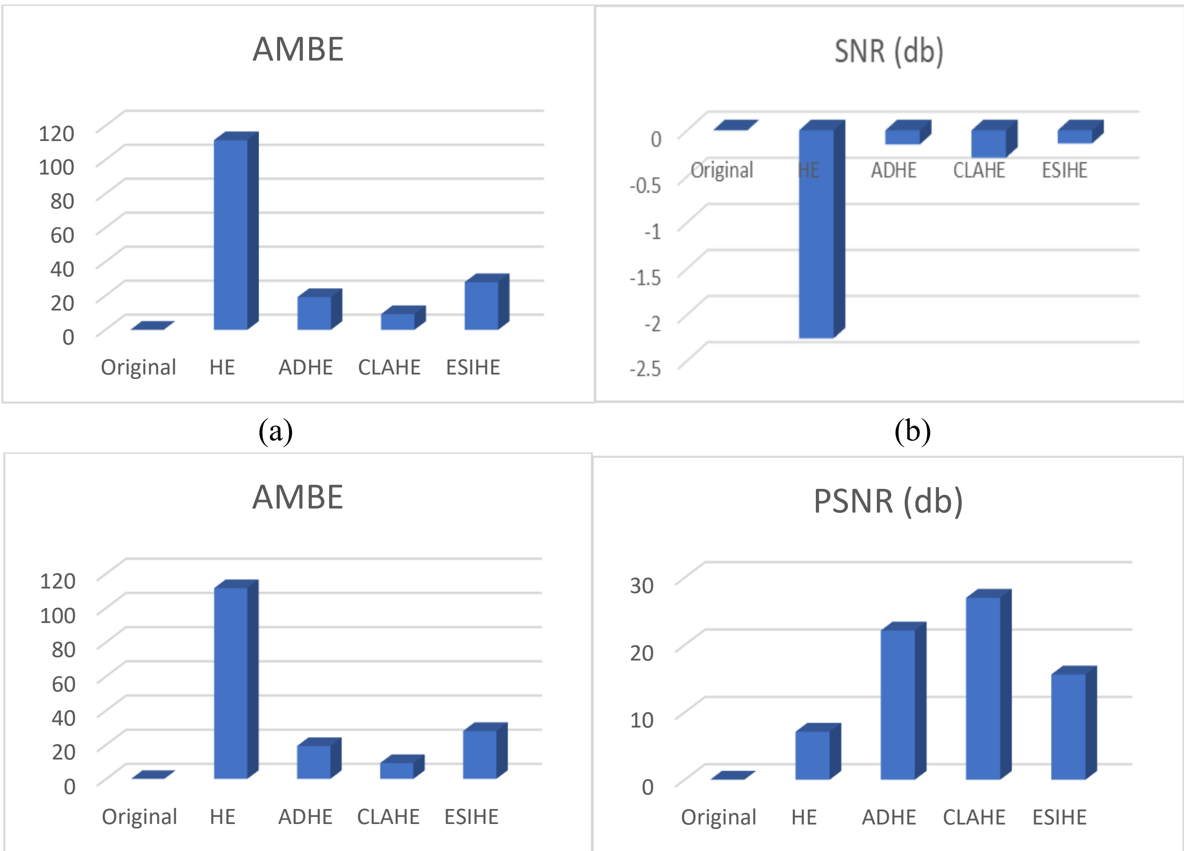
(e) (f)

The histogram of the original fundus image and its improved variants, which were produced by using different enhancement approaches, are displayed in Fig. 2. A high-quality photograph must have a flat histogram with a broad range of gray levels. Compared to previous methods, the ESIHE histogram is flatter and has a wider variety of gray levels. Despite having a virtually flat histogram, HE lacks a wide gray level range, which makes its dark areas brighter. Conversely, ADHE and CLAHE do not have a large range or a flatter histogram. ESIHE has a superior histogram than the others, as can be seen.

Table 1 Performance evaluation of various enhancement techniques

Fundus Image	Entropy	SNR (db)	AMBE	PSNR (db)
Original	4.5769	0	0	0
HE	4.1524	-2.2571	111.5712	7.1247
ADHE	4.9543	-0.1532	15.2543	22.1470
CLAHE	4.8659	-0.2965	9.2586	27.0046
ESIHE	4.7125	-0.1420	28.0215	15.6231

Figure: 3 Comparison of (a) entropy, (b) SNR, (c) AMBE and (d) PSNR for various enhancement techniques



(a) (b)

(c) (d)

An analytical view of entropy is provided in Figure 3 (a). According to entropy analysis, the original image has a specific average information (4.5 in this instance). Using HE causes the entropy to drop (to 4), indicating some information loss. This will result in DR being falsely detected. Conversely, ADHE and CLAHE appear to have higher entropy than the original image, indicating that the noise components are being amplified by these methods. The entropy of the ESIHE is almost identical to that of the original. Therefore, without adding (increasing) noise, the ESIHE approach improves the quality of fundus images. The original image in Figure 3(b) is considered as a signal, whereas the equivalent augmented fundus images are regarded as noise. SNR is close to 0 dB in the improved result, indicating unamplified noise. The fact that ESIHE's SNR is so near to 0 dB indicates that the original and enhanced have the same average power. Figure 3(c) demonstrates that the CLAHE technique has the lowest AMBE value and that it keeps more brightness than other methods. As illustrated graphically in fig. 1(C), the HE has the highest AMBE value. Aside from them, ADHE has a notably low AMBE and maintains brightness to a certain degree. ESIHE's AMBE value is modest. Among the others, CLAHE has the highest PSNR in Fig. 3(d). As a result, CLAHE is superior to other contrast enhancers. While HE has a low value, ADHE and ESIHE both have greater PSNR. An image with a higher PSNR has better contrast, whereas one with a lower PSNR has worse contrast.

IV. Result and conclusion

In order to improve fundus images for the purpose of identifying diabetic retinopathy, this study compared many preprocessing methods. It was discovered that ESIHE and CLAHE outperformed the other histogram equalization strategies for preprocessing fundus images. With ESIHE, the significant issue of noise overamplification was eliminated. The fundus image quality was improved by using the CLAHE preprocessing approach. ESIHE was shown to have moderate AMBE and PSNR but superior entropy and SNR. Therefore, using the ESIHE technique in DR preprocessing will undoubtedly aid in lowering the number of false disease detections. For additional histogram technique analysis, the recursion of the ESIHE technique must be examined. Recursive exposure based sub-image histograms (R-ESIHE) and reclusively separated exposure based sub-image histograms (RS-ESIHE) are becoming more and more popular among academics for low exposure photos.

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