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Comparison of Image Enhancement Methods for Diabetic Retinopathy Screening

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Abstract

The most common factor contributing to visual abnormalities that result in blindness is known as diabetic retinopathy (DR). Retinal fundus scanning, a non-invasive method that is integral to the picture pre-processing phase, can be used to identify and monitor DR. Low intensity, irregular lighting, and inhomogeneous color are some of the main issues with DR fundus photographs. Analysis of aberrant characteristics on retinal fundus pictures to identify diabetic retinopathy is one of the key responsibilities of image enhancement. However, a variety of approaches have been created, and it is unknown whether one is best suited for use with retinal fundus images. This study investigated various image enhancement methods in order to see aberrant abnormalities on retinal fundus pictures more clearly. This study investigated various image enhancement methods in order to see aberrant abnormalities on retinal fundus pictures more clearly. Contrast Limited Adaptive Histogram Equalization (CLAHE) method, Gray Level Slicing method, Median Filtering method, and Low Light method are image improvement methods used to enhance retinal fundus images. The parameters Natural Image Quality Evaluator (NIQE), Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and entropy will be used to assess each image enhancement technique's performance. An ophthalmologist from Hospital University Sains Malaysia (HUSM) provided the image data. The findings indicate that while each technique has its own benefits, the CLAHE technique, with a standard deviation MSE of 0.0004, is the best.

Keywords: *image enhancement; diaebetic retinopathy; image processing; fundus image.*

1. Introduction

Image enhancement is a digital image processing technique designed to enhance human understanding of the details and data in visual images [1]–[3]. The quality of digital images will be high enough to provide a more precise description of the details found in them [4], [5]. Through image analysis, valuable information can be generated by optimizing image functionalities such as increasing brightness and sharpening images [6], [7]. Various forms of analysis can be performed using this method.

Currently retinal fundus images are the most precise and easy way to track complex eye disorders [8]. With the advancement of compact fundus cameras and computer-assisted diagnostics (CAD), state-of-the-art devices used in the therapeutic treatment of eye conditions have been used for the early identification of eye disorders [9]. Fundus image transparency is a prerequisite for proper treatment by smart devices. Retinal images obtained through the fundus camera are often contrastingly low resolution due to retinal disease and imaging setup [10], [11].

The primary factor recognized as causing eye blindness in working-age adults is diabetic retinopathy (DR) [12]. There are two phases of DR: non-proliferative (NPDR) and proliferative (PDR). Retinal fundus scanning is a non-invasive method for detecting or monitoring DR [13]. Currently, there are many automated techniques for identifying retinal retinal irregularities [14], most of them including segmentation of the retinal vessels [15].

Fundus pictures are employed in digital image analysis to extract diagnostic functionality for automatic DR identification [16]. The photos, however, could be challenging to interpret with the naked eye due to the

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fundus flash of the camera. It is a challenging task for image pre-processing to accurately segment fundus images for early detection analysis, and this task has important clinical value. It is crucial to keep in mind that the field of image processing known as enhancement is quite subjective.

Diabetes is a common cause of impaired visual function, and DR is the leading cause of adult blindness. [17]. This occurs when high blood glucose levels injure the blood vessels in the eyes. Such blood vessels might expand, leak, or even close, which would cease the blood flow. New, abnormal blood vessels frequently develop in the retina. Due to a lack of infrastructure and treatments, most DR victims are located in developed countries [18]. Patients are 25% more likely to develop DR. The retina of the eye has characteristics that are utilized to identify DR, including blood vessels, exudate, hemorrhage, microaneurysm, and texture. Image processing is required to provide greater understanding because these aspects are challenging to separate and spot faults in [19].

Early symptoms must be identified as the disease progresses over time in order to provide fast and efficient treatment [20]–[23]. Clinicians may err while manually segmenting retinal images because it is difficult [24], [25]. Early detection of diabetic eye illness, prompt treatment, and sufficient follow-up care can prevent vision loss [26]. However, because a grainy image contains some noise, it is not advisable to utilize one if you wish to automatically detect any information from the retina image. For the image to be acceptable for further processing, each photo processing technique requires the completion of a few fundamental procedures. The goal is to create the ideal raw image input for real-time processing [27]. Therefore, prior to any treatment, pictures must be pre-processed [28].

Digital images are represented using different color models. The initial stage in preprocessing might be considered the selection of an appropriate model [27]. In general, the goal of image restoration in image analysis is to relieve human observers of this mission by reconstructing a realistic approximation of the original image from obscuring or noisy observations [28], [29]. Many methods have been suggested to minimize object distortion using strategies such as brightness enhancement, low light images, gray level cropping, CLAHE, sharpness enhancement and filtering techniques [30]–[33], according to fundus image abnormalities . It is therefore important to measure the efficiency of these six image processing techniques (brightness enhancement, low light images, gray level cropping, CLAHE, sharpness enhancement and filtering techniques) to increase the value of graphic rendering and enhance retinal image clarity and sharpness to facilitate future studies [34], [35].

From an extensive literature review, emerging problems were identified in the compatibility of the techniques used in improving low quality fundus images in Computer Assisted Diagnostic Systems [36]. for examination DR. At present, many researchers focus on improving one image enhancement technique and there are several techniques that have been implemented in the system but most of them usually focus on one particular technique in a system. In general, there is actually no universal unifying principle of image enhancement, because there are no basic requirements for image quality that can act as development requirements for such image enhancement tools [37].

2. Research Methods

The main approach of this research is the experimental approach. The experimental approach is the most scientifically sophisticated research method. The purpose of this method is to maintain control over all factors that may affect the results of this study. Design starts with awareness of the issue; Existing knowledge will be used to provide suggestions to find the desired solution. This stage is followed by constructing experiments that represent all elements, conditions, and relationships to consequences. This experimental stage includes determining the abnormal features of the fundus image, determining the appropriate enhancement technique, and conducting experiments. Finally, the evaluation and validation of the results will be tested with appropriate performance metrics to test their significance. The steps or framework of this research include: (i) Preliminary Investigation, (ii) Data Collection and Identification of Abnormal Features, (iii) Experiments and (iv) Evaluation and assessment, as shown in Figure 1.

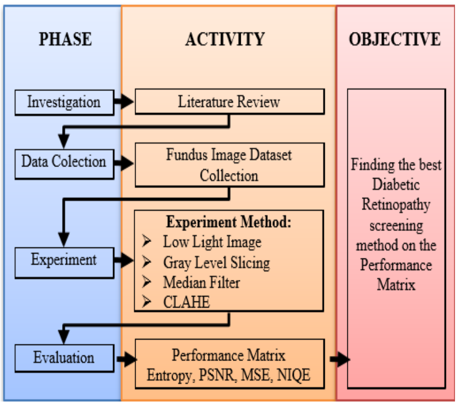

Figure 1. Research Stage

The aim of the Investigation phase is to critically analyze existing research to identify issues that require further research and investigation, which can support existing research studies. This analysis is based on a variety of sources, including previous research published in reputable journals, conference articles, and books.

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However, the compatibility and suitability of this technique is important to ensure that the image provides more accurate data for the system to capture DR detection information. The performance of the technique affects the yield of enhanced fundus images and directly affects the accuracy of identifying abnormal features for DR screening. Therefore, to determine the performance of the image enhancement technique, it leads to the next section which describes the experimental design of the technique to achieve the targeted objective.

Data collection phase for this experiment will be done at this time. information obtained from the ophthalmology division of the HUSM in Kelantan. A total of 80 fundus pictures were included in the collection, 55 of which represented non-proliferative diabetic retinopathy (NPDR) and 25 of which represented proliferative diabetic retinopathy (PDR).

The patients' left and right eyes were used to acquire images. 50 photos were chosen to represent the test set in a subsequent division of the dataset. The captured photos were in the JPEG format and had a resolution of 3008 x 2000 pixels. Ophthalmologists or technicians at HUSM used a fundus camera to record these fundus photographs. The main source of data for this study will be these photographs. After the data was gathered, aberrant features for DR screening using fundus pictures, such as cotton wool, exudate, and hemorrhage, were discovered. The confirmation of expertise features led to the selection of raw fundus photos for this study. The chosen algorithm for the picture enhancement technique is used to test the effectiveness of the method. Formula 1 is used to convert the RGB color channel into grayscale image.

$$y = rgb2gray(x); \tag{1}$$

x is the the original image and y is the grayscale conversion.

The procedure of image enhancement is carried out in this Phase Experiment stage. Due of the system's ability to save time and money compared to current manual processes and treatments, it will be able to assist ophthalmologists in more quickly and accurately identifying DR illness from fundus images.

The experiment performs the picture enhancement process on the MAtrix LABoratory Tools (MATLAB) platform. The RGB (red, green, and blue) components of the color fundus images were separated before each experiment. According to histogram analysis, this RGB image decomposition aids in the individual and distinct filtering of each noise image component. Like other histograms, image histograms display frequencies. After that, the frequency is adjusted in accordance with the reference image using the histogram matching approach. In order to simplify blood vessel segmentation and speed up processing, the color fundus image is transformed to a grayscale image after histogram matching. After subtracting hue and saturation, a grayscale image offers the brightness information of a color image.

On the basis of the acquired gray scale image, a comparison of refining approaches is done. This experiment's major goal is to compare and contrast the image improvement methods that are frequently employed in this field, including low light picture methods, gray level slicing methods, median filtering methods, and CLAHE methods..

The image is transformed to a grayscale image before being subjected to image pre-processing. The process of image enhancement is used to make visual images look better or to change them into easily-analyzed forms. Six fundamental strategies for improving images were chosen, including CLAHE method, Median Filtering method, Low Light Image method, and Gray Level Slicing method.

The performance of each augmented image will be assessed using MSE, PSNR, NIQE, and entropy. The image is converted to an RGB image for user viewing only following performance evaluation.

In the Evaluation phase, the output parameters used in this study are the peak Entropy, signal-to-noise ratio (PSNR), Natural Image Quality Evaluator (NIQE), and mean square error (MSE).

The design phrase for the ratio between the maximum conceivable control of the flag and the control of noise that affects the consistency of its representation is peak signal-to-noise ratio, which is frequently abbreviated by the PSNR. Given its extensive energy range and large number of signals, PSNR is expressed using a logarithmic decibel scale. The mean square error (MSE) is the best indicator of PSNR.

In mathematics, the mean square error (MSE) in Formula 2 or mean square deviation (MSD) of an estimator determines the blunder squares normal, or the difference in squares between the predicted values and the actual values.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - y_i)^2 \tag{2}$$

$\hat{y}_i$ is the the model's expectation and y_i is the actual liable output.

The foundation of Natural Image Quality Evaluator (NIQE) is the selection and fitting of Gaussian multi variates (MVG) features for natural scene statistics (NSS) characteristics. The difference between a reference image's MVG pattern and the typical pattern, which is derived by removing non-overlapping areas from clear photographs, serves as a measure of the consistency of the image. The difference between the content-aware NSS function model and the MVG that

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accommodates the distorted picture features is used to represent the image quality as seen in Formula 3.

$$D(v_1, v_2, \Sigma_1, \Sigma_2) = \left(\sqrt{(v_1 - v_2)^T \left(\frac{\Sigma_1 + \Sigma_2}{2}\right)^{-1} (v_1 - v_2)} \right) \quad (3)$$

The mean vectors and covariance matrices for the natural MVG model and the MVG model of the deformed picture, respectively, are v1, v2, and Σ1, Σ2.

For estimating picture consistency, the mean value of knowledge, denoted as entropy, is utilized as seen in Formula 4. The knowledge quality of the image increases with increasing entropy value.

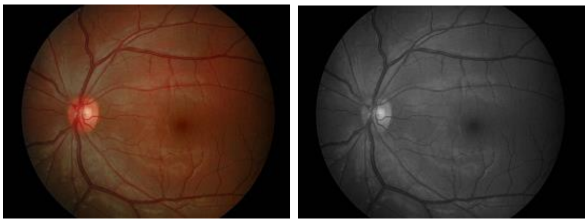
$$ENT = -\sum_{i=0}^{L=1} I\,(l) \log I(l) \quad (4)$$

ENT (i) is the entropy and I (l) is the probability density function of an image with l levels of intensity and L levels of gray.

3. Results and Discussions

Red, green, and blue make up the three layers that make up the fundus image. The image is made grayscale to help with image processing chores like contrast improvement, contrast feature size adjustment, and noise reduction. By reducing the image to a two-dimensional format, this makes it simpler to edit the image to meet the demands of the application for which it is designed [38]. To improve the quality of retinal pictures, a specific pre-processing technique was used.

The following are the experimental findings for normal and pathological fundus images both before and after the enhancing procedure. Figure 2(b) contrasts the raw image of the normal fundus in figure 2(a) with the grayscale image of the normal fundus before enhancement.



(a). raw picture (b). Greyscale picture
Figure 2. Normal fundus image

The outcomes of using image enhancing techniques on standard fundus photos are shown in the accompanying grayscale pictures in Figure 3 until 6.

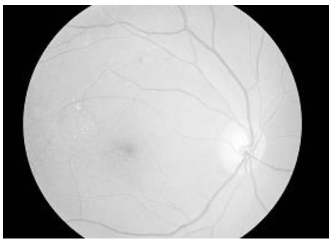


Figure 3. Low light image

Figure 4. Gray level slicing

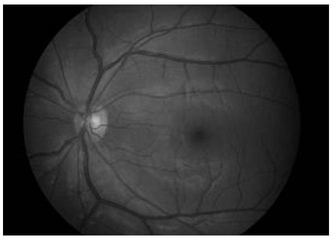
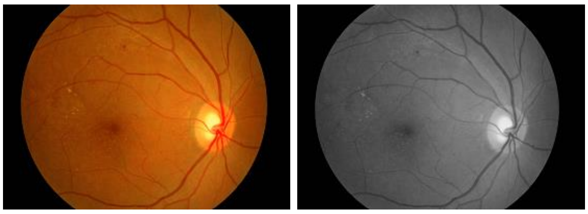


Figure 5. Median filtering

Figure 6. CLAHE

Figure 7(b) shows the grayscale version of the abnormal fundus image before enhancement, while Figure 7(a) shows the raw image for an abnormal fundus image. The results of using image enhancing techniques led to the grayscale images for aberrant fundi that are displayed Figure 7.



(a). raw picture (b). Greyscale picture
Figure 7. Abnormal fundus image

The improved fundus images in Figure 8 were created using low light images. Gray level slicing was used to enhance the fundus image in Figure 9. The enlarged fundus image with median filtering is shown in Figure 10. Figure 11 depicts the improved aberrant fundus image created by the CLAHE approach

Table 1 displays the outcomes of each technique's performance evaluation. These results were generated by averaging the mean and standard deviation of each performance indicator across 50 test photos. The average discrepancy between data values and the mean is measured by the standard deviation. While a bigger standard deviation shows that the data points are more

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dispersed across a wider range of values, a smaller standard deviation says that the data points are relatively close to the mean. The standard deviation would be nearer 0 if all data values were the same. Consequently, examining the standard deviation enables a more accurate evaluation of the data values.

Table 1. Performance assessment of various enhancing methods

Enhancement Techniques		Low Light Image	Gray Level Slicing	Median Filtering	CLAHE
MSE	Mean	4,857638889	3,911111111	4,858333333	5,09375
	Standard Deviation	0,084027778	0,30625	0,084027778	**0.0004**
PSNR	Mean	496.836	506.378	496.832	494.766
	Standard Deviation	0,553472222	2,444444444	**6,802777778**	0.0023
NIQE	Mean	107.515	84.911	54.899	99.455
	Standard Deviation	4,997222222	12.111	**2,247222222**	5,217361111
Entropy	Mean	50.904	39.575	51.368	57.857
	Standard Deviation	1,488194444	**5,229166667**	1,429861111	0,965972222

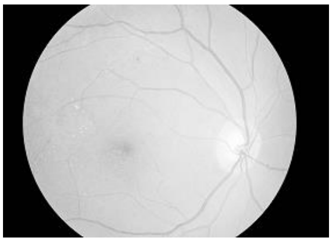

Figure 8. Low light image

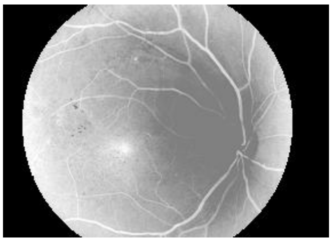

Figure 9. Gray level slicing

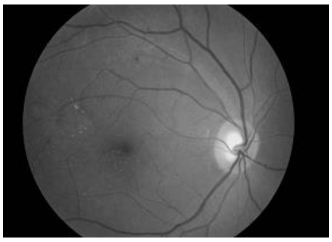

Figure 10. Median filtering

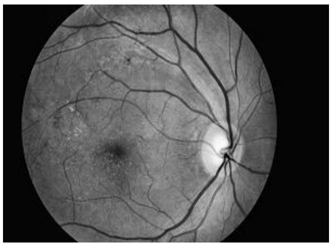

Figure 11. CLAHE

All approaches have MSE values between 0 and 1, which means that the produced images have extremely little noise. While the MSE values of the other procedures are somewhat lower than the greatest value, Table 1 demonstrates that the CLAHE methodology presents the lowest MSE value, closer to zero, indicating that it successfully lowers picture noise compared to the other ways. A greater PSNR number, on the other hand, denotes a well-contrasted image, whereas a lower PSNR value denotes a poor contrast-enhanced image [39]. The Median Filtering technique has the greatest PSNR value of all the techniques, which shows that it generates images with good contrast in comparison to the other techniques. The human eye's sensitivity to high-contrast regions in images served as the foundation for the NIQE metric's development. A lower NIQE score denotes a perceptual result of higher quality [40]. According to human visual perception, the median filtering technique offers better contrast enhancement because it has the lowest NIQE score. More information is preserved when the entropy value is greater. The Gray Level Slicing technique in this instance has the highest entropy value of the other strategies, demonstrating its superiority in maintaining picture information. This study leads us to the conclusion that the standard deviation numbers are nearly comparable and very low. As a result, it is clear from observation that the CLAHE technique performs better than the other image enhancement strategies examined in this study.

4. Conclusion

In order to improve fundus images for the initial screening of diabetic retinopathy, this article compares various image processing methods. CLAHE is discovered to provide important advantages over the other enhancement techniques for fundus imaging. With the help of a process that restricts contrast amplification and applies it to each nearby pixel, the CLAHE technique creates a transformation mechanism that significantly minimizes noise problems. Observation reveals that all methods are capable of enhancing visual contrast to the same degree. The median filtering technique has the lowest performance value for the naturalness image quality evaluator

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(NIQE) at 0.3236 and the greatest peak signal-to-noise ratio (PSNR) value of 0.9796. Additionally, the Gray Level Slicing method has the maximum entropy value of 0.7530, guaranteeing the preservation of images with significant information richness. On the other hand, the CLAHE method shows a better mean squared error (MSE) standard deviation value of 0.0004, suggesting its effective noise reduction capability and higher image enhancement.. Careful analysis and observation show that the CLAHE technique is more likely to reduce disease detection errors by removing noise and improving contrast in enhancing fundus images for diabetic retinopathy, even though the PSNR standard deviation values suggest better image quality for the Median Filtering technique. There is still a considerable gap between research results and clinical application, necessitating additional analysis using a broader database of fundus photos from various hospitals.

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