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THE CUCKOO OPTIMIZATION ALGORITHM ENHANCED VISUALIZATION OF MORPHOLOGICAL FEATURES OF DIABETIC RETINOPATHY

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ABSTRACT
This research compares strategies for identifying diabetic retinopathy (DR) using fundus image and discusses the efficiency of various image pre-processing techniques to enhance the quality of fundus images. Fundus images in medical image processing often suffer from non-uniform lighting, low contrast, and noise issues, which necessitate image pre-processing to enhance their quality. The study evaluates the effectiveness of several optimization techniques in selecting the best technique for identifying DR. One of the image pre-processing techniques compared in the study involves comparing negative images, dark contrast stretch, light contrast stretch, and partial contrast stretch, which are then evaluated using standard performance metrics such as NIQE, PNSR, MSE, and entropy. The results are further optimized using the Cuckoo Search Algorithm. The proposed technique produces better image quality improvements in several performance metrics, such as MSE, NIQE, PSNR, and entropy. Bright Contrast Stretch outperforms other techniques in NIQE Mean 5.2850, Entropy 5.0193, NIQE Standard deviation 0.2261, and Entropy 0.2612.
Keywords : *Diabetic Retinopathy, Fundus Image, Cuckoo Algorithm, Image Enhancement.*

1. Introduction

To perform fundus imaging, a blinking sensor mounted on a microscope is used. The fundus consists of the retina, optic disc, macula, and fovea, which are located in a position opposite to the lens of the eye (Pundikal & Holi, 2022). Retinal fundus images can provide essential information for diagnosing various diseases, including diabetic retinopathy, stroke, macular degeneration, bleeding, and arterial occlusion. As such, they can serve as significant predictors in diagnosing these conditions. (Salazar-Gonzalez et al., 2014). Elevated blood sugar levels can increase the presence of reactive oxygen species in the blood, which can impact the vascular structures in the retina and lead to the formation of retinal lesions (Deng et al., 2022). The appearance of lesions in the retina is typically the initial symptom of diabetic retinopathy. Figure 1 illustrates the fundamental block diagram for the retinal imaging process.

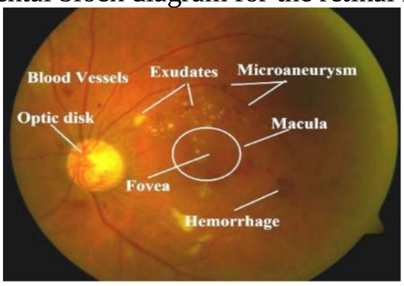

Fig. 1. Main areas of the retina

Diabetic retinopathy is a condition that can cause vision loss (Soares et al., 2023). Therefore, detecting this condition at an early stage can help prevent more severe vision loss (Bhimavarapu & Battineni, 2022). Within the eye, blood vessels play a role in supplying blood and oxygen to the eye. If the flow of oxygen to the eye is unstable, this can cause other health problems, such as hypertension and cardiovascular problems (Kusuma Whardana & Suciati, 2014; Toresa et al., 2021). Red lesions and cottony patches are the most characteristic symptoms of diabetic retinopathy. Red lesions may occur in the form of micro aneurysms and exudates, whereas cotton patches are examples of mild lesions of the retina (Astorga et al., 2022). The appearance of red lesions on retinal fundus images may be an early indication of retinopathy in diabetics, with micro aneurysms seen as red dots (Pendekal & Gupta, 2022). Mild retinal lesions, on the other hand, can escalate when blood loss results from retinal obstructions (Maheswari & Punnolil, 2014).

Retinal hemorrhage is a form of damage to the retina that can be seen as a dark area on an image of the retina. Bleeding on the retina can be of various sizes and appear as a dark or reddish color (Bhateja et al., 2021). Types of bleeding in the retina can be grouped into point hemorrhages and spotting hemorrhages. Point bleeding is made up of scattered tiny red dots, while spotting tends to be more frequent (Yadav et al., 2021). Tumors in the fan-shaped head of the optic nerve are not associated with retinal hemorrhages (Swathi et al., 2017).

Diabetic retinopathy is divided into two stages, namely Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Retinopathy. In the NPDR stage, the main symptoms are the appearance of microaneurysms and exudates. A small, circular, dark microaneurysm occurs in a red spot with a border that extends toward the macula (Gayathri et al., 2014). Changes in retinal blood vessel morphology such as width, branching angle, and volume are the main indicators of DR (Tavakoli et al., 2021). In the advanced stages of proliferative DR, development of new dysfunctional vessels throughout the retina occurs, which is associated with the NPDR stage (Mayya et al., 2021). New blood vessels can spread through the retina and cause complete vision loss (Kaur & Singh, 2016). Vascular monitoring systems can be used to identify blood vessels located on the retina of the eye(Bennet et al., 2016).

Pre-processing is an important stage in the production of medical images to remove image noise and improve certain characteristics (Subramanian et al., 2022). Noise, poor quality, inappropriate lighting, and dim issues are some of the problems that often occur with fundus images (Mazlan et al., 2018; Sengupta et al., 2020). Identifying characteristics of DR on fundal features, such as microaneurysms (MA), cottony patches, exudates, and hemorrhages, is made difficult by this question. (Rosas-Romero et al., 2015) .

In this study, images will be enhanced using negative image techniques, bright contrast stretching, dark contrast stretching, and partial contrast stretching, and optimized with Cuckoo search optimization. The purpose of this optimization is to improve the performance of the image enhancement function and enable the function to work optimally or within the limits set by the user to produce the desired results. In Munteanu and Rosa's research (2000), Genetic algorithms have been used to solve most of the problems of human judgment and have demonstrated increased capability of additional image-altering functions. This research is instrumental in introducing a metaheuristic algorithm to assist in boost operations. (Munteanu & Rosa, 2000) .

Being one of the newest and most efficient optimization techniques developed, Cuckoo Optimization produces a much better solution than genetic algorithms and particle swarm optimization. The main feature of Cuckoo search optimization is to achieve the best segmentation results by finding the optimal threshold value. This algorithm can also provide fast solutions for non-linear problems, by following the well-known Levy Flight optimization concept in metaheuristic algorithms. This study aims to compare image results before and after optimization using PSNR, MSE, Entropy, and NIQE as evaluation measures. Introduction contains brief and concise research backgrounds, and objectives.

2. Literature Review

Gupta compared the adaptive automatic histogram equalization (ADHE) technique, sub-image histogram equalization based on exposure (ESIHE), and adaptive histogram equalization technique with contrast constraints (CLAHE) in fundus image pre-processing to detect DR. Datta and colleagues devised the CLAHE algorithm as a tool for detecting retinal shifts in DR images (Datta et al., 2013) . This research resulted in an average accuracy of 82.64 percent and an accuracy of 99.98 percent. In addition, researchers also tried a noise reduction strategy by using a median filter and a wiener filter to improve image quality (Jadhav & Patil, 2018) . This research uses PSNR, RMSE, and correlation coefficient to measure efficiency. The findings show that typical filters are superior to other methods in removing noise. Color image enhancements depend on local processing, including contrast enhancement using techniques such as Bottom Cap, Transform, Contrast Enhancement with Histograms, Equalization, Noise Reduction using Adaptive Wiener Filters, Median Filters, and CLAHE. This research found that an effective approach combines several techniques to produce better results (Ramasubramanian & Selvaperumal, 2016) . It is recommended to enhance the color of the image using local processing tools. The experimental results show that the photos repaired with the recommended algorithm are cleaner and look more natural compared to other techniques to improve images.

Sun et al., (2022) in his research to improve the quality of health images using the ABC Optimization algorithm due to generally poor health image quality and loss of detailed information in the process of low light image enhancement, low light image enhancement, experimental results verified the rationality of the algorithm in their paper, and which achieved results which is better both subjectively and objectively, but still needs to be improved for better image quality improvement results and tested using other optimization algorithms such as PSO, Cuckoo algorithm and genetic algorithm. To increase the convergence rate of the Cuckoo Search Algorithm to get more accurate and efficient results and prove to be a solution to increase efficiency, and still has a lot of room for improvement, which should be focused (Shiralkar et al., 2022).

Most medical images are digital images or converted into digital formats. The digital field offers many advantages in handling images, but there are many challenges to digital medical images during the optimization process, such as image quality control, image clarity, noise and other challenges. There are several recommended optimization algorithms including cuckoo optimization and genetic optimization (Acharya & Kumar, 2021; Alyoubi et al., 2020; Chen, 2022). Image enhancement has a broad application domain, such as medical images and satellite images, a contrast-based image enhancement approach using the Cuckoo algorithm for improving the quality of satellite images and medical images that have low contrast, in addition to removing image noise refers to a process in which images can be reconstructed by eliminating unwanted noise. This process is very useful for medical imaging applications to separate the original image from the noise. A hybrid filter is proposed through the Cuckoo algorithm, where the Cuckoo algorithm is designated as the most appropriate and effective optimization algorithm (Zhang et al., 2019)

Chen, (2022) In his research, used the cuckoo algorithm to optimize the firefly algorithm. Through a simulation experiment of six standard function tests, compared with the results of the existing heuristic test algorithms, an optimal solution with higher accuracy was obtained. In terms of application, the CSFA algorithm is used in pressure vessel design, which also reflects better optimization performance.

3. Research Methods

This study tested a raw retinal fundus image dataset provided by Ophthalmology, Hospital Universiti Sains Malaysia (HUSM), Kubang Kerian, Kelantan. This dataset consists of 90 fundus images with a resolution of 3008 x 2000 and the Joint Photographic Experts Group (*.jpg) format. In this experiment, 50 images were selected, among which were 10 normal fundus images, 20 fundus images with NPDR, and 20 fundus images with PDR. The images were taken by an ophthalmologist technologist from HUSM using a fundus camera. One example of a raw retinal fundus image used in the study is shown in Figure 2

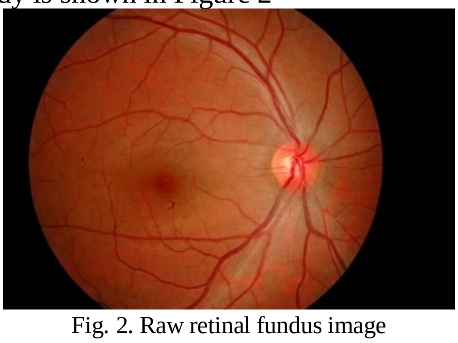

Fig. 2. Raw retinal fundus image

The methodology proposed in this study consists of two stages of processing. The first stage involves increasing the contrast of the fundus image. The second stage involves optimizing the fundus image. Figure 3 shows the overall stage flow.

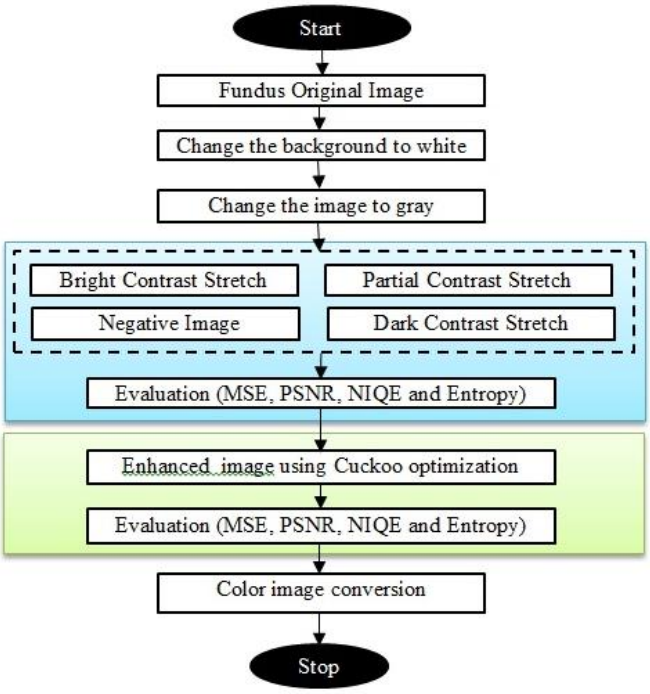

Fig. 3. Image Enhancement and Optimization Flow

The procedure used to develop a system to compare selected improvement techniques is as follows:

Step1 : Upload a fundus image with 3008 x 2000 resolution in Joint Photographic Experts Group (*.jpg) format into the system

Step2 : Change the image background to white using the HSV color space. This process will focus on the fundus image boundary on the optimization process on the fundus image itself.

Step3 : Apply the Negative Image Statement, Light Contrast Stretch, Dark Contrast Stretch, and Partial Contrast Stretch techniques.

Step4: Record the performance metric values for each improvement technique.

Step5: Apply the Cuckoo Search algorithm for optimization.

Step6: Record the performance metric values for each improvement technique after optimization.

Step 7: Extract the RGB color values from the optimized image.

Image Preprocessing

Medical image improvement methods often attract the interest of researchers. Negative image technique is considered as an alternative to improve fundus image quality. Other techniques called dark contrast stretching technique, light contrast stretching technique, and partial contrast stretching technique will also be compared in this paper

Negative Image Technique.

In digital image processing, the most basic and easiest procedure to improve the contrast of an image is to change the image to be negative. Negative images are ideal for enhancing hidden detail in dark areas and have diagnostic use in imaging. In this procedure, the gray values of the pixels are reversed to produce a negative image (Maini & Aggarwal, 2010) . Negative images are useful for highlighting white or gray information contained in dark areas of the image.

Dark and Light Contrast Stretching Technique, Images with low contrast tend to be of poor quality because the details are difficult for the human eye to read directly. To improve image efficiency, it is necessary to carry out a contrast stretching process kontras (Firdausy et al., 2007) . Contrast stretching is a procedure that can improve the quality of low-contrast images. This process is a point procedure where the pixel gray level is changed to a certain gray level based on certain features. In point processing, each image pixel is transferred independently to other pixels, so that the image can be easily viewed and analyzed after the contrast enhancement process is performed.

Two automatic scaling methods that are usually used to increase the brightness and contrast levels of an image are by using the linear mapping feature. This method focuses on the initial brightness and contrast levels of the photo to create a change.

$$p_k = \frac{(\max - \min)}{(f_{\max} - f_{\min})}(q_k - f_{\min}) + \min$$

Figure 4 is an illustrative example of applying the dark stretch method, where the threshold value used is 100 and the dark stretch element value is 250

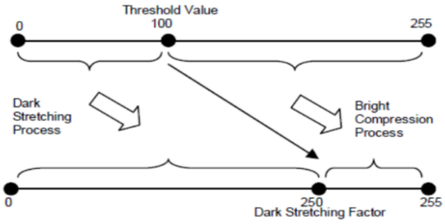

Fig. 4. Light dark stretching method

Bright stretch techniques often use automatic scaling in the form of linear mapping to increase the brightness and contrast of an image. This approach can be described by Equation 1. The stretching and compression processes for the bright stretching technique can be seen in Figure 5.

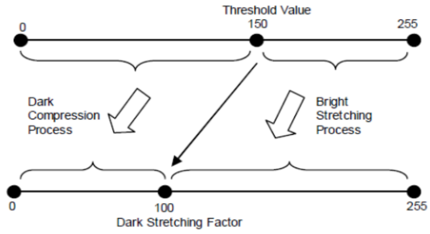

Fig. 5. Light stretching method

For a threshold value of 150 and a dark stretching factor of 100, the light intensity in the input image spectrum from 0 to the threshold value is compressed into a range of 0 to the dark threshold factor value. Light intensity that is not included in that range will be maintained according to the intensity of the original output.

The Partial Contrast Stretch Technique, Partial contrast is a linear mapping technique used to increase the contrast and brightness levels of an image. This technique is based on the initial brightness and contrast levels of dynamic images (Salihah et al., 2010) .

Figure 6 shows the compression and stretching processes used in the Partial Contrast Stretch technique. When implementing this strategy, pixels in the lower threshold value (minTH) and upper threshold value (maxTH) ranges can be converted to a new range and expanded linearly to a larger set of pixels in the new lower value (NminTH) and new upper value ranges (NmaxTH), so that the dynamic range of the histogram is achieved. Meanwhile, the remaining pixels will experience distortion (Abdul-nasir et al., 2013) .

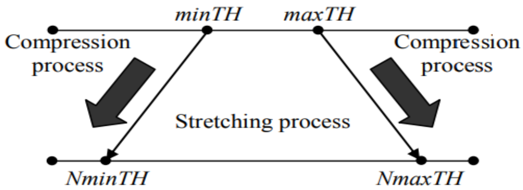

Fig. 6. Partial contrast stretching process

Image Optimization

One of the new and effective optimization strategies developed is the Cuckoo Optimization Algorithm. This algorithm is inspired by the behavior of cuckoo birds in breeding. Several species of cuckoo birds deposit their eggs in the nests of male host birds. In some cases, the cuckoo bird kills the host bird's eggs to increase the chances that the eggs themselves will survive. When the host bird becomes aware of the presence of cuckoo eggs, it either leaves the nest or discards the cuckoo eggs. Studies show that cuckoo eggs tend to closely resemble those of their hosts, and some types of cuckoo chicks may even mimic the sounds of their host chicks to increase the chances that the chicks will survive. Cuckoo algorithm optimization is considered more effective compared to other algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) because it uses Lévy random walk rather than isotropic random walk which requires many parameters to be modified. In this paper, performance metrics such as entropy, PSNR, MSE, and NIQE are compared for 4 image processing techniques, namely Image Negative, Dark Stretch, Bright Stretch, and Partial Contrast Stretch after image processing and optimization.

4. Results and Discussions

In order to compare the effectiveness of the selected enhancement techniques, it is necessary to compare the performance metrics on the enhanced images. In this assessment, we use NIQE, PSNR, MSE, and entropy. The lower the NIQE value, the better the enhanced image quality. A lower PSNR indicates a better increase in image contrast, while a higher PSNR will provide lower contrast. A lower MSE value indicates better noise reduction in the image. The higher the entropy value, the more information is stored in the image. In the initial stage, each image was enhanced using the technique selected in this paper, and a performance score was recorded. The mean and standard deviation are calculated and listed in Table 1

Figure 7a shows the fundus images that have been enhanced using the negative technique, with the lowest NIQE score among all the techniques. This shows that this technique produces images that are less clear to the observer. Figure 7b shows a fundus image that has been enhanced by the dark contrast stretching technique, and has slightly better NIQE and entropy scores than the negative technique. Figure 7c shows the fundus images that have been enhanced by the bright contrast stretching technique, with the highest entropy among all the techniques. This suggests that the bright contrast stretching technique can better retain details in an image. The partial contrast stretching technique shows the highest NIQE score and the lowest entropy score, and the enhanced yield images are shown in Figure 7d. Despite the high contrast, detailed information is lacking. Overall, the MSE score for all selected techniques is close to zero which means that all techniques are effective in noise reduction.

A comparative picture of upgrades and optimizations is shown below

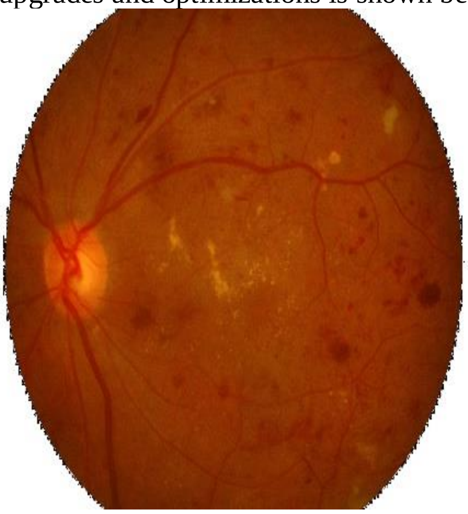

Fig. 7. Original fundus image with background masking done

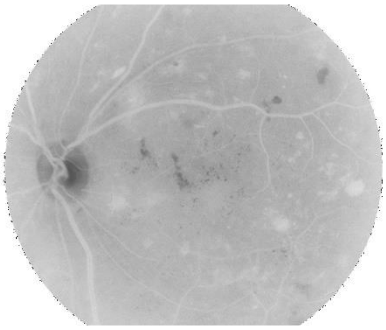

Fig. 7a. Negative image before optimization

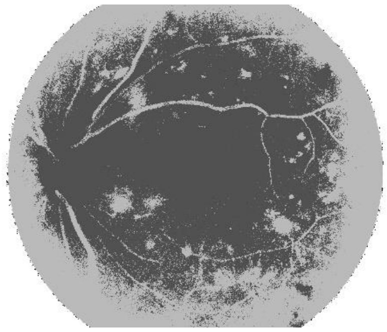

Fig. 8a. Negative Image after optimization

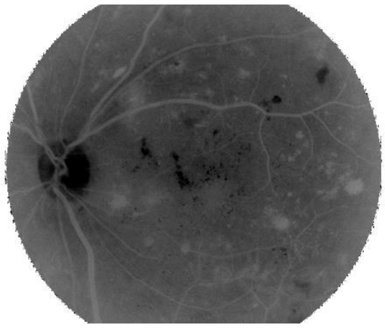

Fig. 7b. Dark Contrast Stretch before optimization

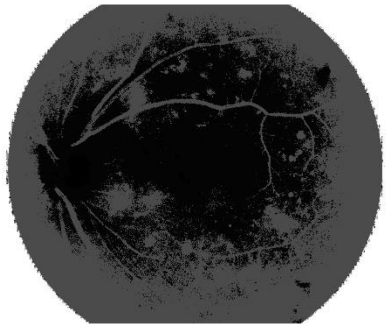

Fig. 8b. Dark Contrast Stretch after optimization

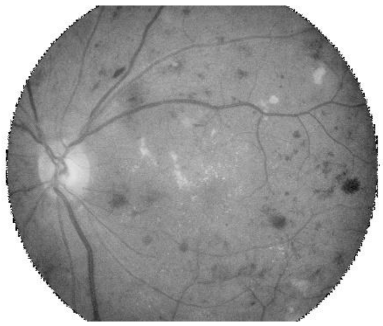

Fig. 7c. Bright Contrast Stretch before optimization

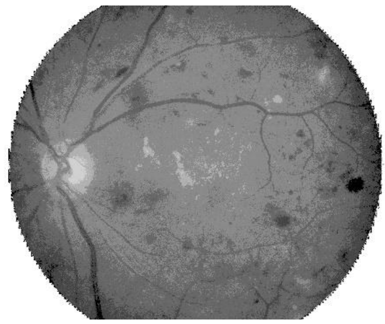

Fig. 8c. Bright Contrast Stretch after optimization

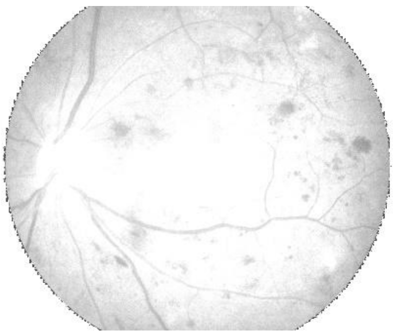

Fig. 7d. Partial Contrast Stretch before optimization

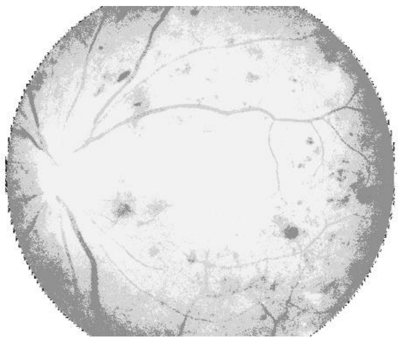

Fig. 8d. Partial Contrast Stretch after optimization

Table 1 - Performance Metrics of Improvement Before Optimization Techniques

Upgrade Technique	Mean				Standart Deviation			
	NIQE	PSNR	MSE	Entropi	NIQE	PSNR	MSE	Entropi
Negative Image	**2.8834**	50.7627	≈ 0	5.1682	**0,2257**	0,0039	≈ 0	0,2219
Dark Contrast Stretch	3.0449	**50.8303**	≈ 0	5.2083	0,3565	0,1074	≈ 0	0,2867
Bright Contrast Stretch	4.0582	50.7794	≈ 0	**5.7246**	0,4305	0,0213	≈ 0	0,1544

Partial Contrast Stretch	4.3227	51.7438	≈ 0	3.0910	1,4643	**0,5767**	≈ 0	**1.4008**

However, after performing image optimization, the evaluation results show differences as shown in Table 2. Cuckoo optimization proved to be more efficient in setting up the image enhancement function. The performance metrics used are NIQE, PSNR, MSE, and entropy. The Bright Contrast Stretch had the lowest NIQE score, while the highest entropy value was on the Bright Contrast Stretch, but decreased slightly after optimization, indicating that some information was lost. The optimized image can be seen clearly, as shown in Figure 8d. In addition, Dark Contrast Stretching has the highest PSNR among other techniques, while partial contrast stretching has the lowest PSNR. Therefore, Dark Contrast Stretch provides better image contrast than any other technique. Unlike the results of image enhancement in Table 1, Partial Contrast Stretching provides better contrast with the highest PSNR. For the MSE evaluation, Image Negative performs best with the lowest consistent value, while Dark Contrast Stretching has the lowest MSE value but with a high standard deviation, showing inconsistent results. Of all the techniques, it appears that Bright Contrast Stretching has the lowest NIQE, better entropy, but moderate PSNR. Histogram Equalization has the second lowest NIQE, moderate entropy, and good MSE and PSNR values

Table 2 - Performance Metrics of Improvement After Optimization Techniques

Enhancement Techniques	Mean				Standart Deviation			
	NIQE	PSNR	MSE	Entropi	NIQE	PSNR	MSE	Entropi
Negative Image	5.4746	50.2330	**0,6163**	2.8572	0,8885	0,0139	**0,0019**	1,0197
Dark Contrast Stretch	6.0102	**50.7259**	0,5559	2.4922	2.1319	**0,6538**	0,0751	1.0151
Bright Contrast Stretch	**5.2850**	49.5141	0,7273	**5.0193**	**0,2262**	0,0426	0,0070	**0,2612**
Partial Contrast Stretch	6.0838	40.4990	0,7299	1,8564	1.1357	0,0889	0,0143	1.2779

Each technique shows a different performance in enhancing the image. After optimization with the Cuckoo algorithm, the results of image enhancement show a significant improvement compared to before optimization. The performance of all techniques, in terms of NIQE scores, improved after optimization. Although the optimization may limit performance in terms of MSE for all enhancement techniques, the resulting images still have greater clarity, allowing the ophthalmologist to see abnormal features more clearly. Overall, the entropy performance values tend to decrease after optimization, except for the bright contrast stretching technique, which performs very well and does not require optimization.

5. Conclusion

There are various types of image preprocessing methods contained in the literature. However, in several studies, fundus image preprocessing methods were compared only in a limited number. In this research, five image enhancement techniques are compared and each technique has different advantages. The difference between the results before and after optimization shows the effect of using the Cuckoo optimization technique. Of all the negative image techniques, light contrast expansion, dark contrast expansion, and partial contrast expansion, it can be seen that the results obtained from the enhancement process show better results before optimization is carried out. It can also be seen that the PSNR yield decreases after optimization, which indicates lower quality in the segmentation process. The NIQE result should have been lower after optimization, but in fact it has actually increased. From the experimental results obtained using PSNR, MSE, entropy, and NIQE, it appears that the performance metrics for PSNR, NIQE, and entropy are better after the upgrade process. The proposed technique produces better image quality improvements in several performance metrics, such as MSE, NIQE, PSNR, and entropy. Bright Contrast Stretch outperforms other techniques in NIQE Mean (5.2850), Entropy (5.0193), NIQE Standard deviation (0.2261), and Entropy (0.2612).

Even so, MSE is better after optimization. However, among the four enhancement techniques proposed for image enhancement, Bright Contrast widening has a greater advantage over other techniques. This study provides insight into retinal image enhancement techniques that provide ophthalmologists with different options in image enhancement techniques, which helps them have clear vision to more accurately detect DR. However, the big challenge in image processing, in this case image enhancement, is the necessity for humans to determine whether an image matches the role requested. The limitation of this study is that there are several indicators that do not match the optimization of the Cuckoo algorithm. Therefore, further studies are needed to study the improvement of techniques and optimization of algorithms that are more compatible and suitable.

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