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# Optimization Of Histogram Equation With The Cuckoo Algorithm to Improve Fundus Image Quality

**Dafwen Toresa[1*], Keumala Anggraini[2], Pandu Pratama Putra[3], Taslim[4], Edriyansyah[5]**
[1,2,3,4] Dept. of Informatics Engineering, Universitas Lancang Kuning
[5] Dept. of Informatics Engineering, Universitas Hang Tuah Pekanbaru
dafwen@unilak.ac.id*, keumala@unilak.ac.id, pandupratamaputra@unilak.ac.id, taslim@unilak.ac.id, sinksonk@gmail.com

**Abstract.** This study discusses strategies for identifying Diabetic Retinopathy (DR) using fundus images and the efficiency of image pre-processing techniques to improve their quality. Fundus images in medical image processing often experience problems with non-uniform lighting, low contrast, and noise, thus requiring pre-processing of images to improve their quality. This study evaluates the effectiveness of standard histogram equation techniques and optimized histogram equations with cuckoo optimization in order to choose the best technique to improve fundus image quality to identify DR. The proposed technique to produce better image quality improvements will be tested in several performance metrics, such as NIQE, PSNR, and Entropy. the results of this study, the average PNSR before optimization was 50,8, whereas after optimization it became 49,8239. The average entropy before optimization is 4.5514, while after optimization it becomes 3.8577. The average NIQE before optimization was 3,4046, while after optimization it was 4,73. In general, the results of this study indicate that the quality of the fundus image is better using the histogram equation before optimization than after optimization. In other words, Cuckoo optimization is not suitable for increasing the performance of the histogram equation in improving fundus image quality

**Keywords**: Cuckoo Optimization, Diabetic Retinopathy, fundus image, histogram equation, image enhancement

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## INTRODUCTION

To perform fundus imaging, a blink sensor is used attached to a microscope to capture the retina of the patient's eye[1]. The fundus consists of the retina, optic disc, macula, and fovea, which are located in a position opposite to the lens of the eye [2][3]. 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. [4]. 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 [5]. The appearance of lesions in the retina is typically the initial symptom of diabetic retinopathy. Figure 1 illustrates a normal retina and an abnormal retina (diabetic retinopathy).

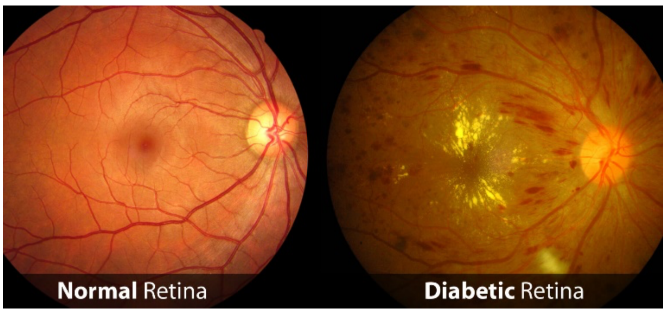


Fig 1. llustrates a normal retina and diabetic retina

Diabetic retinopathy is a condition that can cause vision loss [3]. Therefore, detecting this condition at an early stage can help prevent more severe vision loss [6]. 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 [7], [8]. 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 [9]. 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 [10]. Mild retinal lesions, on the other hand, can escalate when blood loss results from retinal obstructions [11].

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 [12]. 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 [13]. Tumors in the fan-shaped head of the optic nerve are not associated with retinal hemorrhages [14].

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 [15]. Changes in retinal blood vessel morphology such as width, branching angle, and volume are the main indicators of DR [16]. In the advanced stages of proliferative DR, development of new dysfunctional vessels throughout the retina occurs, which is associated with the NPDR stage [17]. New blood vessels can spread through the retina and cause complete vision loss [18]. Vascular monitoring systems can be used to identify blood vessels located on the retina of the eye [19].

Pre-processing is an important stage in the production of medical images to remove image noise and improve certain characteristics [20]–[23]. Noise, poor quality, inappropriate lighting, and dim issues are some of the problems that often occur with fundus images [24], [25]. Identifying characteristics of DR on fundal features, such as microaneurysms (MA), cottony patches, exudates, and hemorrhages, is made difficult by this question [1].

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 (CS). 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[26], [27]. In [28], 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.

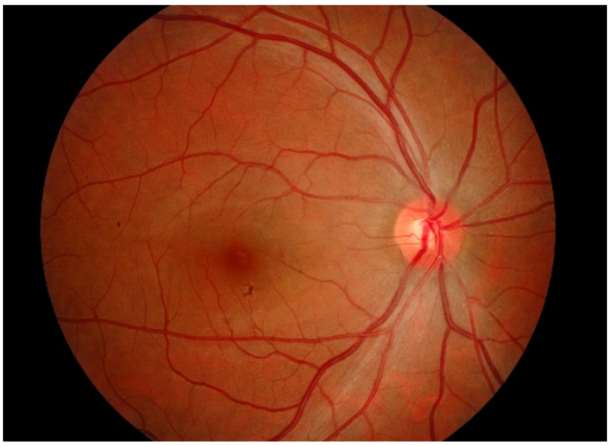

Fig 2. Raw Retinal Fundus Image

## METHODS

This research is a quantitative-based research that relies on technical experimental works. The research framework as a whole involves three phases, namely the first phase is the initial study phase, the second phase is the proposed model/technique and the last phase is performance evaluation. These three phases will cover all the necessary steps to fulfill the objectives of this study.

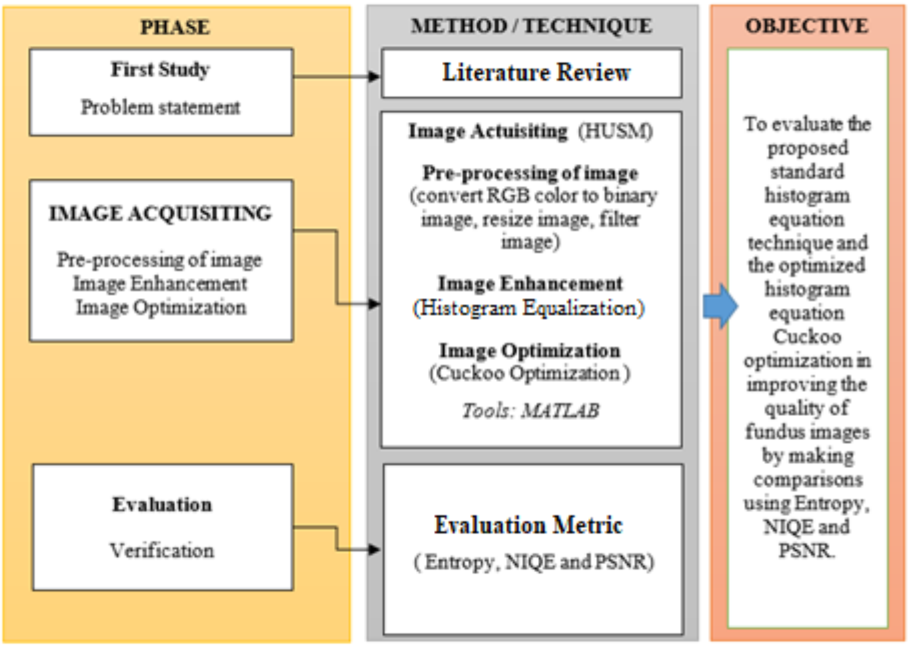


Fig 3. Research framework

### Phase 1 : First Study – Problem identification and knowledge acquisition

The aim of this phase is to critically analyze existing research to identify issues requiring further research. This analysis is based on various sources, including previous research published in official journals, conference reports, books, and expert experience. Knowledge acquisition (KA) is the process of extracting, structuring and synchronizing knowledge gathered from various sources such as experts in areas of interest, textbooks, technical papers, databases, reports and environmental.

Relevant papers, journals, conferences and articles were retrieved manually from the database as a review source. An initial search identified sixty articles using the keywords "Performance Comparison" or "Image Enhancement Techniques" or "DR" or "Fundus Image" or "Fundus Image Enhancement" or "Diabetic Retinopathy". The classification has been made by separating them into the year of publication. Only journals were selected as potentially relevant for this review. To make this paper credible, research that lacks validation and duplication is deliberately excluded [29]. Finally, studies that passed this screening process were selected for further analysis. This review includes follow-up studies between 2015 and 2022. All papers, journals, conferences, and articles published before 2000 were ignored and not considered in the review process, but exceptions were made if papers were significantly linked and primary sources and still valid today.

After a process of selecting appropriate documents, publications, seminars, and papers. This collection is based on the most interesting research, prior, and in related domains. A secondary search was also carried out based on references found in primary sources. Accessibility to a digital repository of many accessible sources of information provides reasonable confidence for all applicable journals. Some keywords are taken from the research title.

### Phase 2 : Image acquisition and image processing

In this architecture, as shown in Figure 3, the images were obtained from an ophthalmologist clinic at HUSM, Kubang Kerian, Kelantan. A total of 50 images will be used consisting of 10 normal images and

40 abnormal fundus images. Fundus image set through the proposed model performance analysis process. The fundus image collected is the primary image of the dataset.

Attempts to upgrade the image by analyzing the image enhancement technique before upgrading the fundus image A binary image is an image with only two acceptable color levels per pixel. They are usually shown in black and white. The two values are often 0 for black, and 1 or 255 for white. In order to separate the entities in the image from their context, discrete images are often generated by thresholding a color or grayscale image. The process consists of cropping the image followed by resizing, then converting the RGB image by extracting the background into a binary image. In image processing, converting a grayscale image to a binary image produces an image with one of two values for each pixel. Image processing is one of many applications that use binarization as a common tool for image segmentation. Segment the gray image intensity range first at several intervals and calculate the average intensity value for each interval, then repeat the integration of the intervals until the final threshold value is reached [30]. The grayscale image then undergoes an upscaling process. Then image optimization will be carried out after image enhancement using Cuckoo search optimization.

Histogram equalization is a method for changing the intensity of a contrast enhancing image. This is achieved by efficiently multiplying the most frequently encountered intensity levels, i.e. broadening the intensity spectrum of the image. In general, this approach increases the global contrast of the image because the same comparison value reflects the usable data. Contrast in this case will not always decrease. The histogram equalization is obtained by changing the gray degree of the pixel (r) with a new gray degree (s) with a transformation function T, in this case s = T(r). This means that r can be recovered from s by the inverse transformation r =T-1(s) where, 0≤ s ≤ 1. For 0 ≤ ri≤1. For 0 ≤T(r) ≤1. To guarantee contrast over the allowable range of values. The goal of the histogram equalization itself is to obtain a complete histogram spread, so that each gray degree has approximately the same number of pixels. Because the histogram indicates the probability of a pixel with a certain degree of gray, the formula used to calculate the histogram alignment is:

$$P_r\, r_k = \frac{n_k}{n} \text{ in this case } r_k = \frac{k}{L-1}, \; 0 \le k \le L-1 \; \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; (1)$$

Where, the gray degree (k) is normalized to the large gray degree (L-1). The value rk = 0 represents black, and rk = 1 represents white in the specified grayscale

Cuckoo optimization is inspired by Cuckoo's replication technique, the cuckoo lays its eggs in the nest of another host bird which may be of a different species. The host bird entity may notice that the egg is not its own, and destroy the egg or leave the nest for the most part. This culminates in the creation of cuckoo eggs that mimic the nests of local host birds. The three concepts that will be used as part of the CS algorithm are (i) at any given moment each cuckoo lays eggs and lays it in a randomly selected nest, (ii) the best nest with the most amazing set of eggs (setting) survives for the next few decades, (iii) number of open host nests resolved and hosts likely to find intruder eggs Pa (0, 1). The host bird discards the eggs or gives up the nest to build another nest at an alternative site in this case

**Phase 3: Evaluation**

Based on model validation that can describe a series of expert consultation sessions conducted to ensure that the knowledge embedded in the model accurately represents the problem domain. As for model verification, data is collected and used as training data and evaluation data to ensure the model can run and function as it should. The performance parameters used are NIQE, PSNR and Entropy

## RESULT AND DISCUSSION

To calculate the efficiency of the image enhancement technique on retinal fundus images through the histogram equation, the standard histogram equation will be compared with the optimized histogram equation, while for evaluation the NIQE, PSNR, MSE, and entropy will be used. A lower NIQE value indicates a perceptually better output.

Lower PSNR values produce images with poor contrast, and larger PSNR values produce images with good contrast. A lower MSE value indicates good noise reduction in the image. Higher entropy values indicate that more information is stored. At first, each image was enhanced using the histogram equation technique in this paper, and performance scores were recorded. The mean and standard deviation are calculated and listed in table 1 contain the mean and standard deviation of Performance Metrics of histogram equation before and after Optimization.

The enhanced fundus image with optimized histogram equalization using cuckoo optimization is shown in Figure 4b, which demonstrates better enhancement compared to standard histogram equalization shown in Figure 4a. This technique exhibits improved NIQE, PSNR, and entropy scores.

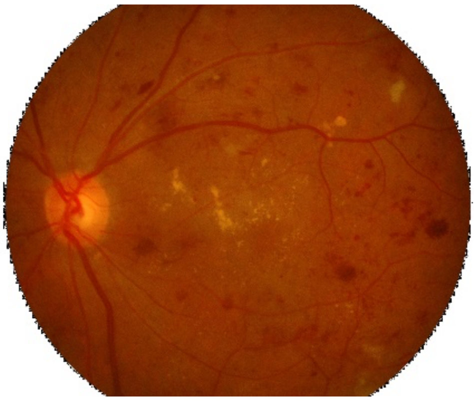

Fig 4. Original fundus image after masking the background using HSV

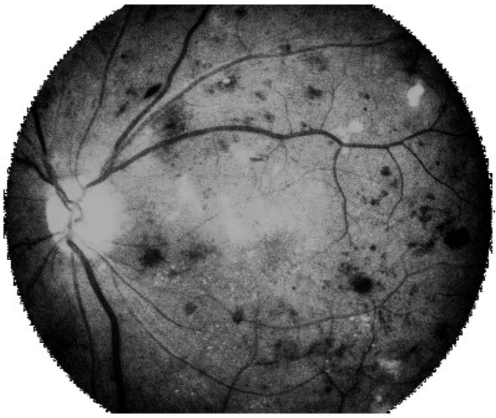

Fig 4a. Histogram Equalization before optimization

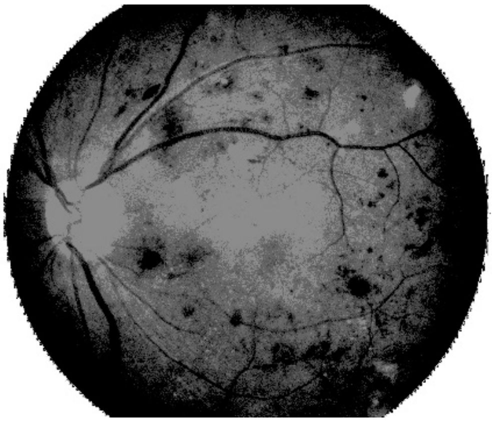

Fig 4b. Histogram Equalization after optimization

Nonetheless, the evaluation of the results after image optimization showed significant differences, as can be seen in Table 1. Cuckoo optimization proved to be more effective in tuning the image enhancement function. The performance metrics used in this research are NIQE, PSNR, MSE, and entropy. Although optimization can limit MSE performance for all image enhancement techniques, the resulting images are clearer and help ophthalmologists better see abnormal features.

Table 1. Performance Metrics of  histogram equation before and after Optimization

| Evaluation | | Before | After |
|---|---|---|---|
| Mean | NIQE | 3.4046 | 4.7300 |
| | PSNR | 50.8000 | 49.8239 |
| | MSE | ≈ 0 | 0.6790 |
| | Entropy | 4.5514 | 3.8577 |
| Standard Deviation | NIQE | 0.3521 | 0.5323 |
| | PSNR | 0.0042 | 0.3302 |
| | MSE | ≈ 0 | 0.0488 |
| | Entropy | 0.0427 | 0.8137 |

**CONCLUSION**

There are various kinds of image preprocessing methods that have been described in the literature, but the fundus image pre-processing method only seeks to improve image quality by using standard histogram equations and histograms optimized with cuckoo optimization. The hope is that this method can become a recommendation and reference to improve image quality when the original image has low intensity, non-uniform lighting, low contrast, and a lot of noise. The difference between the results before and after optimization shows the effect of using the Cuckoo optimization technique. If you compare the results before the upgrade and after the optimization, the difference can be seen clearly. The value used to calculate the amount of information called entropy shows that the results of the enhancement process are better than after optimization. However, the PSNR yield decreased after optimization, indicating lower quality in the segmentation process. Even though the NIQE result is expected to be lower after optimization, in reality the value actually increases. From the experimental results using PSNR, MSE, entropy, and NIQE performance metrics, it appears that PSNR, NIQE, and entropy performance results are better after the upgrade process, but MSE is better after optimization.

However, the proposed improvement technique, namely Histogram Equalization with Cuckoo optimizationis. This study provides insights into retinal image enhancement techniques which provide different technique options for ophthalmologists to enhance images to detect DR more accurately. However, the big challenge faced in image processing, especially in terms of image enhancement, is that humans must determine whether the image is in accordance with the existing demands. Therefore, further studies need to be carried out to research more compatible and suitable improvement techniques and optimization algorithms

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