A Qualitative Approach for Enhancing Fundus Images with Novel CLAHE Methods

Vijaya Madhavi V.
Department of CSE, Koneru Lakshmaiah Education Foundation, Hyderabad, Telangana, India | Department of CSE, Neil Gogte Institute of Technology, Hyderabad, Telangana, India
madhavikrishnat@klh.edu.in

P. Lalitha Surya Kumari
Department of CSE, Koneru Lakshmaiah Education Foundation, Hyderabad, Telangana, India
vlalithanagesh@gmail.com (corresponding author)

Received: 7 November 2024 | Revised: 28 November 2024, 4 December 2024, and 10 December 2024 | Accepted: 14 December 2024

Licensed under a CC-BY 4.0 license | Copyright (c) by the authors | *DOI: https://doi.org/10.48084/etasr.9525*

ABSTRACT

Glaucoma is a progressive eye disease. This study presents a custom technique to enhance retinal fundus images to detect glaucoma. Contrast enhancement is a crucial stage in medical image analysis to improve the visual impression of diseases. CLAHE is a common technique to improve images. Clip Limit (CL) and subimages may restrict the potential benefits of the typical approach and pose difficulties. This study introduces Enhanced CLAHE and Automated CLAHE to address the shortcomings of the base method. These methods demonstrate progress in improving retinal landmarks in various ways by looking directly at the in-depth description of retinal images. The proposed methods, along with the baseline CLAHE, were compared using quality assessment tools such as the Peak-Signal-to-Noise Ratio (PSNR). The results help to determine the degree of contrast enhancement and the overall richness of the image.

Keywords-CLAHE; enhanced-CLAHE; auto-CLAHE; glaucoma; image enhancement; PSNR

I. INTRODUCTION

Image preprocessing is used to improve the contrast of an image [1]. Contrast enhancement can bring out an image's hidden qualities with the adjustment of bright and dark areas. Professionals can screen and diagnose retinal diseases with the help of digital retinal fundus images. Glaucoma is a condition that mainly affects the retina. Analyzing the anatomy of the retina is made easier by taking fundus images using a fundus camera [2, 3]. Anomalies are obstructed by artifacts of the retinal fundus. The optical disk moves in the direction of the brain as a result of electrical pulses from the photoreceptors of the retina. The fundus image's augmentation of the retinal areas is crucial since it improves the visibility of blood vessels and boosts the accuracy of abnormality detection. In [5], a technique was presented to improve fundus images using vessel extraction and histogram equalization with cumulative density function (PDFF). The green plane of the fundus image displays the darkest area that contrasts most with the background [6]. To find DR anomalies, the fundus image's green channel is extracted as a preprocessing step [7]. Machine Learning (ML) algorithms can detect glaucoma, increasing diagnostic accuracy by detecting subtle structural changes in optic nerve heads in retinal images and allowing timely intervention and treatment to prevent irreversible vision loss. ML algorithms facilitate efficient analysis of large retinal image datasets, allowing systematic diagnosis and screening of glaucoma in various patient populations. Glaucoma diagnosis can be performed reliably and consistently with ML, reducing subjectivity in assessments and ensuring uniformity across different healthcare settings.

Preprocessing techniques are often used for image enhancement. Edge detection techniques, such as Gaussian high-pass filters, are used with Laplacian filters. Typically, edge detection involves applying some basic methods such as the Sobel, Prewitt, or the Gaussian Laplacian operator [8]. Morphological techniques that address object shape and size seem more complex than HPF masks such as Prewitt and Sobel. For example, noise from the item's exterior and interior can be effectively removed using morphological opening and closing transforms, respectively [9-12]. Depending on the shape of the object, it is further improved by choosing suitable masks, such as discs or lines. Another method to improve the fundus image is the wavelet transform. In this case, the high-frequency components of an image are extracted using a wavelet. To reduce noise, soft thresholding is applied to the high-frequency regions of the spectrum. After that, the inverse wavelet transform is applied to provide a better image [13]. Gamma correction is another technique to enhance medical images [14]. Gamma optimization is accomplished by reducing homogeneity using the input image's co-occurrence matrix. This method increases the range of pixel values while improving the quality of the image. In [15], the bi- and multi-histogram approaches were proposed. Increasing the contrast of an image preserves its brightness, unlike a standard display where brightness is compromised by the bi-histogram approach.

CNN and MobileNetV2 have been used for the early diagnosis of eye diseases [16]. OHTS aims to delay or prevent visual field loss in people with high intraocular pressure, especially those with a moderate risk of glaucoma. Because phases 1 and 2 span approximately 16 years, it is possible to develop algorithms that predict glaucoma before symptoms appear. The reading center must have two recurrent abnormal visual fields for glaucoma labeling, and these must be examined by a different endpoint committee. MobileNetV2, a very efficient CNN, is chosen due to its performance in scenarios with limited training data and processing resources. In [16], a new fuzzy logic and histogram-based approach was proposed to improve low-contrast color images. This method was computationally fast compared to other advanced enhancement techniques and conventional methods, and it was based on two crucial factors, M and K, where M is the contrast intensification parameter and K is the average intensity value of the image as determined by the histogram [17, 18].

This study focuses on the tremendous potential for innovative medical products and the significant cost savings in healthcare. The original fundus images were cropped, with the optical disc as the main focus. A modified G-net was used to precisely segment the optic disc and optic cup. Two distinct CNNs were trained for the disc segmentation task, using the red signal for the disc and the entire RGB channel for the cup. For both segmentation models, a total of 31 layers were used. First, the model examines cropped retinal fundus images. Second, it splits the cup using images trimmed according to the shape of the segmented disc. The cup-to-disc ratio is obtained as the ratio between the disc and the cup area in the segmented masks. A set of 508 fundus images was assembled from 25 distinct classes. After being tagged, the dataset was divided into training and testing sets. A CNN was designed with multiple layers to analyze images. After development, the CNN model was tested to ensure that it met the requirements. CNN uses GPU processing to produce an image as the output data, using Keras for operations such as covering, cutting, and horizontal flipping. The glaucoma detection model was trained on a dataset of 450 samples from the DRIVE database, including 250 normal and 200 glaucomatous images that were used for image enhancement [19, 20]. The CNN model consists of three fully linked layers and ten convolutional layers. Batch normalization accelerates learning by stabilizing input images. The input images were downsampled using max pooling, while dropout layers were used to prevent overfitting. The final fully connected layers with SoftMax activation evaluate the class probabilities. Max pooling is used to minimize spatial dimensions by using the stride lengths of two layers and a 3×3 filter. The model was trained using the max pooling layer and the RELU layer. The RELU layer not only adds nonlinearity but also ensures convergence learning. To determine whether an image is in the glaucomatous category, a dataset must be input into the training procedure. Deep learning techniques are used to detect fundus diseases. These techniques can provide accurate classification results on ocular scans and also enable the precise automated detection of fundus diseases.

In [22], three openly accessible datasets were used to overcome these limitations and automatically classify a variety of eye conditions. Transfer learning was used to create a deep neural network for retinal fundus disease classification and contrast it with four well-known pre-trained models (EfficientNetB7, EfficientNetB0, UNet, and ResNet152). Manual diagnosis of eye conditions using ocular fundus scans is a difficult and complex process, as it takes a lot of time and is prone to errors [23, 24].

II. DATASET

The Digital Retinal Image for Vessel Extraction (DRIVE) dataset [19], generated by a joint research team, can be used to compare different artificial segmentation methods on retinal images. The masks are provided as a ground truth standard along with the FOV and segmented vessel tree for every image in the collection.

III. CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION

CLAHE, a twist on the traditional Histogram Equalization (HE) method, adjusts pixel intensities to improve the apparent level of detail in images. By adapting its contrast enhancement process to the features of different regions within an image, it ensures that the enhancement is customized for certain features and structures. Histogram equalization is applied to every little tile that makes up the image. A non-linear adjustment is mainly used to map the cumulative distribution of pixel intensities. CLAHE has the benefit of increasing contrast between the foreground and background of the image. Furthermore, the surrounding areas mitigate the difficulty of contrast.

IV. HISTOGRAM EQUALIZATION

HE is a contrast enhancement technique that distributes dynamic range intensity values evenly across histogram bins. The main drawback of HE is that it enhances the overall image content. The result of HE sharpens the image and decreases the local details of the border, but it introduces saturation artifacts. Cumulative Density (CPD) is used in the Conventional HE (CHE) method. The drawback of CHE is that there is no pixel-by-pixel variation throughout the equalization procedure. CLAHE techniques reduce artifacts and enhance image quality even more. The procedure may dynamically adjust the scale at which it processes the tiles to maximize the trade-off, increasing detail and decreasing noise depending on the characteristics of the local image content. To optimize image quality with the CLAHE approach, it is critical to determine the value of clip limit subimages [14]. The algorithmic definition of the Enhanced-CLAHE is as follows:

```
Algorithm 1:Enhanced-CLAHE
1: Use a fundus image processing library
   to load the fundus image.
2: Since CLAHE only works with single-
   channel images, if the image is in
   color, convert it to grayscale.
3: Make n×n subsections of the image
4: Finish each subsection's instructions.
   Identify the maximum intensity value
```

and the histogram of every tile.
Utilizing the half-interval search strategy, ascertain the value of the Clip Limit (CL).
Distribute the pixel value larger than CL equally among the histogram bins of a tile for histogram equalization.

5: To achieve the best quality using image processing, map each pixel with the weighted sum of its four neighbors or the pixel itself, depending on which it is located.

V. AUTOMATED CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION

Through automated image analysis techniques, an algorithm can assess local contrast changes and decide the optimum level of augmentation at different locations. The technique suggested in En-CLAHE is still arbitrary and reliant on the number of tiles or sub-images n that the user selects. This study considered the limitations of the En-CLAHE method and presented a completely automated CLAHE. The overall entropy values of the image are used by the approach to split it into sub-images. This instance involves adjusting n between 2 and 12 and choosing an n that will divide the input image into the sub-images with the highest corresponding entropy values.

Algorithm2: Auto-CLAHE

1: Use an image processing library to load the fundus retinal image.
2: Extract the green plane from the image.
3: Compute the entropy values between the smallest and highest value of n and then save the results in an array called entropy[n].
4: Choose the value of n that corresponds to the maximum entropy value.
5: nxn is the total of the images.
6: Repeat steps 3 to 5 of the Enhanced-CLAHE process.

CLAHE enhances feature localization by emphasizing the salient features of images.

VI. RESULTS

The methods were tested on the High-Resolution Fundus (HRF) dataset. Here, for ease of understanding, the results are displayed on images from the dataset. The results of the healthy fundus images under the HSV and BGR-plane CLAHE algorithms are shown in Figure 1, and the results of the glaucoma fundus with the HSV and BGR-image algorithms of CLAHE are shown in Figure 2. Images (a, c) use a clip limit value of 2.0, and images (b, d) use a clip limit value of 0.8.

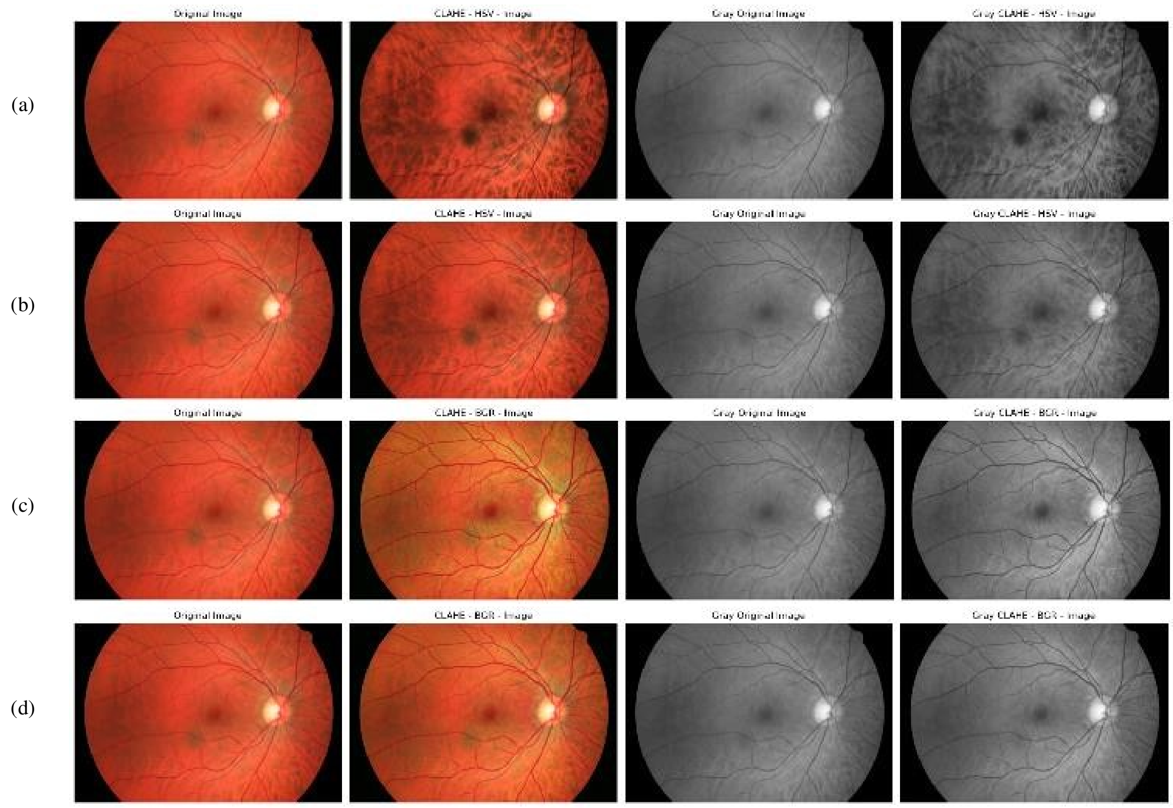

Fig. 1. Images of healthy fundus.

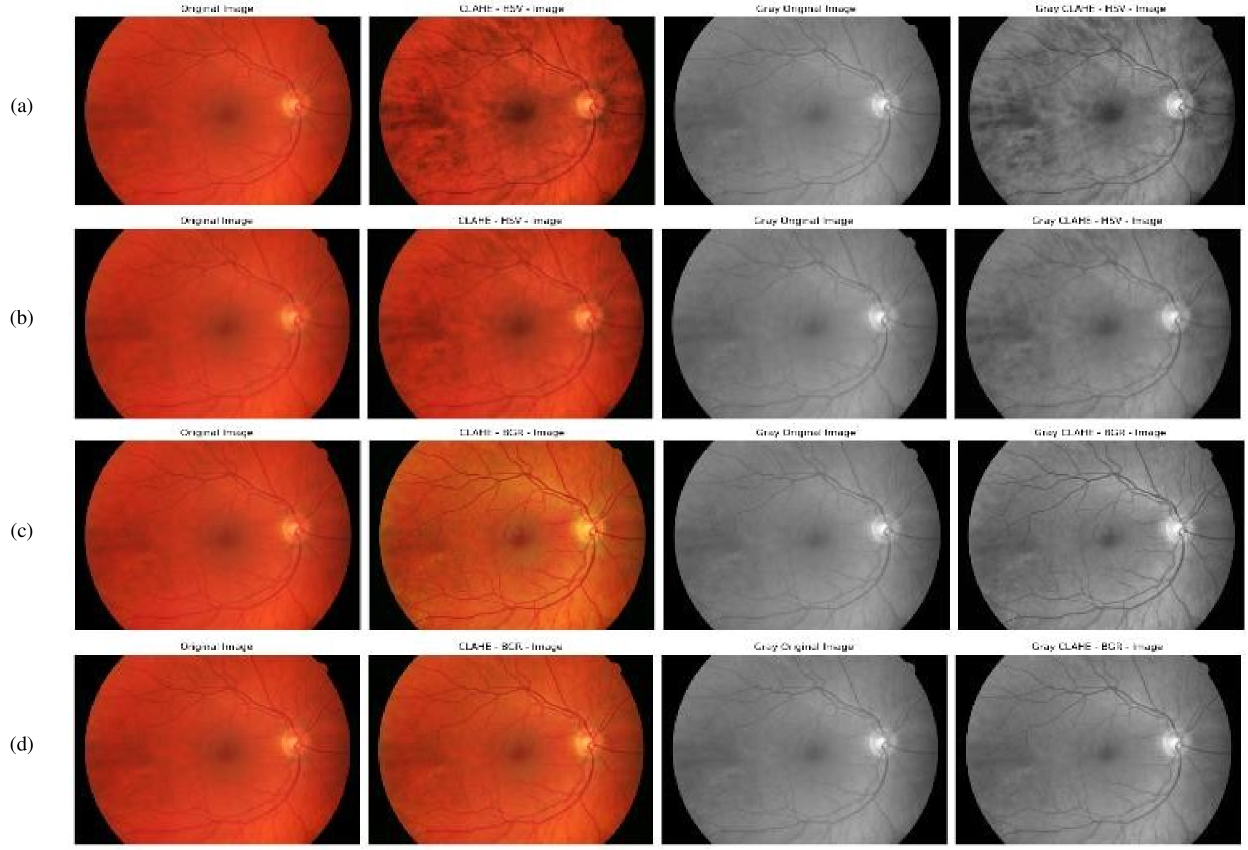

Fig. 2. Images of fundus with glaucoma.

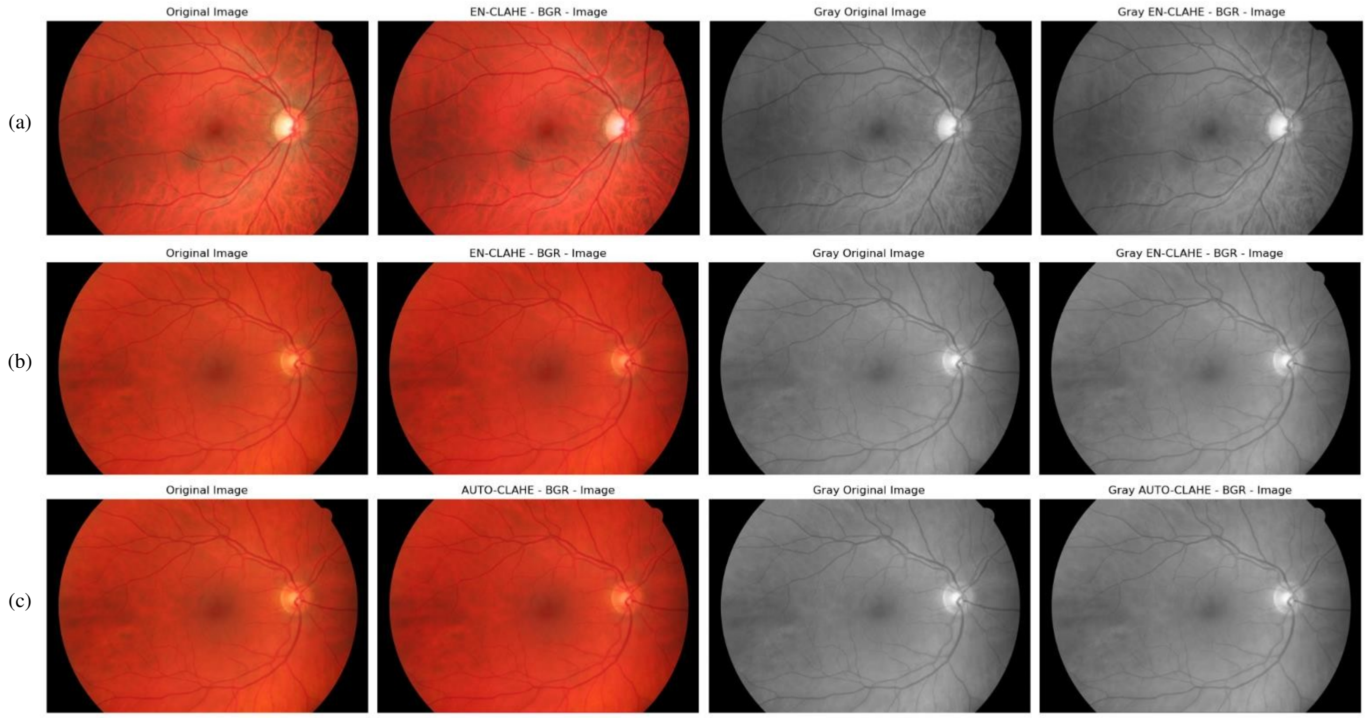

Fig. 3. (a, b): En-CLAHE, (c) auto-CLAHE.

A. Enhanced -CLAHE Observations

In this instance, eight tiles were used. The result of the healthy fundus using the En-CLAHE algorithm is shown in Figure 3(a). The result of a fundus with glaucoma under the suggested En-CLAHE algorithm is shown in Figure 3(b).

B. Findings and Analysis

The experiments were carried out using a PC with Python 3.9. Two steps are involved in implementing the CLAHE algorithm: First, the clip limit was set from 0.8 to 2.0, and the number of tiles was fixed at 8. The second step maintains the same clip restriction as the first but with a different number of tiles. The CLAHE results demonstrate that to achieve the maximum possible improvement, the selection of the appropriate clip limit value was crucial. En-CLAHE offers a solution for the problem by adaptively choosing the clip limit based on the sub-image histogram. The number of tiles n was the same when tested using the En-CLAHE approach. Therefore, a method that determines n and the clip limit based on the contents of an image is required. The Auto-CLAHE process takes one to two minutes on the aforementioned equipment. Table I shows a comparison of the methods using Peak-Signal-to-Noise Ratios (PSNR). Img1 and Img2 denote healthy fundus while Img3 and Img4 denote glaucomatous fundus. The table above describes the comparison of CLAHE with Enhanced-CLAHE and Auto-CLAHE. This approach offers an efficient and accurate solution to detect fundus diseases and also supports early diagnosis and treatment. Figure 4 shows a graph representation of the above table.

TABLE I. COMPARISON OF CLAHE WITH ENHANCED-CLAHE AND AUTO-CLAHE

Methods	Img1	Img2	Img3	Img4
CLAHE under HSV	31.450	32.494	32.100	32.332
CLAHE under BGR	34.447	35.423	34.339	34.384
Enhanced-CLAHE	66.596	66.387	68.499	68.417
Auto-CLAHE	69.587	69.374	69.483	69.407

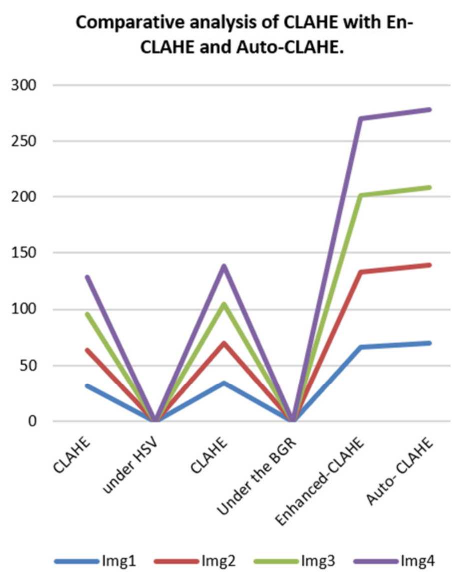

Fig. 4. Plot of comparative analysis.

VII. CONCLUSION

This study introduces a robust and clinically oriented pipeline for the diagnosis of glaucoma using enhanced image processing on retinal fundus images. Glaucoma is one of the leading causes of vision loss and its detection at an early stage is critical. The primary challenge addressed in this study is the enhancement of retinal fundus images for early glaucoma detection. This study used two innovative methods, named En-CLAHE and Auto-CLAHE, which significantly improve image quality and detection accuracy. En-CLAHE effectively minimizes the noise of the image by dynamically adjusting the clip limit based on the intensity of the sub-images. However, it remains partially subjective due to the use of a limited number of sub-images. In contrast, Auto-CLAHE automates the selection of clip limits and tile counts, making it more adaptable and capable of consistently producing better results.

The novelty of this approach lies in its ability to enhance low-contrast retinal images, thereby increasing their clarity and diagnostic value. With high-resolution techniques, this study compared the results with original images and obtained excellent image quality to detect diseases more efficiently and also to support early diagnosis of the disease and treatment.

REFERENCES

[1] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, 2nd ed. Upper Saddle River, NJ, USA: Prentice Hall, 2002.

[2] P. J. Saine and M. E. Tyler, *Ophthalmic Photography: Retinal Photography, Angiography, and Electronic Imaging*, 2nd ed. Boston, MA, USA: Butterworth-Heinemann, 2001.

[3] D. Wong, "Fundus photography and fluorescein angiography," *Journal of Ophthalmic Photography*, vol. 2, no. 1, pp. 37–45, Aug. 1979.

[4] M. H. A. Fadzil, H. A. Nugroho, H. Nugroho, and I. L. Iznita, "Contrast Enhancement of Retinal Vasculature in Digital Fundus Image," in *2009 International Conference on Digital Image Processing*, Bangkok, Thailand, Mar. 2009, pp. 137–141, https://doi.org/10.1109/ICDIP.2009.32.

[5] P. Choukikar, A. K. Patel, and R. S. Mishra, "Segmenting the optic disc in retinal images using thresholding," *International Journal of Computer Applications*, vol. 94, no. 11, 2014.

[6] H. A. Rahim, A. S. Ibrahim, W. M. D. W. Zaki, and A. Hussain, "Methods to enhance digital fundus image for diabetic retinopathy detection," in *2014 IEEE 10th International Colloquium on Signal Processing and its Applications*, Kuala Lumpur, Malaysia, Mar. 2014, pp. 221–224, https://doi.org/10.1109/CSPA.2014.6805752.

[7] K. A. Goatman, A. D. Fleming, S. Philip, G. J. Williams, J. A. Olson, and P. F. Sharp, "Detection of New Vessels on the Optic Disc Using Retinal Photographs," *IEEE Transactions on Medical Imaging*, vol. 30, no. 4, pp. 972–979, Apr. 2011, https://doi.org/10.1109/TMI.2010.2099236.

[8] A. Huertas and G. Medioni, "Detection of Intensity Changes with Subpixel Accuracy Using Laplacian-Gaussian Masks," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PAMI-8, no. 5, pp. 651–664, Sep. 1986, https://doi.org/10.1109/TPAMI.1986.4767838.

[9] X. J. Jing, N. Yu, and Y. Shang, "Image filtering based on mathematical morphology and visual perception principle," *Chinese Journal of Electronics*, vol. 13, no. 4, pp. 612–616, 2004.

[10] F. Ortiz and F. Torres, "Vectorial morphological reconstruction for brightness elimination in colour images," *Real-Time Imaging*, vol. 10, no. 6, pp. 379–387, Dec. 2004, https://doi.org/10.1016/j.rti.2004.10.002.

[11] X. Bai, F. Zhou, and B. Xue, "Image enhancement using multi scale image features extracted by top-hat transform," *Optics & Laser*

Technology, vol. 44, no. 2, pp. 328–336, Mar. 2012, https://doi.org/10.1016/j.optlastec.2011.07.009.

[12] Y. Yang, Z. Su, and L. Sun, "Medical image enhancement algorithm based on wavelet transform," *Electronics Letters*, vol. 46, no. 2, pp. 120–121, Jan. 2010, https://doi.org/10.1049/el.2010.2063.

[13] S. A. Amiri and H. Hassanpour, "A preprocessing approach for image analysis using gamma correction," *International Journal of Computer Applications*, vol. 38, no. 12, pp. 38–46, 2012.

[14] J. Majumdar and S. Kumar, "Modified CLAHE: An adaptive algorithm for contrast enhancement of aerial, medical and underwater images," *International Journal of Computer Engineering and Technology (IJCET)*, vol. 11, pp. 32–47, 2014.

[15] M. Farhan Khan, E. Khan, and Z. A. Abbasi, "Multi Segment Histogram Equalization for Brightness Preserving Contrast Enhancement," in *Advances in Computer Science, Engineering & Applications*, New Delhi, India, 2012, pp. 193–202, https://doi.org/10.1007/978-3-642-30157-5_20.

[16] K. Hasikin and N. A. M. Isa, "Fuzzy image enhancement for low contrast and non-uniform illumination images," in *2013 IEEE International Conference on Signal and Image Processing Applications*, Melaka, Malaysia, Oct. 2013, pp. 275–280, https://doi.org/10.1109/ICSIPA.2013.6708017.

[17] G. Raju and M. S. Nair, "A fast and efficient color image enhancement method based on fuzzy-logic and histogram," *AEU - International Journal of Electronics and Communications*, vol. 68, no. 3, pp. 237–243, Mar. 2014, https://doi.org/10.1016/j.aeue.2013.08.015.

[18] T. Kauppi *et al.*, "The DIARETDB1 diabetic retinopathy database and evaluation protocol," in *Proceedings of the British Machine Vision Conference 2007*, Warwick, 2007, https://doi.org/10.5244/C.21.15.

[19] "DRIVE - Grand Challenge." [Online]. Available: https://drive.grand-challenge.org/.

[20] "DRIVE Digital Retinal Images for Vessel Extraction." Kaggle, [Online]. Available: https://www.kaggle.com/datasets/andrewmvd/drive-digital-retinal-images-for-vessel-extraction.

[21] S. S. Mahmood, S. Chaabouni, and A. Fakhfakh, "Improving Automated Detection of Cataract Disease through Transfer Learning using ResNet50," *Engineering, Technology & Applied Science Research*, vol. 14, no. 5, pp. 17541–17547, Oct. 2024, https://doi.org/10.48084/etasr.8530.

[22] Z. S. Alzamil, "Advancing Eye Disease Assessment through Deep Learning: A Comparative Study with Pre-Trained Models," *Engineering, Technology & Applied Science Research*, vol. 14, no. 3, pp. 14579–14587, Jun. 2024, https://doi.org/10.48084/etasr.7294.

[23] A. Sarhan, J. Rokne, and R. Alhajj, "Glaucoma detection using image processing techniques: A literature review," *Computerized Medical Imaging and Graphics*, vol. 78, Dec. 2019, Art. no. 101657, https://doi.org/10.1016/j.compmedimag.2019.101657.

[24] A. Shoukat, S. Akbar, S. A. E. Hassan, A. Rehman, and N. Ayesha, "An Automated Deep Learning Approach to Diagnose Glaucoma using Retinal Fundus Images," in *2021 International Conference on Frontiers of Information Technology (FIT)*, Islamabad, Pakistan, Dec. 2021, pp. 120–125, https://doi.org/10.1109/FIT53504.2021.00031.