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An improved neighbourhood-based contrast limited adaptive histogram equalization method for contrast enhancement on retinal images

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Abstract

● **AIM:** To find the effective contrast enhancement method on retinal images for effective segmentation of retinal features.

● **METHODS:** A novel image preprocessing method that used neighbourhood-based improved contrast limited adaptive histogram equalization (NICLAHE) to improve retinal image contrast was suggested to aid in the accurate identification of retinal disorders and improve the visibility of fine retinal structures. Additionally, a minimal-order filter was applied to effectively denoise the images without compromising important retinal structures. The novel NICLAHE algorithm was inspired by the classical CLAHE algorithm, but enhanced it by selecting the clip limits and tile sized in a dynamical manner relative to the pixel values in an image as opposed to using fixed values. It was evaluated on the Drive and high-resolution fundus (HRF) datasets on conventional quality measures.

● **RESULTS:** The new proposed preprocessing technique was applied to two retinal image databases, Drive and HRF, with four quality metrics being, root mean square error (RMSE), peak signal to noise ratio (PSNR), root mean square contrast (RMSC), and overall contrast. The technique performed superiorly on both the data sets as compared to the traditional enhancement methods. In order to assess the compatibility of the method with automated diagnosis, a deep learning framework named ResNet was applied in the segmentation of retinal blood vessels. Sensitivity, specificity, precision and accuracy were used to analyse the performance. NICLAHE–enhanced images outperformed the traditional techniques on both the datasets with improved accuracy.

● **CONCLUSION:** NICLAHE provides better results than traditional methods with less error and improved contrast-related values. These enhanced images are subsequently measured by sensitivity, specificity, precision, and accuracy, which yield a better result in both datasets.

● **KEYWORDS:** contrast limited adaptive histogram equalization; retinal imaging; image preprocessing; contrast enhancement

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INTRODUCTION

The human eye is a vital component of the body. It offers us a clear vision. People view and appreciate the world's beauty with their eyes. Vision issues like diabetic retinopathy (DR), cataracts, and glaucoma will arise as a result of certain unhealthy factors like stress, heart disease, diabetes, aging, and medications. With early detection and appropriate treatment, 90% of diabetes-related vision impairments can be resolved[1]. To diagnose retinal illness, ophthalmologists do fundus examinations of the eyes. They take retinal fundus pictures, which they subsequently analyze to determine the precise ailment. Occasionally, inadequate lighting and digital noise will result in a low-quality image. Occasionally, the picture gets too bright or too black. Figure 1 shows the different type of fundus images.

Images of the fundus of the eye show pathological features like microaneurysms, haemorrhages, exudates, and cotton wool patches, in addition to retinal structural structures like the optic disc and blood vessels. Lesions known as microaneurysms manifest as tiny red dots in the retina. Haemorrhages are areas of blood leaking in the retina that manifest as red patches.

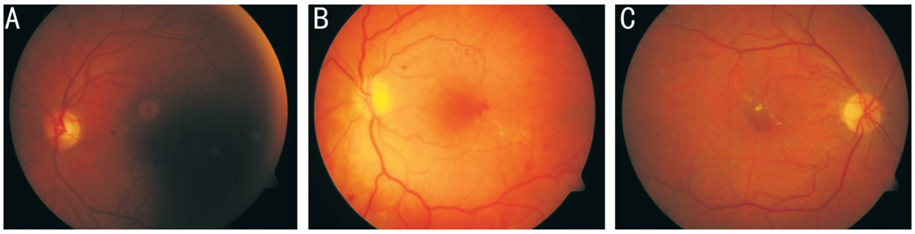

Figure 1 Types of fundus images A: Too dark image; B: Too bright image; C: Normal image.

Protein leakage in the retinal vessels causes exudates and cotton-wool patches. On the retina, these appear as vibrant colors. The different retinal and pathogenic structures are displayed in Figure 2.

In the manual contrast improvement on retinal fundus images, traditional procedures are usually inadequate owing to varied illuminations, noises as well as anatomical variations. In order to mitigate those drawbacks and maximize the quality of inputs to artificial intelligence (AI) models, different contrast enhancement methods are used[2]. Among them are histogram equalization, which increases the overall contrast distribution; contrast limited adaptive histogram equalization (CLAHE) which locally increases the contrast but limits the noise amplification; and gamma correction which maps the brightness nonlinearly[3]. Also, the Retinex algorithm is applied to emulate human visual system and recover the illumination problems and adaptive contrast enhancement (ACE) is a dynamic contrast adjusting method depending on the local image statistics. Homomorphic filtering is also used to box out the boost reflectance components, diminishing lighting artifacts and boosting precision.

Numerous methods are available for detecting retinal fundus disease related to contrast enhancement. Some of the existing detection approaches are studied and reviewed below.

The gamma correction using singular value decomposition (SVD) and discrete wavelet transformation (DWT) picture-enhancing techniques was proposed by Sharma and Verma[4]. To enhance the contrast of the fundus images, Huang *et al*[3] presented the adaptive gamma correction using weighing distribution. The contrast enhancement method based on normal convolution with noise removal was proposed by Dai *et al*[5]. To increase the contrast of fundus images, Zhou *et al*[6] offered a combination of approaches that comprise gamma correction on the V-channel of Hue-saturation-value (HSV) color space and CLAHE on the luminosity channel of L*a*b color space. Palanisamy *et al*[7] suggested an enhancement to Zhou *et al*'s[6] approach. It applies CLAHE to the luminosity channel of the L*a*b color space image after applying DWT to the gamma corrected V-channel of the HSV color space image. An enhanced technique for histogram analysis was suggested by Intajag *et al*[8]. To increase the contrast of the fundus image, they used index of fuzziness logic and histogram partitioning

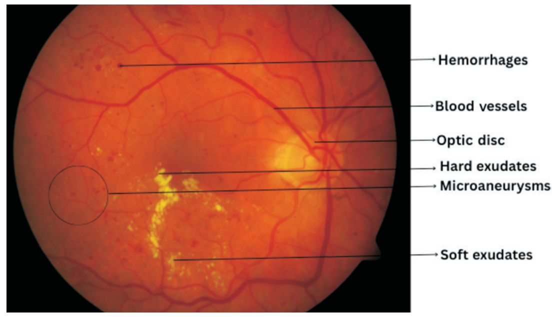

Figure 2 Retinal fundus image with anatomical and pathological structures.

on the green channel. The pipeline of image improvement and noise removal method for fundus images acquired by smartphones was proposed by Elloumi *et al*[9]. It has a Butterworth filter to reduce noise and a CLAHE for picture enhancement. Sonali *et al*[10] used various denoising filters on the improved image to reduce noise and the CLAHE on three separate channels to boost contrast. They demonstrated that the weighted average filter and CLAHE outperformed other filters on fundus pictures by comparing the findings. To improve the contrast of the fundus image, Mitra *et al*[11] presented a histogram equalization-based method on the image's HSV color space. Kumar *et al*[12] implemented the Moth Swarm Algorithm on the value channel of the HSV color model. Then applied CLAHE technique to the Luminosity (L) channel of the L*a*b color space. Singh *et al*[13] provided a contrast enhancement algorithm which varies with gamma correction through cumulative histogram and uses median filtering to enhance the contrast of the retinal fundus images. Hou *et al*[14] offered reference-free image quality enhancement (RF-IQE) framework that can facilitate the convenient and reference-free optimization of low-quality fundus images, without the costly paired data available, and enhance the visual image quality and the diagnostic value of the imaging operations in a clinical setting. Naz and Ahuja[15] showed a good example of the preprocessing pipeline composed of the median filtering and the histogram equalization in the HSV color space to perform the usefulness of the contrast enhancement. Srinivas and Bhandari[16] suggested an approach that involves the use of the Hopfield Neural Network with modification to calculate the energy curve of the image. Then they used the energy curve equalization technique in enhancing the better contrast.

A generative adversarial network model was presented by You *et al*[17] for the purpose of enhancing contrast in retinal fund images. Aurangzeb *et al*[18] have developed a variation of CLAHE whileapplying modified particle swarm optimization (MPSO) for CLAHE parameter tuning. Some researchers proposed a variant of CLAHE by altering parameters like tile size, clipping limit, and color space processing[19-20]. Some proposed with the carrying on of fuzzy modules[21-22]. Vasa *et al*[23] offer a deep unpaired optimal transfer learning framework, which aligns the distribution of images with the preservation of local structures. A residual densely linked UNet architecture model was presented by Raj *et al*[24] in an effort to enhance the contrast of retinal fundus images. It is also worth mentioning that recently machine learning and deep learning were explored to be applied to the image-contrast enhancement and showed promising results[25-28].

Although many contrast enhancement methods have been proven to effectively enhanced the quality of retinal fundus images, they are associable with significant drawbacks. Although histogram equalization increases global contrast, it can cause over-saturation and loss of fine details, particularly in areas where intensity variations are subtle[29]. More adaptive, CLAHE might, in homogeneous regions, enhance noise, which could interfere with the correct detection of subtle retinal structures like microaneurysms or hemorrhages. Gamma correction is also particular about the value of gamma used and it might not behave uniformly when applied to images which have differing lighting conditions[30]. The Retinex algorithm, which is effective at fixing uneven illumination, may add artifacts or unnatural color shifts when not carefully adjusted. ACE can lead to unnatural-looking contrast that can distort anatomical structures, and homomorphic filtering needs careful setting of parameters, and can attenuate low-frequency information that is important[31]. Also, such methods typically do not have the adaptive flexibility to deal with a large dynamic range of retinal images without use interaction. These discrepancies have the capacity to decrease the accuracy of automated analysis systems[32]. On the whole, these techniques improve visibility but are inferior in maintaining diagnostic information and managing diversity of images, thus not so robust unless delicately adapted or combined with smart algorithms. In order to overcome such constraints, a new neighbourhood-based improved contrast limited adaptive histogram equalization (NICLAHE) method is suggested in the preprocessing stage. The successive application of NICLAHE allows a better enhancement of local contrast, taking into account the neighborhood of pixels, and fine details is preserved in the retina. It lessens the magnification of noise as well as upholds the structural constancy in the diverse regions of the images.

Based on the review described, it can be seen that some of the limitations that are being addressed by the existing retinal fundus disease detection method with the described contrast enhancement. Such methods especially standard CLAHE and other histogram based methods can easily boost both significant details and noise, resulting in false implications[18]. Excessive enhancement may cause distortion of important structures like blood vessels and lesions making diagnosis less reliable. Equal enhancement cannot respond well to the uneven illumination and different image quality[33]. Because of this, even subtle pathological indications can be overlooked or incorrectly stressed. Such approaches tend to lack consistency in various imaging conditions and datasets. Besides, they are not flexible in handling low-contrast or poor quality fundus images. These disadvantages limit their usefulness in the actual clinical practice[34]. To overcome the identified research gap, the novel method of NICLAHE is proposed which determine the parameters of CLAHE dynamically for each and every image. As a result, this proposed technique prevents excessive enhancement of the homogeneous region and enhances the visibility in the region of the diagnostically relevant characteristics and also guarantees that tiny blood vessels, and abnormal retinal structures like microaneurysms are highlighted without alteration. Better contrast enhancement makes it easier to see abnormal characteristics, which directly helps ophthalmologists and enhance automated diagnostic system performance.

MATERIALS AND METHODS

Proposed Method Raw fundus images need to be processed before advanced analysis can be done on the retinal images. This done to enhance the quality of the image such that important clinical parameters like vessels, the optic disc, and the pathological alterations can be viewed easily. The significance of preprocessing cannot be assessed solely using preprocessing metrics; segmentation is also essential to evaluate its effectiveness. This research introduces a novel contrast enhancement method aimed at improving the visibility of features in retinal fundus images. After preprocessing, semantic segmentation is performed using ResNet-18. The segmentation results are compared across multiple evaluation metrics to validate the impact of different preprocessing methods. The overall pipeline of the proposed work is showed in Figure 3.

Initially, raw input images are collected and passed into the preprocessing module. Within this module, N-CLAHE is applied. The resulting preprocessed images are fed into a semantic segmentation model that identifies and classifies specific regions of interest within the retina. This step enables precise localization of clinical features. Finally, the segmented data is analyzed to generate results, which may assist in diagnosis, monitoring, or further research applications. The

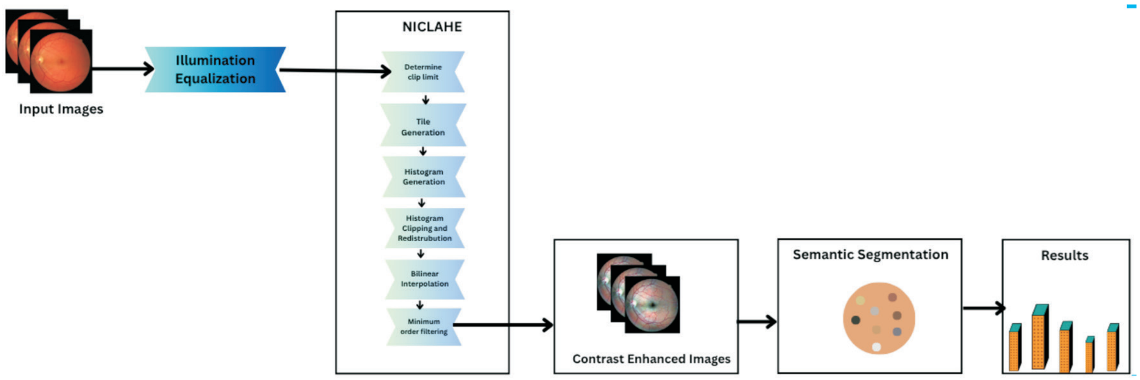

Figure 3 Architecture of proposed work NICLAHE: Neighbourhood-based improved contrast limited adaptive histogram.

detailed step-by-step process of the proposed method is explained below.

Illumination Equalization Illumination refers to the uneven distribution of light intensity in a retinal image. This non-uniformity often occurs due to variations in the fundus camera's focus on the retina[35]. During the preprocessing stage, illumination equalization is essential because it corrects these variations, particularly the darker edges commonly seen in retinal images.

In most cases, equalization is applied to the green channel of a color fundus image, as this channel provides the best contrast for retinal structures[24,36-37].

In our proposed method, illumination equalization is carried out using the following formula Equation 1[38].

$$I_{ie}=I+m-I_f \tag{1}$$

In this case, I_{ie} stands for illumination equalized image, I for original image, m for original image mean value, and I_f for mean filter with large window size. The coefficient of picture width or height divided by ten determines the window size of the mean filter in this case. For all size-invariant datasets, this window size is adaptable. It varies according to the size of the image in various data sets since it is not a constant value.

Neighbourhood-Based Improved Contrast Limited Adaptive Histogram Equalization Even after illumination equalization, some retinal images remain low in contrast, especially in cases with hady media or poor image capture. Low contrast reduces the visibility of small-caliber vessels and early microaneurysms. The traditional CLAHE is referred to as CLAHE. In this technique, the image was divided into various sections, or tiles, using the CLAHE technique. Each tile was then subjected to histogram equalization before being combined to make the entire image. Typically, global noise in photos is eliminated using CLAHE[39]. Standard CLAHE enhances contrast by adjusting local brightness. While effective, it sometimes fails when applied to diverse retinal datasets because the clipping threshold is fixed. To address this, NICLAHE is proposed. It uses adaptive fuzzy rules to set the lcip limit depending on each image's brightness; It applied

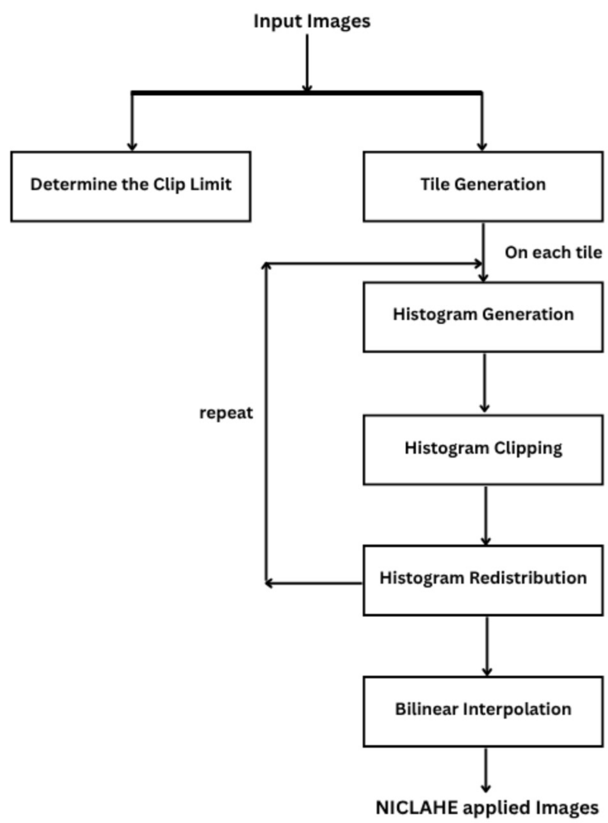

Figure 4 Flowchart of the proposed NICLAHE approach NICLAHE: Neighbourhood-based improved contrast limited adaptive histogram.

adaptive tile sizes; It reconstructs the full images by combining all locally enhanced tiles with bilinear interpolation to avoid artificial edges. This approach ensures consistent improvement across bright, dark and normal retinal images. The flowchart for the propose NICLAHE is shown in Figure 4.

Step 1 The clip limit in a typical CLAHE is determined empirically using the image. Regarding retinal fundus images, a dataset includes a range of images, including those with normal contrast, too bright, and too dark. Using a static clip limit in this situation does not work. It increases the luminance of the image[40].

We suggest the adaptive fuzzy-based clip limit as a way to prevent this. Each pixel's fuzzy neighborhood similarity for a picture is computed[41]. Equation 2, is used to determine the similarity of each pixel in an image with a 3×3 neighborhood.

$$fuzz(x,y) = max\left\{1 - I_{ie}(x,y) - \frac{I(u,v)}{\sigma}, 0\right\} \quad (2)$$

Here, *fuzz(x,y)* is the fuzzy neighborhood similarity, *I(x,y)* is the original image, *I(u,v)* is the movable window with size 3×3. σ is the standard deviation of the original image.

Standard deviation of the Fuzzy neighborhood similarity image is calculated and it is used as clip limit for the proposed CLAHE. This clip limit is not constant one and it varies for each image in the dataset based on its intensity level.

Step 2 In normal CLAHE image is decomposed into several parts which is called tiles. Here, we select the adaptive tile size. Adaptive tile size is selected based on the below Equation 3.

$$Num\ of\ Tiles = max\ (height,\ width)/100 \quad (3)$$

Step 3 Histogram is created for every single tile. A histogram of an image is a visual mapping of the occurrence of pixel intensity (brightness levels) in a given image.

Step4 Histogram is clipped based on the calculated clip limit and the clipped histograms are redistributed.

Step 5 Here after completing NICLAHE on each tile, all the tiles are combined by using bilinear interpolation method to form full complete image.

The above steps are done on each color channel.

Denoising Noise-especially "salt-and-pepper" artifacts-can mimic small hemorrhages or exudates, leading to false positives in diagnosis or segmentation. The image denoising technique is used on the contrast-enhanced image with NICLAHE in order to eliminate a few small, unique artifacts that could lead to this false positive segmentation. In this case, a 3×3 window with an ordered filter of minimum value is used. Well, it gets rid of the pepper and salt noise[42]. A 3×3 filter window is positioned across the image, and its pixel values are sorted before the least value is chosen. It prevents false detection and provides a smoother image for both human graders and AI models. The functioning of the designated filtering mechanism is shown in Figure 5.

The image denoising technique is used on the contrast-enhanced image with NICLAHE in or the 3×3 filter window is positioned so that its center is on the designated pixel that will be altered, allowing it to move through the image. The values of the nine pixels are sorted in ascending order, and the pixel location corresponds to the least value that is chosen.

Figure 6 shows the resultant images for every step of the proposed preprocessing method. Figure 6A is an input image; 6B presents each color channels of the input image; 6C shows the illumination equalized green channel; 6D displays the tiles generated for each color channel; 6E shows the histogram of each tiles; 6F presents the histogram equalized tiles; 6G shows the combined image formed from all histogram equalized tiles;

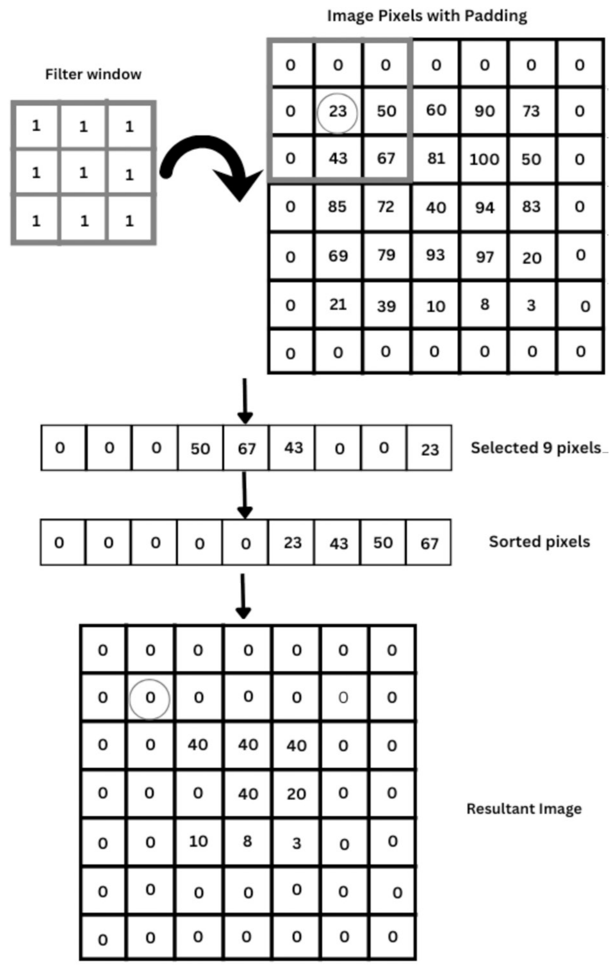

Figure 5 Working of minimum order filter.

6H displays the denoised image; 6I shows the final enhanced color image, created by combining all the processed color channels. Because of the size of the figure showed in 6E is too small to recognize, the histogram of a single tile is showed in Figure 7 as enhanced manner. Here, horizontal axis represent the gray levels of an image which 0 to 255; vertical axis represent the number of pixels in the particular gray level.

Semantic Segmentation with Resnet-18 This study employs a semantic segmentation technique, commonly referred to as pixel segmentation. Semantic segmentation connects each pixel with its class, resulting in an image where each pixel is a member of a particular group. Different colors are applied to various groups in order to differentiate them from one another. The initial semantic segmentation techniques were swiftly superseded by classical machine learning algorithms. They were then surpassed by deep learning, which was developed and turned out to be significantly more effective than humans[43].

In this work, suggested and additional contrast enhancement approaches are used to perform semantic segmentation of retinal blood vessels on pre-processed images. Their segmentation outcomes are assessed using metrics including accuracy, sensitivity, specificity, and confusion matrix. For

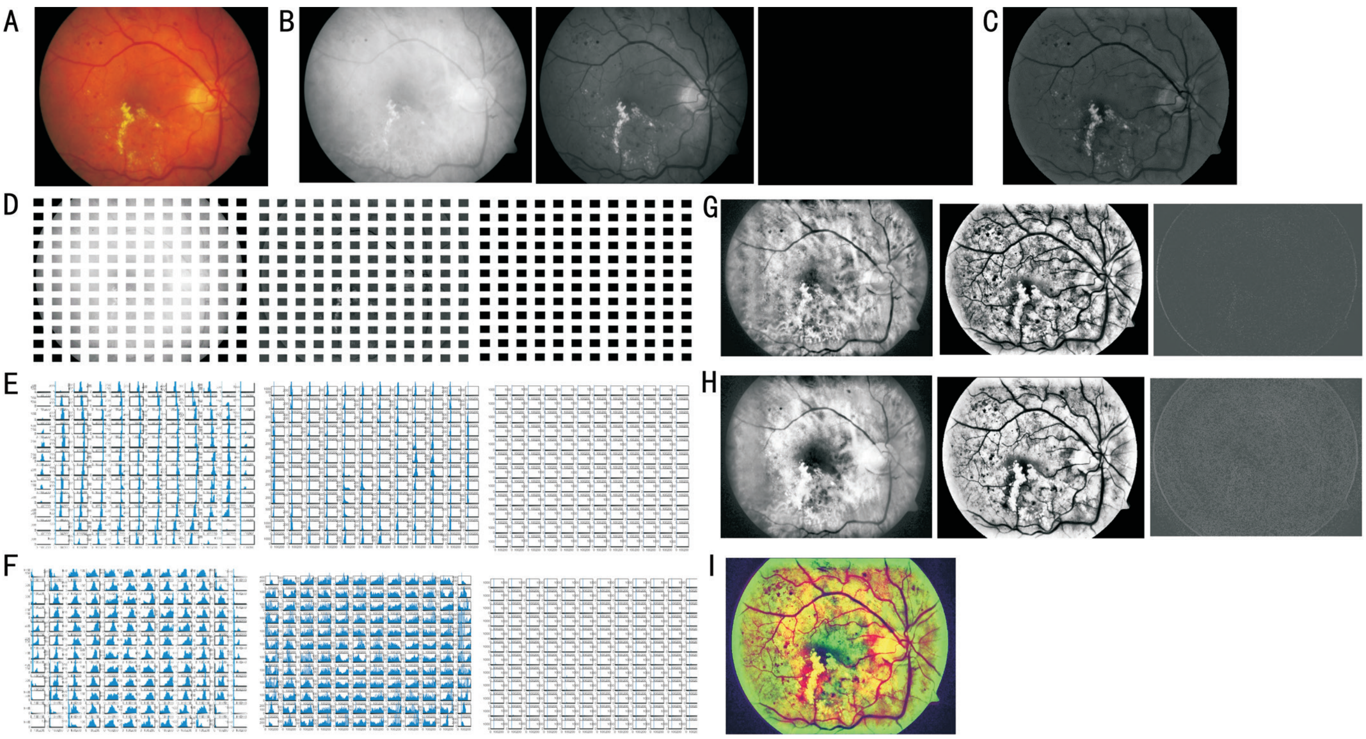

Figure 6 Resultant images of the proposed preprocessing method A: Input RGB fundus images; B: Three color channels of input image; C: Illumination equalized green channel; D: Tiles of each color channel; E: Histogram of each tile; F: Histogram-equalized tiles; G: NICLAHE applied images; H: Denoised images; I: Final enhanced color image. NICLAHE: Neighbourhood-based improved contrast limited adaptive histogram.

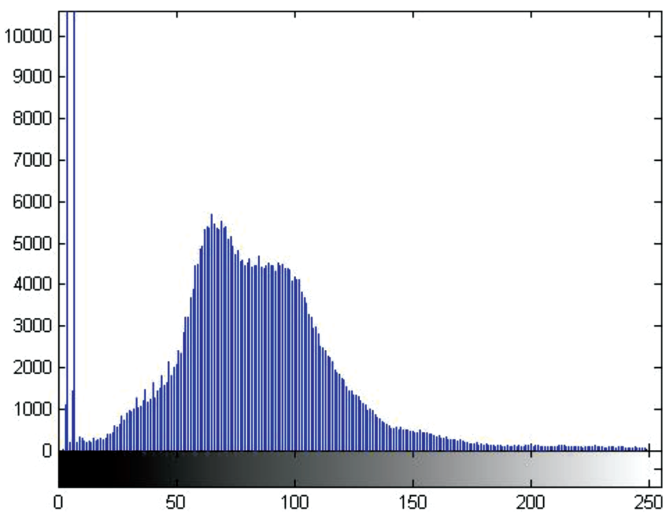

Figure 7 Histogram of a single tile of an image.

semantic segmentation, the "Resnet-18" model is used. This particular model is intended for semantic segmentation. A convolutional neural network with eighteen layers is called Resnet-18. In order to facilitate the easy flow of information from one layer to the next, residual networks typically use skip connections. A kind of residual network is called Resnet-18. The image with an input size of 224×224×3 is used. In this case, 224×224 denotes an image's height and weight. The image's color channel is denoted by 3. The retinal blood vessels are separated from the previously processed contrast-enhanced pictures using this approach. The ResNet-18 architecture design can be seen in Figure 8.

MATERIALS

Dataset Description The images of Drive dataset[44] were acquired using a Canon CR5 non-mydriatic 3CCD camera with a 45 degree field of view (FOV). Each image was captured using 8 bits per color plane at 768 by 584 pixels. The FOV of each image is circular with a diameter of approximately 540 pixels. For this database, the images have been cropped around the FOV. For each image, a mask image is provided that delineates the vascular regions. The set of 40 images has been divided into a training and a test set, both containing 20 images. For the training images, a single manual segmentation of the vasculature is available. For the test cases, two manual segmentations are available; one is used as gold standard, the other one can be used to compare computer generated segmentations with those of an independent human observer. Furthermore, a mask image is available for every retinal image, indicating the region of interest. All human observers that manually segmented the vasculature were instructed and trained by an experienced ophthalmologist. They were asked to mark all pixels for which they were for at least 70% certain that they were vessel.

High-resolution retinal fundus images[45], which are commonly utilised for the diagnosis and detection of DR, a disorder that damages diabetic patients' eyes, are included in the high-resolution fundus (HRF) collection. These pictures can assist computer vision algorithms or machine learning models in identifying retinal symptoms of DR. It contains retinal fundus

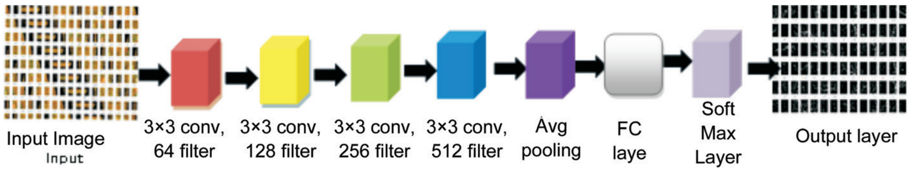

Figure 8 Architecture of ResNet 18 for semantic segmentation.

images, which show the back of the eye with symptoms of DR, including exudates, haemorrhages, and microaneurysms. A detailed description of these datasets is provided in Table 1.

RESULTS

After applying the propose NICLAHE method on fundus images, the images are divided into 224×224 patches. The patches are now divided into two halves. Of all the patches, 75% are chosen for training, while the remaining 25% are chosen for testing. With the hyper parameters discussed on Table 2, semantic segmentation is experimented.

The hyper-parameters outlined in Table 2 were selected for the experiment after evaluating multiple configurations. Among these, the ADAM optimizer delivered the most effective performance. Specifically, the combination of 200 training epochs, a mini-batch size of 4, and a learning rate of 0.001 yielded better results compared to other settings. This configuration consistently demonstrated improved accuracy and stability throughout the evaluation process. As a result, it was adopted for the final implementation.

To evaluate the suggested methodology, two categories of metrics are utilized. The first set focuses on assessing the contrast enhancement technique. Metrics used include root mean square error (RMSE), peak signal-to-noise ratio (PSNR), root mean square contrast (RMSC), and contrast (Tables 3-4). These help determine the visual quality and enhancement effectiveness. The second set evaluates the segmentation performance. Accuracy, sensitivity, specificity, and precision are considered. These metrics measure how the enhancement impacts the detection of retinal features.

Metrics for Contrast Enhancement Evaluation

Root mean square error The level of noise amplification during contrast enhancement is measured using this measure. The Equation 4 is used to calculate an RMSE

$$RMSE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(I(i,j)-Ie(i,j))^2}{m*n} \tag{4}$$

A low RMSE score shows that the contrast enhancement has not degraded the image quality. Low RMSE further suggests that the contrast enhancement is not amplifying noise. A high RMSE indicates that the image noise is increased by the contrast enhancement approach.

Peak signal to noise ratio PSNR determine that the noise level enhanced during the contrast enhancement. It is calculated using the Equation 5.

Table 1 Dataset information

Name	No. of images	Resolution
Drive	40	565×584
HRF	45	3504×2336

HRF: High-resolution fundus.

Table 2 Hyper-parameters used in ResNet-18

Optimizer	Epochs	Mini-Batch size	Learning rate
-	250	32	-
ADAM	200	16	0.001
SGDM	150	8	0.0001
-	100	4	-

Table 3 Measures of proposed method on HRF dataset

Method	RMSE	PSNR	RMSC	Contrast
NICLAHE	2.065054	11.16751	2.323706	2.60408

RMSE: Root mean square error; PSNR: Peak signal to noise ratio; RMSC: Root mean square contrast; NICLAHE: Neighbourhood-based improved contrast limited adaptive histogram.

Table 4 Measures of proposed method on DRIVE dataset

Method	RMSE	PSNR	RMSC	Contrast
NICLAHE	2.877595	23.20348	3.148947	5.491212

RMSE: Root mean square error; PSNR: Peak signal to noise ratio; RMSC: Root mean square contrast; NICLAHE: Neighbourhood-based improved contrast limited adaptive histogram.

$$PSNR = 10\ \log_{10}\frac{MAX\ VAL}{MSE} \tag{5}$$

Here, "MAX VAL" represents the maximum intensity of the image. Mean square error (MSE) is the basis for the PSNR value. PSNR will increase if the MSE value is low. PSNR will decrease if the MSE value is large. When the PSNR is high, it indicates that there is no noise amplified in the contrast-enhanced image. A low PSNR indicates that the noise is amplified in the contrast-enhanced image.

Root mean square contrast This metric is used to measure the contrast level increase due to the contrast enhancement. It is calculated using the Equation 6

$$RMSC = \sqrt{\frac{1}{XY}\sum_{i=0}^{X-1}\sum_{j=0}^{Y-1}(I_{ij}-\bar{I})^2} \tag{6}$$

Here, X and Y represent the height and width of the image. I_{ij} represents the pixel of the image in ij^{th} position. $\bar{I}$ represents the mean value of the image.

If the RMSC value is high, then it indicates that the contrast of the image is increased. If the RMSC value is low, then it indicates that the contrast of the image is decreased[46-47].

Contrast This metric is used to asses how the contrast of the image is increased. It is calculated using the Equation 7.

$$Contrast = \frac{1}{N}\sum_{i=1}^{U}\sum_{j=1}^{V} I^2(i,j) - \left(\frac{1}{N}\sum_{i-1}^{U}\sum_{j=1}^{V} I(i,j)\right)^2 \quad (7)$$

It is defined as the variance between the image pixel and its surrounding pixels. Here, U and V represents the height and width of the image. N represents the maximum intensity of the image. I represents the image.

If the contrast metric is high, then it indicates that the contrast enhancement of the image is good. If the contrast metric is low, then it indicates that the contrast enhancement of the image is poor.

Metrics for Segmentation of Retinal Features Evaluation

After contrast enhancement, semantic segmentation is done on the contrast-enhanced images to know how the contrast enhancement made an impact on the segmentation of retinal structures. Using ResNet-18, the pixels of an image are classified into two categories. They are pixels that belong to blood vessels or pixels that belong to the background. After the segmentation, the results are evaluated using the following metrics.

Accuracy The segmentation algorithm is assessed using the metric of accuracy. It establishes how the pixels are accurately categorized into the appropriate groupings, such as background and blood vessels. Equation 8 is used in the calculation.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (8)$$

Sensitivity Sensitivity is the metric, which measures how many pixels are correctly classified as blood vessels. It is calculated using the Equation Equation 9

$$Sensitivity = \frac{TP}{TP+FN} \quad (9)$$

Specificity Specificity is the metric, which is used for analyzing the semantic segmentation. It measures how many pixels are correctly classified as background. It is calculated using the Equation 10.

$$Specificity = \frac{TN}{TN+FP} \quad (10)$$

Precision It is the measure used to compare the correctly classified blood vessels with the correctly classified blood vessels and background pixels. It is calculated using the Equation 11

$$Precision = \frac{TP}{TP+FP} \quad (11)$$

Here all, true positive (TP) are the pixels that are correctly classified as blood vessels. True negative (TN), are the pixels that are correctly classified as background. False positive (FP) are the background pixels, that are wrongly classified as blood vessels. False negative (FN) are the blood vessels pixels, that are wrongly classified as background.

Table 5 Semantic segmentation results on HRF dataset

Method	Sensitivity	Specificity	Precision	Accuracy
NICLAHE	0.89	0.963	0.674	0.9265

NICLAHE: Neighbourhood based contrast limited adaptive histogram equalization; HRF: High-resolution fundus.

Table 6 Semantic segmentation results on drive dataset

Method	Sensitivity	Specificity	Precsion	Accuracy
NICLAHE	0.932	0.923	0.9236	0.9275

NICLAHE: Neighbourhood based contrast limited adaptive histogram equalization.

Tables 5 and 6 shows the semantic segmentation results in terms of sensitivity, specificity, precision and accuracy measures on HRF and Drive dataset. The blood vessel segmentation achieved 0.9265 accuracy on HRF dataset and 0.9275 accuracy on Drive dataset. Among all the measures, NICLAHE yields the good results on semantic segmentation using ResNet-18. It clearly exhibits that the retinal fundus images which are enhanced using NICLAHE yields the good segmentation on retinal features segmentation for Drive and HRF datasets.

DISCUSSION

The proposed NICLAHE method is analysed by the beside metrics RMSE, PSNR, RMSC and Contrast, and compared with the conventional contrast enhancement methods such as histogram equalization (HE), adaptive histogram equalization (AHE), and CLAHE.

The comparison of such traditional methods with NICLAHE on HRF and Drive datasets are shown in the Figures 9 and 10.

From the Figures 9 and 10, it is evident that the proposed NICLAHE method outperforms existing contrast enhancement techniques. On the HRF dataset, the proposed NICLAHE approach achieved superior results than the conventional methods. These values reflect its strong ability to enhance image detail and clarity. Among all compared methods, NICLAHE delivers the highest contrast, ensuring better visual distinction. The elevated PSNR indicates improved image quality with minimal distortion. Although the RMSE is high, it corresponds with enhanced edge sharpness rather than noise. The maximum RMSC further confirms its effectiveness in contrast preservation. Overall, NICLAHE performs exceptionally on the HRF dataset. On the Drive dataset, the proposed NICLAHE achieved greatest results. These results indicate a significant enhancement in image quality. Compared to other methods, NICLAHE yields the highest PSNR, RMSC, and Contrast. Although RMSE is also higher, it reflects sharper transitions rather than degradation. The overall results demonstrate superior visual enhancement. Thus, NICLAHE proves to be highly effective for Drive dataset images.

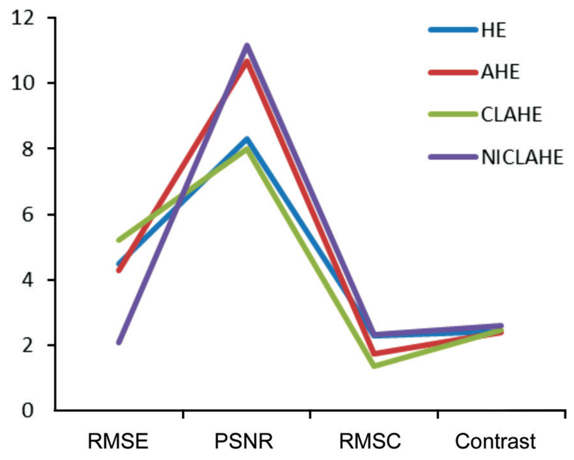

Figure 9 Comparison of NICLAHE with other conventional methods on HRF dataset HRF: High-resolution fundus; HE: Histogram equalization; AHE: Adaptive histogram equalization; CLAHE: Contrast limited adaptive histogram equalization; NICLAHE: Neighbourhood-based contrast limited adaptive histogram equalization; RMSE: Root mean square error; PSNR: Peak signal to noise ratio; RMSC: Root mean square contrast.

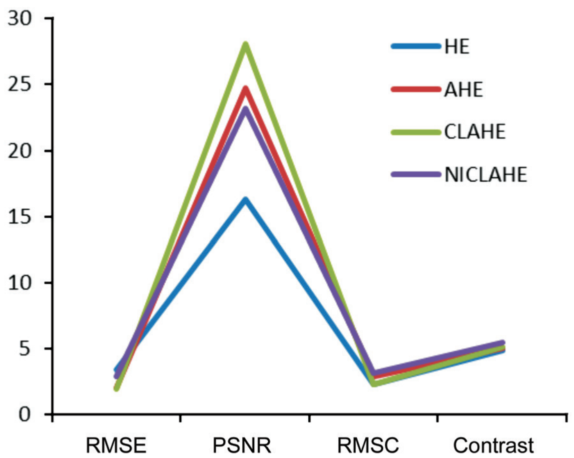

Figure 10 Comparison of NICLAHE with other conventional methods on Drive dataset HE: Histogram equalization; AHE: Adaptive histogram equalization; CLAHE: Contrast limited adaptive histogram equalization; NICLAHE: Neighbourhood-based contrast limited adaptive histogram equalization; RMSE: Root mean square error; PSNR: Peak signal to noise ratio; RMSC: Root mean square contrast.

The impact of the proposed contrast enhancement in the semantic segmentation process is going to be evaluated with the metrics of sensitivity, specificity, precision, and accuracy and those results are going to be compared with the images which are enhanced with the traditional contrast enhancement methods such as HE, AHE, and CLAHE.

Tables 7 and 8 have shown the results of the semantic segmentation on various contrast enhancement applied images of HRF and Drive datasets.

These metrics offer a comprehensive understanding of the model's capability in identifying and classifying regions of interest. These consistently high values reflect the effectiveness

Table 7 Comparison of semantic segmentation results on HRF dataset

Methods	Sensitivity	Specificity	Precision	Accuracy
HE	0.826	0.886	0.49	0.856
AHE	0.841	0.924	0.501	0.8825
CLAHE	0.830	0.959	0.508	0.895
NICLAHE	0.89	0.963	0.674	0.9265

HE: Histogram equalization; AHE: Adaptive histogram equalization; CLAHE: Contrast limited adaptive histogram equalization; NICLAHE: Neighbourhood based contrast limited histogram equalization; HRF: High-resolution fundus.

Table 8 Comparison semantic segmentation results on drive dataset

Methods	Sensitivity	Specificity	Precision	Accuracy
HE	0.956	0.886	0.893	0.921
AHE	0.968	0.861	0.8744	0.9145
CLAHE	0.953	0.90	0.905	0.9265
NICLAHE	0.932	0.923	0.9236	0.9275

HE: Histogram equalization; AHE: Adaptive histogram equalization; CLAHE: Contrast limited adaptive histogram equalization; NICLAHE: Neighbourhood based contrast limited histogram equalization.

and adaptability of the method in handling diverse retinal imaging tasks and datasets. The performance metrics further highlight the superiority of the NICLAHE method over conventional approaches. The improvements are evident across all datasets. This suggests that NICLAHE enhances critical features that contribute to more accurate segmentation. The method's consistency and robustness make it effective for retinal image analysis.

The results of the comparison of the impacts of the proposed NICLAHE in the semantic segmentation using ResNet-18 on the different supervised and unsupervised semantic segmentation were demonstrated in Table 9[18,33,48-54].

Despite the outstanding sensitivity rates of the proposed NICLAHE approach with semantic segmentation on Drive and HRF datasets, the accuracy rates of the method comprise rather nearly levels of 0.9275 and 0.9265 on the Drive and HRF datasets, respectively, which is somewhat low, particularly in contrast with the other recent approaches. This amount of difference can be attributed to the increased number of false positives as witnessed by the much lower precision value of 0.674 on the HRF dataset. The decreased accuracy implied that despite the efficiency of the model in labeling a greater proportion of the true positive vessels pixels, the model has an issue attaining a high precision likely due to misclassifications of vessel boundaries or of complex background pixels. This kind of misclassification may contribute dilution to the overall accuracy measure, especially on datasets like HRF where images and pathologies offer additional challenges. The other approaches presented in the Table 9 employ complicated

Table 9 Comparison of semantic segmentation and NICLAHE with previous literature models

Methods	Year	Dataset	Sensitivity	Specificity	Precision	Accuracy
MF-FDOG[48]	2010	Drive	0.712	-	-	0.9382
B-COSFIRE filter[49]	2015	Drive	0.7655	0.9704	-	0.9442
LAD-OS[50]	2016	Drive	0.7743	0.9725	-	0.9476
LAD-OS[50]	2016	HRF	0.7978	0.9717	-	0.9556
CNN+structured prediction[51]	2017	Drive	0.7691	0.9801	0.8498	0.9533
DCNN[52]	2019	Drive	0.7839	0.989	-	0.9709
SS+MPSO[18]	2021	Drive	0.8315	0.9787	-	0.962
ANN with Zernike Features[53]	2020	Drive	0.6994	0.9811	0.8484	0.945
SS with CNN[33]	2023	Drive	0.7092	0.982	-	0.9447
Attention U-Net[54]	2025	HRF	0.9266	-	-	0.9673
Attention U-Net[54]	2025	Drive	0.8756	-	-	0.9497
SS+NICLAHE[Proposed]	2025	Drive	0.932	0.923	0.9236	0.9275
SS+NICLAHE[Proposed]	2025	HRF	0.89	0.963	0.674	0.9265

MF-FDOG: Multi-scale frangi-filtered difference of Gaussian; B-COSFIRE: Bar-selective combination of shifted filter responses; LAD-OS: Adaptive derivative filter on orientation score; DCNN: Dilated multi-scale convolutional neural network; SS: Semantic segmentation; NICLAHE: Neighbourhood based contrast limited adaptive histogram equalization.

preprocessing and semantic segmentation of blood vessels methods. This research achieves the high sensitivity and high precision on Drive datasets using our simplified proposed method. It achieves a bit less specificity and accuracy than the prior literature.

Clinical Significance The above results show that NICLAHE achieves the high contrast and vessel visibility were achieved without significant noise amplification. It helps in the early detection of micro vascular changes. This proposed NICLAHE works on both bright and dark fundus photographs and supports screening and automated diagnosis of retinal vascular diseases.

Future Work Although the proposed approach get satisfactory RMSE, PSNR, RMSC and contrast measures, it obtain slightly low accuracy as compared to the past literatures. As a future work, it is planned to investigate adaptive preprocessing techniques that are guided by deep learning to achieve robustness. Segmentation with attention based mechanisms can also increase accuracy. Besides, the system can be further developed to accommodate multi-modal medical imaging to give a holistic diagnosis. They could also be implemented in real time to be used in practical clinical use.

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