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Research paper

Efficient Segmentation of Retinal Blood Vessels in The Fundus Images Using Morphological Image Processing

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Abstract

The segmentation of retinal blood vessels is critical in diagnosing and monitoring a variety of retinal disorders, such as hypertension, diabetes, glaucoma, and other ocular and cardiovascular problems. Retinal fundus pictures can aid in the early identification and management of these disorders by providing essential details about the status of the blood vessels in the retina. Manual evaluation of retinal fundus pictures by qualified ophthalmologists or experts takes time and requires competence. To address these issues, an automated system for the purpose of diagnosing and treating eye illnesses, a computerized image processing tool to divide the blood vessels that comprise of the retina. The vessel extraction methodology is carried out in three stages: preprocessing, blood vessel segmentation, and performance metric analysis. The green channel is extracted from the input image during preprocessing, and the contrast is enhanced using CLAHE. After preprocessing, the image undergoes a morphological operation followed by Otsu thresholding to segment the image has pixels that represent vessels and non-vessels, respectively. This method is validated on the DRIVE and HRF datasets, and the performance is measured in terms of accuracy, sensitivity, and specificity.

Keywords: *Fundus Image; Blood Vessels; CLAHE; Segmentation; Otsu Thresholding.*

1. Introduction

In the discipline of ophthalmology, the segmentation of the blood vessels in the retina is a critical component of medical image processing. It includes extracting and delineating the blood vessels from retinal fundus images, which are non-invasive pictures taken by specialized cameras to see the retina. In the diagnosis, surveillance, and treatment of several retinal illnesses, including hypertension, diabetes, glaucoma, and cardiovascular disorders, the segmentation of retinal blood vessels is of utmost importance. These disorders may be present if abnormalities in the patient's condition are shown via the retinal blood vessels. Retinal blood vessel segmentation was traditionally done by skilled ophthalmologists doing manual examinations, which is time-consuming and sensitive to inter-observer variability. As a result, the development of automated retinal blood vessel segmentation systems has become critical to increase diagnostic speed, accuracy, and consistency. Image processing and machine learning techniques are commonly used in automatic retinal blood vessel segmentation. These approaches use picture properties such as intensity, texture, and vessel shape to identify blood vessels from other retinal structures and the backdrop. A fundus photograph or fundus image, also known as a retinal fundus image, is a specialized type of medical image that the technique captures the internal structures of the eye, focusing particularly on the retina and the arteries carrying blood within it. A vital part of vision is the retina, a light-sensitive tissue in the rear of the eye. Digital cameras designed for this purpose are used to take images of the retinal fundus. The camera captures a high-resolution retinal picture with a broad field of view while placed close to the patient's eye. The procedure is painless and non-invasive, making it a helpful tool in ophthalmology for identifying and tracking eye problems. The optic disc, macula, blood vessels, and other anatomical elements of the posterior segment of the eye are all visible in this figure, as shown in Fig. 1. The macula controls central vision and is essential for tasks like reading and recognizing faces, whereas the optic disc is where the optic nerve enters the eye. Improvements have helped the creation of computer-assisted methods for studying retinal fundus pictures in image processing approaches and artificial intelligence. These automated algorithms can help identify and categorize different eye conditions, giving medical personnel another tool to improve diagnostic precision and effectiveness. The proposed work incorporates innovation by optimizing the integration of CLAHE, morphological approaches, and Otsu thresholding, resulting in computational efficiency and adaptability for low-resource contexts. Comparing the literature to U-Net and other deep learning methods reinforces it by illustrating their superior efficiency and utility in comparison to resource-intensive methods.

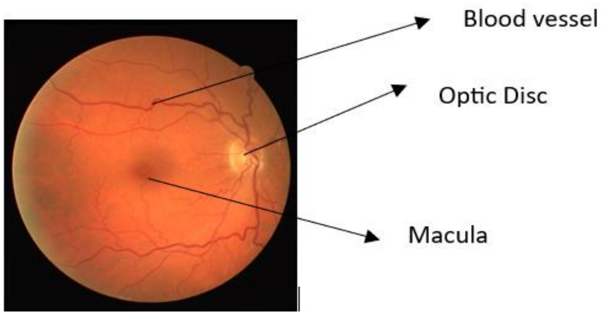


Fig. 1: Retinal Fundus Image.

2. Related Works

The segmentation of retinal blood vessels is crucial for diagnosing and treating specific eye disorders. This study looks into current improvements in deep learning-based models and traditional approaches to retinal blood vessel segmentation. It also examines commonly used datasets and performance evaluation metrics. The survey aims to provide researchers and practitioners with a comprehensive understanding of the current state-of-the-art in retinal blood vessel segmentation by critically analyzing existing studies.
Aslan et al. [1] method for blood vessel detection utilizing a combination of Gabor filters and Extreme Learning Machines (ELMs). Gabor filters and the Top-Hat transform were employed to enhance features, while ELMs classified the blood vessels. Their approach yielded an accuracy of when evaluated on the DRIVE dataset 94.59%. Another study utilized morphological operations and Otsu's thresholding [2] to segment blood vessels, attaining 95.61% accuracy on the DRIVE dataset. Li et al. [3] developed a hybrid model combining U-Net and DenseNet architectures for blood vessel segmentation in fundus images, achieving an accuracy of 96.98% on the DRIVE dataset. Additionally, Tuba et al. [4] implemented DWT coefficients as features to teach a Support Vector Machine classifier to differentiate between pictures that have blood vessels and those that don't. Both supervised and unsupervised approaches are used to propose a deformable Convolutional M-Shaped Network with a pulse-linked neural network, X. Deng et al [5] to extract blood vessels with a 96.83% accuracy. The MCET-HHO Ramos-Soto et al [6], U-net network Y. Ma et al[7], and the Improved U-net network Z. Huang et al[8] multilevel segmentation algorithms are also utilized to distinguish between the retina's blood vessels in fundus images. Reinforcement of local features M. Li et al[9], which mixes line set-based features Dash et al[10], local intensity features Upadhyay [11], and morphological gradient features Toptaş et al[12], are used to train SVM classifiers Ramos-Soto et al[13], with a 95.31% success rate on the DRIVE database.

3. Methodology for Blood Vessel Segmentation

Automated methods Sathananthavathi et al[14] for segmenting retinal vessels Dash et al[15] often include multiple phases as shown in Figure 2. First, preprocessing procedures like noise reduction Enireddy et al[16] and image enhancement can be used to enhance the fundus image Srikanth et al[17]. The blood vessels are then distinguished from the background and other retinal characteristics using segmentation methods Sivakumar Rajendran et al[18], and finally, the performance analysis is done for the segmented output.

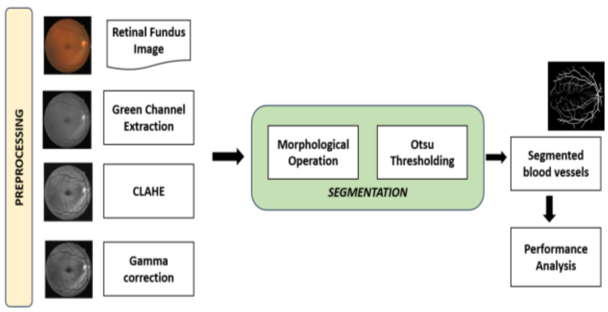


Fig. 2: Morphological Operation.

3.1. Preprocessing

a) Green channel extraction: A 24-bit RGB image with 8 bits per channel was used to create the original retinal fundus image. (red, green, and blue) as shown in Fig. 3. Analyzing each channel reveals that the green channel has high vessel-background contrast, but the red and blue channels have significant noise and poor contrast. Furthermore, the human eye's vision produces a higher reaction to green channel visual perception than to other channels. As a result, the green channel is extracted as a grayscale image.

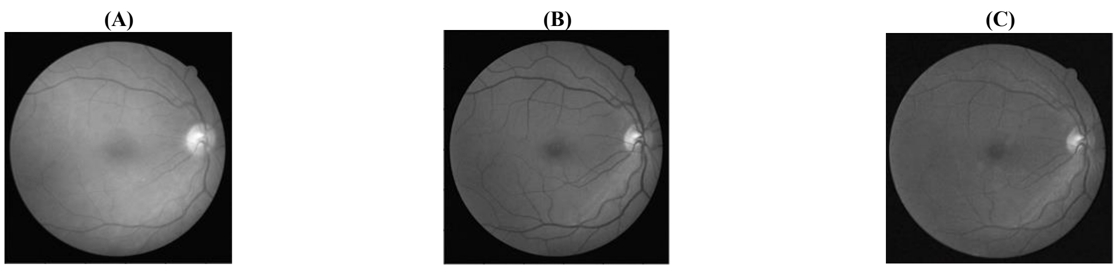
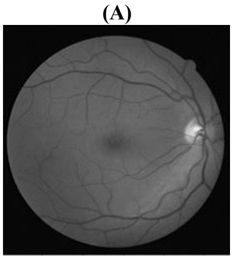


Fig. 3: A) Red Channel Image. B) Green Channel Image. C) Green Channel Image.

b) CLAHE: Following the isolation of the green channel, a method known as Contrast Limited Adaptive Histogram Equalization (CLAHE) is typically used. CLAHE improves the image's local contrast, Ravikumar et al[19] by dispersing pixel intensities, bringing forth more details, and increasing the visibility of blood vessels which as shown in Figure 4.

(A)



(B)

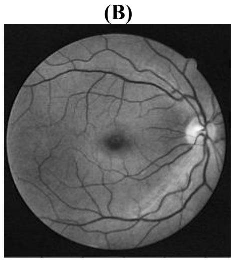


Fig. 4: A) Green Channel Image. B) CLAHE Output Image

c) Gamma Correction: Gamma correction attempts to fix this non-linear connection by applying an inverse power-law transformation Sathish, K et al[20]) to an image's pixel values. The transformation entails increasing the pixel values to a given power, commonly called the gamma value ().

The gamma correction is given by:

$$\text{output} = \text{Input}^{\text{gamma}} \tag{1}$$

The "input" represents the original pixel value, while the "output" reflects the corrected pixel value after gamma correction. When the gamma value is larger than one, it causes gamma expansion, which brightens the image's darker portions while improving features in the shadows. When the gamma value is less than one, gamma compression occurs, lessening the brighter regions, minimizing overexposure, and maintaining highlight details. Figure 5 shows the output image after gamma correction.

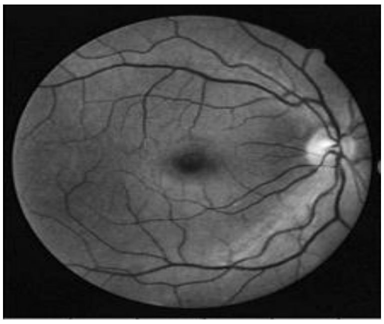


Fig. 5: Gamma Correction Image.

3.2. Segmentation

Retinal blood vessel segmentation is a computer vision task focused on identifying and isolating blood vessels within retinal images. This process is essential for various medical applications, such as diagnosing and tracking retinal such as diabetic retinopathy and glaucoma. However, segmentation is challenging because of the intricate layout of blood vessels and their disparate visual traits, and the presence of noise and artifacts in retinal images.

Morphological Operation:

A group of image processing methods known as morphological operations works with the morphology or form of objects in an image. Tasks including picture augmentation, noise reduction, image segmentation, and feature extraction frequently require these procedures. A tiny, predetermined form known as a structuring element is used to explore an image as the fundamental idea underlying morphological procedures. The structuring element serves as a probe or filter that is moved over the picture and contrasted with the values of the pixels in its vicinity. The interaction between the structuring element and the picture pixels determines the operation's outcome.

Two basic morphological procedures exist:

Dilation: In an image, dilation enlarges or widens the borders of things. The structuring element is positioned at each image's pixel location, and the pixel value is then changed to the highest value found in the neighborhood that the structuring element defines. Dilation can be employed to thicken or link disparate parts. It is mathematically represented by,

$$A \oplus B = \left\{ z / (\hat{B})_z \cap A \neq \Phi \right\} \tag{2}$$

Erosion: The borders of items in a picture are shrunk or eroded by erosion. Placing the structuring element at each pixel position and changing each pixel value to the lowest value found in the neighborhood specified by the structuring element is how it is done. For tasks like eliminating tiny things, separating linked objects, or smoothing the borders, erosion is helpful. Mathematically, it is represented as,

$$A \ominus B = \{ z / (B)_z \subseteq A \} \tag{3}$$

Other morphological procedures can be used, in addition to dilation and erosion, to produce specific results.

Opening: Erosion and dilation are both components of the opening process. While maintaining the general structure of bigger items, it aids in the removal of noise, tiny objects, and thin branches.

$$A \circ B = (A \ominus B) \oplus B \tag{4}$$

Closing: Closing is the result of erosion followed by dilation. It assists in filling up gaps and holes as well as enhancing object boundaries.

$$A \cdot B = (A \oplus B) \ominus B \tag{5}$$

A is the gamma-corrected image, and B stands for the structuring elements for closing and opening operators.
Top Hat Transform: The top-hat transform is a morphological technique used in image processing and computer vision to enhance or isolate specific features or structures within an image. The term "top hat" refers to removing the backdrop from an image, leaving only the brighter areas that stand out. This process is accomplished by combining two basic morphological operations: subtracting and opening. The original image is deducted from the opening of the Top Hat operations to get the desired result. These processes allow for the enhancement of specific aspects or structures within the image. The following equation can represent the top hat transform:

$$\text{TopHat(image)} = \text{image} - \text{Opening(image)} \tag{6}$$

$$H_f(x, y) = \begin{bmatrix} f_{xx} & f_{xy} \\ f_{xy} & f_{yy} \end{bmatrix} \tag{7}$$

4. Result and Discussion

To evaluate the effectiveness of retinal blood vessel segmentation, as well as the DRIVE as in Fig. 6, and the HRF dataset, as in Fig. 7, publicly accessible retinal imaging datasets are used. These datasets include manual segmentations or ground truth for performance evaluation; thus, other researchers frequently utilize them to test the algorithms that they developed to segment vessels.
The DRIVE database comprises 40 color retinal pictures, each with a 656 x 584 pixel resolution. It is separated into two parts: training and testing. Each one has 20 different retinal images. Both sets also include hand segmentation field of view (FOV) masks for the relevant pictures. In practice, researchers mainly use the training set to create algorithms and the test set to evaluate them. The dataset augmentation incorporates high-resolution pathogenic occurrences from HRF, as well as healthy and unhealthy retinal images. This ensures that the dataset is robust and diversified. This comprehensive inclusion increases the method's utility in real-world clinical situations and improves evaluation reliability by making it easier to generalize across contexts.
The HRF database comprises 45 color retinal pictures, each with a 3504 ×2336 pixels resolution. It is separated into training and test data with 33 and 12 images. Each retinal image has a segmented mask.

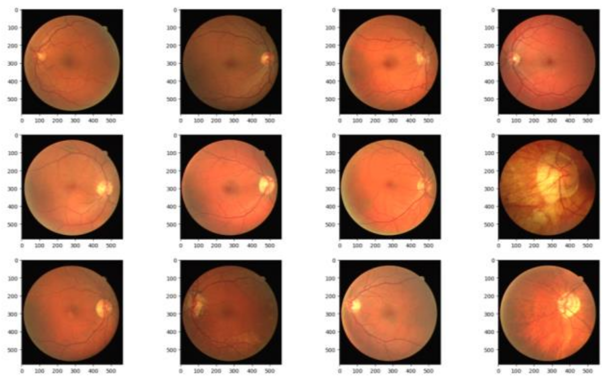


Fig. 6: Sample Images from DRIVE Dataset.

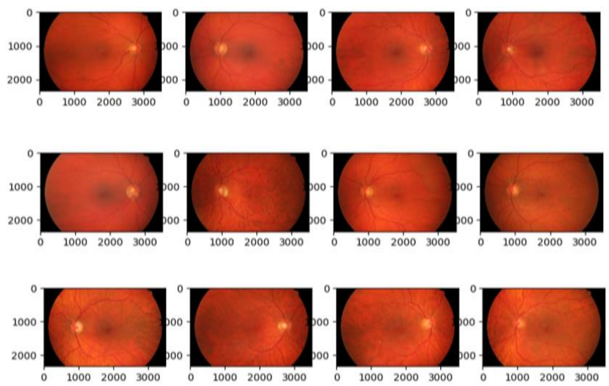


Fig. 7: Sample Images from HRF Dataset.

Performance metric analysis:
To analyze the performance of the suggested algorithm's segmentation results, evaluation indices such as specificity (Sp), sensitivity (Sn), and accuracy (Acc) were utilized, which were defined as follows in Table 1:

Table 1: Performance Metric Description

Measure	Description
True Positive (TP)	Correctly classified blood vessel pixels
True Negative (TN)	Correctly classified background pixels
False positive (FP)	Incorrectly classified blood vessel pixels

False Negative (FN)	Incorrectly classified background pixels
Specificity	$Sp = \frac{TN}{TN+FP}$
Sensitivity	$Se = \frac{TP}{TP+FN}$
Accuracy	$Acc = \frac{TP+TN}{TP+FN+TN+FP}$

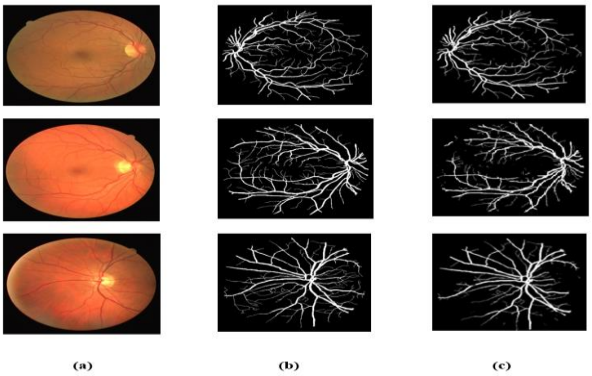


Fig. 8: Segmented Output of DRIVE Dataset: a) Input Image. b) Ground truth Image. c) Segmented Image.

On the DRIVE dataset for images depicted in Figs 8 and 9, Table 2 and Table 3 performance evaluation of the suggested approach for segmenting retinal blood vessels as shown in Fig 10, yielded average values of 87.28% sensitivity, 93.36% specificity, and 97.76% accuracy.

Table 2: Performance Evaluation of Proposed Method on DRIVE Dataset

Image	Sensitivity (%)	Specificity (%)	Accuracy (%)
01_test	83.6	96.6	97.3
02_test	85.7	96.2	97.8
03_test	85.3	87.3	97.5
04_test	87.6	96.8	97.8
05_test	86.8	97.5	96.9
06_test	85.7	97.2	98.1
07_test	88.5	96.5	97.3
08_test	87.6	96.4	97.3
09_test	87.3	95.6	97.5
10_test	88.2	97.6	97.6
11_test	88.8	94.5	97.9
12_test	88.7	96.3	98.2
13_test	89.4	95.4	97.9
14_test	89.7	97.2	97.6
15_test	89.3	87.8	97.6
16_test	86.5	89.7	98.2
17_test	84.7	86.9	98.3
18_test	87.5	89.2	98.2
19_test	86.3	86.5	97.9
20_test	88.4	86.1	98.3
Average	87.28	93.36	97.76

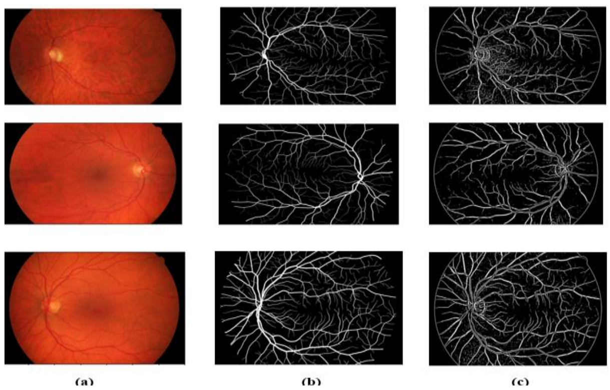


Fig. 9: Segmented Output of HRF Dataset: (a) Input Image (b) Ground Truth Image (c) Segmented Image.

Table 3: Performance Evaluation of Proposed Method on HRF Dataset

Image	Sensitivity (%)	Specificity (%)	Accuracy (%)
01_g	74.86	93.85	95.57
01_h	72.65	95.89	96.6
02_h	75.81	94.59	97.34
03_dr	76.3	93.74	95.93
03_g	73.53	93.73	97.03
03_h	74.83	94.89	95.12
05_h	72.97	92.59	95.65
06_dr	72.47	94.95	93.51

06_h	71.76	95.52	95.62
10_dr	76.82	94.42	97.23
12_g	74.58	95.75	94.54
14_g	76.3	93.45	96.52
Average	73.49	94.44	95.88

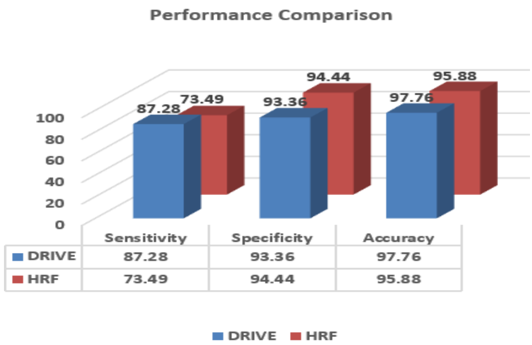


Fig. 10: Performance Metric Comparison.

5. Conclusion

One of the most important steps in identifying the cause of vision impairment is automated retinal blood vessel segmentation. CLAHE and morphological filters were employed in our suggested framework for vessel improvement, and Otsu thresholding was used to extract vessel characteristics and region features based on the threshold value to separate vessel and non-vessel pixels. When applied to DRIVE datasets, the proposed technique obtained a sensitivity of 87.28%, a specificity of 93.36%, and an accuracy of 97.76%. Segmented pictures generated by the suggested technology will be utilized to identify disorders like as hypertension and diabetic retinopathy in the future. The technique for low-quality retinal images will be modified in the future to ensure that it operates properly even under difficult acquisition settings. We plan to use hybrid deep learning algorithms to improve accuracy, efficiency, and scalability for use in healthcare. We will also investigate ways to employ these technologies in real-time in clinical contexts.

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