Retinal Vessel Image Segmentation

Ananya Goyal (2021011) **Himanshu Shekhar (2021152)** **Priyanshi Sharma (MT23064)**

Utsav Garg (2021108) **Vasu Bhatia (MT23104)**

1 Introduction

Retinal vessel segmentation is a crucial task in medical image analysis, providing valuable insights into the diagnosis and monitoring of various ophthalmological and cardiovascular diseases. It involves the process of partitioning a retinal image into various regions or segments, typically to identify and isolate different structures of interest within the image. Retinal vessel segmentation constitutes an essential part of computer-assisted tools for the diagnosis of ocular diseases. However, it is a challenging task due to the variability in the appearance of the vessels. In this project, we will develop and evaluate a machine-learning model for retinal vessel segmentation using the CHASEDB1 dataset. We will address the challenges of imbalanced data and variability in vessel appearance by exploring various machine learning architectures and data processing techniques. We aim to develop a model that is robust and accurate and can be applied to real-world clinical datasets to aid in the diagnosis and monitoring of various diseases.

2 Exploratory Data Analysis

2.1 Exploring and Analyzing Different Color Channels

In the initial stages of our retinal vessel segmentation process, we begin by dividing the original image into its constituent channels: Red, Green, and Blue (RGB). This is a standard procedure in image processing, as it allows us to isolate and manipulate individual color components separately, which can be crucial in tasks such as segmentation where color information can be a key differentiator. However, for our specific task of retinal vessel segmentation, we focus on the Green channel. This is due to the fact that the Green channel has been found to exhibit superior contrast between the vessels and the background compared to the other channels. This contrast is beneficial as it enhances the visibility of the vessels, making them easier to detect and segment.

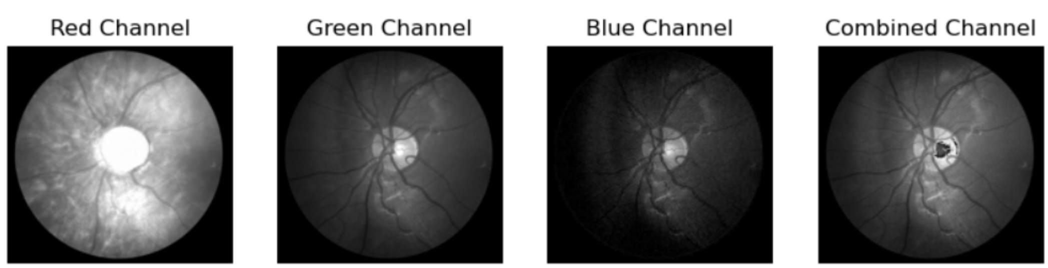


Figure 1: The different channel confirms our hypothesis that the green channel exhibits better contrast between the vessels and the background.

2.2 Contrast Enhancement Techniques and Analysis

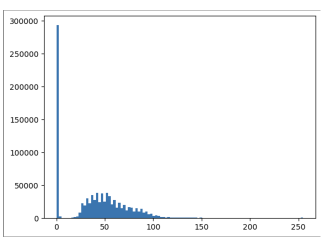
The next step in our preprocessing pipeline is contrast enhancement. This is a crucial step as it significantly impacts the visibility of the vessels in the image, making the subsequent segmentation process more effective. There are several techniques used for contrast enhancement, including Gamma Correction, Histogram Equalization, and Contrast Limited Adaptive Histogram Equalization (CLAHE)

Gamma Correction is a technique used to enhance the contrast of an image by modifying its gamma value, which is a measure of the nonlinear chromaticity of a display device. Histogram Equalization is a method in image processing of contrast adjustment using the image's histogram. It transforms the intensity values so that the histogram of the output image approximately matches a specified histogram. CLAHE, on the other hand, is an advanced normalization technique that can handle a wide range of contrast in an image

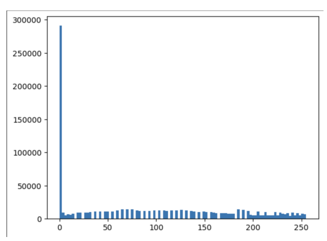
We first apply Gamma Correction to our Green channel image to generate a gamma corrected image. We then compare the Green channel image and the gamma corrected image by plotting their histograms and making relevant observations.

Next, we attempt to equalize the histogram of both images. However, we observe that this process adds a significant amount of noise to the image, which we found to be detrimental to our segmentation process.

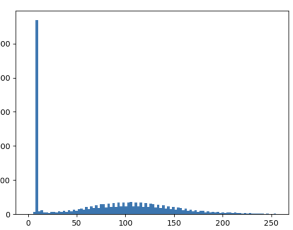
Finally, we apply CLAHE to both the Green channel image and the gamma corrected image. To our surprise, we found that applying CLAHE to the Green channel image produced better results than applying it to the gamma corrected image. This suggests that the Green channel, even after gamma correction, might not be the optimal image for CLAHE.



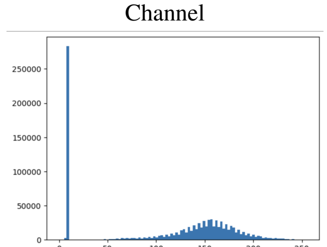
(a) Histogram of Green Channel



(b) Equalized Green Channel



(c) CLAHE on Green Channel



(d) CLAHE on Gamma Channel

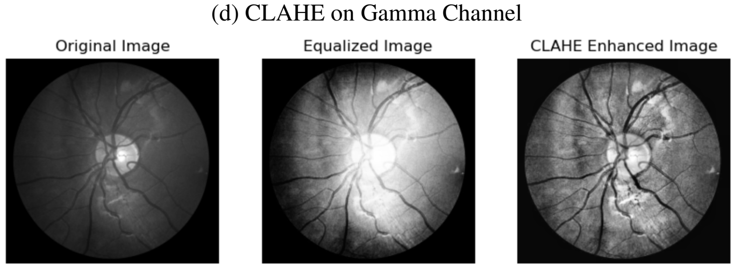


Figure 2: Comparison between different Contrast Enhancement Techniques

Gamma correction is often used to correct for variations in image illumination. However, in this case, the green channel alone already provides sufficient and better contrast for vessel segmentation, thereby eliminating the need for using gamma correction (See Fig. 3).

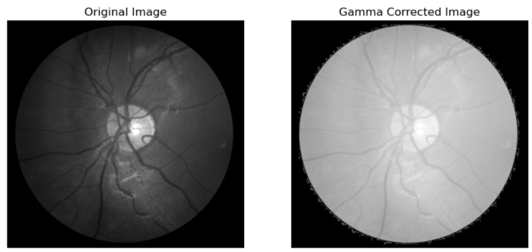


Figure 3: Original image vs Gamma corrected image

2.3 Background Homogenization

The next step in our pipeline involves the process of background homogenization. Background homogenization, also known as uneven illumination removal, is a critical step in image processing that aims to improve the visibility of objects within an image by reducing variations in lighting. This is particularly important for our task of retinal vessel segmentation, as uneven illumination can obscure the details of the vessels. We will explore different morphological operations in this part.

2.3.1 Morphological Operations

Morphological operations are mathematical operations based on the shape of objects within an image. In our pipeline, we apply the top-hat, bottom-hat, and their subtraction to the preprocessed Green channel image.

The top-hat transform is an operation that extracts small elements and details from given images. It is defined as the difference between the input image and its opening by some structuring element. Similarly, a bottom-hat transform is defined as the difference between the closing and the input image.

In mathematical terms, the top-hat transform can be represented as:

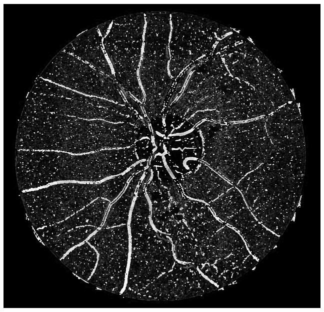
$$\text{Tophat}(f) = f - (f \circ b)^{\text{open}} \tag{1}$$

where (I) is the input image and (Open(I)) is the opening of the input image.

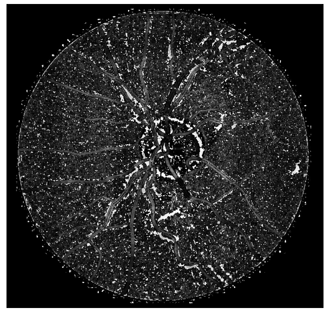
Similarly, the bottom-hat transform can be represented as:

$$\text{Bottomhat}(f) = (f \circ b)^{\text{close}} - f \tag{2}$$

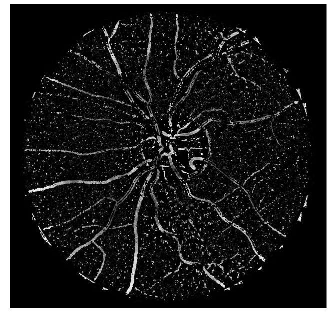
where (Close(I)) is the closing of the input image.



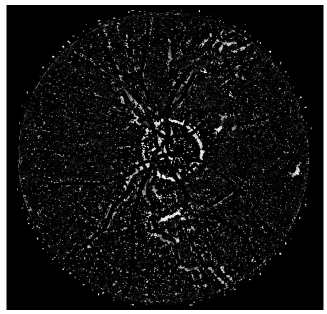
(a) Top Hat Operation



(b) Bottom Hat Operation



(c) Top Hat - Bottom Hat



(d) Bottom Hat - Top Hat

Figure 4: Different Morphological Operations

2.4 Gabor Filters

Gabor features, derived from two-dimensional Gabor filters, play a crucial role in enhancing retinal blood vessels by employing sinusoidally modulated Gaussian functions. These filters, inspired by a multi-scale technique, aim to comprehensively scan the entire image, capturing vessels in diverse orientations. However, the efficacy of this filter heavily relies on its parameterization, namely wavelength, aspect ratio, and bandwidth, profoundly impacting the construction of the Gabor kernel.

Optimal parameter selection significantly influences the filter's performance. For instance, the kernel size must encompass all vessels of varying widths within the image. In this proposed technique, the Gabor filter excels in extracting vessel information when set at wavelengths of 9, 10, and 11, an aspect ratio of 0.5, and a bandwidth of 1. Additionally, the orientation operation begins at 0 and progresses at intervals of 15 degrees. Notably, varying the wavelength values affects the appearance of thin vessels or vessel-like structures. (See Fig. 5)

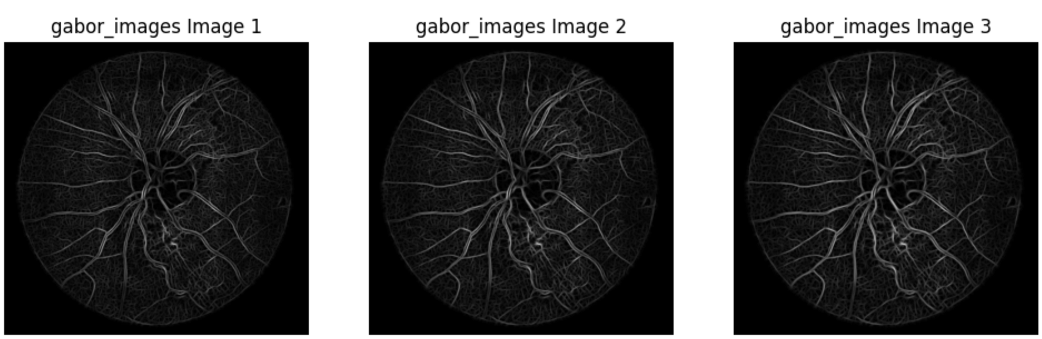


Figure 5: Gabor Filter Images for Wavlength 9, 10, 11 respectively

Following Gabor filtering, a thresholding process converts the resulting images into binary representations, distinguishing vessel and non-vessel pixels. This binarization employs an automated thresholding algorithm. Initially, the Laplace filter is applied to the Gabor filter output images. Subsequently, each image is added to its respective Gabor filter image, and a thresholding operation is performed on the resultant image. This study devises a swift and effective thresholding method, influenced by a known approach. The algorithm computes the frequency of pixel values in the 0-255 range, calculating the ratio of each pixel value's occurrence to the total image size. Multiplying each pixel value by its frequency and summing these products yields an optimal threshold value for the processed image.

Through experiments on various retinal images, this method consistently determines suitable threshold values for different images. The resulting output of the thresholding operation is depicted in Figure 6.

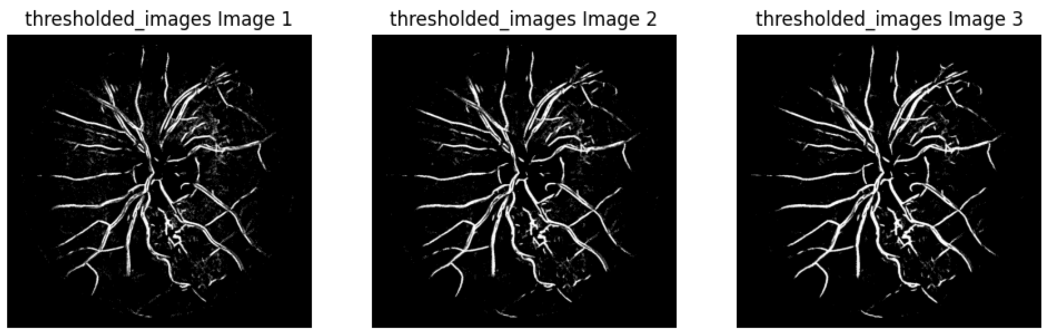


Figure 6: Thresholded Gabor Filter Images for Wavlength 9, 10, 11 respectively

3 Existing Analysis

The vascular structure within both normal and abnormal retinal images exhibits lower contrast when compared to the background of the retina. In contrast, other anatomical features in the retina display higher contrast against surrounding tissues, but they may lack clear features when compared to abnormal structures. Illustrative examples include the optic disc and exudate lesions.

Classical segmentation techniques are not very effective and accurate in handling these challenges and give inefficient and inaccurate results. Consequently, various algorithms and methodologies have been developed and implemented for the sake of automatic identification, localization, and extraction of retinal anatomical structures and can be broadly divided into rule-based and machine-learning techniques. The category of rule-based techniques follows specific rules in an algorithmic framework, whereas machine learning ones utilize a pre-segmented retinal image (ground truth or gold standard) to form a labeled dataset that can be used in the training process

The current study on retinal vessel segmentation is divided into three main stages: preprocessing, which aims to make the vessels stand out more; vessel segmentation; and post-processing, which removes unwanted elements and separates all connected large and small vessels from the fundus image.

The original color retinal fundus photos are tainted with noise, and because the light source is not uniform, the retinal vessels cannot be seen clearly. The preprocessing stage is critical to improving the quality of the image and minimizing the amount of computing work required in the latter stages. Color channel extraction, vessel edge enhancement, and noise reduction make up the preprocessing stage of this study. The optic disc and lesion removal step comes next, and finally the image contrast enhancement.

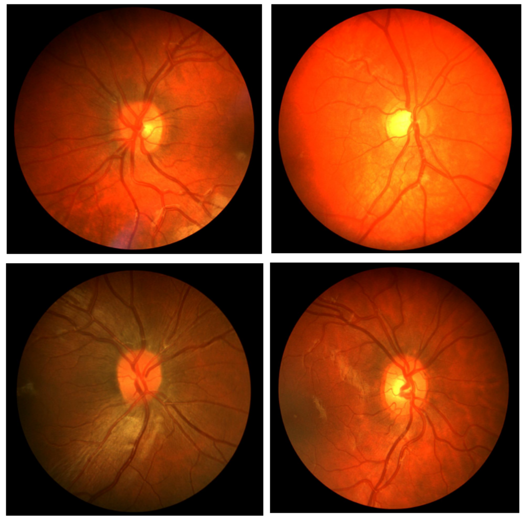


Figure 7: Sample retinal fundus images from the CHASEDB1 database.

The following are the most recent techniques proposed for retinal vessel segmentation in the last five years:

Supervised Methods:

1. **Support Vector Machines (SVMs):**

   Explanation: SVMs are a type of machine learning algorithm used for classification tasks. In the context of retinal vessel segmentation, they are trained on labeled data where each pixel is annotated as either vessel or non-vessel.

   Strengths: SVMs are effective in finding complex decision boundaries in high-dimensional feature spaces, making them suitable for discriminating between vessel and non-vessel pixels.

   Weaknesses: They can be sensitive to the choice of kernel and parameters, and their performance heavily depends on the quality and representativeness of the training data.

2. **AdaBoost:**

   Explanation: AdaBoost is an ensemble learning method that combines multiple weak classifiers to create a strong classifier. In retinal vessel segmentation, it can be used to improve the accuracy of classification.

   Strengths: AdaBoost can handle complex relationships between features and labels. It is less prone to overfitting.

   Weaknesses: It may be sensitive to noisy data and outliers. It can be computationally expensive.

Unsupervised Methods:

1. **Matched Filters:**

   Explanation: Matched filtering involves convolving an image with a template (usually Gaussian) to enhance vessel-like structures. It leverages the fact that vessel cross-sectional intensity profiles often resemble Gaussian curves.

   Strengths: Effective in detecting vessels with well-defined intensity profiles.

   Weaknesses: May struggle in the presence of complex vessel structures and pathologies.

2. **K-Means Clustering:**

   Explanation: K-Means is an unsupervised clustering algorithm. In the context of vessel segmentation, it groups pixels based on their similarity in feature space, potentially separating vessels from the background.

Strengths: K-Means is computationally efficient and can handle large datasets. It can find clusters even with irregular shapes.

Weaknesses: It may require tuning of the number of clusters. It may not perform well if clusters have different densities.

3. **Morphological Processing:**

   Explanation: Morphological operations like erosion, dilation, opening, and closing are used in vessel segmentation to enhance or suppress certain image structures based on their shape and size.

   Strengths: Morphological operations are fast and can effectively filter out noise or enhance certain features.

   Weaknesses: Their performance may be sensitive to the choice of structuring elements. They may not be sufficient for complex vessel structures.

4. **Thresholding:**

   Explanation: Thresholding methods segment pixels based on intensity values, effectively separating vessel structures from the background.

   Strengths: Straightforward and computationally efficient, especially when there are clear intensity differences.

   Weaknesses: Sensitive to variations in illumination and might not perform well in cases with subtle intensity differences.

5. **K-Nearest Neighbors (KNN):**

   Explanation: KNN is a simple but effective classification algorithm. In the context of retinal vessel segmentation, it assigns a pixel to the class (vessel or non-vessel) based on the classes of its nearest neighbors in the feature space.

   Strengths: KNN is easy to understand and implement. It can capture complex decision boundaries.

   Weaknesses: It can be computationally expensive, especially with large datasets. The choice of the number of neighbors (k) is critical and may require tuning.

4 Methodology

4.1 Image Acquisition:

- **Objective:** Retrieve high-resolution retinal images captured in the RGB color space through medical imaging devices.
- Image acquisition involves obtaining pixel values from the captured retinal images in the RGB color space.

4.2 Green Channel Isolation:

- **Objective:** Separate individual color channels—Red, Green, and Blue—and prioritize the Green channel for its efficacy in highlighting retinal vessel structures.
- Utilizes RGB decomposition to extract the Green channel: $G(x, y)$ = Green channel intensity at (x, y).

4.3 Contrast Enhancement: CLAHE, Histogram Equalization, Gamma Correction:

- **CLAHE (Contrast-Limited Adaptive Histogram Equalization):**
  - **Objective:** Enhance local contrast while preventing over-amplification in specific regions.
  - For each pixel (x, y) in the image, CLAHE computes a transformation function based on the histogram of pixel intensities in the local neighborhood.
- **Histogram Equalization:**
  - **Objective:** Adjust overall image contrast by redistributing pixel intensities.

- The transformation function is given by

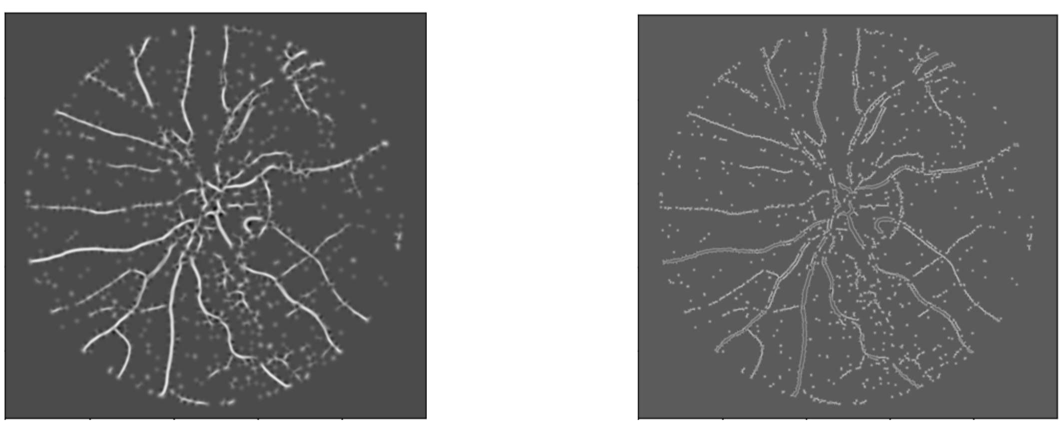
$$T(I) = \text{round}\left(\frac{\text{CDF}(I) - \text{min\_CDF}}{\text{max\_CDF} - \text{min\_CDF}}\right) \times (\text{num\_intensities} - 1) \tag{3}$$

  where num_intensities is the total number of possible intensity levels in the image and the Cumulative Distribution Function (CDF) is calculated from the image histogram. It represents the cumulative probability of pixel intensities up to a certain level. The transformation function uses the CDF to normalize pixel intensities, ensuring that the output values cover the entire intensity range of the image.

- **Gamma Correction:**
  - **Objective:** Adjust image contrast by modifying the gamma value.
  - The gamma correction operation is defined as $I_{\text{out}} = I_{\text{in}}^{\gamma}$, where I_{out} is the output intensity, I_{in} is the input intensity, and γ is the gamma value.

4.4 Hessian Matrix Computation:

- **Objective:** Analyze local geometric properties to identify vessel structures.
- Given an image $I(x, y)$, the Hessian matrix H is calculated using the second-order partial derivatives of intensity: $H = \begin{bmatrix} I_{xx} & I_{xy} \\ I_{yx} & I_{yy} \end{bmatrix}$.
- We have used an innovative method to enhance images that highlight wide and thin vessels. By applying a morphological filter, the Hessian matrix and eigenvalue transformations, we were able to successfully separate varying-width vessels. We computed the second derivative of the image at different scales to focus on either wide or thin vessels. This method utilizes a Hessian matrix and eigenvalue-based approach to isolate the vessels with diverse widths. By leveraging the eigenvalues obtained from the Hessian matrix and their differences, we further improved contrast and reduced non-vasculature structures in the images.



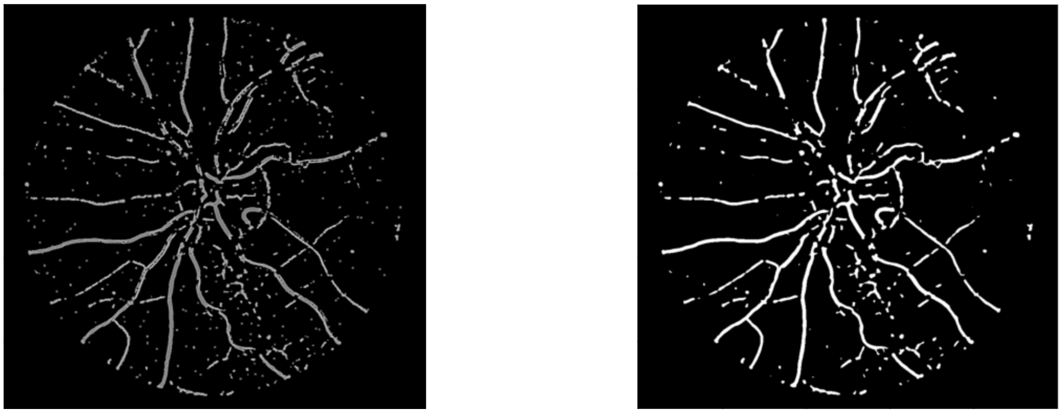
(a) Wide Vessels Enhanced Image

(b) Thin Vessels Enhanced Image

4.5 Otsu's Thresholding:

- **Objective:** Automatically determine an optimal threshold for image segmentation.
- Otsu's method maximizes the variance between two classes (foreground and background) by iteratively selecting a threshold value.
- We have modified Otsu's method to specifically target noise and geometric objects based on vessel structure. Traditionally, Otsu's approach determines pixel classification thresholds globally or locally across images. However, applying it directly to the whole image can be ineffective. To address this, we applied it separately to wide and thin vessel images. By applying a global threshold on enhanced wide vessels and merging the result with thin vessel enhancements, we were able to amplify both thin and wide vessels, increasing their

visibility. This unified image was then subjected to localized thresholding using vessel-based thresholds tied to vessel location, which further refined the thresholds. To better handle noise near wide vessels, we adjusted the global threshold with an offset. Areas away from wide vessels used a lower threshold, which was achieved by subtracting an offset. This fine-tuning aided in extracting smaller vessels from backgrounds with lower intensity, thereby improving the accuracy of the results.



(a) Local Otsu Threshold Image

(b) Global Otsu Threshold Image

5 Novelty

The project introduces a novel and advanced methodology for retinal vessel image segmentation, incorporating cutting-edge techniques to enhance accuracy and applicability in clinical settings. A key innovation lies in the incorporation of Gabor filters within the segmentation process. Gabor filters, known for their effectiveness in detecting texture patterns and edges at various orientations and frequencies, bring a new dimension to vessel segmentation. This inclusion enables the system to capture intricate details and subtle variations in vessel structures, contributing to more precise and tailored segmentation results.

Additionally, the project introduces the use of image fusion specifically for thin and thick vessel detection. The fusion of information from multiple sources enhances the system's ability to distinguish between vessels of varying widths. This approach is particularly significant in the context of retinal pathology diagnosis, where the identification of both thin and thick vessels plays a crucial role.

The emphasis on a comprehensive filter selection process underscores the adaptability of the system to diverse retinal images, showcasing its potential for broader clinical application. The meticulous customization of filters based on image characteristics contributes to a more nuanced and accurate vessel segmentation.

6 Inferences from Existing Research

To obtain inferences from an existing study, we adopted the codebase from the study titled "Impact of Novel Image Preprocessing Techniques on Retinal Vessel Segmentation (Soomro et al)" as a reference to evaluate the performance of our dataset. This code employs a supervised machine learning approach, and we observed an accuracy of 89 percent. Additionally, we assessed our dataset using code obtained from `aravind-3105/Retinal-Blood-Vessels-Segmentation-and-Denoising`[1], where we employed an unsupervised machine learning approach and achieved an accuracy of 92 percent. With these insights, we aim to introduce a novel approach to enhance the efficiency of our model on both training and unseen data.

[1] https://github.com/aravind-3105/Retinal-Blood-Vessels-Segmentation-and-Denoising

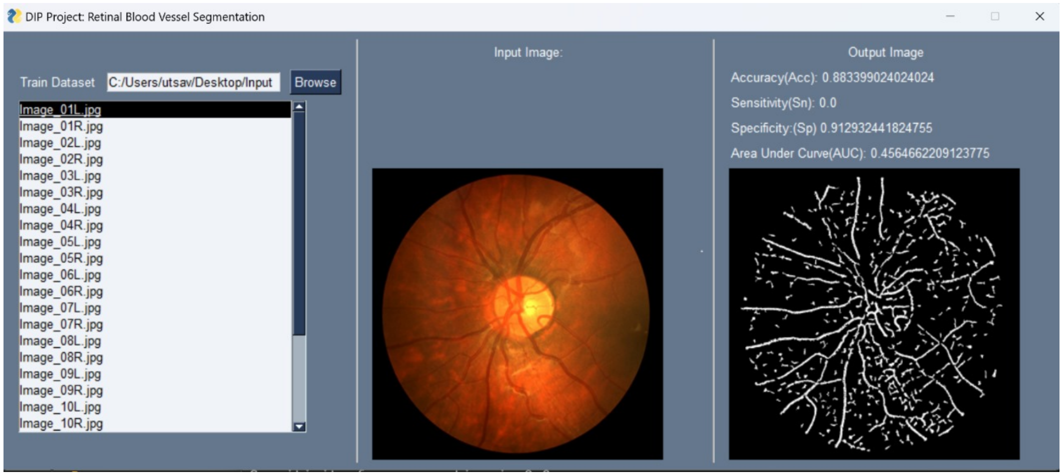


Figure 10: Results obtained from the study titled *Impact of Novel Image Preprocessing Techniques on Retinal Vessel Segmentation.*

7 Evaluation Strategy

Evaluating the performance of retinal vessel image segmentation is a crucial step in assessing the accuracy and effectiveness of the segmentation algorithms. Two commonly used metrics for this purpose are the Structural Similarity Index (SSIM) measure and the Peak Signal-to-Noise Ratio (PSNR).

1. **Structural Similarity Index (SSI):**
   - **Objective:** Quantitatively assess the similarity between segmented and ground truth images.
   - SSI $= \frac{2\cdot\mu_x\cdot\mu_y+c_1}{\mu_x^2+\mu_y^2+c_1} \cdot \frac{2\cdot\sigma_{xy}+c_2}{\sigma_x^2+\sigma_y^2+c_2}$, where μ_x, μ_y are means, σ_x, σ_y are variances, σ_{xy} is the covariance, and c_1, c_2 are constants.
   - This metric provides a comprehensive assessment of the similarity between the segmented vessels and the ground truth. SSIM considers luminance, contrast, and structure in its evaluation, making it suitable for assessing image quality. It produces a value between -1 and 1, with 1 indicating perfect similarity. In the context of retinal vessel segmentation, a higher SSIM score, such as the achieved value of **0.87**, signifies better accuracy and fidelity of the segmented vessels.
2. **Peak Signal-to-Noise Ratio (PSNR):**
   - **Objective:** Measure the quality of the segmented image by evaluating the ratio of signal power to noise.
   - PSNR $= 10 \cdot \log_{10}\left(\frac{\text{Max intensity value}^2}{\text{Mean squared error}}\right)$.
   - PSNR is a widely used metric to quantify the quality of an image by measuring the ratio between the maximum possible power of a signal and the power of corrupting noise. In retinal vessel segmentation, a higher PSNR indicates a clearer and more accurate segmentation result, as it reflects the quality of the segmented vessels concerning the original image. The obtained PSNR value of **55** further affirms the quality and accuracy of the segmented vessel structures, providing insights into the preservation of vessel details during the segmentation process.

8 Results

The results obtained from retinal vessel segmentation exhibit compelling performance metrics. The Structural Similarity Index (SSIM) attains a value of 0.8885, denoting a strong resemblance between the segmented and ground truth images. A notably high Peak Signal-to-Noise Ratio (PSNR) of

55.2866 signifies minimal distortion between these images. Furthermore, the segmentation model achieves an impressive accuracy score of 0.9549, showcasing its capability to accurately classify vessel and non-vessel pixels. While the sensitivity value reaches 0.7269, underscoring the model's proficiency in detecting true positive vessel pixels, the specificity value of 0.9680 highlights its adeptness in identifying true negatives, thus reducing false positives. Additionally, the f1 score of 0.8303, a well-balanced metric accounting for precision and recall, firmly establishes the segmentation method's robustness and effectiveness in accurately delineating retinal vessels.

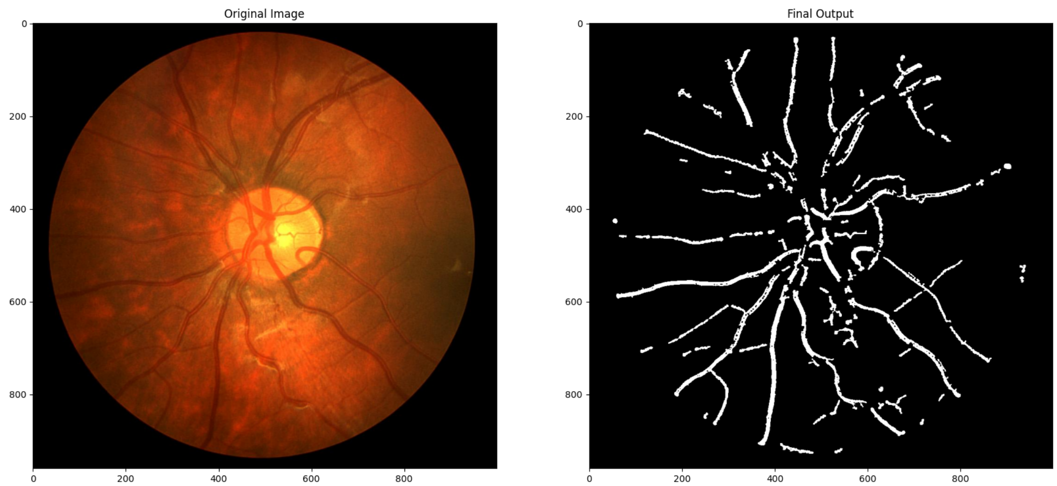


Figure 11: Final Segmentation On Sample Image

References

1. Almotiri, J., Elleithy, K., & Elleithy, A. (2018). Retinal Vessels Segmentation Techniques and Algorithms: A survey. *Applied Sciences, 8*(2), 155. https://doi.org/10.3390/app8020155

2. GeethaRamani, R., & Balasubramanian, L. (2016). Retinal blood vessel segmentation employing image processing and data mining techniques for computerized retinal image analysis. *Biocybernetics and Biomedical Engineering, 36*(1), 102-118. https://doi.org/10.1016/j.bbe.2015.06.004

3. Khan, K. B., Khaliq, A. A., & Shahid, M. (2016). Correction: A morphological Hessian based approach for retinal blood vessels segmentation and denoising using region based OTSU thresholding. *PLOS ONE, 11*(9), e0162581. https://doi.org/10.1371/journal.pone.0162581

4. Maison, T., Lestari, T., & Luthfi, A. (2019). Retinal Blood Vessel Segmentation using Gaussian Filter. In *Journal of Physics: Conference Series*, **1376**, 012023. IOP Publishing Ltd. https://doi.org/10.1088/1742-6596/1376/1/012023

5. Shabani, M. (2017). Master thesis: Retinal Blood Vessel Extraction Based on a Combination of Matched Filter and Level Set Algorithm. https://doi.org/10.13140/RG.2.2.12055.85929/1

6. Soomro, T. A., Ali, A., Jandan, N. A., Afifi, A. J., Irfan, M., Alqhtani, S. M., Głowacz, A., Alqahtani, A., Tadeusiewicz, R., Kańtoch, E., & Zheng, L. (2021). Impact of novel image preprocessing techniques on retinal vessel segmentation. *Electronics, 10*(18), 2297. https://doi.org/10.3390/electronics10182297

7. Srinidhi, C. L., Aparna, P., & Rajan, J. (2017). Recent advancements in retinal vessel segmentation. *Journal of Medical Systems, 41*(4). https://doi.org/10.1007/s10916-017-0719-2