VESSEL EXTRACTION IN RETINAL FUNDUS IMAGES

UCS2523 – Image Processing and Analysis

Assignment 1
Submitted By

K.Harish	3122225001036
Janeshvar Sivakumar	3122225001047

Department of Computer Science and Engineering

Sri Sivasubramaniya Nadar College of Engineering
(An Autonomous Institution, Affiliated to Anna University)
Kalavakkam – 603110

October 2024

Sri Sivasubramaniya Nadar College of Engineering

(An Autonomous Institution, Affiliated to Anna University)

BONAFIDE CERTIFICATE

Certified that this Assignment report titled " **VESSEL EXTRACTION IN RETINAL FUNDUS IMAGES** " is the bonafide work of "K.Harish (3122225001036), Janeshvar Sivakumar (3122225001047) " who carried out the project work in the Course UCS2523 – Image Processing and Analysis during the academic year 2024-25.

Internal Examiner External Examiner

Date

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1. Problem Statement

The objective of the project is to enhance and extract blood vessel information of retinal fundus images to be used in classification tasks. This project can be used in the feature extraction process required by the mentioned classification-based machine learning models. The result of this project is an image containing the mask of the vessels in the image. The mask can further be used to highlight the vessels in the original retinal image.

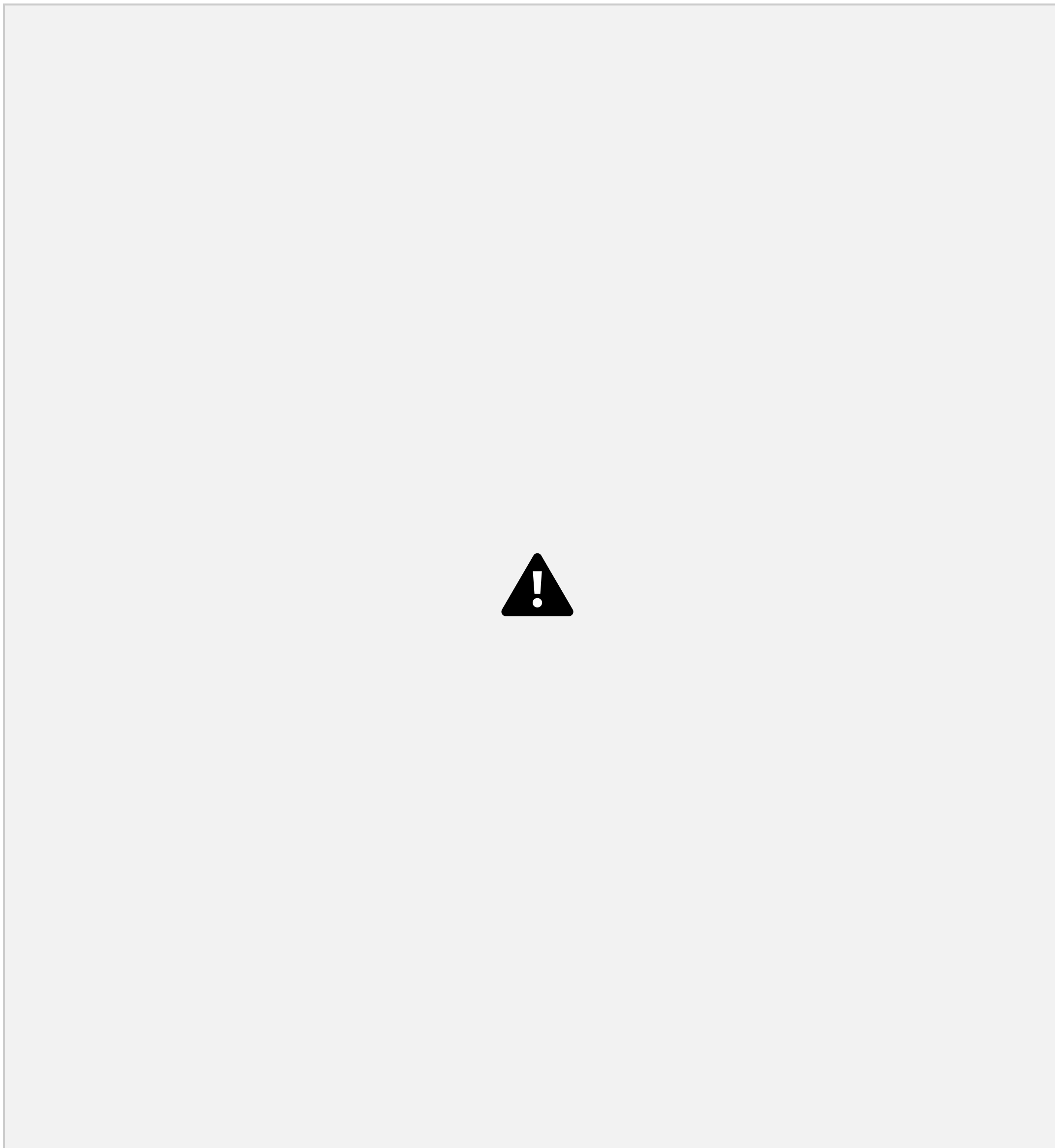
2. Abstract

This report presents the methodology and results obtained in the process of extraction of vessel structures in retinal images. Several image sharpening techniques, smoothing techniques and morphological transformations were considered and through careful trial and error method by considering evaluation metrics and visual characteristics , the optimal methodology was obtained. The metrics for each image enhancement filter included peak signal to noise ratio (PSNR) Contrast Change Index (CCI) and Entropy . Further, for the final image (vessel mask) obtained using morphological operations and gray level slicing Structural Similarity Index (SSIM), Dice Coefficient (Dice Score) and Intersection over Union (IoU).

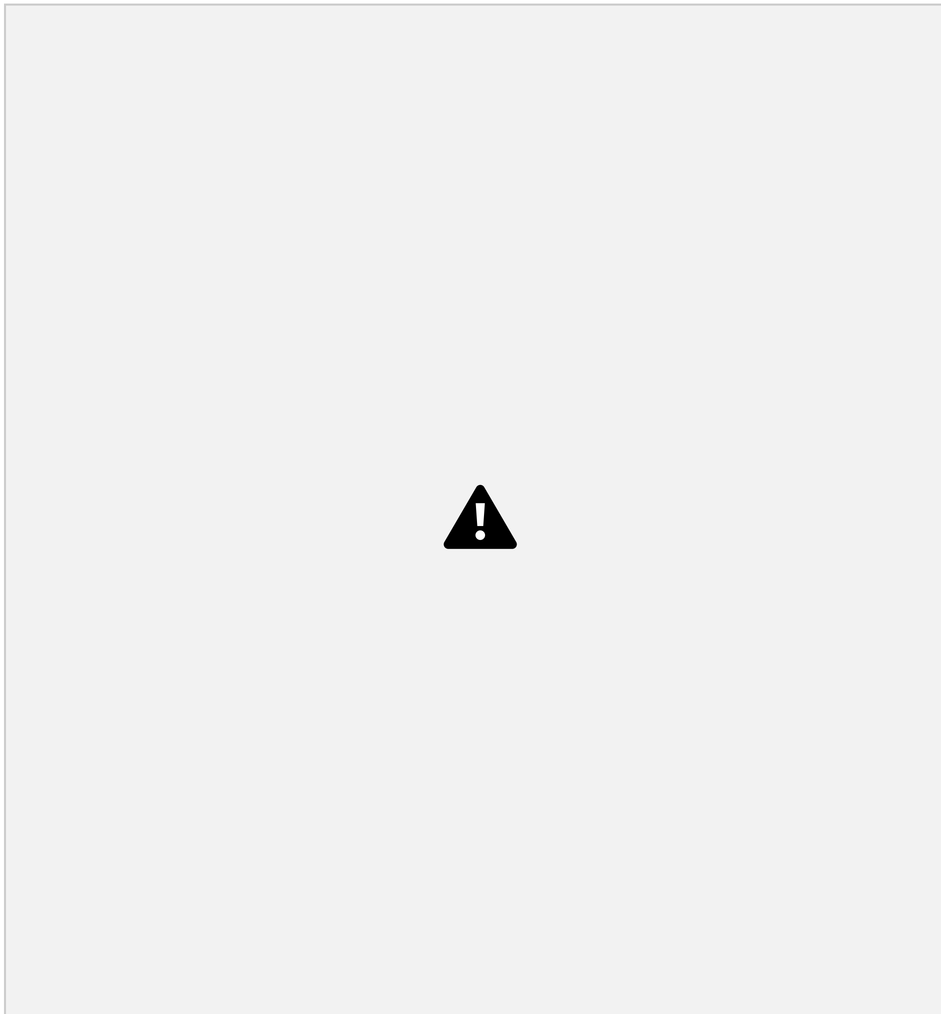
3. Dataset Description

The Retina Blood Vessel Segmentation Dataset from kaggle contains high-resolution retinal fundus images designed for developing and evaluating advanced blood vessel segmentation algorithms. This dataset plays a crucial role in retinal vascular disease analysis, contributing to the early detection of conditions like diabetic retinopathy and macular degeneration.

- The dataset consists of images with varying dimensions, ranging from smaller to larger pixel resolutions, providing a real-world variety in retinal imaging.



- Each image is paired with a binary mask annotation that marks blood vessel pixels as 1 and background pixels as 0. These pixel-level annotations ensure precise segmentation of retinal vessels.



- The dataset covers a diverse range of retinal pathologies, including variations in vessel width, branching patterns, and the presence of anomalies, ensuring that segmentation algorithms can be tested under varied conditions.

Dataset link:
https://www.kaggle.com/datasets/abdallahwagih/retina-blood-vessel

4. Methodology

Techniques considered:

Input Image Preprocessing:

- The green channel of the retinal image is extracted for the task, as this channel provides the highest contrast between vessels and the background.

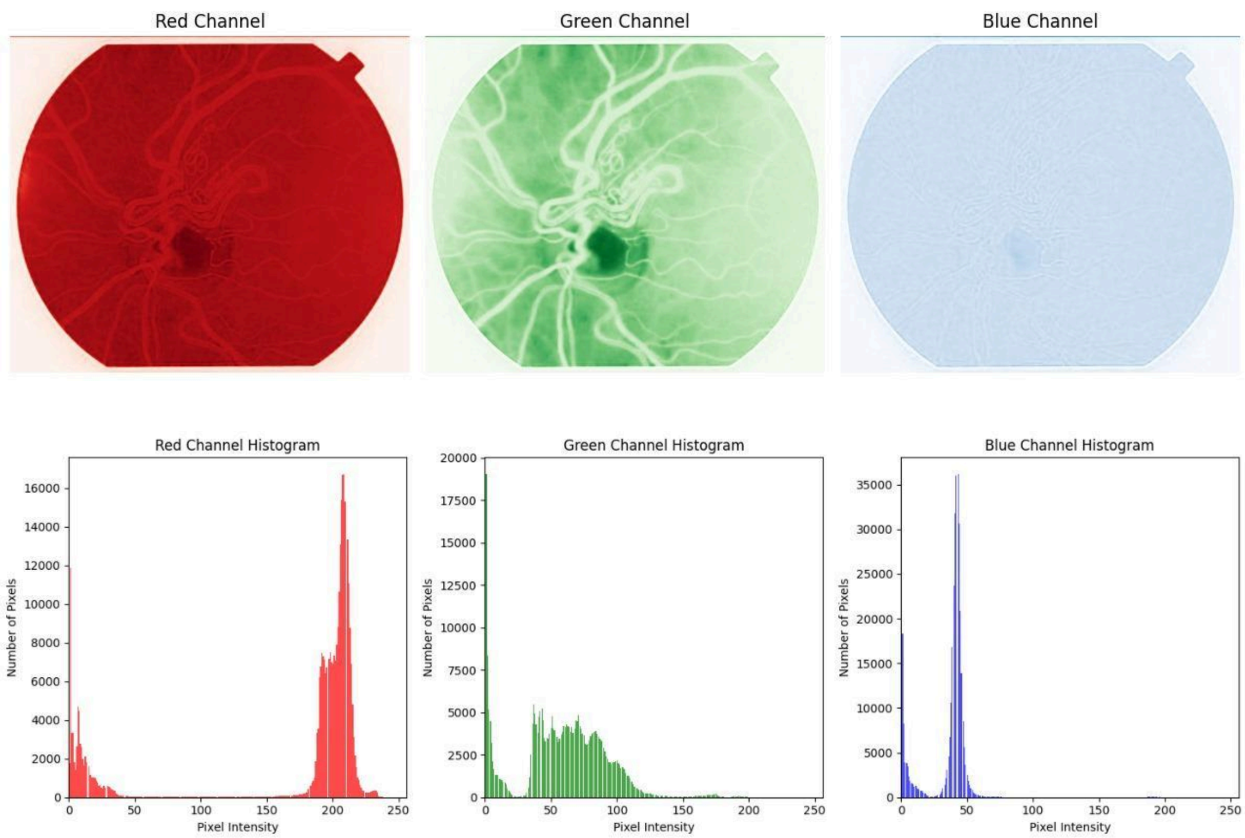
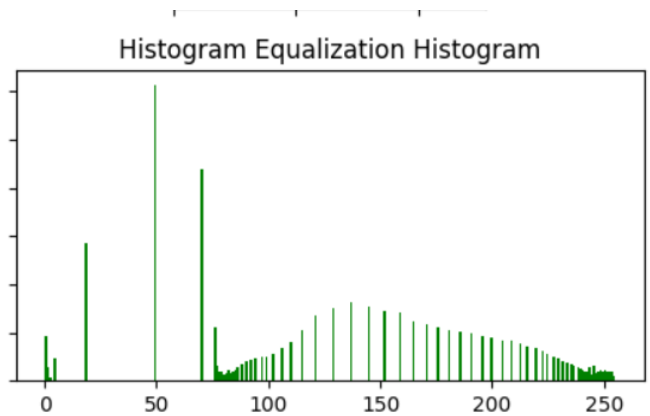
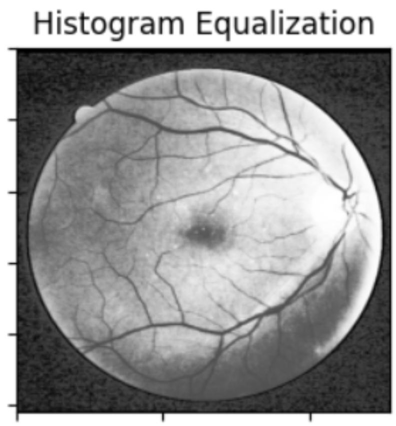


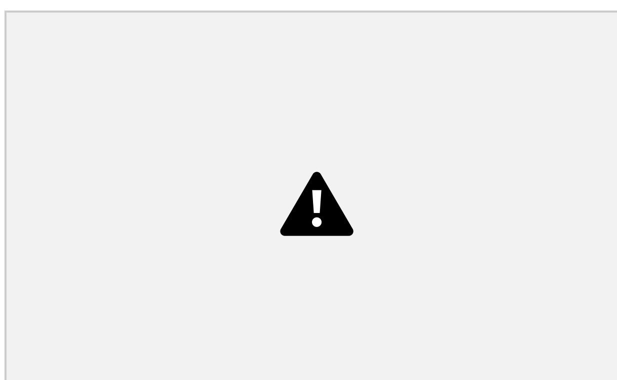
Image Sharpening:

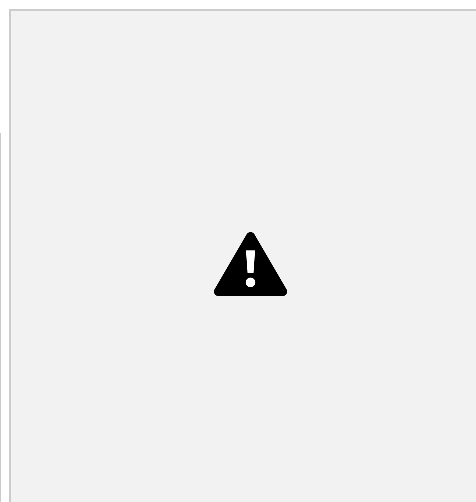
- Histogram equalization: Histogram Equalization is a technique used to enhance the contrast of an image by effectively redistributing its intensity values.



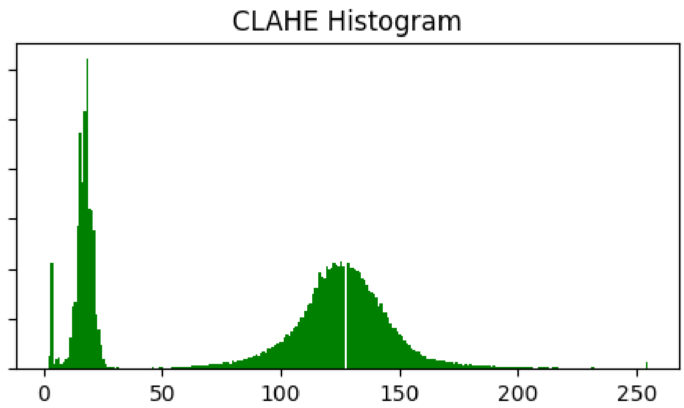


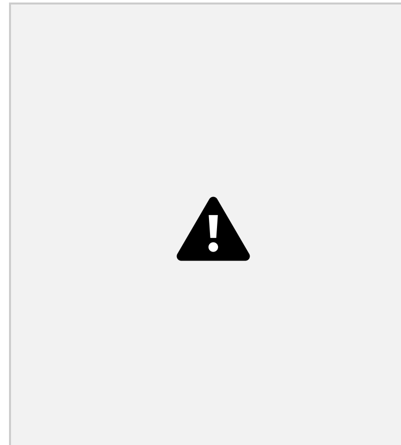
- Adaptive Histogram Equalization: Adaptive Histogram Equalization (AHE) is an advanced technique for enhancing image contrast, particularly useful in situations where the global histogram equalization may not yield satisfactory results due to varying illumination across the image.



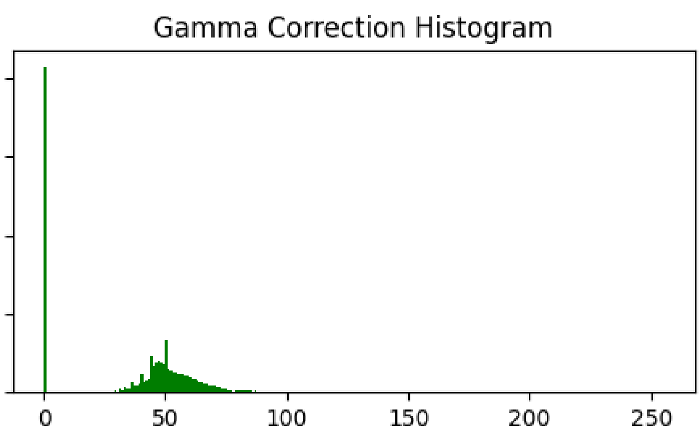


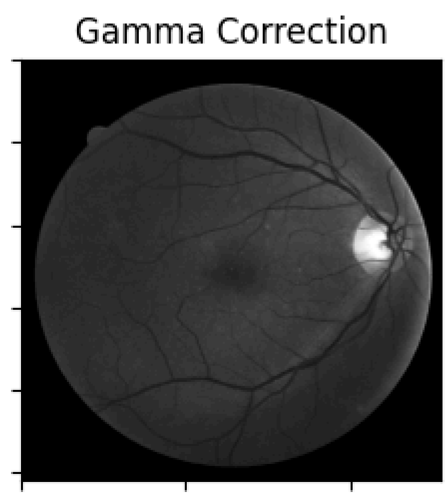
- Contrast Limited Adaptive Histogram Equalisation: Contrast Limited Adaptive Histogram Equalization (CLAHE) is an improved version of Adaptive Histogram Equalization (AHE) designed to overcome the problem of noise amplification.



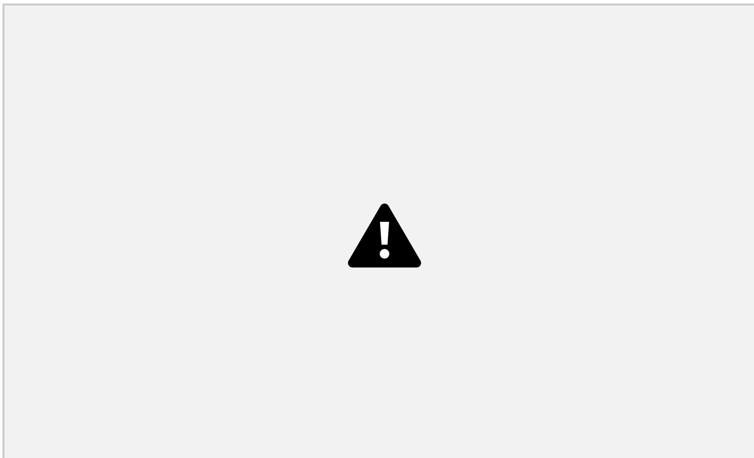


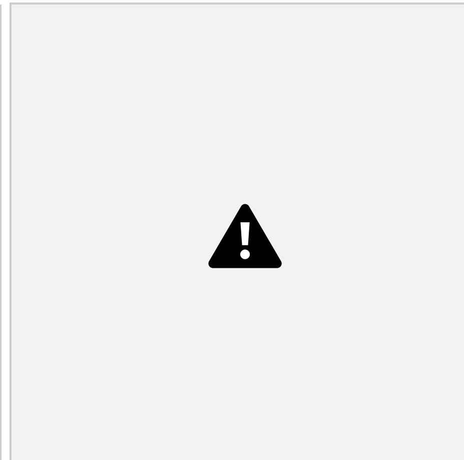
- Gamma Correction: Gamma correction is a nonlinear operation used to adjust the brightness or luminance of an image.



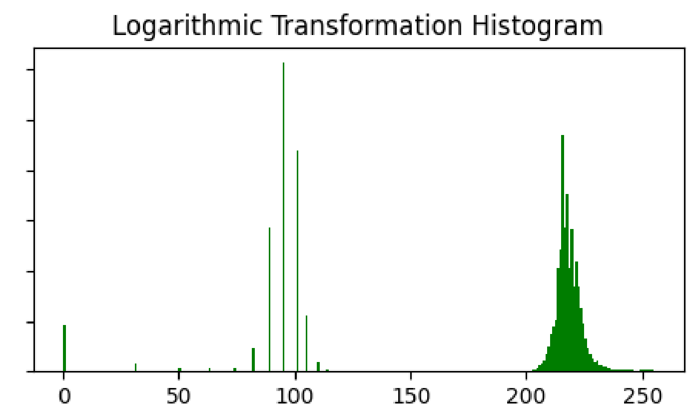


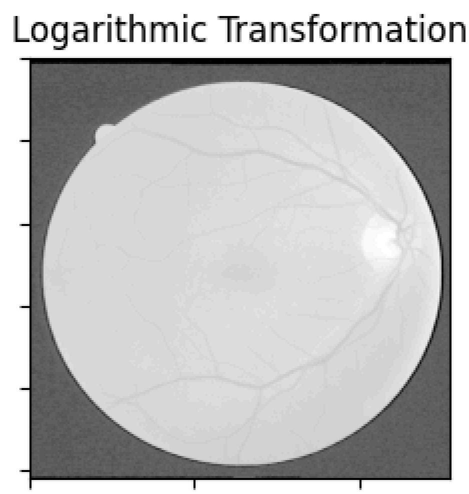
- Unsharp Masking: Unsharp masking is an image sharpening technique used to enhance the edges and fine details in an image.



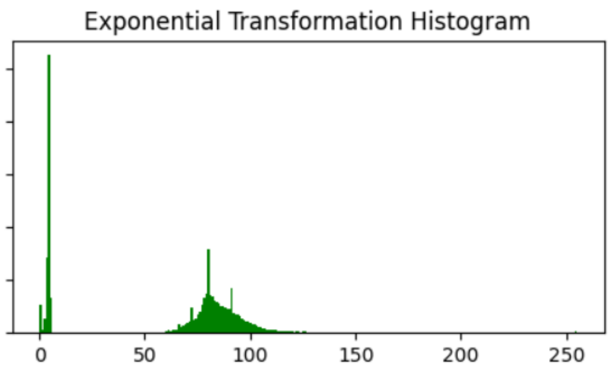


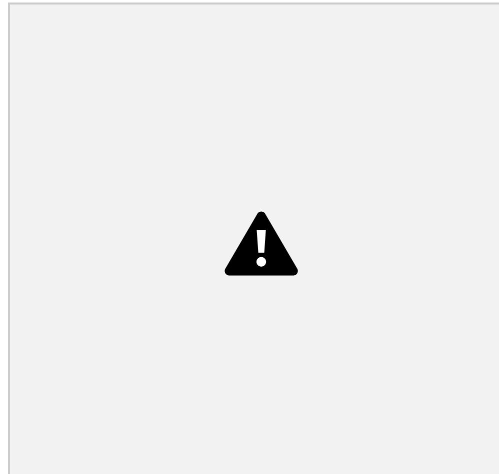
- Logarithmic Transformation: Logarithmic transformation is a non-linear image enhancement technique used to expand the darker regions and compress the brighter regions of an image



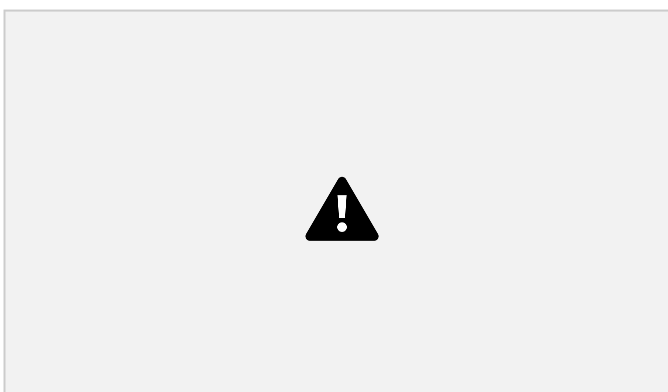


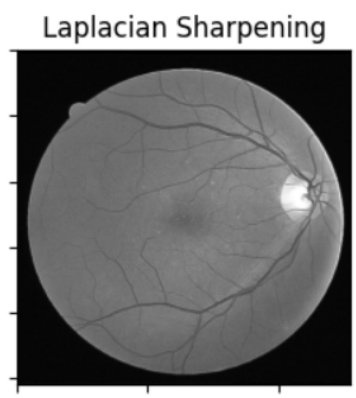
- Exponential transformation: Exponential transformation is a non-linear image enhancement technique that is the inverse of logarithmic transformation. While logarithmic transformation enhances darker areas and compresses brighter areas, exponential transformation does the opposite—it enhances the brighter areas of an image and compresses the darker areas.





- Laplacian Filter:A Laplacian filter is a second-order derivative filter used to highlight areas of rapid intensity change, often used for edge detection. The Laplacian operator calculates the second derivative of the pixel intensity values in an image, which identifies regions where the intensity changes abruptly (i.e., edges). It’s typically applied to grayscale images.

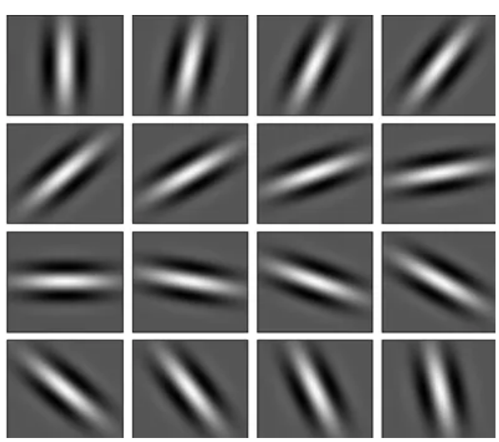




FILTER	PSNR	CII	ENTROPY
Histogram Equalisation	12.845	1.3303	3.789
Adaptive Histogram Equalisation (AHE)	7.889	**1.489**	5.343
CLAHE	25.033	1.024	4.541
Gamma Correction	13.821	0.582	3.303
Unsharp Masking	**37.741**	1.013	3.899
Logarithmic Transformation	8.402	1.141	3.272
Exponential Transformation	20.047	0.782	3.673
Laplacian Sharpening	**29.818**	1.014	**4.405**

Vessel detection - Matched Filtering:

- Matched filtering is an image processing technique used to detect the presence of a known structure in a given environment.
- Retinal vessels are not linear, they vary in their orientation and thickness throughout their structure.
- To capture this wide range of vessel structures, a simple horizontal or vertical filter to detect the edge will not be helpful, hence we iterate through all possible angles.
- For this a gobar Kernel is used as the know structure in matched filtering.



Complex

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma) = \exp\left(-\frac{x'^2+\gamma^2y'^2}{2\sigma^2}\right)\exp\left(i\left(2\pi\frac{x'}{\lambda}+\psi\right)\right)$$

Real

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma) = \exp\left(-\frac{x'^2+\gamma^2y'^2}{2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda}+\psi\right)$$

Imaginary

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma) = \exp\left(-\frac{x'^2+\gamma^2y'^2}{2\sigma^2}\right)\sin\left(2\pi\frac{x'}{\lambda}+\psi\right)$$

where

$$x' = x\cos\theta + y\sin\theta$$

and

$$y' = -x\sin\theta + y\cos\theta$$

In the above equation,

λ — Wavelength of the sinusoidal component.

Θ — The orientation of the normal to the parallel stripes of the Gabor function.

Ψ — The phase offset of the sinusoidal function.

σ — The sigma/standard deviation of the Gaussian envelope

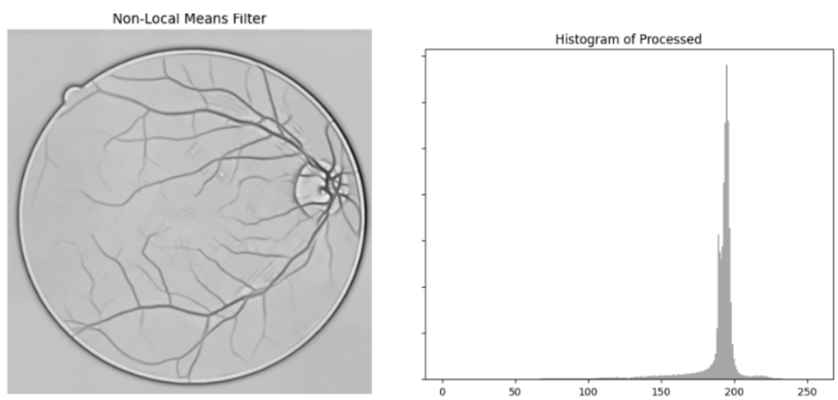
ɣ — The spatial aspect ratio and specifies the ellipticity of the support of the Gabor function.

- Different kernel sizes are used to detect different thickness of vessels.
- The maximum response across all angles and scales is computed to highlight vessels while suppressing non-vessel structures.

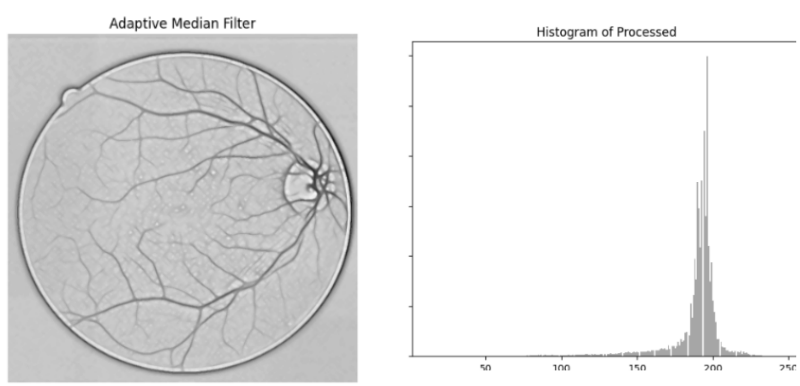
Noise Reduction:

The type of noise that was prevalent in the dataset was speckle noise - resulting from contrast enhancement which increased the intensity of the inherent noise in medical imaging.

- Non Local Means Filter: A denoising technique that averages similar pixel values from a larger neighborhood, effectively reducing noise while preserving image details.



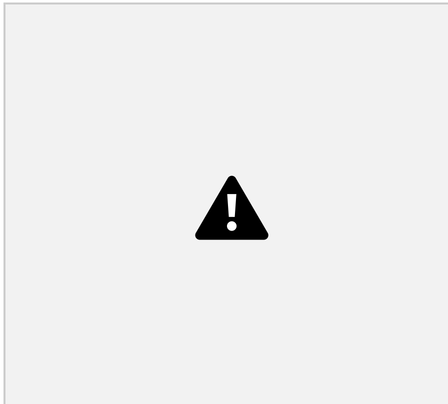
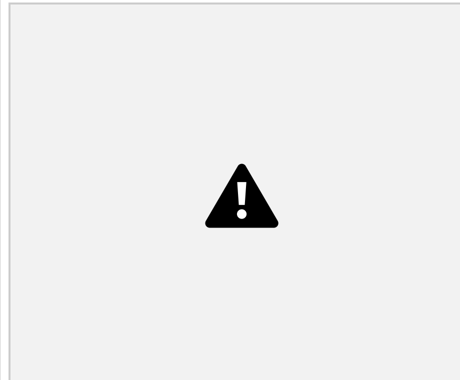
- Adaptive Median Filter: A noise reduction filter that replaces a pixel's value with the median of its surrounding pixels, adapting to local noise conditions to preserve edges.



- Gaussian Low pass filter: A frequency domain filter that attenuates high-frequency components in an image while allowing low-frequency components to pass, resulting in a smooth image.

- Butterworth low pass filter: A type of frequency domain filter characterized by a smooth frequency response, which attenuates high frequencies without introducing ripples in the passband.

- Mean Low pass filter: A simple averaging filter that replaces each pixel value with the mean of its neighboring pixels, effectively blurring the image and reducing high-frequency noise.

FILTER	PSNR	CII	ENTROPY
Non Local Means Filter	**36.964**	**1.000**	4.955
Adaptive Median Filter	36.445	0.922	**5.333**
Gaussian Low pass filter	32.627	0.588	5.076
Butterworth low pass filter	23.872	-0.529	4.951
Mean Low pass filter	33.362	0.698	5.273

Morphological Operations:

We are using morphological closing which includes the following steps:

- Dilation: Expands the boundaries of foreground objects, filling small holes and connecting nearby objects.
- Erosion: Shrinks the expanded objects back down, effectively removing small gaps and noise while preserving the overall shape of the larger structures.

Morphological closing is done to remove boundary noise that was found in the dataset.

Adaptive Thresholding:

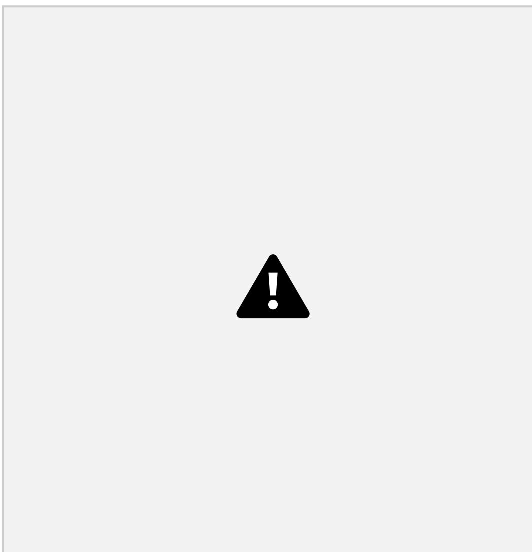
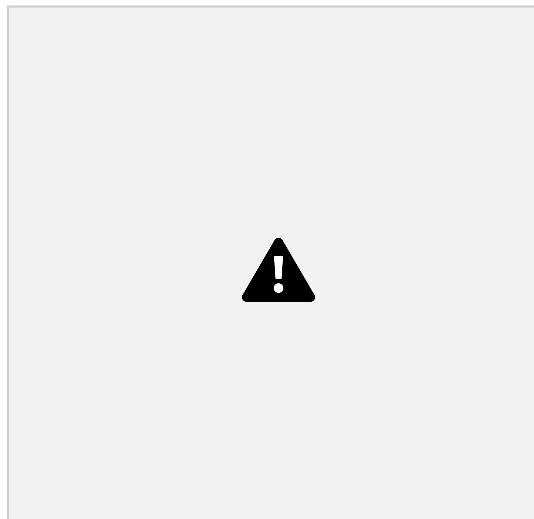
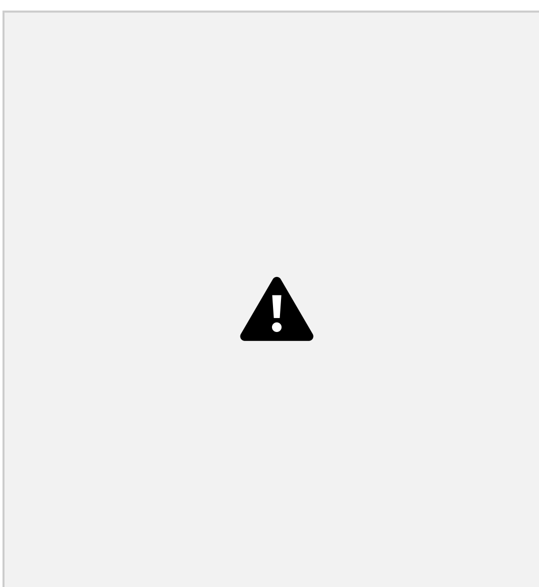
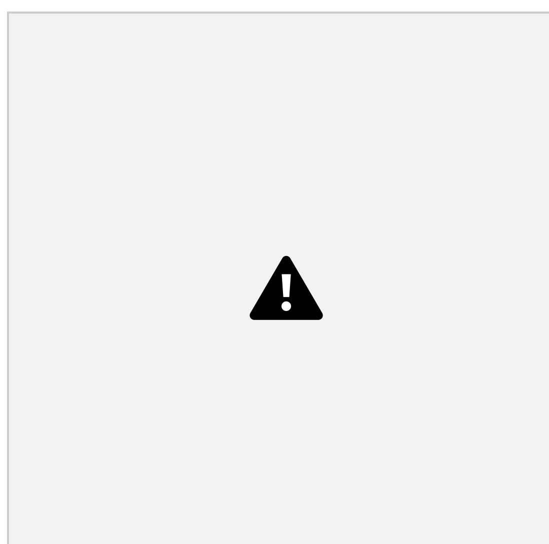
Adaptive Thresholding Converts the grayscale image to binary image by considering the local threshold whose region is defined as a parameter.

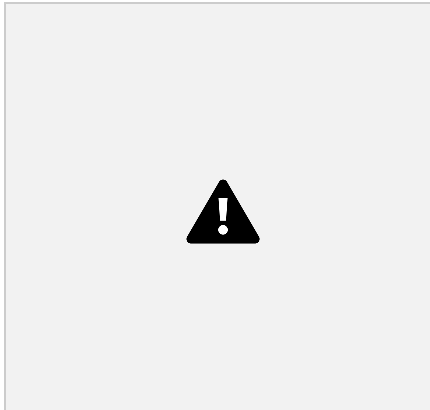
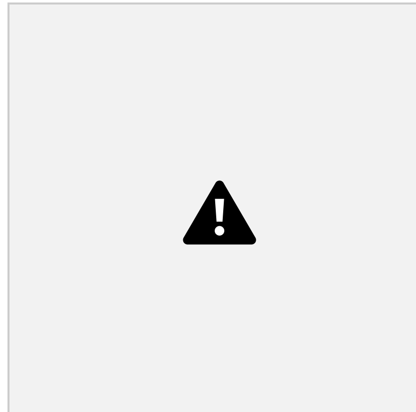
The threshold is calculated as the mean of the pixel values in the local neighborhood around the pixel.

Image Processing Approaches:

1. First Approach:

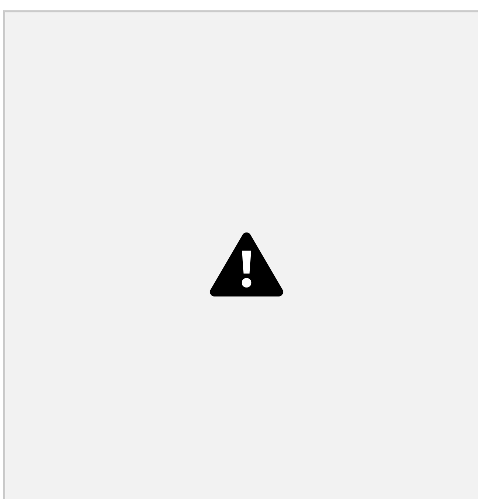
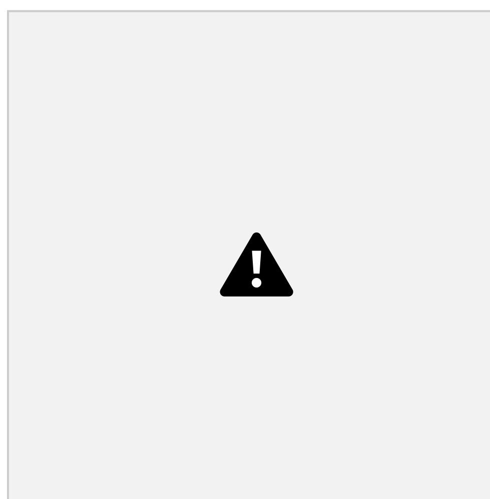
Through empirical data it was found that reducing noise before applying laplacian severely deteriorates the quality of the image.

The left image(no initial noise reduction) contains a lot more minute vessel structure compared to the right image(noise reduced). Furthermore all the vessels are relatively more structured and defined in the left image thus proving the necessity to not apply any noise reduction prior to vessel detection.Here we found out, empirically that applying an noise reduction filter results in too much of a contrast loss and a lot of the information in the image.

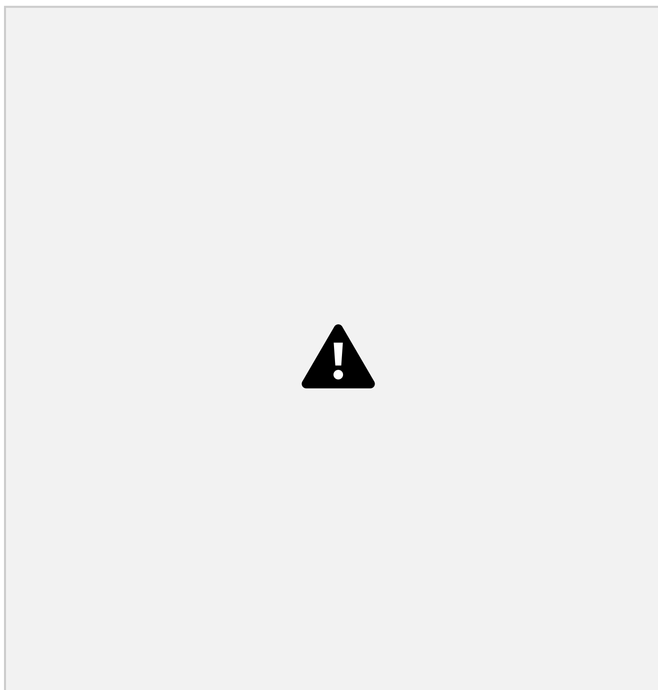
Sharpening prior to laplacian also leads to noise increase and noise corruption.

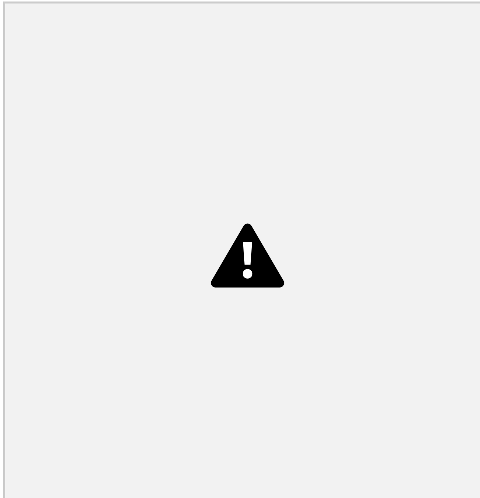
 

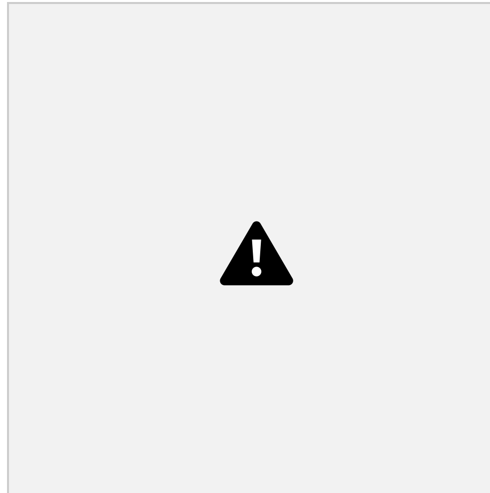
even though reapplying laplacian on the image to sharpen/highlight the vessels, it also enhances any region of rapid intensity increase/decrease which further increases the noise and the artifacts around the vessel. Further other artifacts like Fovea Centralis and the optic disk are also enhanced.since laplacian filter is a high pass filter it enhances edges and noises and enhancing/sharpening the image would further amplifies the noise.

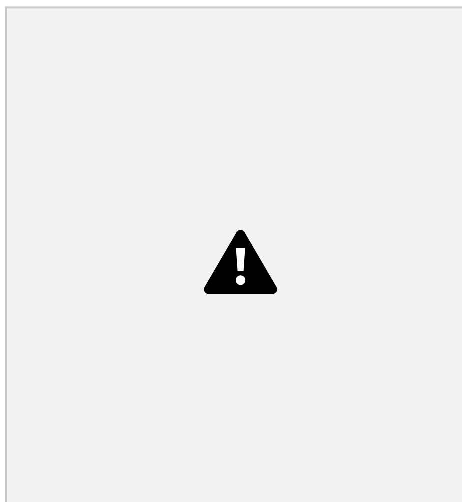
Another finding is that applying inversion does not change the outcome of the matched filter since the filter essentially highlights edges and the laplacian in itself identifies the borders only and not enhances them.

Hence the green channel Image was directly fed into the laplacian filter.Laplacian filter was chosen as it is good at detecting regions of rapid intensity change, thereby highlighting the edges of the vessels.









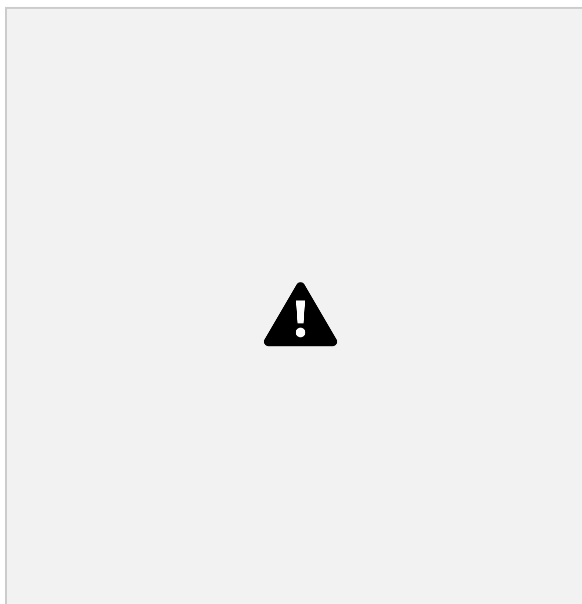
FILTER	**PSNR**	**CII**	**ENTROPY**
Histogram Equalisation	10.9	**8.9**	2.95
CLAHE	28.22	1.91	**4.01**
Unsharp Masking	**35.95**	1.48	3.26

To further improve the contrast between the foreground and background, CLAHE was used. All image enhancement techniques were chosen through trial and error method by considering metrics and perceptive quality.All the above enhancement techniques were used to prepare the image for vessel extraction. Although the laplacian is good at edge detection, it does not provide a concrete and specific identification of vessels. This can only be achieved through using a filter that can correlate with the varying thickness and orientation of the vessels. Hence a matched filter using a Gobar Kernel is used. The kernel is rotated through 360 degrees to cover all the orientations of the vessels.

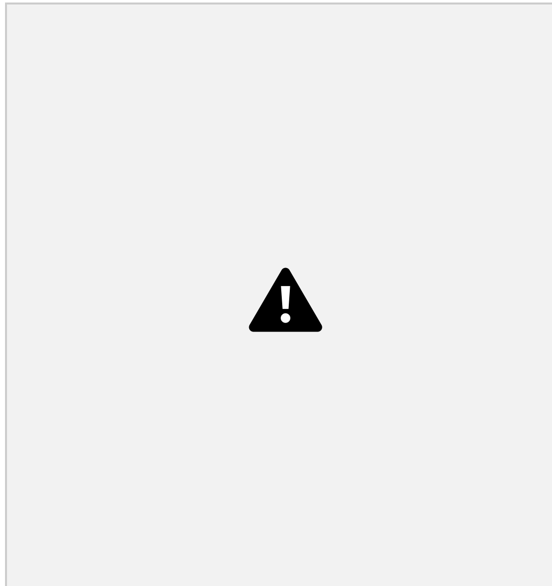
To further improve the contrast without increasing the noise or reducing the edge quality, an unsharp filter was used.

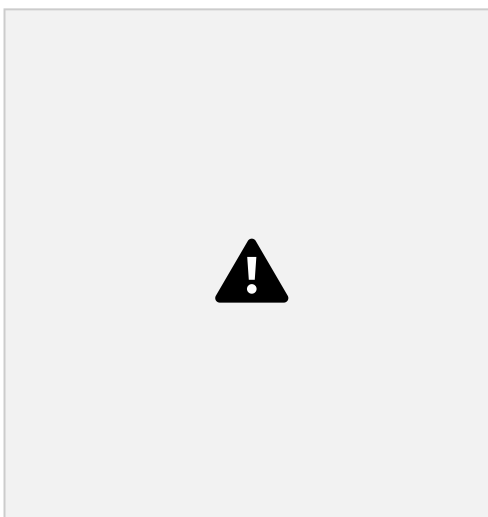
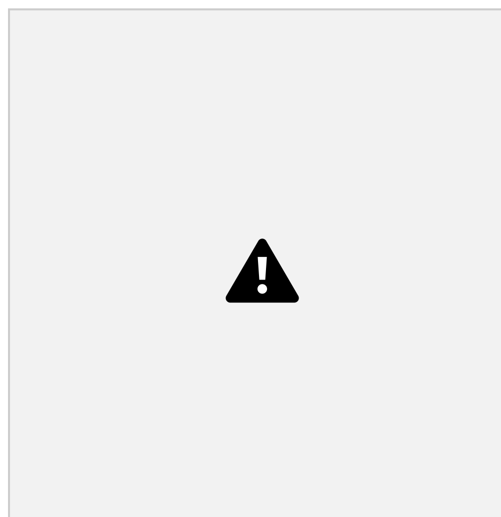
FILTER	PSNR	CII	ENTROPY
Histogram Equalisation	8.066	**4.013**	3.44
CLAHE	24.07	1.46	**4.26**
Unsharp Masking	**32.34**	1.29	3.64
Laplacian Sharpening	25.29	1.55	4.00

To remove the noise around the vessel edges a morphological closing transformation which comprises dilation followed by erosion is used.Before binarizing the image , a non-local means filter is used to remove any and all noises that were generated throughout the process.



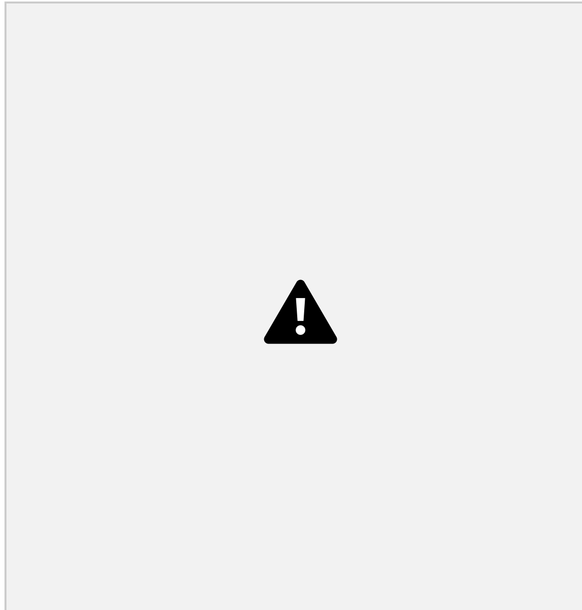
Before binarizing the image , it is first morphologically transformed to smooth boundaries to remove artifacts that interfere with the vessel extraction process.



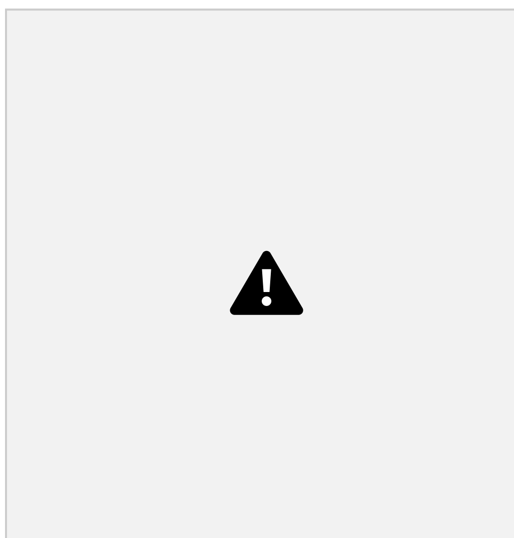



It is clear that the minute noise around hinders the thresholding operation thereby resulting in a poor quality mask.

Finally an adaptive filter is used to binarize the image.

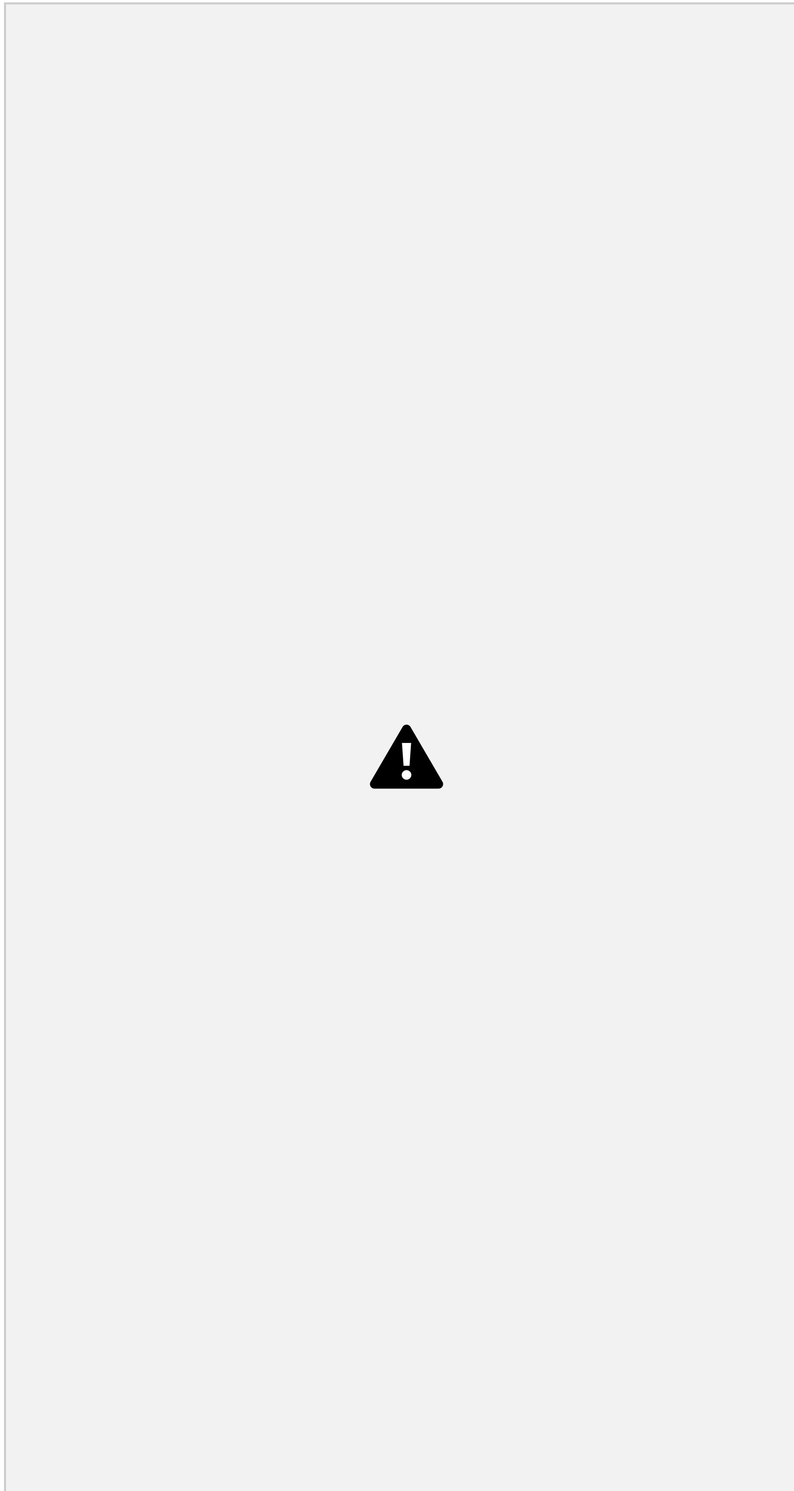


To utilize the hand labeled masks as reference we invert the image for evaluation metrics.

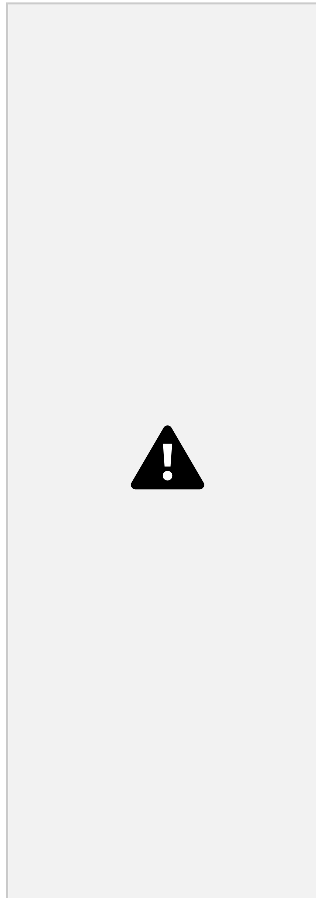


Once the binary image is generated, the Connected Set operation is applied.The operation identifies connectivity in the image and assigns labels to them. Further, to remove noisy-sets we set a threshold on the number of pixels in each set.

Steps Involved:

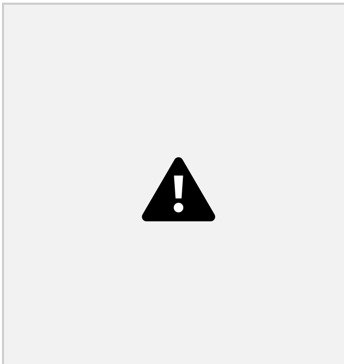
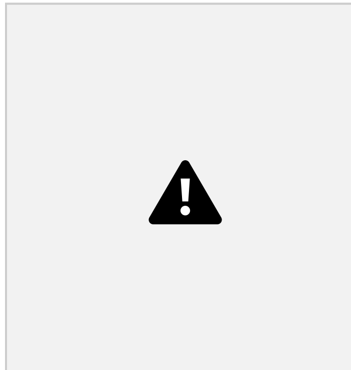
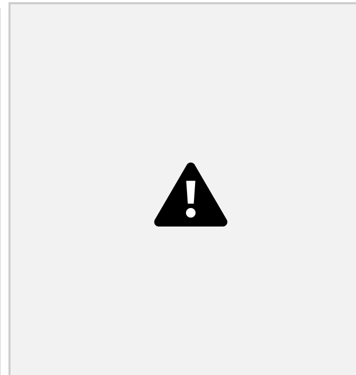
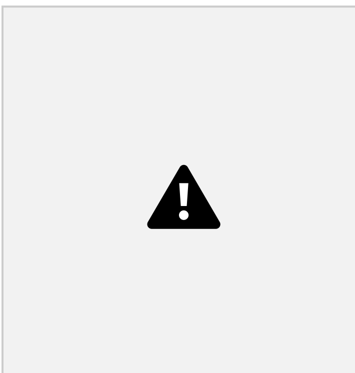
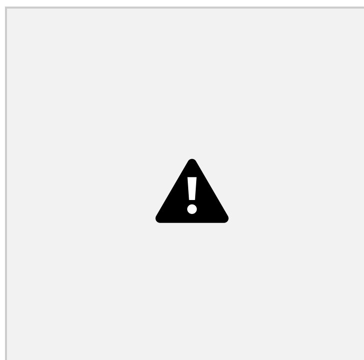
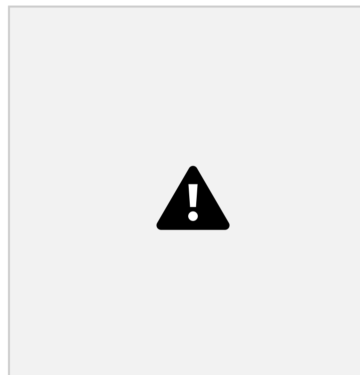
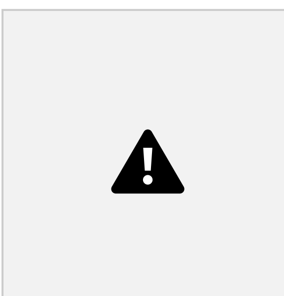
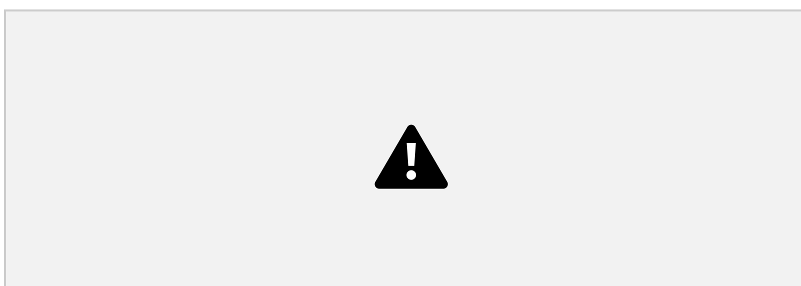
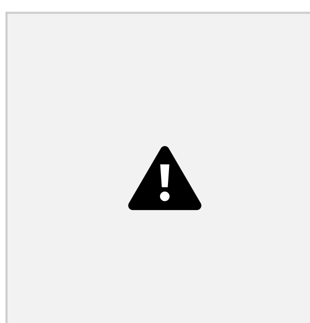


2. **Second Approach:**

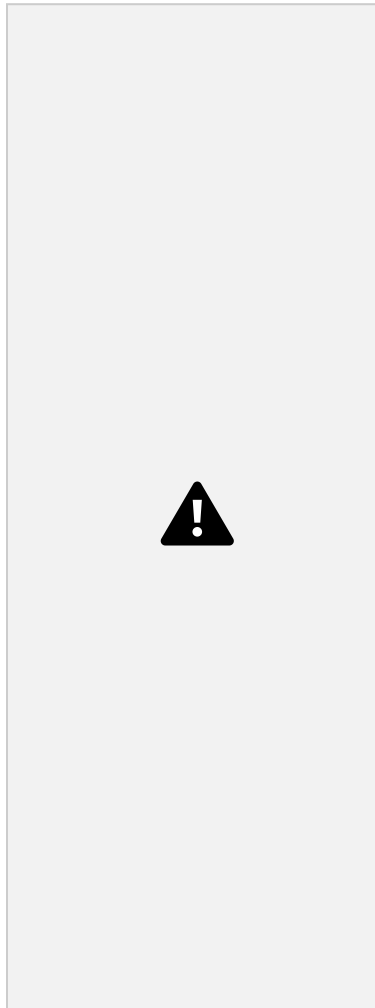


Since we need to extract the vessels from the image, any noise in the image is detrimental to the process. Applying LOG on the green channel, although does not increase the noise but the quality of the edges are slightly reduced. To reduce this effect CLAHE is used. In order to highlight the vessels we use the Matched Filter and to further increase the contrast for the final gray level slicing, CLAHE is applied again. To finally reduce the amount of noise present at the end of the process before gray level slicing , Non-Local means Filter is applied.

Steps Involved:

3. **Third Approach:**



Applying LOG on the green channel, although does not increase the noise but the quality of the edges are slightly reduced. To reduce this effect CLAHE is used. In order to highlight the vessels we use the Matched Filter. Since we are using dilations prior to reducing noise, through experimentation it is found that applying a CLAHE filter is not useful.

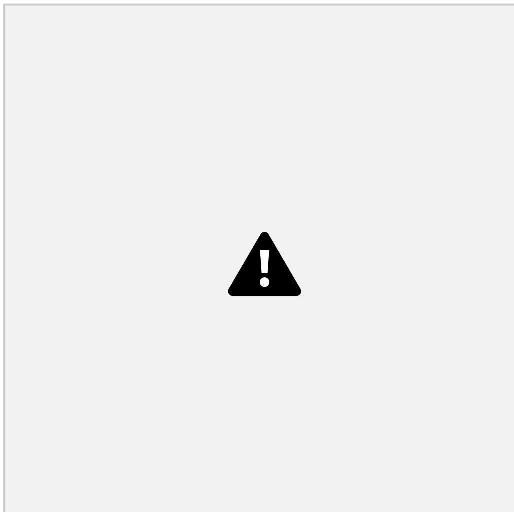
Steps Involved:

4. **Fourth Approach:** We introduced a gaussian blur before applying the laplacian to remove noise. This resulted in the loss of edge information.

Steps Involved:

Comparing 4 Approaches:

1



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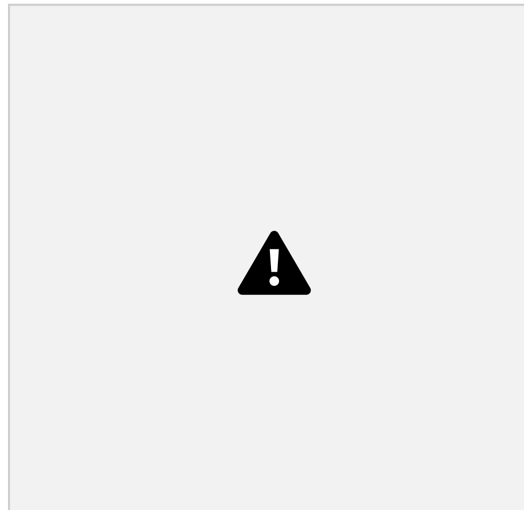

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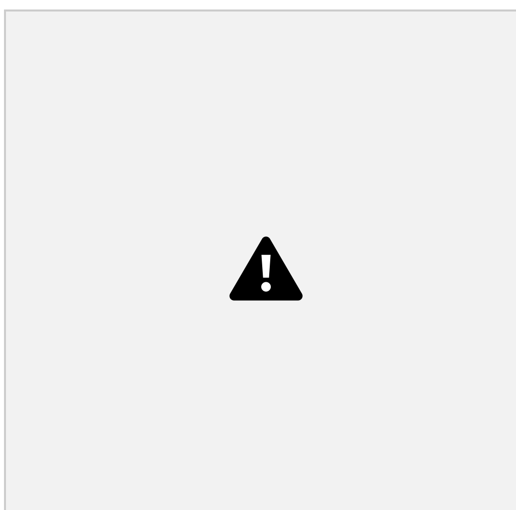

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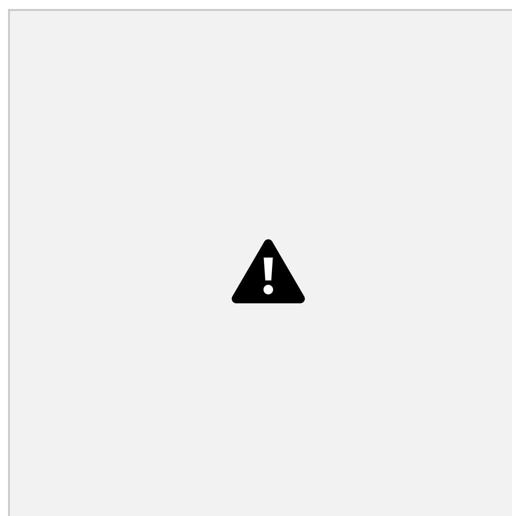


5. Novelty

Research on vessel extraction has relied on manual labeling followed by machine learning algorithms.

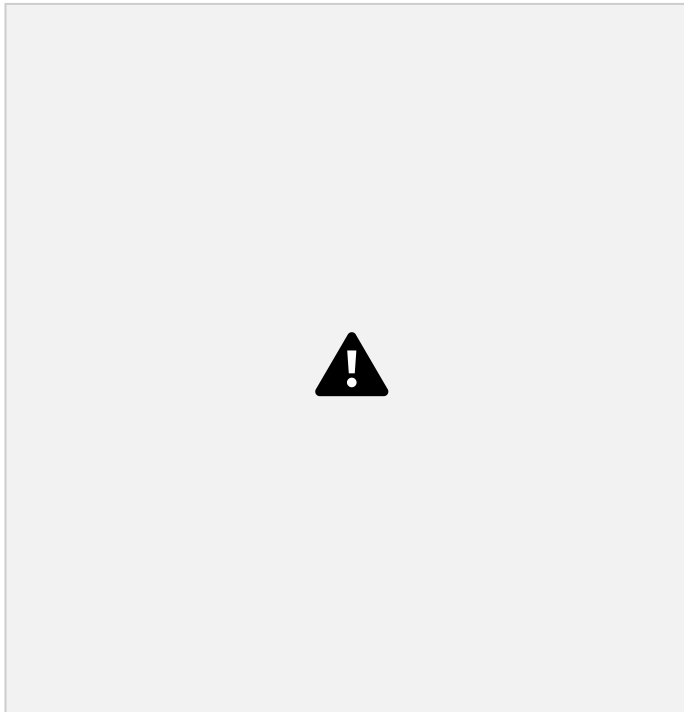
Work on image processing has essentially focused on Speeded Up Adaptive Contrast Enhancement (SUACE) which is a modification of the Tyler Coye Algorithm . Other methods include Histogram Equalization, Gabor wavelet, Local Normalization and Unsharp Masking, Wavelet, Contourlet and Curvelet methods separately applied to the filter.

Our novel approach introduces a combination of preexisting separate works, combined using a well empirically defined approach.

1. We extract the green channel image from the fundus image for processing
2. We apply 2 filters, essentially for intensity change detection and vessel detection. This helps in the fine tuning of the vessel extraction by reducing the dominance of unnecessary artifacts in the image.
3. A CLAHE filter between the edge and vessel detection is applied furthering the contrast of the image. This is again followed by an unsharp filter after the vessel extraction.
4. This is a dual pass vessel extraction technique.
5. A morphological operation is performed on the image to further separate the pixel intensities of the vessels from its neighbors.
6. Segmentation includes an adaptive thresholding followed by a connected component analysis to further clean the image.

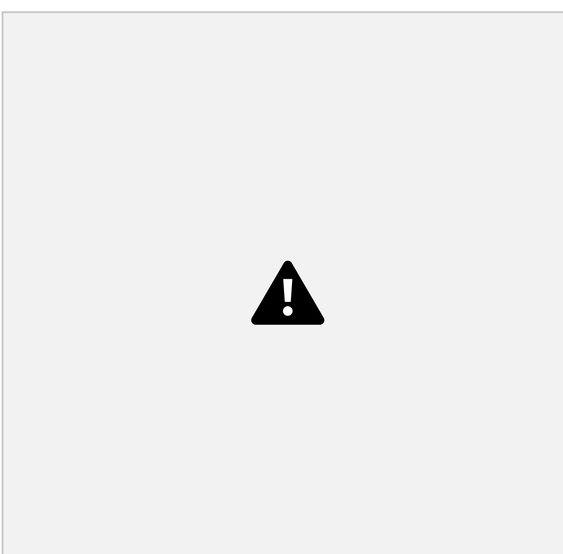
6. Sample Input and Output

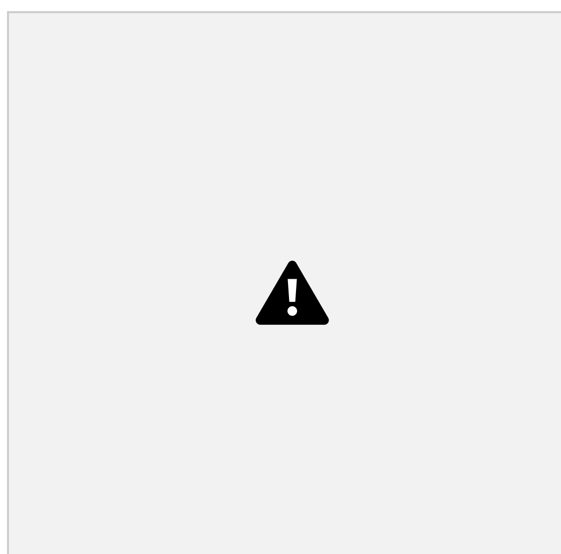
Input:



Output:

Highlighted vessels **output mask**

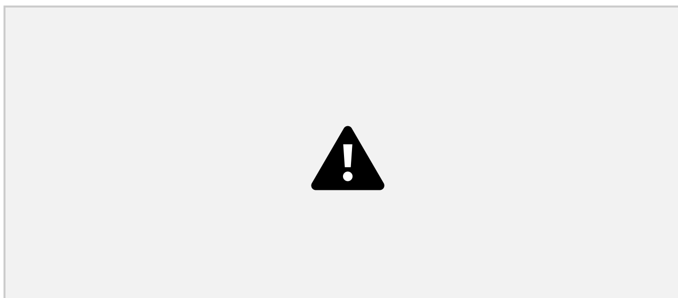




7. Performance Metrics

1. IoU (Intersection over Union):

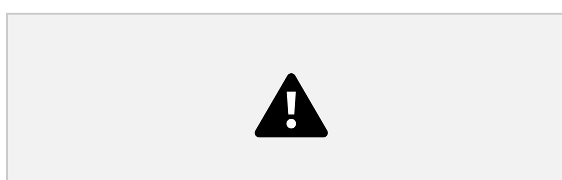
- Definition: IoU measures the overlap between the predicted segmentation and the ground truth. It is the ratio of the intersection of the predicted and ground truth areas to their union.
- Formula:



  - TP: True Positive
  - FP: False Positive
  - FN: False Negative

2. Dice Coefficient :

- Definition: Dice coefficient is a metric similar to IoU but is generally more sensitive to small object segmentations. It is the harmonic mean of precision and recall.



3. Precision:

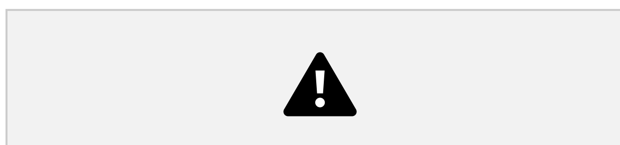
- Precision is the ability of a model to identify only relevant objects. It is the percentage of correct positive predictions.

4. Recall:

- Recall is the ability of a model to find all relevant cases (all ground-truth bounding boxes). It is the percentage of correct positive predictions among all given ground truths.

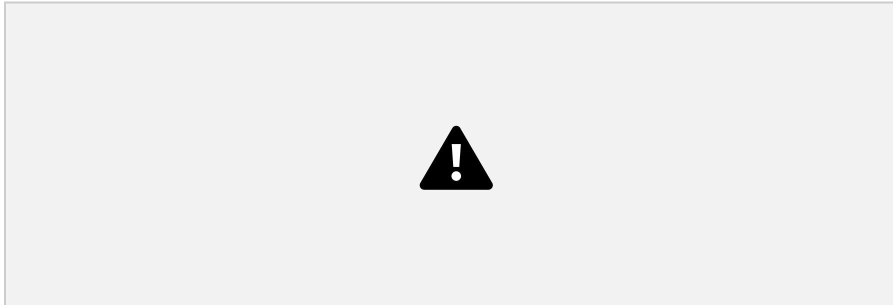
5. Accuracy:

    - Accuracy is the proportion of correct predictions (both true positives and true negatives) out of all predictions made.



6. Peak Signal-to-Noise Ratio (PSNR):

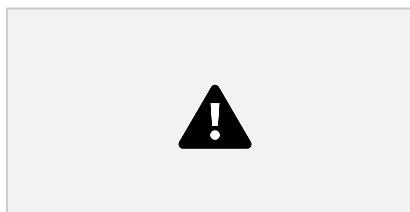
- PSNR is a measure used to assess the quality of reconstructed or compressed images compared to the original image. It quantifies the ratio between the maximum possible power of a signal (the original image) and the power of corrupting noise (the differences between the original and compressed images).



MAX is the maximum possible pixel value of the image.

7. CII (Colorfulness Index Indicator):

- CII is a metric used to quantify the colorfulness of an image. It measures the intensity and variety of colors in an image, considering both saturation and brightness.



C enhanced and C original denote the contrast of the enhanced and original images, respectively.

8. Entropy:

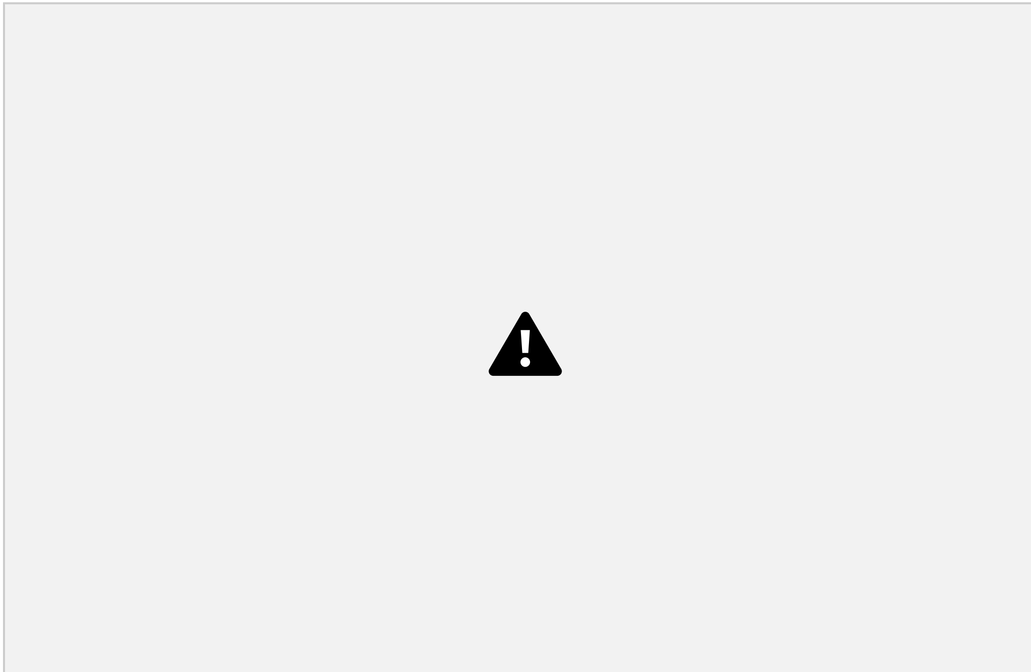
- Entropy in image processing refers to a measure of the amount of information or uncertainty contained in an image. It quantifies the randomness or complexity of pixel values in the image. Entropy can be used to judge image quality because greater entropy values often reflect more detailed and complex images.

$$H(X) =- i = 1\sum Np(xi)\cdot log2(p(xi))$$

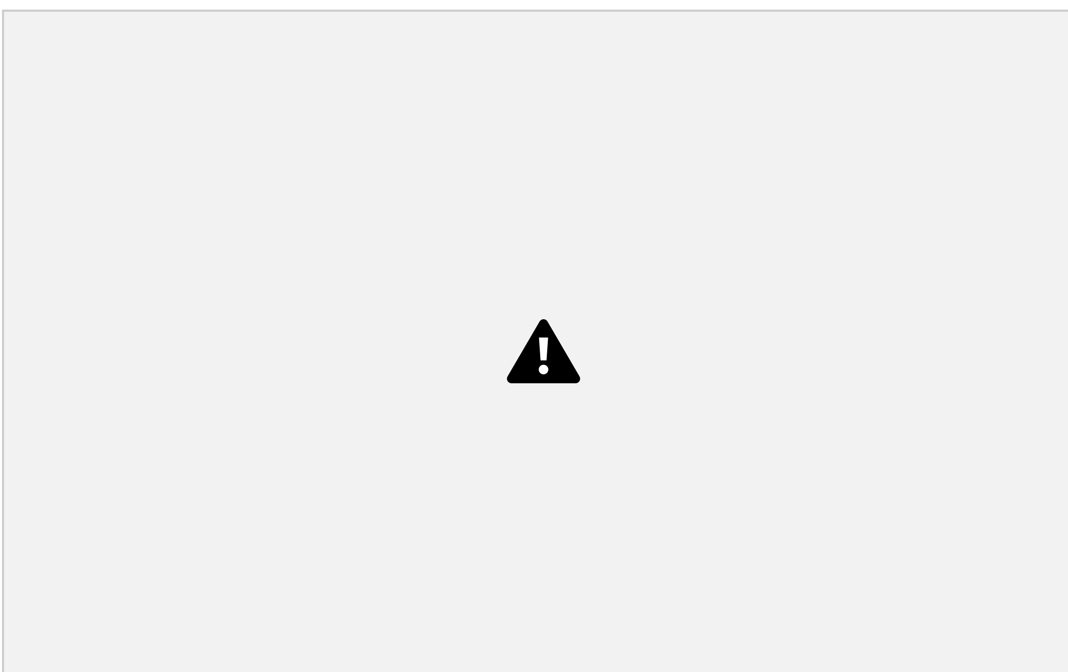
  - H(X) is the entropy of the image.
  - $p(xi)$ is the probability of occurrence of pixel value xi
  - N is the total number of unique pixel values.

Evaluating Filters:

- Optimizing the Laplacian Filter



- Optimizing Contrast Limited Adaptive Thresholding Filter

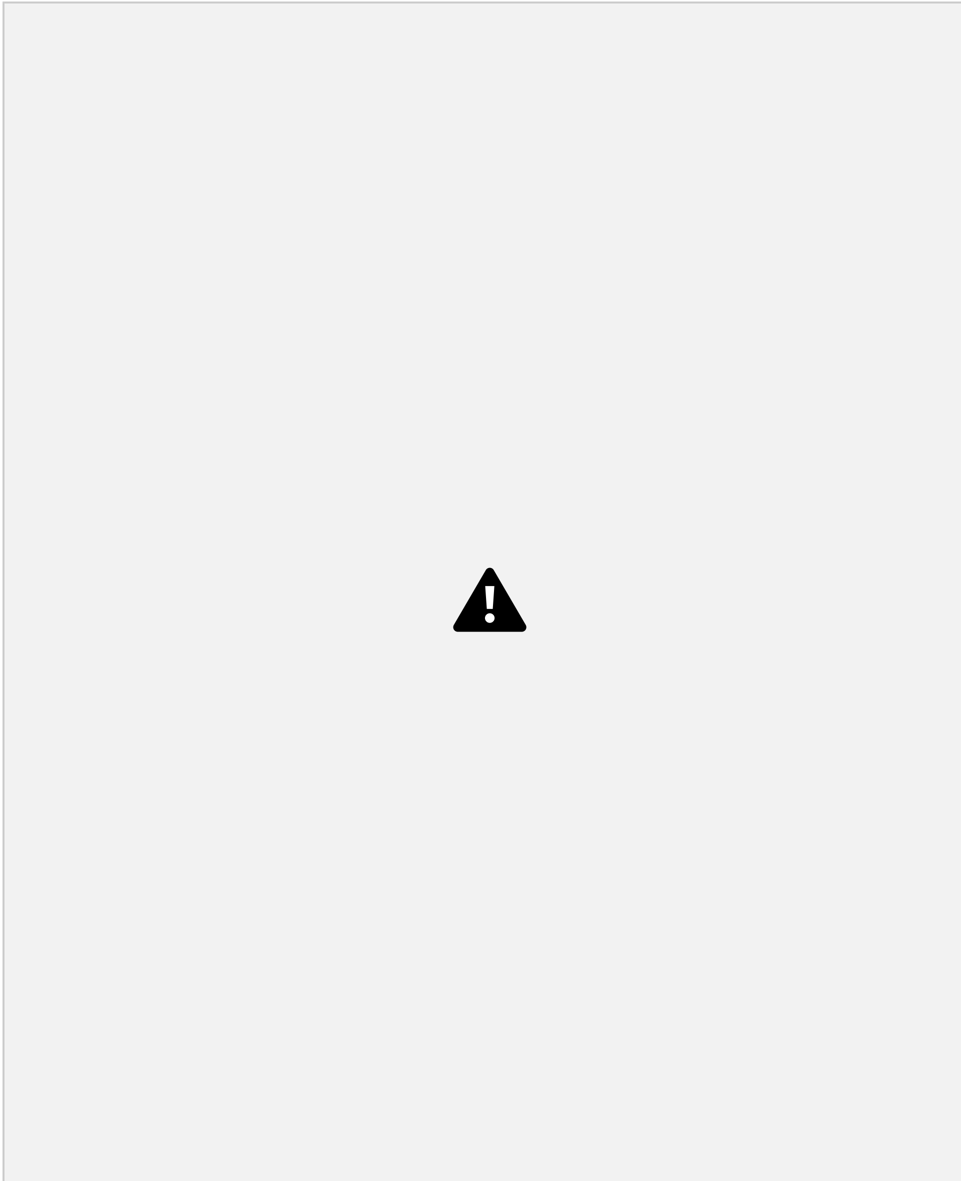


- Optimizing the Matched Filter

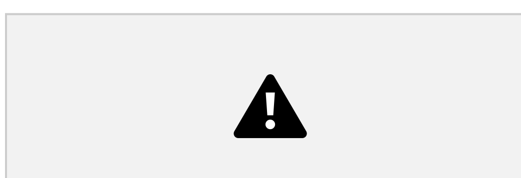
- Optimizing the unsharp masking Filter

- Optimizing the Non local Means Noise Filter

Comparing Final Mask with hand labeled Mask



The processed mask and hand labeled mask is compared and evaluated based on their IoU, Dice Coefficient, Precision, Recall and Accuracy. All the images in the dataset are compared and average metrics across the dataset is obtained.



The mask is more conservative in identifying positives but misses some true positive regions.
The mask performs well overall in terms of predicting both classes (positive and negative) pixels - the vessel structures.

Future improvements:

1. To further enhance the vessel structure quality , an edge linking process can be implemented
2. In a few images the corneal structure is retained.
3. Since the dataset contains no circumferential artifact , image preprocessing can be done to increase the accuracy of the evaluation metrics. This can be done by applying a mask on the input image. Since the exact positioning of each image was not accurate and there exists a small variation in the retinal size , the results were not positive enough to be implemented.

8. Conclusion

The complete process has been thoroughly experimented and obtained for retinal blood vessel extraction by utilizing various image processing techniques. The obtained results are compared with the hand labeled masks in the dataset and the comparison is evaluated.

9. References:

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OCULAR ABNORMALITY CLASSIFICATION FROM PROCESSED VESSEL STRUCTURES

UCS2523 – Image Processing and Analysis

Assignment 2
Submitted By

K.Harish 3122225001036
Janeshvar Sivakumar 3122225001047

Department of Computer Science and Engineering

Sri Sivasubramaniya Nadar College of Engineering
(An Autonomous Institution, Affiliated to Anna University)

Kalavakkam – 603110

October 2024

Sri Sivasubramaniya Nadar College of Engineering

(An Autonomous Institution, Affiliated to Anna University)

BONAFIDE CERTIFICATE

Certified that this Assignment report titled “ **OCULAR ABNORMALITY CLASSIFICATION FROM PROCESSED VESSEL STRUCTURES** ” is the bonafide work of “K.Harish (3122225001036), Janeshvar Sivakumar (3122225001047) ” who carried out the project work in the Course UCS2523 – Image Processing and Analysis during the academic year 2024-25.

Internal Examiner External Examiner

Date

TABLE OF CONTENTS

1. Problem Statement

To introduce a machine learning based ocular disease classification model using vessel extraction as a preprocessing method.

2. Abstract

Even though there has been research in correlating retinal vessel structures, their deformities and ocular diseases, there has not been enough work done inferring from this research to further use machine learning to provide patient care and pre-clinical image processing and analysis.

Hence we introduce a vessel structure based classification model trained using a CNN architecture.This work focuses on the machine learning aspect of the project and refers to its previous submission on vessel extraction from fundus images for preprocessing.

3. Dataset Description

Ocular Disease Intelligent Recognition (ODIR) is a structured ophthalmic database of 5,000 patients with age, color fundus photographs from left and right eyes and doctors' diagnostic keywords from doctors.

This dataset is meant to represent ‘‘real-life’’ set of patient information collected by Shanggong Medical Technology Co., Ltd. from different hospitals/medical centers in China. In these institutions, fundus images are captured by various cameras in the market, such as Canon, Zeiss and Kowa, resulting into varied image resolutions.
Annotations were labeled by trained human readers with quality control management. They classify patient into eight labels including:

1. Normal (N)
2. Diabetes (D)
3. Glaucoma (G)
4. Cataract (C)
5. Age related Macular Degeneration (A)
6. Hypertension (H)
7. Pathological Myopia (M)
8. Other diseases/abnormalities (O)

4. Recent works

All recent works have approached the problem with a medical perspective, utilizing various domain specific factors such as oxygen saturation and aging.

Miri et al. (2017) [2]mentions that inhomogeneous contrast and illumination, caused by imaging processes and biological characteristics, are significant challenges in retinal image analysis. They point out that color variations within and across images arise from factors like hemoglobin oxygen saturation, aging, cataract development, flash intensity and spectrum, camera distortions, flash artifacts, and focus. To address these issues, some researchers analyze and correct the image background to detect and adjust contrast and illumination changes. However, the paper does not delve into specific preprocessing techniques employed.

Zhang et al. (2023) focuses on a particular preprocessing method called adaptive contrast enhancement (ACE) applied to the RITE dataset. They explain that ACE addresses the issues of uneven lighting, low overall illumination, and low contrast between blood vessels and the background, which are common in retinal fundus images and can negatively impact classification accuracy.

In its essence, no research has been done in correlating vessel structure with diseases and utilizing this inference to build a classification model.

The study by Ajaz et al.[3] specifically focuses on the relationship between retinal vessel geometrical features and the incidence and progression of DME. They found that while four retinal vessel geometric features (RVGF) showed significant differences between healthy controls and DME cases, Average Branching Angle (ABA) was the only parameter that exhibited a monotonic increase with disease severity. This suggests that ABA could be a valuable biomarker for assessing DME progression and could be incorporated into computerized assessment tools.

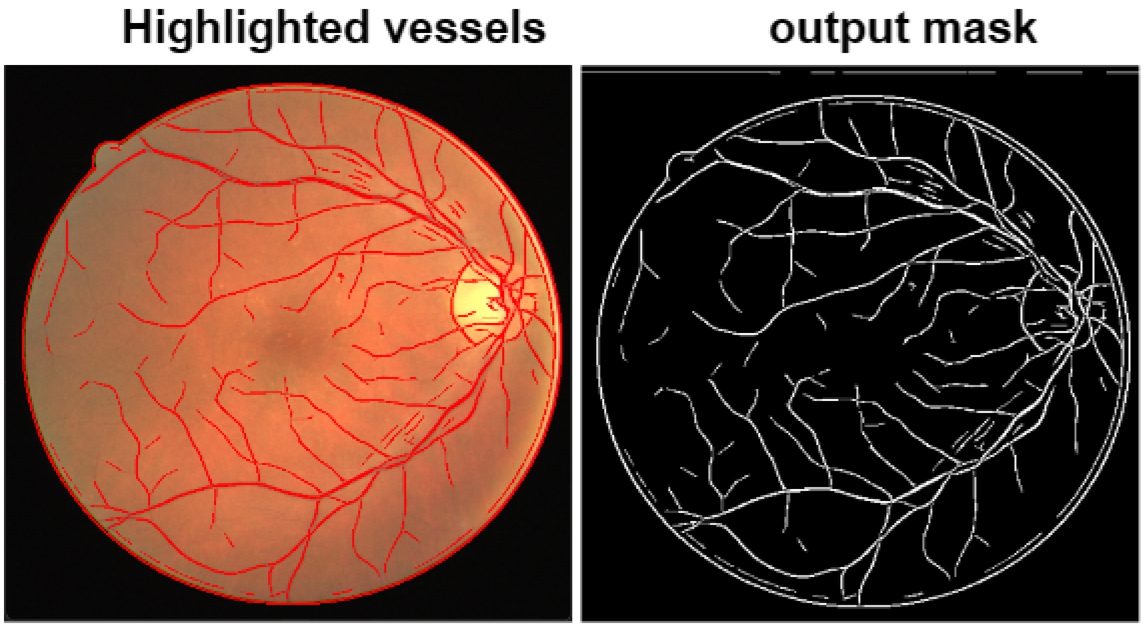
The study by Guo et al. [4] investigates the association between retinal information and CVD in patients with type 2 diabetes, independent of traditional cardiovascular risk factors. They found that retinal information, including vessel diameter and bifurcation-related parameters, is independently associated with CVD in type 2 diabetes patients. The study involved an age-sex matched case-control design with participants undergoing retinal imaging and standardized physical examinations.

5. Methodology

As mentioned previously we utilize the dual pass vessel extraction technique that was introduced previously to preprocess the image and extract vessel structures which has achieve promising results in the Digital Retinal Image for Vessel Extraction (DRIVE) dataset.

```
Average IoU: 0.3482
Average Dice Coefficient: 0.5158
Average Precision: 0.5656
Average Recall: 0.4793
Average Accuracy: 0.9217
```

original image



We preprocess all the images in the dataset to obtain such masked single channel images.

The dataset is processed by first creating target labels for all images and creating a balanced data to avoid unnecessary bias. The dataset is split into train(80%) and test (20%).

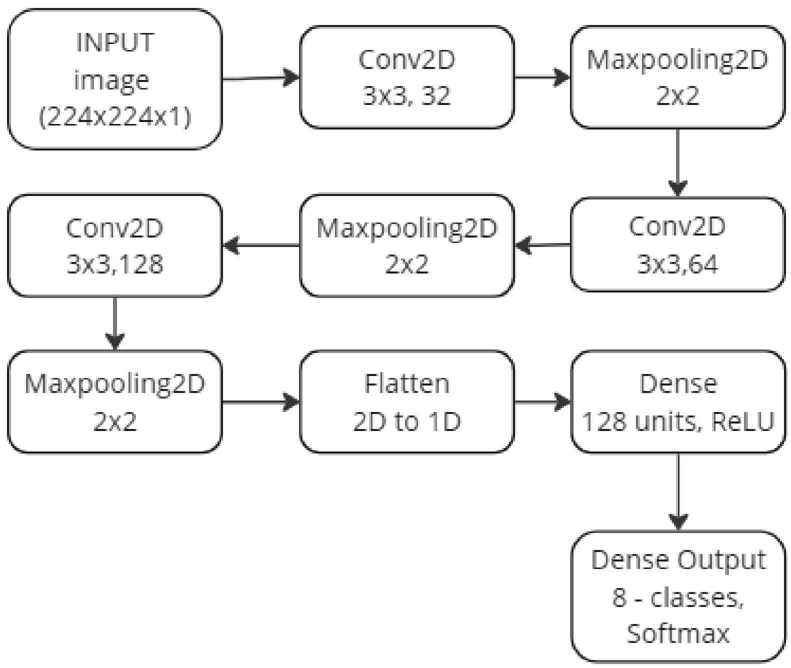
The proposed model is a convolutional neural network (CNN) designed to classify fundus images into various disease categories based on grayscale fundus images. Given the single-channel (grayscale) nature and the input size of 224x224 pixels, the architecture is optimized to balance accuracy and efficiency and to avoid overfitting. The model consists of 3 convolutional and pooling layers followed by fully connected (dense) layers, which culminate in a softmax output layer for multi-class classification.

The Convolutional layers uses ReLU (Rectified Linear Unit) activation is applied to introduce non-linearity.We use 32 filters with a small 3x3 kernel to capture features in the first convolutional layer. In the next layer we double the number of filters to 64 to increase the model's capacity to detect more nuanced patterns related to disease-specific structures. The

3x3 kernel captures slightly larger features than the previous layer. The third convolutional layer contains 128 filters.

Max pooling helps retain dominant features in the receptive fields while discarding less significant details, making the model more translation-invariant to small movements in the input image.

Model Architecture

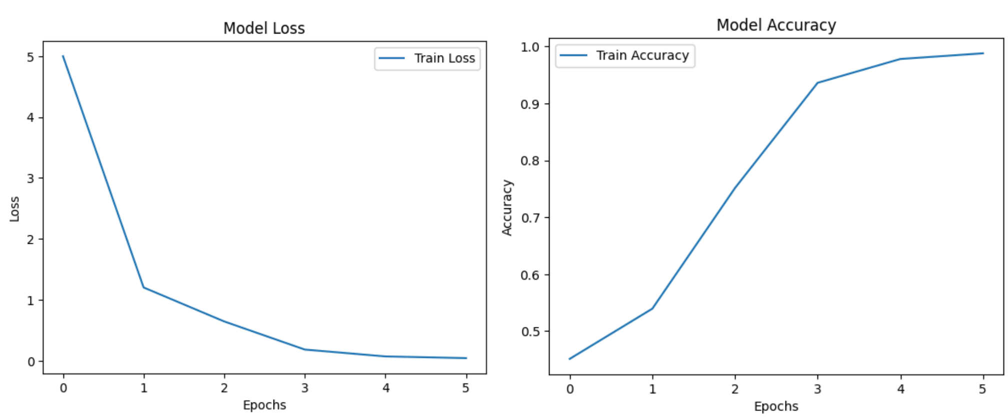



```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 222, 222, 32)      320

 max_pooling2d (MaxPooling2D  (None, 111, 111, 32)     0
 )

 conv2d_1 (Conv2D)           (None, 109, 109, 64)      18496

 max_pooling2d_1 (MaxPooling  (None, 54, 54, 64)       0
 2D)

 conv2d_2 (Conv2D)           (None, 52, 52, 128)       73856

 max_pooling2d_2 (MaxPooling  (None, 26, 26, 128)      0
```

```
                                          2D)

       flatten (Flatten)             (None, 86528)               0

    dense (Dense)                 (None, 128)                11075712

      dense_1 (Dense)               (None, 6)                   903

=================================================================
                         Total params: 11,169,287
                       Trainable params: 11,169,287
                         Non-trainable params: 0
_________________________________________________________________
```

To optimize model performance, the model was trained using categorical cross-entropy as the loss function, which is suitable for multi-class classification. The model also employs early stopping to avoid overfitting, especially given the high-dimensional nature of medical image data, which can make the model prone to memorizing training samples rather than generalizing to unseen data.

6. Results:



Class	Precision	Recall	F1-Score	Support
Normal (N)	0.85	0.90	0.87	575
Diabetes (D)	0.75	0.65	0.70	322
Glaucoma (G)	0.60	0.55	0.57	57
Cataract (C)	0.80	0.85	0.82	59
Age-related Macular Degeneration (A)	0.65	0.60	0.62	53
Hypertension (H)	0.55	0.50	0.52	25
Pathological Myopia (M)	0.70	0.65	0.67	46
Other Diseases (O)	0.60	0.50	0.55	142
Accuracy			**0.76**	**1279**
Macro Average	**0.69**	**0.65**	**0.66**	**1279**

The model performs well on classes with higher support, such as Normal (N), with a high precision (0.85), recall (0.90), and F1-score (0.87). This indicates that the model is very effective at distinguishing normal cases from disease-related ones, likely due to the larger number of samples.Diabetes (D) also shows reasonably good performance, with a balanced F1-score of 0.70. However, its recall is slightly lower than precision, indicating that some diabetic cases may be misclassified as non-diabetic.For Cataract (C), the model achieves both high precision and recall, resulting in an F1-score of 0.82, which suggests strong classification ability for this disease.Glaucoma (G), Age-related Macular Degeneration (A), and Pathological Myopia (M) have moderate F1-scores, but their recall is lower, suggesting that the model may struggle to correctly identify these diseases in all cases.Hypertension (H) and Other Diseases (O) show the lowest performance metrics, with F1-scores of 0.52 and 0.55, respectively. The limited support for these classes likely contributes to lower model performance, as the model might not have sufficient examples to learn robust features.

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