# Image Dataset:

https://www.kaggle.com/datasets/gunavenkatdoddi/eye-diseases-classification/data

**Glaucoma Retinal Image**

# Proposed Methodology

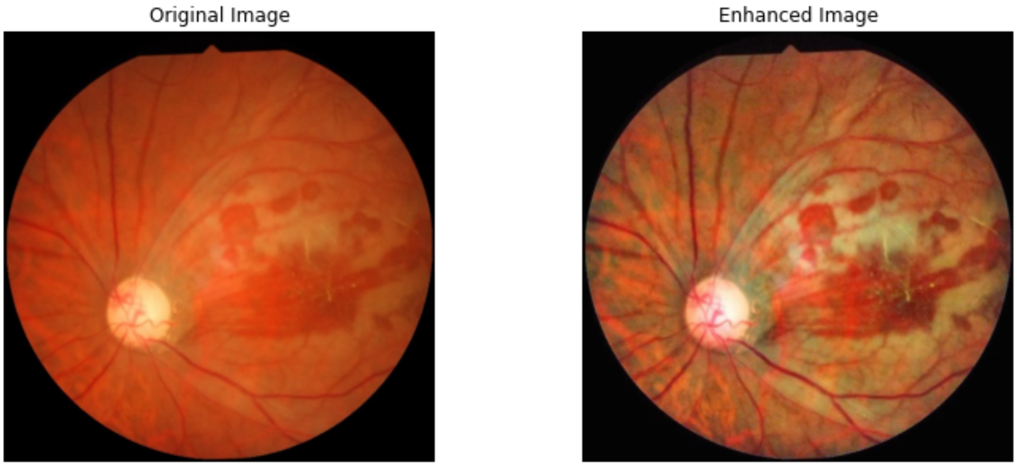
### A. IMAGE ENHANCEMENT method using Gaussian-CLAHE

**CODE:**

```
import cv2
import numpy as np
from IPython.display import display, Image
import matplotlib.pyplot as plt
```

```
# Load the glaucoma eye color image
image = cv2.imread('left_eye.jpg')

# Convert the image to grayscale for processing
gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)

# Noise Reduction: Apply Gaussian filtering to reduce noise
blurred = cv2.GaussianBlur(gray, (5, 5), 0)

# CLAHE (Contrast Limited Adaptive Histogram Equalization)
clahe = cv2.createCLAHE(clipLimit=2.0, tileGridSize=(8, 8))

# Apply CLAHE independently to each color channel
enhanced_channels = [clahe.apply(image[:, :, i]) for i in range(3)]
enhanced_image = cv2.merge(enhanced_channels)

# Display the original and enhanced images in the Jupyter Notebook
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.title('Original Image')
plt.imshow(cv2.cvtColor(image, cv2.COLOR_BGR2RGB))
plt.axis('off')
plt.subplot(1, 2, 2)
plt.title('Enhanced Image')
plt.imshow(cv2.cvtColor(enhanced_image, cv2.COLOR_BGR2RGB))
plt.axis('off')
plt.show()
```

**OUTPUT:**




**B. IMAGE SEGMENTATION method with CDOD-Glaucoma**

**CODE:**

```
import cv2
import numpy as np
from IPython.display import display, Image
import matplotlib.pyplot as plt

original_image = cv2.imread('left_eye.jpg', cv2.IMREAD_COLOR)
image = cv2.imread('left_eye.jpg', cv2.IMREAD_COLOR)

# Convert the image to grayscale
gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)

# We will use a circular Hough transform to detect the optic disc.
circles = cv2.HoughCircles(
    gray,
    cv2.HOUGH_GRADIENT,
```

```
    dp=1,
    minDist=30,
    param1=100,
    param2=30,
    minRadius=10,
    maxRadius=50
)

if circles is not None:
    circles = np.uint16(np.around(circles))
    for i in circles[0, :]:
        # circle around the optic disc in red
        cv2.circle(image, (i[0], i[1]), i[2], (0, 0, 255), 2)

_, binary_vessels = cv2.threshold(gray, 150, 255, cv2.THRESH_BINARY)

# Combine the optic disc and blood vessel segmentation for glucoma detection.
glaucoma_regions = cv2.bitwise_and(image, image, mask=binary_vessels)

# Display the original color image, segmented optic disc, and detected
glaucoma regions
plt.figure(figsize=(15, 5))
plt.subplot(1, 4, 1)
plt.title('Original Color Image')
plt.imshow(cv2.cvtColor(original_image, cv2.COLOR_BGR2RGB))
plt.axis('off')

plt.subplot(1, 4, 2)
plt.title('Optic Disc Segmentation')
```

```
plt.imshow(cv2.cvtColor(image, cv2.COLOR_BGR2RGB))
plt.axis('off')

plt.subplot(1, 4, 3)
plt.title('Glaucoma-affected Regions')
plt.imshow(cv2.cvtColor(glaucoma_regions, cv2.COLOR_BGR2RGB))
plt.axis('off')
plt.show()
```

**OUTPUT:**

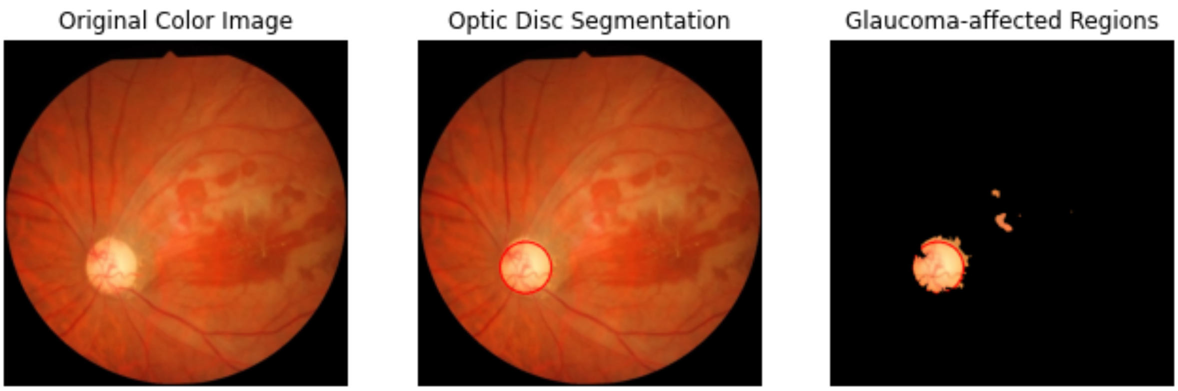
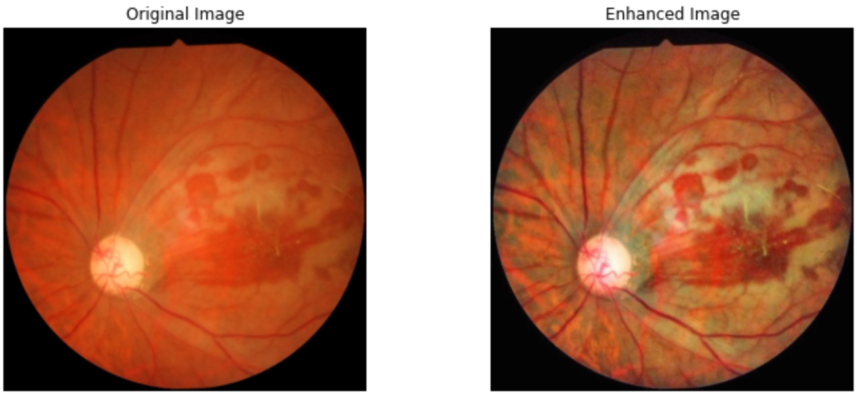



**IMAGE ENHANCEMENT:**

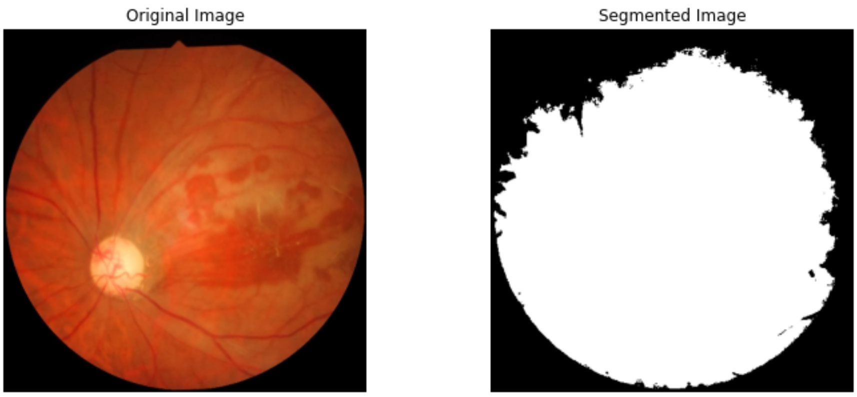
**<u>Existing Output:</u>**

## Proposed Output:

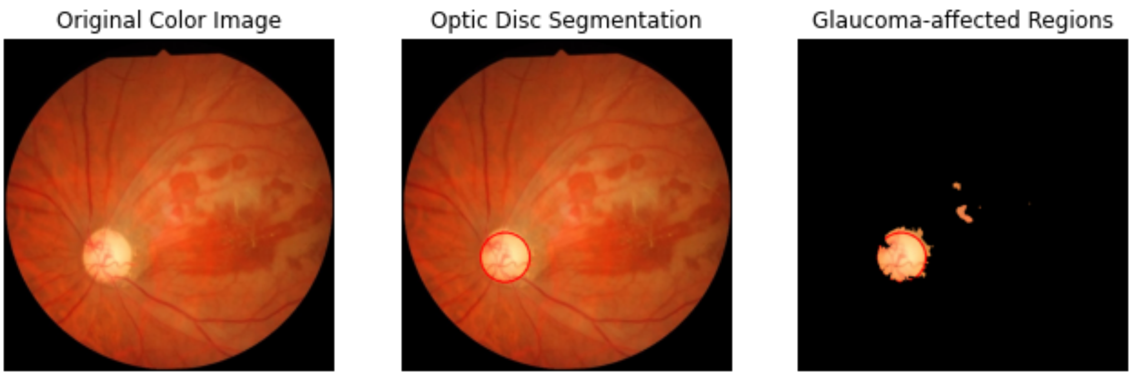



# IMAGE SEGMENTATION:

## Existing Output:




## Proposed Output:



# Comparison Table

## Proposed vs Existing (Enhancement)

| Criteria | Proposed Approach (Gaussian-CLAHE) | Existing Approach (Contrast Stretching) |
|---|---|---|
| Contrast Enhancement | Uses CLAHE for adaptive contrast enhancement, improving visibility of details in both dark and bright regions. | Utilizes linear contrast stretching to expand the entire intensity range, enhancing global contrast. |
| Detail Preservation | Preserves fine details in the image while enhancing contrast, maintaining intricate features. | May lead to some loss of fine details as it stretches the entire intensity range uniformly. |
| Adaptability to Variance | Adapts to local contrast, making it suitable for images with non-uniform illumination and varying contrast. | Applies a global contrast adjustment, less suitable for images with non-uniform illumination. |
| Risk of Over-Enhancement | Less prone to over-enhancement, as CLAHE limits contrast enhancement in local areas, reducing the risk of artifacts. | Prone to over-enhancement in bright regions, potentially causing clipping and loss of information. |
| Dynamic Range Adjustment | Effectively extends the dynamic range in a balanced manner, improving visibility of a wide range of intensities. | Extends the dynamic range but may not balance it as effectively, leading to a wider but less balanced range. |

## Proposed vs Existing (Segmentation)

| Criteria | Proposed Approach (CDOD-Glaucoma) | Existing Approach (Thresholding) |
|---|---|---|
| Detail Preservation | The CDOD-Glaucoma approach aims to preserve fine details in retinal images. | Thresholding may not effectively preserve fine details and can lead to information loss. |
| Adaptability | CDOD-Glaucoma adapts to the local characteristics of retinal images, making it suitable for images with varying features and illumination. | Thresholding is a global approach and may not adapt well to images with non-uniform illumination. |
| Segmentation Complexity | The proposed approach involves multiple steps and techniques, potentially offering more sophisticated segmentation. | Thresholding is a straightforward technique that may not handle complex images as effectively. |
| Theoretical Benefits | Theoretical benefits of CDOD-Glaucoma include improved accuracy, detail preservation, adaptability, and complex image handling. | Thresholding provides basic segmentation but may not meet the demands of complex medical image analysis. |
| Typical Applications | CDOD-Glaucoma is well-suited for medical images, including retinal images, and any images requiring accurate glaucoma segmentation. | Thresholding is a basic technique used for simpler segmentation tasks. |

### Enhancement Implementation link:

https://colab.research.google.com/drive/1mVy0FXMcZ9Yl2xNAE3QmGj746ZCtrLR7?usp=sharing

### Segmentation Implementation link:

https://colab.research.google.com/drive/1Kb-GqGcZXexsUNk5lQaOfkJVLh3Wds4g?usp=sharing