

Heaven's Light is Our Guide



**Department of Electronics & Telecommunication Engineering
Rajshahi University of Engineering & Technology**

Laboratory Report
on
ETE 4226: Sessional Based on ETE 4225

Submitted by:

Md. Darul Atfal Palash
Roll No. 1804005

Submitted to:

Dr. Shah Ariful Hoque Chowdhury
Associate Professor
Dept. of ETE, RUET

Contents

List of Figures	ii
Experiment 1: Study of Geometric Transformations of Image.	1
Experiment 2: Study of Histogram Equalization, Image Intensity Transformations, and Image Filtering in Spatial Domain.	11
Experiment 3: Study of Frequency Domain Image Filtering.	32
Experiment 4: Study of Line & Edge Detection and Image Segmentation.	47
Experiment 5: Study of Feature Extraction and Image Pattern Classification.	56

List of Figures

Experiment 1:	1
1.1 Original Image and Zoomed-in Part of the Image.	2
1.2 Original Image and Shrunked Image.	3
1.3 Original Image and Rotated Image.	4
1.4 Original Image and Scaled Image.	6
1.5 Video with with Image Rotation, Shearing, and Translation.	8
Experiment 2:	11
2.1 Histogram of original image and histogram equalized image.	12
2.2 Histogram of original image and histogram equalized image.	14
2.3 Original Image and Log Transformed Image.	15
2.4 Original Image and Inverse Log Transformed Image.	17
2.5 Power Law (Gamma) Transformation with Different Value of Gamma (0.2, 1.4, 4.0).	20
2.6 Original Image and Negative Transformed Image.	22
2.7 Original Image and Transformed Image with Corresponding Histogram.	25
2.8 Original Image and Blurred Image with Corresponding Histogram.	27
2.9 Original Image and Filtered Image with Corresponding Histogram.	29
Experiment 3:	32
3.1 Original Image and Ideal Filtered Image (Lowpass, Highpass, Bandpass, Band-reject Filtering).	36

3.2 Original Image and Butterworth Filtered Image (Lowpass, Highpass, Bandpass, Band-reject Filtering).	40
3.3 Original Image and Gaussian Filtered Image (Lowpass, Highpass, Bandpass, Band-reject Filtering).	44
Experiment 4:	47
4.1 Original Image and Edges & Lines of the Image.	49
4.2 Original Image and K-Means Clustered Image.	52
4.3 Original Image and Superpixel Based Clustered Image.	54
Experiment 5:	56
5.1 Original Image and Corner Detected Image Using Harris-Stephens (HS) Corner Detection.	57
5.2 Handwritten Digits with Its True and Predicted Value.	60
5.3 Accuracy and Loss Plot.	61
5.4 Handwritten Digits with Its True and Predicted Value.	64
5.5 Accuracy and Loss Plot.	64

Heaven's Light is Our Guide

Rajshahi University of Engineering & Technology

Department of Electronics & Telecommunication Engineering



ETE 4226: Sessional Based on ETE 4225

Experiment 1

Study of Geometric Transformations of Image.

Submitted by:

Md. Darul Atfal Palash

Roll: 1804005

Session: 2018-19

Submitted to:

Dr. Shah Ariful Hoque Chowdhury

Associate Professor

Dept. of ETE, RUET

Date of Experiment : 01/10/2023

Date of Submission : 25/01/2024

<u>Report</u>	(Teacher's Section)	<u>Viva</u>
<input type="checkbox"/> Excellent		<input type="checkbox"/> Excellent
<input type="checkbox"/> Very Good		<input type="checkbox"/> Very Good
<input type="checkbox"/> Good	_____	<input type="checkbox"/> Good
<input type="checkbox"/> Moderate	Signature	<input type="checkbox"/> Moderate
<input type="checkbox"/> Poor		<input type="checkbox"/> Poor

Experiment 1

Study of Geometric Transformations of Image.

Objectives

The main objectives of this experiment are:

- To understand and implement image zooming, shrinking, rotation, scaling, and histogram equalization using Python.
- To observe the effects of each image processing technique on the visual appearance of digital images.
- To analyze the computational efficiency of the implemented algorithms.

1.1 Required Apparatus/Softwares

- Python.
- A Highly Configured PC.

1.2 Program Code and Output

1.2.1 Image Zooming

Code :

```
1 import cv2
2 import matplotlib.pyplot as plt
3 input_image = cv2.imread('cameraman.jpg')
4 # Define the coordinates of the ROI (region of interest)
5 x, y, width, height = 100, 100, 200, 200
6 roi = input_image[y:y+height, x:x+width]
7 zoomed_in_roi = cv2.resize(roi, (width * 2, height * 2))
8 plt.figure(figsize=(10, 5))
9 plt.subplot(1, 2, 1)
10 plt.title("Original Image")
11 plt.imshow(cv2.cvtColor(input_image, cv2.COLOR_BGR2RGB))
```

```

12 plt.subplot(1, 2, 2)
13 plt.title("Zoomed-In Part")
14 plt.imshow(cv2.cvtColor(zoomed_in_roi, cv2.COLOR_BGR2RGB))
15 plt.show()

```

Output:

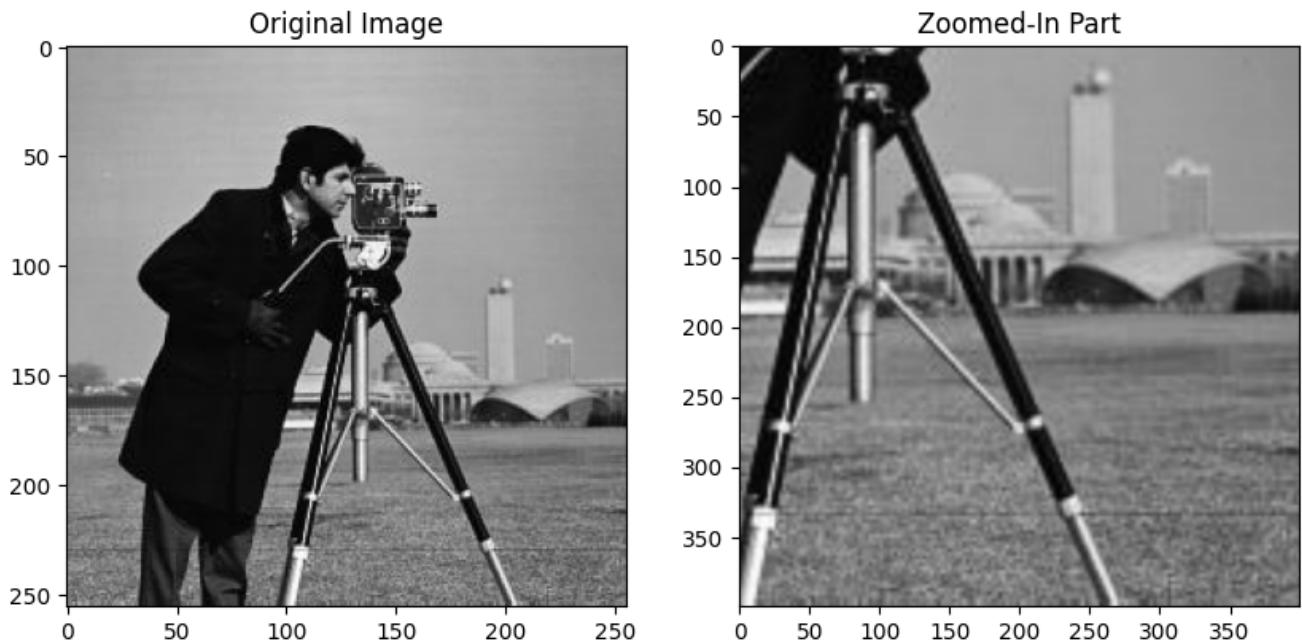


Figure 1.1: Original Image and Zoomed-in Part of the Image.

1.2.2 Image Shrinking

Code :

```

1 import cv2
2 import numpy as np
3 image = cv2.imread('cameraman.jpg')
4 scale_x = .5
5 scale_y = .5
6 translation_matrix = np.array([[scale_x, 0, 0], [0, scale_y,
0]], dtype=np.float32)

```

```

7 scaled_image = cv2.warpAffine(image, translation_matrix, (int(
8     image.shape[1]*scale_x), int(image.shape[0]*scale_y)))
9
10 print('Original Image')
11 cv2.imshow(image)
12 print('Shrunked Image')
13 cv2.imshow(scaled_image)
14 cv2.waitKey(0)
15 cv2.destroyAllWindows()

```

Output:

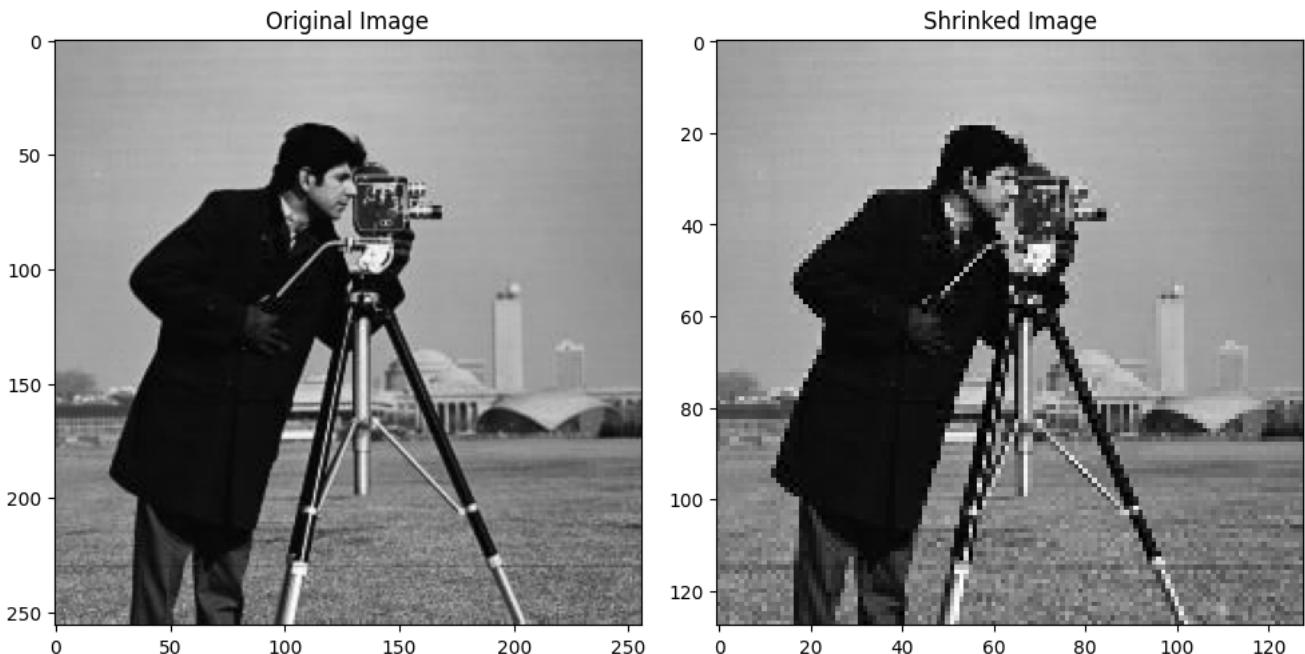


Figure 1.2: Original Image and Shrunked Image.

1.2.3 Image Rotation

Code :

```

1 import cv2
2 import numpy as np
3 from google.colab.patches import cv2_imshow

```

```

4 image = cv2.imread('/content/cameraman.jpg')
5 # Image rotation
6 h, w, _ = image.shape
7 angle = 90
8 rotation_matrix = cv2.getRotationMatrix2D((w/2, h/2), angle,
1)
9 rotated_image = cv2.warpAffine(image, rotation_matrix, (w, h))
10 plt.subplot(1, 2, 1)
11 plt.title("Original Image")
12 plt.imshow(cv2.cvtColor(image, cv2.COLOR_BGR2RGB))
13 plt.subplot(1, 2, 2)
14 plt.title("Rotated Image")
15 plt.imshow(cv2.cvtColor(rotated_image, cv2.COLOR_BGR2RGB))
16 plt.show()

```

Output:

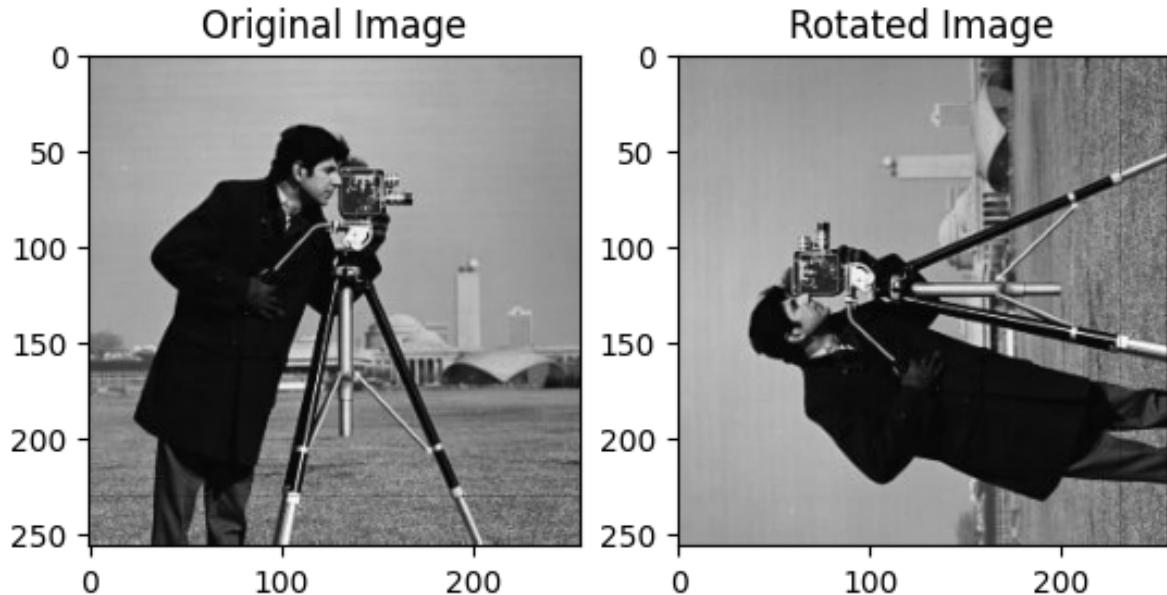


Figure 1.3: Original Image and Rotated Image.

1.2.4 Image Scalling

Code :

```
1 import cv2
2 import numpy as np
3 image = cv2.imread('cameraman.jpg')
4
5 # Define the scale factors for x and y directions
6 scale_x = 1.5
7 scale_y = 1.5
8
9 translation_matrix = np.array([[scale_x, 0, 0], [0, scale_y,
0]], dtype=np.float32)
10
11 scaled_image = cv2.warpAffine(image, translation_matrix, (int(
image.shape[1]*scale_x), int(image.shape[0]*scale_y)))
12
13 # Display the original and scaled images
14 plt.subplot(1, 2, 1)
15 plt.title("Original Image")
16
17 plt.imshow(cv2.cvtColor(image, cv2.COLOR_BGR2RGB))
18 plt.subplot(1, 2, 2)
19 plt.title("Scaled Image")
20 plt.imshow(cv2.cvtColor(scaled_image, cv2.COLOR_BGR2RGB))
21
22 plt.show()
```

Output:

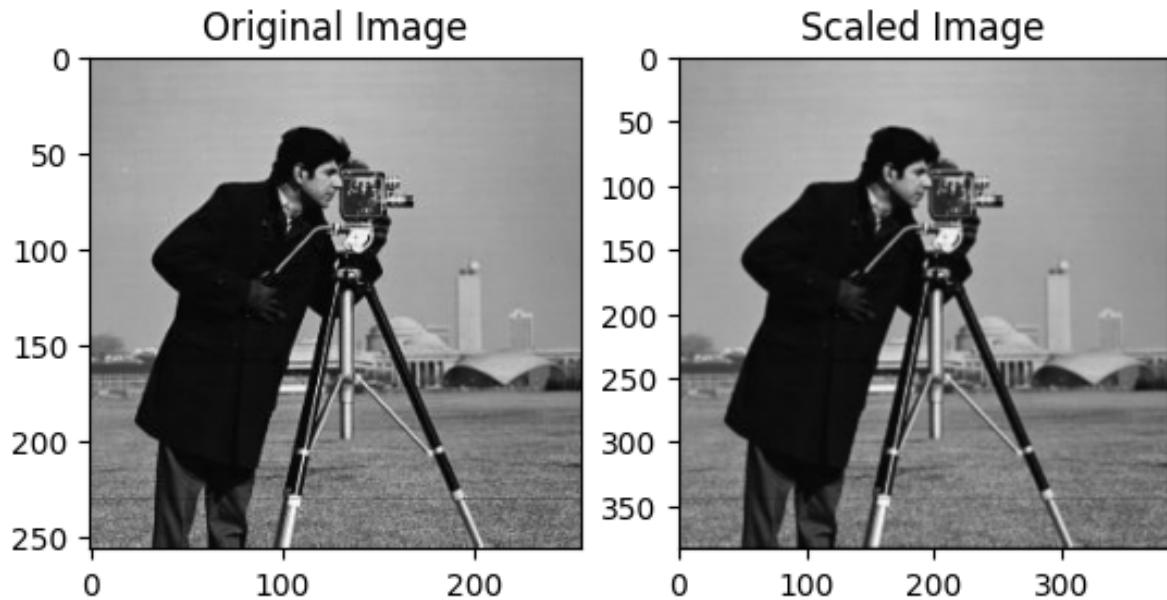


Figure 1.4: Original Image and Scaled Image.

1.2.5 Video Making with Image Rotation, Shearing, and Translation

Code :

```
1 import cv2
2 import numpy as np
3 image = cv2.imread('/content/cameraman.jpg')
4
5 # Get the dimensions of the image
6 height, width = image.shape[:2]
7 # Create a video writer object
8 fourcc = cv2.VideoWriter_fourcc(*'mp4v')
9 video_writer = cv2.VideoWriter('/content/transformations_video
10 .mp4', fourcc, 1, (width * 2, height * 2))
11 # Number of frames
12 num_frames = 30
```

```

13
14 for i in range(num_frames):
15     # Vary the rotation angle
16     rotation_angle = i * 360 / num_frames
17     rotation_matrix = cv2.getRotationMatrix2D((width / 2,
18                                                 height / 2), rotation_angle, 1)
19     rotated_image = cv2.warpAffine(image, rotation_matrix, (
20                                     width, height))

21     # Vary the shearing factor
22     shearing_factor = i / num_frames
23     shearing_matrix = np.array([[1, shearing_factor, 0], [0,
24                                 1, 0]], dtype=np.float32)
25     sheared_image = cv2.warpAffine(rotated_image,
26                                    shearing_matrix, (width, height))

27     # Vary the translation
28     translation_x = int(i * width / num_frames)
29     translation_y = int(i * height / num_frames)
30     translation_matrix = np.array([[1, 0, translation_x], [0,
31                                 1, translation_y]], dtype=np.float32)
32     translated_image = cv2.warpAffine(sheared_image,
33                                      translation_matrix, (width, height))

34     # Create a frame
35     frame = np.zeros((height * 2, width * 2, 3), dtype=np.
uint8)
36     # Place the images in different positions
37     frame[:height, :width] = image
38     frame[:height, width:] = rotated_image
39     frame[height:, :width] = sheared_image
40     frame[height:, width:] = translated_image

```

```

36     frame[height:, :width] = sheared_image
37     frame[height:, width:] = translated_image
38
39     cv2.putText(frame, 'Original', (10, 30), cv2.
40                 FONT_HERSHEY_SIMPLEX, 1, (255, 255, 255), 2)
41     cv2.putText(frame, 'Rotated', (width + 10, 30), cv2.
42                 FONT_HERSHEY_SIMPLEX, 1, (255, 255, 255), 2)
43     cv2.putText(frame, 'Sheared', (10, height + 30), cv2.
44                 FONT_HERSHEY_SIMPLEX, 1, (255, 255, 255), 2)
45     cv2.putText(frame, 'Translated', (width + 10, height + 30)
46                 , cv2.FONT_HERSHEY_SIMPLEX, 1, (255, 255, 255), 2)
47
48     video_writer.write(frame)
49
50 # Release the video writer
51 video_writer.release()

```

Output:

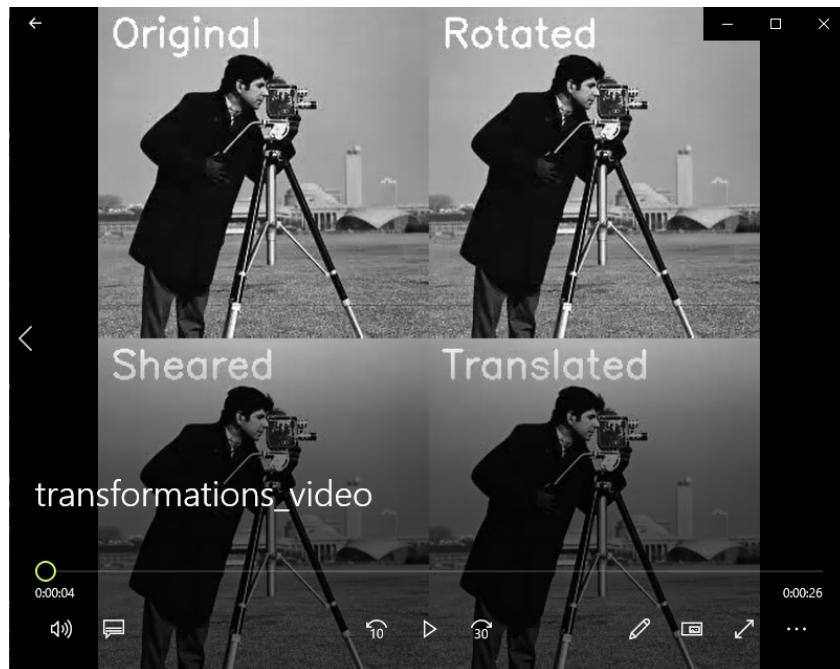


Figure 1.5: Video with with Image Rotation, Shearing, and Translation.

1.3 Conclusion

In conclusion, the study of image processing techniques, including zooming, shrinking, rotation, and scaling, was conducted using Python programming within the Google Colab platform. Each operation was applied to input images utilizing the OpenCV library, a powerful tool for computer vision tasks. Commonly used functions such as ‘imread’ for reading images, ‘resize’ for resizing images, ‘warpAffine’ for geometric transformations, and ‘imshow’ for displaying images were employed. Additionally, numpy’s ‘array’ facilitated efficient data manipulation, while Matplotlib’s ‘imshow’ aided in visualizing the results. The experimentation culminated in creating a video incorporating image rotation, shearing, and translation, showcasing the versatility of the OpenCV library. This study demonstrated the significance of these image processing techniques in computer vision applications and their seamless implementation using Python libraries.

Heaven's Light is Our Guide

Rajshahi University of Engineering & Technology

Department of Electronics & Telecommunication Engineering



ETE 4226: Sessional Based on ETE 4225

Experiment 2

Study of Histogram Equalization, Image Intensity Transformations, and Image Filtering in Spatial Domain.

Submitted by:

Md. Darul Atfal Palash

Roll: 1804005

Session: 2018-19

Submitted to:

Dr. Shah Ariful Hoque Chowdhury

Associate Professor

Dept. of ETE, RUET

Date of Experiment : 15/10/2024

Date of Submission : 25/01/2024

<u>Report</u>	(Teacher's Section)	<u>Viva</u>
<input type="checkbox"/> Excellent		<input type="checkbox"/> Excellent
<input type="checkbox"/> Very Good		<input type="checkbox"/> Very Good
<input type="checkbox"/> Good	_____	<input type="checkbox"/> Good
<input type="checkbox"/> Moderate	Signature	<input type="checkbox"/> Moderate
<input type="checkbox"/> Poor		<input type="checkbox"/> Poor

Experiment 2

Study of Histogram Equalization, Image Intensity Transformations, and Image Filtering in Spatial Domain.

Objectives

The primary objectives of this experiment include:

- Understanding the theoretical foundations of Histogram Equalization, Image Intensity Transformations, and Image Filtering in the Spatial Domain.
- Implementing these techniques using Python programming.
- Analyzing the effects of each technique on digital images.
- Drawing conclusions on the applicability and significance of these techniques in image processing.

2.1 Required Apparatus/Softwares

- Python.
- A Highly Configured PC.

2.2 Program Code and Output

2.2.1 Histogram Equalization for Gray Image

Code :

```
1 import cv2
2 import numpy as np
3 import matplotlib.pyplot as plt
4 image = cv2.imread('/content/einstein.jpg', cv2.
IMREAD_GRAYSCALE) # Convert to grayscale for histogram
equalization
5 # Apply histogram equalization
6 equ = cv2.equalizeHist(image)
```

```

7 # Display images and their histograms
8 plt.figure(figsize=(12, 6))
9 plt.subplot(2, 2, 1)
10 plt.imshow(image, cmap='gray')
11 plt.title('Original Image')
12 plt.subplot(2, 2, 3)
13 plt.hist(image.ravel(), 256, [0, 256])
14 plt.title('Histogram (Original)')
15 plt.subplot(2, 2, 2)
16 plt.imshow(equ, cmap='gray')
17 plt.title('Histogram Equalized Image')
18 plt.subplot(2, 2, 4)
19 plt.hist(equ.ravel(), 256, [0, 256])
20 plt.title('Histogram (Equalized)')
21 plt.show()

```

Output:

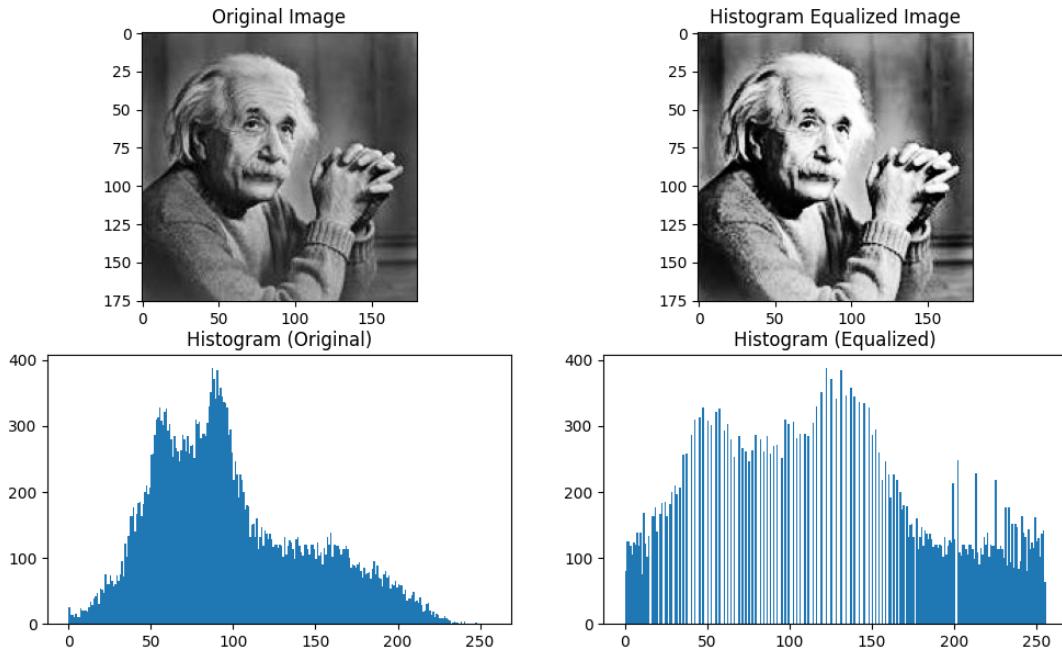


Figure 2.1: Histogram of original image and histogram equalized image.

2.2.2 Histogram Equalization for Color Image

Code :

```
1 import cv2
2 import matplotlib.pyplot as plt
3 image= cv2.imread("/content/einstein_img2.jpg")
4
5 ycrcb_img = cv2.cvtColor(image, cv2.COLOR_BGR2YCrCb)
6 ycrcb_img[:, :, 0] = cv2.equalizeHist(ycrcb_img[:, :, 0])
7 equalized_img = cv2.cvtColor(ycrcb_img, cv2.COLOR_YCrCb2RGB)
8 original_img = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
9
10 fig = plt.figure(figsize=(12,8))
11 fig.add_subplot(2,2,1)
12 plt.imshow(original_img)
13 plt.title("Original Image")
14 plt.axis(False)
15 fig.add_subplot(2,2,2)
16 plt.imshow(equalized_img)
17 plt.title("Histogram Equalized Image")
18 plt.axis(False)
19 fig.add_subplot(2,2,3)
20 color = ('b','g','r')
21
22 for channel,col in enumerate(color):
23     histr = cv2.calcHist([image],[channel],None,[256],[0,256])
24     plt.plot(histr,color = col)
25     plt.xlim([0,256])
26 plt.title('Histogram of Original Color Image')
27 fig.add_subplot(2,2,4)
```

28

```
29 for channel,col in enumerate(color):
30     histr = cv2.calcHist([equalized_img],[channel],None
31             ,[256],[0,256])
32     plt.plot(histr,color = col)
33     plt.xlim([0,256])
34 plt.title('Histogram of Equalized Color Image')
35 plt.show()
```

Output:

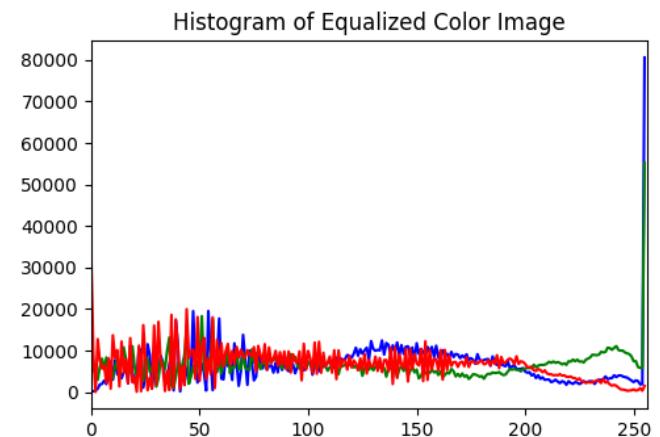
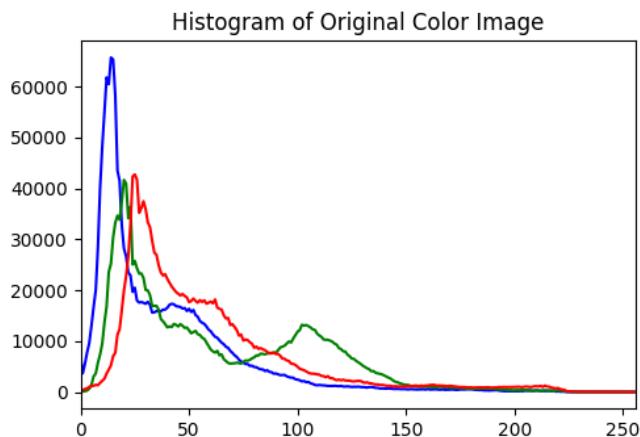
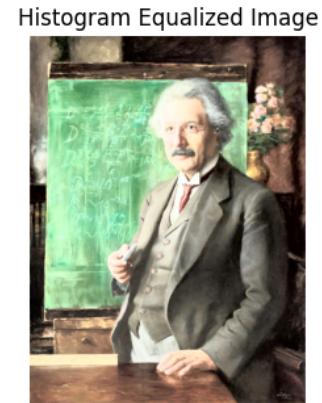


Figure 2.2: Histogram of original image and histogram equalized image.

2.2.3 Log Transform of an Image

Code :

```
1 import cv2
2 import numpy as np
3 import matplotlib.pyplot as plt
4 image = cv2.imread("/content/einstein.jpg")
5 c = 255 / np.log(1 + np.max(image))
6 log_image = c * (np.log(image + 1))
7 log_image = np.array(log_image, dtype = np.uint8)
8 fig = plt.figure(figsize=(20,20 ))
9 disp_img1= cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
10 disp_img2= cv2.cvtColor(log_image, cv2.COLOR_BGR2RGB)
11 fig.add_subplot(1,2,1)
12 plt.imshow(disp_img1)
13 plt.title("Original")
14 fig.add_subplot(1,2,2)
15 plt.imshow(disp_img2); plt.title("Log Transformed")
```

Output:

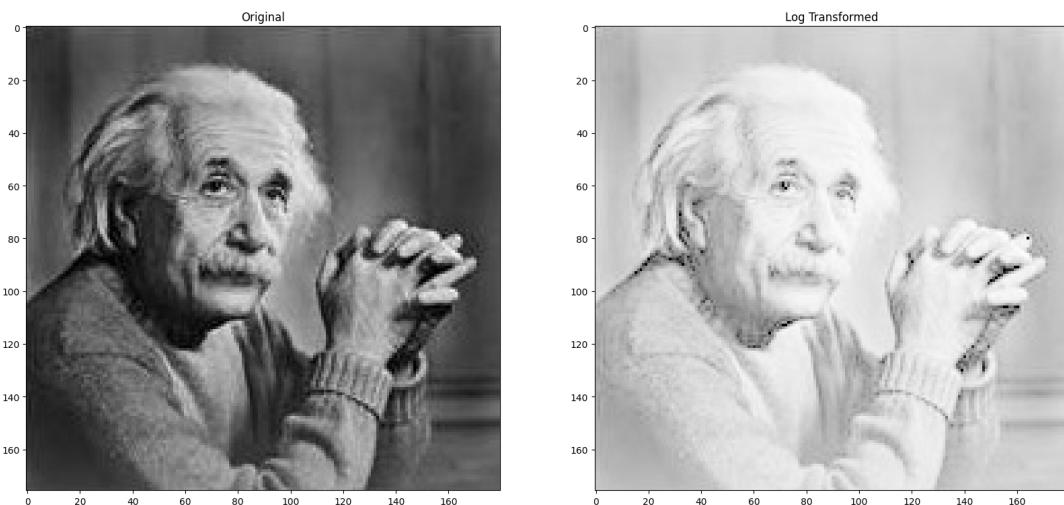


Figure 2.3: Original Image and Log Transformed Image.

2.2.4 Inverse Log Transform

Code :

```
1 import cv2
2 import numpy as np
3 import matplotlib.pyplot as plt
4 image = cv2.imread('/content/einstein.jpg', cv2.
IMREAD_GRAYSCALE) # Convert to grayscale for histogram
equalization
5
6 equ = cv2.equalizeHist(image)
7 c = 255 / np.log(1 + np.max(image))
8 log_image = c * (np.log(image + 1))
9 log_image = np.array(log_image, dtype=np.uint8)
10
11 # Apply inverse log transformation method
12 inverse_log_image = np.exp(log_image / c) - 1
13 inverse_log_image = np.clip(inverse_log_image, 0, 255).astype(
np.uint8)
14
15 # Display images and their histograms
16 plt.figure(figsize=(12, 8))
17
18 # Input image and histogram
19 plt.subplot(2, 2, 1)
20 plt.imshow(image, cmap='gray')
21 plt.title('Original Image')
22 plt.subplot(2, 2, 3)
23 plt.hist(image.ravel(), 256, [0, 256])
24 plt.title('Histogram (Original)')
```

```

25
26 # Inverse log transformed image and histogram
27 plt.subplot(2, 2, 2)
28 plt.imshow(inverse_log_image, cmap='gray')
29 plt.title('Inverse Log Transformed Image')
30 plt.subplot(2, 2, 4)
31 plt.hist(inverse_log_image.ravel(), 256, [0, 256])
32 plt.title('Histogram (Inverse Log Transformed)')
33 plt.show()

```

Output:

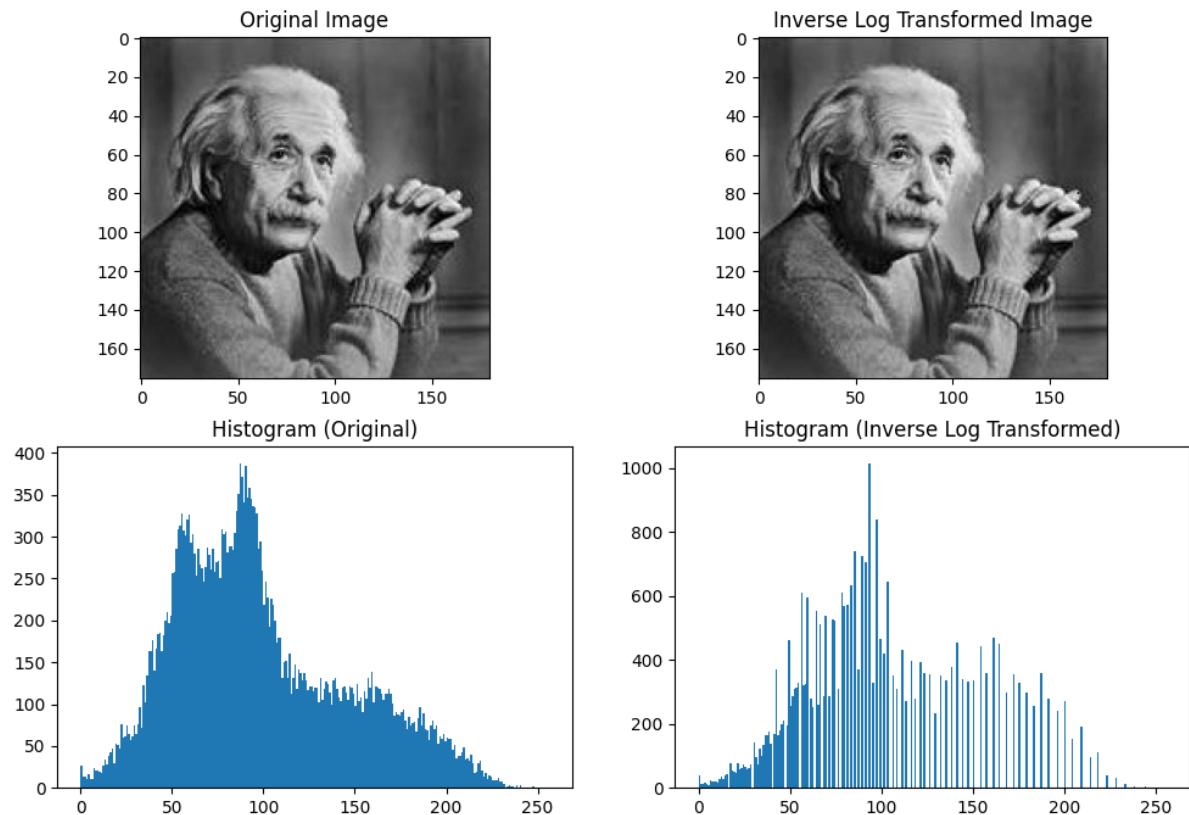


Figure 2.4: Original Image and Inverse Log Transformed Image.

2.2.5 Power Law (Gamma) Transformation

Code :

```
1 import cv2
2 import numpy as np
3 import matplotlib.pyplot as plt
4
5 # Read an image
6 image = cv2.imread('/content/imgh.jpg', cv2.IMREAD_GRAYSCALE)
    # Convert to grayscale for histogram equalization
7
8 # Apply histogram equalization
9 equ = cv2.equalizeHist(image)
10
11 # Define a range of gamma values
12 gamma_values = [0.2, 1.4, 4.0]
13
14 # Display images and their histograms for different gamma
    values
15 plt.figure(figsize=(13, 10))
16 rows = len(gamma_values) + 1 # Number of rows in the subplot
    grid
17
18 # Original image and histogram
19 plt.subplot(rows, 3, 1)
20 plt.imshow(image, cmap='gray')
21 plt.title('Original Image')
22 plt.subplot(rows, 3, 2)
23 plt.hist(image.ravel(), 256, [0, 256])
24 plt.title('Histogram (Original)')
```

```

25
26 # Loop through gamma values
27 for i, gamma in enumerate(gamma_values, start=1):
28     # Apply power law transformation method
29     power_log_image = np.power(image / 255.0, gamma) * 255
30
31     # Specify the data type so that
32     # float value will be converted to int
33     power_log_image = np.array(power_log_image, dtype=np.uint8
34 )
35
36     # Display power law transformed image and histogram
37     plt.subplot(rows, 3, i * 3 + 1)
38     plt.imshow(power_log_image, cmap='gray')
39     plt.title(f'Power Law Transformed (Gamma={gamma})')
40
41     plt.subplot(rows, 3, i * 3 + 2)
42     plt.hist(power_log_image.ravel(), 256, [0, 256])
43     plt.title(f'Histogram (Gamma={gamma})')
44
45     # Show the plots
46 plt.tight_layout()
47 plt.show()

```

Output:

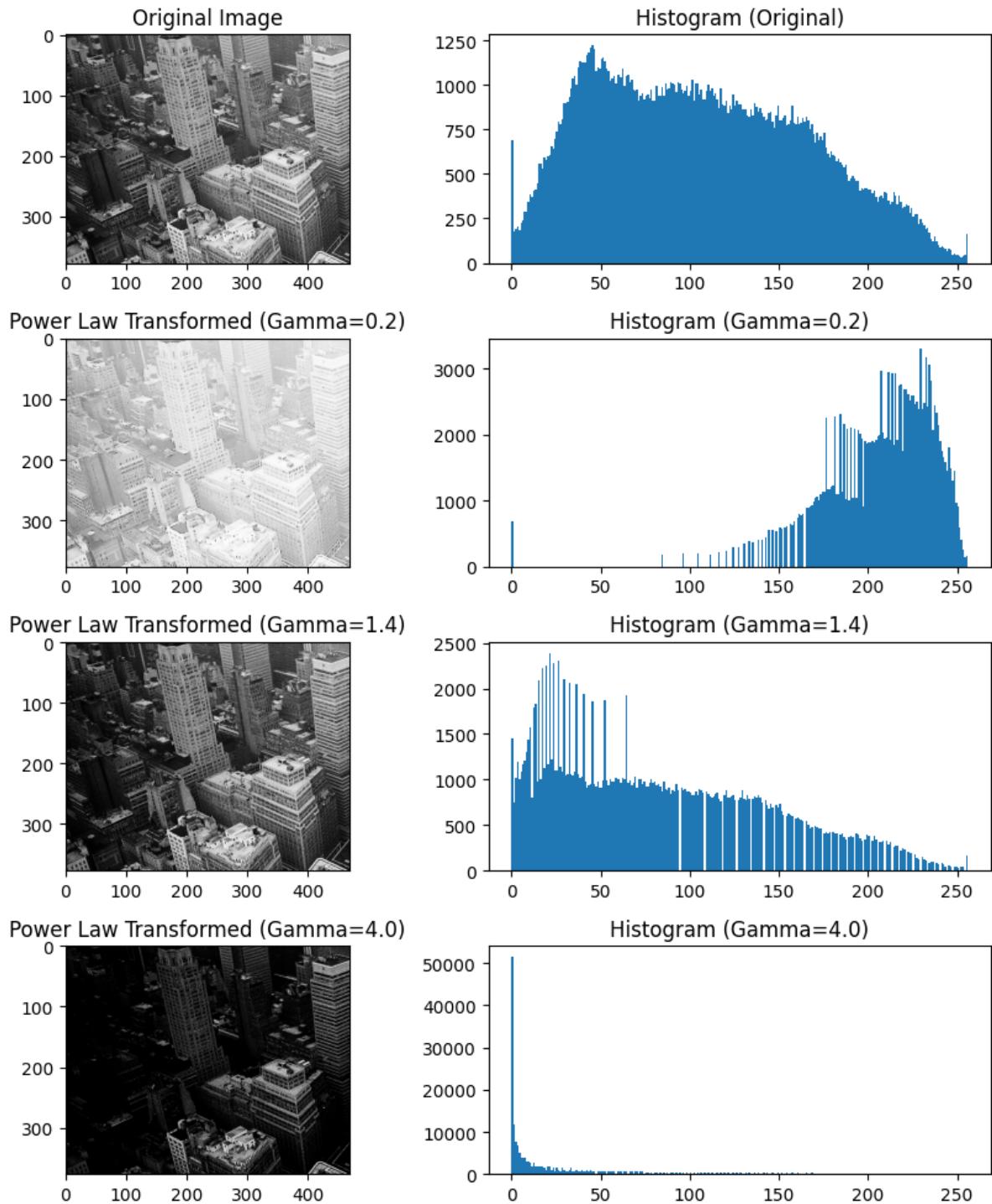


Figure 2.5: Power Law (Gamma) Transformation with Different Value of Gamma (0.2, 1.4, 4.0).

2.2.6 Image Negatives

Code :

```
1 import cv2
2 import numpy as np
3 import matplotlib.pyplot as plt
4 image = cv2.imread('/content/einstein.jpg', cv2.
5                         IMREAD_GRAYSCALE)
6
7 # Compute the negative of the image
8 negative_image = 255 - image
9
10 # Display images and their histograms
11 plt.figure(figsize=(12, 8))
12 plt.subplot(2, 2, 1)
13 plt.imshow(image, cmap='gray')
14 plt.title('Original Image')
15 plt.subplot(2, 2, 2)
16 plt.hist(image.ravel(), 256, [0, 256])
17 plt.title('Histogram (Original)')
18 # Negative transformed image
19 plt.subplot(2, 2, 3)
20 plt.imshow(negative_image, cmap='gray')
21 plt.title('Negative Transformed Image')
22 plt.subplot(2, 2, 4)
23 plt.hist(negative_image.ravel(), 256, [0, 256])
24 plt.title('Histogram (Negative Transformed)')
25
26 plt.show()
```

Output:

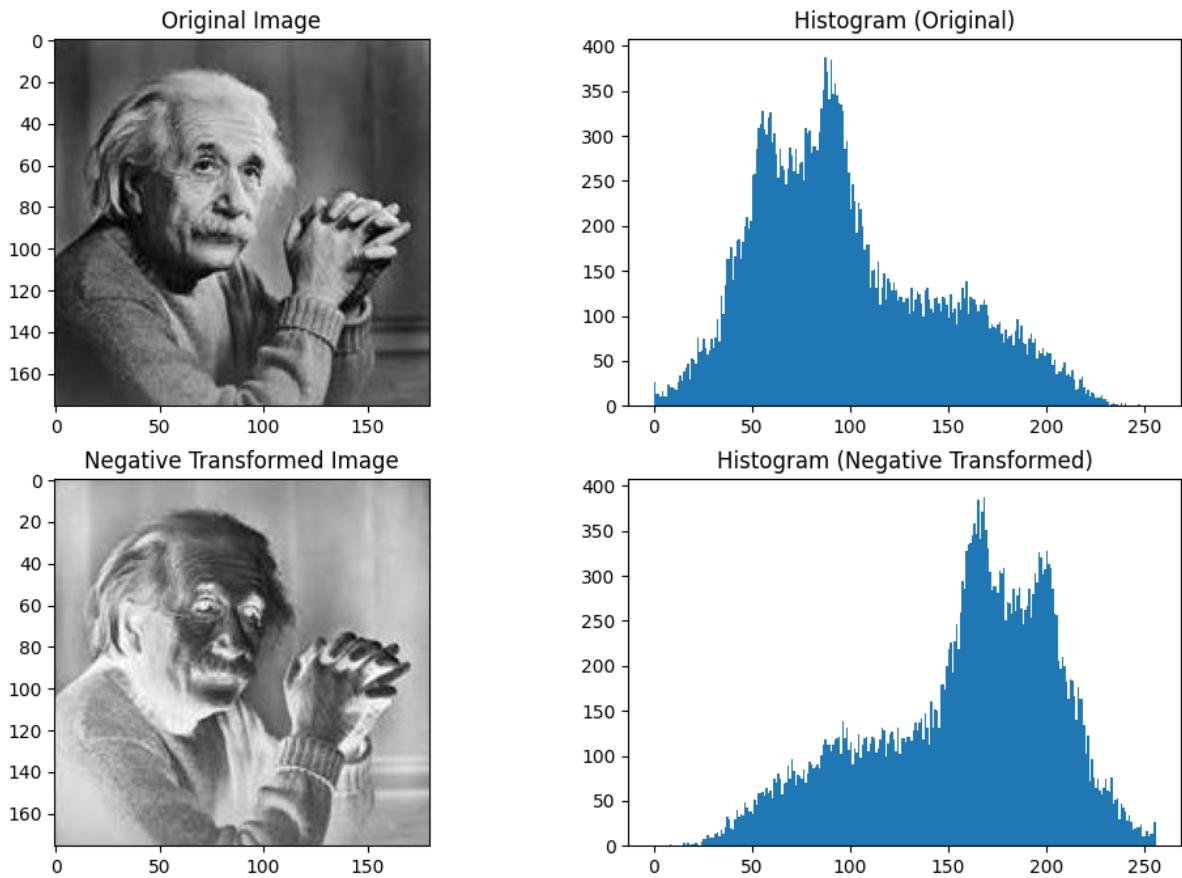


Figure 2.6: Original Image and Negative Transformed Image.

2.2.7 Some Basic Intensity Transformations

Code :

```
1 import cv2
2 import numpy as np
3 import matplotlib.pyplot as plt
4
5 # Load an image from file
6 image = cv2.imread('/content/einstein.jpg', cv2.
IMREAD_GRAYSCALE) # Convert to grayscale
```

7

```
8 # Check if the image was loaded successfully
9 if image is None:
10     print("Image not found. Please provide a valid image path
11 .")
12 else:
13     # Plot original and transformed images side by side with
14     # histograms
15     plt.figure(figsize=(18, 16))
16
17     transformations = [
18         ("Original", image),
19         ("Log Transform", np.log1p(image.astype(float)).astype
20 (np.uint8)),
21         ("Inverse Log Transform", np.expm1(np.log1p(image.
22 astype(float))).astype(np.uint8)),
23         ("Power-law Transform", (np.power(image / 255.0, 0.5)
24 * 255.0).astype(np.uint8)),
25         ("Gamma Correction (Gamma=0.4)", (np.power(image /
26 255.0, 0.4) * 255.0).astype(np.uint8)),
27         ("Negative Image", 255 - image),
28         ("Smoothing (Gaussian Blur)", cv2.GaussianBlur(image,
29 (5, 5), 0)),
30         ("Sharpening", cv2.filter2D(image, -1, np.array([[[-1,
31 -1], [-1, 9, -1], [-1, -1, -1]]])))
32     ]
33
34     for i in range(0, len(transformations), 2):
35         title1, transformed_image1 = transformations[i]
36         title2, transformed_image2 = transformations[i + 1]
```

```

30         # Display original and log-transformed images side by
31         side
32
33         plt.subplot(4, 4, i // 2 * 4 + 1)
34         plt.imshow(transformed_image1, cmap='gray') # Use
35         cmap='gray' for grayscale images
36
37         plt.title(title1)
38         plt.axis('off')
39
40
41         # Display histograms below the images
42         plt.subplot(4, 4, i // 2 * 4 + 3)
43
44         plt.hist(transformed_image1.ravel(), bins=256, range
45         =[0, 256], color='blue', alpha=0.7)
46
47         plt.title(f'{title1} Histogram')
48         plt.xlabel('Pixel Value')
49         plt.ylabel('Frequency')
50
51
52         plt.subplot(4, 4, i // 2 * 4 + 4)
53
54         plt.hist(transformed_image2.ravel(), bins=256, range
55         =[0, 256], color='blue', alpha=0.7)
56
57         plt.title(f'{title2} Histogram')
58         plt.xlabel('Pixel Value')
59         plt.ylabel('Frequency')
60
61         plt.tight_layout()
62
63         plt.show()

```

Output:

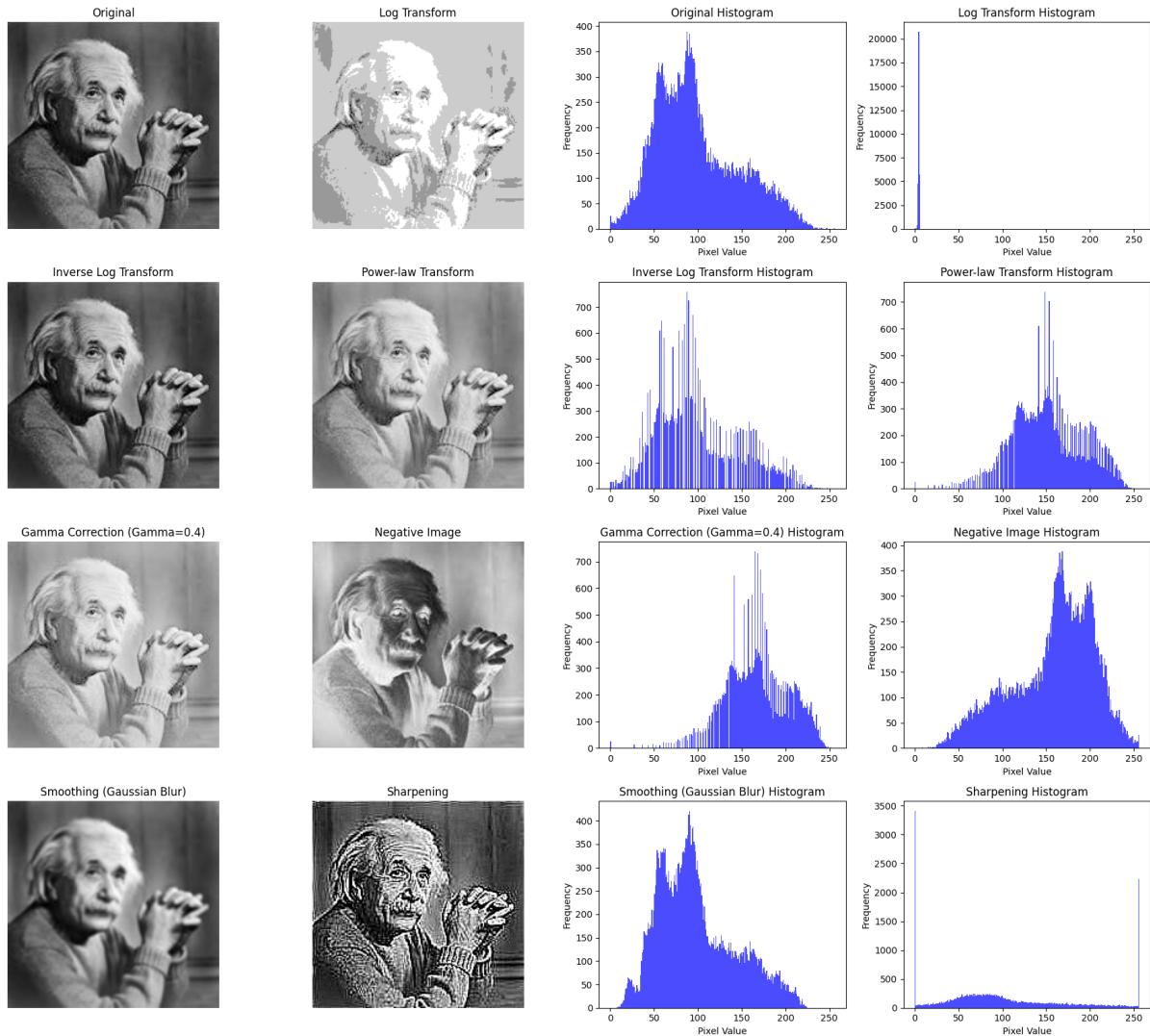


Figure 2.7: Original Image and Transformed Image with Corresponding Histogram.

2.2.8 Image Blurring with Simple, Median, Gaussian Blur

Code :

```
1 import cv2  
2 import numpy as np  
3 from matplotlib import pyplot as plt  
4 image = cv2.imread('/content/einstein_img3.jpg')  
5 # Apply a simple blur
```

```

6 blurred = cv2.blur(image, (5, 5))
7 # Apply a median blur
8 median_blurred = cv2.medianBlur(image, 5)
9 # Apply a Gaussian blur
10 gaussian_blurred = cv2.GaussianBlur(image, (5, 5), 0)

11
12 # Plot the original and blurred images side by side
13 plt.figure(figsize=(8, 9))
14 plt.subplot(4, 2, 1), plt.imshow(cv2.cvtColor(image, cv2.
    COLOR_BGR2RGB)), plt.title('Original')
15 plt.subplot(4, 2, 2), plt.imshow(cv2.cvtColor(blurred, cv2.
    COLOR_BGR2RGB)), plt.title('Blurred')
16 plt.subplot(4, 2, 3), plt.imshow(cv2.cvtColor(median_blurred,
    cv2.COLOR_BGR2RGB)), plt.title('Median Blurred')
17 plt.subplot(4, 2, 4), plt.imshow(cv2.cvtColor(gaussian_blurred
    , cv2.COLOR_BGR2RGB)), plt.title('Gaussian Blurred')

18
19 # Plot histograms
20 plt.subplot(4, 2, 5), plt.hist(image.flatten(), 256, [0, 256],
    color='r', histtype='step'), plt.title('Histogram of
        Original Image')
21 plt.subplot(4, 2, 6), plt.hist(blurred.flatten(), 256, [0,
    256], color='r', histtype='step'), plt.title('Histogram of
        Blurred Image')
22 plt.subplot(4, 2, 7), plt.hist(median_blurred.flatten(), 256,
    [0, 256], color='r', histtype='step'), plt.title('Histogram
        of Median Blurred')
23 plt.subplot(4, 2, 8), plt.hist(gaussian_blurred.flatten(),
    256, [0, 256], color='r', histtype='step'), plt.title('
        Histogram of Gaussian Blurred')

```

24

```
25 plt.tight_layout()  
26 plt.show()
```

Output:

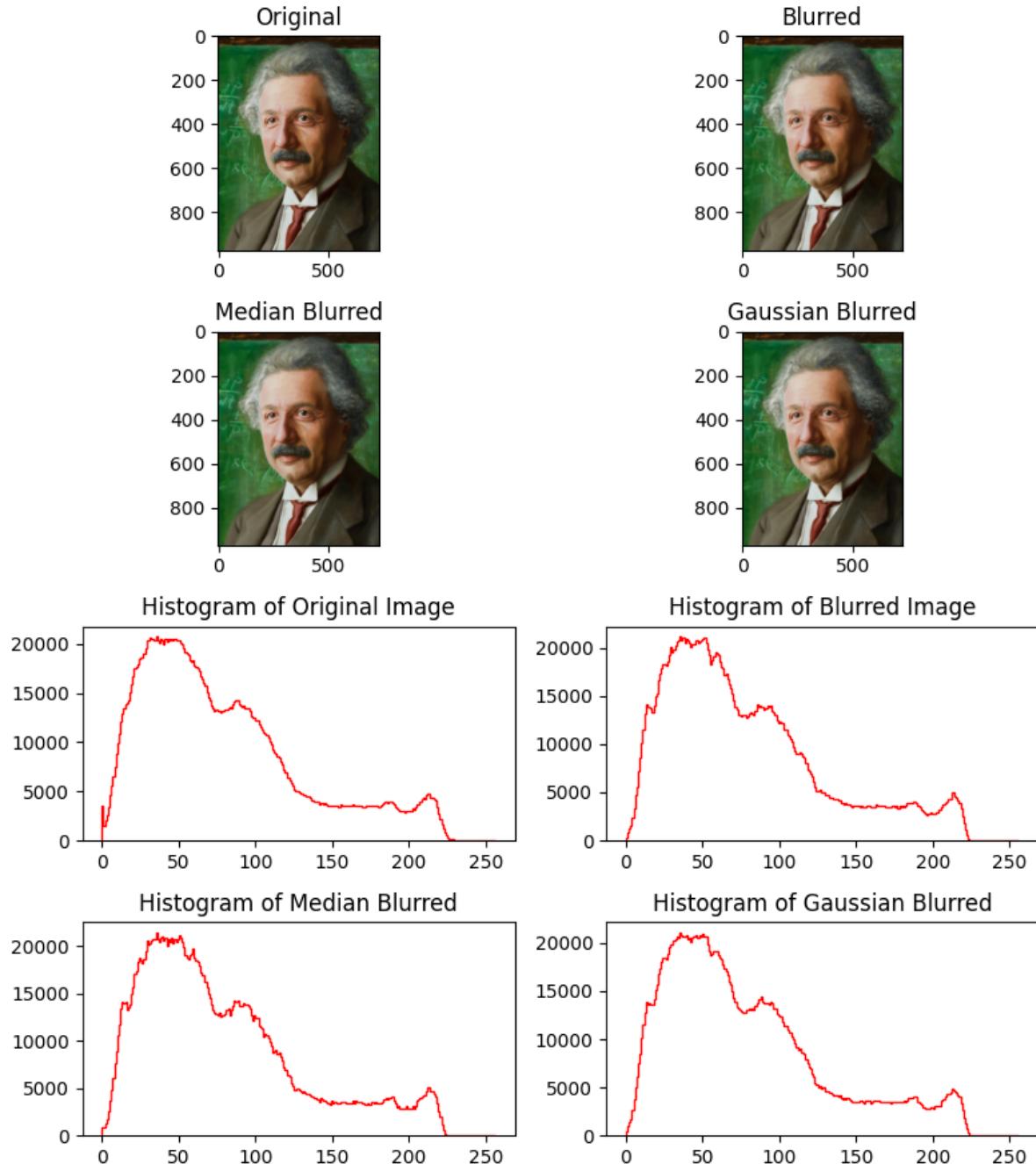


Figure 2.8: Original Image and Blurred Image with Corresponding Histogram.

2.2.9 Image Filtering with Laplacian, Sobel, Scharr Filter

Code :

```
1 import cv2;import numpy as np
2 from matplotlib import pyplot as plt
3 image = cv2.imread('/content/einstein.jpg', cv2.
4                     IMREAD_GRAYSCALE)
5 # Apply Laplacian filter
6 laplacian = cv2.Laplacian(image, cv2.CV_64F)
7 laplacian_sharpened = image - laplacian
8 # Apply Sobel filter
9 sobelx = cv2.Sobel(image, cv2.CV_64F, 1, 0, ksize=3)
10 sobely = cv2.Sobel(image, cv2.CV_64F, 0, 1, ksize=3)
11 sobel_sharpened = image - sobelx - sobely
12 # Apply Scharr filter
13 scharrx = cv2.Scharr(image, cv2.CV_64F, 1, 0)
14 scharry = cv2.Scharr(image, cv2.CV_64F, 0, 1)
15 scharr_sharpened = image - scharrx - scharry
16 plt.figure(figsize=(9, 8))
17 plt.subplot(4, 2, 1), plt.imshow(image, cmap='gray'), plt.
18     title('Original')
19 plt.subplot(4, 2, 2), plt.imshow(laplacian_sharpened, cmap='
20     gray'), plt.title('Laplacian Sharpened')
21 plt.subplot(4, 2, 3), plt.imshow(sobel_sharpened, cmap='gray'
22 ), plt.title('Sobel Sharpened')
23 plt.subplot(4, 2, 4), plt.imshow(scharr_sharpened, cmap='gray'
24 ), plt.title('Scharr Sharpened')
25 plt.subplot(4, 2, 5), plt.hist(image.flatten(), 256, [0, 256],
26     color='r', histtype='step'), plt.title('Original Histogram
27 ')
```

```

21 plt.subplot(4, 2, 6), plt.hist(laplacian_sharpened.flatten(),
22                                256, [0, 256], color='r', histtype='step'), plt.title('
Laplacian Sharpened Histogram')
23 plt.subplot(4, 2, 7), plt.hist(sobel_sharpened.flatten(), 256,
[0, 256], color='r', histtype='step'), plt.title('Sobel
Sharpened Histogram')
24 plt.tight_layout();plt.show()

```

Output:

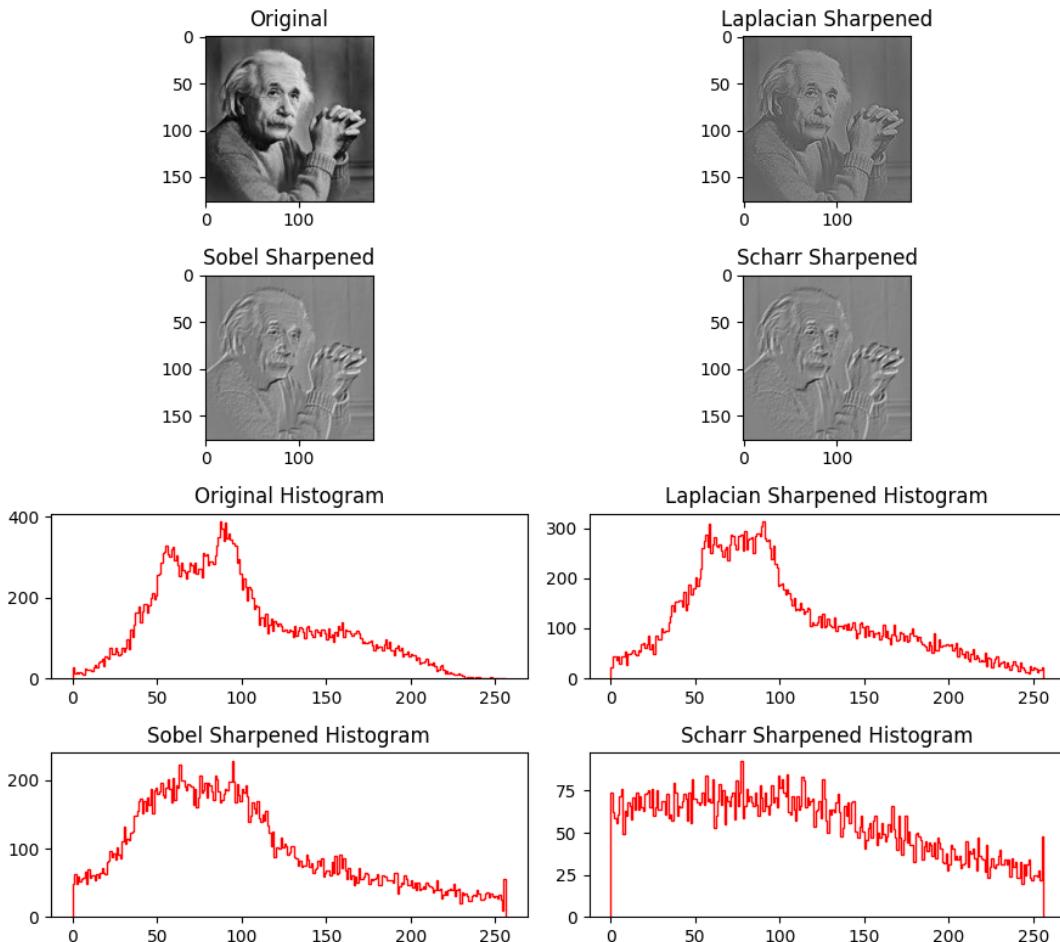


Figure 2.9: Original Image and Filtered Image with Corresponding Histogram.

2.3 Conclusion

In conclusion, the tasks of Histogram Equalization, Image Intensity Transformations, and Image Filtering in the Spatial Domain were systematically conducted using Python programming in the Google Colab environment. Images were employed as inputs, and the OpenCV library operations were performed. Crucial functions, such as ‘imread’, ‘imshow’, ‘warpAffine’, ‘equalizeHist’, ‘cvtColor’, ‘calcHist’, ‘filter2D’, ‘medianBlur’, ‘GaussianBlur’, and various edge detection operators like ‘Sobel’, ‘Laplacian’, and ‘Scharr’ from OpenCV were applied.

The OpenCV library facilitated seamless implementation, allowing for the exploration of diverse image-processing techniques. Numpy and Matplotlib complemented these operations, enhancing data manipulation and visualization. Throughout the experiments, the significance of each technique in image enhancement and analysis became evident. Utilizing these libraries in a collaborative platform like Google Colab offered a streamlined environment for comprehensive exploration. Overall, this study delved into the intricacies of image processing, providing valuable insights into the capabilities of Python and associated libraries for effective spatial domain operations.

Heaven's Light is Our Guide

Rajshahi University of Engineering & Technology

Department of Electronics & Telecommunication Engineering



ETE 4226: Sessional Based on ETE 4225

Experiment 3

Study of Frequency Domain Image Filtering.

Submitted by:

Md. Darul Atfal Palash

Roll: 1804005

Session: 2018-19

Submitted to:

Dr. Shah Ariful Hoque Chowdhury

Associate Professor

Dept. of ETE, RUET

Date of Experiment : 12/11/2023

Date of Submission : 25/01/2024

<u>Report</u>	(Teacher's Section)	<u>Viva</u>
<input type="checkbox"/> Excellent		<input type="checkbox"/> Excellent
<input type="checkbox"/> Very Good		<input type="checkbox"/> Very Good
<input type="checkbox"/> Good	_____	<input type="checkbox"/> Good
<input type="checkbox"/> Moderate	Signature	<input type="checkbox"/> Moderate
<input type="checkbox"/> Poor		<input type="checkbox"/> Poor

Experiment 3

Study of Frequency Domain Image Filtering.

Objectives

The primary objectives of this experiment include:

- Understand the theoretical foundations of frequency domain image filtering.
- Implement frequency domain filters, including Ideal, Butterworth, and Gaussian filters, using Python.
- Analyze the effects of different filter parameters on images.
- Compare the performance of the three types of filters in terms of image quality and computational efficiency.

3.1 Required Apparatus/Softwares

- Python.
- A Highly Configured PC.

3.2 Program Code and Output

3.2.1 Ideal Image Filtering

Code :

```
1 #IDEAL
2 import cv2
3 import numpy as np
4 import matplotlib.pyplot as plt
5
6 def ideal_filter(shape, D0, filter_type='lowpass'):
7     rows, cols = shape
8     center_row, center_col = rows // 2, cols // 2
9
10    # Create a meshgrid of distances from the center
```

```

11     x = np.arange(cols) - center_col
12     y = np.arange(rows) - center_row
13     x, y = np.meshgrid(x, y)
14
15     # Compute the distance matrix
16     distance = np.sqrt(x^2 + y^2)
17
18     # Create the filter based on the filter type
19     if filter_type == 'lowpass':
20         H = (distance <= D0).astype(float)
21     elif filter_type == 'highpass':
22         H = (distance > D0).astype(float)
23     elif filter_type == 'bandpass':
24         H = ((distance >= D0[0]) & (distance <= D0[1])).astype(
25             float)
26     elif filter_type == 'bandreject':
27         H = ((distance < D0[0]) | (distance > D0[1])).astype(
28             float)
29     else:
30         raise ValueError("Invalid filter type")
31
32     return H
33
34     def apply_frequency_filter(image, filter_type='lowpass', D0
35     =30):
36
37         # Convert the image to grayscale
38         if len(image.shape) == 3:
39             image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
40
41         # Apply the Fourier transform

```

```

38     f_transform = np.fft.fft2(image)
39     f_shift = np.fft.fftshift(f_transform)
40
41     # Create the frequency filter
42     rows, cols = image.shape
43     H = ideal_filter(image.shape, D0, filter_type)
44
45     # Apply the filter in the frequency domain
46     f_filtered = f_shift * H
47
48     # Inverse Fourier transform to get the image back to
49     # spatial domain
50
51     img_filtered = np.abs(np.fft.ifft2(np.fft.ifftshift(
52         f_filtered)))
53
54     return img_filtered
55
56     # Read an example image
57     image = cv2.imread('/content/flw.jpg', cv2.IMREAD_GRAYSCALE)
58
59     # Apply lowpass filter
60     lowpass_filtered = apply_frequency_filter(image, filter_type='
61         lowpass', D0=5)
62
63     # Apply highpass filter
64     highpass_filtered = apply_frequency_filter(image, filter_type='
65         highpass', D0=2)
66
67     # Apply bandpass filter

```

```

63 bandpass_filtered = apply_frequency_filter(image, filter_type=
64     'bandpass', D0=(5, 40))
65
66 # Apply bandreject filter
67 bandreject_filtered = apply_frequency_filter(image,
68     filter_type='bandreject', D0=(20, 40))
69
70
71 plt.subplot(2, 3, 1)
72 plt.imshow(image, cmap='gray')
73 plt.title('Original Image')
74
75 plt.subplot(2, 3, 2)
76 plt.imshow(lowpass_filtered, cmap='gray')
77 plt.title('Lowpass Filtered')
78
79 plt.subplot(2, 3, 3)
80 plt.imshow(highpass_filtered, cmap='gray')
81 plt.title('Highpass Filtered')
82
83 plt.subplot(2, 3, 4)
84 plt.imshow(bandpass_filtered, cmap='gray')
85 plt.title('Bandpass Filtered')
86
87 plt.subplot(2, 3, 5)
88 plt.imshow(bandreject_filtered, cmap='gray')
89 plt.title('Bandreject Filtered')
90 plt.show()

```

Output:

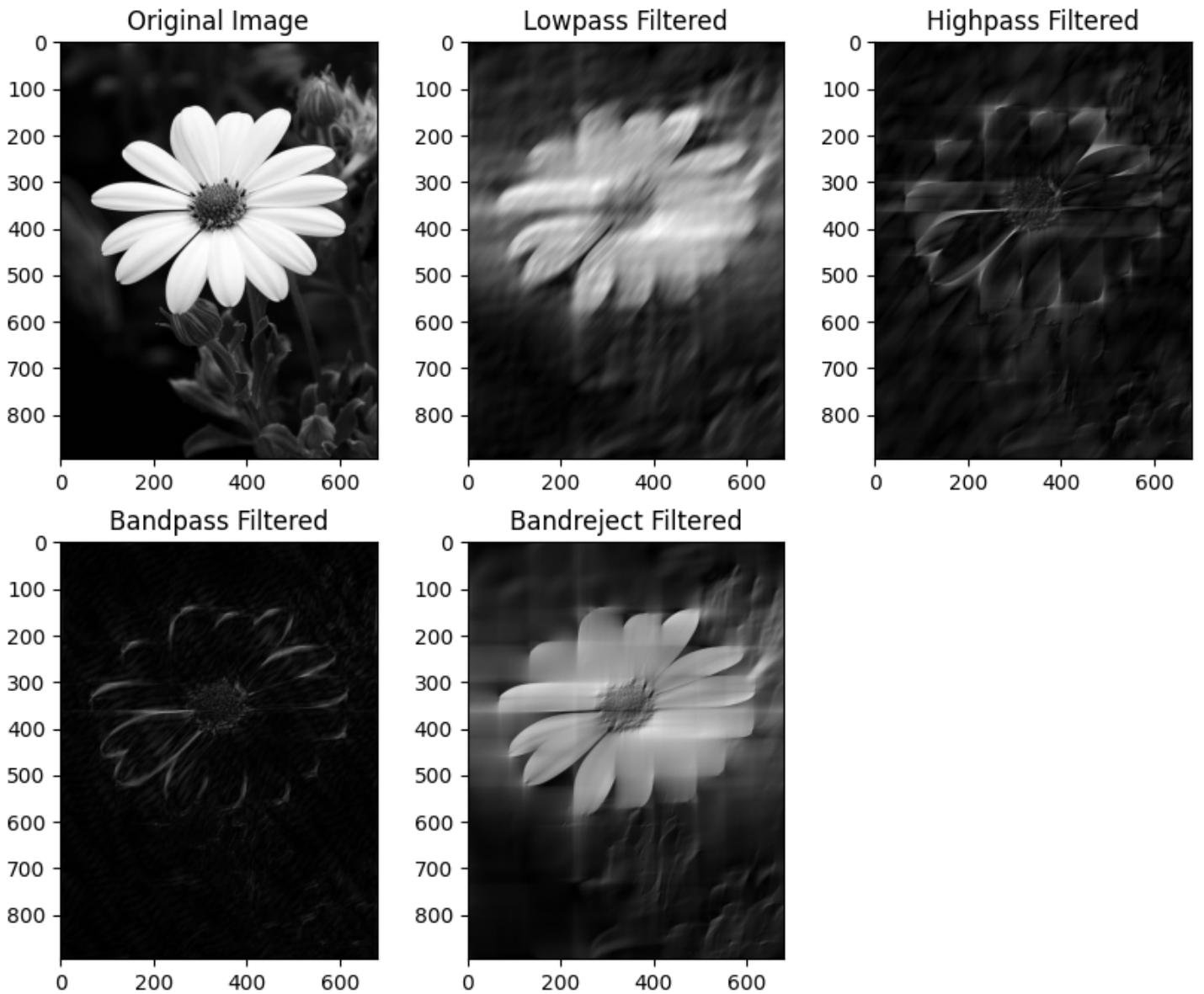


Figure 3.1: Original Image and Ideal Filtered Image (Lowpass, Highpass, Bandpass, Bandreject Filtering).

3.2.2 Butterworth Image Filtering

Code :

```
1 #Butterworth  
2 import cv2
```

```

3 import numpy as np
4 import matplotlib.pyplot as plt
5
6 def butterworth_filter(shape, D0, n, filter_type='lowpass'):
7     rows, cols = shape
8     center_row, center_col = rows // 2, cols // 2
9
10    # Create a meshgrid of distances from the center
11    x = np.arange(cols) - center_col
12    y = np.arange(rows) - center_row
13    x, y = np.meshgrid(x, y)
14
15    # Compute the distance matrix
16    distance = np.sqrt(x**2 + y**2)
17
18    # Create the filter based on the filter type
19    if filter_type == 'lowpass':
20        H = 1 / (1 + (distance / D0)**(2 * n))
21    elif filter_type == 'highpass':
22        H = 1 - 1 / (1 + (distance / D0)**(2 * n))
23    elif filter_type == 'bandpass':
24        H = 1 / (1 + ((distance**2 - D0[0]**2) / (distance *
25                    D0[1]**2 - D0[0]**2)))**(2 * n))
26    elif filter_type == 'bandreject':
27        H = 1 - 1 / (1 + ((distance**2 - D0[0]**2) / (distance
28                    * (D0[1]**2 - D0[0]**2)))**(2 * n))
29    else:
30        raise ValueError("Invalid filter type")
31
32    return H

```

```

31 def apply_butterworth_filter(image, filter_type='lowpass', D0
32     =30, n=2):
33     # Convert the image to grayscale
34     if len(image.shape) == 3:
35         image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
36
37     # Apply the Fourier transform
38     f_transform = np.fft.fft2(image)
39     f_shift = np.fft.fftshift(f_transform)
40
41     # Create the frequency filter
42     rows, cols = image.shape
43     H = butterworth_filter(image.shape, D0, n, filter_type)
44
45     # Apply the filter in the frequency domain
46     f_filtered = f_shift * H
47
48     # Inverse Fourier transform to get the image back to
49     # spatial domain
50     img_filtered = np.abs(np.fft.ifft2(np.fft.ifftshift(
51         f_filtered)))
52
53     return img_filtered
54
55     # Read an example image
56     image = cv2.imread('/content/flw.jpg', cv2.IMREAD_GRAYSCALE)
57
58     # Define the cutoff frequency and filter order
59     cutoff_frequency = 30
60     filter_order = 2

```

```

58
59 # Apply Butterworth lowpass filter
60 butterworth_lowpass_filtered = apply_butterworth_filter(image,
   filter_type='lowpass', D0=cutoff_frequency, n=filter_order
)
61 # Apply Butterworth highpass filter
62 butterworth_highpass_filtered = apply_butterworth_filter(image
   , filter_type='highpass', D0=cutoff_frequency, n=
   filter_order)
63 # Apply Butterworth bandpass filter
64 butterworth_bandpass_filtered = apply_butterworth_filter(image
   , filter_type='bandpass', D0=(20, 40), n=filter_order)
65 # Apply Butterworth bandreject filter
66 butterworth_bandreject_filtered = apply_butterworth_filter(
   image, filter_type='bandreject', D0=(40, 45), n=
   filter_order)

67
68 # Plotting the results
69 plt.figure(figsize=(10, 8))
70 plt.subplot(2, 3, 1)
71 plt.imshow(image, cmap='gray')
72 plt.title('Original Image')
73 plt.subplot(2, 3, 2)
74 plt.imshow(butterworth_lowpass_filtered, cmap='gray')
75 plt.title('Butterworth Lowpass Filtered')
76 plt.subplot(2, 3, 3)
77 plt.imshow(butterworth_highpass_filtered, cmap='gray')
78 plt.title('Butterworth Highpass Filtered')
79 plt.subplot(2, 3, 4)
80 plt.imshow(butterworth_bandpass_filtered, cmap='gray')

```

```

81 plt.title('Butterworth Bandpass Filtered')
82 plt.subplot(2, 3, 5)
83 plt.imshow(butterworth_bandreject_filtered, cmap='gray')
84 plt.title('Butterworth Bandreject Filtered')
85 plt.show()

```

Output:

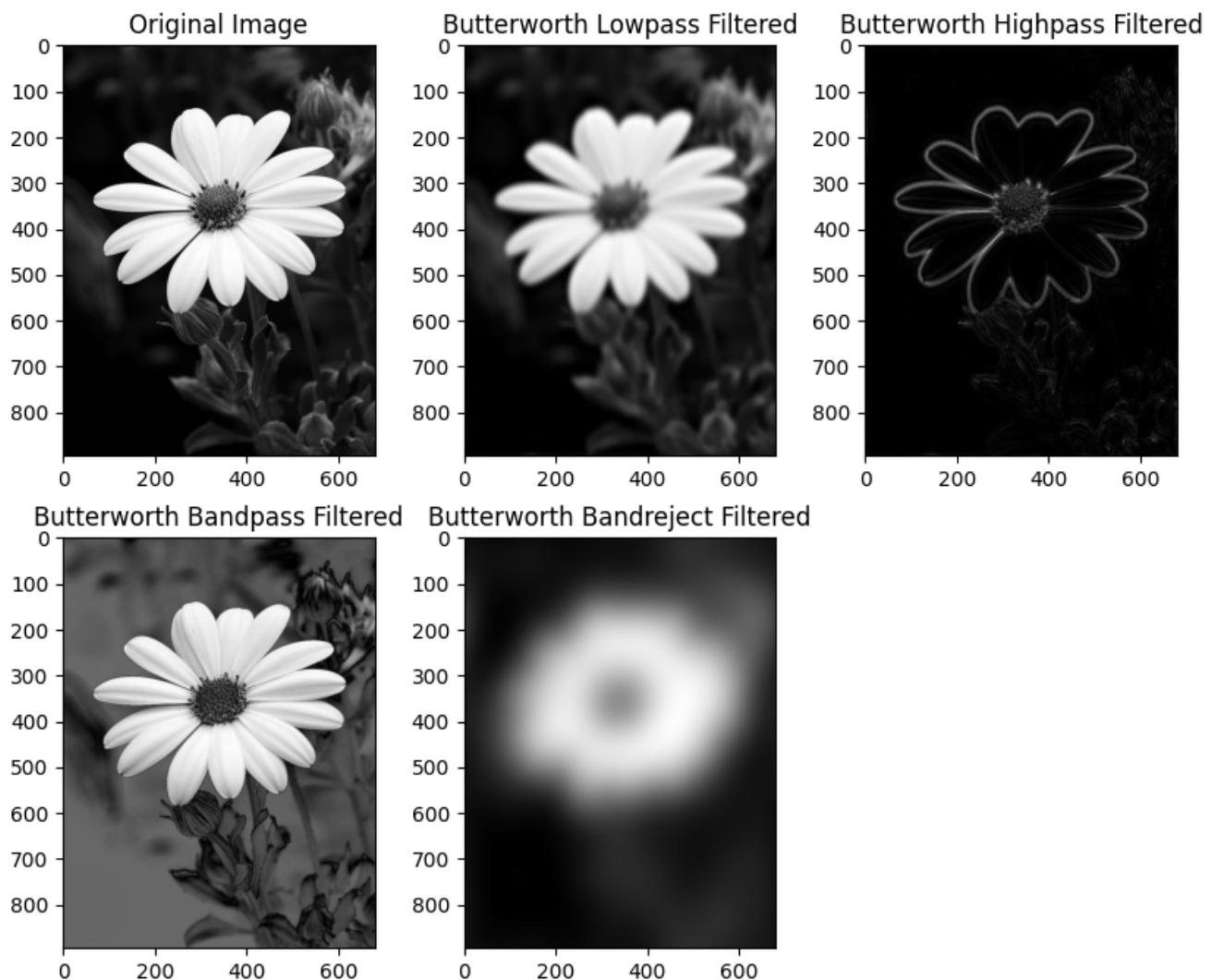


Figure 3.2: Original Image and Butterworth Filtered Image (Lowpass, Highpass, Bandpass, Band-reject Filtering).

3.2.3 Gaussian Image Filtering

Code :

```
1 #Gaussian
2 import cv2
3 import numpy as np
4 import matplotlib.pyplot as plt
5
6 def gaussian_filter(shape, D0, filter_type='lowpass'):
7     rows, cols = shape
8     center_row, center_col = rows // 2, cols // 2
9
10    # Create a meshgrid of distances from the center
11    x = np.arange(cols) - center_col
12    y = np.arange(rows) - center_row
13    x, y = np.meshgrid(x, y)
14
15    # Compute the distance matrix
16    distance = np.sqrt(x**2 + y**2)
17
18    # Create the filter based on the filter type
19    if filter_type == 'lowpass':
20        H = np.exp(-(distance**2) / (2 * (D0**2)))
21    elif filter_type == 'highpass':
22        H = 1 - np.exp(-(distance**2) / (2 * (D0**2)))
23    elif filter_type == 'bandpass':
24        H = 1 - np.exp(-(distance**2) / (2 * (D0[1]**2))) - (
25            np.exp(-(distance**2) / (2 * (D0[0]**2))))
26    elif filter_type == 'bandreject':
27        H = np.exp(-(distance**2) / (2 * (D0[1]**2))) + (1 -
28            np.exp(-(distance**2) / (2 * (D0[0]**2))))
```

```

26     else:
27         raise ValueError("Invalid filter type")
28
29     return H
30
31 def apply_gaussian_filter(image, filter_type='lowpass', D0=30):
32     :
33     # Convert the image to grayscale
34     if len(image.shape) == 3:
35         image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
36
37     # Apply the Fourier transform
38     f_transform = np.fft.fft2(image)
39     f_shift = np.fft.fftshift(f_transform)
40
41     # Create the frequency filter
42     rows, cols = image.shape
43     H = gaussian_filter(image.shape, D0, filter_type)
44
45     # Apply the filter in the frequency domain
46     f_filtered = f_shift * H
47
48     # Inverse Fourier transform to get the image back to
49     # spatial domain
50     img_filtered = np.abs(np.fft.ifft2(np.fft.ifftshift(
51         f_filtered)))
52
53     return img_filtered
54
55     # Read an example image

```

```

53 image = cv2.imread('/content/flw.jpg', cv2.IMREAD_GRAYSCALE)
54
55 # Define the cutoff frequency
56 cutoff_frequency = 30
57
58 # Apply Gaussian lowpass filter
59 gaussian_lowpass_filtered = apply_gaussian_filter(image,
60           filter_type='lowpass', D0=cutoff_frequency)
60 # Apply Gaussian highpass filter
61 gaussian_highpass_filtered = apply_gaussian_filter(image,
62           filter_type='highpass', D0=cutoff_frequency)
62 # Apply Gaussian bandpass filter
63 gaussian_bandpass_filtered = apply_gaussian_filter(image,
64           filter_type='bandpass', D0=(20, 40))
64 # Apply Gaussian bandreject filter
65 gaussian_bandreject_filtered = apply_gaussian_filter(image,
66           filter_type='bandreject', D0=(20, 40))

66
67 # Plotting the results
68 plt.figure(figsize=(10, 8))
69 plt.subplot(2, 3, 1)
70 plt.imshow(image, cmap='gray')
71 plt.title('Original Image')
72 plt.subplot(2, 3, 2)
73 plt.imshow(gaussian_lowpass_filtered, cmap='gray')
74 plt.title('Gaussian Lowpass Filtered')
75 plt.subplot(2, 3, 3)
76 plt.imshow(gaussian_highpass_filtered, cmap='gray')
77 plt.title('Gaussian Highpass Filtered')
78 plt.subplot(2, 3, 4)

```

```

79 plt.imshow(gaussian_bandpass_filtered, cmap='gray')
80 plt.title('Gaussian Bandpass Filtered')
81 plt.subplot(2, 3, 5)
82 plt.imshow(gaussian_bandreject_filtered, cmap='gray')
83 plt.title('Gaussian Bandreject Filtered')
84 plt.show()

```

Output:

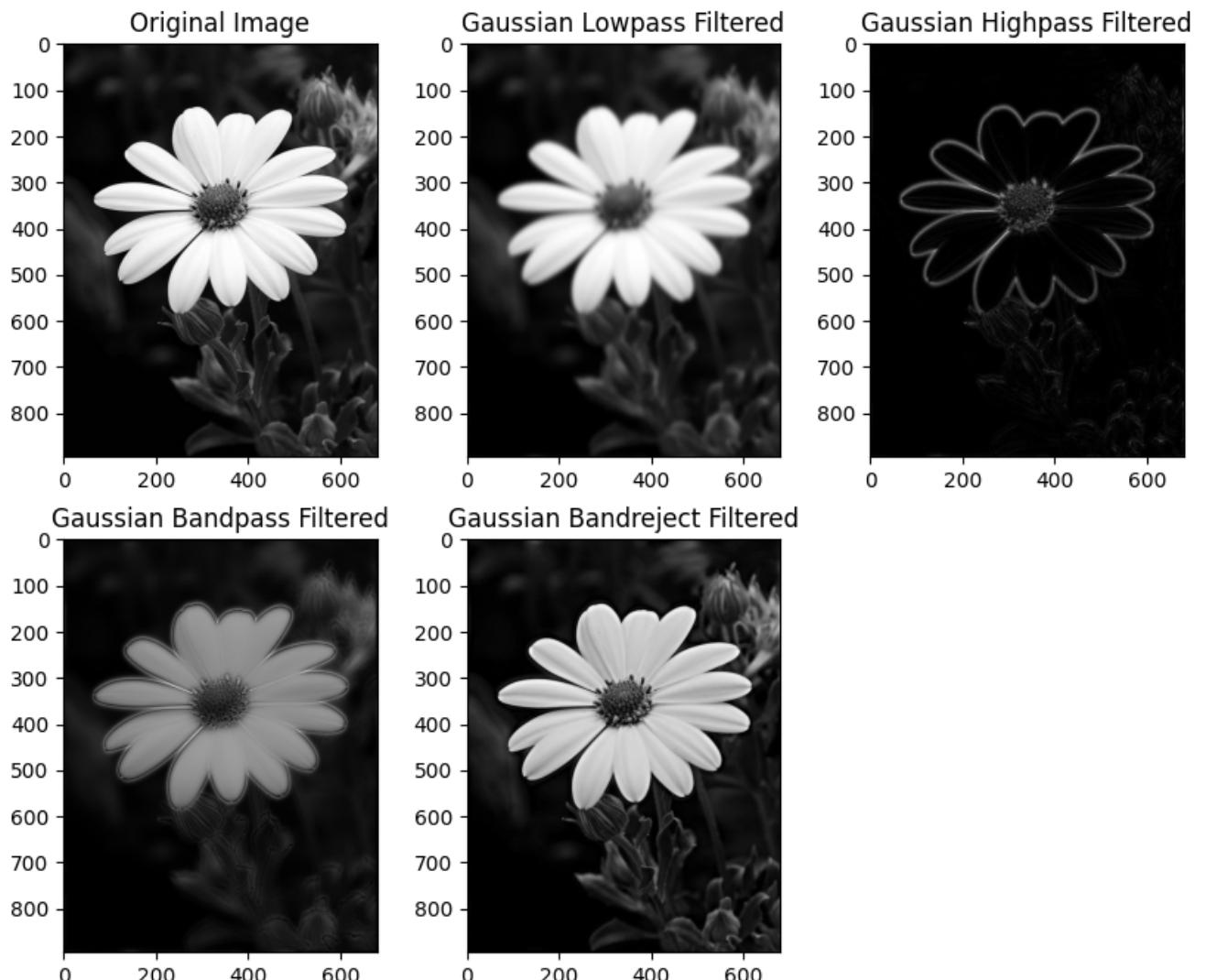


Figure 3.3: Original Image and Gaussian Filtered Image (Lowpass, Highpass, Bandpass, Bandreject Filtering).

3.3 Conclusion

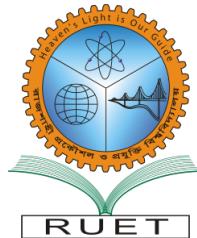
In conclusion, the tasks of Histogram Equalization, Image Intensity Transformations, and Image Filtering in the Spatial Domain were systematically conducted using Python programming in the Google Colab environment. Images were employed as inputs, and the OpenCV library operations were performed. Crucial functions, such as ‘imread’, ‘imshow’, ‘warpAffine’, ‘equalizeHist’, ‘cvtColor’, ‘calcHist’, ‘filter2D’, ‘medianBlur’, ‘GaussianBlur’, and various edge detection operators like ‘Sobel’, ‘Laplacian’, and ‘Scharr’ from OpenCV were applied.

The OpenCV library facilitated seamless implementation, allowing for the exploration of diverse image-processing techniques. Numpy and Matplotlib complemented these operations, enhancing data manipulation and visualization. Throughout the experiments, the significance of each technique in image enhancement and analysis became evident. Utilizing these libraries in a collaborative platform like Google Colab offered a streamlined environment for comprehensive exploration. Overall, this study delved into the intricacies of image processing, providing valuable insights into the capabilities of Python and associated libraries for effective spatial domain operations.

Heaven's Light is Our Guide

Rajshahi University of Engineering & Technology

Department of Electronics & Telecommunication Engineering



ETE 4226: Sessional Based on ETE 4225

Experiment 4

Study of Line & Edge Detection and Image Segmentation.

Submitted by:

Md. Darul Atfal Palash

Roll: 1804005

Session: 2018-19

Submitted to:

Dr. Shah Ariful Hoque Chowdhury

Associate Professor

Dept. of ETE, RUET

Date of Experiment : 26/11/2023

Date of Submission : 25/01/2024

<u>Report</u>	(Teacher's Section)	<u>Viva</u>
<input type="checkbox"/> Excellent		<input type="checkbox"/> Excellent
<input type="checkbox"/> Very Good		<input type="checkbox"/> Very Good
<input type="checkbox"/> Good	_____	<input type="checkbox"/> Good
<input type="checkbox"/> Moderate	Signature	<input type="checkbox"/> Moderate
<input type="checkbox"/> Poor		<input type="checkbox"/> Poor

Experiment 4

Study of Line & Edge Detection and Image Segmentation.

Objectives

The primary objectives of this experiment are as follows::

- Understand the theoretical foundations of image segmentation.
- Implement and analyze Hough Transform for line and edge detection.
- Explore K-means clustering for image segmentation.
- Investigate Superpixel-based clustering methods.

4.1 Required Apparatus/Softwares

- Python.
- A Highly Configured PC.

4.2 Program Code and Output

4.2.1 Line and Edge Detection Using Hough Transformation

Code :

```
1 import cv2
2 import numpy as np
3 import matplotlib.pyplot as plt
4
5 def detect_lines(image):
6     # Convert the image to grayscale
7     gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
8     # Apply Gaussian blur to reduce noise and help with line
9     detection
10    blurred = cv2.GaussianBlur(gray, (5, 5), 0)
11    # Use the Canny edge detector
12    edges = cv2.Canny(blurred, 50, 150)
```

```

12     # Use the Hough Line Transform to detect lines
13     lines = cv2.HoughLines(edges, 1, np.pi / 180, threshold
14                             =100)
15
16     # Draw the lines on a copy of the original image
17     lines_image = image.copy()
18
19     if lines is not None:
20
21         for line in lines:
22
23             rho, theta = line[0]
24
25             a = np.cos(theta)
26
27             b = np.sin(theta)
28
29             x0 = a * rho
30
31             y0 = b * rho
32
33             x1 = int(x0 + 1000 * (-b))
34
35             y1 = int(y0 + 1000 * (a))
36
37             x2 = int(x0 - 1000 * (-b))
38
39             y2 = int(y0 - 1000 * (a))
40
41             cv2.line(lines_image, (x1, y1), (x2, y2), (0, 0,
42
43                                         255), 2)
44
45     return edges, lines_image
46
47     # Example usage:
48
49     image = cv2.imread('/content/logo.png')
50
51     # Perform line detection
52
53     edges, lines_image = detect_lines(image)
54
55     # Display the original, Canny edges, and lines-detected images
56
57     plt.figure(figsize=(15, 5))
58
59     plt.subplot(1, 3, 1), plt.imshow(cv2.cvtColor(image, cv2.
60
61                                         COLOR_BGR2RGB))
62
63     plt.title('Original Image'), plt.xticks([]), plt.yticks([])
64
65     plt.subplot(1, 3, 2), plt.imshow(edges, cmap='gray')
66
67     plt.title('Canny Edges'), plt.xticks([]), plt.yticks([])

```

```

39 plt.subplot(1, 3, 3), plt.imshow(cv2.cvtColor(lines_image, cv2
    .COLOR_BGR2RGB))
40 plt.title('Lines Detected'), plt.xticks([]), plt.yticks([])
41 plt.show()

```

Output:

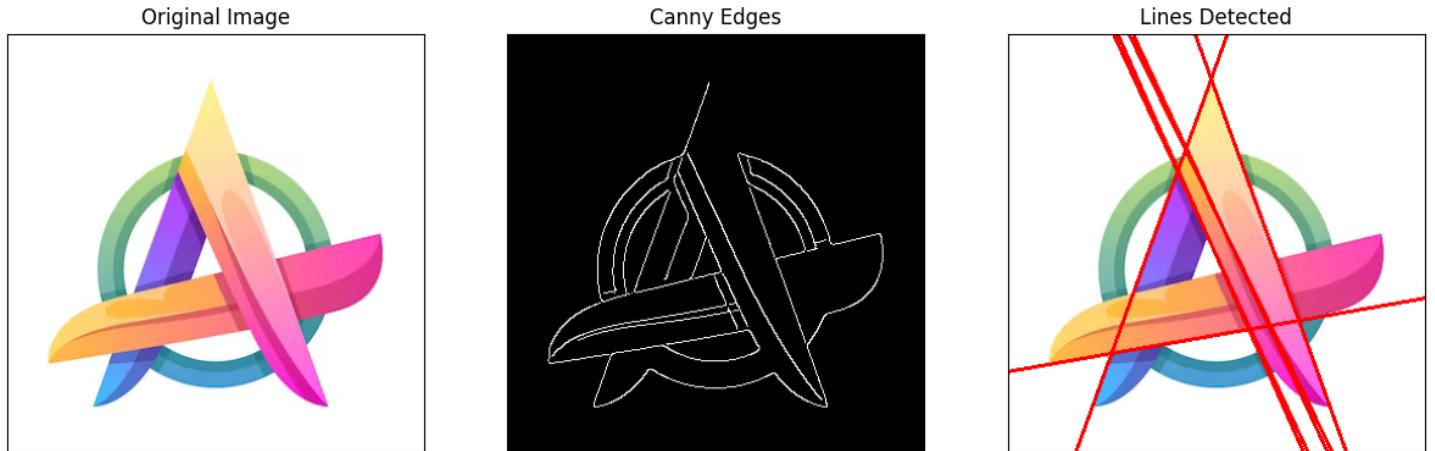


Figure 4.1: Original Image and Edges & Lines of the Image.

4.2.2 Image Segmentation using K-means Clustering

Code :

```

1 import numpy as np
2 import matplotlib.pyplot as plt
3 from PIL import Image
4
5 def initialize_centroids(data, k):
6     # Randomly initialize centroids
7     indices = np.random.choice(len(data), k, replace=False)
8     centroids = data[indices]
9     return centroids
10
11 def assign_to_clusters(data, centroids):

```

```

12     # Assign each data point to the nearest centroid
13     distances = np.linalg.norm(data[:, np.newaxis, :] -
14         centroids, axis=2)
15     clusters = np.argmin(distances, axis=1)
16
17 def update_centroids(data, clusters, k):
18     # Update centroids based on the mean of the assigned data
19     # points
20     centroids = np.array([np.mean(data[clusters == i], axis=0)
21                           for i in range(k)])
22
23     return centroids
24
25
26 def kmeans(data, k, max_iterations=100):
27     centroids = initialize_centroids(data, k)
28     for _ in range(max_iterations):
29         clusters = assign_to_clusters(data, centroids)
30         new_centroids = update_centroids(data, clusters, k)
31         # Check for convergence
32         if np.all(centroids == new_centroids):
33             break
34         centroids = new_centroids
35
36     return centroids, clusters
37
38 def display_segmentation(image, clusters, k):
39     # Create a mask based on the cluster labels
40     mask = (clusters * 255 / (k - 1)).astype(np.uint8)
41
42
43     # Display the original image and the mask
44     plt.subplot(1, 2, 1)

```

```

39     plt.imshow(image)
40     plt.title('Original Image')
41     plt.subplot(1, 2, 2)
42     plt.imshow(mask, cmap='gray')
43     plt.title('Segmentation Mask (K = 7)')
44
45     plt.show()
46
47 def main():
48     # Load image
49     image_path = "/content/ishihara_5_h.jpg"
50     image = np.array(Image.open(image_path))
51     # Flatten the image to use RGB values as features
52     data = image.reshape((-1, 3))
53
54     # Number of clusters
55     k = 7
56     # Run k-means clustering
57     centroids, clusters = kmeans(data, k)
58
59     # Reshape the cluster assignments to the original image
60     shape
61     clusters = clusters.reshape(image.shape[:2])
62     # Display the segmentation results
63     display_segmentation(image, clusters, k)
64 if __name__ == "__main__":
65     main()

```

Output:

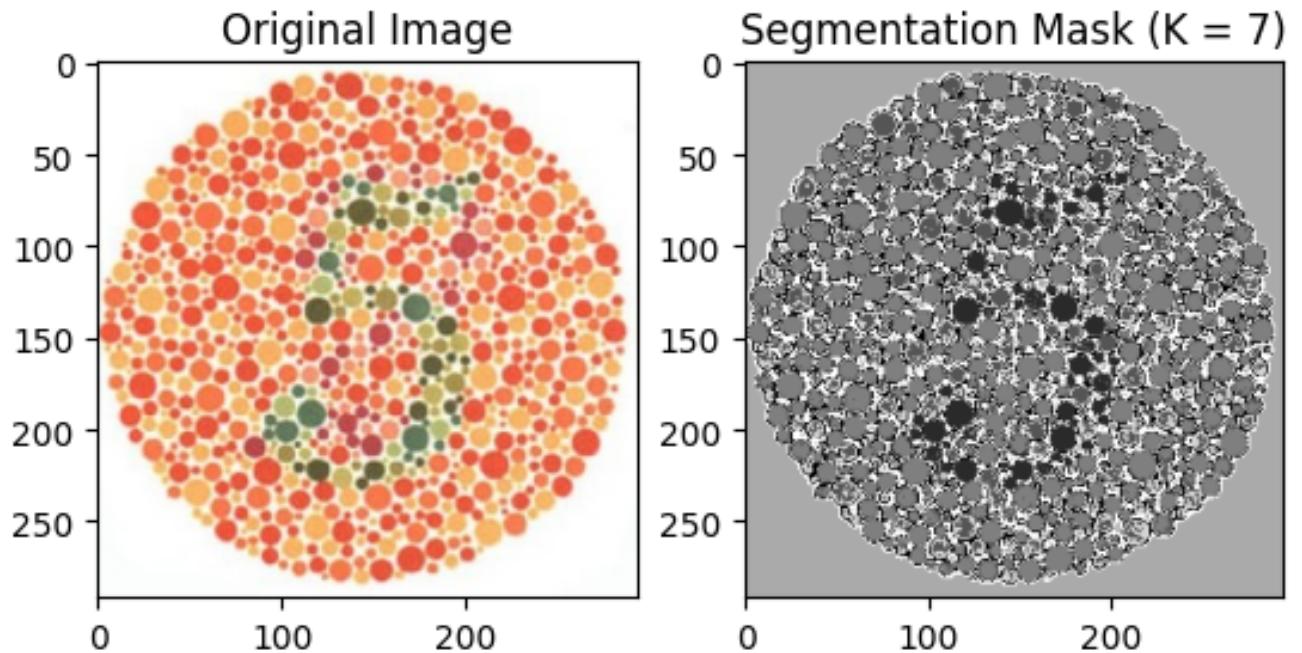


Figure 4.2: Original Image and K-Means Clustered Image.

4.2.3 Image Segmentation Using Superpixels Based Clustering

Code :

```

1 import numpy as np
2 from skimage import color, segmentation
3 from skimage import io
4 import matplotlib.pyplot as plt
5
6 def slic(image, num_segments, compactness):
7     # Convert the image to Lab color space
8     image_lab = color.rgb2lab(image)
9
10    # Initialize cluster centers
11    h, w, _ = image.shape
12    step = int(np.sqrt((h * w) / num_segments))

```

```

13     grid_y, grid_x = np.meshgrid(np.arange(0, h, step), np.
14         arange(0, w, step))
15
16     centers = np.vstack((grid_x.flatten(), grid_y.flatten())).
17         T
18
19
20     # Iterate until convergence
21     max_iter = 10
22
23     for _ in range(max_iter):
24
25         # Assign pixels to clusters
26
27         labels = segmentation.slic(image_lab, n_segments=
28             num_segments, compactness=compactness)
29
30         # Update cluster centers
31
32         for i in range(num_segments):
33
34             mask = (labels == i)
35
36             centers[i] = np.mean(np.nonzero(mask), axis=1)
37
38
39     return labels
40
41
42     # Example usage:
43
44     image = io.imread('/content/download.jpg')
45
46     num_segments = 5
47
48     compactness = 20
49
50     segmented_image = slic(image, num_segments, compactness)
51
52
53     # Display the original and segmented images
54
55     fig, ax = plt.subplots(1, 2, figsize=(12, 6))
56
57     ax[0].imshow(image)
58
59     ax[0].set_title('Original Image')
60
61     ax[1].imshow(segmented_image, cmap='nipy_spectral')

```

```

40 ax[1].set_title('Segmented Image')
41 plt.show()

```

Output:

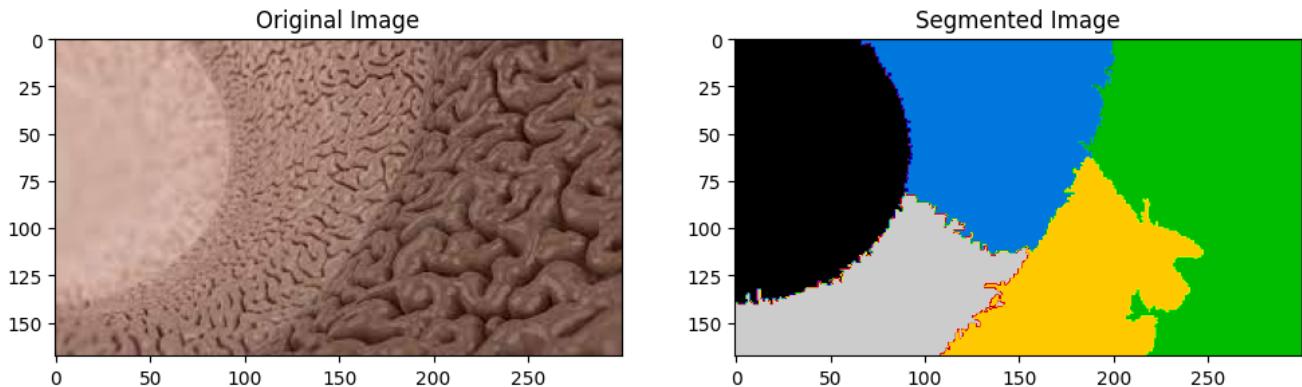


Figure 4.3: Original Image and Superpixel Based Clustered Image.

4.3 Conclusion

In this study of image segmentation conducted on the Google Colab platform using Python, a series of image processing operations were performed, encompassing line and edge detection through Hough Transformation, and image segmentation using K-means clustering as well as superpixels-based clustering. The openCV library, along with skimage, numpy, and matplotlib, played pivotal roles in the implementation of these tasks. HoughLines, slic, range, rgb2lab, vstack, mean, reshape, BGR2RGB, GaussianBlur, Canny, imread, imshow, and various other functions from these libraries were strategically employed.

The Hough Transformation facilitated the extraction of lines and edges from images, providing insights into their structural features. K-means clustering enabled efficient segmentation by grouping similar pixels, offering a means to understand and isolate distinct regions within an image. Superpixels-based clustering, specifically using the slic function, further improved segmentation precision. The employed functions collectively contributed to the analytical processes, fostering a comprehensive exploration of image segmentation techniques. This study highlights the significance of these approaches, showcasing their versatility and applicability in image analysis and computer vision applications.

Heaven's Light is Our Guide

Rajshahi University of Engineering & Technology

Department of Electronics & Telecommunication Engineering



ETE 4226: Sessional Based on ETE 4225

Experiment 5

Study of Feature Extraction and Image Pattern Classification.

Submitted by:

Md. Darul Atfal Palash

Roll: 1804005

Session: 2018-19

Submitted to:

Dr. Shah Ariful Hoque Chowdhury

Associate Professor

Dept. of ETE, RUET

Date of Experiment : 17/12/2023

Date of Submission : 25/01/2024

<u>Report</u>	(Teacher's Section)	<u>Viva</u>
<input type="checkbox"/> Excellent		<input type="checkbox"/> Excellent
<input type="checkbox"/> Very Good		<input type="checkbox"/> Very Good
<input type="checkbox"/> Good	_____	<input type="checkbox"/> Good
<input type="checkbox"/> Moderate	Signature	<input type="checkbox"/> Moderate
<input type="checkbox"/> Poor		<input type="checkbox"/> Poor

Experiment 5

Study of Feature Extraction and Image Pattern Classification.

Objectives

The primary objectives of this experiment are as follows:

- Understand the theoretical foundations of image segmentation.
- Implement and analyze Hough Transform for line and edge detection.
- Explore K-means clustering for image segmentation.
- Investigate Superpixel-based clustering methods.

5.1 Required Apparatus/Softwares

- Python.
- A Highly Configured PC.

5.2 Program Code and Output

5.2.1 Harris-Stephens (HS) Corner Detection

Code :

```
1 import cv2
2 import numpy as np
3 from matplotlib import pyplot as plt
4 image = cv2.imread('/content/chess.jpg')
5 gray_image = cv2.cvtColor(image, cv2.COLOR_RGB2GRAY)
6 float_image = np.float32(gray_image)
7
8 threshold=0.15
9 new_image = cv2.cornerHarris(gray_image,20,3,0.04)
10 new_image =cv2.dilate(new_image,None)
11 image[new_image > threshold * new_image.max() ] = [255,0,0]
12
```

```

13 # Display the images
14 image2= cv2.imread('/content/chess.jpg')
15 plt.subplot(1, 2, 1)
16 plt.imshow(image2)
17 plt.title('Original Image')
18 plt.subplot(1, 2, 2)
19 plt.imshow(image)
20 plt.title('Harris Corner Detection')
21 plt.show()

```

Output:

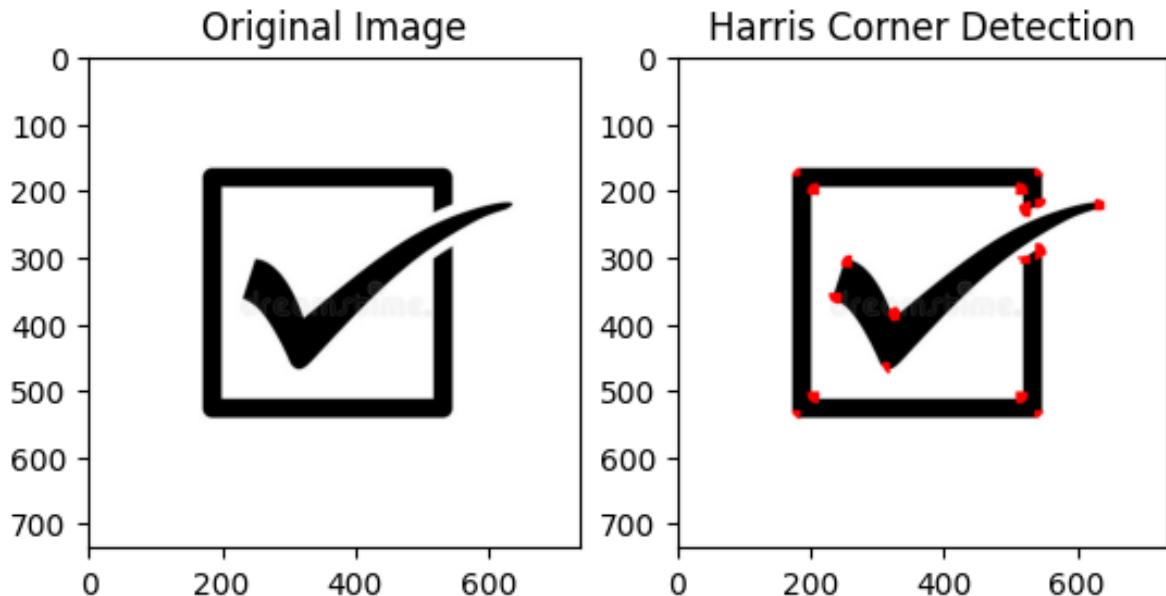


Figure 5.1: Original Image and Corner Detected Image Using Harris-Stephens (HS) Corner Detection.

5.2.2 Implement and Train a Fully Connected Neural Network

Code :

```

1 import numpy as np
2 import keras
3 from keras.datasets import mnist

```

```

4 from keras.models import Sequential
5 from keras.layers import Dense, Flatten
6 import matplotlib.pyplot as plt
7
8 # the data, split between train and test sets
9 (x_train, y_train), (x_test, y_test) = mnist.load_data()
10
11 batch_size = 128
12 num_classes = 10
13 epochs = 5
14
15 x_train = x_train.reshape(x_train.shape[0], 28, 28, 1)
16 x_test = x_test.reshape(x_test.shape[0], 28, 28, 1)
17 input_shape = (28, 28, 1)
18
19 y_train = keras.utils.to_categorical(y_train, num_classes)
20 y_test = keras.utils.to_categorical(y_test, num_classes)
21
22 x_train = x_train.astype('float32')
23 x_test = x_test.astype('float32')
24 x_train /= 255
25 x_test /= 255
26
27 model = Sequential()
28 model.add(Flatten())
29 model.add(Dense(256, activation='relu'))
30 model.add(Dense(num_classes, activation='softmax'))
31
32 model.compile(
33     optimizer='adam',

```

```

34     loss='categorical_crossentropy',
35     metrics=['accuracy']
36 )
37
38 history = model.fit(x_train, y_train, epochs=epochs,
39                       validation_data=(x_test, y_test))
40
41 score = model.evaluate(x_test, y_test, verbose=0)
42 print("Test loss:", score[0])
43 print("Test accuracy:", score[1])
44
45 y_pred = model.predict(x_test)
46 y_pred_classes = np.argmax(y_pred, axis=1)
47
48 plt.figure(figsize=(8, 5.5))
49 for i in range(6):
50     plt.subplot(2, 3, i + 1)
51     plt.imshow(x_test[i].reshape(28, 28), cmap='gray')
52     plt.title(f"True: {np.argmax(y_test[i])}, Predicted: {y_pred_classes[i]}")
53     plt.axis('off')
54 plt.show()
55
56 plt.figure(figsize=(8, 4))
57 # Accuracy plot
58 plt.subplot(1, 2, 1)
59 plt.plot(history.history['accuracy'], label='Training Accuracy')
60
61 plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
62 plt.title('Accuracy vs. Epoch')

```

```

60 plt.xlabel('Epoch')
61 plt.ylabel('Accuracy')
62 plt.legend()
63 plt.grid(False)
64 # Loss plot
65 plt.subplot(1, 2, 2)
66 plt.plot(history.history['loss'], label='Training Loss')
67 plt.plot(history.history['val_loss'], label='Validation Loss')
68 plt.title('Loss vs. Epoch')
69 plt.xlabel('Epoch')
70 plt.ylabel('Loss')
71 plt.legend()
72 plt.grid(False)
73 plt.tight_layout()
74 plt.show()

```

Output:

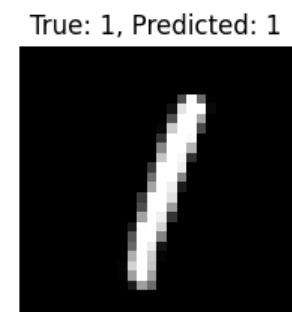
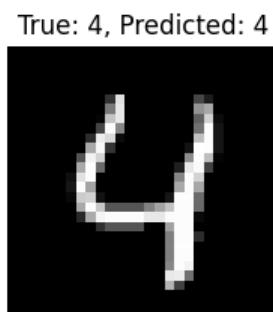
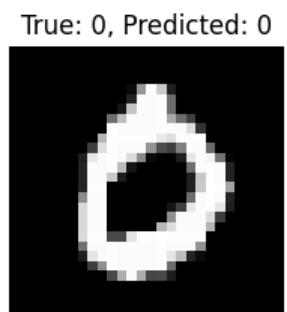
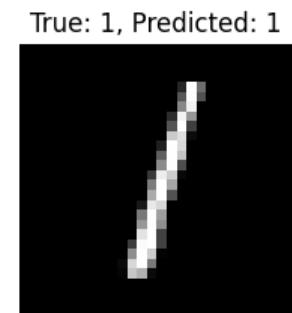
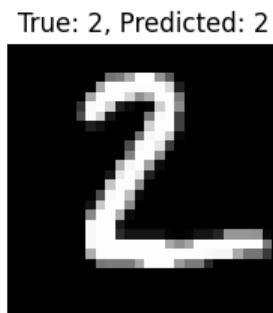
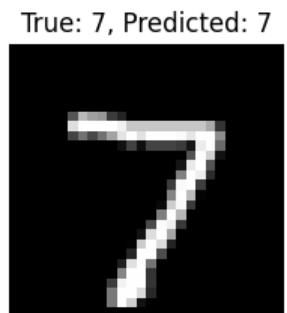


Figure 5.2: Handwritten Digits with Its True and Predicted Value.

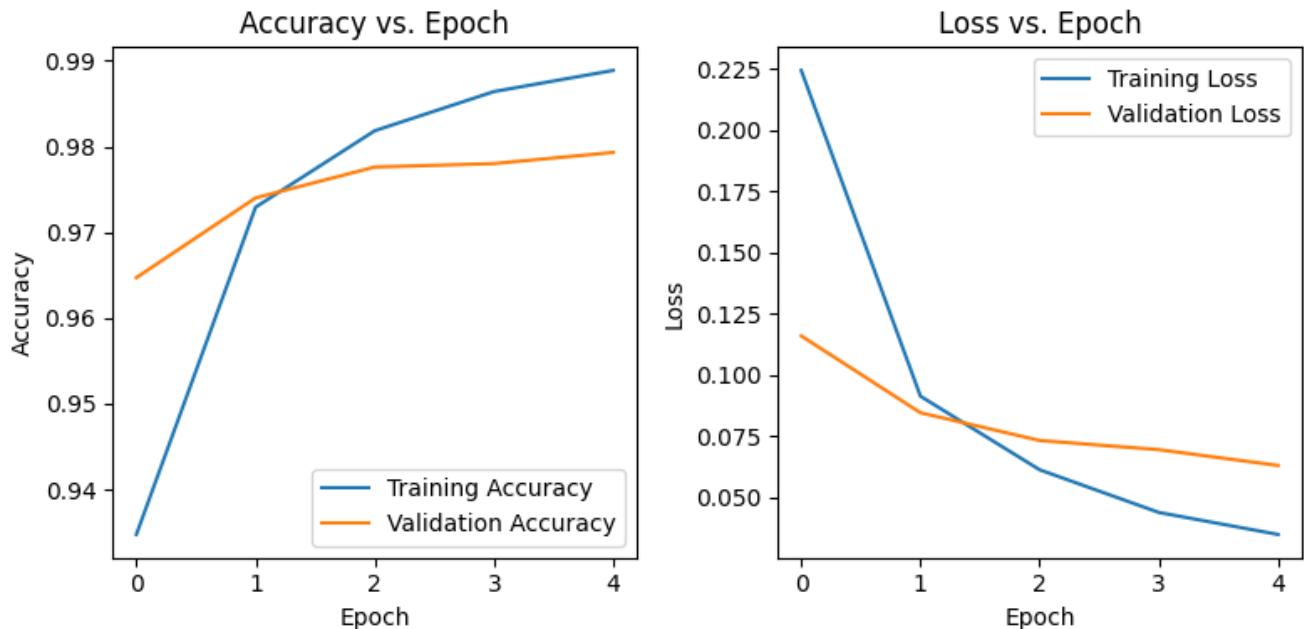


Figure 5.3: Accuracy and Loss Plot.

5.2.3 Implement and Train a Convolution Neural Network

Code :

```

1 import keras
2 from keras.datasets import mnist
3 from keras.models import Sequential
4 from keras.layers import Dense, Flatten
5 from keras.layers import Conv2D, MaxPooling2D
6 from keras import backend as K
7 import matplotlib.pyplot as plt
8 import numpy as np
9 (x_train, y_train), (x_test, y_test) = mnist.load_data()
10 batch_size = 128
11 num_classes = 10
12 epochs = 5 # Changed the number of epochs for faster training
13 x_train = x_train.reshape(x_train.shape[0], 28, 28, 1)
14 x_test = x_test.reshape(x_test.shape[0], 28, 28, 1)

```

```

15 input_shape = (28, 28, 1)
16 y_train = keras.utils.to_categorical(y_train, num_classes)
17 y_test = keras.utils.to_categorical(y_test, num_classes)
18 x_train = x_train.astype('float32')
19 x_test = x_test.astype('float32')
20 x_train /= 255
21 x_test /= 255
22 model = Sequential()
23 model.add(Conv2D(32, kernel_size=(3, 3), activation='relu',
                  input_shape=input_shape))
24 model.add(Conv2D(64, (3, 3), activation='relu'))
25 model.add(MaxPooling2D(pool_size=(2, 2)))
26 model.add(Flatten())
27 model.add(Dense(256, activation='relu'))
28 model.add(Dense(num_classes, activation='softmax'))
29 model.compile(
30     optimizer='adam',
31     loss='categorical_crossentropy',
32     metrics=['accuracy']
33 )
34
35 history = model.fit(x_train, y_train, epochs=epochs,
36                       validation_data=(x_test, y_test))
37 score = model.evaluate(x_test, y_test, verbose=0)
38 print("Test loss:", score[0])
39 print("Test accuracy:", score[1])
40 y_pred = model.predict(x_test)
41 y_pred_classes = np.argmax(y_pred, axis=1)
42

```

```

43 plt.figure(figsize=(8, 5.5))
44 for i in range(6):
45     plt.subplot(2, 3, i + 1)
46     plt.imshow(x_test[i].reshape(28, 28), cmap='gray')
47     plt.title(f"True: {np.argmax(y_test[i])}, Predicted: {y_pred_classes[i]}")
48     plt.axis('off')
49 plt.show()
50 plt.figure(figsize=(8, 4))
51 # Accuracy plot
52 plt.subplot(1, 2, 1)
53 plt.plot(history.history['accuracy'], label='Training Accuracy')
54 plt.plot(history.history['val_accuracy'], label='Validation
55 Accuracy')
56 plt.title('Accuracy vs. Epoch')
57 plt.xlabel('Epoch')
58 plt.ylabel('Accuracy')
59 plt.legend()
60 plt.grid(False)
61 # Loss plot
62 plt.subplot(1, 2, 2)
63 plt.plot(history.history['loss'], label='Training Loss')
64 plt.plot(history.history['val_loss'], label='Validation Loss')
65 plt.title('Loss vs. Epoch')
66 plt.xlabel('Epoch')
67 plt.ylabel('Loss')
68 plt.legend()
69 plt.grid(False)
70 plt.tight_layout()

```

```
70 plt.show()
```

Output:

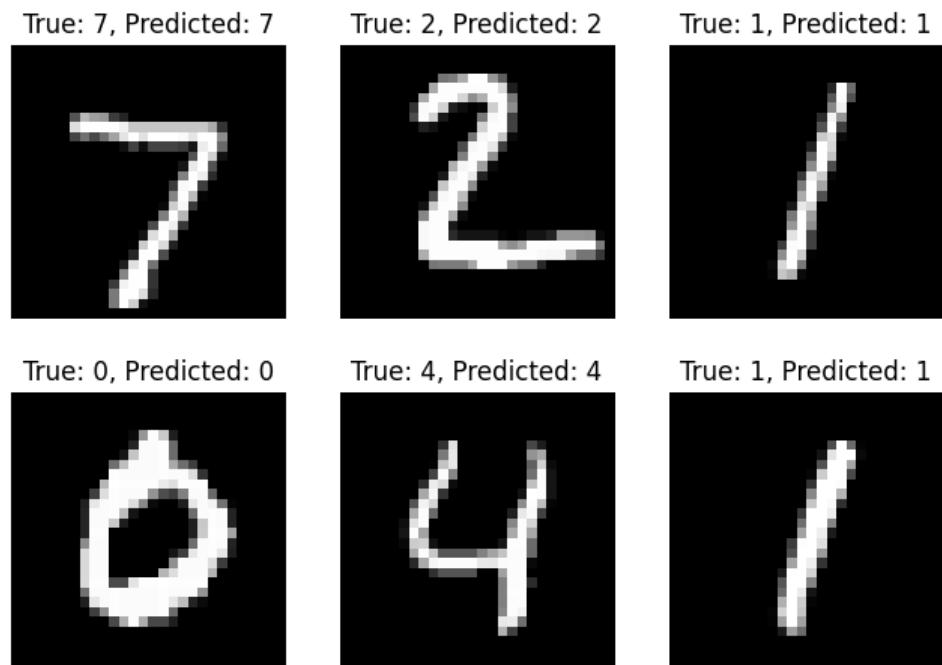


Figure 5.4: Handwritten Digits with Its True and Predicted Value.

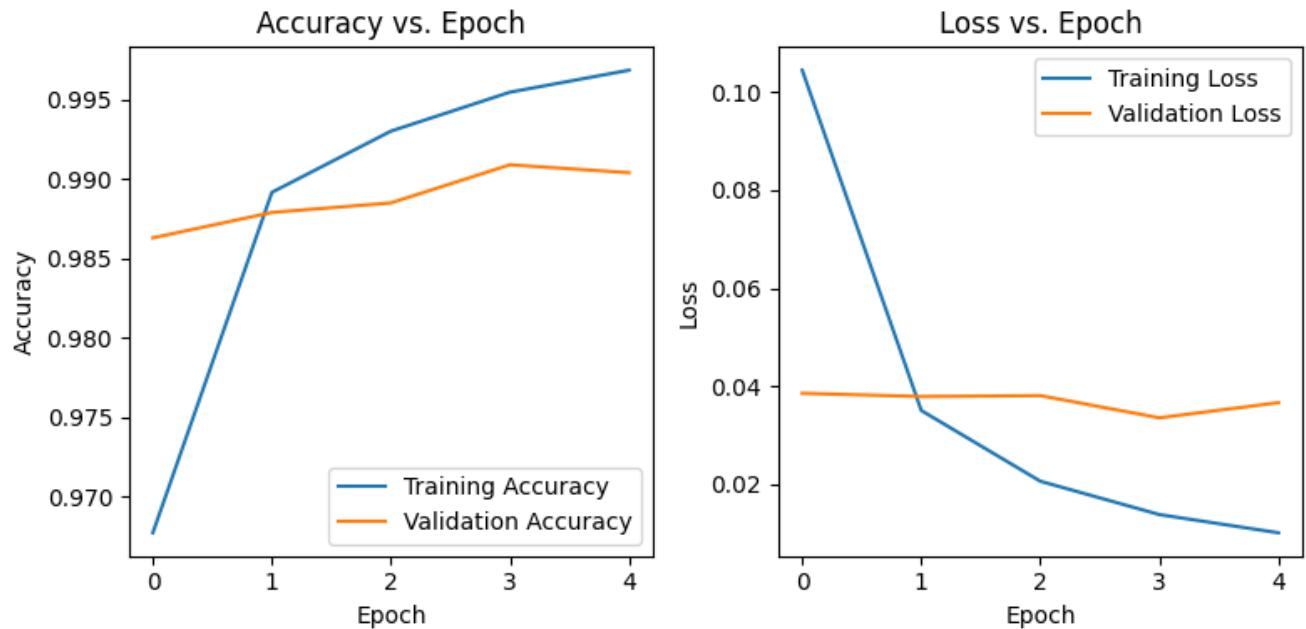


Figure 5.5: Accuracy and Loss Plot.

5.3 Conclusion

In this study, the exploration of feature extraction and image pattern classification was conducted on the Google Colab platform using Python. For corner detection, the Harris-Stephens Corner Detection algorithm was employed, utilizing OpenCV functions such as '**cornerHarris**' and '**dilate**' to identify key points and enhance corner visibility in the given image. The application of corner detection serves as a fundamental step in understanding the structure and salient features of the image.

Moving toward image pattern classification, Fully Connected Neural Network (FCNN) and Convolutional Neural Network (CNN) architectures were implemented and trained for handwritten digit recognition, leveraging the capabilities of the Keras library. Commonly used functions like '**Conv2D**', '**MaxPooling2D**', '**Flatten**', and '**Dense**' were integral in constructing and configuring the neural networks. The models were compiled with the '**adam**' optimizer and '**softmax**' activation function for accurate predictions.

The employed convolution and fully connected layers facilitated the learning of intricate patterns within the digit images. The integration of numpy and matplotlib supported data manipulation and visualization, enhancing the comprehension of feature extraction and classification processes. This study underscores the significance of these techniques in computer vision applications, showcasing their adaptability and effectiveness in analyzing and classifying visual data.

Assignment

Problem - 1: K-means Clustering without Using Built-in Functions.

Code :

```
1 import numpy as np
2
3 import cv2
4
5 import matplotlib.pyplot as plt
6
7
8 def k_means_clustering_custom(image, k=3, max_iters=100):
9
10     # Flatten the image to a 1D array of pixels
11     pixels = image.reshape((-1, 3))
12
13     # Randomly initialize k cluster centers
14     centers = pixels[np.random.choice(pixels.shape[0], k,
15                                         replace=False)]
16
17
18     for _ in range(max_iters):
19
20         # Calculate distances from each point to each cluster
21         center
22
23             distances = np.linalg.norm(pixels - centers[:, np.
24                                         newaxis], axis=2)
25
26             # Assign each pixel to the cluster with the nearest
27             center
28
29             labels = np.argmin(distances, axis=0)
30
31             # Update cluster centers
32
33             new_centers = np.array([pixels[labels == i].mean(axis
34                                         =0) for i in range(k)])
35
36             # Check for convergence
37
38             if np.all(np.abs(centers - new_centers) < 1e-4):
39
40                 break
```

```

21     centers = new_centers
22
23     # Map each pixel to its cluster center
24     clustered_pixels = centers[labels]
25
26     # Reshape the clustered pixels back to the original image
27     # shape
28
29     clustered_image = clustered_pixels.reshape(image.shape)
30
31     return clustered_image, centers, labels
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47

```

21 centers = new_centers
22
23 # Map each pixel to its cluster center
24 clustered_pixels = centers[labels]
25
26 # Reshape the clustered pixels back to the original **image**
27 # shape
28
29 clustered_image = clustered_pixels.reshape(**image**.shape)
30
31 **return** clustered_image, centers, labels
32
33
34
35
36
37
38
39
40 clustered_image, centers, labels = k_means_clustering_custom(
41 **image**, k=k_clusters)
42
43 # Plot the clustered **image**
44
45 plt.subplot(1, 2, 2)
46 plt.imshow(clustered_image.astype(np.uint8))
47 plt.title(f'Clustered Image (k={k_clusters})')

Output:

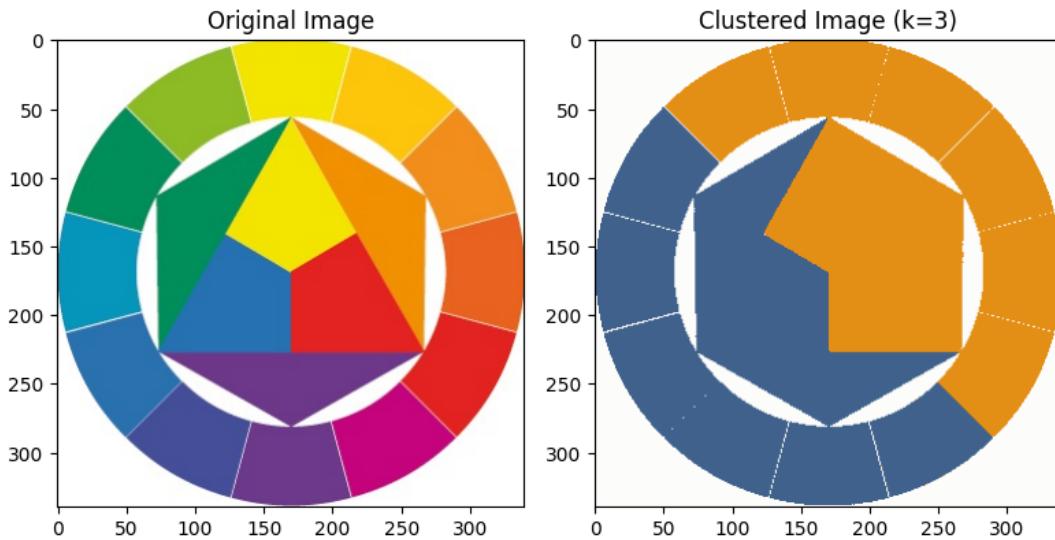


Figure 1.1: Original Image and K-Means Clustered Image.

Problem - 2: Image Segmentation Using Simple Linear Iterative Clustering (SLIC) Superpixel Algorithm (without Using Built-in Functions).

Code :

```
1 import numpy as np
2 from skimage import color, segmentation
3 from skimage import io
4 import matplotlib.pyplot as plt
5
6 def slic(image, num_segments, compactness):
7     # Convert the image to Lab color space
8     image_lab = color.rgb2lab(image)
9
10    # Initialize cluster centers
11    h, w, _ = image.shape
12    step = int(np.sqrt((h * w) / num_segments))
13    grid_y, grid_x = np.meshgrid(np.arange(0, h, step), np.
arange(0, w, step))
```

```

14     centers = np.vstack((grid_x.flatten(), grid_y.flatten())).
15
16     # Iterate until convergence
17     max_iter = 10
18
19     for _ in range(max_iter):
20
21         # Assign pixels to clusters
22
23         labels = segmentation.slic(image_lab, n_segments=
24             num_segments, compactness=compactness)
25
26
27     return labels
28
29
30     # Example usage:
31
32     image = io.imread('/content/download.jpg')
33     num_segments = 5
34     compactness = 20
35     segmented_image = slic(image, num_segments, compactness)
36
37     # Display the original and segmented images
38     fig, ax = plt.subplots(1, 2, figsize=(12, 6))
39
40     ax[0].imshow(image)
41     ax[0].set_title('Original Image')
42
43     ax[1].imshow(segmented_image, cmap='nipy_spectral')
44     ax[1].set_title('Segmented Image')
45
46     plt.show()

```

Output:

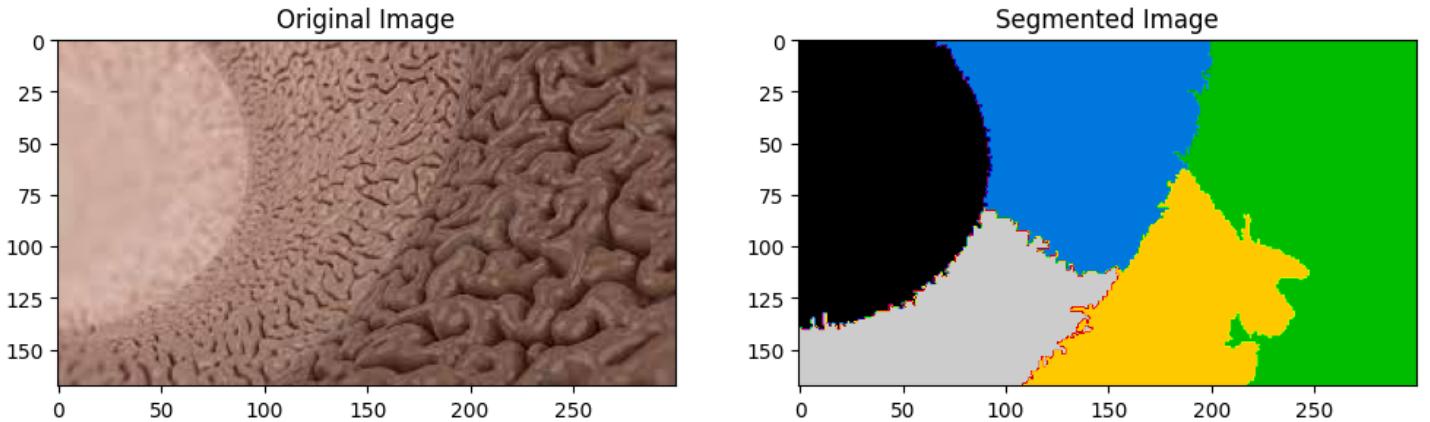


Figure 1.2: Original Image and SLIC Superpixel Clustered Image.

Problem - 3: Harris-Stephens (HS) Corner Detection without Using Built-in Functions.

Code :

```
1 import cv2
2 import numpy as np
3 import matplotlib.pyplot as plt
4
5 def harris_corner_detection(image, k=0.04, threshold=0.005):
6     # Convert the image to grayscale
7     gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY).astype(np.
float32)
8     # Compute derivatives
9     Ix = cv2.Sobel(gray, cv2.CV_64F, 1, 0, ksize=3)
10    Iy = cv2.Sobel(gray, cv2.CV_64F, 0, 1, ksize=3)
11    # Compute products of derivatives at each pixel
12    Ixx = Ix * Ix
13    Iyy = Iy * Iy
14    Ixy = Ix * Iy
```

```

15     # Compute sums of products of derivatives using a Gaussian
16     filter
17
18     window_size = 5
19
20     kernel = np.ones((window_size, window_size), np.float32) /
21         (window_size ** 2)
22
23     Sxx = cv2.filter2D(Ixx, -1, kernel)
24     Syy = cv2.filter2D(Iyy, -1, kernel)
25     Sxy = cv2.filter2D(Ixy, -1, kernel)
26
27     # Compute Harris corner response
28
29     det_M = Sxx * Syy - Sxy**2
30
31     trace_M = Sxx + Syy
32
33     R = det_M - k * trace_M**2
34
35     # Apply thresholding to detect corners
36
37     corners = np.zeros_like(R)
38
39     corners[R > threshold * R.max()] = 255
40
41     return corners.astype(np.uint8)

42 # Read an example image
43
44 image = cv2.imread('/content/chess.jpeg')
45
46 # Perform Harris corner detection
47
48 corners_image = harris_corner_detection(image)
49
50 # Display the original and corner-detected images
51
52 plt.figure(figsize=(10, 6))
53
54 # Original Image
55
56 plt.subplot(1, 2, 1)
57
58 plt.imshow(cv2.cvtColor(image, cv2.COLOR_BGR2RGB))
59
60 plt.title('Original Image')
61
62 plt.axis('off')
63
64 # Corners Detected Image
65
66 color_corners_image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)

```

```
42 color_corners_image[corners_image > 0] = [255, 0, 0] # Mark  
    corners in red  
43 plt.subplot(1, 2, 2)  
44 plt.imshow(color_corners_image)  
45 plt.title('Corners Detected')  
46 plt.axis('off')  
47 plt.show()
```

Output:

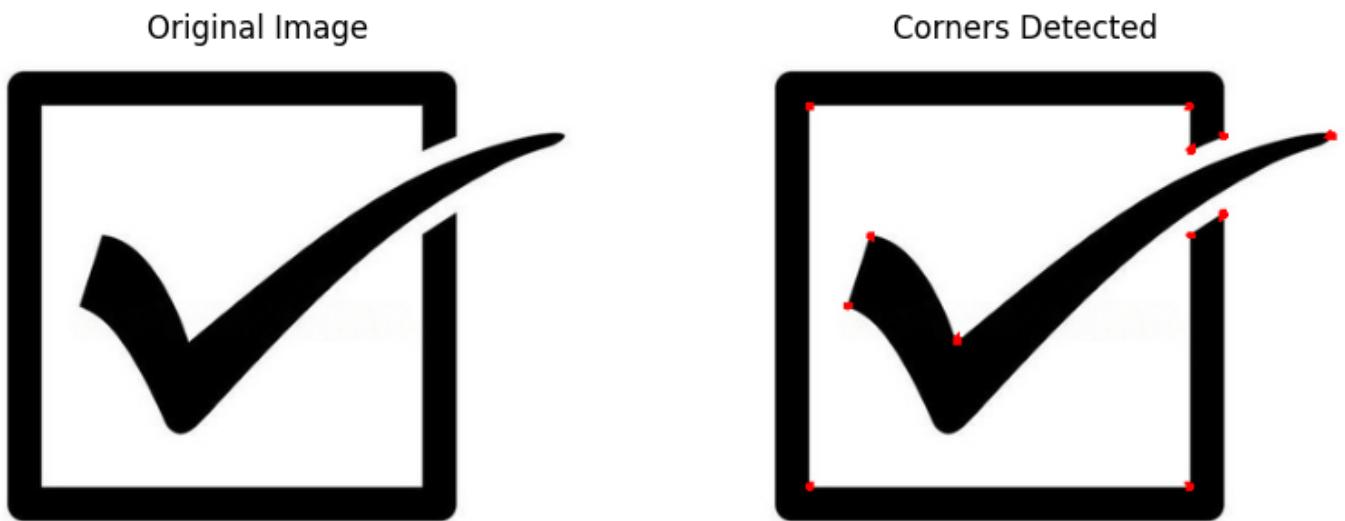


Figure 1.3: Original Image and HS Corner Detected Image.