EN3160 – Image Processing and Machine Vision

Assignment 1 - Intensity Transformations and Neighborhood Filtering

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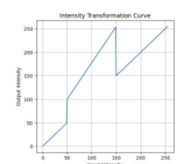
Assignment Codes on: [Google Colab]()

Question 1 – Implementing an intensity transformation on Emma Watson

Original Image

Transformed Image

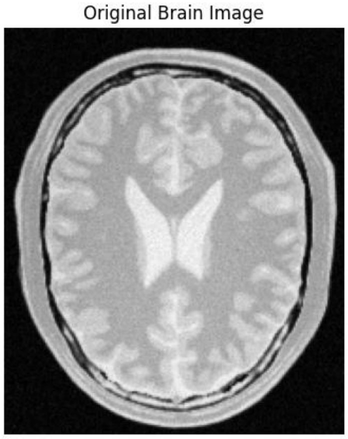
```
# Read the image
image = cv2.imread('./a1images/emma.jpg', cv2.IMREAD_GRAYSCALE) # PC

# Define the intensity transformation function
def intensity_transformation(input_intensity):
  # Assuming a piecewise linear function for intensity transformation
  if input_intensity < 50:
    return input_intensity
  elif input_intensity < 150:
    return (1.55*input_intensity + 22.5)
  else:
    return input_intensity

# Vectorize the function to apply to the image
vectorized_transformation = np.vectorize(intensity_transformation)

# Apply the transformation to the image
transformed_image = vectorized_transformation(image).astype(np.uint8)

# Plot the original and transformed images
plt....
```



Discussion: Pixel values in the [0,50] and [150,255] ranges are mapped similarly, resulting in little change in her hair color, which falls in the lower range. Mid-range values (50-150) are exaggerated, causing white patches on the right side of the face, while the left side, being in the 150+ range, shows minimal change.

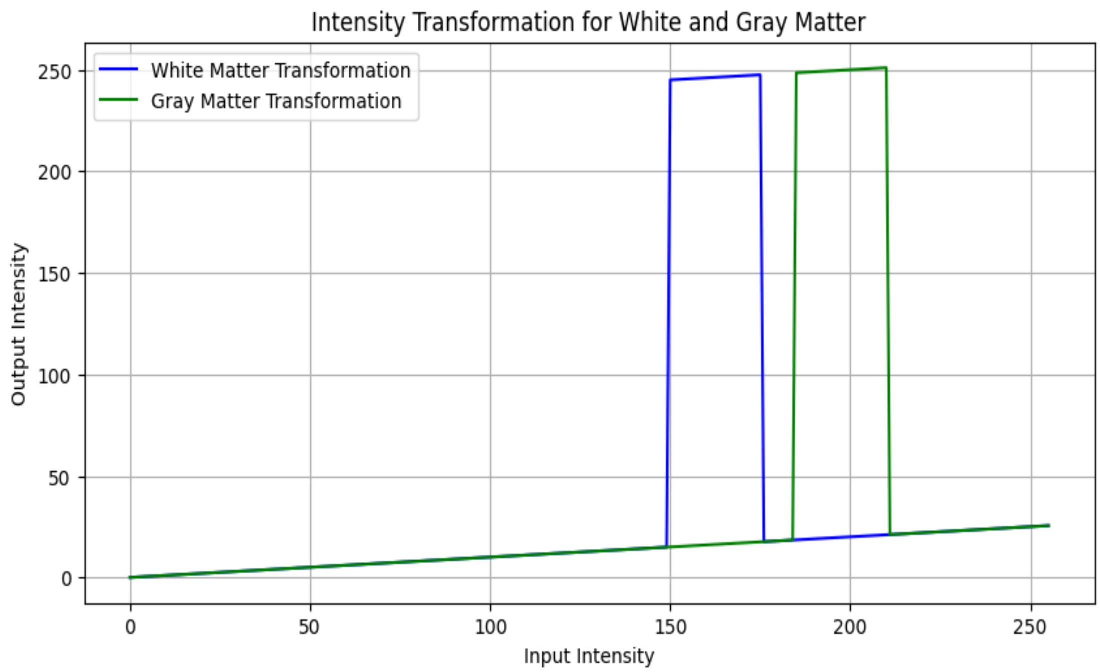
Question 2 – Intensity transformation on brain proton density image

Original Brain Image



White Matter Accentuated

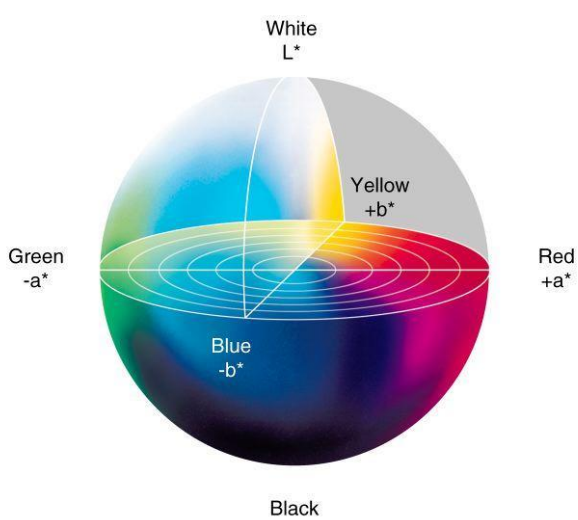
Gray Matter Accentuated



Discussion: The Intensities measured for white matter and gray matter using my special function **get_pixel_intensity(event, x, y, flags, param).** Then next 2 functions accentuate white matter; range 150 to 175 and accentuate gray matter; range 185 to 210 intensities will be exaggerated as we did in the Question 1. This will allow us to view clearly the regions of white and gray matter in the brain.

```
# Define intensity transformation functions for white matter and gray matter

def accentuate_white_matter(intensity):
    # Custom function to enhance white matter
    if intensity < 150:
        return intensity*0.1
    elif intensity >= 150 and intensity <= 175:
        return (255 - 25 + intensity*0.1)
    else:
        return intensity*0.1

def accentuate_gray_matter(intensity):
    # Custom function to enhance gray matter
    if intensity < 150:
        return intensity*0.1
    elif intensity >= 185 and intensity <= 210:
        return (255 - 25 + intensity*0.1)
    else:
        return intensity*0.1
```

Question 3 – Gamma correction to the L plane in the L∗a∗b∗ color space

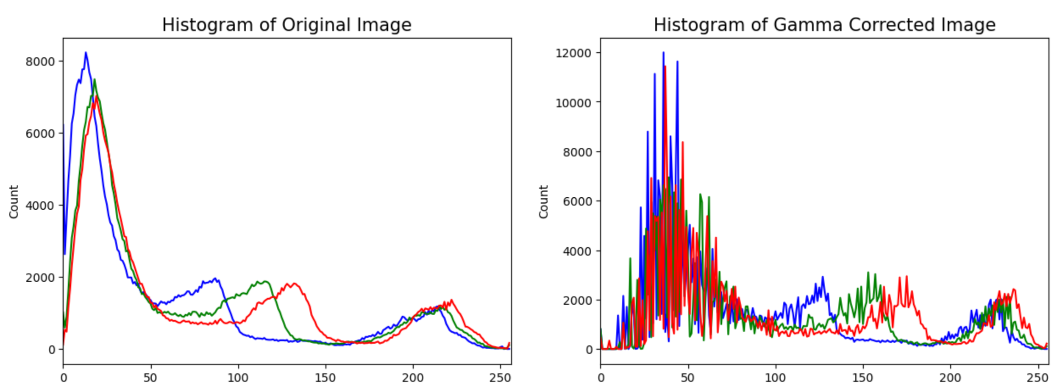



```
# Load the image and convert BGR to LAB color space
img3 = cv.imread("images/highlights_and_shadows.jpg", cv.IMREAD_COLOR)
img3_lab = cv.cvtColor(img3, cv.COLOR_BGR2LAB)

# Set the gamma value for correction
gamma = 0.6

# Create a gamma transformation lookup table
gamma_transform = np.array([(i / 255.0) ** gamma * 255.0 for i in np.arange(256)]).astype('uint8')

# Apply gamma correction to the L plane (brightness channel)
img3_lab[:, :, 0] = gamma_transform[img3_lab[:, :, 0]]

# Convert back to BGR for display
gamma_corrected_img = cv.cvtColor(img3_lab, cv.COLOR_LAB2BGR)

# Display the original and gamma corrected images
plt...
```

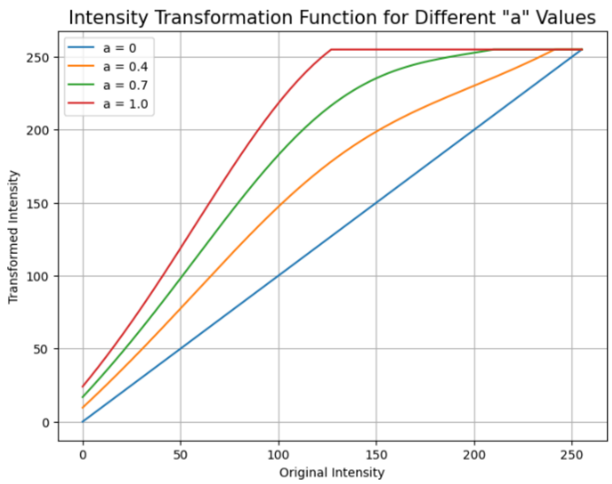
Gamma correction with different values; **γ = 0.3,0.6,0.9**

Discussion: Gamma correction affects the brightness and contrast of an image depending on the value of gamma. When the gamma value is set to 1, the gamma correction curve is linear, meaning the image remains unchanged and the histogram retains its original distribution. When the gamma value is less than 1 (for example, 0.2), gamma compression occurs, which darkens the image and shifts the histogram towards the left, concentrating more pixel values in the darker regions. Conversely, when the gamma value is greater than 1 (for example, 2.0), gamma expansion occurs, brightening the image and shifting the histogram to the right, thereby increasing the concentration of pixel values in the lighter regions. After testing various gamma values, it was found that a gamma value of 0.6 provided the best result for this image, enhancing the contrast while maintaining a natural look.

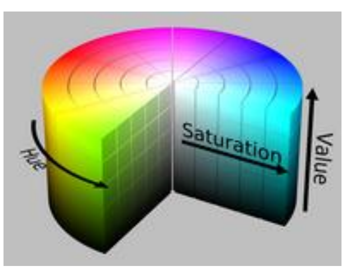
For gamma = 0.6 : Histograms for all 3 color planes before and after applying the correction



Question 4 – Intensity transformation to the saturation plane for increase the vibrance

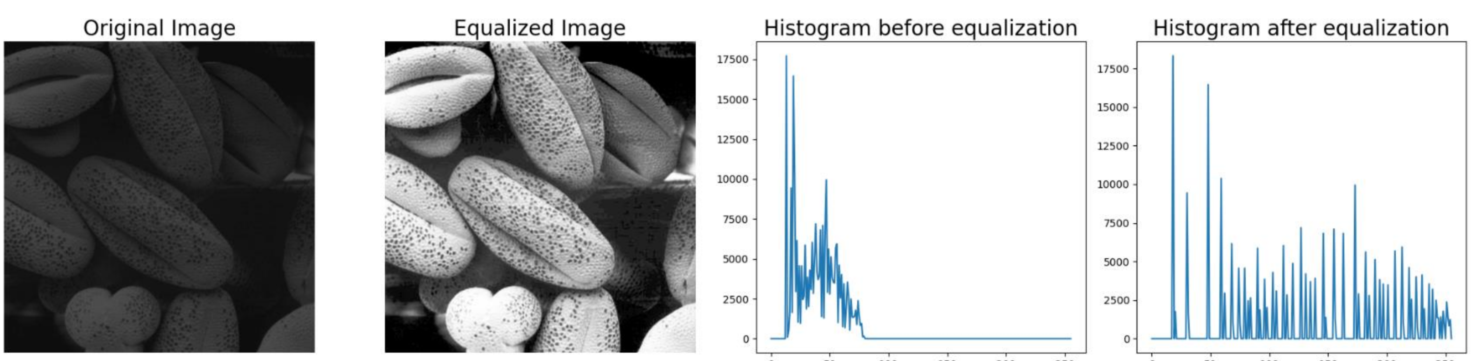



```
# Transformation function for vibrance enhancement
a = 0.3  # Adjusted value of 'a' for a natural vibrance
sigma = 70
def f(x):
    return np.minimum(255, x + (a * 128) * np.exp(-(x - 128)**2 / (2 * sigma**2)))

# Load the image and convert to HSV color space
img4 = cv.imread("images/spider.png", cv.IMREAD_COLOR)
img4_hsv = cv.cvtColor(img4, cv.COLOR_BGR2HSV)

# (a) Apply transformation only to the saturation plane
img4_hsv[:, :, 1] = f(img4_hsv[:, :, 1])

# (d) Recombine the three planes
vibrance_enhanced_img = cv.cvtColor(img4_hsv, cv.COLOR_HSV2BGR)

# (e) Display the original and enhanced images side by side
plt.figure....
```



Discussion: The saturation plane is modified by applying an intensity transformation, increasing the vibrancy of the image. Areas with low saturation become more vivid, enhancing color contrast. Fine-tuning the parameter a is essential; when a approaches 1, the image can appear overly vibrant. A **value of a = 0.4** provided a natural vibrance level, keeping the image visually pleasing without oversaturation.

Question 5 – Histogram equalization



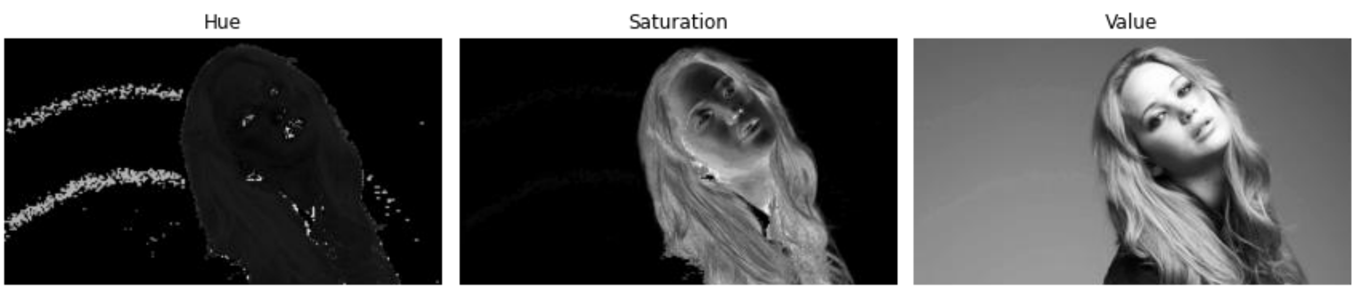
```
# Function for histogram equalization
def histogram _equalize(image):
   total = image.size  # Total number of pixels
   hist, _ = np.histogram(image.ravel(), 256, [0, 256])  # Calculate histogram
   cdf = hist.cumsum()  # Cumulative distribution function (CDF)
   cdf_normalized = (cdf * 255 / total).astype(np.uint8)  # Normalize CDF to [0, 255]
   equalized_image = cdf_normalized[image]  # Map original image pixel values
using the CDF
   return equalized_image

# Load the grayscale image
img = cv.imread("image.png", cv.IMREAD_GRAYSCALE)

# Apply custom histogram equalization
equalized_img = histogram _equalize(img)
```

Discussion:

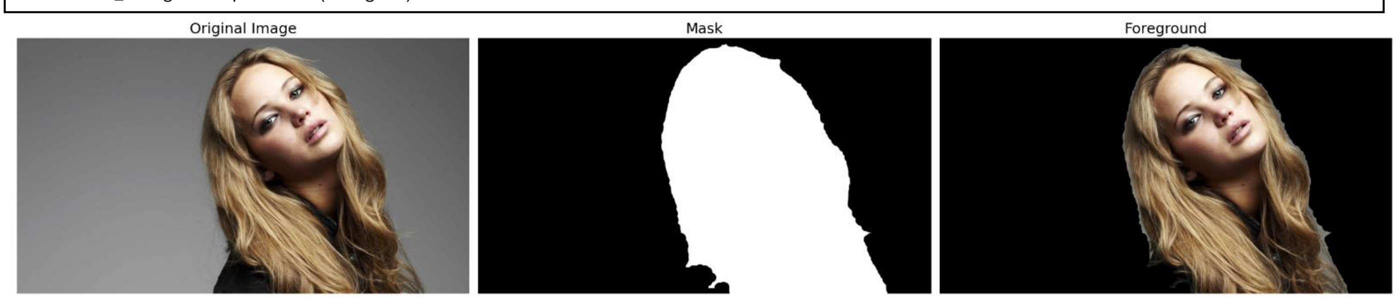
This function computes the histogram and performs histogram equalization by mapping original pixel intensities to the full dynamic range using the cumulative distribution function (CDF). As a result, the darker regions in the image are brightened, providing a more balanced intensity distribution and enhancing image contrast.

Question 6 – Histogram equalizing the foreground of an image

```
# (a) Convert image to HSV and split into hue, saturation, and value channels
hsv_image = cv.cvtColor(image, cv.COLOR_BGR2HSV)
hue, saturation, value = cv.split(hsv_image)
```

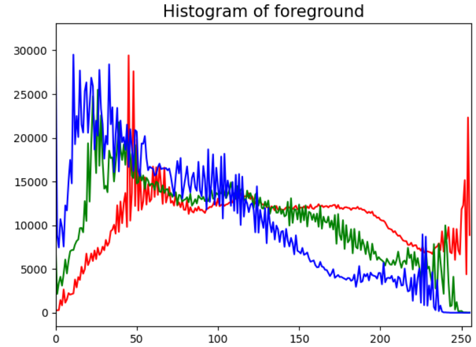



```
# (b) Threshold the saturation plane to extract the foreground mask
saturation_min, saturation_max = 15, 255
foreground_mask = cv.inRange(saturation, saturation_min, saturation_max)
foreground_mask = cv.morphologyEx(foreground_mask, cv.MORPH_CLOSE, cv.getStructuringElement(cv.MORPH_ELLIPSE, (80, 80)))  # Apply morphological closing to
clean up the mask
# (c) Obtain the foreground using the mask and compute its histogram
foreground = cv.bitwise_and(image, image, mask=foreground_mask)
histogram = cv.calcHist([foreground], [0], foreground_mask, [256], [0, 256])
# (d) Compute the cumulative histogram (CDF)
cumulative_histogram = np.cumsum(histogram)
```




```
# (e) Apply histogram equalization to the foreground's value plane
hsv_foreground = cv.cvtColor(foreground, cv.COLOR_BGR2HSV)
value_foreground = hsv_foreground[:, :, 2]
equalized_value_foreground = cv.equalizeHist(value_foreground)
hsv_foreground[:, :, 2] = equalized_value_foreground
# (f) Extract the background and combine it with the equalized foreground
background_mask = cv.bitwise_not(foreground_mask)
extracted_background = cv.bitwise_and(image, image, mask=background_mask)
result = cv.add(extracted_background, cv.cvtColor(hsv_foreground, cv.COLOR_HSV2BGR))
```

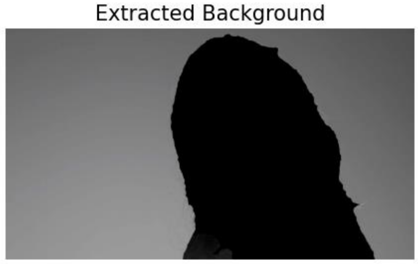
Histogram of foreground



Discussion: The saturation plane was chosen for thresholding since the foreground is more saturated than the background. After thresholding with cv.inRange(), morphological operations were used to clean the mask and capture darker foreground details like the eyes. Histogram equalization was applied to enhance contrast in the value plane, and the foreground was combined with the original background to produce the final result.

Equalized Foreground

Extracted Background



Background + Equalized Foreground

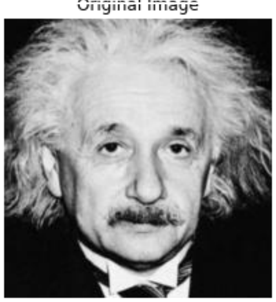
Question 7 – Sobel filtering the photo of Albert Einstein

(a) Using filter2D:This step applies the vertical and horizontal Sobel filters using cv.filter2D() with predefined Sobel kernels. The gradient magnitude is computed using both horizontal and vertical gradients.

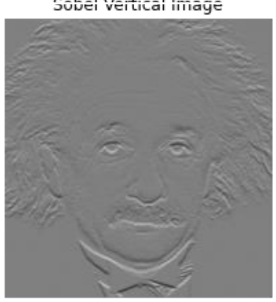
(b) Manual Application:A manual convolution is performed by sliding a 3x3 Sobel kernel over the image and calculating the sum of pixel intensities for both vertical and horizontal directions.

(c) Using sepFilter2D:The separable Sobel filter is applied using cv.sepFilter2D() which decomposes the Sobel filter into two 1D filters and applies them along the rows and columns.

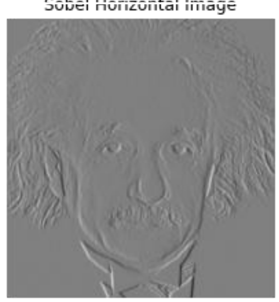
Original Image



Sobel Vertical Image



Sobel Horizontal Image



Gradient Magnitude Image

```
# (a) Using filter2D to apply Sobel filter
sobel_v = np.array([[-1, -2, -1], [0, 0, 0], [1, 2, 1]], dtype='float32')  # Vertical
Sobel kernel
sobel_h = np.array([[-1, 0, 1], [-2, 0, 2], [-1, 0, 1]], dtype='float32')  #
Horizontal Sobel kernel

imv = cv.filter2D(img, -1, sobel_v)  # Apply vertical Sobel
imh = cv.filter2D(img, -1, sobel_h)  # Apply horizontal Sobel
grad_mag = np.sqrt(imv**2 + imh**2)  # Compute gradient magnitude
```

```
# (b) Manually applying the Sobel filter
rows, cols = img.shape
kernel_size = 3
imv_manual = np.zeros((rows - kernel_size + 1, cols - kernel_size + 1), dtype='float32')
imh_manual = np.zeros((rows - kernel_size + 1, cols - kernel_size + 1), dtype='float32')

for row in range(rows - kernel_size + 1):
    for col in range(cols - kernel_size + 1):
        imv_manual[row, col] = np.sum(img[row:row + kernel_size, col:col + kernel_size] * sobel_v)
        imh_manual[row, col] = np.sum(img[row:row + kernel_size, col:col + kernel_size] * sobel_h)

grad_mag_manual = np.sqrt(imv_manual**2 + imh_manual**2)  # Compute gradient magnitude
```

```
# (c) Using sepFilter2D for Sobel filtering
sobel_h_kernel = np.array([1, 2, 1], dtype=np.float32)
sobel_v_kernel = np.array([1, 0, -1], dtype=np.float32)

im1 = cv.sepFilter2D(img, -1, sobel_h_kernel, sobel_v_kernel)  # Separable Sobel filtering
im2 = cv.sepFilter2D(img, -1, sobel_v_kernel, sobel_h_kernel)  # Separable Sobel filtering
grad_mag_sep = np.sqrt(im1**2 + im2**2)  # Compute gradient magnitude
```

Discussion:

All methods yield similar results. The Sobel vertical filter emphasizes vertical edges, detecting intensity changes from top to bottom, while the horizontal filter emphasizes horizontal edges. Combining both gradients provides the overall gradient magnitude at each pixel. The output image dimensions are reduced by the kernel size during convolution.

Question 8 – Zooming an image with nearest-neighbor and bilinear interpolation

1. **Nearest Neighbor**:

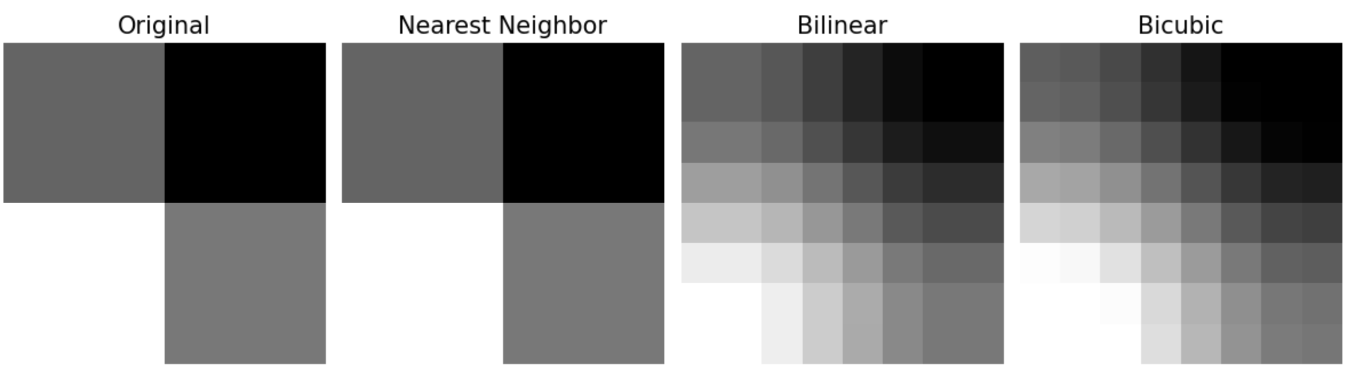
$$I(x', y') = I(\text{round}(x), \text{round}(y))$$

2. **Bilinear**:

$$I(x', y') = (1 - \Delta x)(1 - \Delta y)I(x_1, y_1) + \Delta x(1 - \Delta y)I(x_2, y_1) + (1 - \Delta x)\Delta y I(x_1, y_2) + \Delta x \Delta y I(x_2, y_2)$$

3. **Bicubic**:

$$I(x', y') = \sum_{i=0}^{3} \sum_{j=0}^{3} w(i, j) \cdot I(x + i - 1, y + j - 1)$$




```
# Zoom function to handle nearest-neighbor and bilinear interpolation
def zoom_image(image, scale, method):
    rows, cols = int(image.shape[0] * scale), int(image.shape[1] * scale)  # New dimensions
    zoomed = np.zeros((rows, cols), dtype=image.dtype)  # Initialize zoomed image

    # (a) Nearest-neighbor interpolation
    if method == 'nearest-neighbour':
        for i in range(rows):
            for j in range(cols):
                original_i = min(int(round(i / scale)), image.shape[0] - 1)
                original_j = min(int(round(j / scale)), image.shape[1] - 1)
                zoomed[i, j] = image[original_i, original_j]

    # (b) Bilinear interpolation
    elif method == 'bilinear':
        for i in range(rows):
            for j in range(cols):
                x, y = i / scale, j / scale
                x1, y1 = int(np.floor(x)), int(np.floor(y))
                x2, y2 = min(int(np.ceil(x)), image.shape[0] - 1), min(int(np.ceil(y)), image.shape[1] - 1)
```

```
                dx, dy = x - x1, y - y1
                zoomed[i, j] = (
                    image[x1, y1] * (1 - dx) * (1 - dy) +
                    image[x1, y2] * (1 - dx) * dy +
                    image[x2, y1] * dx * (1 - dy) +
                    image[x2, y2] * dx * dy
                )
    return zoomed

# Compute normalized sum of squared differences (SSD)
def compute_ssd(image1, image2):
    image2_resized = cv.resize(image2, (image1.shape[1], image1.shape[0]))  # Ensure same size
    return np.sum((image1 - image2_resized) ** 2) / np.prod(image1.shape)

# Example usage with image and scale factor
scale_factor = 4
zoomed_nn = zoom_image(img, scale_factor, method='nearest-neighbour')
zoomed_bilinear = zoom_image(img, scale_factor, method='bilinear')

ssd_nn = compute_ssd(zoomed_nn, original_large_image)  # SSD for nearest-neighbor
ssd_bilinear = compute_ssd(zoomed_bilinear, original_large_image)  # SSD for bilinear
```

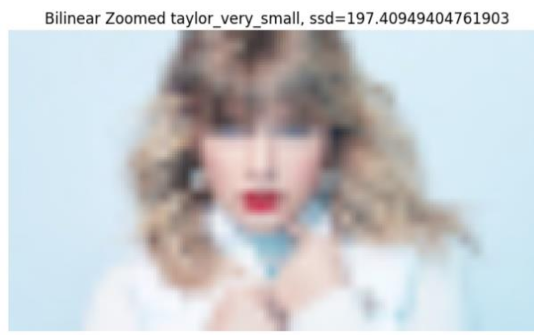
Code:

1] Nearest-Neighbor Interpolation: Each pixel in the zoomed image is assigned the value of the nearest pixel from the original image.

2] Bilinear Interpolation: Uses linear interpolation in both x and y directions, resulting in smoother but slightly blurred images.

3] SSD Calculation: The compute_ssd() function computes the normalized sum of squared differences between the zoomed image and the original large image after resizing.

Discussion: Bilinear interpolation offers smoother results compared to nearest-neighbor, which can cause blocky artifacts. However, some blurring may still occur. Normalized SSD helps compare the resized image with the original, but results may still show noise and artifacts despite size adjustments.



Question 9 – Segmentation of a Yellow Daisy

```
# Initialize mask and models for GrabCut
mask = np.zeros(img.shape[:2], np.uint8)
bg_model = np.zeros((1, 65), np.float64)
fg_model = np.zeros((1, 65), np.float64)
rect = (40, 10, 505, 505)

# Apply GrabCut for initial segmentation
cv.grabCut(img, mask, rect, bg_model, fg_model, 5, cv.GC_INIT_WITH_RECT)

# Extract foreground mask and foreground image
mask1 = np.where((mask == 2) | (mask == 0), 0, 1).astype('uint8')
foreground = img * mask1[:, :, np.newaxis]

# Extract background mask and background image
mask2 = np.where((mask == 3) | (mask == 1), 0, 1).astype('uint8')
background = img * mask2[:, :, np.newaxis]

# Apply Gaussian blur to the background and combine with the foreground
blurred_img = foreground + cv.GaussianBlur(background, (15, 15), 0)
```

Dark Edge Explanation: The dark edge in the enhanced image occurs because background pixels near the boundary, especially those inaccurately segmented, mix with black pixels (masked) during Gaussian blurring, creating a dark halo around the flower.