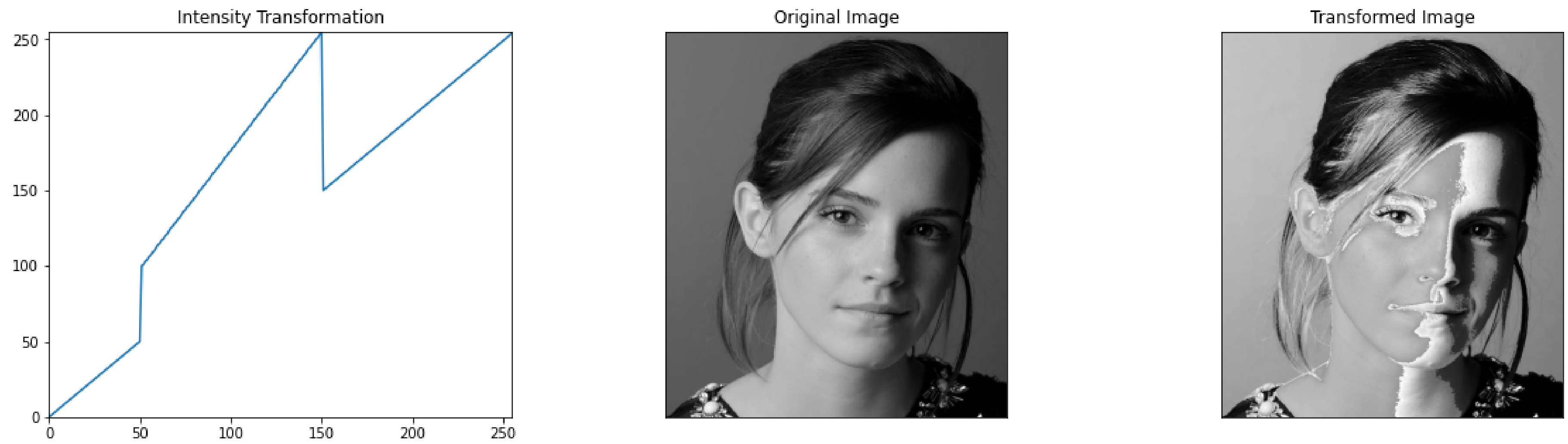
Assignment1\ 190639*B* - B.D.S. Udayantha

In [ ]:
```python
import numpy as np
import matplotlib.pyplot as plt
import cv2 as cv
%matplotlib inline
```

Question 1

In [ ]:
```python
emma_img=cv.imread(r"emma_gray.jpg",cv.IMREAD_GRAYSCALE)
assert emma_img is not None
t1=np.linspace(0,50,51).astype(np.uint8)
t2=np.linspace(100,255,100).astype(np.uint8)
t3=np.linspace(150,255,105).astype(np.uint8)
t=np.concatenate((t1,t2,t3),axis=0)
assert len(t)==256

new_emma_img=cv.LUT(emma_img,t)
fig,ax=plt.subplots(1,3,figsize=(20,5))

ax[0].plot(t)
ax[0].set_title("Intensity Transformation")
ax[0].set_xlim(0,255),ax[0].set_ylim(0,255)

ax[1].imshow(emma_img,cmap='gray',vmin=0,vmax=255)
ax[1].set_xticks([]),ax[1].set_yticks([])
ax[1].set_title("Original Image")

ax[2].imshow(new_emma_img,cmap='gray',vmin=0,vmax=256)
ax[2].set_xticks([]),ax[2].set_yticks([])
ax[2].set_title("Transformed Image")
plt.show()
```



In this question we keep the intensities of pixels as it is from 0-50 and 150- 255.But we change the original pixel values from 51-149 and the result is shwon in right most image. That is why in the result figure it has a light background and gray color effect on the left side of the face

Question 2(a)

In [ ]:
```python
brain_img=cv.imread(r'brain_proton_density_slice.png',cv.IMREAD_GRAYSCALE)
assert brain_img is not None
t1=np.array([0 for r in range(0,215)])
t2=np.array([255 for r in range(215,256)])
t=np.concatenate((t1,t2),axis=0)
assert len(t)==256

fig,ax=plt.subplots(1,3,figsize=(20,5))
ax[0].plot(t)
ax[0].set_title("Intensity Transformation")

new_brain_img=cv.LUT(brain_img,t)
ax[1].imshow(brain_img,cmap='gray',vmin=0,vmax=255)
ax[1].set_xticks([]),ax[1].set_yticks([])
ax[1].set_title("Original Image")

ax[2].imshow(new_brain_img,cmap='gray',vmin=0,vmax=256)
ax[2].set_xticks([]),ax[2].set_yticks([])
ax[2].set_title("Transformed Image")
plt.show()
```

In [ ]:

```python
#2(b)
t1=np.array([0 for r in range(0,101)])
t2=np.array([256 for r in range(101,215)])
t3=np.array([0 for r in range(215,256)])
t=np.concatenate((t1,t2,t3),axis=0)
assert len(t)==256

fig,ax=plt.subplots(1,3,figsize=(20,5))
ax[0].plot(t)
ax[0].set_title("Intensity transformation")

new_brain_img=cv.LUT(brain_img,t)

ax[1].imshow(brain_img,cmap='gray',vmin=0,vmax=255)
ax[1].set_xticks([]),ax[1].set_yticks([])
ax[1].set_title("Original Image")

ax[2].imshow(new_brain_img,cmap='gray',vmin=0,vmax=256)
ax[2].set_xticks([]),ax[2].set_yticks([])
ax[2].set_title("Transformed Image")
plt.show()
```

In 2(a) and 2(b) white matter and gray matter is clearly shown in the right most figures in pure white color.Although pure white color has 255 intensity it is relevent to use a range to define white and gray colour in the original pictures as our naked eyes detect thse two ranges as white and gray respectively. With simple intensity transformations showed in the LHS figures we can get the required output

Question 3(a)

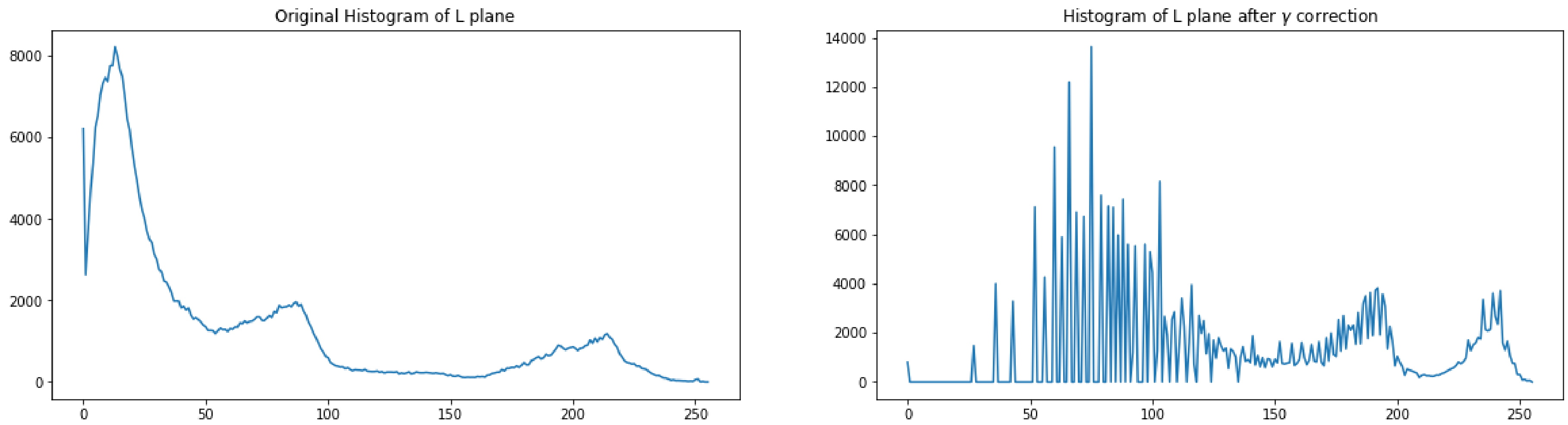
In [ ]:

```python
#gamma value is 0.4
gamma_img=cv.imread(r'highlights_and_shadows.jpg',cv.IMREAD_COLOR)
assert gamma_img is not None

LAB_img=cv.cvtColor(gamma_img,cv.COLOR_BGR2LAB)
gamma=0.4
t=np.array([(p/255)**gamma*255 for p in range(0,256)]).astype(np.uint8)
assert len(t)==256
L,A,B=cv.split(LAB_img)
new_L=cv.LUT(L,t)
new_gamma_img=cv.merge((new_L,A,B))

fig,ax=plt.subplots(1,2,figsize=(20,6))
ax[0].imshow(cv.cvtColor(gamma_img,cv.COLOR_BGR2RGB))
ax[0].set_xticks([]),ax[0].set_yticks([])
ax[0].set_title("Original Image")

ax[1].imshow(cv.cvtColor(new_gamma_img,cv.COLOR_Lab2RGB))
ax[1].set_xticks([]),ax[1].set_yticks([])
ax[1].set_title("${\gamma}$=0.4 corrected image")
plt.show()
```

in this question I used 0.4 for gamma value and only L plane of the Lab* color space is underging through this intensity transformation. Due to that we have clear picture compared to the original picture. L means the lightness of the picture, so by this transformation I could increase the lightness of the picture. It is obvious in the γ corrected image

In [ ]:

```
# 3(b)
hist_gamma_img=cv.calcHist([gamma_img],[0],None,[256],[0,255])
hist_new_gamma=cv.calcHist([new_gamma_img],[0],None,[256],[0,255])
fig,ax=plt.subplots(1,2,figsize=(20,5))
ax[0].plot(hist_gamma_img)
ax[0].set_title("Original Histogram of L plane")

ax[1].plot(hist_new_gamma)
ax[1].set_title("Histogram of L plane after ${\gamma}$ correction")
plt.show()
```



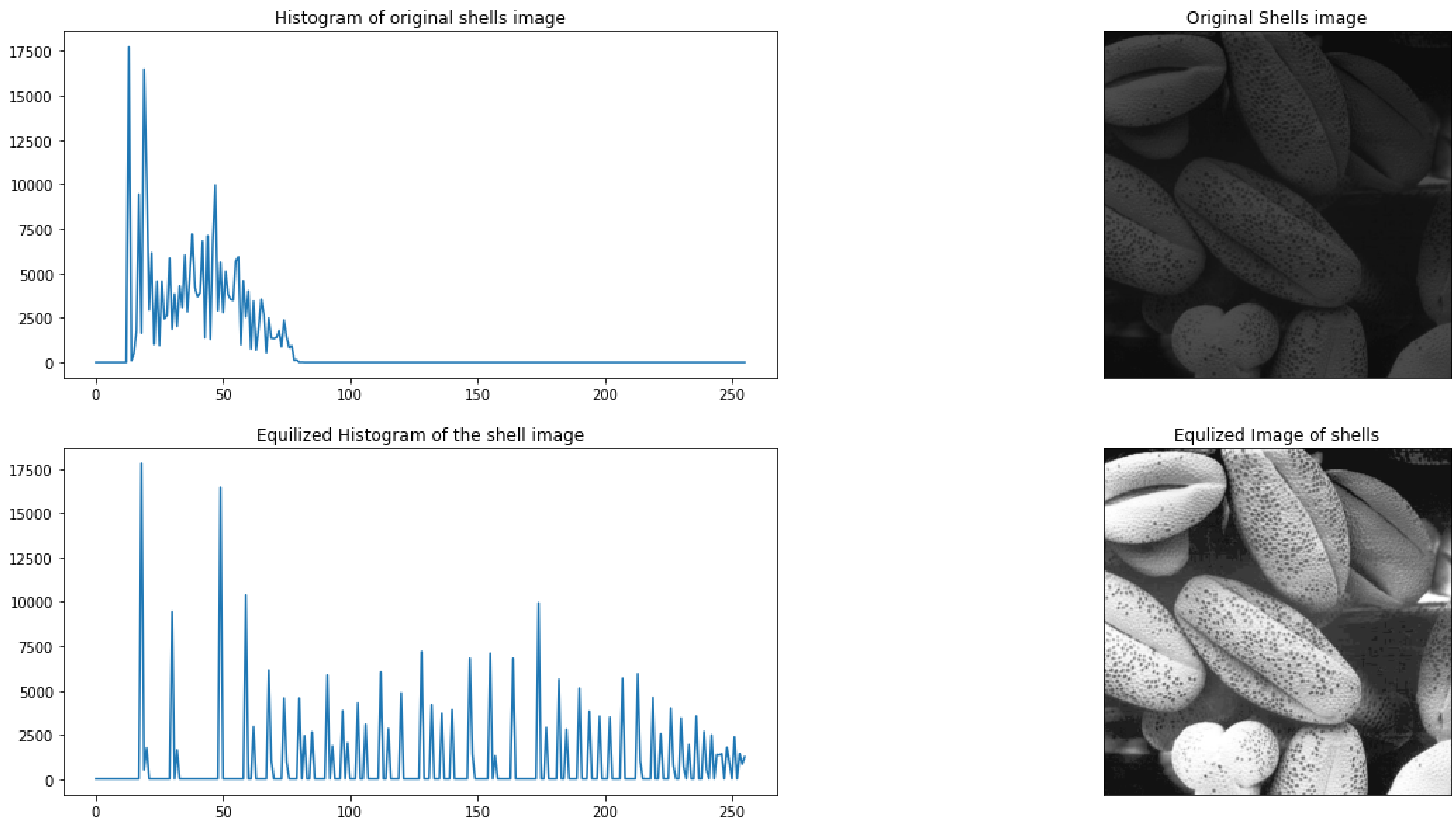
In question(3) I use 0.4 as the gamma value. It quite obvious that the original picture is dark and we can't see the details well. After aplying gamma correction to the L plane we can see many details of the image. when we compare the histograms it is very clear that adrk colors dominate the original picture while gray and light colors dominate in the γ corrected image

Question 4

In [ ]:

```
def plot_histograms(image):
    shell_img=cv.imread(image,cv.IMREAD_GRAYSCALE)
    assert shell_img is not None
    arrayOfNumberOfResalutionPoints=np.zeros((1,256))
    for r in range(0,256):
        arrayOfNumberOfResalutionPoints[0][r]=np.count_nonzero(shell_img==r)

    fig,axes=plt.subplots(2,2,figsize=(20,10))
    number_of_rows,number_of_coloumns=shell_img.shape

    axes[0][0].plot(arrayOfNumberOfResalutionPoints[0])
    axes[0][0].set_title("Histogram of original shells image")

    axes[0][1].imshow(shell_img,cmap='gray',vmin=0,vmax=255)
    axes[0][1].set_title("Original Shells image")
    axes[0][1].set_xticks([]),axes[0][1].set_yticks([])
    a=arrayOfNumberOfResalutionPoints
    equilized_values_of_histogram=np.zeros((1,256))
    for r in range(0,256):
        s=(255/(number_of_coloumns*number_of_rows))*np.sum(arrayOfNumberOfResalutionPoints[:,:r+1])
        equilized_values_of_histogram[0][r]=np.round(s)

    new_hist_equilized_img=cv.LUT(shell_img,equilized_values_of_histogram)
    arrayOfNumberOfResalutionPoints_ofNewEquilizedImg=np.zeros((1,256))
    for r in range(0,256):
        arrayOfNumberOfResalutionPoints_ofNewEquilizedImg[0][r]=np.count_nonzero(new_hist_equilized_img==r)
    axes[1][0].plot(arrayOfNumberOfResalutionPoints_ofNewEquilizedImg[0])
    axes[1][0].set_title("Equilized Histogram of the shell image")
```

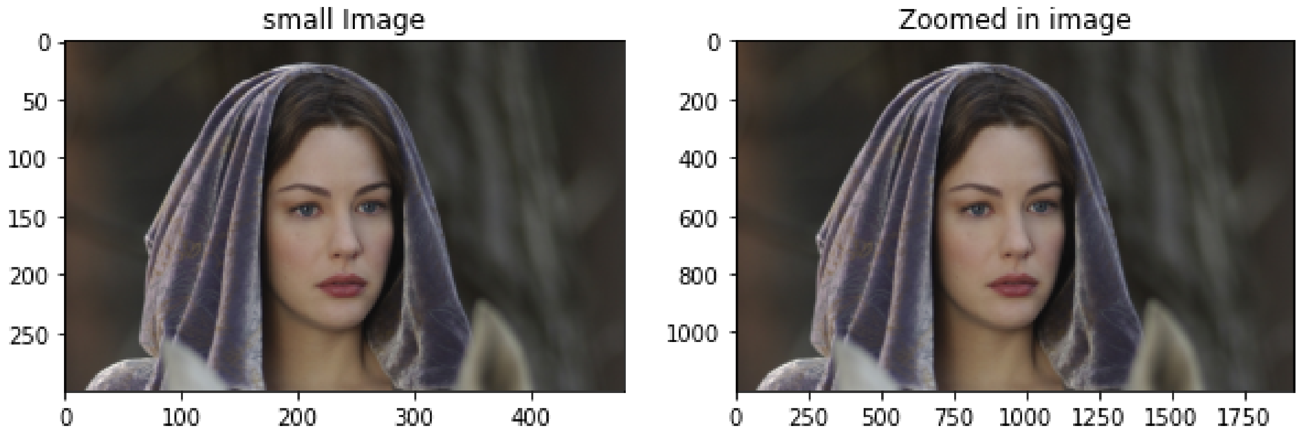
```
    axes[1][1].imshow(new_hist_equilized_img,cmap='gray',vmin=0,vmax=255)
    axes[1][1].set_title("Equlized Image of shells")
    axes[1][1].set_xticks([]),axes[1][1].set_yticks([])
    plt.show()
plot_histograms('shells.png')
```



In the question 4 I've defined a funtion plot_histograms(image) to calculate the equilized histogram and plot both original and equilized hitograms and images.\ In the equilized histogram we can see that there is nearly flat spectrum compared to the original signal. Thats why we can see an enhaced more detailed image as the equilized image. Most of the pixel colours has the nearly same probability.

Question 5 (a)

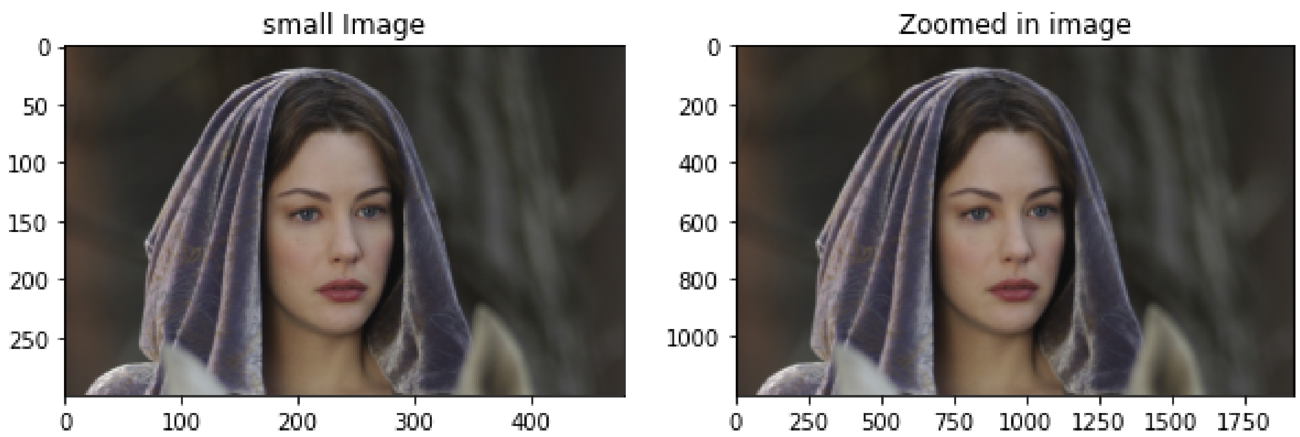
In [ ]:
```
def nearestNeighbourZoom(image,scale):
    newImageRows=int(image.shape[0]*scale)
    newImagecolumns=int(image.shape[1]*scale)
    newImage=np.zeros((3,newImagecolumns,newImageRows),dtype=np.float32)

    for j in range(newImageRows):
        for i in range(newImagecolumns):
            i_old=round(i/scale)
            j_old=round(j/scale)
            if i_old==image.shape[1]:
                i_old-=1
            if j_old==image.shape[0]:
                j_old-=1
            newImage[:,i,j]=image[int(j_old),int(i_old),:]
    return newImage.astype(np.uint8)

image1=cv.imread(r'D:\4th sem uom\machine vision\Assignment\a1q5images\a1q5images\im02small.png',cv.IMREAD_COLOR)
image2=cv.imread(r'D:\4th sem uom\machine vision\Assignment\a1q5images\a1q5images\im02.png',cv.IMREAD_COLOR)

new_img=nearestNeighbourZoom(image1,4)

fig,axes=plt.subplots(1,2,figsize=(10,5))
axes[0].imshow(cv.cvtColor(image1,cv.COLOR_BGR2RGB))
axes[0].set_title("small Image")
axes[1].imshow(cv.cvtColor(new_img.T,cv.COLOR_BGR2RGB))
axes[1].set_title("Zoomed in image")
plt.show()

NSSD2 = cv.matchTemplate(image2,new_img.T,cv.TM_SQDIFF_NORMED)
print("Noramalized sum of squared difference =",NSSD2[0,0])
print("Shape of the original image=",image2.shape)
print("Shape of the zoomed image=",new_img.T.shape)
```




```
Noramalized sum of squared difference = 0.010222389
Shape of the original image= (1200, 1920, 3)
Shape of the zoomed image= (1200, 1920, 3)
```

In [ ]:

```python
# 5(b)
def BilinearZoom(image,scale):
    newImageRows=int(image.shape[0]*scale)
    newImagecolumns=int(image.shape[1]*scale)
    newImage=np.zeros((3,newImagecolumns,newImageRows),dtype=np.float32)

    for j in range(newImageRows):
        for i in range(newImagecolumns):
            i_old=i/scale
            j_old=j/scale
            lu_cx,lu_cy=int(i_old),int(j_old)
            ru_cx,ru_cy=int(i_old)+1,int(j_old)
            lb_cx,lb_cy=int(i_old),int(j_old)+1
            rb_cx,rb_cy=int(i_old)+1,int(j_old)+1
            if ru_cx==image.shape[1]:ru_cx=lu_cx
            if rb_cx==image.shape[1]:rb_cx=lb_cx
            if rb_cy==image.shape[0]:rb_cy=ru_cy
            if lb_cy==image.shape[0]:lb_cy=ru_cy
            p1=image[lu_cy,lu_cx,:]
            p2=image[ru_cy,ru_cx,:]
            p3=image[rb_cy,rb_cx,:]
            p4=image[lb_cy,lb_cx,:]
            p11=p1*(ru_cx-i_old)+p2*(i_old-lu_cx)
            p12=p4*(ru_cx-i_old)+p3*(i_old-lu_cx)
            if ru_cx==lu_cx:
                p11=p1
                p12=p4
            p13=p11*(rb_cy-j_old)+p12*(j_old-ru_cy)
            if rb_cy==ru_cy:p13=p11
            newImage[:,i,j]=p13.astype(np.uint8)
    return newImage.astype(np.uint8)

image1=cv.imread(r'D:\4th sem uom\machine vision\Assignment\a1q5images\a1q5images\im02small.png',cv.IMREAD_COLOR)
image2=cv.imread(r'D:\4th sem uom\machine vision\Assignment\a1q5images\a1q5images\im02.png',cv.IMREAD_COLOR)

new_img=BilinearZoom(image1,4)

fig,axes=plt.subplots(1,2,figsize=(10,5))
axes[0].imshow(cv.cvtColor(image1,cv.COLOR_BGR2RGB))
axes[0].set_title("small Image")

axes[1].imshow(cv.cvtColor(new_img.T,cv.COLOR_BGR2RGB))
axes[1].set_title("Zoomed in image")
plt.show()

NSSD2 = cv.matchTemplate(image2,new_img.T,cv.TM_SQDIFF_NORMED)
print("Noramalized sum of squared difference =",NSSD2[0,0])
print("Shape of the original image=",image2.shape)
print("Shape of the zoomed image=",new_img.T.shape)
```

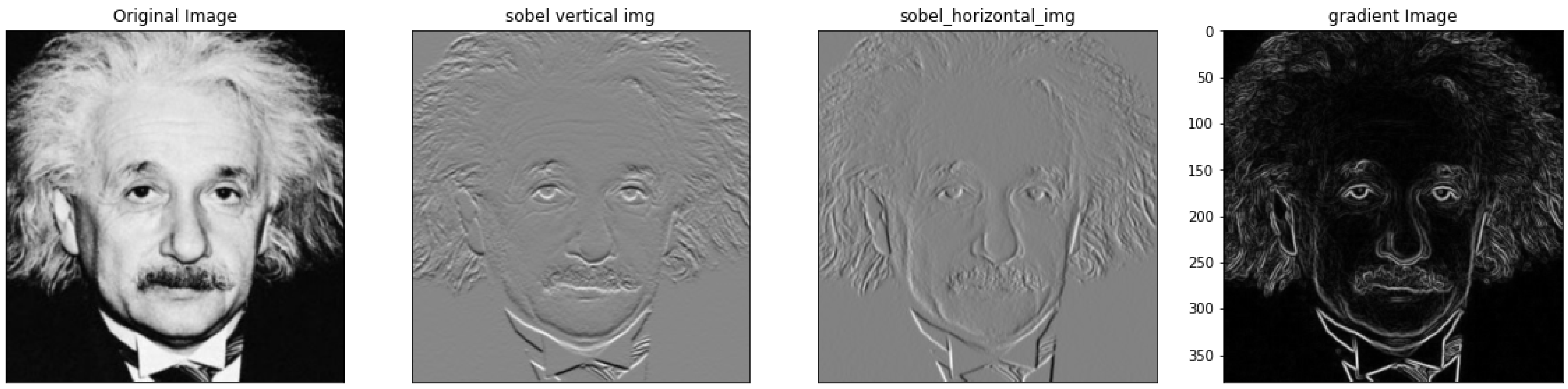



```
Noramalized sum of squared difference = 0.0077916514
Shape of the original image= (1200, 1920, 3)
Shape of the zoomed image= (1200, 1920, 3)
```

In the question 5 (a) and (b) I have defined two funtion for nearest neighbor zooming and Bilinear zooming respectively. In each function I go through all the defined pixels in new_Image and given image for zooming. then calculte the required pixel values according to these two different methods. biliear Interpolation is better compared to the other moethod

Question 6(a)

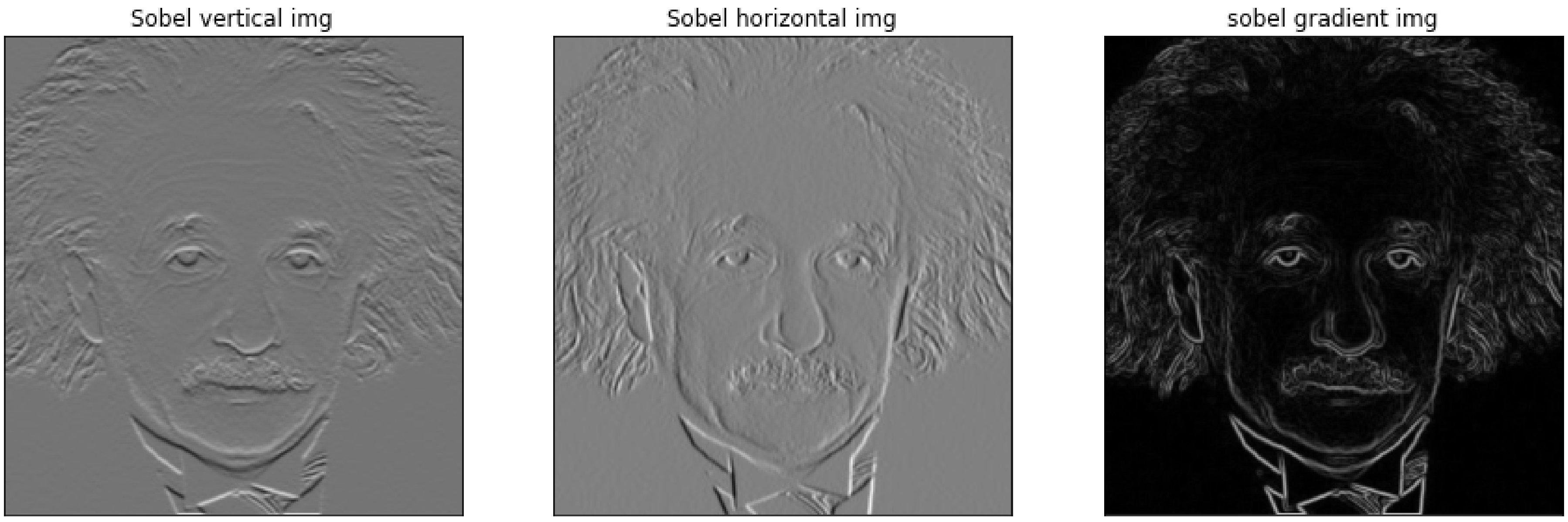
In [ ]:
```
einsteine_img=cv.imread(r'einstein.png',cv.IMREAD_GRAYSCALE).astype(np.float32)
assert einsteine_img is not None

vertical_kernel=np.array([[-1,-2,-1],[0,0,0],[1,2,1]],dtype=np.float32)
horizontal_kernel=np.array([[-1,0,1],[-2,0,2],[-1,0,1]],dtype=np.float32)
sobel_vertical_img=cv.filter2D(einsteine_img,-1,vertical_kernel)
sobel_horizontal_img=cv.filter2D(einsteine_img,-1,horizontal_kernel)
gradient_img=np.sqrt(sobel_horizontal_img**2+sobel_vertical_img**2)

fig,axes=plt.subplots(1,4,figsize=(20,5))
axes[0].imshow(einsteine_img,cmap='gray')
axes[0].set_xticks([]),axes[0].set_yticks([])
axes[0].set_title('Original Image')

axes[1].imshow(sobel_vertical_img,cmap='gray')
axes[1].set_xticks([]),axes[1].set_yticks([])
axes[1].set_title('sobel vertical img')

axes[2].imshow(sobel_horizontal_img,cmap='gray')
axes[2].set_xticks([]),axes[2].set_yticks([])
axes[2].set_title('sobel_horizontal_img')

axes[3].imshow(gradient_img,cmap='gray')
axes[3].set_xticks([]),axes[2].set_yticks([])
axes[3].set_title('gradient Image')

plt.show()
```



In the sobel vertical filtered image we can see the horizontal lines of the image and in the soble horizontal image we can clearly see the vertical lines of the image. In the gradient image we can see all the edges of the picture.

In [ ]:
```
#part b
def sobel_filter(Image,kernel):
    y_len_of_kernel,x_len_of_kernel=kernel.shape
    assert x_len_of_kernel%2==1 and y_len_of_kernel%2==1
    midx_ofKernel,midy_ofKernel=x_len_of_kernel//2,y_len_of_kernel//2

    padding1,padding2=midx_ofKernel,midy_ofKernel
    padded_img= np.zeros((Image.shape[0] + padding1*2, Image.shape[1] + padding2*2))
    padded_img[int(padding1):int(-1 * padding1), int(padding2):int(-1 * padding2)] = Image

    resulted_img=np.zeros(Image.shape,dtype=np.float32)
    for x in range(Image.shape[1]):
        for y in range(Image.shape[0]):
            resulted_img[y,x]=(kernel*padded_img[y:y+y_len_of_kernel,x:x+x_len_of_kernel]).sum()
    return resulted_img

#part C

einsteine_img=cv.imread(r'einstein.png',cv.IMREAD_GRAYSCALE).astype(np.float32)
new_horizontal_kernel=np.array([[1,0,-1],[2,0,-2],[1,0,-1]])
new_vertical_kernel=np.fliplr(np.flipud(np.array([[-1,-2,-1],[0,0,0],[1,2,1]],dtype=np.float32)))
img1=sobel_filter(einsteine_img,new_horizontal_kernel)
img2=sobel_filter(einsteine_img,new_vertical_kernel)
im3=np.sqrt(img1**2+img2**2)
fig,ax=plt.subplots(1,3,figsize=(15,5))
ax[0].imshow(img2,cmap='gray')
ax[0].set_xticks([]),ax[0].set_yticks([])
ax[0].set_title('Sobel vertical img')

ax[1].imshow(img1,cmap='gray')
```

```
ax[1].set_xticks([]),ax[1].set_yticks([])
ax[1].set_title('Sobel horizontal img')

ax[2].imshow(im3,cmap='gray')
ax[2].set_xticks([]),ax[2].set_yticks([])
ax[2].set_title('sobel gradient img')
plt.show()
```



As sobel filtering is done with convolution between padded image and the kernal we first need to rotate the the kernal by 180^0 to do the convolution properly. So the given kernal in Assignment is the rotated version of the sobel horizontal kernal. Therefore we can plug that kernal to the defined funtion directly. But we have to rotate sobel vertical kernel before plugging it to the function

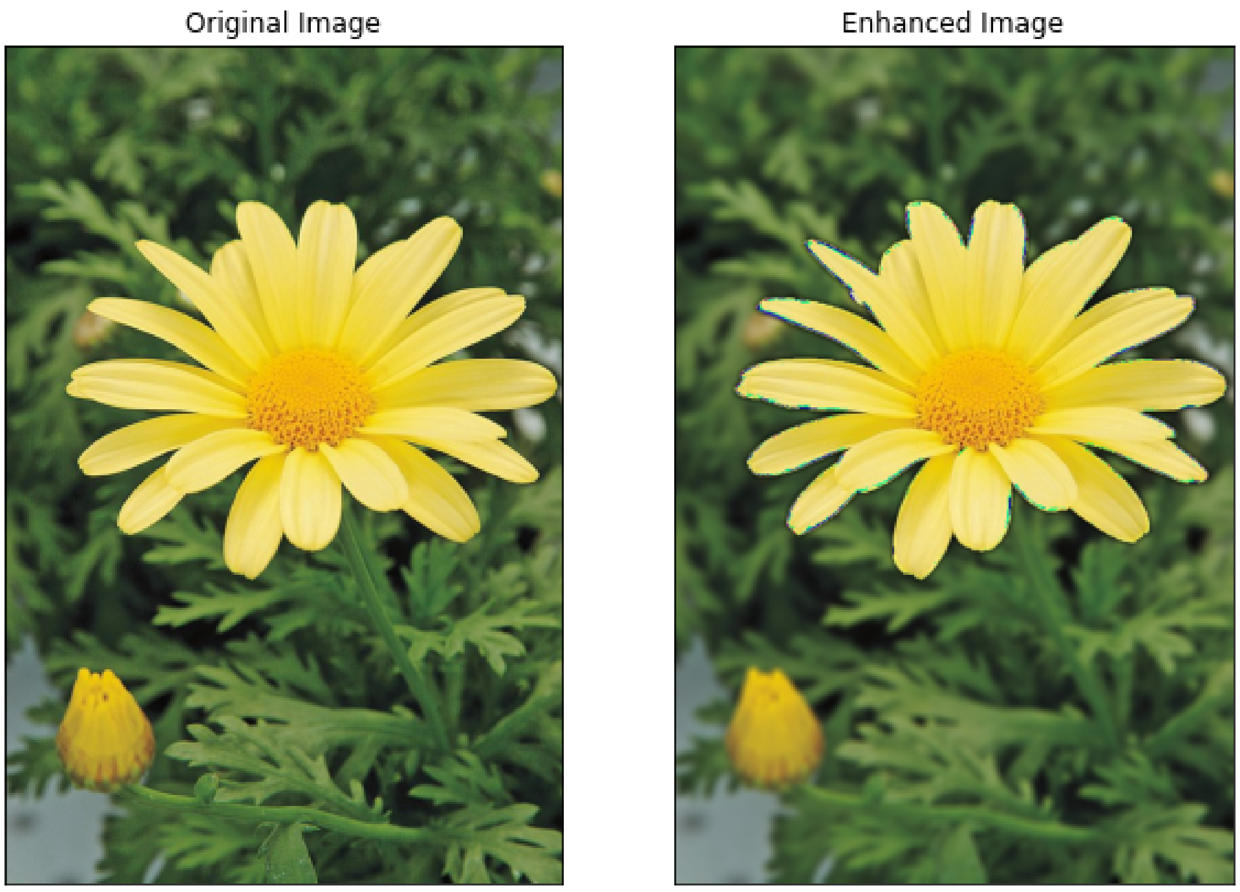
Question 7 (a)

In [ ]:

```
image = cv.imread(r'daisy.jpg',cv.IMREAD_COLOR)
mask = np.zeros(image.shape[:2], np.uint8)
bgModel = np.zeros((1, 65), np.float64)
fgModel = np.zeros((1, 65), np.float64)

rectangle = (25,125,530,450)
(mask,bgModel,fgModel)=cv.grabCut(image, mask, rectangle,bgModel, fgModel,3, cv.GC_INIT_WITH_RECT)
outputMask = np.where((mask == cv.GC_BGD) | (mask == cv.GC_PR_BGD),0, 1)
outputMask = (outputMask * 255).astype("uint8")
output = cv.bitwise_and(image, image, mask=outputMask)

backImage=image-output
fig,axes=plt.subplots(1,3,figsize=(20,10))
axes[0].imshow(cv.cvtColor(outputMask,cv.COLOR_BGR2RGB))
axes[0].set_xticks([]),axes[0].set_yticks([])
axes[0].set_title('segmentation mask')

axes[1].imshow(cv.cvtColor(output,cv.COLOR_BGR2RGB))
axes[1].set_xticks([]),axes[1].set_yticks([])
axes[1].set_title('foreground image')

axes[2].imshow(cv.cvtColor(backImage,cv.COLOR_BGR2RGB))
axes[2].set_xticks([]),axes[2].set_yticks([])
axes[2].set_title('background image')
plt.show()
```

In this question I first defined a bounding box of the flower therefore I can take the segmentation mask properly. It is shown in the LHS image. when compared to the background image and the foreground image we can see that the sunflower is perfectly removed from its background.

In [ ]:
```
kernel_size=9
sigma=9
blurred_back=cv.GaussianBlur(backImage,(kernel_size,kernel_size),sigma)
enhanced_img=output+blurred_back
fig,axes=plt.subplots(1,2,figsize=(10,10))
cv.imshow('Image',enhanced_img)
cv.waitKey(0)
cv.destroyAllWindows()
axes[0].imshow(cv.cvtColor(image,cv.COLOR_BGR2RGB))
axes[0].set_xticks([]),axes[0].set_yticks([])
axes[0].set_title('Original Image')
axes[1].imshow(cv.cvtColor(enhanced_img,cv.COLOR_BGR2RGB))
axes[1].set_xticks([]),axes[1].set_yticks([])
axes[1].set_title('Enhanced Image')
plt.show()
```



7(c)\ After applying gaussian blur to the background image pixel values of the edges of the forground image is different fro the pixel values of the blured background image. Due to that there is a difference in probability of pixel values at the edges of the forground image. Therefore edge of the flower of enhanced image is quite dark compared to the original image

https://github.com/Dinuka-1999/Assignment