RAMAIAH UNIVERSITY OF APPLIED SCIENCES

ASSIGNMENT

Course Code	CSE407A
Course Name	Computer Vision
Programme	B. Tech.
Department	Computer Science & Engineering
Faculty	Faculty of Engineering & Technology

Name of the Student	Subhendu Maji
Reg. No	18ETCS002121
Semester/Year	7th semester / 2018 batch
Course Leader/s	Dr. Subarna Chatterjee

Declaration Sheet				
Student Name	Subhendu Maji			
Reg. No	18ETCS002121			
Programme	B. Tech.		Semester/Year	7th sem /2018 batch
Course Code	CSE407A			
Course Title	Computer Vision			
Course Date		to		
Course Leader	Dr. Subarna Chatterjee			

Declaration

The assignment submitted herewith is a result of my own investigations and that I have conformed to the guidelines against plagiarism as laid out in the Student Handbook. All sections of the text and results, which have been obtained from other sources, are fully referenced. I understand that cheating and plagiarism constitute a breach of university regulations and will be dealt with accordingly.

Signature of the Student		Date	
Submission date stamp (by Examination & Assessment Section)			

Signature of the Course Leader and date	Signature of the Reviewer and date

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Total Assignment Marks			**50**		

Course Marks Tabulation				
Question	**First Examiner**	**Remarks**	**Moderator**	**Remarks**
1				
2				
3				
Marks (Max 50)				

Signature of First Examiner **Signature of Moderator**

Question No. 1

Solution to Question No. 1:

1.1 Implement the noise reduction for the noisy image Q1_1.tif and submit your code and the denoised image.

As seen in the input image *Q1_1.tif*, there is a constant repeating noise pattern on the image, this usually happens in the case of periodic noise.

Periodic noise in an image arises typically from electrical or electromechanical interference during image acquisition. This gives rise to regular noise patterns in an image. Frequency domain techniques in the Fourier domain are most effective at removing periodic noise.

To remove periodic noise from an image, we need to remove a particular range of frequencies from that image. This can be done using **Band-reject filter**, in ideal band reject, the centered Fast Fourier Transform (FFT) is filtered by the following function, where D_L is the lower bound of the frequency band, D_H is the upper bound of the frequency band, and $D(u,v)$ is the distance between a point *(u, v)* in the frequency domain and the center of the frequency rectangle.

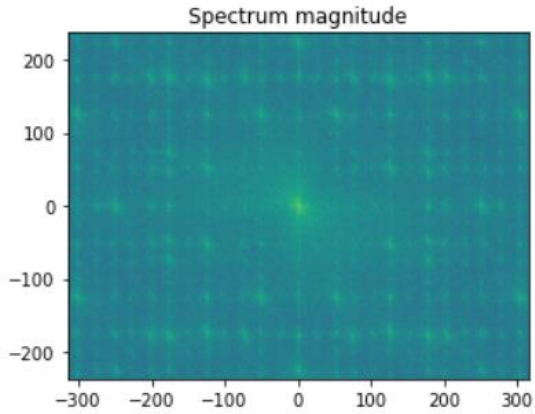
$$H(u,\ v) = \begin{cases} 0 \text{ if } D_L \trianglelefteq D(u,\ v) \trianglelefteq D_H \\ 1 \text{ otherwise} \end{cases}$$

In [1]:
```
# importing packages
import numpy as np
import pandas as pd
from scipy import fftpack
import matplotlib.pyplot as plt
import cv2
```

In [2]:
```
# reading image in grayscale
image = cv2.imread('images/Q1_1.tif',cv2.IMREAD_GRAYSCALE)
M, N = image.shape
```

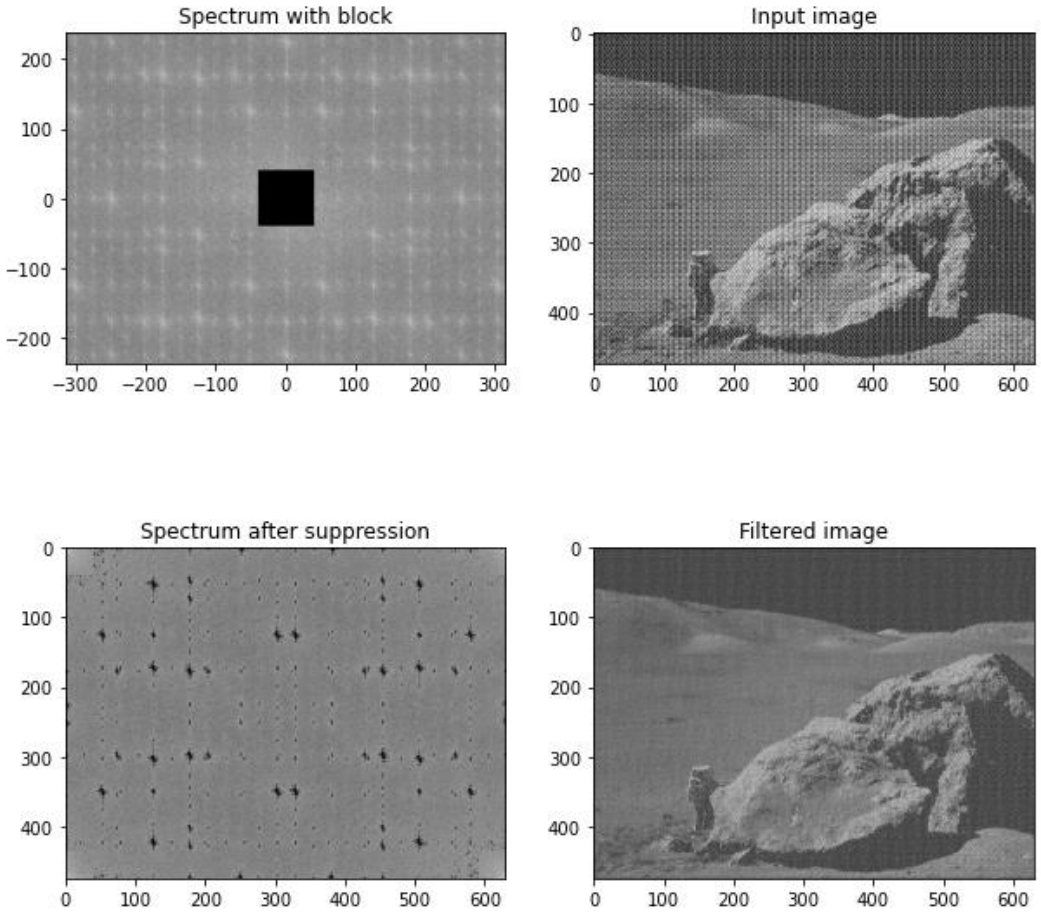
In [3]:
```
# To examine the spectrum of the image, we use fftn (instead of fft)
# to compute the DFT, since it has more than one dimension.
# The 2D FFT is equivalent to taking the 1D FFT across
# rows and then across columns, or vice versa.

F = fftpack.fftn(image)
F_magnitude = np.abs(F)
F_magnitude = fftpack.fftshift(F_magnitude)
```

In [4]:
```
# we take the log of the spectrum to compress the range of values,
f, ax = plt.subplots(figsize=(4.8, 4.8))

ax.imshow(np.log(1 + F_magnitude), cmap='viridis',
          extent=(-N // 2, N // 2, -M // 2, M // 2))
ax.set_title('Spectrum magnitude');
```



In [5]:
```
# Set block around center of spectrum to zero
K = 40
F_magnitude[M // 2 - K: M // 2 + K, N // 2 - K: N // 2 + K] = 0

# Find all peaks higher than the 98th percentile
peaks = F_magnitude < np.percentile(F_magnitude, 98)

# Shift the peaks back to align with the original spectrum
peaks = fftpack.ifftshift(peaks)

# Make a copy of the original (complex) spectrum
F_dim = F.copy()

# Set those peak coefficients to zero
F_dim = F_dim * peaks.astype(int)

# Do the inverse Fourier transform to get back to an image.
# Since we started with a real image, we only look at the real part of
# the output.
image_filtered = np.real(fftpack.ifft2(F_dim))


# plotting images
f = plt.figure(figsize=(10,10))

ax1 = f.add_subplot(221)
ax1.imshow(np.log(1 + F_magnitude),
          extent=(-N // 2, N // 2, -M // 2, M // 2), cmap='gray')
ax1.set_title('Spectrum with block')

ax2 = f.add_subplot(222)
ax2.imshow(image,cmap="gray")
ax2.set_title('Input image')

ax3 = f.add_subplot(223)
ax3.imshow(np.log10(1 + np.abs(F_dim)), cmap='gray')
ax3.set_title('Spectrum after suppression')

ax4 = f.add_subplot(224)
ax4.imshow(image_filtered, cmap='gray')
ax4.set_title('Filtered image')
```

```
Out[5]: Text(0.5, 1.0, 'Filtered image')
```



1.2 Implement the histogram equalization to the input images Q1_2.tif and Q1_3.tif and submit your code and the output images.

Histogram equalization is a method in image processing of contrast adjustment using the image's histogram. This method usually increases the global contrast of many images, especially when the image is represented by a narrow range of intensity values. Through this adjustment, the intensities can be better distributed on the histogram utilizing the full range of intensities evenly. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the highly populated intensity values which use to degrade image contrast.

The method is useful in images with backgrounds and foregrounds that are both bright or both dark.

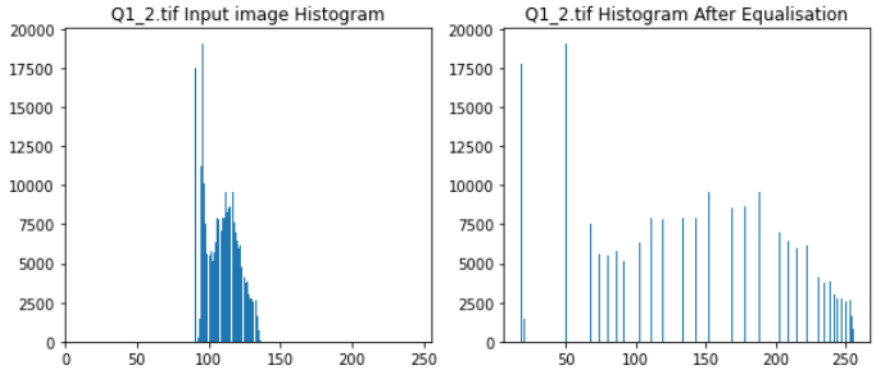
In particular, the method can lead to better views of bone structure in x-ray images, and to better detail in photographs that are either over or under-exposed.

- A key advantage of the method is that it is a fairly straightforward technique adaptive to the input image and an invertible operator. So, in theory, if the histogram equalization function is known, then the original histogram can be recovered. The calculation is not computationally intensive.
- A disadvantage of the method is that it is indiscriminate. It may increase the contrast of background noise, while decreasing the usable signal.

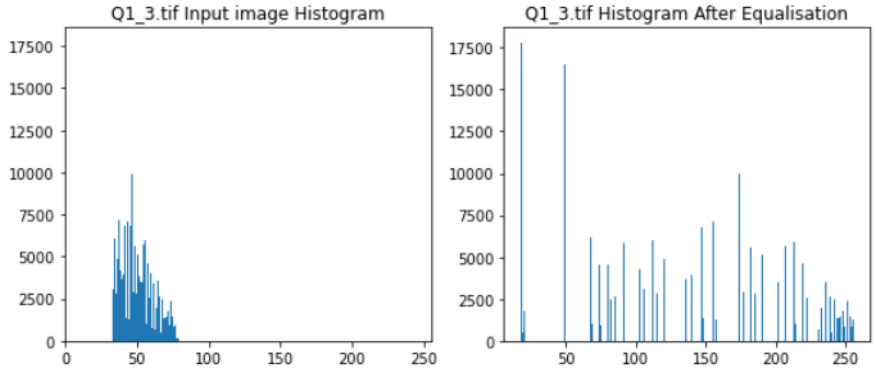
In [2]:
```
# importing images
img2= cv2.imread("images/Q1_2.tif",cv2.IMREAD_GRAYSCALE)
img3 = cv2.imread("images/Q1_3.tif",cv2.IMREAD_GRAYSCALE)
```

In [3]:
```
def histogramEqualize(img,title):
    mat = img.copy()

    image_histogram,bins = np.histogram(mat.flatten(),256,density=True)
    cdf = image_histogram.cumsum()
    cdf = 255 * cdf / cdf[-1]
    image_equalized = np.interp(mat.flatten(), bins[:-1], cdf)
    r = np.round(image_equalized.reshape(mat.shape)).astype("uint8")

    # plotting histogram
    f = plt.figure(figsize=(10,4))

    rk,nk = np.unique(img,return_counts=True)
    ax = f.add_subplot(1,2,1)
    ax.set_xlim([0, 255])
    ax.bar(rk,nk)
    ax.set_title(f"{title}Input image Histogram")

    rk2,nk2 = np.unique(r,return_counts=True)
    ax2 = f.add_subplot(1,2,2)
    ax2.bar(rk2,nk2)
    ax2.set_title(f"{title}Histogram After Equalisation")

    return r
```

In [14]:
```
img_out2 = histogramEqualize(img2,"Q1_2.tif ")
```



In [15]:
```
img_out3 = histogramEqualize(img3,"Q1_3.tif ")
```



In [11]:
```
# custom function to save image and display in a different window

def displayAndSaveImg(title="Result",*img):
    cv2.imwrite(f"{title}.png", np.concatenate(img,axis=1))
    cv2.imshow(title, np.concatenate(img,axis=1))
    cv2.waitKey(0)
    cv2.destroyAllWindows()
```

In [12]:
```
displayAndSaveImg("Histogram Equalization of Q1_2.tif",img2,img_out2)
displayAndSaveImg("Histogram Equalization of Q1_3.tif",img3,img_out3)
```

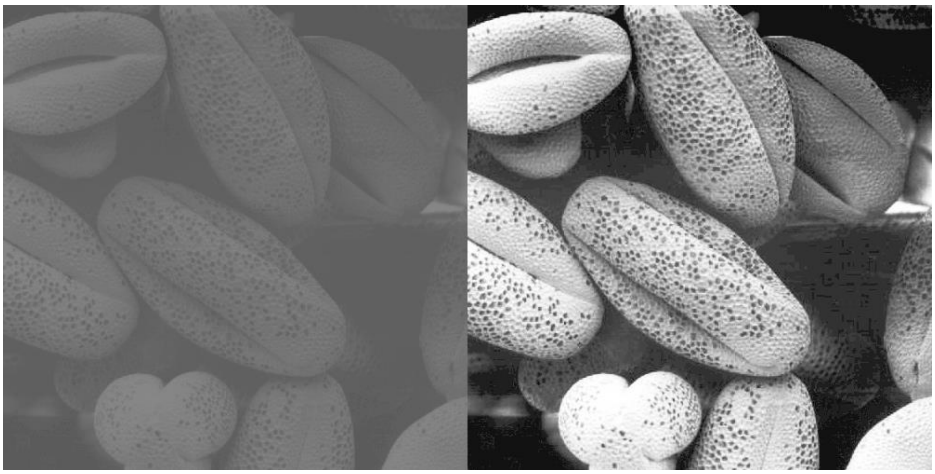


Figure 1 histogram equalized on Q1_2.tif

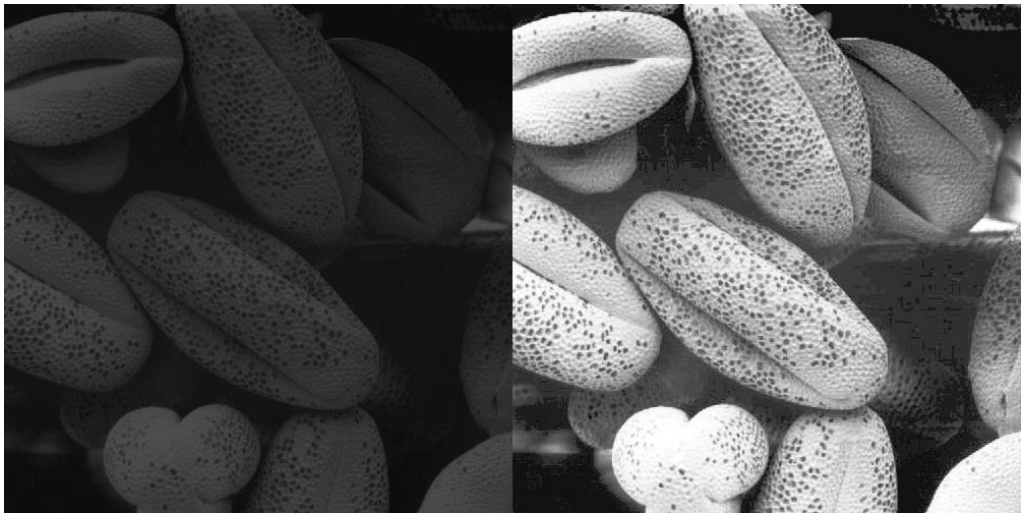


Figure 2 histogram equalized on Q1_3.tif

1.3 Reduce the salt-and-pepper noise from the input image Q1_4.tif and submit your code and the output image.

Salt-and-pepper noise is a form of noise sometimes seen on images. It is also known as **impulse noise.** This noise can be caused by sharp and sudden disturbances in the image signal. It presents itself as sparsely occurring white and black pixels. An effective noise reduction method for this type of noise is a **median filter.**

In [42]:
```
# reading image in grayscale
img = cv2.imread('images/Q1_4.tif',cv2.IMREAD_GRAYSCALE)
```

In [43]:
```
x = np.array([[-1,0,1],[-1,0,1],[-1,0,1]])
y = np.array([[-1,-1,-1],[0,0,0],[1,1,1]])

mat = img.copy()

# add padding in matrix
mat_padded = np.pad(img, [1, 1], mode='edge')
# mat_padded = np.pad(img, [1, 1], mode='constant')

m,n = img.shape

for i in range(1,m+1):
    for j in range(1,n+1):
        mat[i-1,j-1] = np.median(mat_padded[x+i,y+j])
```

In [44]:
```
displayAndSaveImg("median filter in Q1_4", img, mat)
```

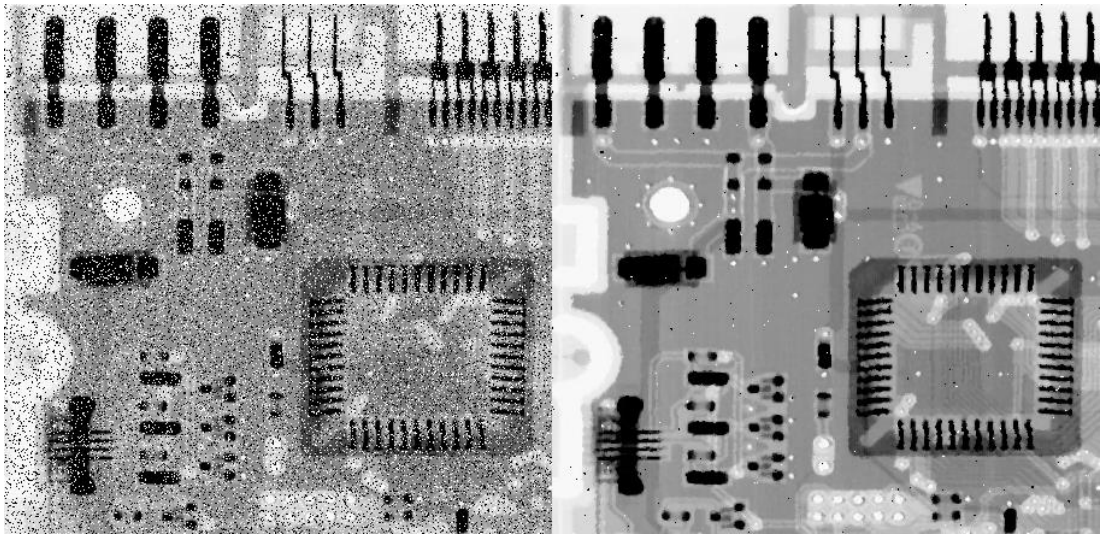


Figure 3 Reduced Salt and Pepper noise using Median filter from Q1_4.tif

1.4 Extract the gradient parts from the input image Q1_5.tif and submit your code and the output image.

An image gradient is a directional change in the intensity or color in an image. The gradient of the image is one of the fundamental building blocks in image processing.

For example, the Canny edge detector uses image gradient for edge detection. The most common way to approximate the image gradient is to convolve an image with a kernel, such as the **Sobel operator** or **Prewitt operator**.

Sobel and Prewitt Filter

The operator uses two 3×3 kernels which are convolved with the original image to calculate approximations of the derivatives – one for horizontal changes, and one for vertical. If we define A as the source image, and G_x and G_y are two images which at each point contain the horizontal and vertical derivative approximations respectively, the computations are as follows:

Sobel Operator

$$\mathbf{G}_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} * \mathbf{A} \quad \text{and} \quad \mathbf{G}_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * \mathbf{A}$$

Prewitt Operator

$$\mathbf{G_x} = \begin{bmatrix} +1 & 0 & -1 \\ +1 & 0 & -1 \\ +1 & 0 & -1 \end{bmatrix} * \mathbf{A} \quad \text{and} \quad \mathbf{G_y} = \begin{bmatrix} +1 & +1 & +1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} * \mathbf{A}$$

Final gradient

$$\mathbf{G} = \sqrt{\mathbf{G}_x^{\,2} + \mathbf{G}_y^{\,2}}$$

Gaussian Smoothing

Gaussian smoothing is commonly used with edge detection. Most edge-detection algorithms are sensitive to noise; the 2-D Laplacian filter, built from a discretization of the Laplace operator, is highly sensitive to noisy environments.

In [34]:
```
img = cv2.imread('images/Q1_5.tif',cv2.IMREAD_GRAYSCALE)
img.shape
```

Out[34]: (512, 512)

In [35]:
```
# mat_padded = np.pad(img, [1, 1], mode='edge')
mat_padded = np.pad(img, [1, 1], mode='constant')
mat_padded.shape
```

Out[35]: (514, 514)

In [36]:
```
def sobelFilter(mat,filter_type='x'):
    mask = np.array([[-1,0,1],
                     [-2,0,2],
                     [-1,0,1]])
    if filter_type=='y':
        mask = np.flip(mask.T,axis=0)

    return (mat*mask).sum()
```

In [37]:
```
def prewittFilter(mat,filter_type='x'):
    mask = np.array([[1,0,-1],
            [1,0,-1],
            [1,0,-1]])
    if filter_type=='y':
        mask = np.flip(mask.T,axis=0)

    return (mat*mask).sum()
```

In [38]:
```
x = np.array([[-1,0,1],[-1,0,1],[-1,0,1]])
y = np.array([[-1,-1,-1],[0,0,0],[1,1,1]])

sobel_filtered_x = np.zeros(img.shape)
sobel_filtered_y = np.zeros(img.shape)

prewitt_filtered_x = np.zeros(img.shape)
prewitt_filtered_y = np.zeros(img.shape)

m,n = img.shape

for i in range(1,m+1):
    for j in range(1,n+1):
        sobel_filtered_x[i-1,j-1] = sobelFilter(mat_padded[x+i,y+j],'x')
        sobel_filtered_y[i-1,j-1] = sobelFilter(mat_padded[x+i,y+j],'y')
        prewitt_filtered_x[i-1,j-1] = prewittFilter(mat_padded[x+i,y+j],'x')
        prewitt_filtered_y[i-1,j-1] = prewittFilter(mat_padded[x+i,y+j],'y')


sobel_gradient = np.sqrt(sobel_filtered_x**2 + sobel_filtered_y**2)
prewitt_gradient = np.sqrt(prewitt_filtered_x**2 + prewitt_filtered_y**2)

sobel_gradient *= 255.0 / sobel_gradient.max()
prewitt_gradient *= 255.0 / prewitt_gradient.max()

sobel_gradient = sobel_gradient.astype('uint8')
prewitt_gradient = prewitt_gradient.astype('uint8')
```

In [39]:
```
displayAndSaveImg("gradient_filtered", img,sobel_gradient,prewitt_gradient)
```

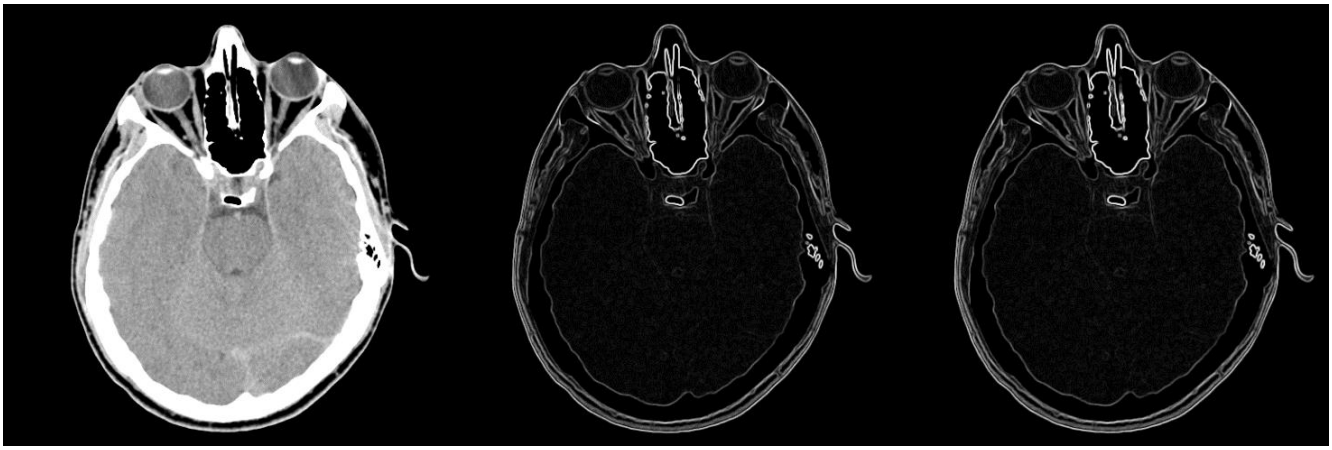


Figure 4 Sobel and Prewitt filter applied on Q1_5.tif to extract gradient parts

1.5 Conclusion and Recommendation

As it can be seen in the image *Q1_1.tif*, there is a constant repeating noise pattern on the image, this usually happens in the case of periodic noise. To remove periodic noise from an image, we need to remove a particular range of frequencies from that image. This can be done using **Band-Reject filter.**

In section 1.2, we were asked to implement histogram equalization. Histogram equalization is a method in image processing of contrast adjustment using the image's histogram. This method usually increases the global contrast of many images, especially when the image is represented by a narrow range of intensity values. We can see in (Figure 1, Figure 2) histogram equalized images have balanced contrast.

In section 1.3, we were asked to reduce Salt and Pepper noise which can effectively remove by median filter.

In section 1.4, we were asked to extract gradient parts of an image. The most common way to approximate the image gradient is to convolve an image with a kernel, such as the **Sobel operator** or **Prewitt operator**.

Hence, we have implemented band reject filter, histogram equalizer, median filter, Sobel and Prewitt filter successfully. Although all the filters are working as expected but there is a delay in getting the result. This is due to the reason we used Python 3.9 (comparatively slower than some other programming language) for the implementation. We can get a faster result using MATLAB.

Question No. 2

Solution to Question No. 2:

2.1 Introduction to the Segmentation techniques

Image segmentation is the process of dividing an image (a digital image) into multiple disjoint regions, where pixels in the same region share similar properties or belong to the same object. Image segmentation changes the representation of an object, making it meaningful and easier to analyze.

Image segmentation has variety of applications.

- Medical Imaging

  Image segmentation is applied extensively in medical applications to locate tumors and other pathologies, measure tissue volume, diagnosis and surgery planning, simulation, and navigation.
- Recognition

  Image segmentation is applied in face recognition to identify multiple faces in an image, fingerprint recognition to highlight the contours and edges of a fingerprint and in iris recognition.
- Object detection

  Image segmentation is applied in pedestrian detection, to identify the pedestrians on a road, brake light segmentation, and locating objects in satellite images.

Image segmentation is a mid-level processing technique used to analyze the image and can be defined as a processing technique used to classify or cluster an image into several disjoint parts by grouping the pixels to form a region of homogeneity based on the pixel characteristics like gray level, color, texture, intensity and other features. The main purpose of the segmentation process is to get more information in the region of interest in an image which helps in annotation of the object scene. Image segmentation aims at domain-independent partition of the image into a set of visually distinct and homogeneous regions with respect to certain properties. The main goal of segmentation is to clearly differentiate the object and the background in an image.

If R represents an image, then the image segmentation is simply division of R into subregions $R_1, R_2 \ldots\ldots R_n$ such that

$$R = \bigcup_{i=1}^{n} R_i$$

and is governed by following set of rules:

1) R_i is a connected set, $i = 1, 2 \ldots n$.
2) $R_i \cap R_j = \emptyset$ for all i and j, $i \neq j$
3) $Q(R_i)$ = True for $i = 1,2, \ldots n$.
4) $Q(R_i \cup R_j)$ = False for adjoint regions, R_i and R_j

Where, $Q(R_k)$ is a logical predicate.

The rules described above mentions about continuity, one-to-one relationship, homogeneity and non-repeatability of the pixels after segmentation respectively.

Dataset creation is a long and drawn-out process which involves collection of the data samples (such as images, or any other required data) and to label the images in an appropriate manner which depends on the problem that is being tackled. Dataset creation plays an important role in segmentation algorithms that involve neural networks. Errors during the creation of a dataset significantly impacts the performance of the segmentation model, often leading to disastrous consequences.

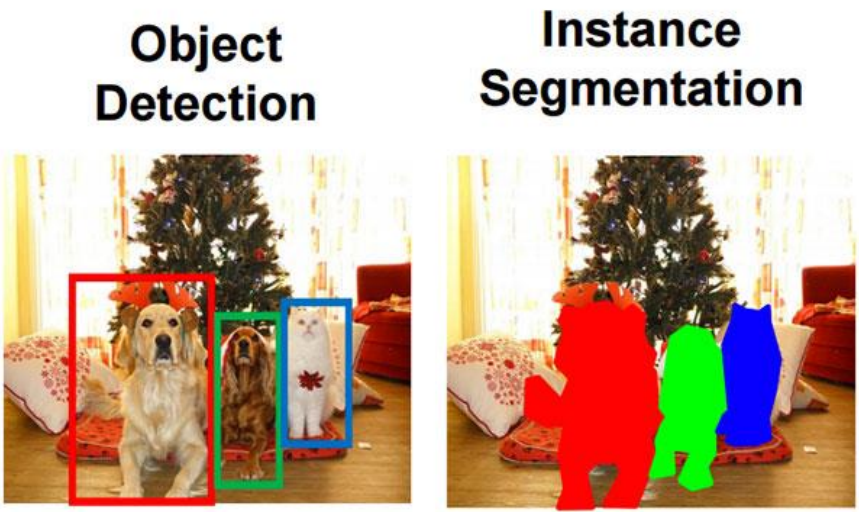


Figure 5 Example of Segmentation of an image

2.2 Identify and explain the appropriate pre-processing techniques.

Image preprocessing techniques help to prepare the image for segmentation. Almost always, the image to segment that is obtained in a production environment are not as “perfect” as the ones that are available during testing or deployment. Often, the images received will have noise, objects in the image will not be aligned properly, the image can be blurry, etc.
The primary focus on pre-processing techniques in the training phase of a neural network-based segmentation algorithm is to augment the dataset and try to represent real world scenarios during training.

Image processing could be simple tasks like image resizing. In order to feed a dataset of images to a convolutional network, they must all be the same size. Other processing tasks can take place like geometric and color transformation or converting color to grayscale and many more.

Data preprocessing techniques might include:

1. Convert color images to grayscale to reduce computation complexity

   In certain problems we’ll find it useful to lose unnecessary information from our images to reduce space or computational complexity.

   For example, converting our colored images to grayscale images. This is because in many objects, color isn’t necessary to recognize and interpret an image. Grayscale can be good enough for recognizing certain objects. Because color images contain more information than black and white images, they can add unnecessary complexity and take up more space in memory (Remember how color images are represented in three channels, which means that converting it to grayscale reduces the number of pixels that need to be processed).
2. Standardize images

   One important constraint that exists in some machine learning algorithms, such as CNN, is the need to resize the images in our dataset to a unified dimension. This implies that our images must be preprocessed and scaled to have identical widths and heights before fed to the learning algorithm.
3. Data augmentation

Another common pre-processing technique involves augmenting the existing dataset with perturbed versions of the existing images. Scaling, rotations and other affine transformations are typical. This is done to enlarge our dataset and expose the neural network to a wide variety of variations of our images. This makes it more likely that our model recognizes objects when they appear in any form and shape. Here's an example of image augmentation applied to a butterfly image:

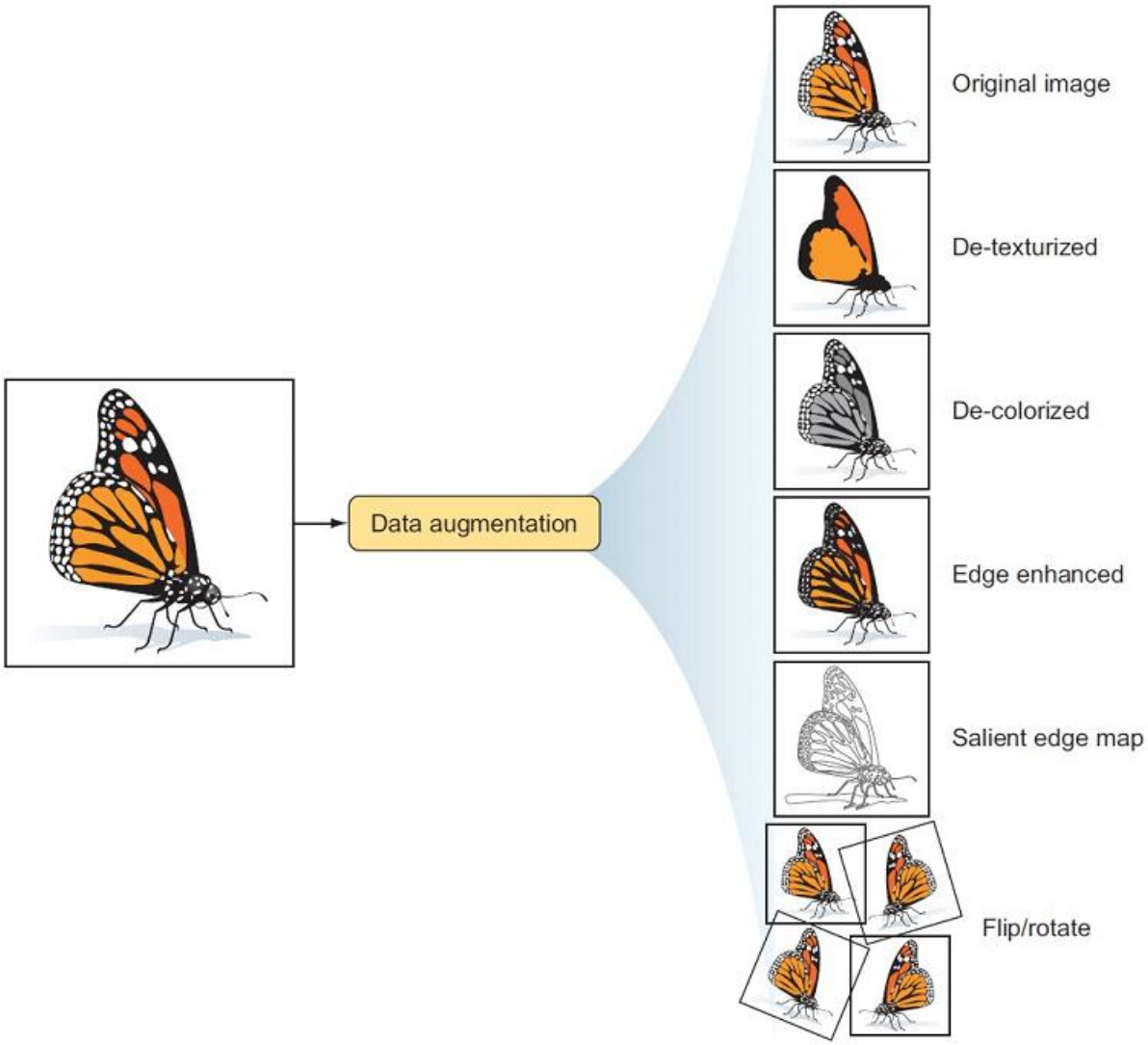


Figure 6 Data augmentation example on a butterfly image

4. Other techniques

   Many preprocessing techniques can be used to get our images ready to train the machine learning model. In some projects, we might need to remove the background color from our images to reduce the noise. Other projects might require that we brighten or darken our images. In short, any adjustments that we need to apply to our dataset are considered a sort of preprocessing. And we'll select the appropriate processing techniques based on the

dataset at hand and the problem we're solving. That builds our intuition of which ones we need when working on our own projects.

Identifying the correct preprocessing and augmentation steps most useful for increasing model performance requires a firm understanding of the problem, data collected, and production environment. What may work well in one situation is not appropriate in all others.
Thus, considering techniques and why each may be valuable enables informed decisions. In this post, we'll surface considerations and provide recommendations that are generally best.

1. Resize

   Changing the size of an image sounds trivial, but there are considerations to take into account.

   Many model architectures call for square input images, but few devices capture perfectly square images. Altering an image to be a square call for either stretching its dimensions to fit to be a square or keeping its aspect ratio constant and filling in newly created "dead space" with new pixels. Moreover, input images may be various sizes, and some may be smaller than the desired input size.

2. Orientation

   When an image is captured, it contains metadata that tells our machines the orientation by which to display that input image relative to how it is stored on disk. That metadata is called its EXIF orientation, and inconsistent handling of EXIF data has long been a bane of developers everywhere.

   This applies to models, too: if we've created annotated bound boxes on how we perceived an image to be oriented but our model is "seeing" that image in a different orientation, we're training the model completely wrong!

3. Grayscale

   Color changes are an example of image transformations that may be applied to all images (train and test) or randomly altered in training only as augmentations. Generally, gray

scaling is a color change applied to all images. While we may think “more signal is always better; we should show the model color,” we may see timelier model performance when images are gray scaled. Color images are stored as red, green, and blue values, whereas grayscale images are only stored as a range of black to white. This means for CNNs, our model only needs to work with one matrix per image, not three.

4. Random Flips

   Randomly mirroring an image about its x- or y-axis forces our model to recognize that an object need not always be read from left to right or up to down. Flipping may be illogical for order-dependent contexts, like interpreting text.

5. Random Rotations

   Rotating an image is particularly important when a model may be used in non-fixed position, like a mobile app. Rotating can be tricky as it, too, generates “dead pixels” on the edges of our images and, for bounding boxes, requires trigonometry to update any bounding boxes.

6. Random Exposure

   Adjusting image brightness to be randomly brighter and darker is most applicable if a model may be required to perform in a variety of lighting settings. It’s important to consider the maximum and minimum of brightness in the room.

7. Random Noise

   Adding noise to images can take a variety of forms. A common technique is “salt and pepper noise,” wherein image pixels are randomly converted to be completely black or completely white. While deliberately adding noise to an image may reduce training performance, this can be the goal if a model is overfitting on the wrong elements.

2.3 Identify and explain the appropriate Segmentation techniques.

Following are the primary types of image segmentation techniques:

1. Thresholding Segmentation

   The simplest method for segmentation in image processing is the threshold method. It divides the pixels in an image by comparing the pixel’s intensity with a specified value (threshold). It is

useful when the required object has a higher intensity than the background (unnecessary parts).

According to the different threshold values, we can classify thresholding segmentation in the following categories:

- Simple Thresholding

  In this method, you replace the image's pixels with either white or black.

- Otsu's Binarization

  In Otsu binarization, you calculate the threshold value from the image's histogram if the image is bimodal. This process is quite popular for scanning documents, recognizing patterns, and removing unnecessary colors from a file.

- Adaptive Thresholding

2. Edge-Based Segmentation

   Edge-based segmentation is one of the most popular implementations of segmentation in image processing. It focuses on identifying the edges of different objects in an image. This is a crucial step as it helps you find the features of the various objects present in the image as edges contain a lot of information you can use.

   There are many edge-based segmentation methods available. We can divide them into two categories:

   - Search-Based Edge Detection

     Search-based edge detection methods focus on computing a measure of edge strength and look for local directional maxima of the gradient magnitude through a computed estimate of the edge's local orientation.

   - Zero-Crossing Based Edge Detection

     Zero-crossing based edge detection methods look for zero crossings in a derivative expression retrieved from the image to find the edges.

3. Region-Based Segmentation

Region-based segmentation algorithms divide the image into sections with similar features. These regions are only a group of pixels and the algorithm find these groups by first locating a seed point which could be a small section or a large portion of the input image.
After finding the seed points, a region-based segmentation algorithm would either add more pixels to them or shrink them so it can merge them with other seed points.

Based on these two methods, we can classify region-based segmentation into the following categories:

- Region Growing
- Region Splitting and Merging

4. Watershed Segmentation

   In image processing, a watershed is a transformation on a grayscale image. It refers to the geological watershed or a drainage divide. A watershed algorithm would handle the image as if it was a topographic map. It considers the brightness of a pixel as its height and finds the lines that run along the top of those ridges.

5. Clustering-Based Segmentation Algorithms

   Clustering algorithms are unsupervised algorithms and help you in finding hidden data in the image that might not be visible to a normal vision. This hidden data includes information such as clusters, structures, shadings, etc.
   As the name suggests, a clustering algorithm divides the image into clusters (disjoint groups) of pixels that have similar features. It would separate the data elements into clusters where the elements in a cluster are more similar in comparison to the elements present in other clusters.

   - K-means Clustering
   - Fuzzy C Means

6. Neural Networks for Segmentation

   AI is used to analyze an image and identify its different components such as faces, objects, text, etc. Convolutional Neural Networks are quite popular for image segmentation because they can identify and process image data much quickly and efficiently.

Question No. 3

Solution to Question No. 3:

3.1 Perform pre-processing on the images of the created dataset.

Dataset created:

- Image 1: Image of two dices
- Image 2: Potrait of a lady
- Image 3: Image of a hand sign
- Image 4: Image of road sign with a background

As we can in Image 3 and 4 (Figure 7) the conrast between background and foreground is very low. The contrast can be improved by performing histogram equalization.

In [6]:
```
# reading dataset
img1 = cv2.imread("images/q3_1.jpg",cv2.IMREAD_GRAYSCALE)
img2 = cv2.imread("images/q3_2.jpg",cv2.IMREAD_GRAYSCALE)
img3 = cv2.imread("images/q3_3.jpg",cv2.IMREAD_GRAYSCALE)
img4 = cv2.imread("images/q3_4.jpg",cv2.IMREAD_GRAYSCALE)

# displaying dataset
f = plt.figure(figsize=(10,10))

ax1 = f.add_subplot(221)
ax1.imshow(img1, cmap='gray')
ax1.set_title('Image 1')

ax2 = f.add_subplot(222)
ax2.imshow(img2, cmap='gray')
ax2.set_title('Image 2')

ax3 = f.add_subplot(223)
ax3.imshow(img3, cmap='gray')
ax3.set_title('Image 3')


ax4 = f.add_subplot(224)
ax4.imshow(img4, cmap='gray')
ax4.set_title('Image 4')
```

Out[6]: Text(0.5, 1.0, 'Image 4')

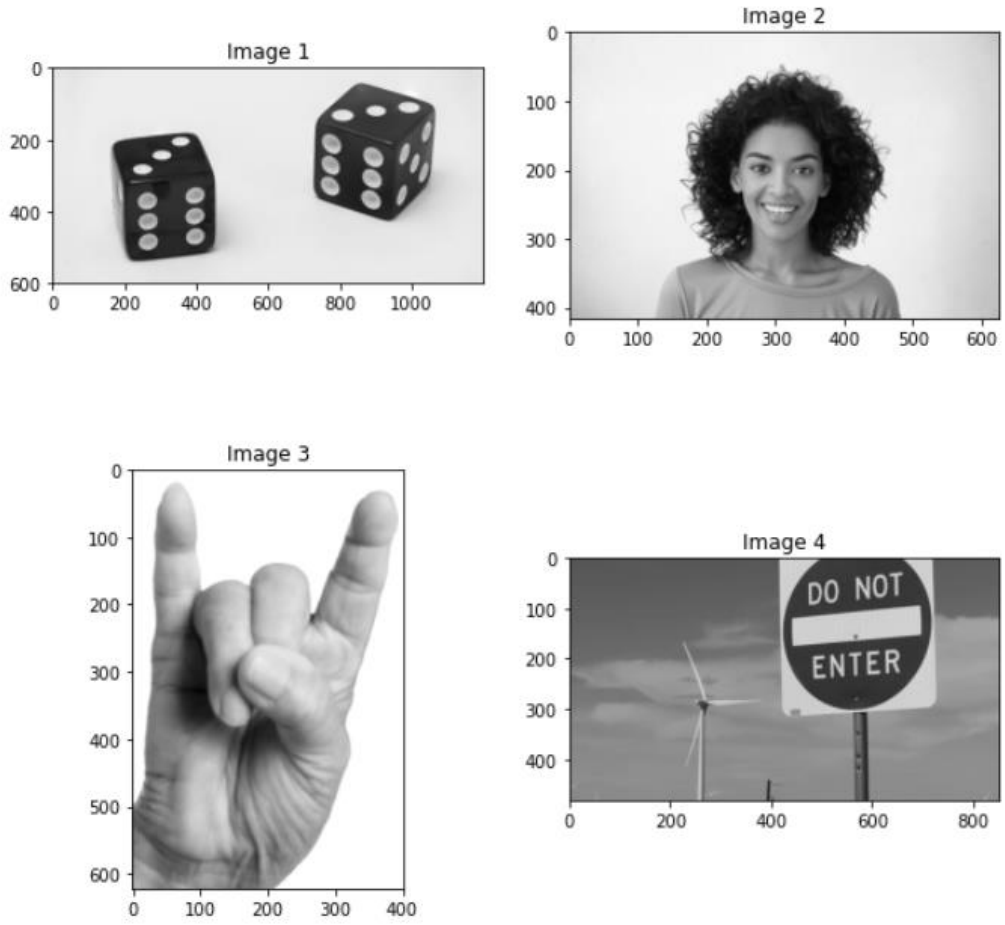
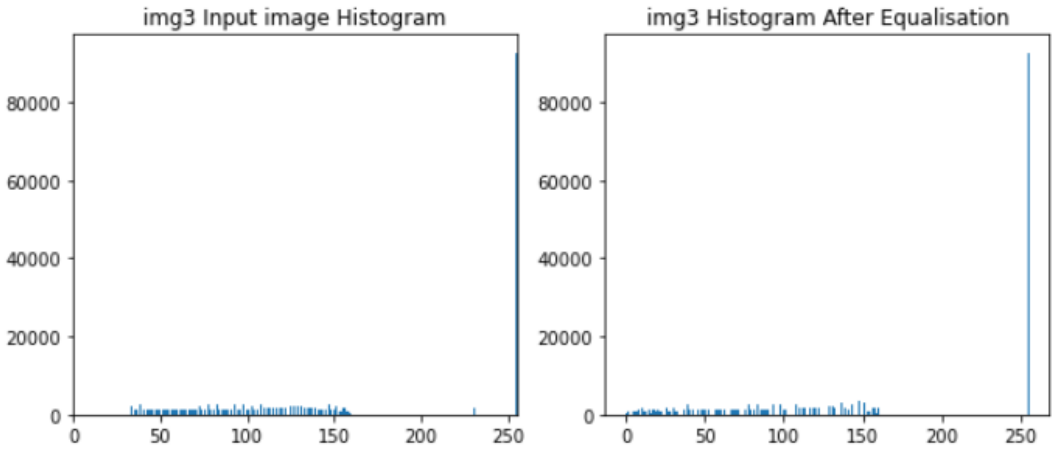
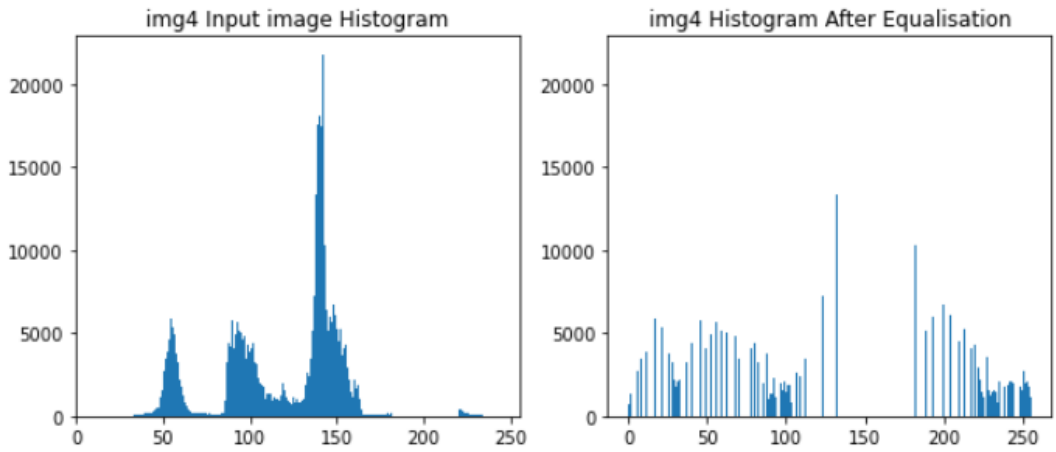


Figure 7 Dataset images

In [27]:
```
# pre processing image 3
# doing histogram equalisation on image 3
img3 = histogramEqualize(img3, "img3 ")
```



```
In [35]: # pre processing image 4
         # doing histogram equalisation on image 4
         img4 = histogramEqualize(img4, "img4 ")
```



3.2 Perform segmentation to segment the image.

We are using thresholding segmentation, specifically Otsu Thresholding for segmentation.

Otsu's thresholding method involves iterating through all the possible threshold values and calculating a measure of spread for the pixel levels each side of the threshold, i.e., the pixels that either fall in foreground or background. The aim is to find the threshold value where the sum of foreground and background spreads is at its minimum.

```
In [7]: def otsu_segmentation(img):
            M,N = img.shape
            rk,nk = np.unique(img,return_counts=True)
            T = pd.DataFrame(columns=["th","wb","wf","mb","mf","Between Class Variance"])

            for t in range(rk.shape[0]):
                wb,wf = (nk[:t].sum()/(M*N)),(nk[t:].sum()/(M*N))
                if nk[:t].sum()!=0:
                    mb,mf = (((nk[:t]*rk[:t]).sum())/(nk[:t].sum())),(((nk[t:]*rk[t:]).sum())/(nk[t:].sum()))
                else:
                    mb,mf = 0,(((nk[t:]*rk[t:]).sum())/(nk[t:].sum()))
                D = { "th":rk[t], "wb":wb, "wf": wf, "mb":mb, "mf": mf, "Between Class Variance": wb*wf*((mb-mf)**2)}
                T = T.append(D,ignore_index= True)
            threshold  = T.sort_values(by=["Between Class Variance"],ascending=False).head(1)["th"].iloc[0]

            return threshold,T
```

```
In [14]: # custom function to save image and display in a different window

         def displayAndSaveImg(title="Result",*img):
             cv2.imwrite(f"{title}.png", np.concatenate(img,axis=1))
             cv2.imshow(title, np.concatenate(img,axis=1))
             cv2.waitKey(0)
             cv2.destroyAllWindows()
```

In [15]:
```
# image 1 segmentation
threshold,T = otsu_segmentation(img1)
displayAndSaveImg("img1 segmentation",img1,((img1>threshold )*255).astype("uint8"))
T
```

Out[15]:

	th	wb	wf	mb	mf	Between Class Variance
0	21.0	0.000000	1.000000	0.000000	195.996410	0.000000
1	22.0	0.000001	0.999999	21.000000	195.996653	0.042462
2	23.0	0.000003	0.999997	21.500000	195.996894	0.084440
3	28.0	0.000004	0.999996	22.000000	195.997134	0.125935
4	29.0	0.000006	0.999994	23.500000	195.997367	0.165031
...	...	...	...	...	...	...
226	251.0	0.999445	0.000555	195.965169	252.292500	1.758740
227	252.0	0.999603	0.000397	195.973872	252.807692	1.280418
228	253.0	0.999847	0.000153	195.987547	254.100000	0.515002
229	254.0	0.999906	0.000094	195.990867	254.779412	0.325835
230	255.0	0.999927	0.000073	195.992074	255.000000	0.255864

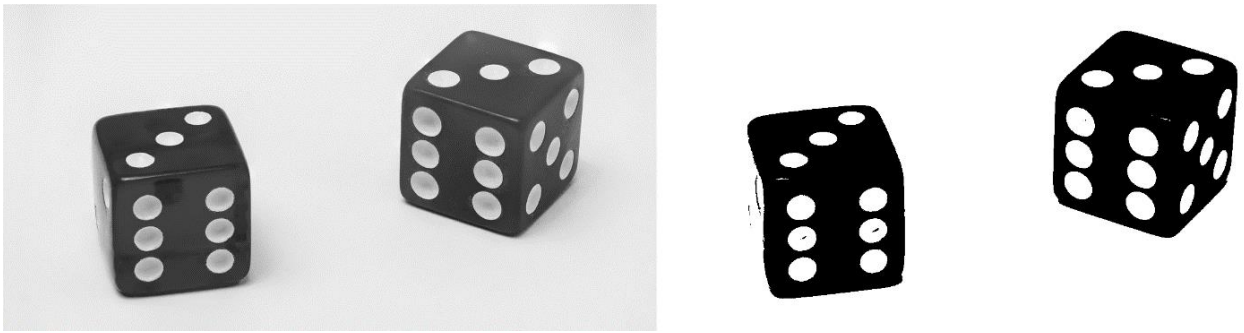


Figure 8 Image1: Input image on the left and segmented image on the right

In [23]:
```
# image 2 segmentation
threshold,T = otsu_segmentation(img2)
displayAndSaveImg("img2 segmentation",img2,((img2>threshold )*255).astype("uint8"))
T
```

Out[23]:

	th	wb	wf	mb	mf	Between Class Variance
0	0.0	0.000000	1.000000	0.000000	181.380406	0.000000
1	1.0	0.000011	0.999989	0.000000	181.382491	0.378091
2	2.0	0.000019	0.999981	0.400000	181.383873	0.627381
3	3.0	0.000042	0.999958	1.272727	181.387996	1.366989
4	4.0	0.000126	0.999874	2.424242	181.403032	4.049037
...	...	...	...	...	...	...
245	245.0	0.999877	0.000123	181.372495	245.906250	0.510458
246	246.0	0.999931	0.000069	181.375908	246.611111	0.293424
247	247.0	0.999973	0.000027	181.378631	247.571429	0.117489
248	248.0	0.999992	0.000008	181.379888	249.000000	0.035032
249	250.0	0.999996	0.000004	181.380143	250.000000	0.018038

Figure 9 Image2: Input image on the left and segmented image on the right

In [32]:
```
# image 3 segmentation
threshold,T = otsu_segmentation(img3)
displayAndSaveImg("img3 segmentation",img3,((img3>threshold )*255).astype("uint8"))
T
```

Out[32]:

	th	wb	wf	mb	mf	Between Class Variance
0	0.0	0.000000	1.000000	0.000000	146.151462	0.000000
1	1.0	0.001800	0.998200	0.000000	146.415033	38.521254
2	2.0	0.005024	0.994976	0.641660	146.886138	106.902544
3	3.0	0.007598	0.992402	1.101847	147.261923	161.071906
4	4.0	0.012028	0.987972	1.801000	147.908819	253.675272
...	...	...	...	...	...	...
113	157.0	0.613534	0.386466	79.138386	252.538276	7129.307682
114	158.0	0.617247	0.382753	79.606703	253.464967	7141.151304
115	159.0	0.619849	0.380151	79.935784	254.118395	7149.103658
116	231.0	0.621669	0.378331	80.167279	254.576025	7154.306161
117	255.0	0.628353	0.371647	81.771606	255.000000	7007.653176

Figure 10 Image3: Segmented image without histogram equalized

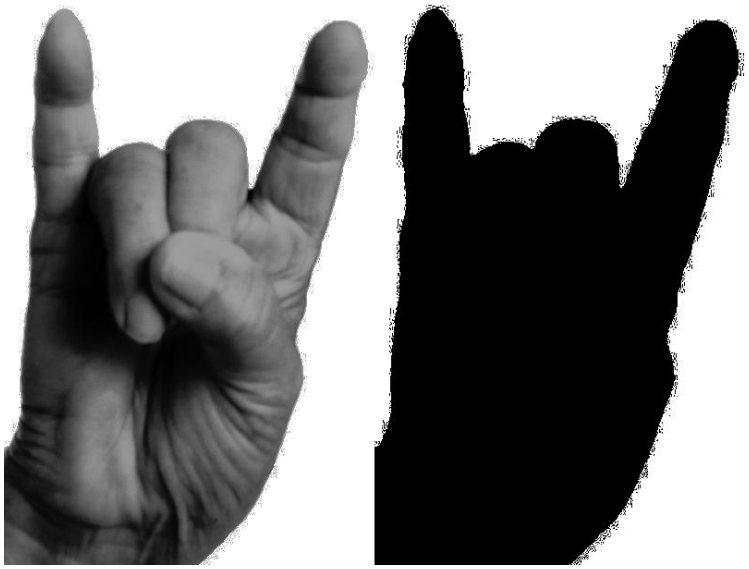


Figure 11 Image3: Otsu Segmentation on histogram equalized image

In [38]:
```
# image 4 segmentation
threshold,T = otsu_segmentation(img4)
displayAndSaveImg("img4 segmentation",img4,((img4>threshold )*255).astype("uint8"))
T
```

Out[38]:

	th	wb	wf	mb	mf	Between Class Variance
0	0.0	0.000000	1.000000	0.000000	131.792958	0.000000
1	1.0	0.001863	0.998137	0.000000	132.038981	32.424143
2	2.0	0.005108	0.994892	0.635232	132.466362	88.322114
3	3.0	0.008624	0.991376	1.191664	132.929103	148.382034
4	4.0	0.011402	0.988598	1.632211	133.294180	195.400180
...	...	...	...	...	...	...
110	251.0	0.976470	0.023530	128.881093	252.630053	351.861288
111	252.0	0.983165	0.016835	129.712683	253.278286	252.722866
112	253.0	0.988067	0.011933	130.319459	253.803484	179.782355
113	254.0	0.993097	0.006903	130.940811	254.388948	104.469822
114	255.0	0.997315	0.002685	131.461274	255.000000	40.865815

Figure 12 Image4: Segmented image without histogram equalized

Figure 13 Image4: Otsu Segmentation on histogram equalized image

3.3 Results and Discussions.

Image segmentation is the process of dividing an image (a digital image) into multiple disjoint regions, where pixels in the same region share similar properties or belong to the same object. Image segmentation changes the representation of an object, making it meaningful and easier to analyze.

We can see for image 1 (Figure 8), the image of two dices is segmented properly without any complex preprocessing. We can clearly detect the regions of the dices and its numbers shown.

For image 2 (Figure 9), the image of a portrait of a girl is segmented. Segmentation algorithm has divided the dark and light regions for easy analyzation.

For image3 (Figure 10), the image of a hand sign is segmented. We can see without any pre processing the segmentation give a bad result and difficult to recognize the hand outline/region. After we processes with histogram equalization (Figure 11) we can see a much better result in segmenting the only the hand region.

For image4 (Figure 12), the image of a road sign with background is segmented. We can see without any pre-processing the segmentation gives a moderately good result but in some places like the background clouds, it is very hard to distinguish. After we processes with histogram equalization (Figure 13) we can see more segmentation in background clouds. Overall, a much better result that before.

1. https://en.wikipedia.org/wiki/Image_segmentation
2. https://www.analyticsvidhya.com/blog/2019/04/introduction-image-segmentation-techniques-python/
3. https://freecontent.manning.com/the-computer-vision-pipeline-part-3-image-preprocessing/
4. https://en.wikipedia.org/wiki/Histogram_equalization
5. https://en.wikipedia.org/wiki/Sobel_operator