## step 1 : Import Libraries

In [268…

```
import numpy as np
import matplotlib.pyplot as plt
import cv2
```

## step - 2

In [269…

```
#load_image
sat_image = cv2.imread("sat_image_plaksha.jpg")
plt.imshow(sat_image)
```

Out[269…

```
<matplotlib.image.AxesImage at 0x14e6bf849d0>
```

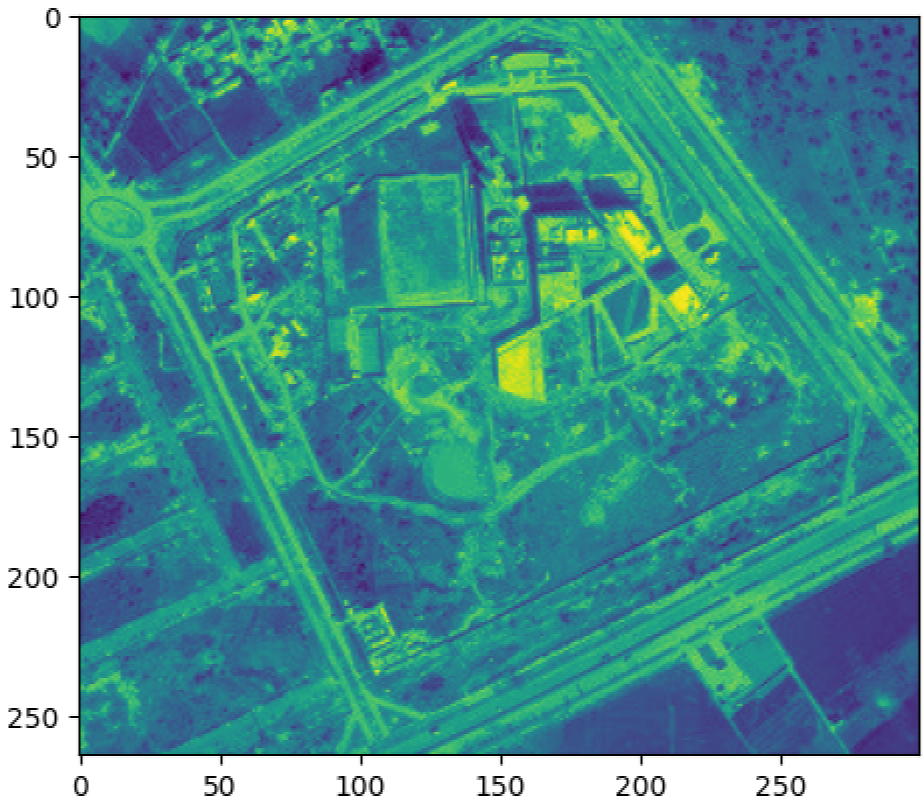

## step-3

In [270…

```
#convert the image into grey-scale
grey_sat_image = cv2.cvtColor(sat_image , cv2.COLOR_BGR2GRAY)
plt.imshow(grey_sat_image)
#grey_sat_image.shape() -> ( 264 , 300 )
```

Out[270…

```
<matplotlib.image.AxesImage at 0x14e6f4c6a50>
```



## step-4

In [271…
```
#convert the image to double precision
grey_sat_image_double = grey_sat_image.astype(np.float64)
#print(grey_sat_image_double.dtype)
```

## step 5

In [272…
```
#print(grey_sat_image_double.shape)
#calculating mean of each coloumn (there are 300 coloums in total )
mean_col = np.mean(grey_sat_image_double, axis=0)
# for mean in mean_col:
#     print(mean)
```

In [273…
```
#subtracting coloumn mean from each pixel to get  image_mean_subtracted.
image_mean_subtracted = grey_sat_image_double - mean_col
new_mean = np.mean(image_mean_subtracted , axis = 0)
'''we subtracte coloumn mean from each pixel inorder to make the data centred .
PCA assumes that data is centred around zero . Our covariance matrix gets affected
and as a result , we have a great chance that wrong Principle components being eval

'''
```

Out[273…

```
'we subtracte coloumn mean from each pixel inorder to make the data centred . \nPC
A assumes that data is centred around zero . Our covariance matrix gets affected
\nand as a result , we have a great chance that wrong Principle components being e
valuated for analysis . \n\n'
```

## step - 6

In [274…

```
#Computing the co variance matrix using numpy
cov_matrix = np.cov(image_mean_subtracted, rowvar=False)
'''we must use rowvar = false since by default , np.cov() assumes that each row
as a variable and coloumn as observation . But in PCA , we do the inverse logic of
coloumn .
'''
#print(cov_matrix.shape)
cov_matrix
```

Out[274…

```
array([[1518.87589296, 1343.12579214, 1121.83208031, ..., -167.01493548,
        -126.55036583, -139.92042574],
       [1343.12579214, 1545.76489227, 1265.9413815 , ..., -140.70183777,
         -89.85392902,  -73.36280101],
       [1121.83208031, 1265.9413815 , 1425.59659811, ..., -144.06704401,
         -86.40752103,  -38.05082671],
       ...,
       [-167.01493548, -140.70183777, -144.06704401, ..., 1254.67990264,
        1140.29068729, 1075.81819622],
       [-126.55036583,  -89.85392902,  -86.40752103, ..., 1140.29068729,
        1184.58519127, 1148.42033932],
       [-139.92042574,  -73.36280101,  -38.05082671, ..., 1075.81819622,
        1148.42033932, 1233.26545397]], shape=(300, 300))
```

## step - 7 and 8

In [275…

```
#computing eigen values and eigen vectors.
eigenvalues, eigenvectors = np.linalg.eigh(cov_matrix)

#sorting eigenvalues
#by defalut , these are sorted in ascending order
'''
we need to sort the evalues in such a way that we have largerst evalues (for which

'''
# in descending order
desc_order_evalues = np.argsort(eigenvalues)[::-1]

sorted_eigenvalues = eigenvalues[desc_order_evalues]
#sorting the evectors
sorted_eigenvectors = eigenvectors[:, desc_order_evalues]

'''
Instead of using np.linalg.eig() , I used the np.linalg.eigh() due to the fact
that eig() was also taking imaginary part of eigenvalues into consideration which a
not compatible to be convertable in float.
'''
print(sorted_eigenvalues[:5])
```

```
[56329.41125092 36634.00158313 29399.48126706 22848.62235279
 17350.88317204]
```

## Step-9

In [276…

```
#Define the number of principal components to keep.
num_components = [10, 20, 30, 40, 50, 60, 91]

# each entry represents the number of first k eigenvectors that are needed to be us
```

## step 10

In [277…

```
output_images = []

for k in num_components:
    #take top-k eigenvectors
    selected_comp = sorted_eigenvectors[: , :k]
    #project the data onto selected components
    projected_data = np.dot(selected_comp.T , image_mean_subtracted.T).T

    #reconstruct the image back
    reconstructed_image = np.dot(selected_comp , projected_data.T).T + mean_col

    #append the reconstructed image
    output_images.append(reconstructed_image)
```

## step - 11

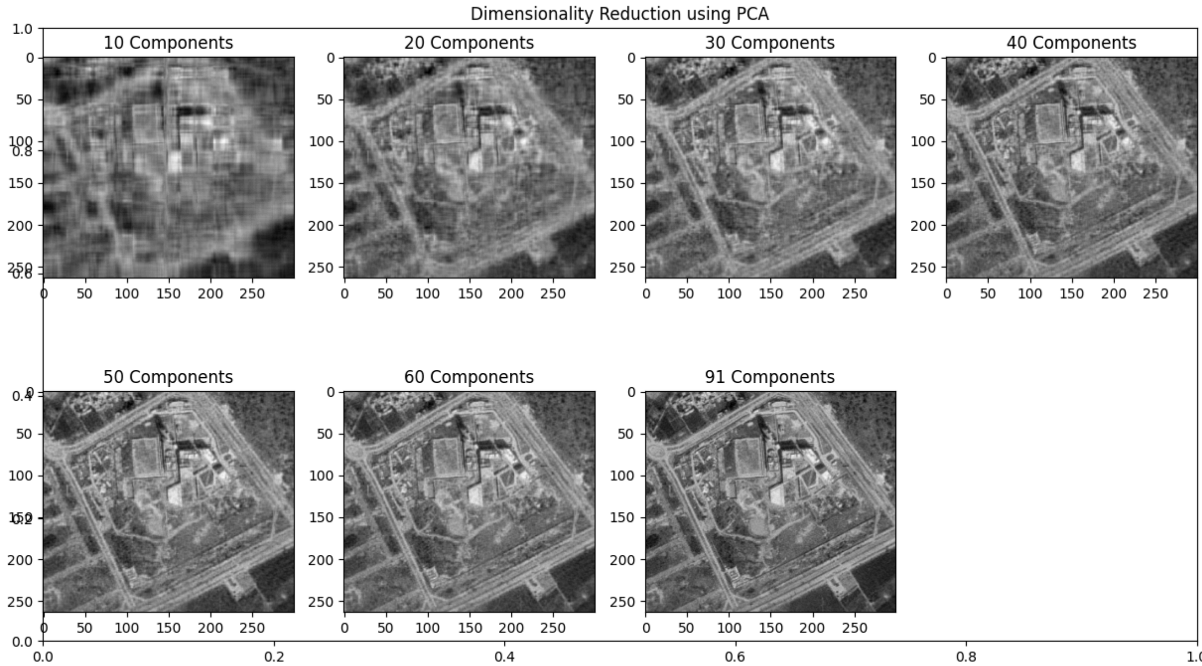
In [278…

```
plt.figure(figsize=(15, 8))

plt.title("Dimensionality Reduction using PCA")

for i in range(len(output_images)):

    plt.subplot(2, 4, i + 1)
    plt.imshow(output_images[i], cmap="gray")
    plt.title(f"{num_components[i]} Components")
plt.show()
```




## step 12

In [279…

```
# direct PCA implementation using in-buit function  :

from sklearn.decomposition import PCA
num_components = 91
pca = PCA(num_components)
pca.fit(image_mean_subtracted)
#printing the amount of variance explained
variance = pca.explained_variance_ratio_
cummu_var = variance.sum()
print(cummu_var)
```

```
0.9505785631863113
```

# MLPR LAB-3 REPORT

**Q1: Difference between PCA and Feature Selection?**
PCA creates new transformed features (principal components) by combining original pixels (in this case) , whereas feature selection keeps only some original features unchanged. PCA reduces dimensions by projection, feature selection reduces by choosing.

**Q2: Why standardize features before applying PCA?**
In this lab, each column of the image is treated as a feature (pixel intensity values). Standardizing/centering ensures PCA captures true variations in the image structure rather than being dominated by overall brightness or large-valued pixels. This makes the covariance matrix and principal components meaningful for dimensionality reduction.

**Q3: Importance of Covariance Matrix in PCA?**
In this lab, the covariance matrix measures how different pixel columns of the grayscale image vary together. PCA uses this matrix to compute eigenvalues and eigenvectors, which define the principal components for compressing and reconstructing the image.

**Q4: Limitations of PCA?**
In image PCA, reducing dimensions too much causes loss of fine details and produces blurry reconstructions. PCA is also linear, so it cannot capture complex non-linear patterns present in real-world images

**Q5: Importance of individual PCs in PCA?**
In this lab, the importance of each principal component is determined by its eigenvalue or explained variance ratio. Components with larger eigenvalues contribute more to reconstructing the satellite image and preserving variance (ex: 91 PCs explaining 95% variance).