Instructions

Follow the instructions given in comments prefixed with ## and write your code below that.

Also fill the partial code in given blanks.

Don't make any changes to the rest part of the codes

Answer the questions given at the end of this notebook within your report.

You would need to submit your GitHub repository link. Refer to the Section 6: Final Submission on the PDF document for the details.

I Completed the code on Kaggle as well but my Kernel was dying so I ran it on Jupyter instead

In [1]:
```
## import cv2
## import numpy
## import matplotlib pyplot
## import KMeans cluster from sklearn
## import distance from scipy.spatial
from matplotlib.offsetbox import OffsetImage, AnnotationBbox
import cv2
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from scipy.spatial import distance
```

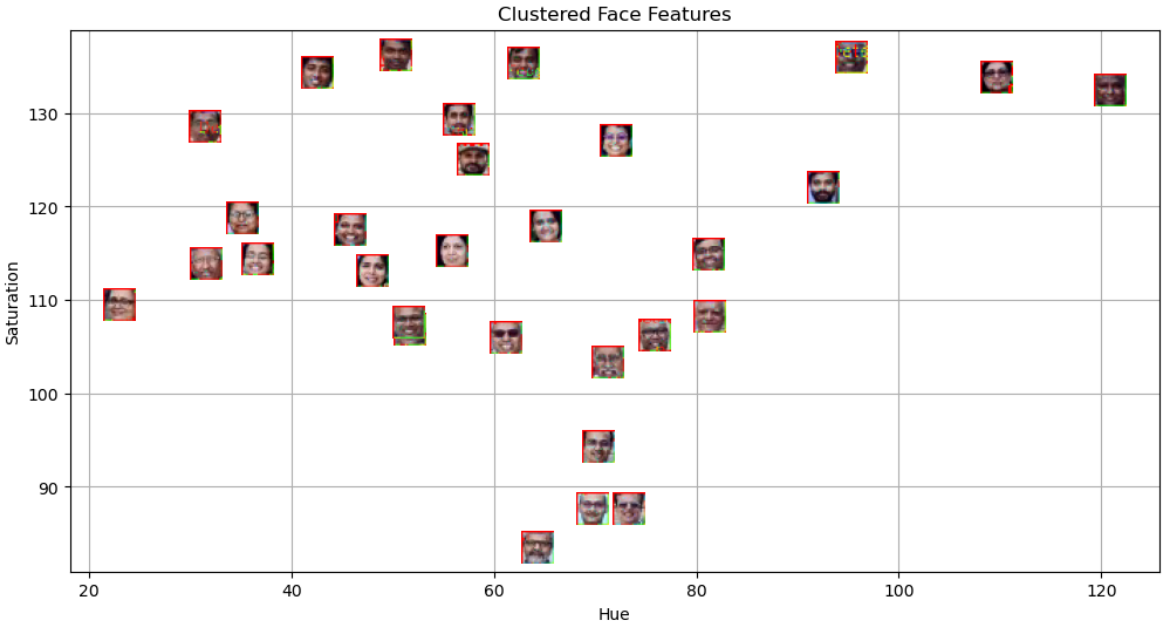
In [2]:
```
## Reading the image plaksha_Faculty.jpg
img = cv2.imread("/kaggle/input/images/Plaksha_Faculty.jpg")


## Convert the image to grayscale
gray_img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

# Loading the required haar-cascade xml classifier file
face_cascade = cv2.CascadeClassifier(cv2.data.haarcascades + "haarcascade_fronta

# Applying the face detection method on the grayscale image.
## Change the parameters for better detection of faces in your case.
faces_rect = face_cascade.detectMultiScale(gray_img, 1.05, 4, minSize=(25,25), m

# Define the text and font parameters
text = "Face Detected"                    ## The text you want to write
font = cv2.FONT_HERSHEY_SIMPLEX           ## Font type
font_scale = 0.5                          ## Font scale factor
font_color = (0, 0, 255)                    ## Text color in BGR format (here, i
font_thickness = 1                        ## Thickness of the text


# Iterating through rectangles of detected faces
for (x, y, w, h) in faces_rect:
    cv2.rectangle(img, (x, y), (x+w, y+h), (0, 0, 255), 2)
    # Use cv2.putText to add the text to the image, Use text, font, font_scale,
```

```
    cv2.putText(img, text, (x, y - 10), font, font_scale, font_color, font_thick

## Display the image and window title should be "Total number of face detected a
cv2.imshow("Total number of face detected are " + str(len(faces_rect)), img)
cv2.waitKey(0)
cv2.destroyAllWindows()
```

In [3]:

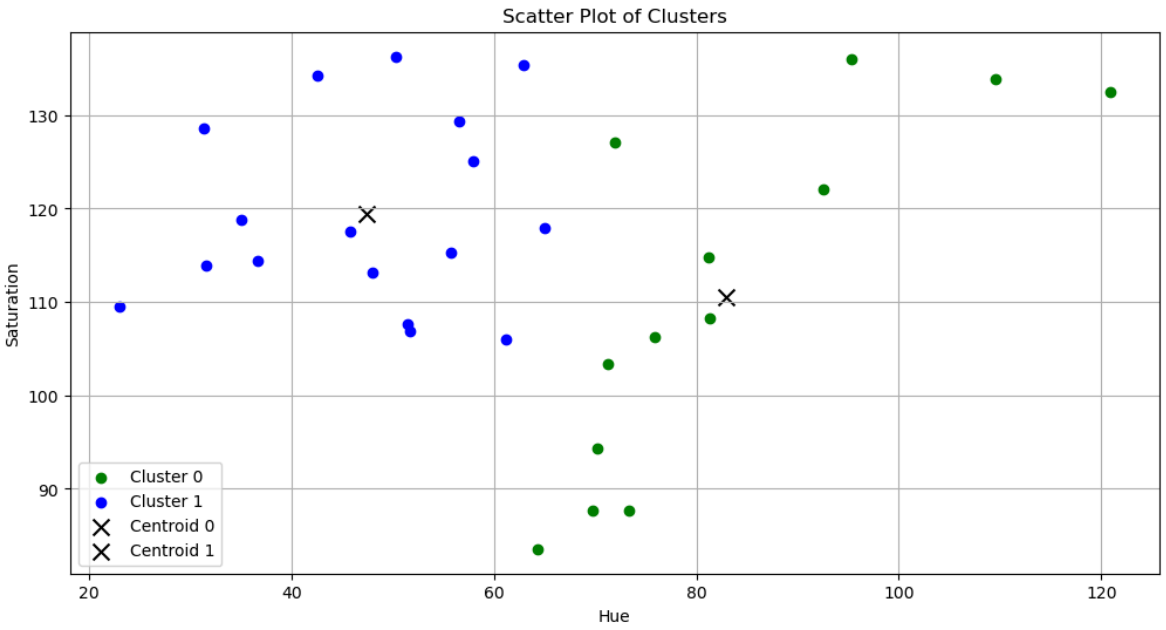
```
from matplotlib.offsetbox import OffsetImage, AnnotationBbox
# Extract face region features (Hue and Saturation)
img_hsv = cv2.cvtColor(img, cv2.COLOR_BGR2HSV) ## call the img and convert it fr
hue_saturation = []
face_images = []  # To store detected face images

for (x, y, w, h) in faces_rect:
    face = img_hsv[y:y + h, x:x + w]
    hue = np.mean(face[:, :, 0])
    saturation = np.mean(face[:, :, 1])
    hue_saturation.append((hue, saturation))
    face_images.append(face)

hue_saturation = np.array(hue_saturation)

## Perform k-Means clustering on hue_saturation and store in kmeans
kmeans = KMeans(n_clusters=2, random_state=42).fit(hue_saturation)
#centroids = kmeans.cluster_centers_
#labels = kmeans.labels_

# Create a figure and axis
fig, ax = plt.subplots(figsize=(12, 6))

# Plot the clustered faces with custom markers
for i, (x,y,w,h ) in enumerate(faces_rect):
    im = OffsetImage(cv2.cvtColor(cv2.resize(face_images[i], (20, 20)), cv2.COLO
    ab = AnnotationBbox(im, (hue_saturation[i, 0], hue_saturation[i, 1]), framec
    ax.add_artist(ab)
    plt.plot(hue_saturation[i, 0], hue_saturation[i, 1])


## Put x label
plt.xlabel("Hue")
## Put y label
plt.ylabel("Saturation")
## Put title
plt.title("Clustered Face Features")
## Put grid
plt.grid(True)
## show the plot
plt.show()
```

```
C:\conda\Lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The def
ault value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_
init` explicitly to suppress the warning
  warnings.warn(
C:\conda\Lib\site-packages\sklearn\cluster\_kmeans.py:1382: UserWarning: KMeans i
s known to have a memory leak on Windows with MKL, when there are less chunks tha
n available threads. You can avoid it by setting the environment variable OMP_NUM
_THREADS=1.
  warnings.warn(
```



In [4]:
```
# Create an empty list to store legend labels
legend_labels = []

# Create lists to store points for each cluster
cluster_0_points = []
cluster_1_points = []

# Your code for scatter plot goes here
fig, ax = plt.subplots(figsize=(12, 6))
for i, (x, y, w, h) in enumerate(faces_rect):
    if kmeans.labels_[i] == 0:
        cluster_0_points.append((hue_saturation[i, 0], hue_saturation[i, 1]))
    else:
        cluster_1_points.append((hue_saturation[i, 0], hue_saturation[i, 1]))


cluster_0_points = np.array(cluster_0_points)
# Plot points for cluster 0 in green
plt.scatter(cluster_0_points[:, 0], cluster_0_points[:, 1], c='green', label='Cl


cluster_1_points = np.array(cluster_1_points)
# Plot points for cluster 1 in blue
plt.scatter(cluster_1_points[:, 0], cluster_1_points[:, 1], c='blue', label='Clu

# Calculate and plot centroids
centroid_0 = kmeans.cluster_centers_[0]
centroid_1 = kmeans.cluster_centers_[1]

# Plot both the centroid for cluster 0 and cluster 1
plt.scatter(centroid_0[0], centroid_0[1], marker='x', c='black', s=100, label='C
plt.scatter(centroid_1[0], centroid_1[1], marker='x', c='black', s=100, label='C

## Put x label
plt.xlabel("Hue")
## Put y label
plt.ylabel("Saturation")
## Put title
plt.title("Scatter Plot of Clusters")
## Add a legend
```

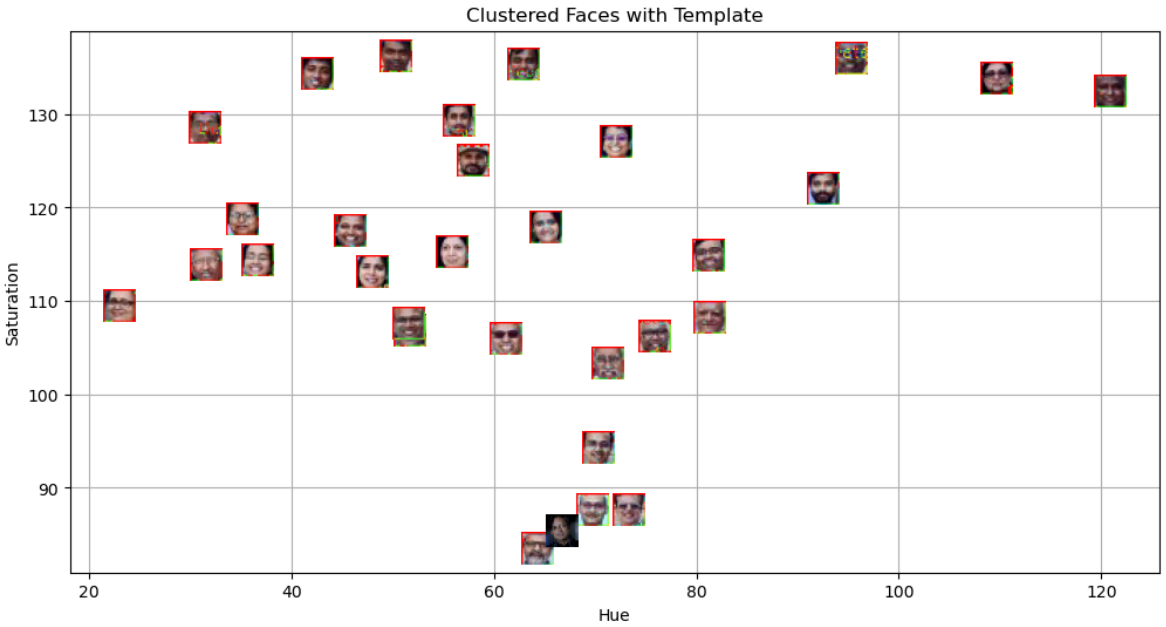
```
plt.legend()
## Add grid
plt.grid(True)
## Show the plot
plt.show()
```



In [5]:
```
## Read the class of the template image 'Dr_Shashi_Tharoor.jpg' using cv2 and st
template_img = cv2.imread("/kaggle/input/images/Dr_Shashi_Tharoor.jpg")
# Detect face  in the template image after converting it to gray and store it in
template_faces = face_cascade.detectMultiScale(cv2.cvtColor(template_img, cv2.CO
# Draw rectangles around the detected faces
for (x, y, w, h) in template_faces:
    cv2.rectangle(template_img, (x, y), (x + w, y + h), (0, 255, 0), 3)
cv2.imshow("Detected Face in Template", template_img)
cv2.waitKey(0)
cv2.destroyAllWindows()
```

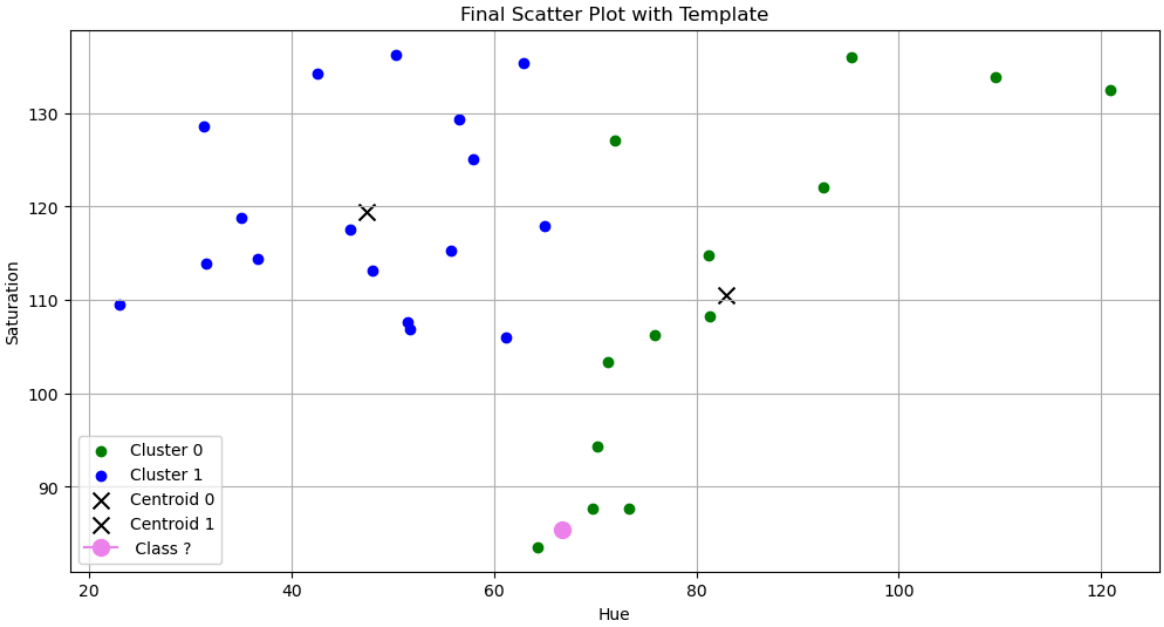
In [6]:
```
# Convert the template image to HSV color space and store it in template_hsv
template_hsv = cv2.cvtColor(template_img, cv2.COLOR_BGR2HSV)

# Extract hue and saturation features from the template image as we did it for d
template_hue = np.mean(template_hsv[:, :, 0])
template_saturation = np.mean(template_hsv[:, :, 1])

# Predict the cluster label for the template image and store it in template_labe
template_label = kmeans.predict([[template_hue, template_saturation]])[0]

# Create a figure and axis for visualization
fig, ax = plt.subplots(figsize=(12, 6))

# Plot the clustered faces with custom markers (similar to previous code)
for i, (x, y, w, h) in enumerate(faces_rect):
    color = 'red' if kmeans.labels_[i] == 0 else 'blue'
    im = OffsetImage(cv2.cvtColor(cv2.resize(face_images[i], (20, 20)), cv2.COLO
    ab = AnnotationBbox(im, (hue_saturation[i, 0], hue_saturation[i, 1]), frameo
    ax.add_artist(ab)
    plt.plot(hue_saturation[i, 0], hue_saturation[i, 1], 'o', markersize=5, colo

# Plot the template image in the respective cluster
if template_label == 0:
```

```
    color = 'red'
else:
    color = 'blue'
im = OffsetImage(cv2.cvtColor(cv2.resize(template_img, (20, 20)), cv2.COLOR_BGR2
ab = AnnotationBbox(im, (template_hue, template_saturation), frameon=False, pad=
ax.add_artist(ab)

## Put x label
plt.xlabel("Hue")
## Put y label
plt.ylabel("Saturation")
## Put title
plt.title("Clustered Faces with Template")
## Add grid
plt.grid(True)
## show plot
plt.show()
```



In [7]:
```
# Create an empty list to store legend labels
legend_labels = []

# Create lists to store points for each cluster
cluster_0_points = []
cluster_1_points = []

# Your code for scatter plot goes here
fig, ax = plt.subplots(figsize=(12, 6))
for i, (x, y, w, h) in enumerate(faces_rect):
    if kmeans.labels_[i] == 0:
        cluster_0_points.append((hue_saturation[i, 0], hue_saturation[i, 1]))
    else:
        cluster_1_points.append((hue_saturation[i, 0], hue_saturation[i, 1]))

# Plot points for cluster 0 in green
cluster_0_points = np.array(cluster_0_points)
plt.scatter(cluster_0_points[:, 0], cluster_0_points[:, 1], c='green', label='Cl

# Plot points for cluster 1 in blue
cluster_1_points = np.array(cluster_1_points)
plt.scatter(cluster_1_points[:, 0], cluster_1_points[:, 1], c='blue', label='Clu
```

```
# Calculate and plot centroids for both the clusters
centroid_0 = kmeans.cluster_centers_[0]
centroid_1 = kmeans.cluster_centers_[1]
plt.scatter(centroid_0[0], centroid_0[1], marker='x', c='black', s=100, label='C
plt.scatter(centroid_1[0], centroid_1[1], marker='x', c='black', s=100, label='C
plt.plot(template_hue, template_saturation, marker='o', c='violet', markersize=1

## Put x label
plt.xlabel("Hue")
## Put y label
plt.ylabel("Saturation")
## Put title
plt.title("Final Scatter Plot with Template")
## Add a legend
plt.legend()
## Add grid
plt.grid(True)
## show the plot
plt.show()
                                                    ## End of the lab 5 ##
```



Report:

Answer the following questions within your report:

1. What are the common distance metrics used in distance-based classification algorithms?

Euclidean, Manhattan, Mahalanobis, Chebyshev and Cosine similarity are common distance metrics.

2. What are some real-world applications of distance-based classification algorithms?

image recognition, recommendation systems, fraud detection, medical diagnosis etc.

3. Explain various distance metrics.

Euclidean distance is the straight-line distance between two points Manhattan is the sum of the absolute differences of their coordinates. Malhanoblis is a distance measure that accounts for correlations between variables and scales the differences according to the data's covariance structure. Chebyshev is the maximum absolute difference along any coordinate dimension. Cosine quantifies how similar two vectors are based on the angle between them.

4. What is the role of cross validation in model performance?

Cross validation helps to assess model performance by partitioning data into training and test sets multiple times to reduce overfitting and estimate generalization.

5. Explain variance and bias in terms of KNN?

In KNN, low k leads to low bias and high variance (overfitting), while high k increases bias and reduces variance (underfitting). The challenge is to find the optimal balance.

In [ ]: