Assignment 1

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In [ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call driv
e.mount("/content/drive", force_remount=True).
```

In [ ]:
```
faces_path = "/content/drive/MyDrive/Colab Notebooks/Pattern/projects/data/faces"
nonfaces_path = "/content/drive/MyDrive/Colab Notebooks/Pattern/projects/data/nonFa
```

In [ ]:
```
from PIL import Image
import numpy as np
import matplotlib.pyplot as plt
from sklearn import metrics
from sklearn.neighbors import KNeighborsClassifier

from pylab import rcParams
```

Loading The Data

In [ ]:
```
ROWS = 400
COLS = 10304

#initiating vectors
data = [[0 for i in range(COLS)] for i in range(ROWS)]
labels = [0 for i in range(ROWS)]

for i in range(40):
    j=0
    for j in range (10):
        img = Image.open( faces_path +'/s' + str(i+1)+'/'+str(j+1)+'.pgm' )

        # convert it to a matrix (vector)
        data[i*10+j] = np.matrix(np.array(img).ravel())

        #IDS Classes
        labels[i*10+j]=i+1
```

In [ ]:
```
#Converting the labels into an array
labels = np.array(labels)
data = np.array(data)
print(labels.shape)
print(data.shape)
```

```
(400,)
(400, 1, 10304)
```

Split The Data

In [ ]:
```
#Odd rows for training and Even for testing
data_train = data.copy()[::2].reshape(ROWS//2, COLS)
data_test = data.copy()[1::2].reshape(ROWS//2, COLS)
labels_train = labels.copy()[::2]
labels_test = labels.copy()[1::2]
print("training data:", data_train.shape, " :: training labels:",labels_train.shape
print("testing data:", data_test.shape, " :: testing labels:",labels_test.shape)
```

```
training data: (200, 10304)  :: training labels: (200,)
testing data: (200, 10304)  :: testing labels: (200,)
```

PCA

In [ ]:
```
#Getting number of directions to be projected on
def get_Dim(eigen_values, alpha):
    total_variance = np.sum(eigen_values)
    fraction_variance = 0
    eigen_values_sum = 0
    r = 0
    while(fraction_variance < alpha):
        eigen_values_sum += eigen_values[r]
        fraction_variance = eigen_values_sum / total_variance
        r+=1
    return r
```

In [ ]:
```
def PCA(train, test, alphas):
  # compute the mean
  mean = np.mean(train, axis = 0)

  # center the data
  Z = train - mean

  # get the covariance matrix
  cov = np.cov(Z, rowvar=False, bias=True)

  # get the eigenvalues and eigenvectors
  eigen_values, eigen_vectors = np.linalg.eigh(cov)

  # get the needed dimension for each alpha
  alphas_dim = []
  for alpha in alphas:
      alphas_dim.append(get_Dim(np.flip(eigen_values, axis=0), alpha))

  print("alphas_dim :",alphas_dim)

  Z_test = test - mean

  eigen_vectors = np.flip(eigen_vectors, axis=1)

  proj_mats = []
  reduced_data_train = []
  reduced_data_test = []
  for i in range(0, len(alphas_dim)):
    proj_mats.append(eigen_vectors[:,0:alphas_dim[i]])
    reduced_data_train.append(np.matmul(proj_mats[i].transpose(), Z.transpose()))
    reduced_data_test.append(np.matmul(proj_mats[i].transpose(), Z_test.transpose(
    print("proj_mat"+str(i)+":", proj_mats[i].shape)
    print("Reduced_data_train"+str(i)+":", reduced_data_train[i].shape)
    print("Reduced_data_test"+str(i)+":", reduced_data_test[i].shape)
```

```
    return {
        "centered_data":Z,
        "eigen_values":eigen_values,
        "eigen_vectors": eigen_vectors,
        "alphas_dim":alphas_dim,
        "proj_matrix": proj_mats,
        "reduced_data_train": reduced_data_strain,
        "reduced_data_test": reduced_data_test
    }
```

In [ ]:
```
alphas = [0.8, 0.85, 0.9, 0.95]
pca = PCA(data_train, data_test, alphas)
```

```
alphas_dim : [36, 51, 76, 115]
proj_mat0: (10304, 36)
Reduced_data_train0: (36, 200)
Reduced_data_test0: (36, 200)
proj_mat1: (10304, 51)
Reduced_data_train1: (51, 200)
Reduced_data_test1: (51, 200)
proj_mat2: (10304, 76)
Reduced_data_train2: (76, 200)
Reduced_data_test2: (76, 200)
proj_mat3: (10304, 115)
Reduced_data_train3: (115, 200)
Reduced_data_test3: (115, 200)
```

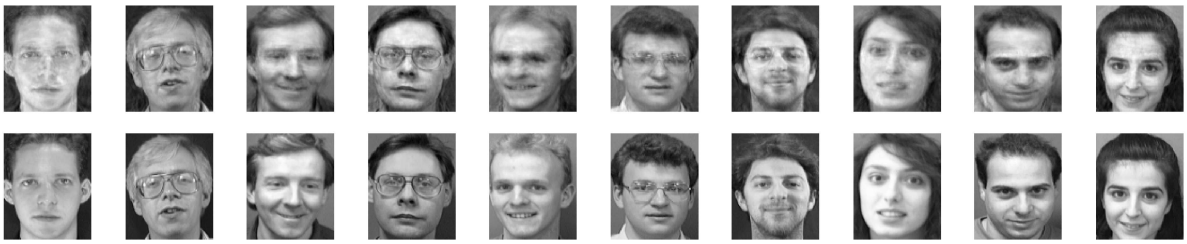
In [ ]:
```
# print("pca.centered_data ",pca["centered_data"])
# print("pca.eigen_values ",pca["eigen_values"])
# print("pca.eigen_vectors ",pca["eigen_vectors"])
# print("pca.alphas_dim ",pca["alphas_dim"])
# print("pca.proj_matrix ",pca["proj_matrix"])
# print("pca.reduced_data_train ",pca["reduced_data_train"])
# print("pca.reduced_data_test ",pca["reduced_data_test"])
```

Faces plots:

In [ ]:
```
#displaying the first 10 eigen vectors as images.(i.e. eigen face)

plt.rcParams["figure.figsize"] = [20.00, 5]

for i in range(0, 10):
    eigen_face = pca["eigen_vectors"][:,i].reshape(112,92)
    plt.subplot(1, 10, i+1)
    plt.imshow(eigen_face, cmap='gray');
    plt.axis('off')
plt.show()
```

In [ ]:
```
# An example of a reconstructed image from the reduced data and the projection matr
# to compare the reconstructed face and the original face.
plt.rcParams["figure.figsize"] = [20.00, 4]
fig, axs = plt.subplots(2, 10)

# reconstruction
```

```
re_faces = np.matmul(pca["reduced_data_train"][-1].T, pca["proj_matrix"][-1].T ) +

for i in range(0, 50, 5):
    axs[0, i//5].imshow(re_faces[i].reshape(112,92), cmap='gray');
    axs[0, i//5].axis('off')
    axs[1, i//5].imshow(data_train[i].reshape(112,92), cmap='gray');
    axs[1, i//5].axis('off')
plt.show()
```



KNN - PCA

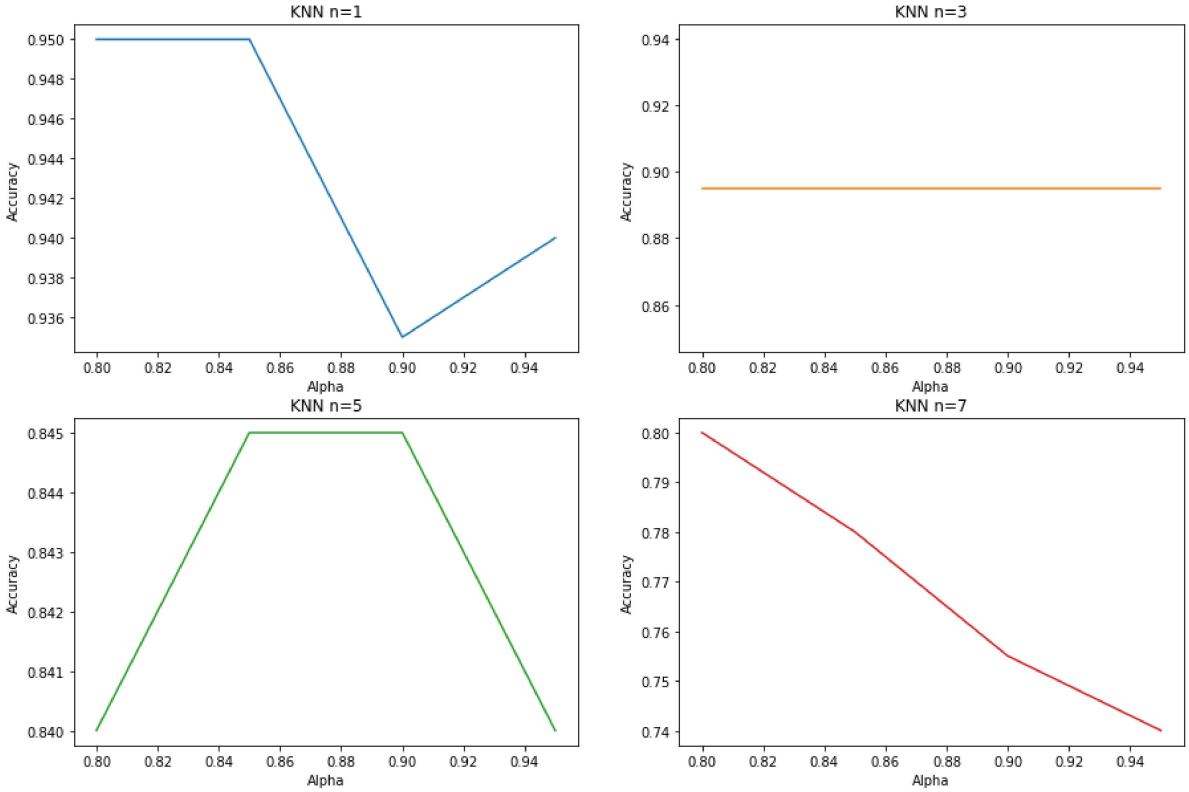
In [ ]:
```
#PCA Nearest Neighbor runs KNN algorithms and returns accuracy depending on number
def KNNPCA(data, proj_mat, numberOfNeighors):
    knn_pca = KNeighborsClassifier(n_neighbors = numberOfNeighors)
    knn_pca.fit(data.T, labels_train)
    mean = np.mean(data_test, axis=0)
    Z2 = data_test - mean
    newTestData = np.matmul(Z2, proj_mat)
    predicted_data = knn_pca.predict(newTestData)
    accuracy = metrics.accuracy_score(labels_test, predicted_data)
    return accuracy
```

In [ ]:
```
#Trying different values with KNN to see how the accuracy varies with the number o
KNNS = [1, 3, 5, 7]

accuracy_KNN1 = []
accuracy_KNN3 = []
accuracy_KNN5 = []
accuracy_KNN7 = []

for i in range(len(KNNS)):
    accuracy_KNN1.append(KNNPCA(pca["reduced_data_train"][i], pca["proj_matrix"][i
    accuracy_KNN3.append(KNNPCA(pca["reduced_data_train"][i], pca["proj_matrix"][i
    accuracy_KNN5.append(KNNPCA(pca["reduced_data_train"][i], pca["proj_matrix"][i
    accuracy_KNN7.append(KNNPCA(pca["reduced_data_train"][i], pca["proj_matrix"][i
```

Plotting Alphas againist Accuracy:

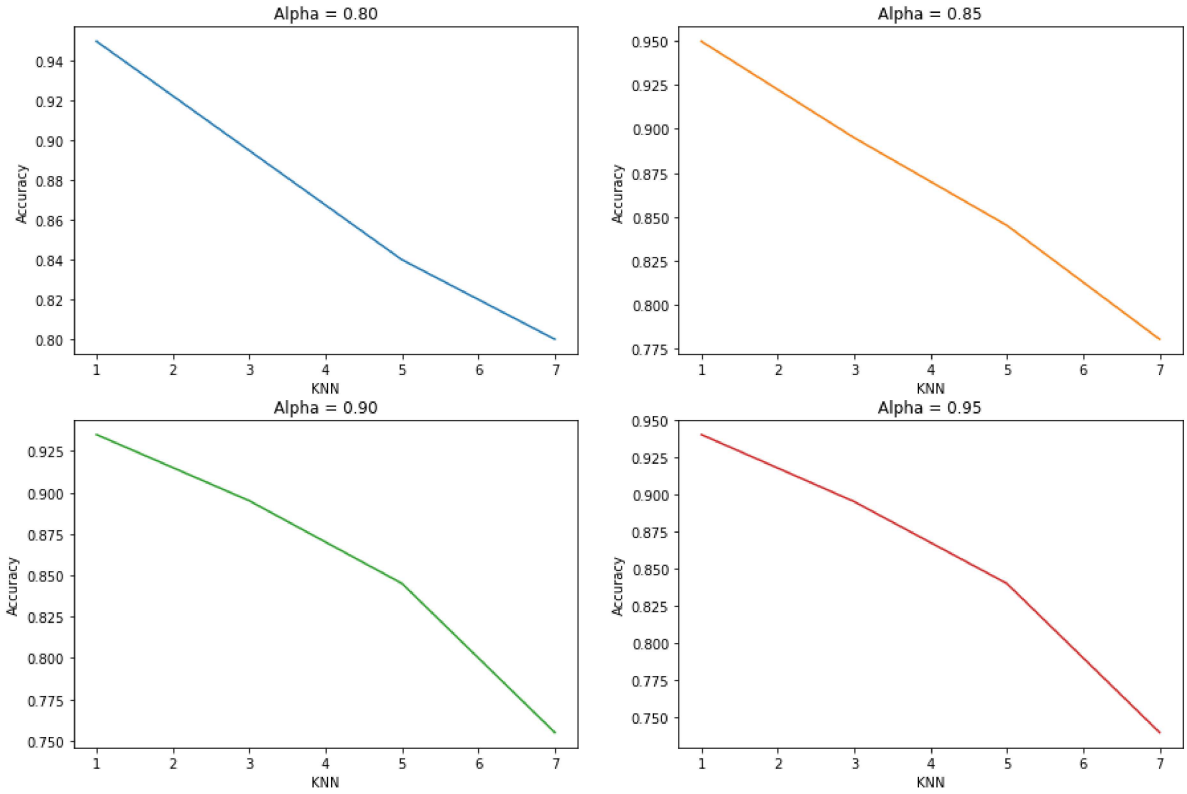
In [ ]:
```
fig, axs = plt.subplots(2, 2)
plt.rcParams["figure.figsize"] = [15, 10]

axs[0, 0].plot(alphas, accuracy_KNN1)
axs[0, 0].set_title('KNN n=1')

axs[0, 1].plot(alphas, accuracy_KNN3, 'tab:orange')
axs[0, 1].set_title('KNN n=3')

axs[1, 0].plot(alphas, accuracy_KNN5, 'tab:green')
axs[1, 0].set_title('KNN n=5')
```

```
axs[1, 1].plot(alphas, accuracy_KNN7, 'tab:red')
axs[1, 1].set_title('KNN n=7')

for ax in axs.flat:
    ax.set(xlabel='Alpha', ylabel='Accuracy')
```



Plotting KNN Againist Accuracy:

In [ ]:
```
fig, axs = plt.subplots(2, 2)
plt.rcParams["figure.figsize"] = [15, 10]

axs[0, 0].plot(KNNS, [ accuracy_KNN1[0], accuracy_KNN3[0], accuracy_KNN5[0], accura
axs[0, 0].set_title('Alpha = 0.80')

axs[0, 1].plot(KNNS, [ accuracy_KNN1[1], accuracy_KNN3[1], accuracy_KNN5[1], accura
axs[0, 1].set_title('Alpha = 0.85')

axs[1, 0].plot(KNNS, [ accuracy_KNN1[2], accuracy_KNN3[2], accuracy_KNN5[2], accura
axs[1, 0].set_title('Alpha = 0.90')

axs[1, 1].plot(KNNS, [ accuracy_KNN1[3], accuracy_KNN3[3], accuracy_KNN5[3], accura
axs[1, 1].set_title('Alpha = 0.95')

for ax in axs.flat:
    ax.set(xlabel='KNN', ylabel='Accuracy')
```



LDA

In [ ]:
```
# mean per class
classified_data = np.split(data_train, 40)
mean_per_class = np.mean(classified_data , axis=1)
print(mean_per_class.shape)
```

```
(40, 10304)
```

In [ ]:
```
# Within class matrix
S = np.zeros((COLS, COLS))
for i in range(0, 40):
    S += np.dot((classified_data[i] - mean_per_class[i]).T,(classified_data[i] - me
S_inv = np.linalg.inv(S)
print("S shape:", S.shape)
print("S inv shape:", S_inv.shape)
```

```
S shape: (10304, 10304)
S inv shape: (10304, 10304)
```

In [ ]:
```
# Overall mean of classes
total_mean = np.mean(data_train ,axis=0)
print(total_mean.shape)
```

```
(10304,)
```

In [ ]:
```
# Between class matrix
B = np.zeros((COLS, COLS))
for i in range(40):
  B += 5 * np.dot( (mean_per_class[i] - total_mean).T , (mean_per_class[i] - total_
print(B.shape)
```

```
(10304, 10304)
```

In [ ]:
```
# Getting Eigen vectors and values
mat = np.dot(B,S_inv)
```

```
eig_values_LDA, eig_vectors_LDA = np.linalg.eigh(mat)
print(eig_vectors_LDA.shape)
```

```
(10304, 10304)
```

In [ ]:
```
# Limiting to 39 dimensions
idx = eig_values_LDA.argsort()[-39:][::-1]
sortedEigVectMatrixLDA = np.real(eig_vectors_LDA[:,idx])
```

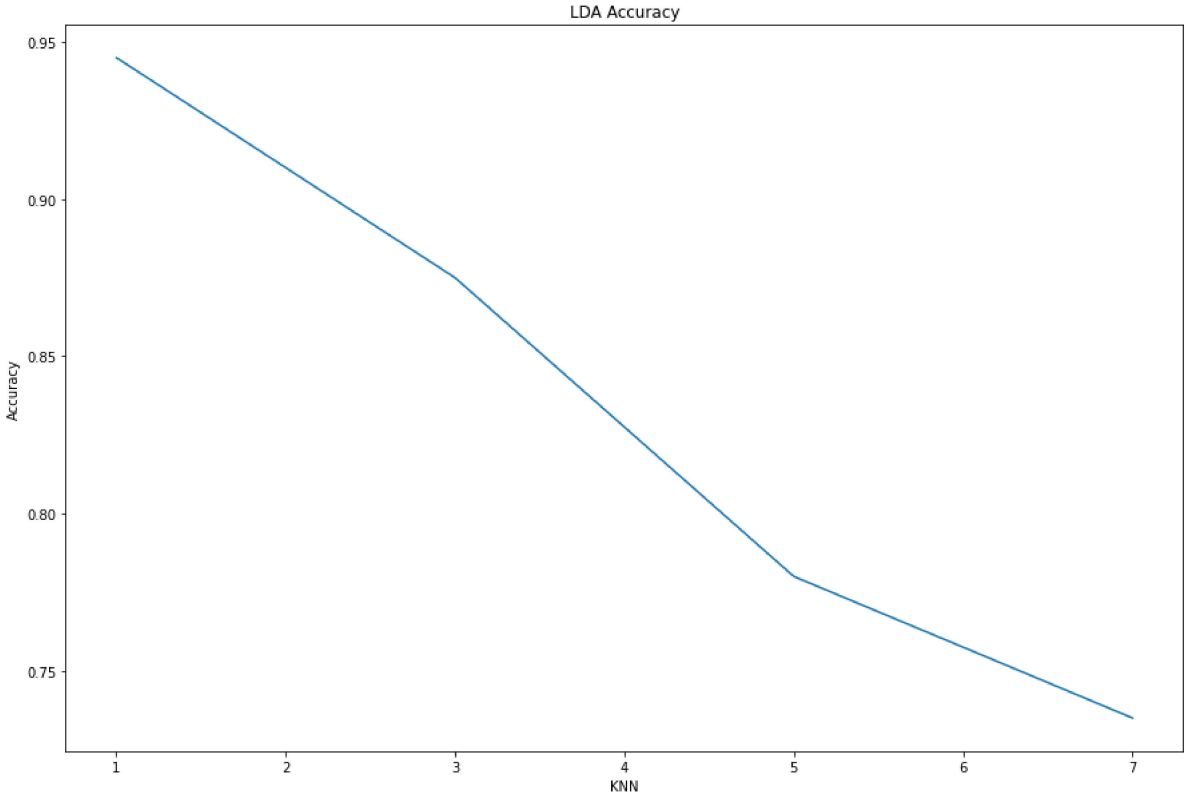
In [ ]:
```
# Getting the new train and test data
new_train_data = np.dot(data_train, sortedEigVectMatrixLDA)
new_test_data = np.dot(data_test, sortedEigVectMatrixLDA)
```

KNN - LDA

In [ ]:
```
# KNN for LDA function that takes return accuracy depending on number of neighbors
def KNNLDA(new_train_data, numberOfNeighors):
    knn_lda = KNeighborsClassifier(n_neighbors=numberOfNeighors)
    knn_lda.fit(new_train_data,labels_train)
    predicted_data = knn_lda.predict(new_test_data)
    accuracy = metrics.accuracy_score(labels_test, predicted_data)
    return accuracy
```

In [ ]:
```
# Appending Different Accuracies Depending On No. Of Neighbors
LDA_accuracy = []
for i in range(len(KNNS)):
    LDA_accuracy.append(KNNLDA(new_train_data, KNNS[i]))
```

In [ ]:
```
# Plotting Accuracies Vs KNN
plt.plot(KNNS, LDA_accuracy)
plt.xlabel('KNN')
plt.ylabel('Accuracy')
plt.title('LDA Accuracy')
plt.show()
```



Faces vs non faces

This dataset belongs to the Cifar-10 dataset that consists of airoplanes , boats , animals , etc...

UsingPCA

In [ ]:
```
# Loading non-faces data
# 4000 Picture of different objects
items = ['airplane','ship','truck','horse']
ROWS = 4000
#initiating vectors
data_nonfaces = [[0 for i in range(COLS)] for i in range(ROWS)]
for i in range(len(items)):
  for j in range(1000):
    img = Image.open('/' + nonfaces_path + '/' + items[i] + '/' + str(j+1).zfill(4
    img = img.convert('L')
    img = img.resize((92,112))
    # plt.imshow(img)
  # convert it to a matrix (vector)
    data_nonfaces[i*1000+j] = np.matrix(np.array(img).ravel())
```

In [ ]:
```
data_nonfaces = np.array(data_nonfaces)
labels_nonfaces = np.array([0 for i in range(ROWS)])
np.random.seed(42)
# Shuffling the non-faces data to mix the objects
np.random.shuffle(data_nonfaces)
```

In [ ]:
```
# Splitting the non-faces objects and labels into train and test
nonfaces_train = data_nonfaces.copy()[0:3800].reshape(3800, COLS)
nonfaces_test = data_nonfaces.copy()[3800::].reshape(200, COLS)
labels_nonfaces_train = labels_nonfaces.copy()[0:3800]
labels_nonfaces_test = labels_nonfaces.copy()[3800::]

print("nonfaces_train :", nonfaces_train.shape)
print("nonfaces_test :", nonfaces_test.shape)
print("labels_nonfaces_train : ", labels_nonfaces_train.shape)
print("labels_nonfaces_test : ", labels_nonfaces_test.shape)
```

```
nonfaces_train : (3800, 10304)
nonfaces_test : (200, 10304)
labels_nonfaces_train :  (3800,)
labels_nonfaces_test :  (200,)
```

In [ ]:
```
# A function plotting samples of success and faliure cases
def plot_case(data, labels, pred_labels, n):
  plt.rcParams["figure.figsize"] = [20.00, 5]
  fig, axs = plt.subplots(2, n)

  success_cases = np.where(labels == pred_labels)[0]
  failure_cases = np.where(labels != pred_labels)[0]
  np.random.shuffle(success_cases)
  np.random.shuffle(failure_cases)
  for i in range(0, n):
      axs[0, i].imshow(np.reshape(data[success_cases[i]], (112, 92)), cmap='gray')
```

```
        axs[0, i].set_title(f'True: {labels[success_cases[i]]}, Pred: {pred_labels[su
        axs[0, i].axis('off')
        axs[1, i].imshow(np.reshape(data[failure_cases[i]], (112, 92)), cmap='gray')
        axs[1, i].set_title(f'True: {labels[failure_cases[i]]}, Pred: {pred_labels[fa
        axs[1, i].axis('off')
    plt.show()
```

In [ ]:
```
# Knn function returns score and predicted labels and displays the confusion matrix
def knn(trainingSet, trainingLabel, testSet, testLabel, k):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(trainingSet, trainingLabel)
    pred = knn.predict(testSet)
    score = metrics.accuracy_score(testLabel, pred)
    confusion_matrix = metrics.confusion_matrix(testLabel, pred)
    cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_matrix
    cm_display.plot()
    return {
        "score":score,
        "pred":pred
        }
```

In [ ]:
```
# We will take samples from this data and concatenate with the faces
# 1 --> faces        0 --> non faces
no_of_non_face_samples = [50, 200, 500, 1000, 3000]
accuracy_0_8 = []
accuracy_0_85 = []
accuracy_0_9 = []
accuracy_0_95 = []
```

In [ ]:
```
# Adding non-faces to faces in test
test = np.concatenate((data_test, nonfaces_test), axis = 0)
labels = np.concatenate((np.full((200), 1), labels_nonfaces_test))
print("test size: ", test.shape)
print("test labels size: ", labels.shape)
```

```
test size:  (400, 10304)
test labels size:  (400,)
```

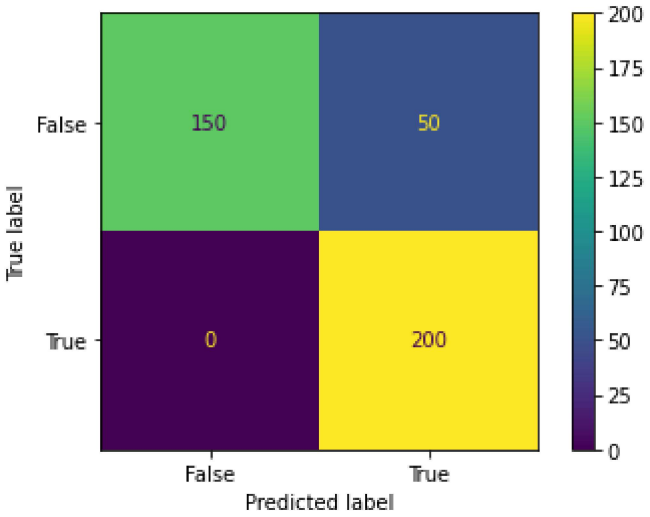
50 nonfaces

In [ ]:
```
# 50 non faces samples
label_train = np.concatenate((np.full((200), 1), labels_nonfaces_train[0:50]))
train200_50 = np.concatenate((data_train, nonfaces_train[0:50]) , axis = 0)

alphas = [0.8, 0.85, 0.9, 0.95]
pca50 = PCA(train200_50, test, alphas)
```

```
alphas_dim : [30, 44, 69, 117]
proj_mat0: (10304, 30)
Reduced_data_train0: (30, 250)
Reduced_data_test0: (30, 400)
proj_mat1: (10304, 44)
Reduced_data_train1: (44, 250)
Reduced_data_test1: (44, 400)
proj_mat2: (10304, 69)
Reduced_data_train2: (69, 250)
Reduced_data_test2: (69, 400)
proj_mat3: (10304, 117)
Reduced_data_train3: (117, 250)
Reduced_data_test3: (117, 400)
```

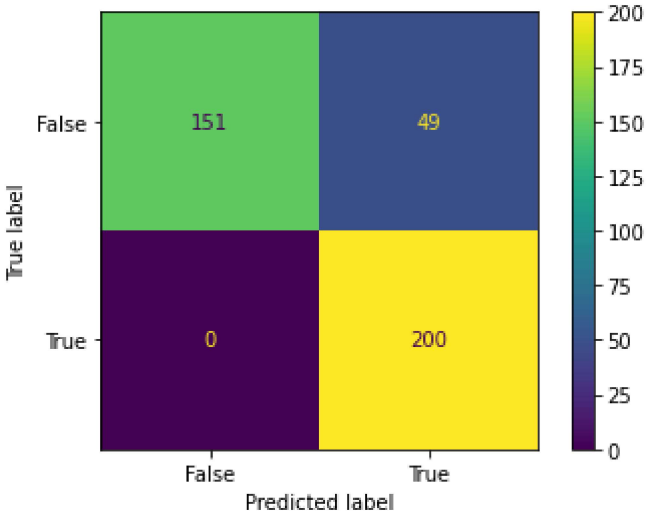
In [ ]:
```
knn50 = knn(pca50["reduced_data_train"][0].T ,label_train ,pca50["reduced_data_tes
accuracy_0_8.append(knn50["score"])
print(knn50["score"])
```

```
0.875
```



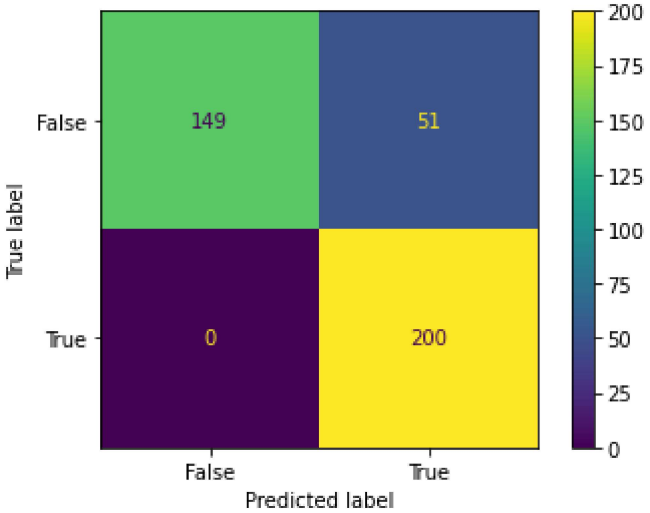
In [ ]:
```
knn50 = knn(pca50["reduced_data_train"][1].T ,label_train ,pca50["reduced_data_tes
accuracy_S.append(knn50["score"])
print(knn50["score"])
```

```
0.8775
```



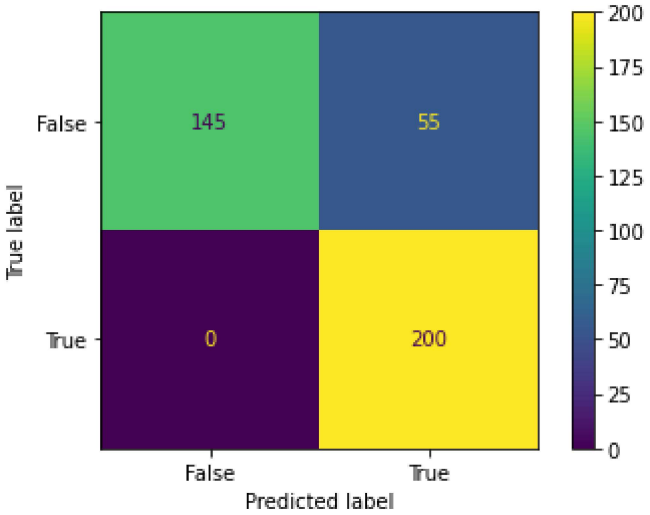
In [ ]:
```
knn50 = knn(pca50["reduced_data_train"][2].T ,label_train ,pca50["reduced_data_tes
accuracy_0_9.append(knn50["score"])
print(knn50["score"])
```

```
0.8725
```

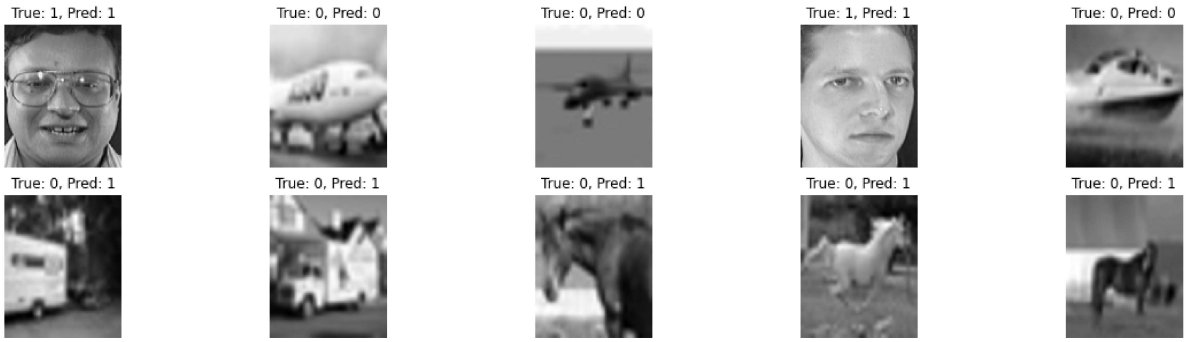


In [ ]:
```
knn50 = knn(pca50["reduced_data_train"][3].T ,label_train ,pca50["reduced_data_tes
accuracy_0_95.append(knn50["score"])
print(knn50["score"])
```

```
0.8625
```



In [ ]:
```
plot_case(test,labels, knn50["pred"], 5)
```



200 nonfaces

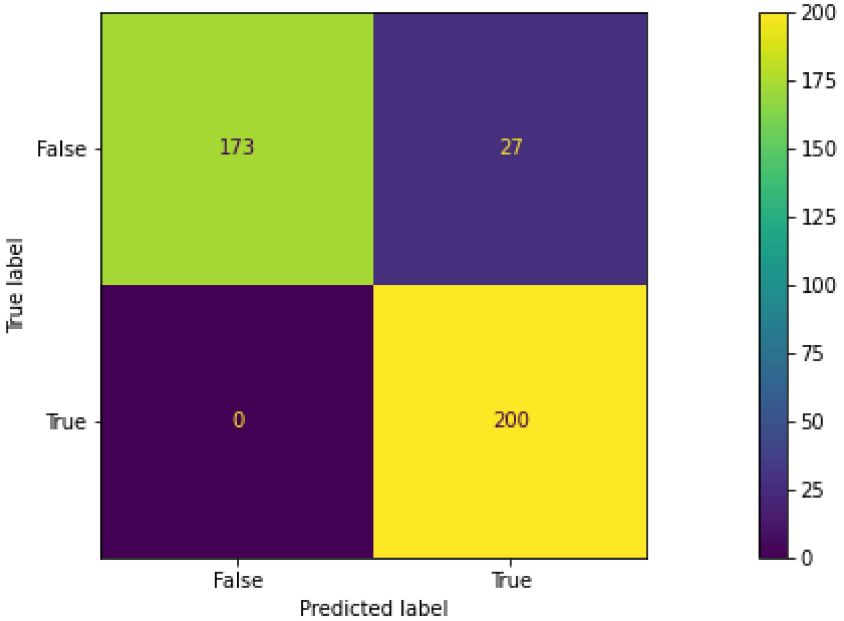
In [ ]:
```
# 200 non faces samples
label_train = np.concatenate((np.full((200), 1), labels_nonfaces_train[0:200]))
train200_200 = np.concatenate((data_train, nonfaces_train[0:200]) , axis = 0)

pca200 = PCA(train200_200, test, alphas)
```

```
alphas_dim : [24, 37, 61, 117]
proj_mat0: (10304, 24)
Reduced_data_train0: (24, 400)
Reduced_data_test0: (24, 400)
proj_mat1: (10304, 37)
Reduced_data_train1: (37, 400)
Reduced_data_test1: (37, 400)
proj_mat2: (10304, 61)
Reduced_data_train2: (61, 400)
Reduced_data_test2: (61, 400)
proj_mat3: (10304, 117)
Reduced_data_train3: (117, 400)
Reduced_data_test3: (117, 400)
```

In [ ]:

```
knn200 = knn(pca200["reduced_data_train"][0].T ,label_train ,pca200["reduced_data_
accuracy_0_8.append(knn200["score"])
print(knn200["score"])
```

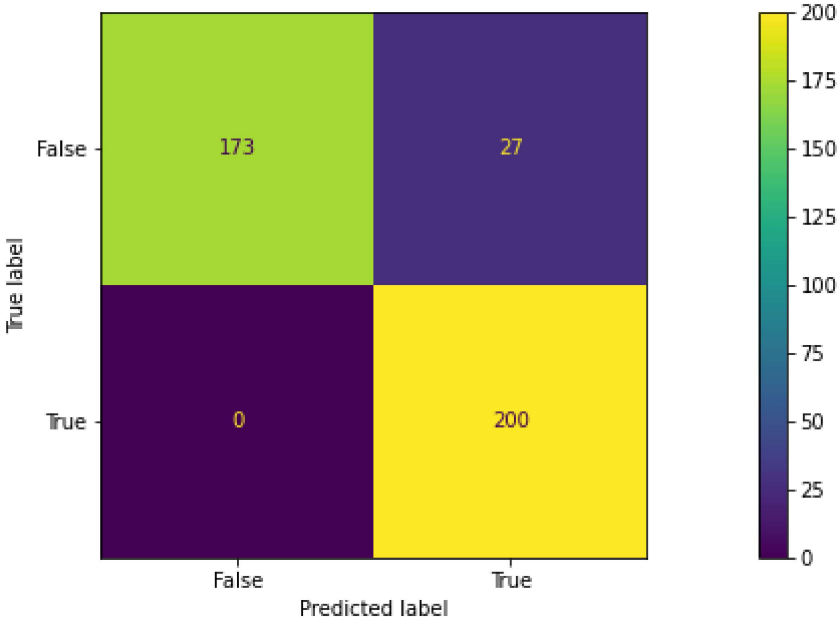
```
0.9325
```



In [ ]:

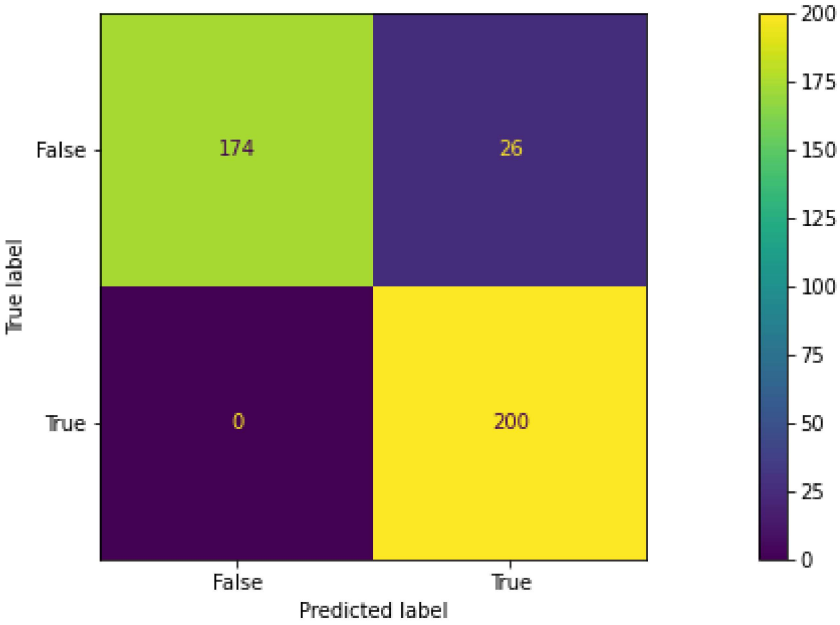
```
knn200 = knn(pca200["reduced_data_train"][1].T ,label_train ,pca200["reduced_data_
accuracy_0_85.append(knn200["score"])
print(knn200["score"])
```

```
0.9325
```



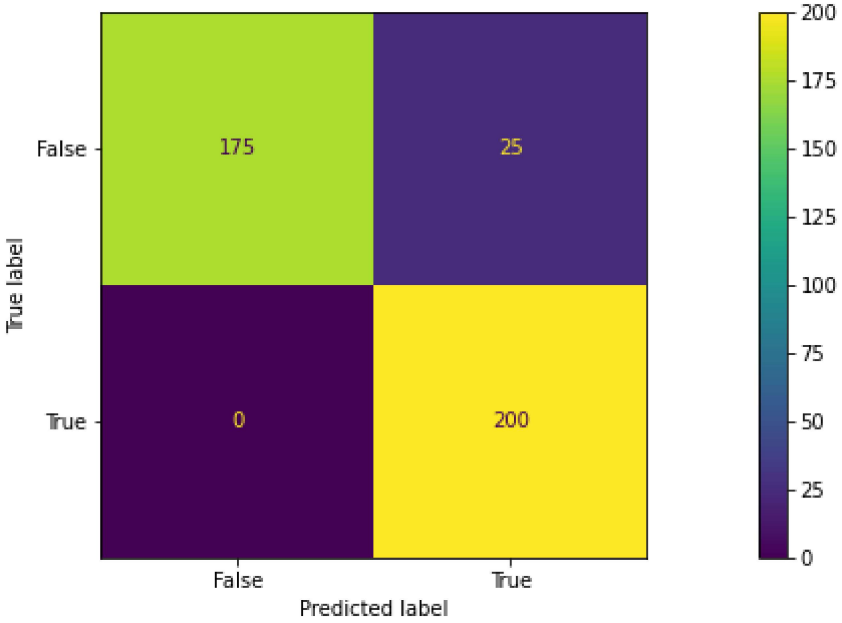
In [ ]:
```
knn200 = knn(pca200["reduced_data_train"][2].T ,label_train ,pca200["reduced_data_
accuracy_0_9.append(knn200["score"])
print(knn200["score"])
```

```
0.935
```

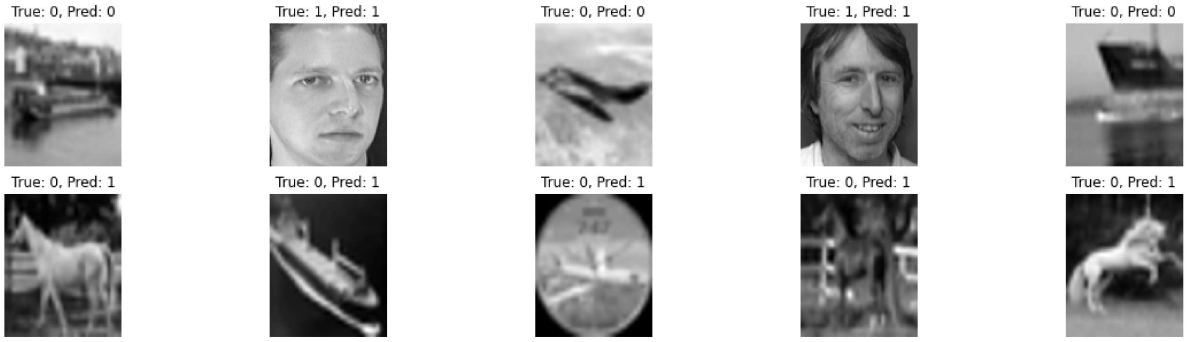


In [ ]:
```
knn200 = knn(pca200["reduced_data_train"][3].T ,label_train ,pca200["reduced_data_
accuracy_0_95.append(knn200["score"])
print(knn200["score"])
```

```
0.9375
```



In [ ]:
```
plot_case(test,labels, knn200["pred"], 5)
```



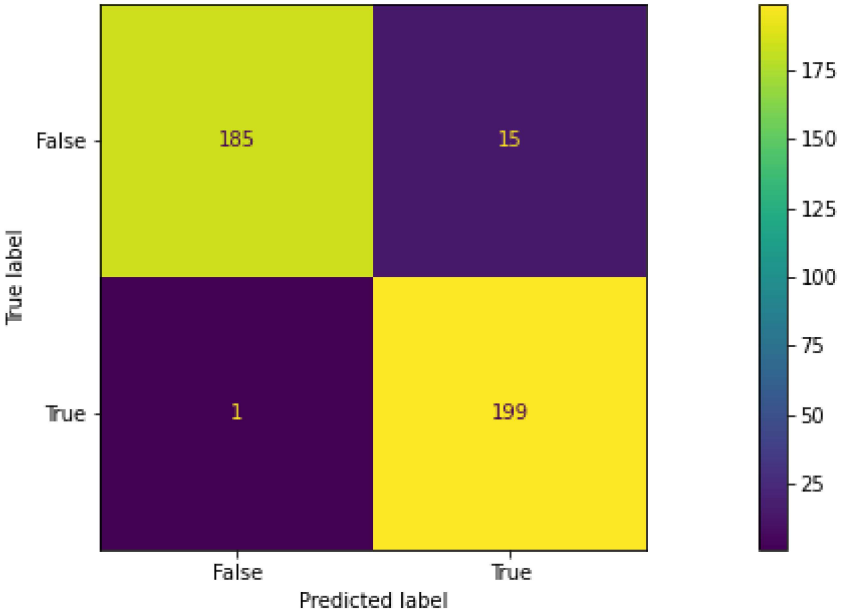
500 nonfaces

In [ ]:
```
# 500 non faces samples
label_train = np.concatenate((np.full((200), 1), labels_nonfaces_train[0:500]))
train200_500 = np.concatenate((data_train, nonfaces_train[0:500]) , axis = 0)

pca500 = PCA(train200_500, test, alphas)
```

```
alphas_dim : [24, 38, 64, 125]
proj_mat0: (10304, 24)
Reduced_data_train0: (24, 700)
Reduced_data_test0: (24, 400)
proj_mat1: (10304, 38)
Reduced_data_train1: (38, 700)
Reduced_data_test1: (38, 400)
proj_mat2: (10304, 64)
Reduced_data_train2: (64, 700)
Reduced_data_test2: (64, 400)
proj_mat3: (10304, 125)
Reduced_data_train3: (125, 700)
Reduced_data_test3: (125, 400)
```

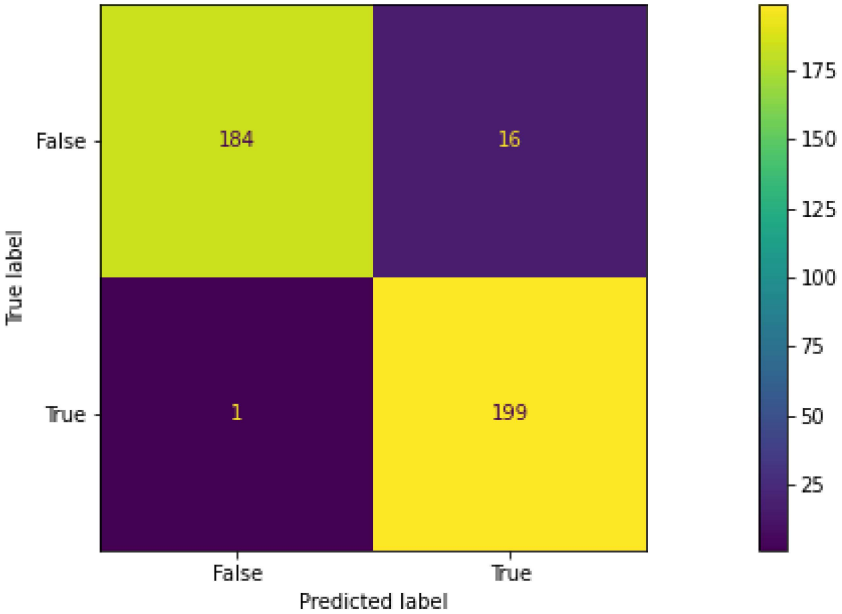
In [ ]:
```
knn500 = knn(pca500["reduced_data_train"][0].T ,label_train ,pca500["reduced_data_
accuracy_0_8.append(knn500["score"])
print(knn500["score"])
```

```
0.96
```



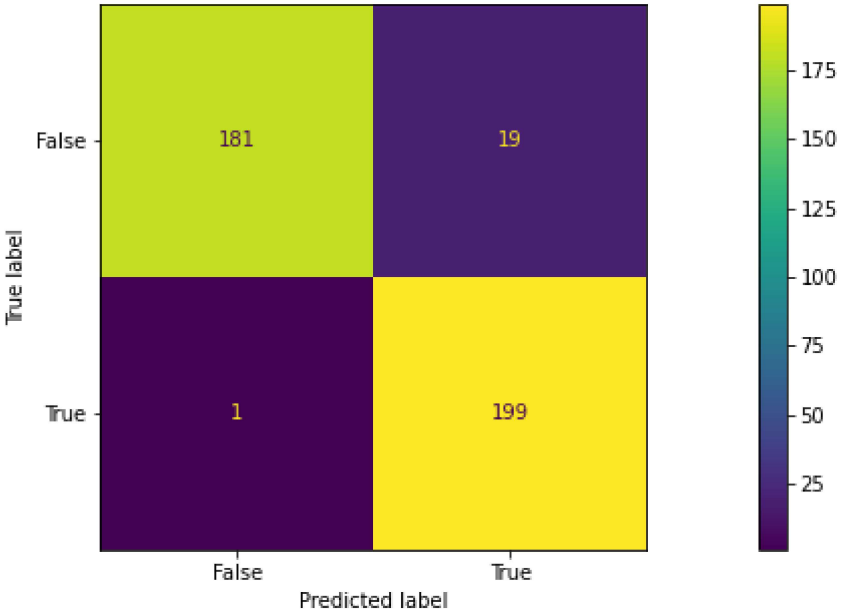
In [ ]:
```
knn500 = knn(pca500["reduced_data_train"][1].T ,label_train ,pca500["reduced_data_
accuracy_0_85.append(knn500["score"])
print(knn500["score"])
```

```
0.9575
```



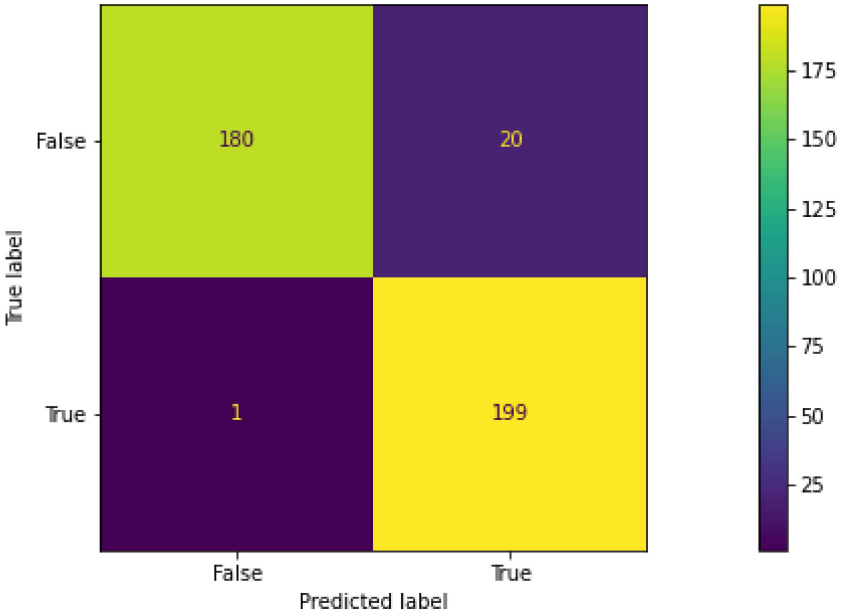
In [ ]:
```
knn500 = knn(pca500["reduced_data_train"][2].T ,label_train ,pca500["reduced_data_
accuracy_0_9.append(knn500["score"])
print(knn500["score"])
```

```
0.95
```

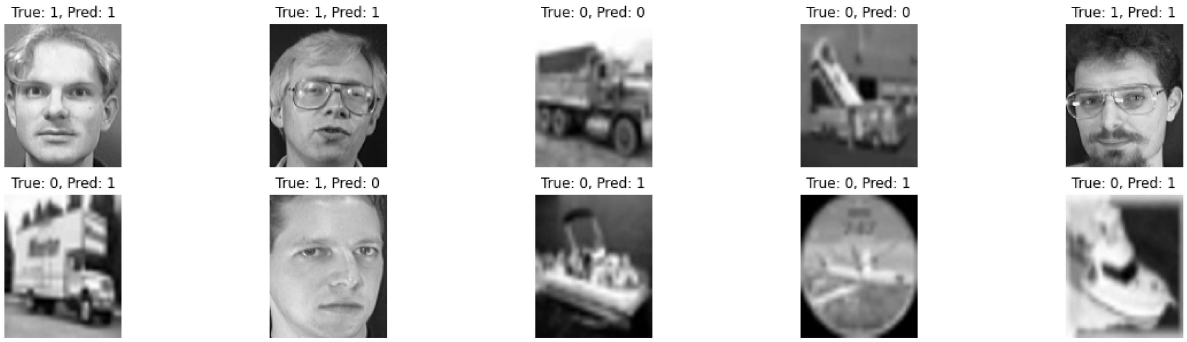


In [ ]:
```
knn500 = knn(pca500["reduced_data_train"][3].T ,label_train ,pca500["reduced_data_
accuracy_0_95.append(knn500["score"])
print(knn500["score"])
```

```
0.9475
```



In [ ]:
```
plot_case(test,labels, knn500["pred"], 5)
```



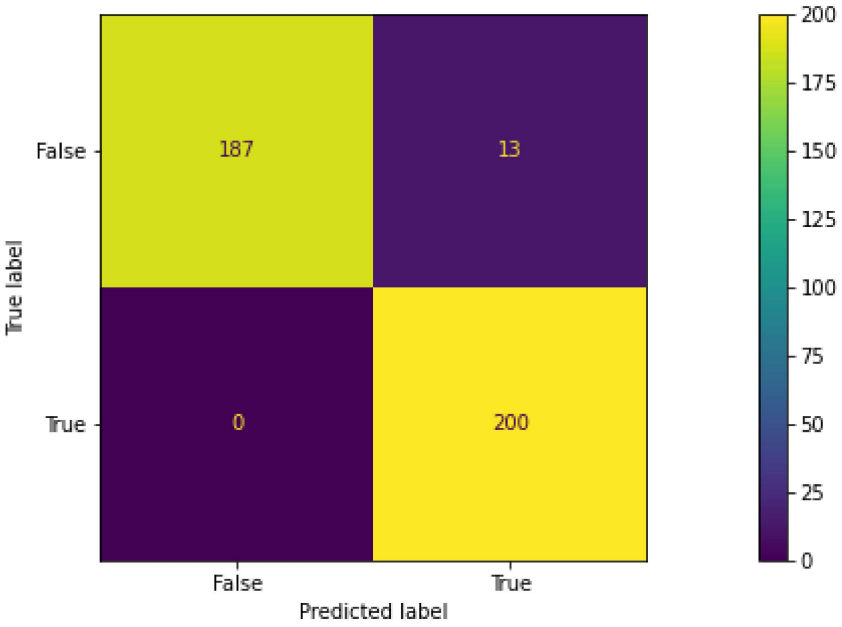
1000 nonfaces

In [ ]:
```
# 1000 non faces samples
label_train = np.concatenate((np.full((200), 1), labels_nonfaces_train[0:1000]))
train200_1000 = np.concatenate((data_train, nonfaces_train[0:1000]) , axis = 0)

pca1000 = PCA(train200_1000, test, alphas)
```

```
alphas_dim : [24, 38, 65, 130]
proj_mat0: (10304, 24)
Reduced_data_train0: (24, 1200)
Reduced_data_test0: (24, 400)
proj_mat1: (10304, 38)
Reduced_data_train1: (38, 1200)
Reduced_data_test1: (38, 400)
proj_mat2: (10304, 65)
Reduced_data_train2: (65, 1200)
Reduced_data_test2: (65, 400)
proj_mat3: (10304, 130)
Reduced_data_train3: (130, 1200)
Reduced_data_test3: (130, 400)
```

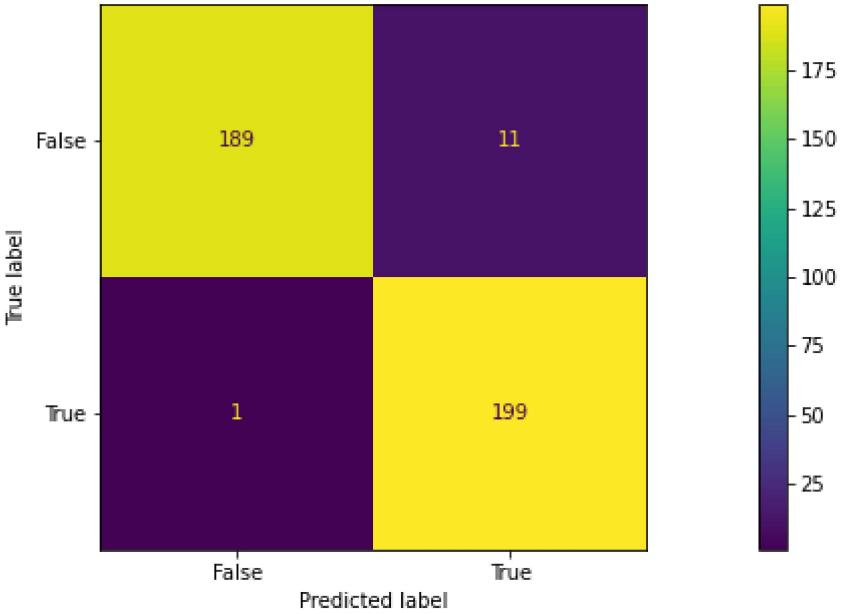
In [ ]:
```
knn1000 = knn(pca1000["reduced_data_train"][0].T ,label_train ,pca1000["reduced_da
accuracy_0_8.append(knn1000["score"])
print(knn1000["score"])
```

```
0.9675
```



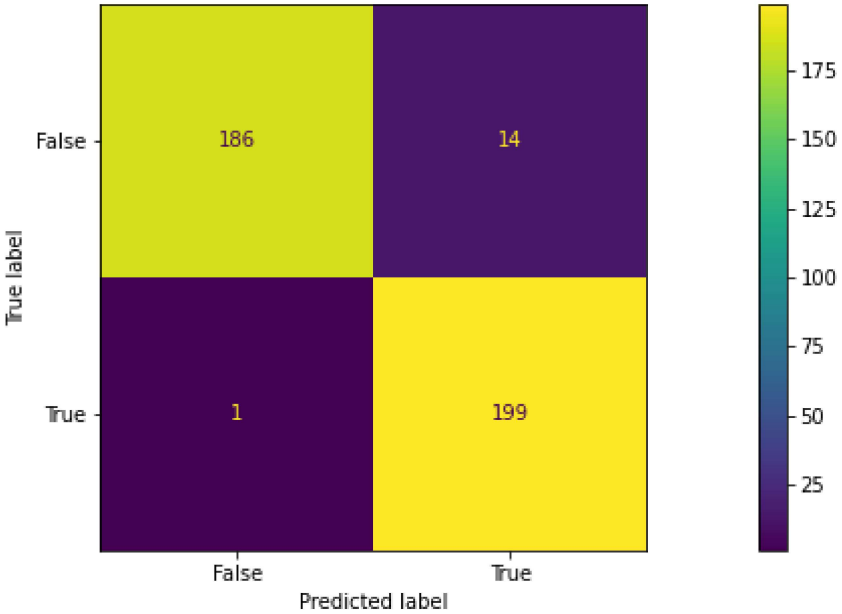
In [ ]:
```
knn1000 = knn(pca1000["reduced_data_train"][1].T ,label_train ,pca1000["reduced_da
accuracy_0_85.append(knn1000["score"])
print(knn1000["score"])
```

```
0.97
```



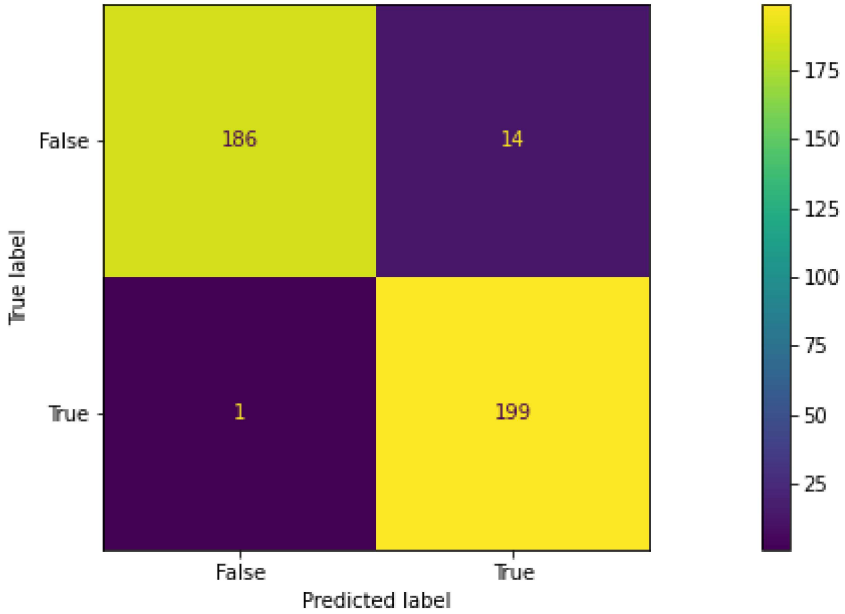
In [ ]:
```
knn1000 = knn(pca1000["reduced_data_train"][2].T ,label_train ,pca1000["reduced_da
accuracy_0_9.append(knn1000["score"])
print(knn1000["score"])
```

```
0.9625
```

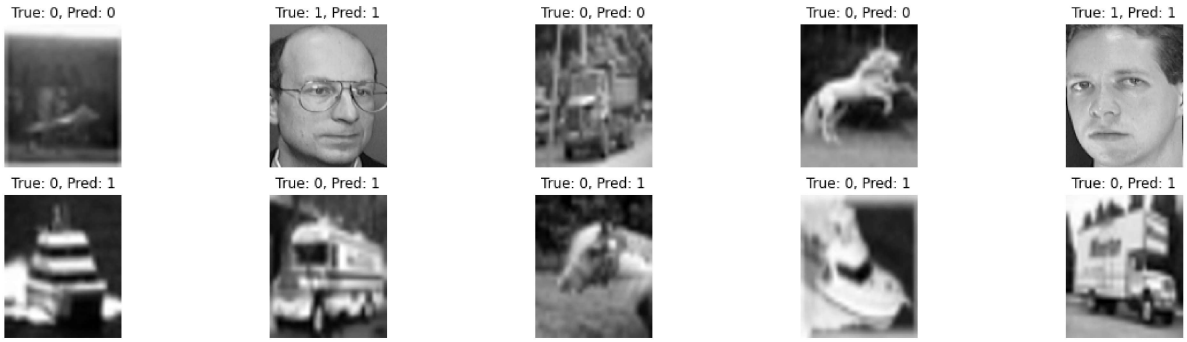


In [ ]:
```
knn1000 = knn(pca1000["reduced_data_train"][3].T ,label_train ,pca1000["reduced_da
accuracy_0_95.append(knn1000["score"])
print(knn1000["score"])
```

```
0.9625
```



In [ ]:
```
plot_case(test,labels, knn1000["pred"], 5)
```



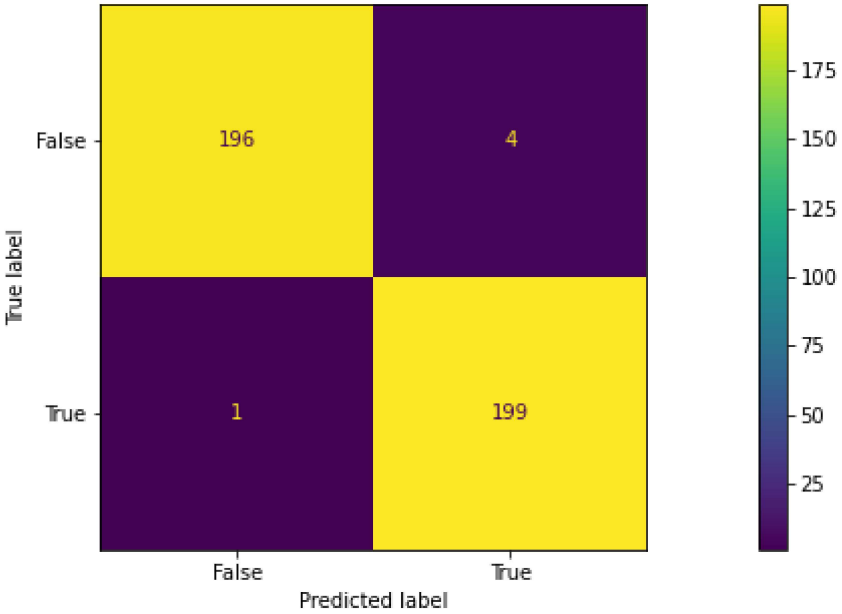
3000 nonfaces

In [ ]:
```
# 3000 non faces samples
label_train = np.concatenate((np.full((200), 1), labels_nonfaces_train[0:3000]))
train200_3000 = np.concatenate((data_train,nonfaces_train[0:3000]) , axis = 0)

pca3000 = PCA(train200_3000, test, alphas)
```

```
alphas_dim : [25, 39, 67, 134]
proj_mat0: (10304, 25)
Reduced_data_train0: (25, 3200)
Reduced_data_test0: (25, 400)
proj_mat1: (10304, 39)
Reduced_data_train1: (39, 3200)
Reduced_data_test1: (39, 400)
proj_mat2: (10304, 67)
Reduced_data_train2: (67, 3200)
Reduced_data_test2: (67, 400)
proj_mat3: (10304, 134)
Reduced_data_train3: (134, 3200)
Reduced_data_test3: (134, 400)
```

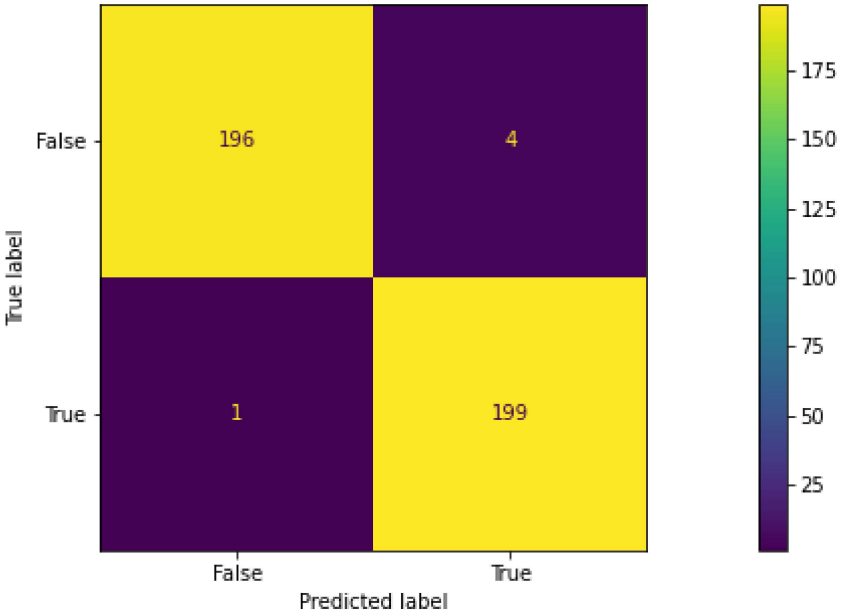
In [ ]:
```
knn3000 = knn(pca3000["reduced_data_train"][0].T ,label_train ,pca3000["reduced_da
accuracy_0_8.append(knn3000["score"])
print(knn3000["score"])
```

```
0.9875
```



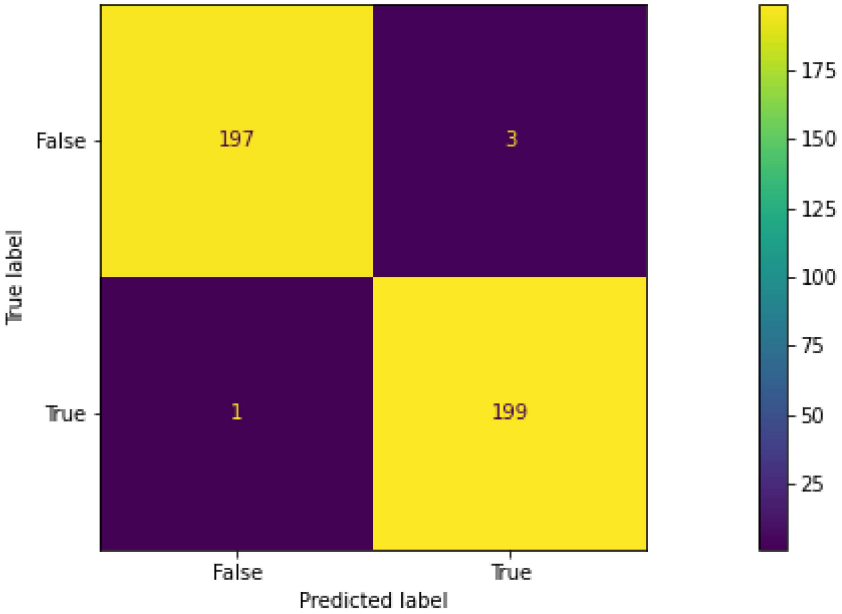
In [ ]:
```
knn3000 = knn(pca3000["reduced_data_train"][1].T ,label_train ,pca3000["reduced_da
accuracy_0_85.append(knn3000["score"])
print(knn3000["score"])
```

```
0.9875
```



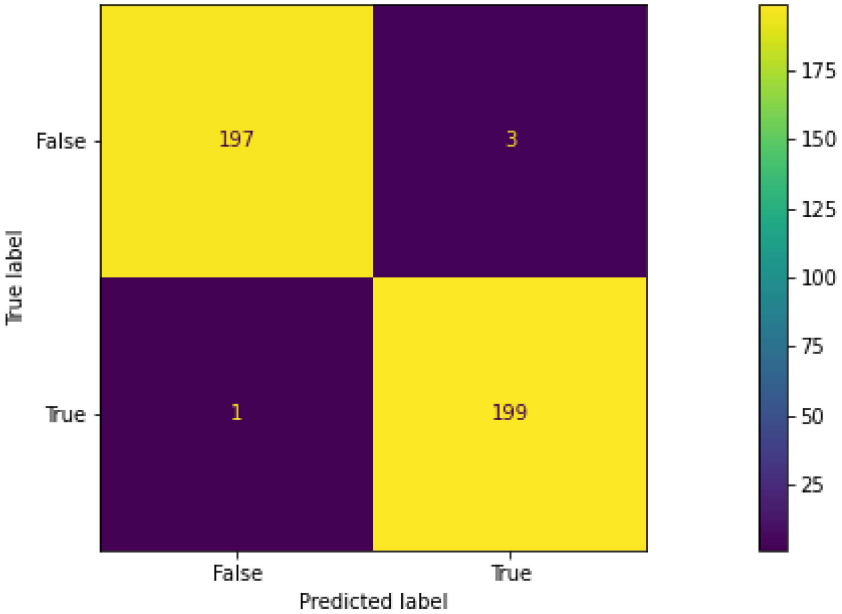
In [ ]:
```
knn3000 = knn(pca3000["reduced_data_train"][2].T ,label_train ,pca3000["reduced_da
accuracy_0_9.append(knn3000["score"])
print(knn3000["score"])
```

```
0.99
```



In [ ]:
```
knn3000 = knn(pca3000["reduced_data_train"][3].T ,label_train ,pca3000["reduced_da
accuracy_0_95.append(knn3000["score"])
print(knn3000["score"])
```

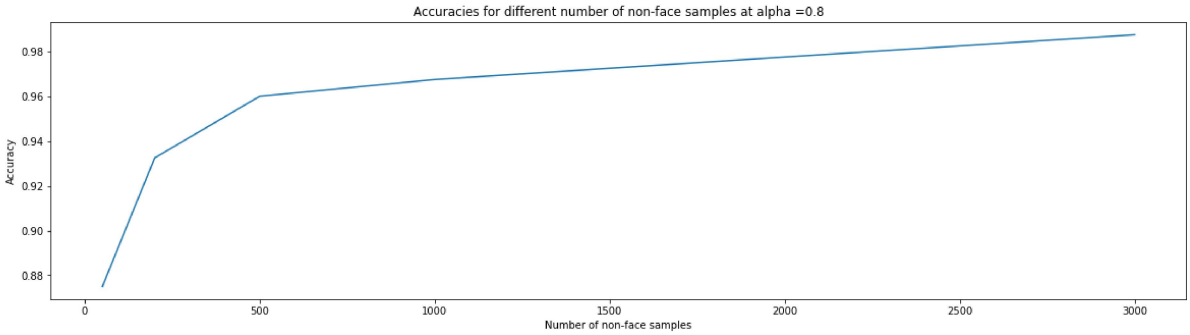
```
0.99
```



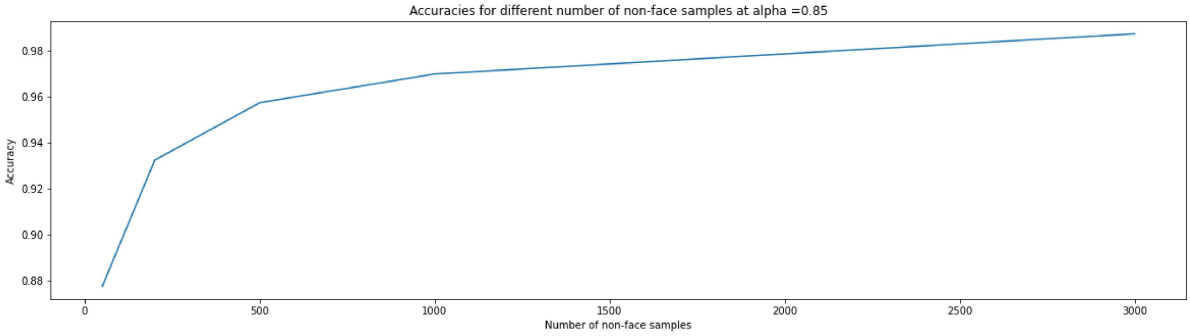
In [ ]:
```
plot_case(test,labels, knn3000["pred"], 4)
```

Plots

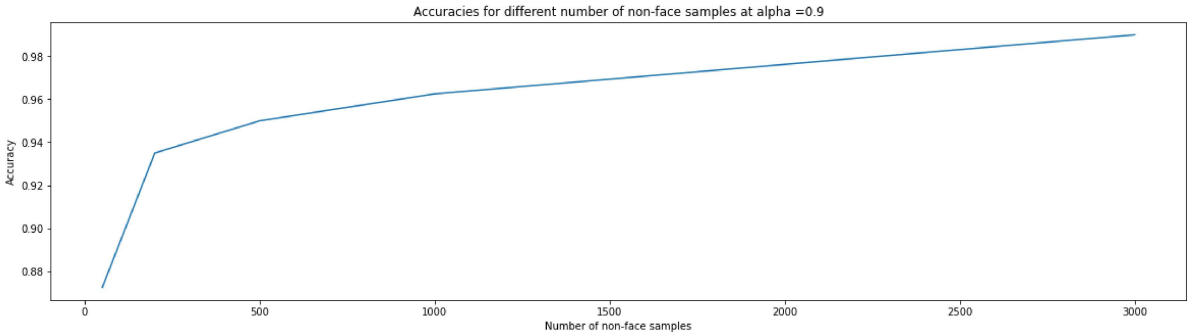
In [ ]:
```
x = [50,200,500,1000,3000]
y = accuracy_0_8
plt.plot(x, y)
plt.xlabel('Number of non-face samples')
plt.ylabel('Accuracy')
plt.title('Accuracies for different number of non-face samples at alpha =0.8')
plt.show()
```



In [ ]:
```
x = [50,200,500,1000,3000]
y = accuracy_0_85
plt.plot(x,y)
plt.xlabel('Number of non-face samples')
plt.ylabel('Accuracy')
plt.title('Accuracies for different number of non-face samples at alpha =0.85')
plt.show()
```

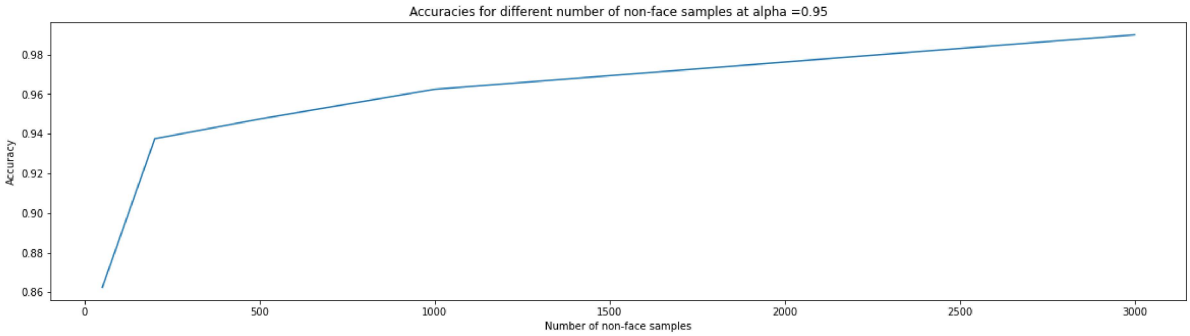


In [ ]:
```
x = [50,200,500,1000,3000]
y = accuracy_0_9
plt.plot(x,y)
plt.xlabel('Number of non-face samples')
plt.ylabel('Accuracy')
plt.title('Accuracies for different number of non-face samples at alpha =0.9')
plt.show()
```



In [ ]:
```
x = [50,200,500,1000,3000]
y = accuracy_0_95
plt.plot(x,y)
plt.xlabel('Number of non-face samples')
```

```
plt.ylabel('Accuracy')
plt.title('Accuracies for different number of non-face samples at alpha =0.95')
plt.show()
```



Using LDA

In [ ]:
```
# Function that assigns how many number of non-faces to 200 face in train set
def splitting_fVnf(sizeOfNonFaces):
  data_fVnf_train = np.concatenate((data_train.copy(), nonfaces_train.copy()[0: si
  labels_fVnf_train = np.concatenate((np.full((200), 1), labels_nonfaces_train[0: 
  return data_fVnf_train, test, labels_fVnf_train, labels
```

In [ ]:
```
# Initializations
data_fVnf_train = [0 for i in range(5)]
data_fVnf_test = [0 for i in range(5)]
labels_fVnf_train = [0 for i in range(5)]
labels_fVnf_test = [0 for i in range(5)]
new_train_data_fVnf = [0 for i in range(5)]
new_test_data_fVnf = [0 for i in range(5)]

accuracy = [0 for i in range(5)]
predicted_data = [0 for i in range(5)]
```

LDA-TEST

In [ ]:
```
# LDA using one dimension and returns the new train and test data
def LDAfVnf(data_fVnf_train,data_fVnf_test):
  classified_fVnf_data = np.split(data_fVnf_train,2)
  mean_per_class = np.mean(classified_fVnf_data , axis=1)
  # Within class matrix
  S = np.zeros((10304,10304))
  for i in range(2):
      S += np.dot((classified_fVnf_data[i] - mean_per_class[i]).T,(classified_fVnf_
  S_inv = np.linalg.inv(S)
  #overall mean of classes
  total_mean = np.mean(data_train ,axis=0)
  B = np.dot((mean_per_class[0] - mean_per_class[1]).T , (mean_per_class[0] - mean_
  mat = np.dot(B,S_inv)
  eig_values_LDA,eig_vectors_LDA = np.linalg.eigh(mat)
  idx = eig_values_LDA.argsort()[-1:][::-1]
  sortedEigVectMatrixLDA = np.real(eig_vectors_LDA[:,idx])
  new_train_data_fVnf = np.dot(data_fVnf_train,sortedEigVectMatrixLDA)
  new_test_data_fVnf = np.dot(data_fVnf_test,sortedEigVectMatrixLDA)
  return new_train_data_fVnf,new_test_data_fVnf

# KNN for LDA faces vs non-faces Returns accuracy and predicted data
def KNN_LDA_NONFACES (new_train_data_fVnf,new_test_data_fVnf,labels_fVnf_train,labe
  knn_lda = KNeighborsClassifier(n_neighbors=1)
```

```
  knn_lda.fit(new_train_data_fVnf,labels_fVnf_train)
  predicted_data = knn_lda.predict(new_test_data_fVnf)
  Accuracy = metrics.accuracy_score(labels_fVnf_test, predicted_data)
  return Accuracy,predicted_data
```

Calculating LDA For All Splits

In [ ]:
```
'''
no_of_non_face_samples = [50,200,500,1000,3000]
0 --> 50-200 split
1 --> 200-200 split
2 --> 500-200 split
3 --> 1000-200 split
4 --> 3000-200 split
'''
for i in range(len(no_of_non_face_samples)):
  data_fVnf_train[i], data_fVnf_test[i], labels_fVnf_train[i], labels_fVnf_test[i]
  new_train_data_fVnf[i], new_test_data_fVnf[i] = LDAfVnf(data_fVnf_train[i],data_
  print('Split No:',i,'\n',no_of_non_face_samples[i],'- 200 -------------- Done')
```

```
Split No: 0
 50 - 200 -------------- Done
Split No: 1
 200 - 200 -------------- Done
Split No: 2
 500 - 200 -------------- Done
Split No: 3
 1000 - 200 -------------- Done
Split No: 4
 3000 - 200 -------------- Done
```

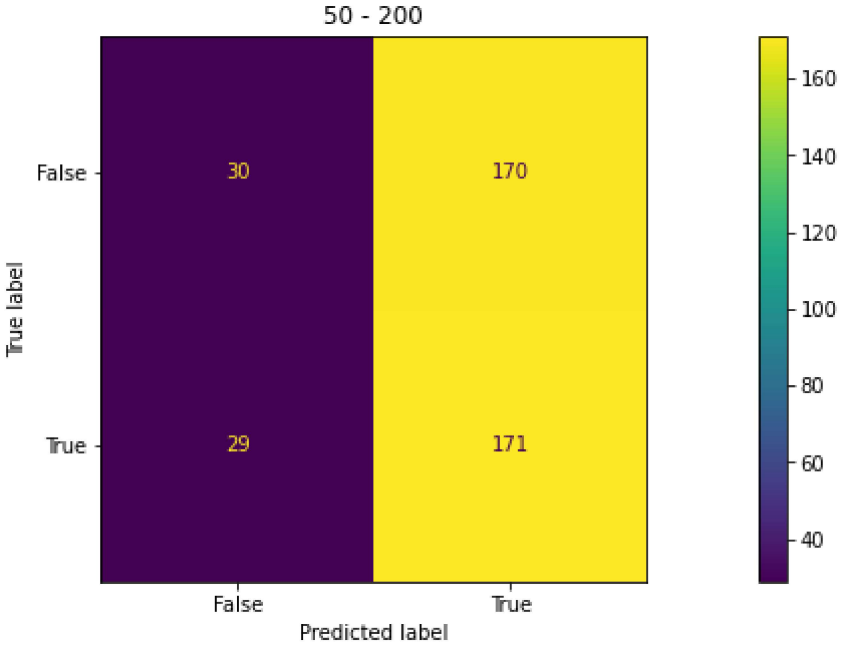
Calculate Accuracy And Predicted Data For All Splits

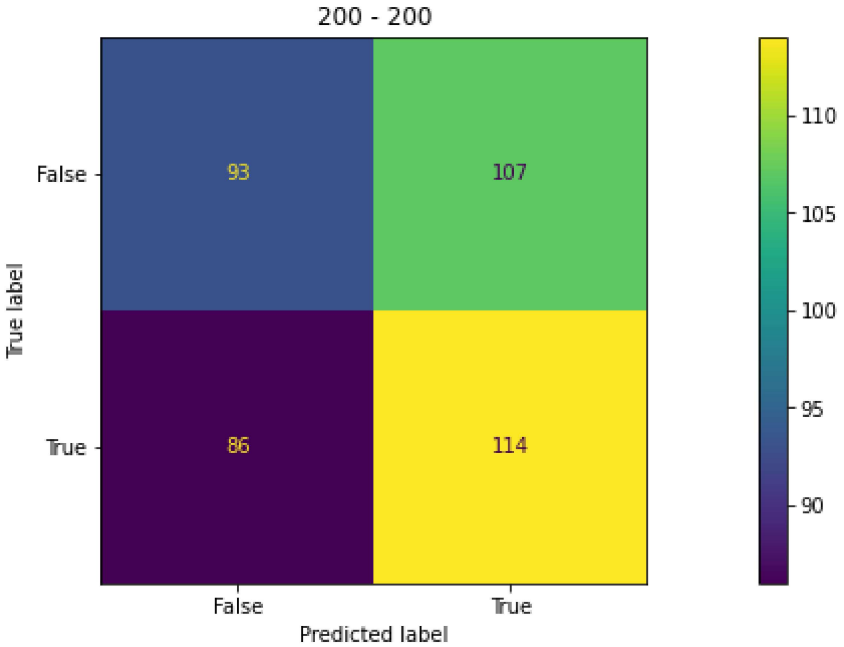
In [ ]:
```
# Calculating Accuracies and Predicted data for different ratios of splits
for i in range(len(no_of_non_face_samples)):
  accuracy[i],predicted_data[i] = KNN_LDA_NONFACES(new_train_data_fVnf[i],new_test_
  print('Accuracy',no_of_non_face_samples[i],'- 200:',accuracy[i]*100,'%')
```

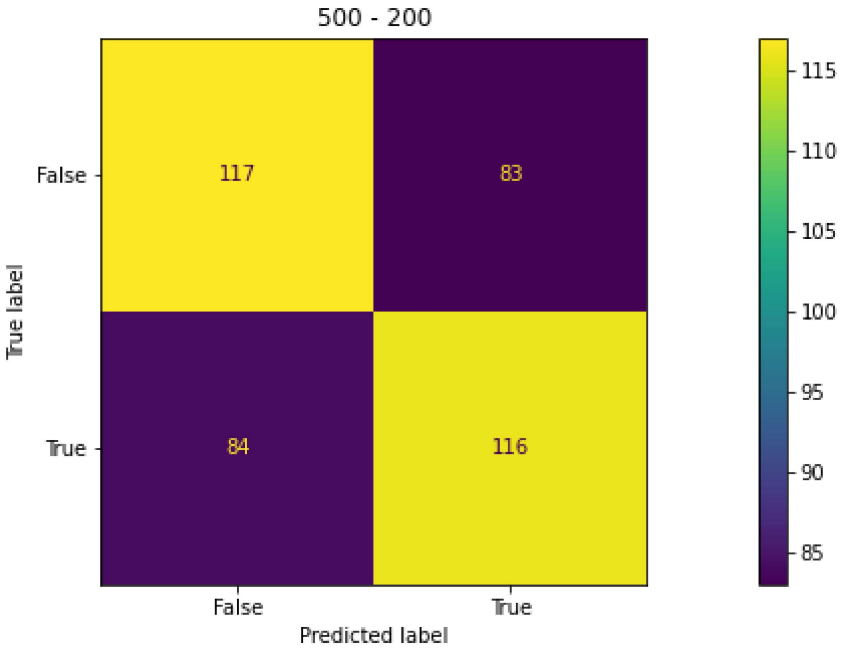
```
Accuracy 50 - 200: 50.24999999999999 %
Accuracy 200 - 200: 51.74999999999999 %
Accuracy 500 - 200: 58.25 %
Accuracy 1000 - 200: 84.25 %
Accuracy 3000 - 200: 91.75 %
```

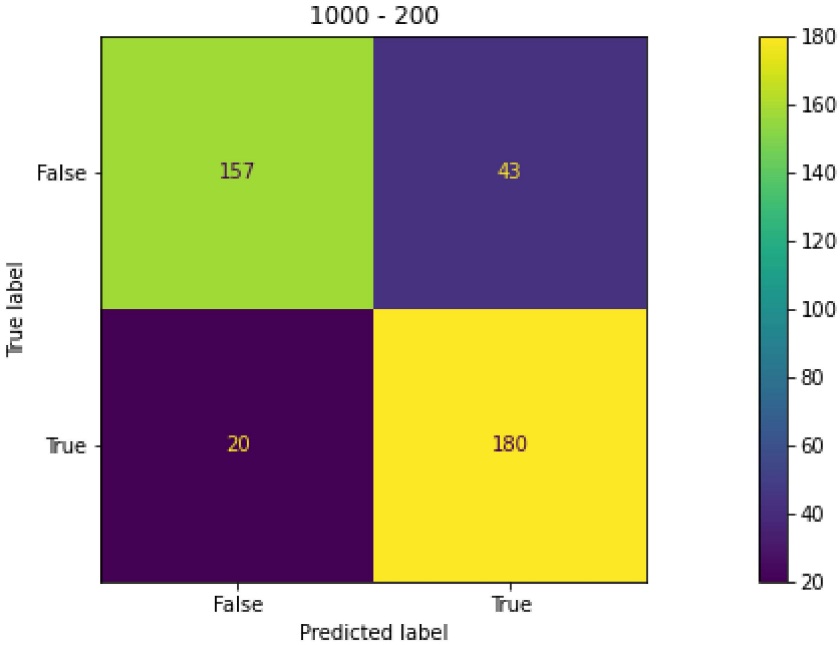
Confusion Matrix

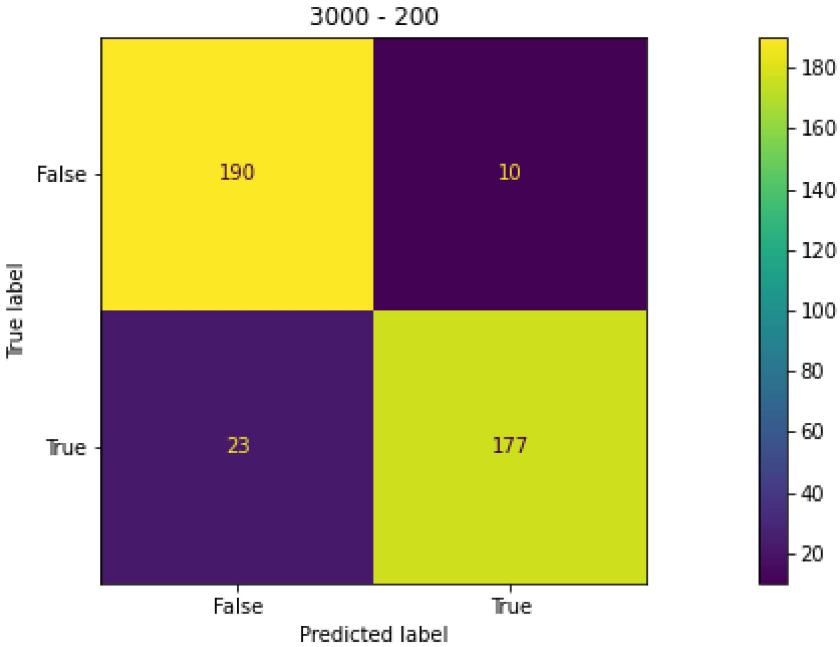
In [ ]:
```
# Displaying Confusion Matrix For All The Ratios
for i in range(len(no_of_non_face_samples)):
  confusion_matrix = metrics.confusion_matrix(labels_fVnf_test[i], predicted_data[
  cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_matrix,
  cm_display.plot()
  plt.title(f'{no_of_non_face_samples[i]} - 200')
  plt.show()
```


50 - 200
False
True
True label
30
170
29
171
False
True
Predicted label
160
140
120
100
80
60
40

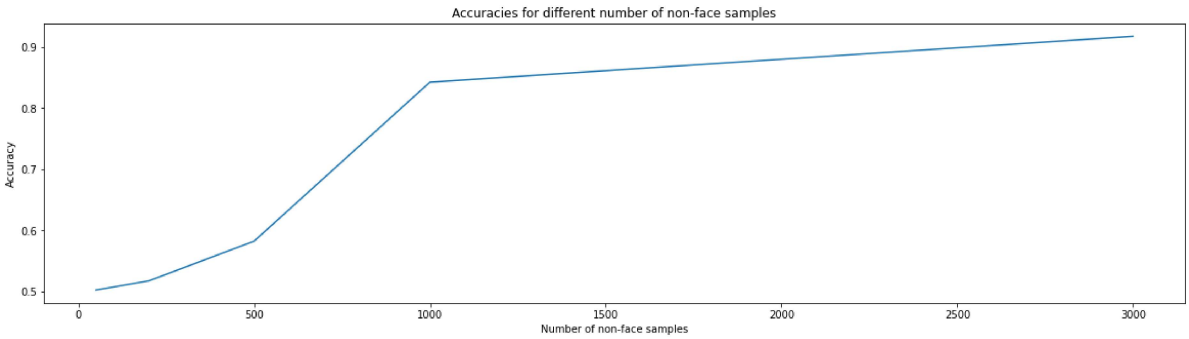

200 - 200
False
True
True label
93
107
86
114
False
True
Predicted label
110
105
100
95
90


500 - 200
False
True
True label
117
83
84
116
False
True
Predicted label
115
110
105
100
95
90
85

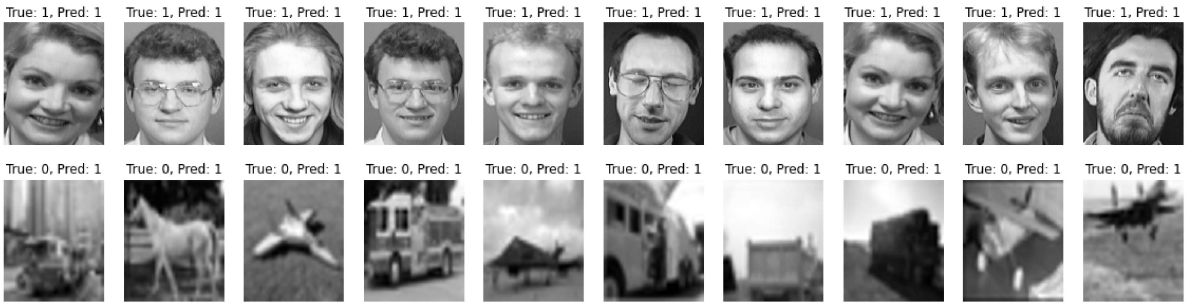




In [ ]:
```
# Plotting Different Number Of Non-Faces Samples With Accuracies
plt.plot(no_of_non_face_samples, accuracy)
plt.xlabel('Number of non-face samples')
plt.ylabel('Accuracy')
plt.title('Accuracies for different number of non-face samples')
plt.show()
```

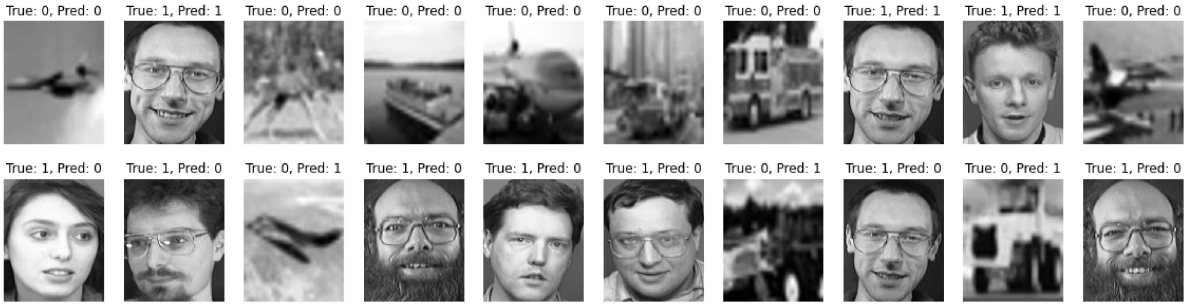


In [ ]:
```
# Accuracy 50 - 200: 50.24 %
plot_case(data_fVnf_test[0], labels_fVnf_test[0], predicted_data[0], 10)
```



In [ ]:
```
# Accuracy 1000 - 200: 84.25 %
plot_case(data_fVnf_test[0], labels_fVnf_test[3], predicted_data[3], 10)
```

In [ ]:
```
# Accuracy 3000 - 200: 91.75 %
plot_case(data_fVnf_test[0], labels_fVnf_test[4], predicted_data[4], 10)
```



BONUS

Variations of PCA

In [ ]:
```
# Importing Different Variations of PCA
from sklearn.decomposition import PCA as ORIG_PCA, KernelPCA, IncrementalPCA
```

PCA:

In [ ]:
```
# Original PCA
orig_pca = ORIG_PCA(n_components = pca["alphas_dim"][-1])
orig_pca.fit(data_train)
data_train_pca = orig_pca.transform(data_train)
data_test_pca = orig_pca.transform(data_test)
```

In [ ]:
```
# Original PCA Accuracy
knn_pca = KNeighborsClassifier(n_neighbors=5)
knn_pca.fit(data_train_pca, labels_train)
```

```
pca_accuracy = knn_pca.score(data_test_pca, labels_test)

print(f"PCA Accuracy: {pca_accuracy:.4f}")
```

```
PCA Accuracy: 0.8450
```

RANDOMIZED PCA:

The classical PCA uses the low-rank matrix approximation to estimate the principal components this method becomes costly and makes the whole process difficult to scale for large datasets.

By randomizing how the singular value decomposition of the dataset happens. we can approximate the first K principal components quickly than classical PCA.

In [ ]:
```
# Randomized PCA
rpca = ORIG_PCA(n_components =  pca["alphas_dim"][-1], svd_solver='randomized')
rpca.fit(data_train)
data_train_rpca = rpca.transform(data_train)
data_test_rpca = rpca.transform(data_test)
```

In [ ]:
```
# Randomized PCA Accuracy
knn_rpca = KNeighborsClassifier(n_neighbors=5)
knn_rpca.fit(data_train_rpca, labels_train)
rpca_accuracy = knn_rpca.score(data_test_rpca, labels_test)

print(f"Randomized PCA Accuracy: {rpca_accuracy:.4f}")
```

```
Randomized PCA Accuracy: 0.8450
```

KERNEL PCA:

PCA is a linear method. It works great for linearly separable datasets. However, if the dataset has non-linear relationships, then it produces undesirable results.

Kernel PCA is a technique which uses the so-called kernel trick and projects the linearly inseparable data into a higher dimension where it is linearly separable.

In [ ]:
```
# Kernel PCA
Kernel_pca = KernelPCA(n_components =  pca["alphas_dim"][-1], kernel='rbf')
Kernel_pca.fit(data_train)

data_train_kpca = Kernel_pca.transform(data_train)
data_test_kpca = Kernel_pca.transform(data_test)
```

In [ ]:
```
# Kernel PCA Accuracy
knn_kpca = KNeighborsClassifier(n_neighbors=2)
knn_kpca.fit(data_train_kpca, labels_train)
kpca_accuracy = knn_kpca.score(data_test_kpca, labels_test)

print(f"Kernel PCA Accuracy: {kpca_accuracy:.4f}")
```

```
Kernel PCA Accuracy: 0.0250
```

Incremental PCA:

In [ ]:
```
# Incremental PCA
ipca = IncrementalPCA(n_components =  pca["alphas_dim"][-1], batch_size=None)
ipca.fit(data_train)

data_train_ipca = ipca.transform(data_train)
data_test_ipca = ipca.transform(data_test)
```

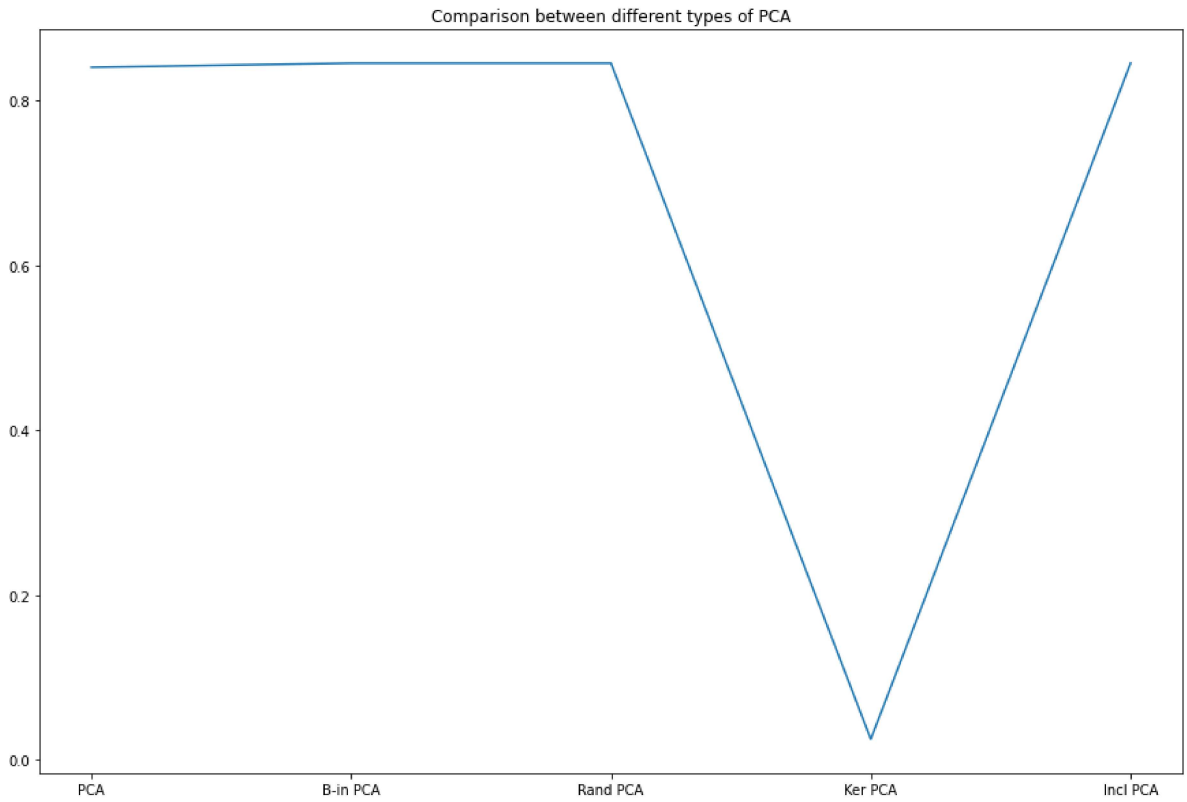
In [ ]:
```
# Incremental PCA
knn_ipca = KNeighborsClassifier(n_neighbors=5)
knn_ipca.fit(data_train_ipca, labels_train)
ipca_accuracy = knn_ipca.score(data_test_ipca, labels_test)

print(f"Incremental PCA Accuracy: {ipca_accuracy:.4f}")
```

```
Incremental PCA Accuracy: 0.8450
```

Comparison between different types of PCA:

In [ ]:
```
# PCA_acc = call KNNPCA or accuracy array K=5, alpha=0.95
plt.plot(["PCA", "B-in PCA", "Rand PCA", "Ker PCA", "Incl PCA"], [accuracy_KNN5[-1
plt.title('Comparison between different types of PCA')
```

Out[ ]:
```
Text(0.5, 1.0, 'Comparison between different types of PCA')
```



Variations of LDA

Quadratic Discriminant Analysis (QDA)

In [ ]:
```
# Importing Different Variations of LDA
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis as QDA
from sklearn.metrics import classification_report
```

In [ ]:
```
qda = QDA()
qda.fit(data_train, labels_train)

data_train_qda = qda.predict_proba(data_train)
data_test_qda = qda.predict_proba(data_test)
```

```
/usr/local/lib/python3.9/dist-packages/sklearn/discriminant_analysis.py:926: UserW
arning: Variables are collinear
  warnings.warn("Variables are collinear")
```

In [ ]:
```
knn = KNeighborsClassifier()
knn.fit(data_train_qda, labels_train)
qda_accuracy = knn.score(data_test_qda, labels_test)

print(f"QDA Accuracy: {qda_accuracy:.4f}")
```

```
QDA Accuracy: 0.0500
```

In [ ]:
```
y_pred = qda.predict(data_test)

print(classification_report(labels_test, y_pred, digits=3))
```

	precision	recall	f1-score	support
1	0.000	0.000	0.000	5
2	0.000	0.000	0.000	5
3	0.333	0.200	0.250	5
4	0.000	0.000	0.000	5
5	0.000	0.000	0.000	5
6	0.111	0.200	0.143	5
7	0.000	0.000	0.000	5
8	0.000	0.000	0.000	5
9	0.000	0.000	0.000	5
10	0.000	0.000	0.000	5
11	0.000	0.000	0.000	5
12	0.000	0.000	0.000	5
13	0.000	0.000	0.000	5
14	0.000	0.000	0.000	5
15	0.000	0.000	0.000	5
16	0.167	0.400	0.235	5
17	0.167	0.200	0.182	5
18	0.250	0.200	0.222	5
19	0.333	0.200	0.250	5
20	0.000	0.000	0.000	5
21	0.000	0.000	0.000	5
22	0.000	0.000	0.000	5
23	0.000	0.000	0.000	5
24	0.000	0.000	0.000	5
25	0.000	0.000	0.000	5
26	0.000	0.000	0.000	5
27	0.000	0.000	0.000	5
28	0.000	0.000	0.000	5
29	0.000	0.000	0.000	5
30	0.200	0.200	0.200	5
31	0.043	0.200	0.071	5
32	0.333	0.200	0.250	5
33	0.000	0.000	0.000	5
34	0.000	0.000	0.000	5
35	0.000	0.000	0.000	5
36	0.000	0.000	0.000	5
37	0.000	0.000	0.000	5
38	0.000	0.000	0.000	5
39	0.000	0.000	0.000	5
40	0.000	0.000	0.000	5
accuracy			0.050	200
macro avg	0.048	0.050	0.045	200
weighted avg	0.048	0.050	0.045	200

```
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344: Un
definedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 i
n labels with no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344: Un
definedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 i
n labels with no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344: Un
definedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 i
n labels with no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```