FacesVsNonFaces

March 6, 2024

1 Faces Vs. Non-Faces

Load the new dataset

[1]:
```
import DatasetSplitter

training_data_50, training_labels_50, testing_data_50, testing_labels_50 =␣
↪DatasetSplitter.splitDataNonFaces50()
training_data_100, training_labels_100, testing_data_100, testing_labels_100 =␣
↪DatasetSplitter.splitDataNonFaces100()
training_data_200, training_labels_200, testing_data_200, testing_labels_200 =␣
↪DatasetSplitter.splitDataNonFaces()
training_data_400, training_labels_400, testing_data_400, testing_labels_400 =␣
↪DatasetSplitter.splitDataNonFaces400()
```

2 Apply the LDA algorithm for two classes

We only use 1 eigenvector, because the number of used eigenvectors = number of classes - 1, where the number of classes = 2 (Faces & Non-Faces)

[2]:
```
# The following code is the implementation of Linear Discriminant Analysis␣
↪(LDA) but for 2 classes only
# (The Sb matrix is the only difference between this and the code in LDA.ipynb).

import numpy as np
import scipy as sp
from sklearn.metrics import accuracy_score
from sklearn.neighbors import KNeighborsClassifier
import matplotlib.pyplot as plt

def get_split_data(training_data):
    mat = np.array(training_data)
    split_data = []
    split_data.append(mat[:200])
    split_data.append(mat[200:])
    return split_data
```

```python
def get_class_means(split_data):
    class_means = []
    for class_matrix in split_data:
        class_means.append(np.mean(class_matrix, axis=0))
    return class_means

def get_centered_classes(split_data, class_means):
    centered_classes = []
    for class_matrix, class_mean in zip(split_data, class_means):
        centered_class = []
        for row in class_matrix:
            centered_class.append(row - class_mean)
        centered_classes.append(centered_class)
    return centered_classes

def get_between_class(class_means):
    Sb = np.outer((class_means[0] - class_means[1]), np.
 ↪transpose(class_means[0] - class_means[1]))
    return Sb

def get_within_class(centered_classes):
    Sw = np.zeros((10304, 10304))
    for centered_class in centered_classes:
        mat = np.array(centered_class)
        Sw += np.dot(np.transpose(mat), mat)
    Sw_inverse = sp.linalg.pinv(Sw)
    return Sw_inverse

def get_eigens(Sw_inverse, Sb):
    eigenvalues, eigenvectors = np.linalg.eig(np.dot(Sw_inverse, Sb))
    return eigenvalues, eigenvectors

def get_U(eigenvalues, eigenvectors):
    sorted_indecies = np.argsort(eigenvalues)[::-1]
    sorted_eigen_vectors = eigenvectors[:,sorted_indecies]
    U = np.real(sorted_eigen_vectors[:,:1])
    return U
```

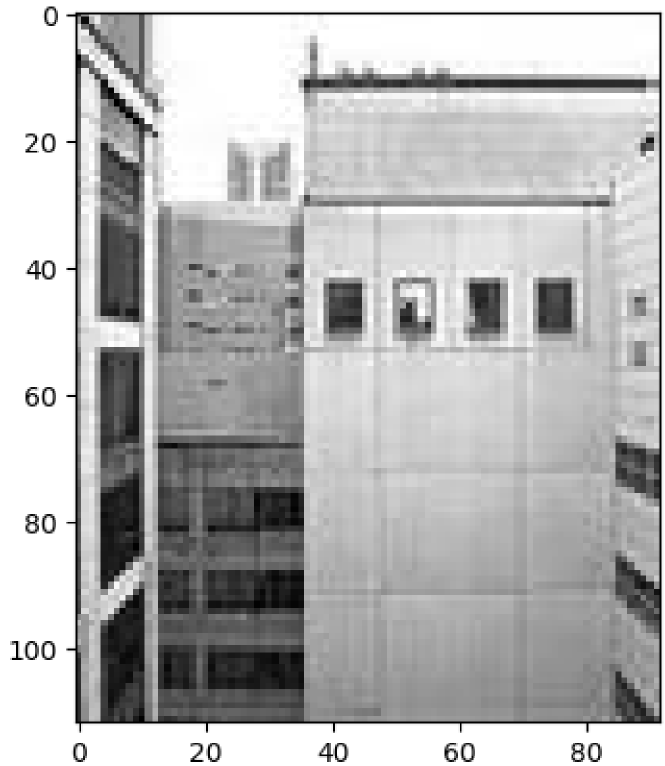
[3]:
```python
def LDA(training_data, training_labels, testing_data, testing_labels):
    split_data = get_split_data(training_data)
    class_means = get_class_means(split_data)
    centered_classes = get_centered_classes(split_data, class_means)
    Sb = get_between_class(class_means)
    Sw_inverse = get_within_class(centered_classes)
    eigenvalues, eigenvectors = get_eigens(Sw_inverse, Sb)
    projection_matrix = get_U(eigenvalues, eigenvectors)
```

```
    projected_training_data = np.dot(training_data , projection_matrix)
    projected_testing_data = np.dot(testing_data , projection_matrix)
    classifier = KNeighborsClassifier(1)
    classifier.fit(projected_training_data, training_labels)
    prediction = classifier.predict(projected_testing_data)

    correctly_classified = []
    incorrectly_classified = []

    for i in range(len(testing_labels)):
        if testing_labels[i] == 2:
            if testing_labels[i] == prediction[i]:
                correctly_classified.append(testing_data[i])
            else:
                incorrectly_classified.append(testing_data[i])

    print("Success cases:")
    for image in correctly_classified[:3]:
        reshaped_image = np.reshape(image, (112, 92))
        plt.imshow(reshaped_image, cmap='gray')
        plt.show()

    print("Failure cases:")
    for image in incorrectly_classified[:3]:
        reshaped_image = np.reshape(image, (112, 92))
        plt.imshow(reshaped_image, cmap='gray')
        plt.show()

    accuracy = accuracy_score(testing_labels, prediction)

    print ("Accuracy = ", accuracy * 100)
```

3 Using 50 non-face images for training

[12]:
```
LDA(training_data_50, training_labels_50, testing_data_50, testing_labels_50)
```

```
Success cases:
```


0
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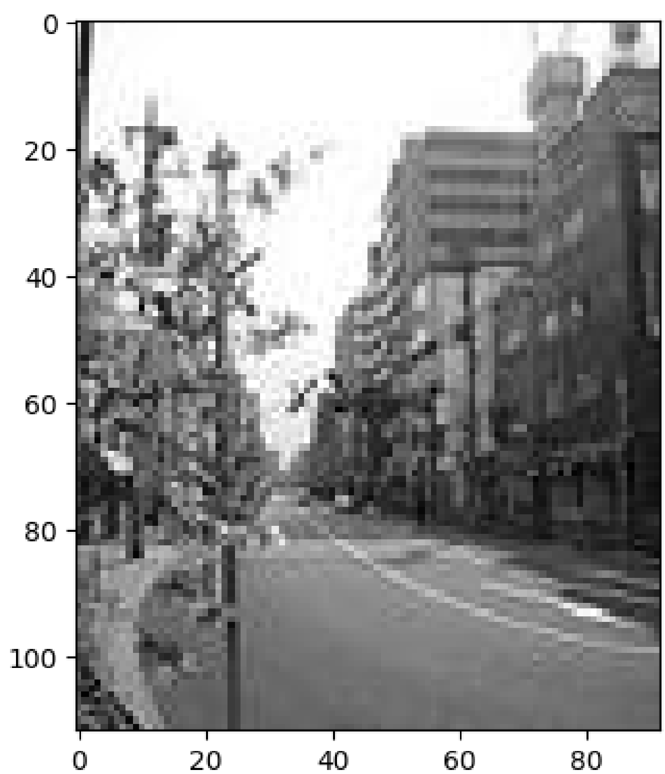
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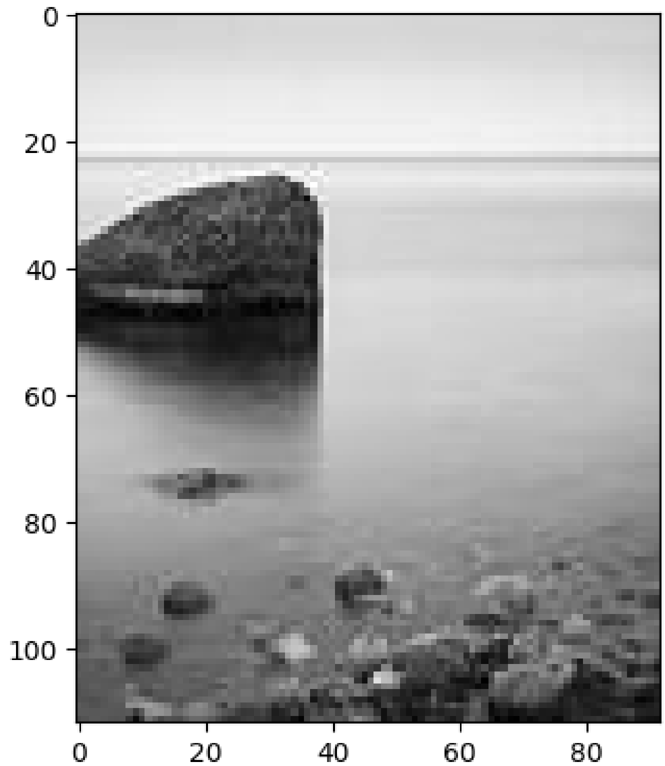
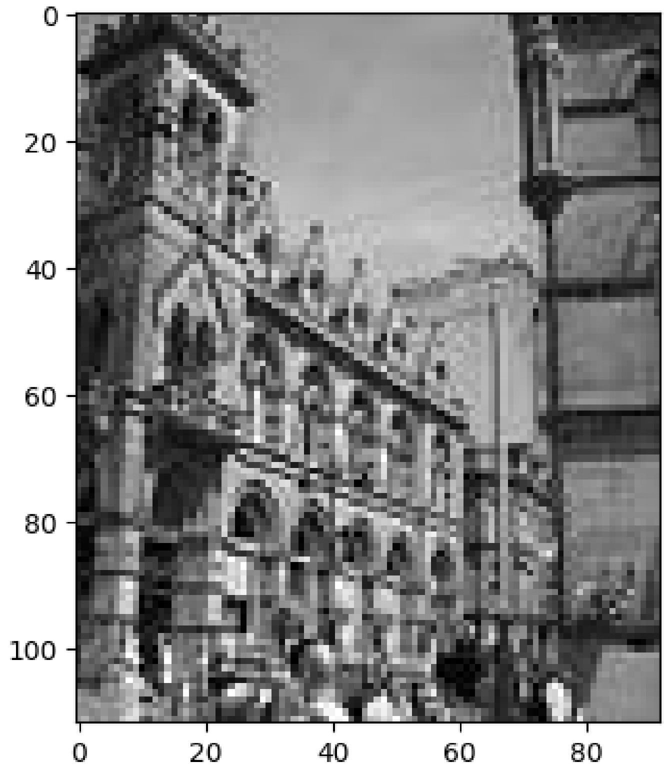


Failure cases: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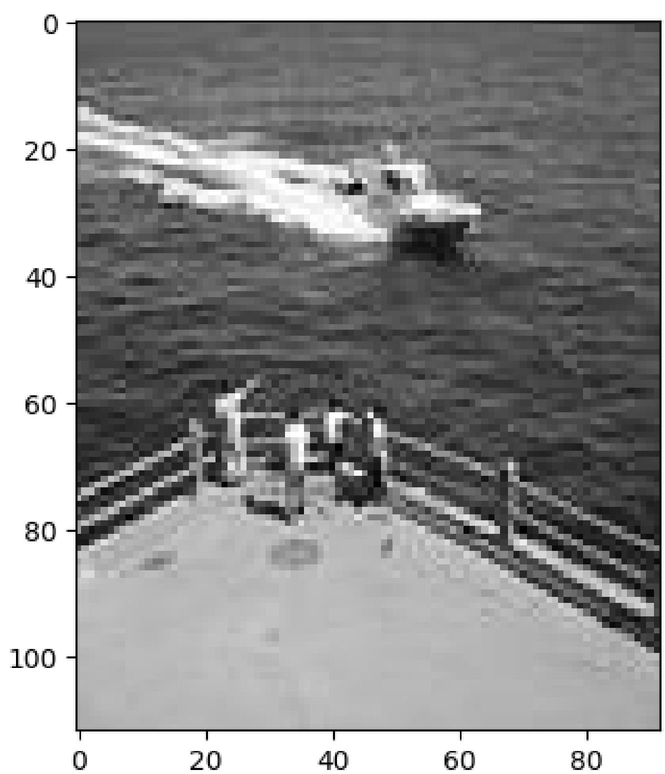
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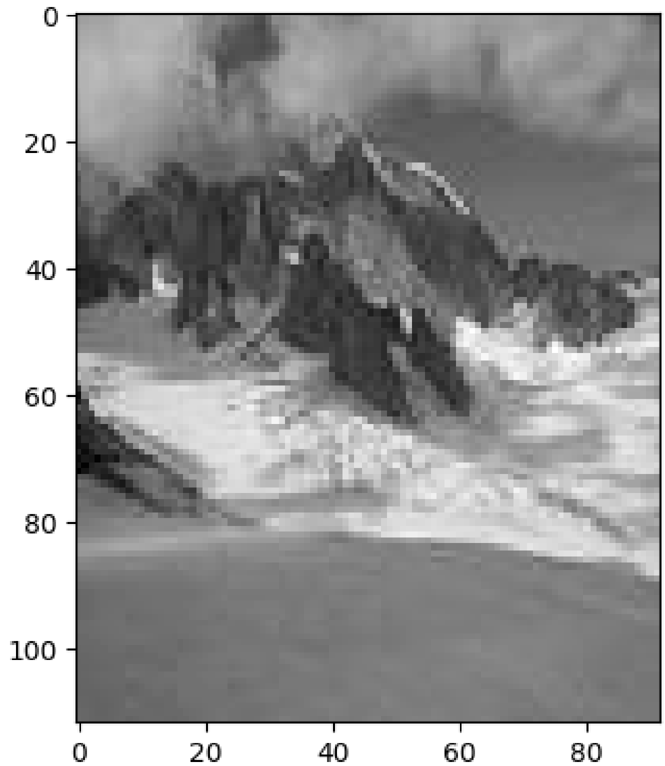
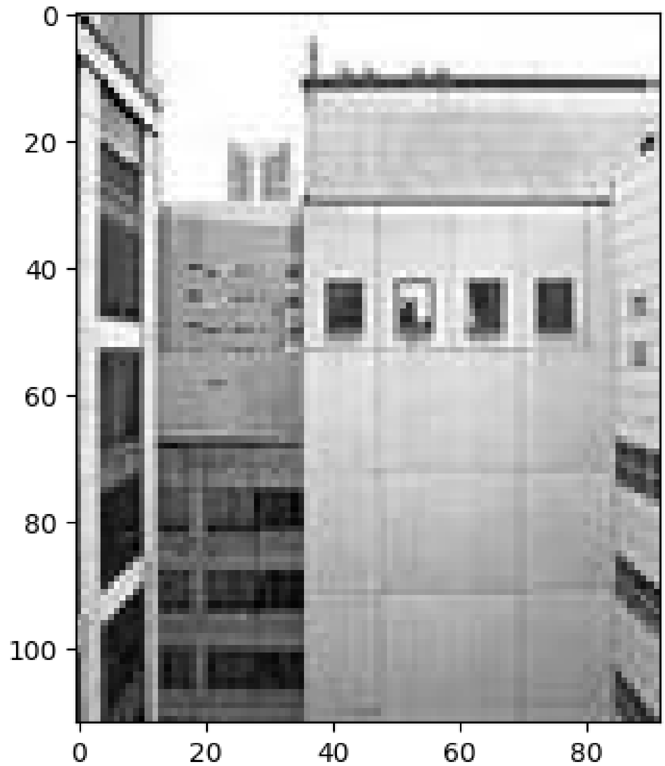



```
Accuracy =  91.25
```

4 Using 100 non-face images for training

[13]:
```
LDA(training_data_100, training_labels_100, testing_data_100,␣
  ↪testing_labels_100)
```

```
Success cases:
```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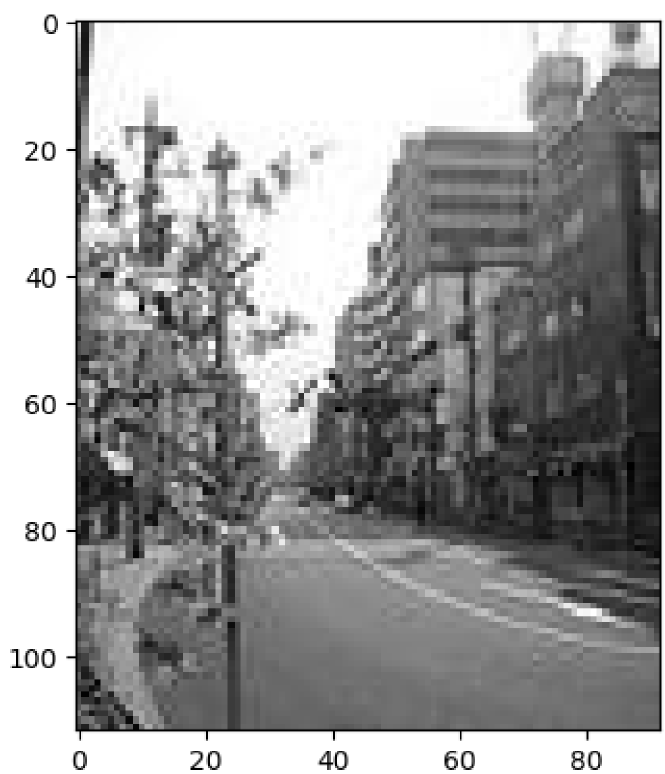
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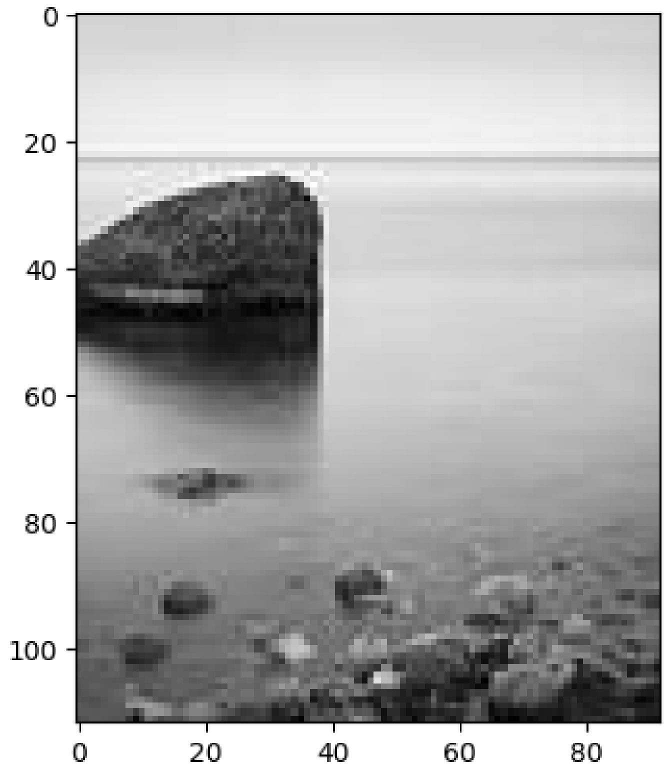
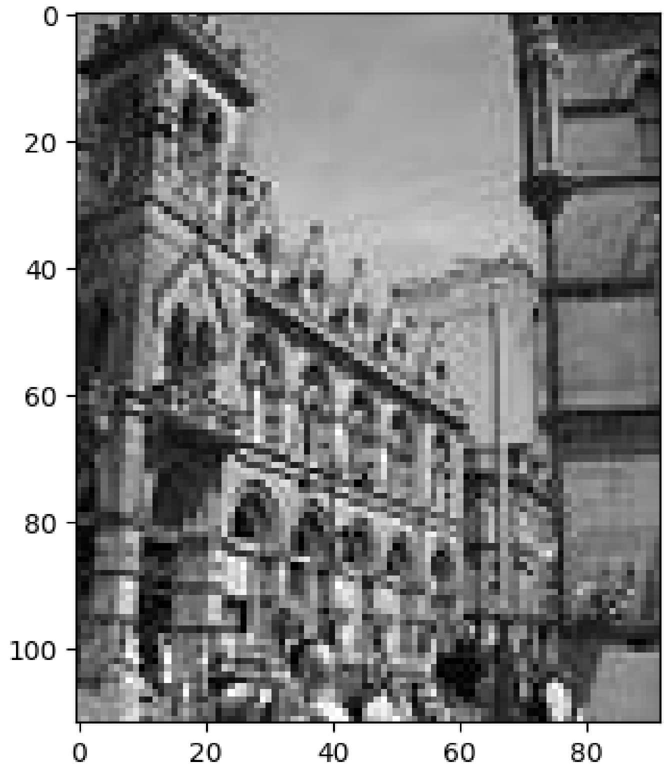


Failure cases: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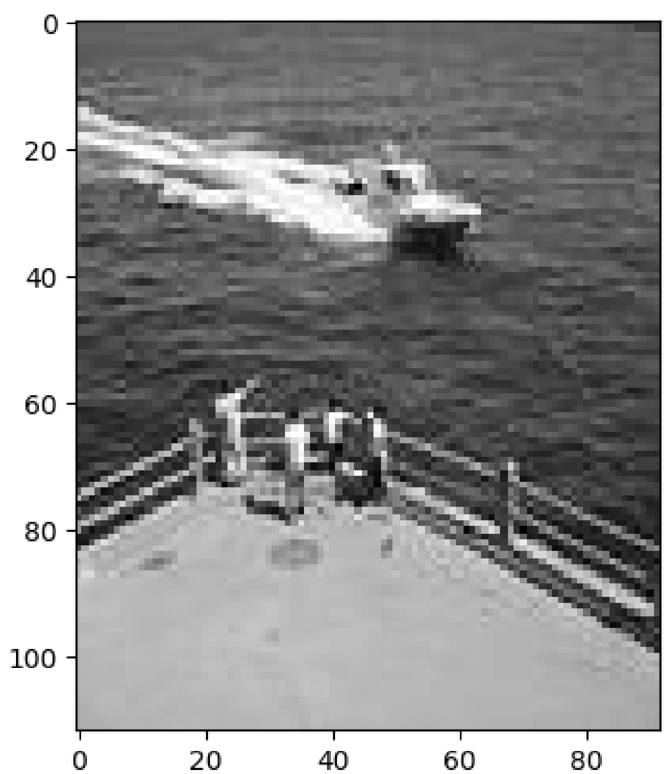
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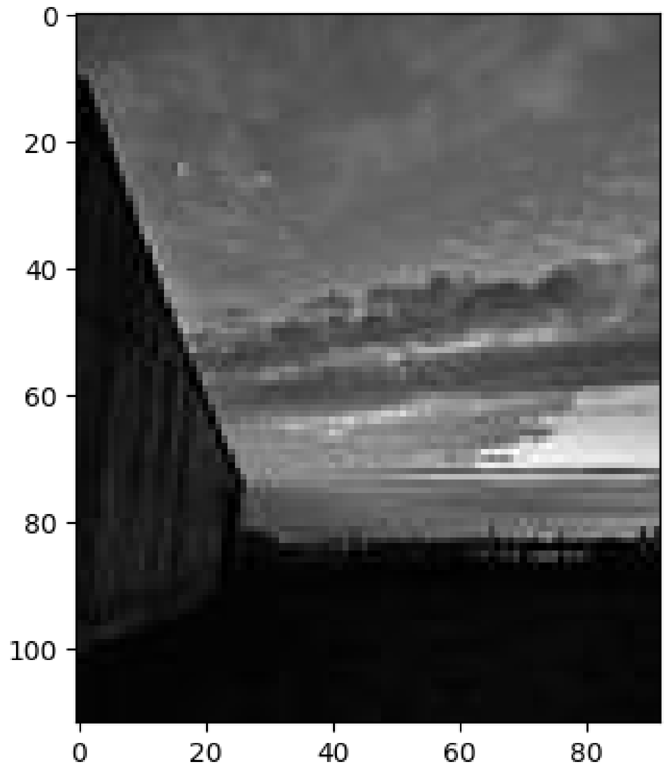
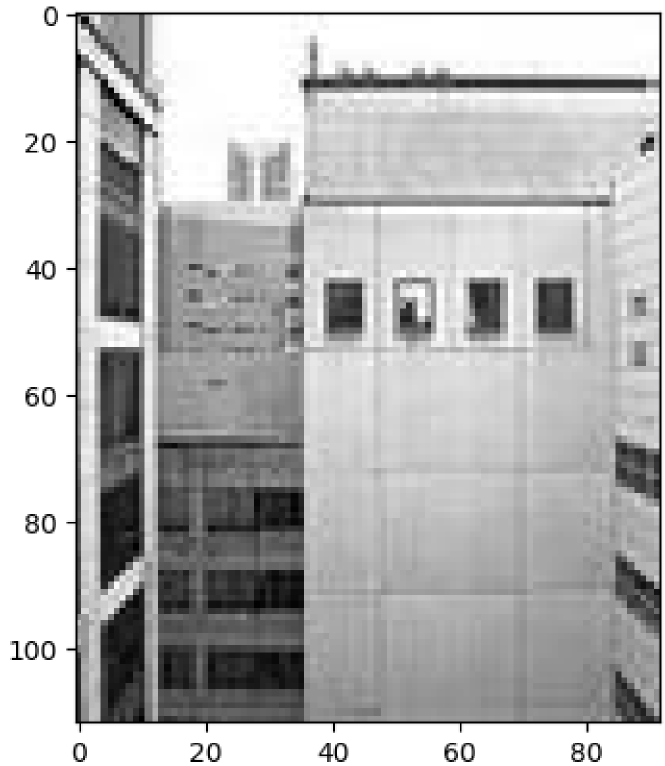


```
Accuracy =  93.5
```

5 Using 200 non-face images for training

[15]:
```
LDA(training_data_200, training_labels_200, testing_data_200,␣
 ↪testing_labels_200)
```

```
Success cases:
```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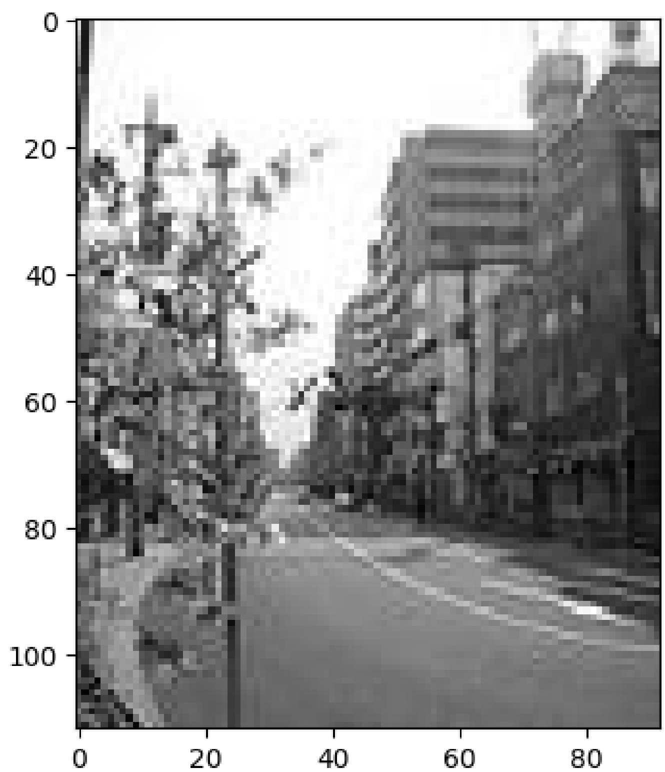
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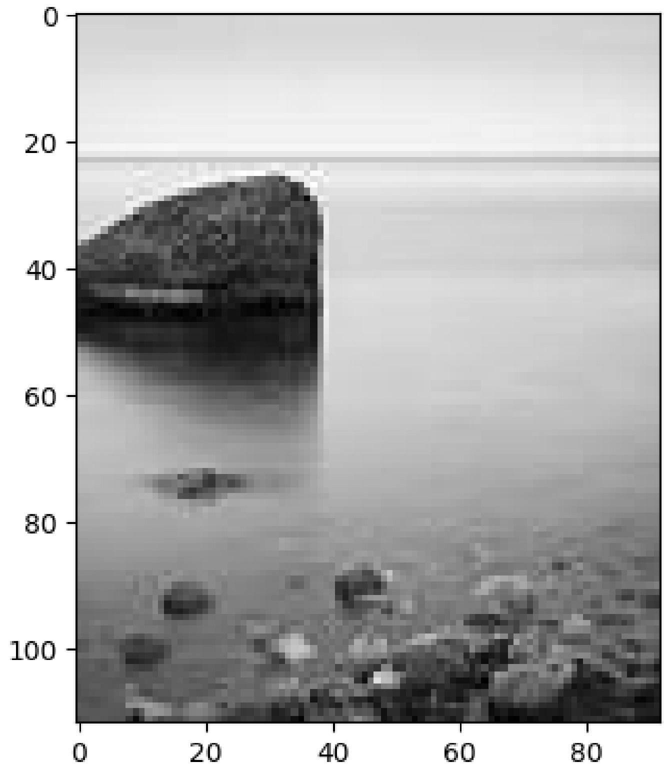
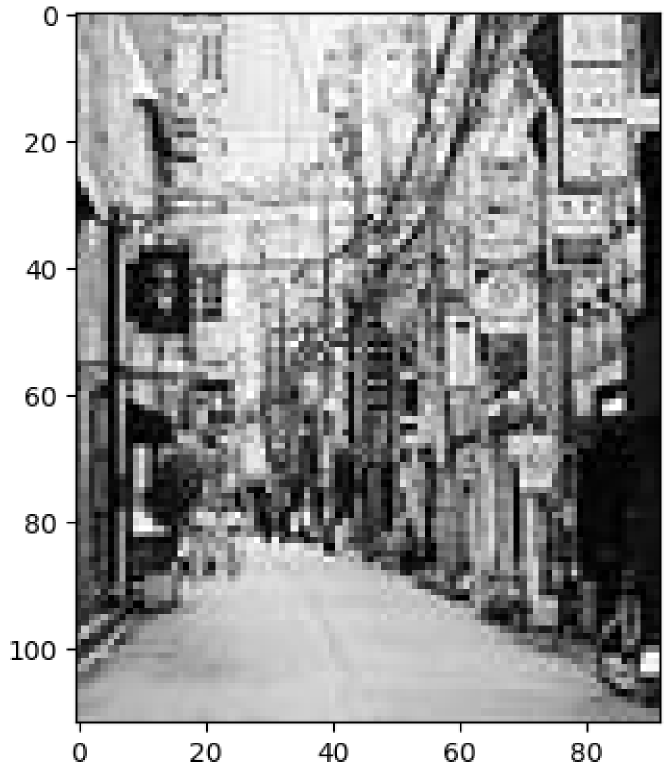


Failure cases: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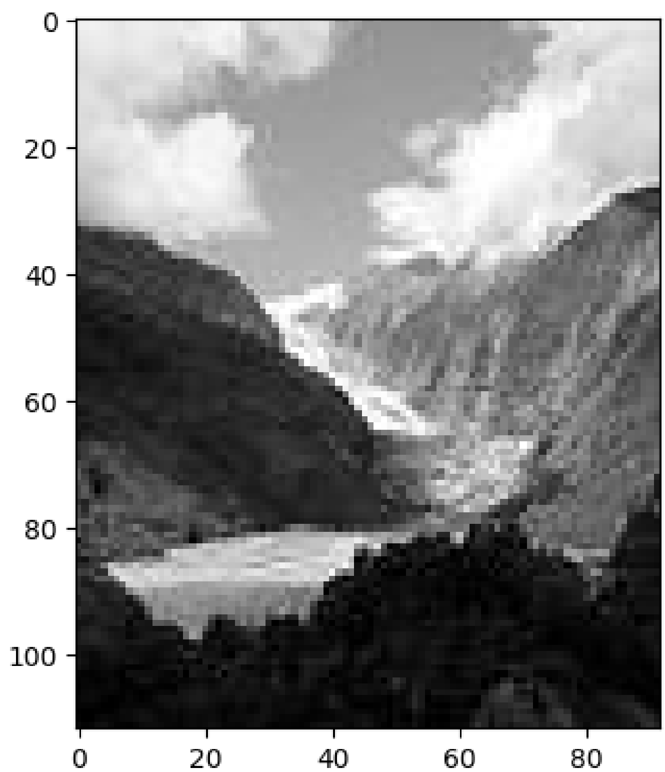
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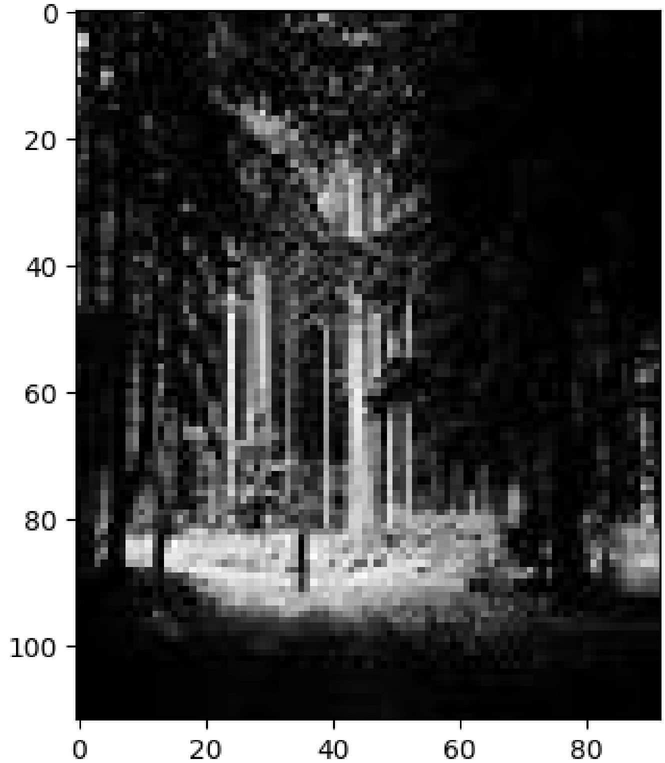
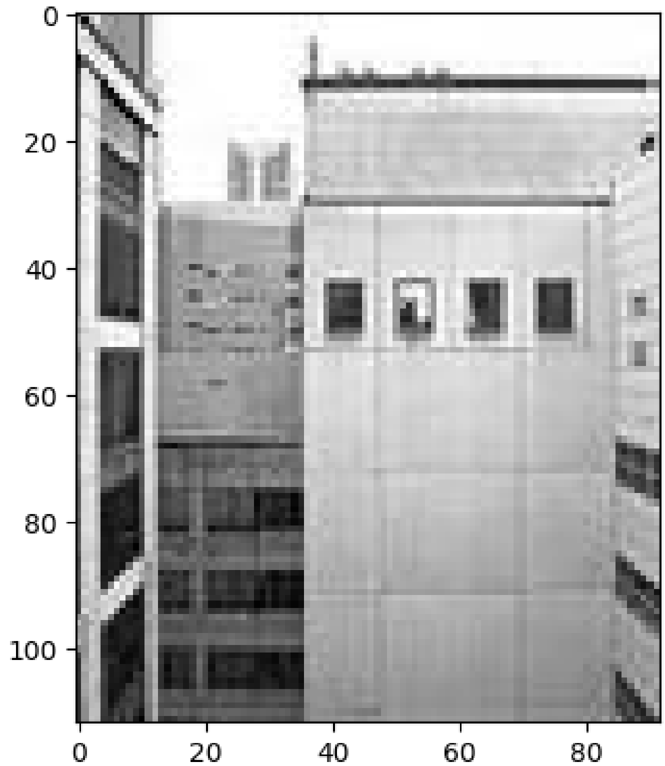



```
Accuracy =  89.5
```

6 Using 400 non-face images for training

[16]:
```
LDA(training_data_400, training_labels_400, testing_data_400,␣
  ↪testing_labels_400)
```

```
Success cases:
```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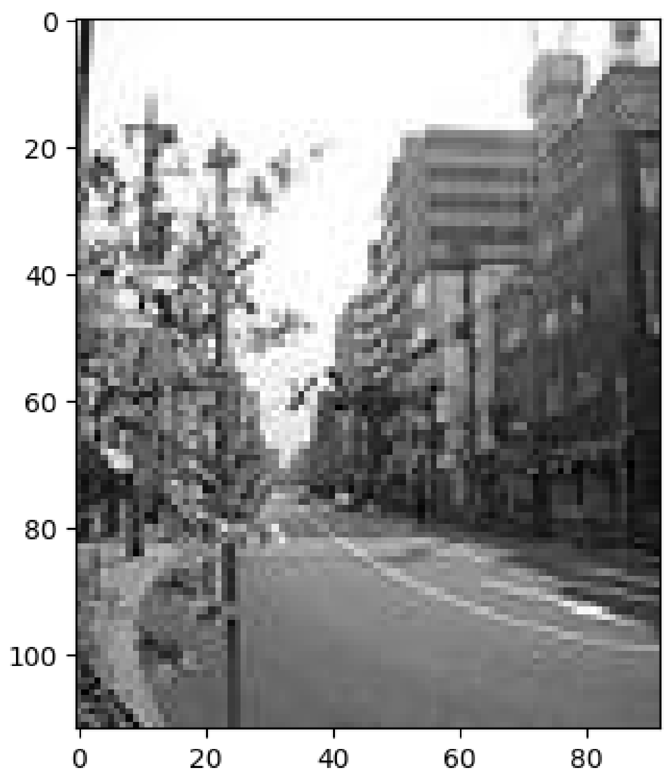
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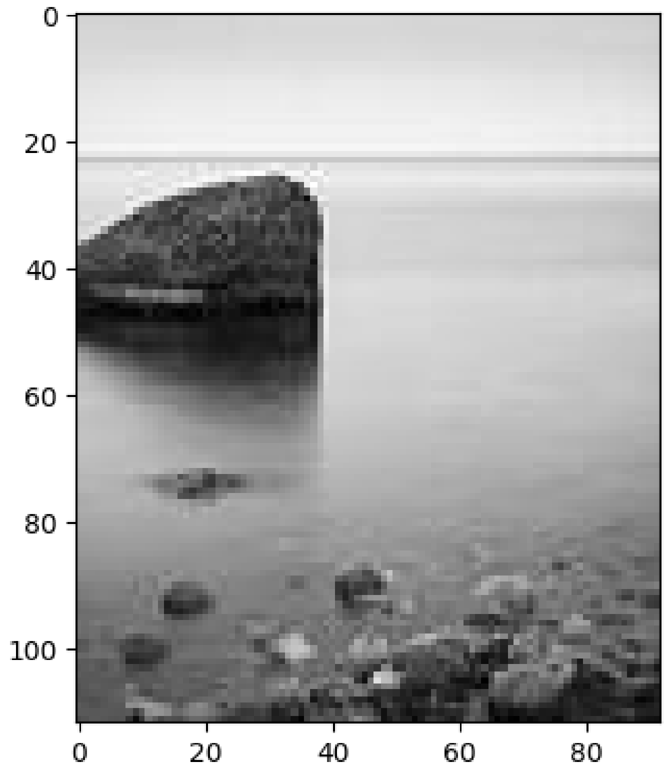
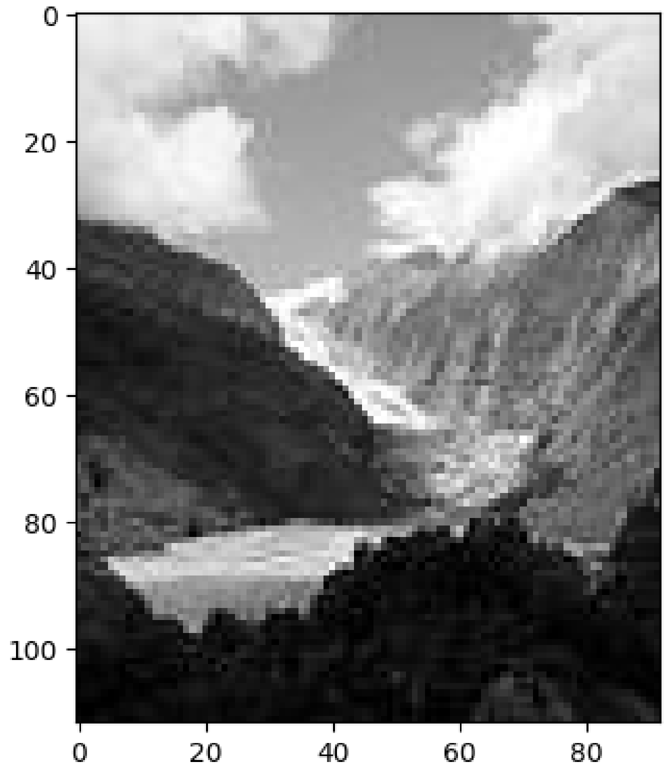


Failure cases: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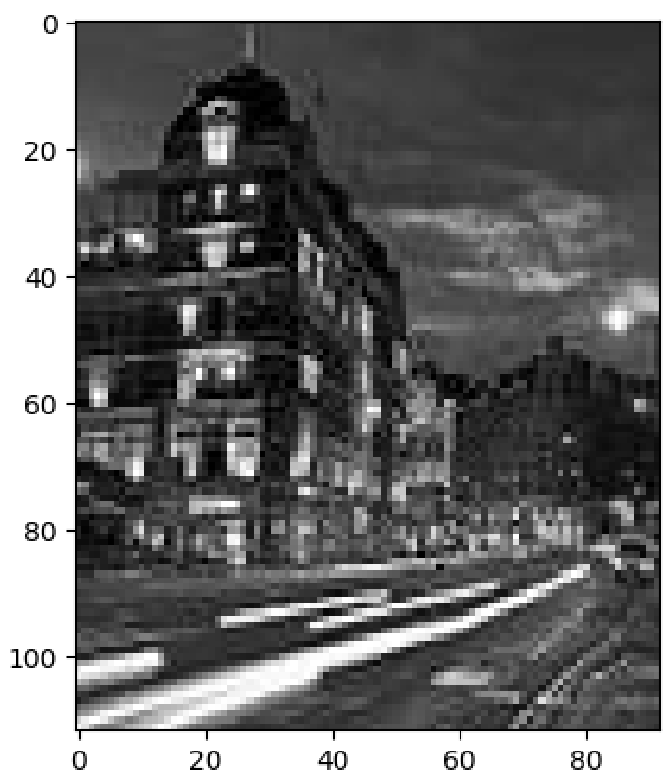
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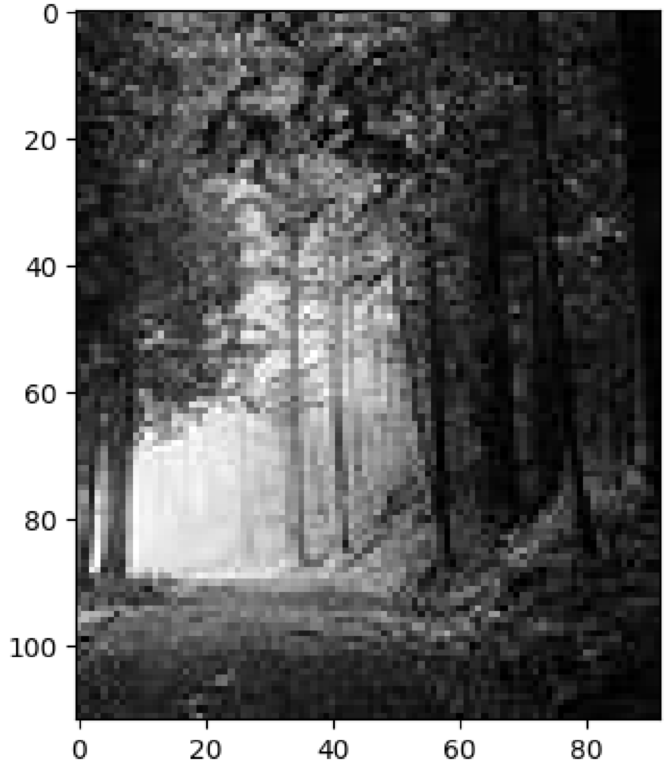



```
Accuracy =  92.75
```

7 Apply the PCA algorithm

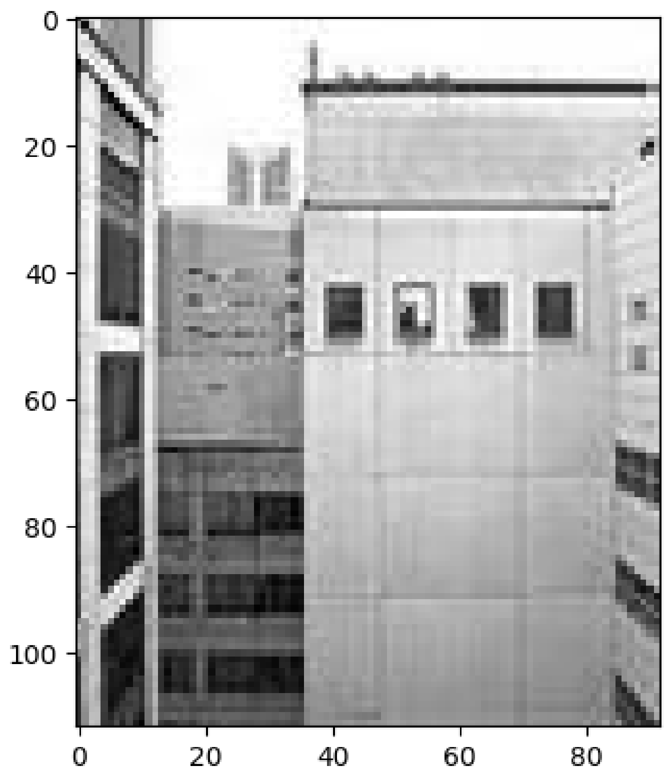
[5]:
```
def covariance(D):
    global mean_vector
    mean_vector = np.mean(D, axis=0)
    Z = D - mean_vector
    cov = (1/len(D)) * (Z.T @ Z)
    return cov

def PCA(D, alpha, trainingLabels, testingData, testingLabels):
    cov = covariance(D)
    eigenvalues, eigenvectors = np.linalg.eigh(cov)

    sorted_idx = eigenvalues.argsort()[::-1]  # Sort in descending order
    eigenvalues = eigenvalues[sorted_idx]
    eigenvectors = eigenvectors[:, sorted_idx]
```

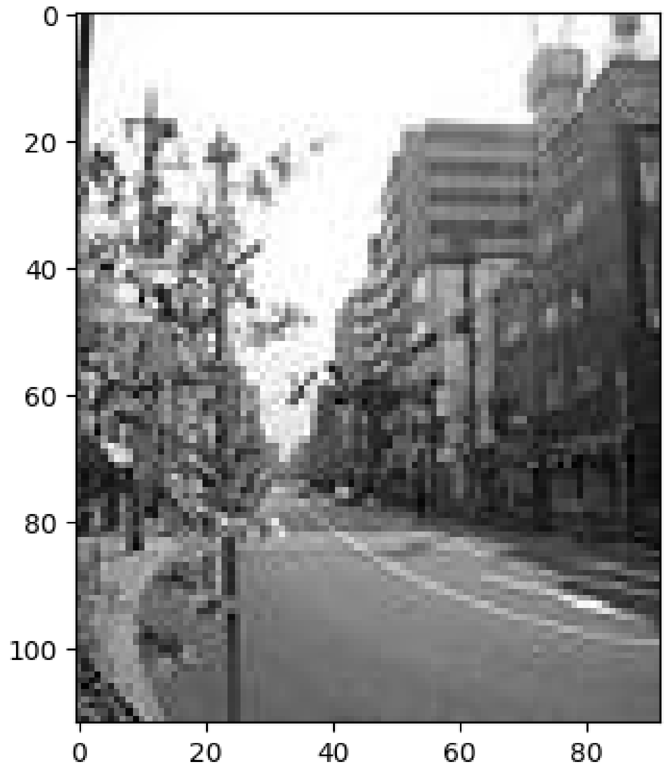
```python
trace = np.trace(cov)
c = 0 # Accumulator for sum of eigenvaleus
lastIndex = 0
for index in range(len(eigenvalues)):
    c += eigenvalues[index]
    if c / trace >= alpha :
        lastIndex = index
        break
P = eigenvectors[:lastIndex + 1, :]# Projection Matrix
# Project training data (correctly subtract mean before projection)
projectedTrainingData = (D - mean_vector) @ P.T

# Project testing data (correctly subtract mean before projection)
projectedTestingData = (testingData - mean_vector) @ P.T

knn = KNeighborsClassifier(n_neighbors=1)
knn.fit(projectedTrainingData, trainingLabels)

predictedClasses = knn.predict(projectedTestingData)

correctly_classified = []
incorrectly_classified = []

for i in range(len(testingLabels)):
    if testingLabels[i] == 2:
        if testingLabels[i] == predictedClasses[i]:
            correctly_classified.append(testingData[i])
        else:
            incorrectly_classified.append(testingData[i])

print("Success cases:")
for image in correctly_classified[:3]:
    reshaped_image = np.reshape(image, (112, 92))
    plt.imshow(reshaped_image, cmap='gray')
    plt.show()

print("Failure cases:")
for image in incorrectly_classified[:3]:
    reshaped_image = np.reshape(image, (112, 92))
    plt.imshow(reshaped_image, cmap='gray')
    plt.show()

accuracy = accuracy_score(testingLabels, predictedClasses)

print(f"Accuracy {100 * (accuracy)}")
```

8 Using 50 non-face images for training

```
[7]: PCA(training_data_50, 0.95, training_labels_50, testing_data_50,
      testing_labels_50)
```

Success cases:

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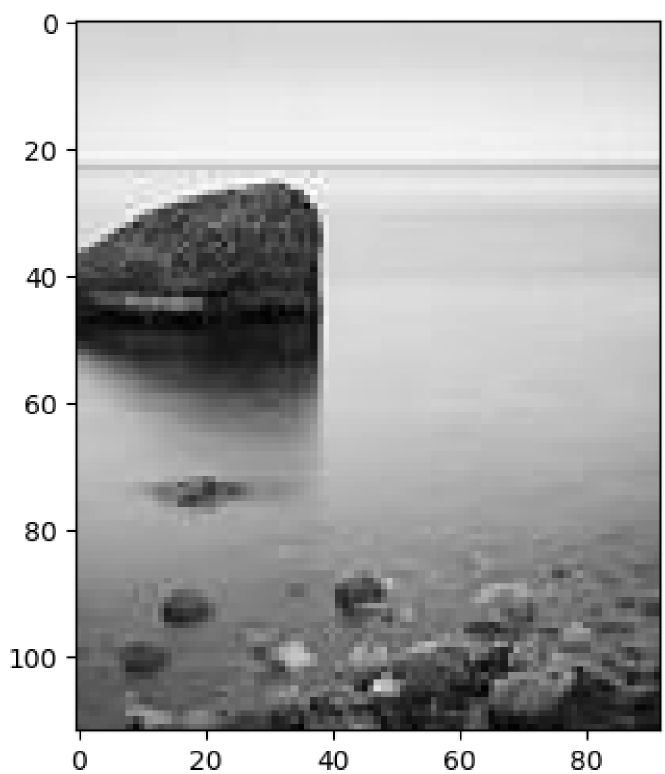
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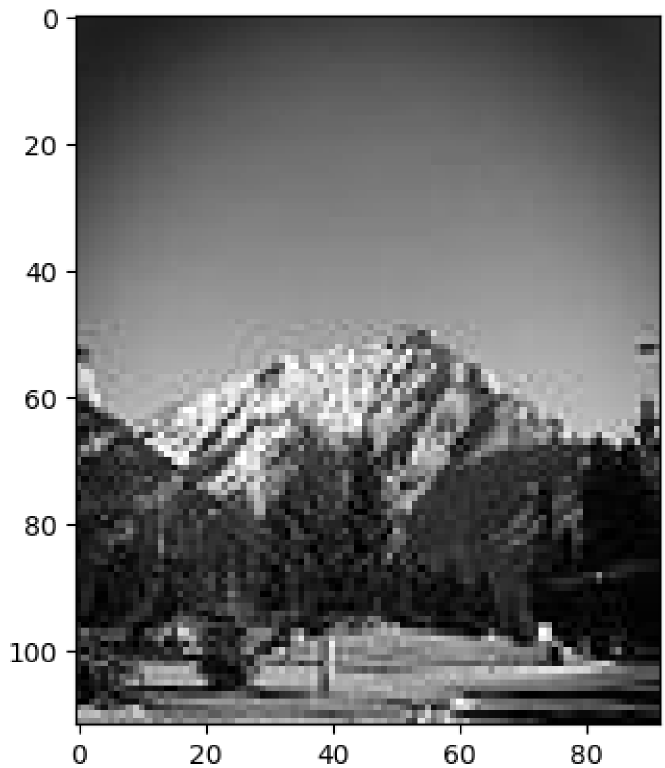
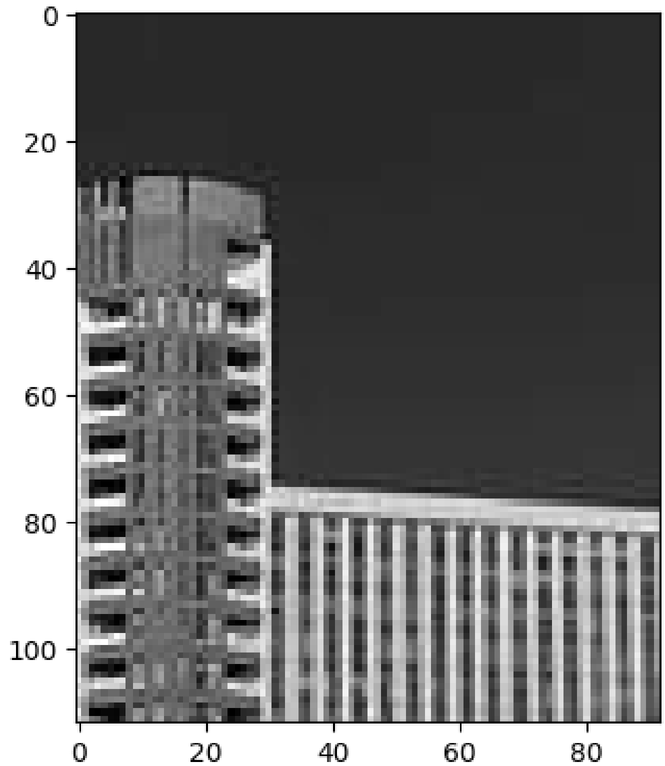
Failure cases:

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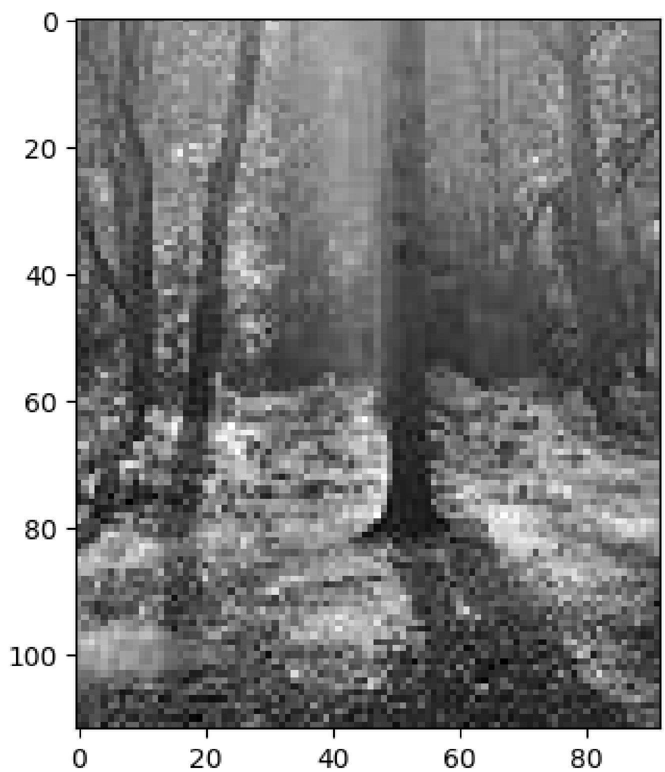
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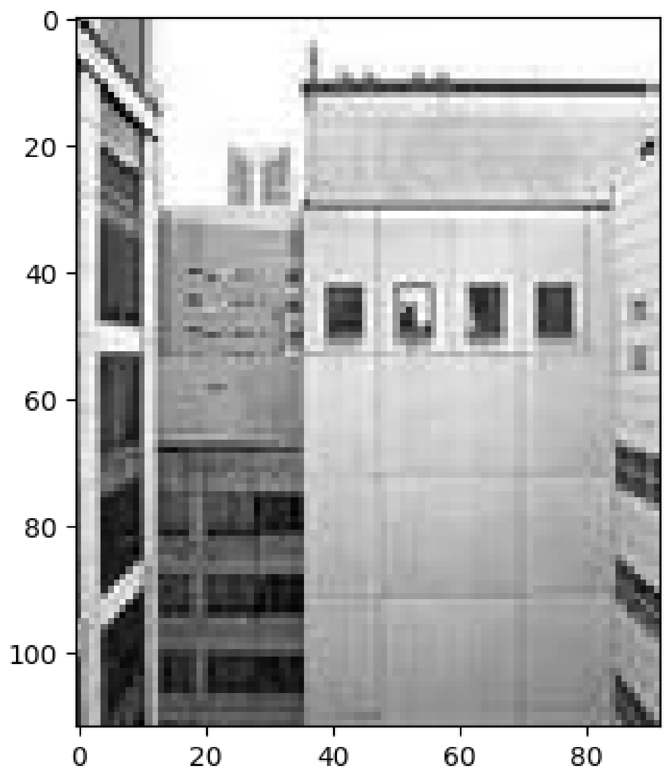
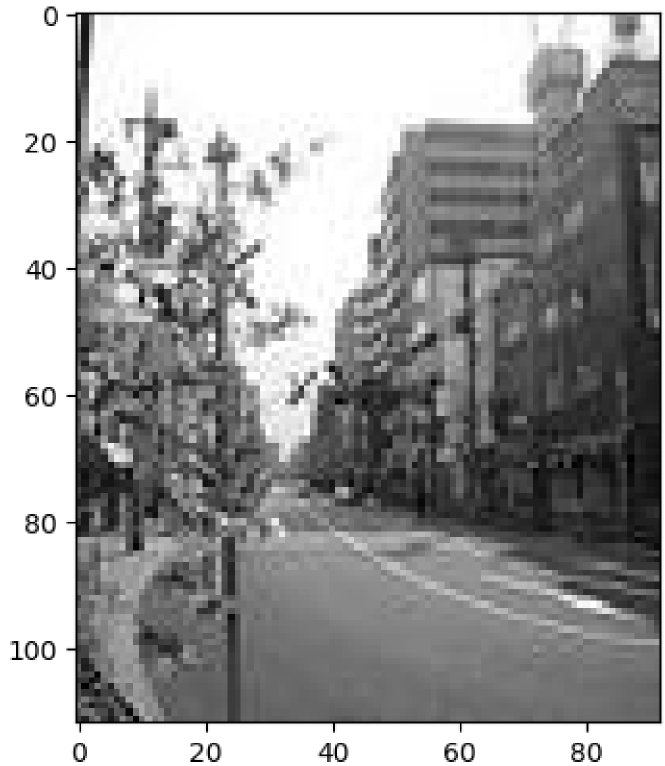
Accuracy 89.25

9 Using 100 non-face images for training

[8]:
```
PCA(training_data_100, 0.95, training_labels_100, testing_data_100,
    testing_labels_100)
```

Success cases:

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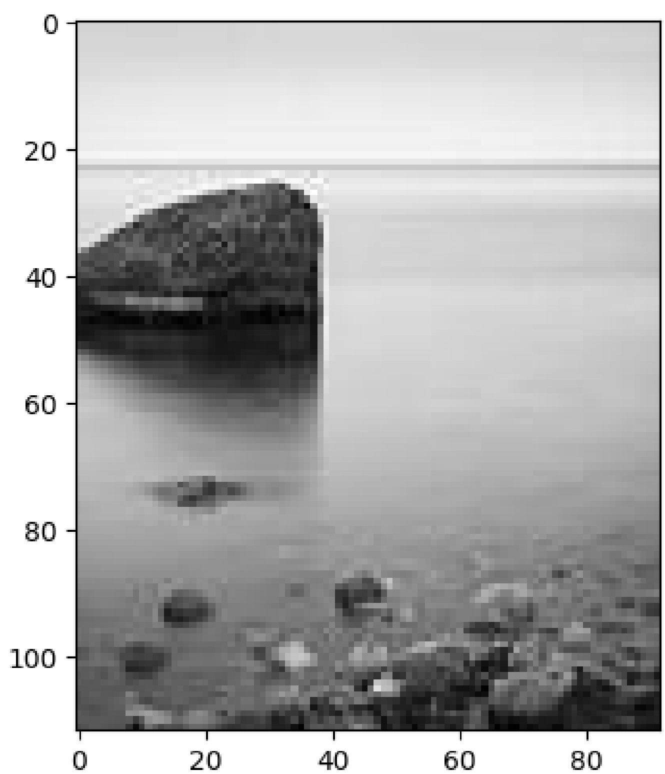
0
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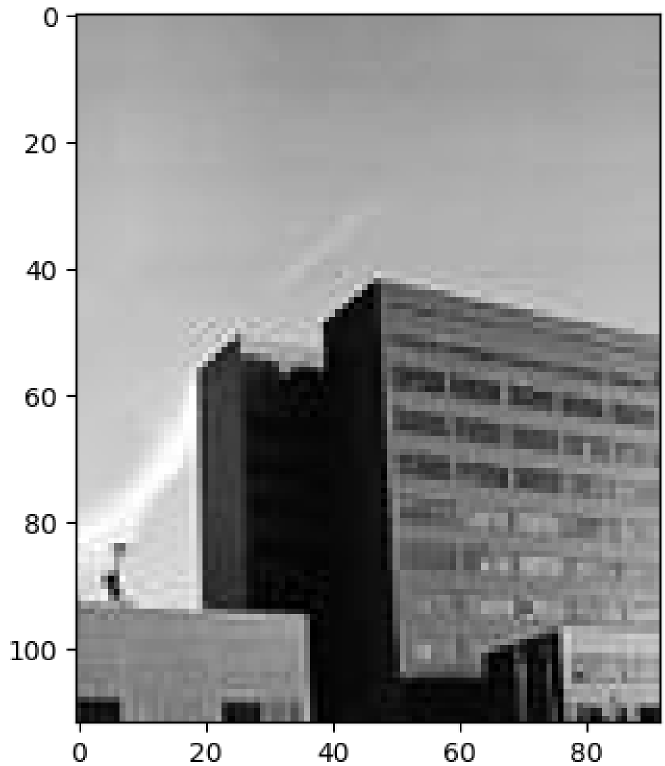
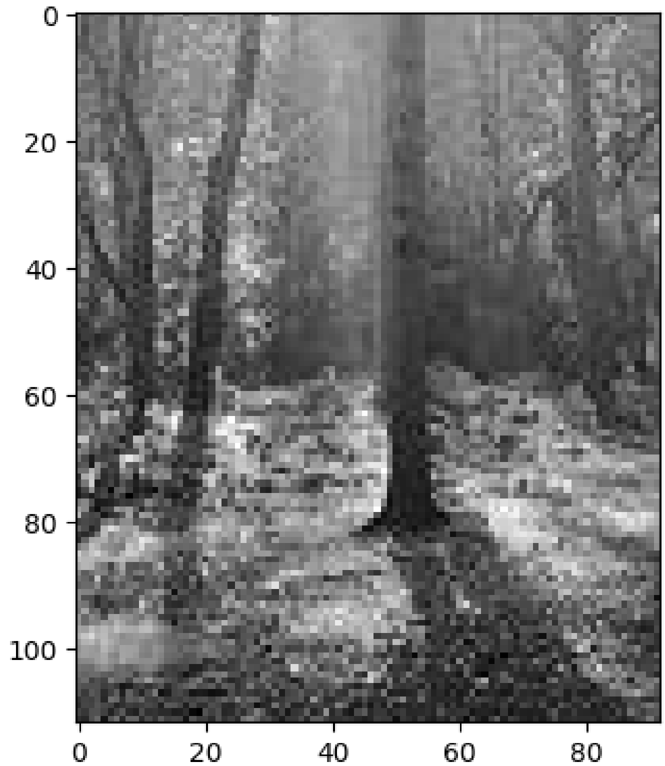
Failure cases:

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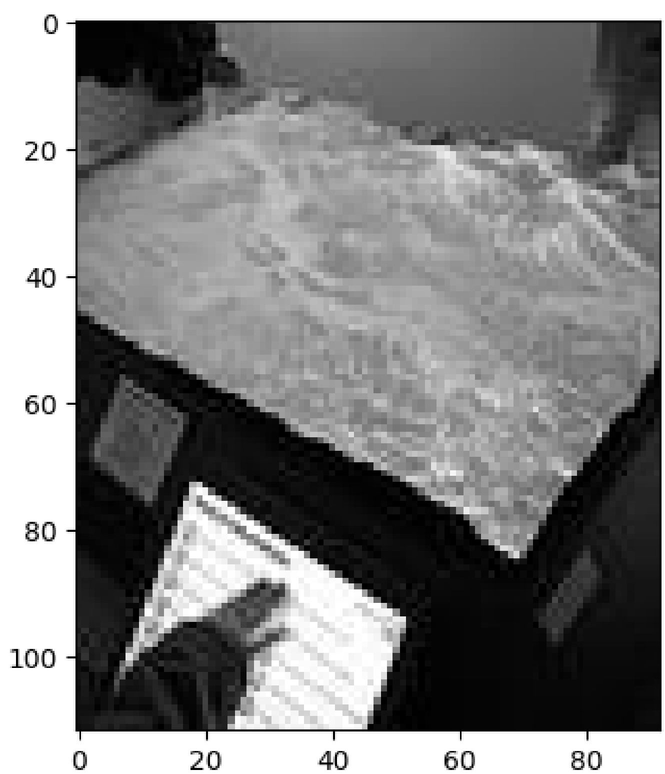
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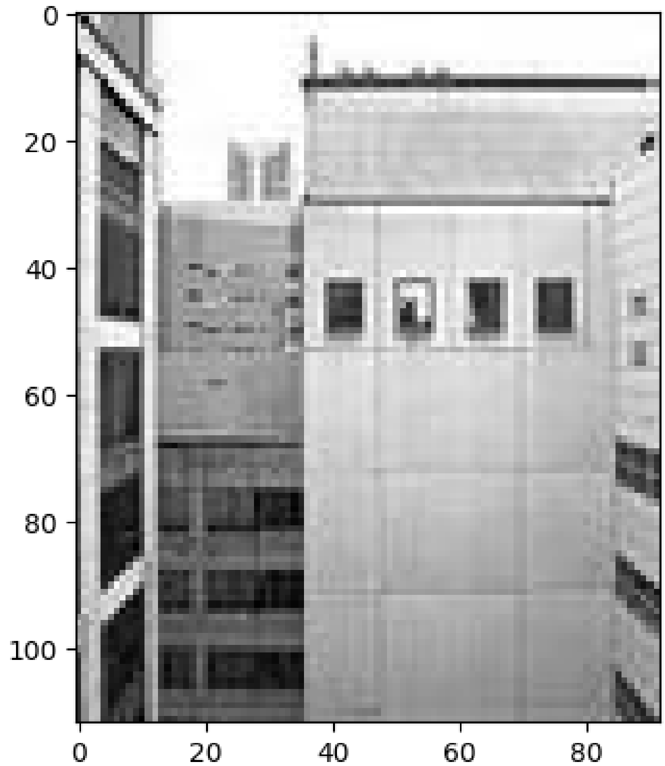
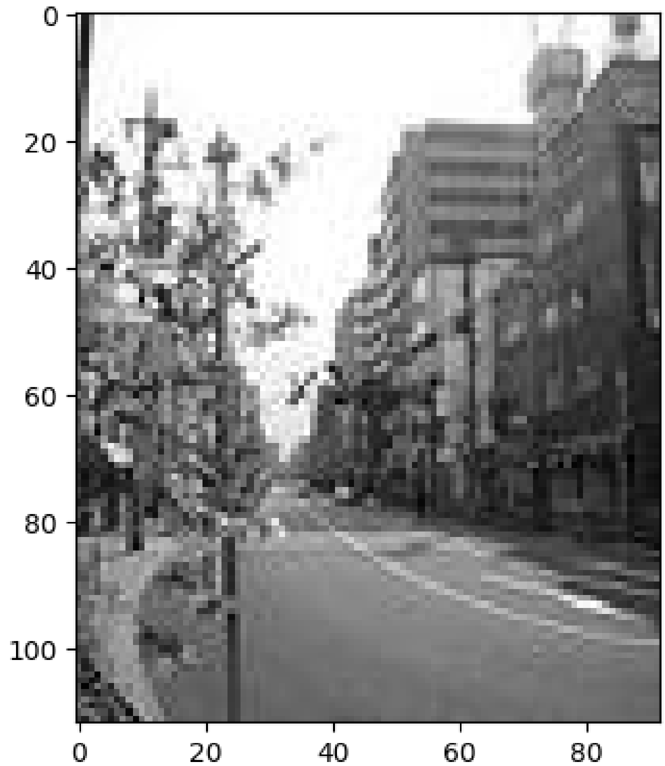
Accuracy 91.0

10 Using 200 non-face images for training

[9]:
```
PCA(training_data_200, 0.95, training_labels_200, testing_data_200,
 testing_labels_200)
```

Success cases:

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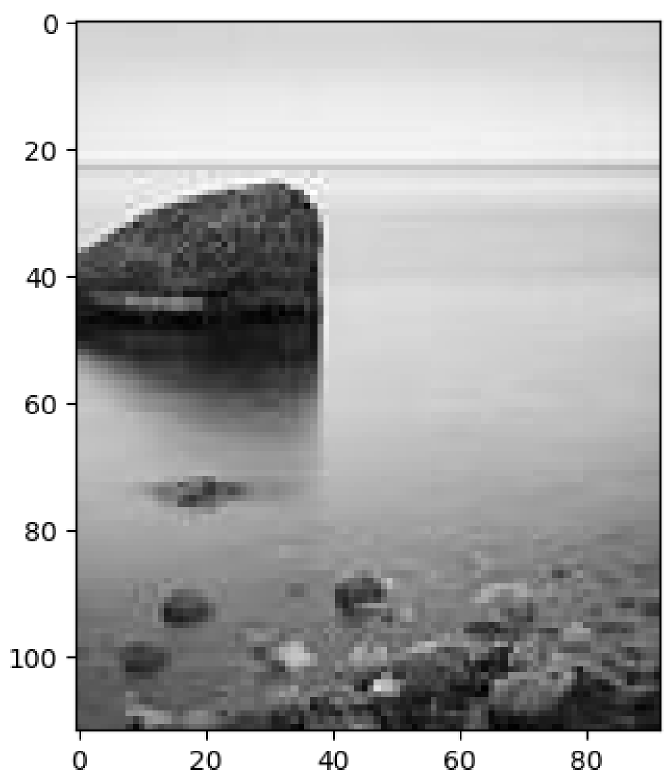
0
20
40
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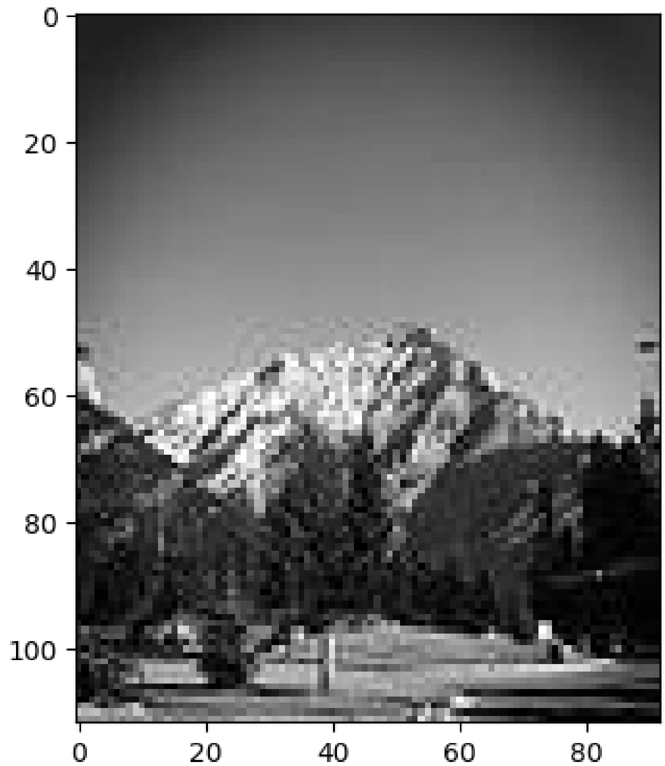
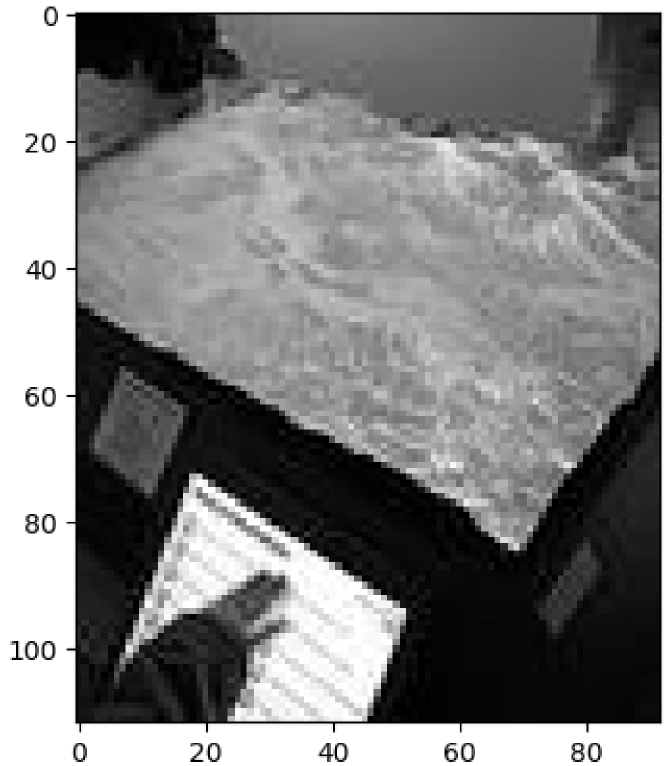
Failure cases:

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100
0
20
40
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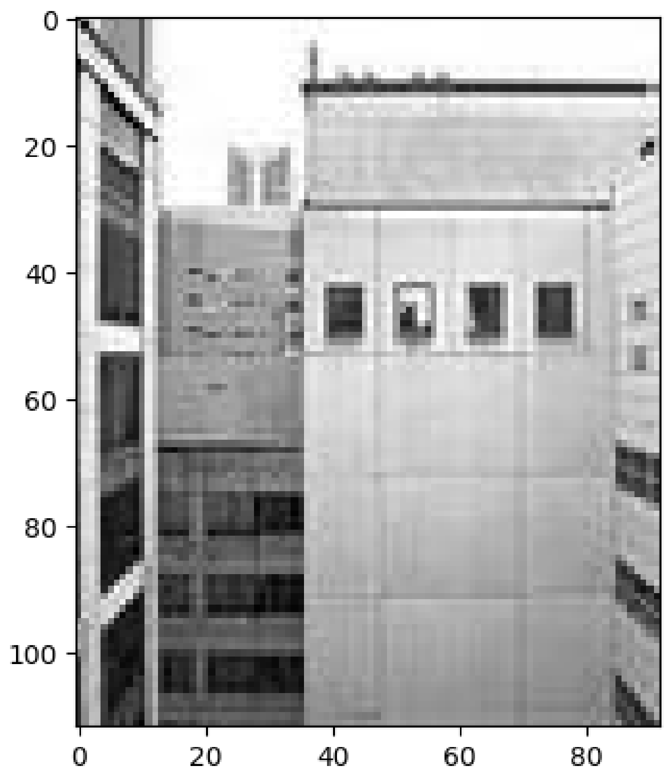
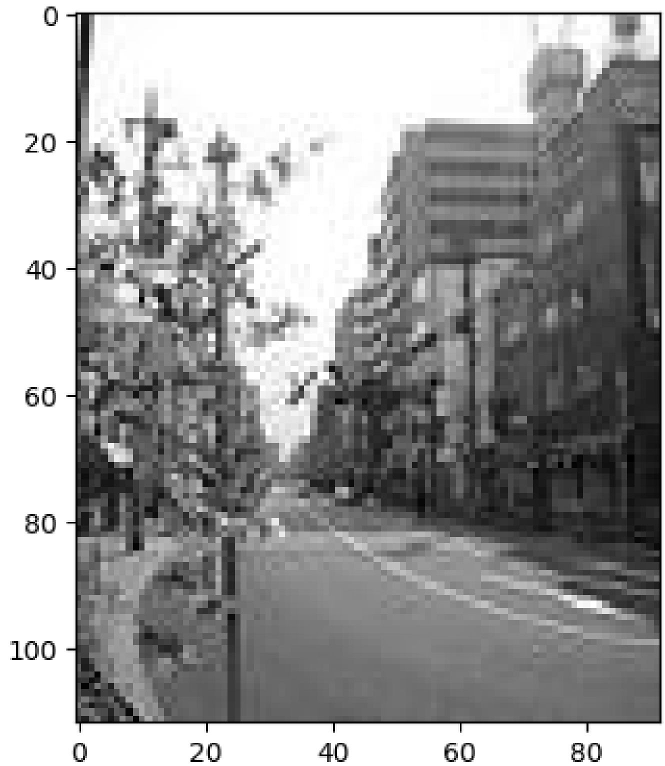
```
Accuracy 92.25
```

11 Using 400 non-face images for training

```
[10]: PCA(training_data_400, 0.95, training_labels_400, testing_data_400,␣
       ↪testing_labels_400)
```

```
Success cases:
```

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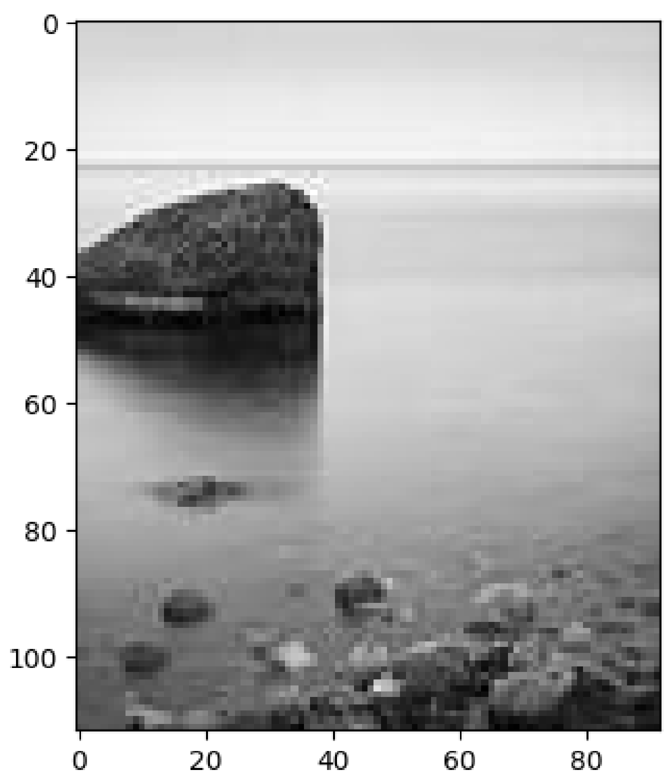
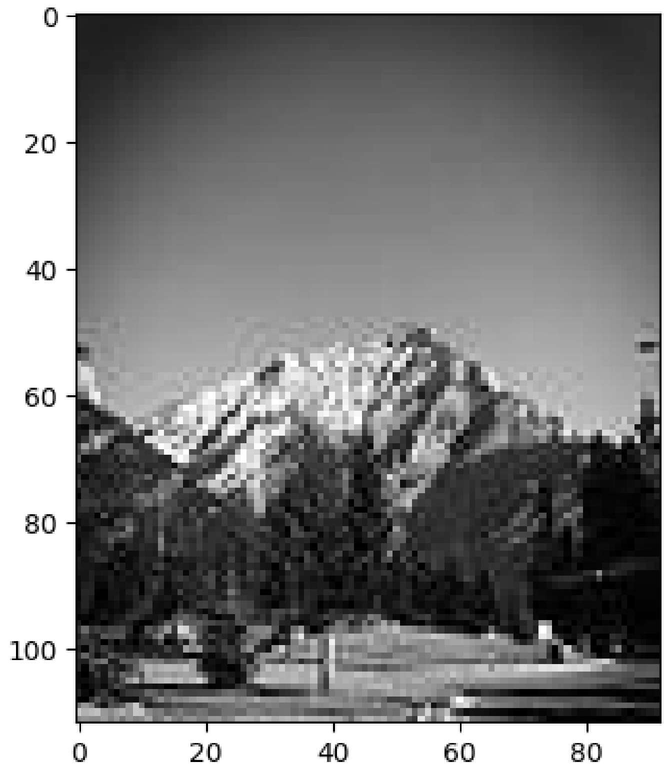
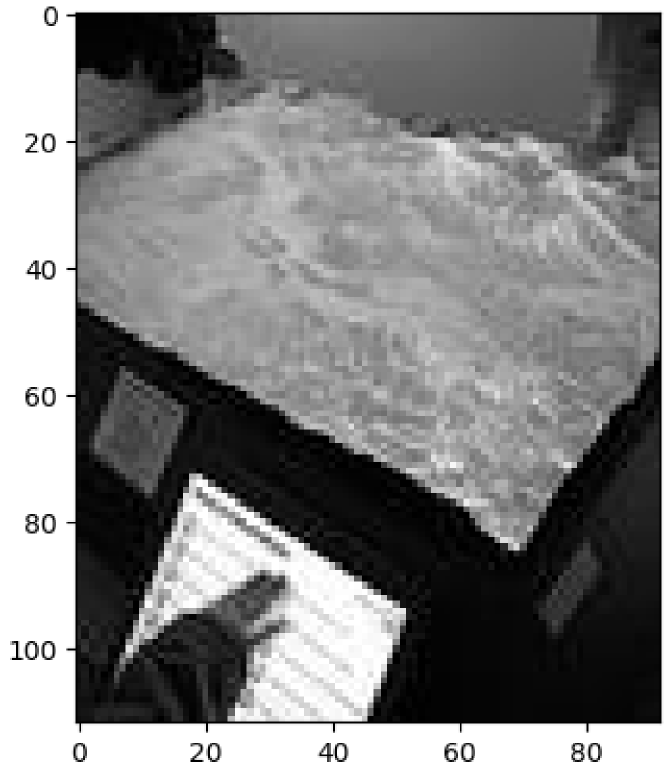
60
80


0
20
40
60
80
100
0
20
40
60
80

Failure cases:




0
20
40
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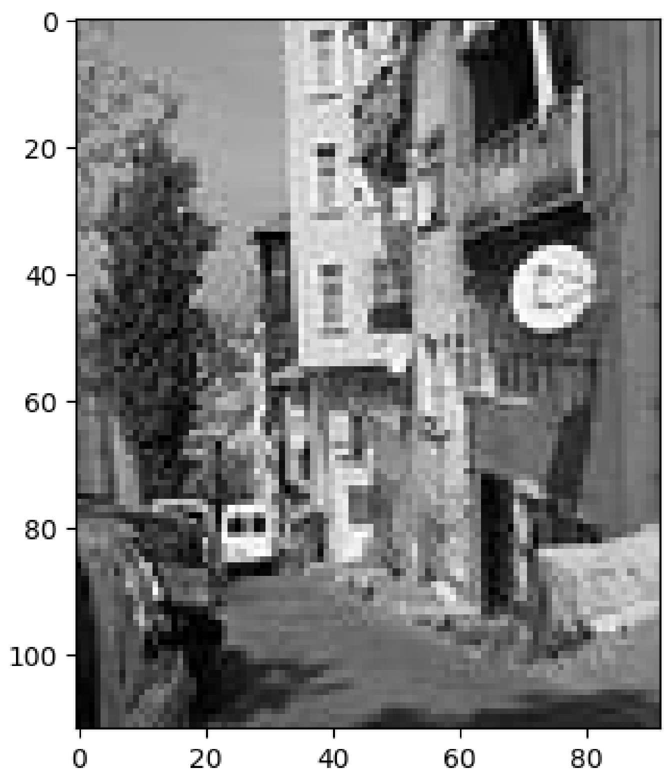
0
20
40
60
80


0
20
40
60
80
100
0
20
40
60
80

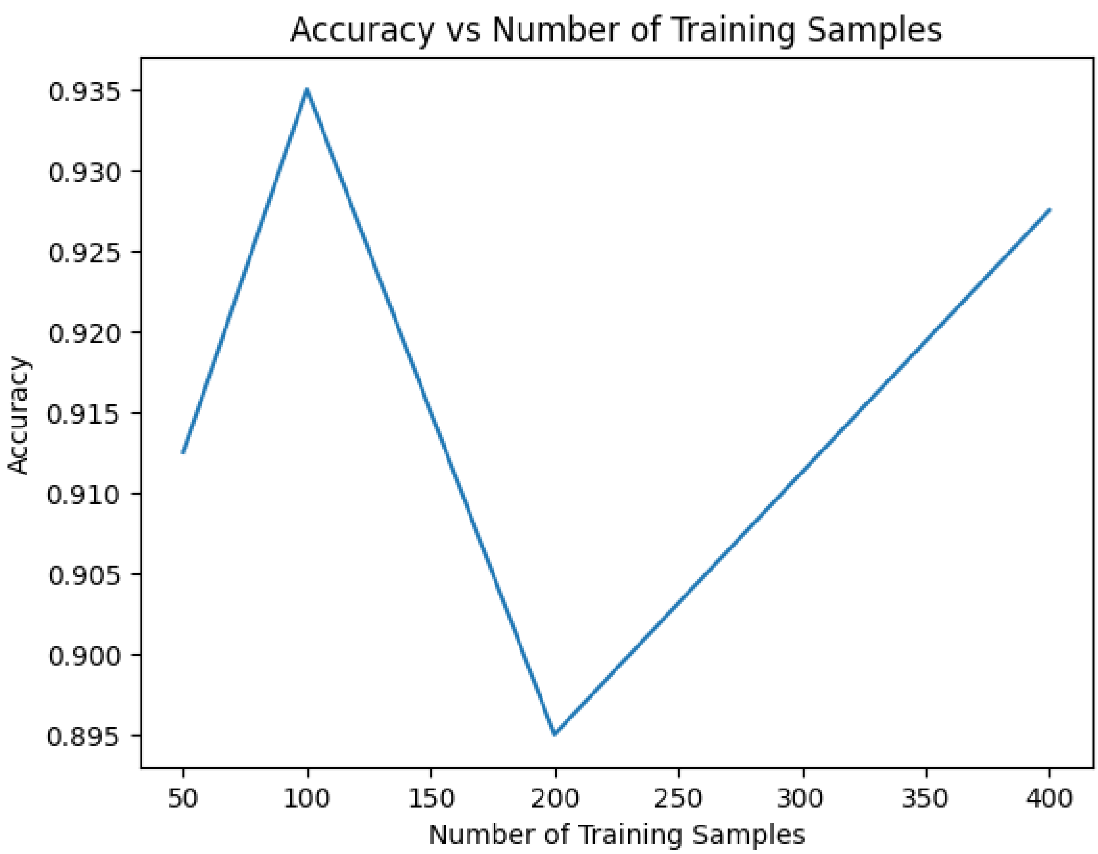
```
Accuracy 92.75
```

12 LDA Accuracy while fixing 200 faces in the training set

[11]:
```python
# List of training sample sizes
training_samples = [50, 100, 200, 400]

# List of corresponding accuracy values
accuracy = [0.9125, 0.935, 0.895, 0.9275]

# Plotting the graph
plt.plot(training_samples, accuracy)
plt.xlabel('Number of Training Samples')
plt.ylabel('Accuracy')
plt.title('Accuracy vs Number of Training Samples')
plt.show()
```



13 PCA Accuracy while fixing 200 faces in the training set

[12]:
```
# List of training sample sizes
training_samples = [50, 100, 200, 400]

# List of corresponding accuracy values
accuracy = [89.25, 91, 92.25, 92.75]

# Plotting the graph
plt.plot(training_samples, accuracy)
plt.xlabel('Number of Training Samples')
plt.ylabel('Accuracy')
plt.title('Accuracy vs Number of Training Samples')
plt.show()
```