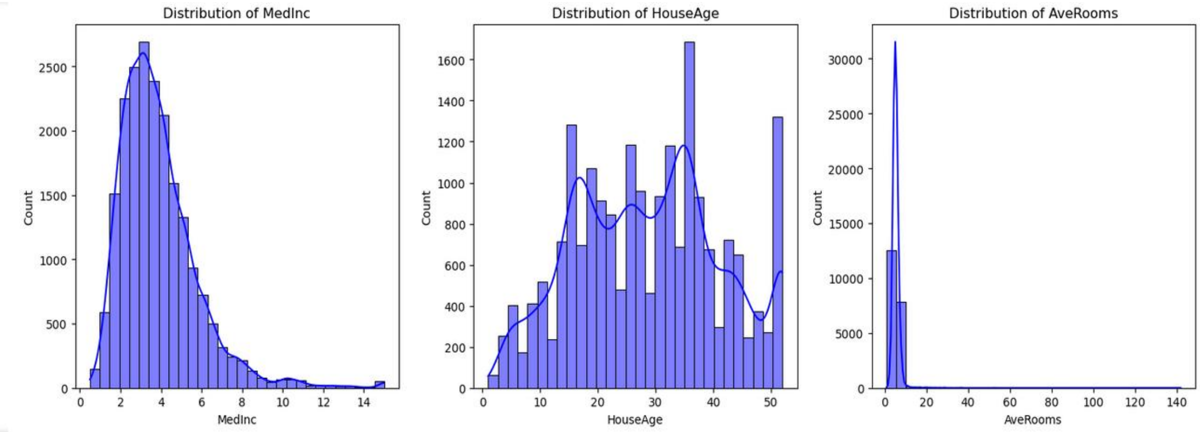
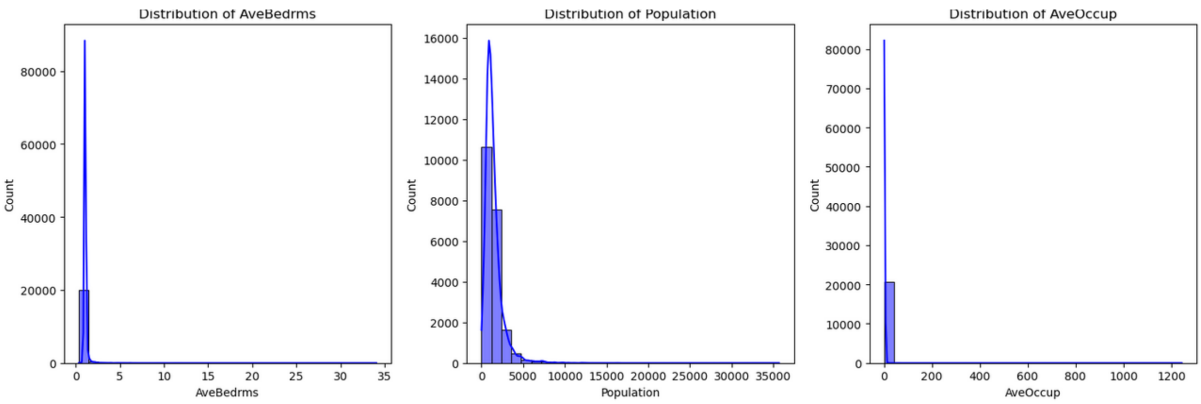
1. Develop a program to create histograms for all numerical features and analyze the distribution of each feature. Generate box plots for all numerical features and identify any outliers. Use California Housing dataset.

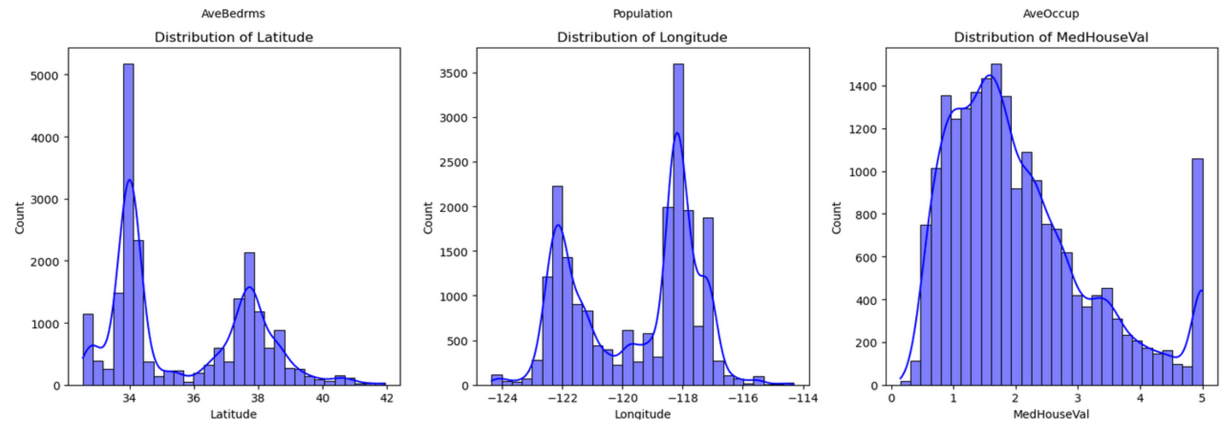
```
 import  pandas as pd

import  numpy as np

import  seaborn as sns

import  matplotlib.pyplot as plt

from  sklearn.datasets  import  fetch_california_housing


# Step 1: Load the California Housing dataset

data = fetch_california_housing(as_frame=True)

housing_df = data.frame


# Step 2: Create histograms for numerical features

numerical_features = housing_df.select_dtypes(include=[np.number]).columns


# Determine grid size for subplots

n_features = len(numerical_features)

n_cols = 3  # Number of columns for subplot grid

n_rows = (n_features // n_cols) + (n_features % n_cols > 0)  # Number of rows needed


# Plot histograms

plt.figure(figsize=(15, 5 * n_rows))

for i, feature in enumerate(numerical_features):

    plt.subplot(n_rows, n_cols, i + 1)

    sns.histplot(housing_df[feature], kde=True, bins=30, color='blue')

    plt.title(f'Distribution of {feature}')

plt.tight_layout()

plt.show()
```

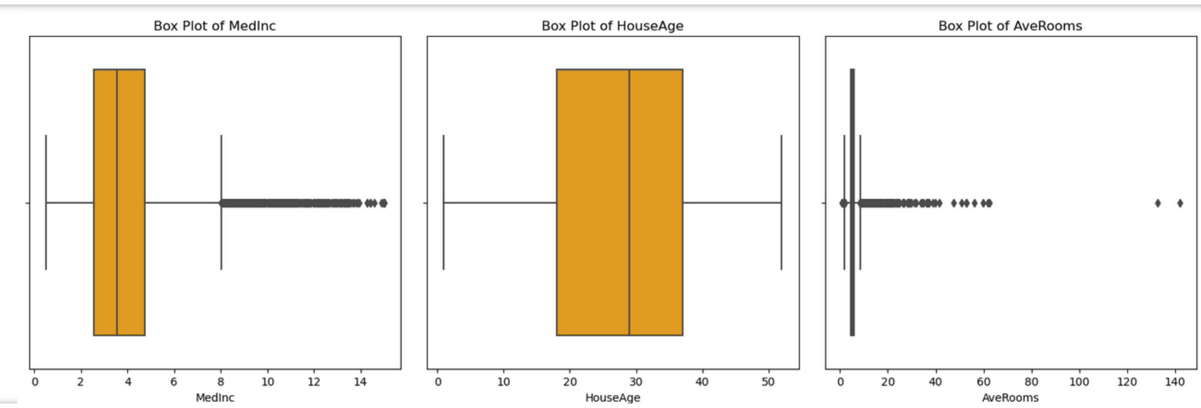
```
# Step 3: Generate box plots for numerical features
plt.figure(figsize=(15, 5 * n_rows))
for i, feature in enumerate(numerical_features):
    plt.subplot(n_rows, n_cols, i + 1)
    sns.boxplot(x=housing_df[feature], color='orange')
    plt.title(f'Box Plot of {feature}')
plt.tight_layout()
plt.show()

# Step 4: Identify outliers using the IQR method
print("Outliers Detection:")
outliers_summary = {}
for feature in numerical_features:
    Q1 = housing_df[feature].quantile(0.25)
    Q3 = housing_df[feature].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = housing_df[(housing_df[feature] < lower_bound) | (housing_df[feature] > upper_bound)]
    outliers_summary[feature] = len(outliers)
    print(f"{feature}: {len(outliers)} outliers")

# Optional: Print a summary of the dataset
print("\nDataset Summary:")
print(housing_df.describe())
```

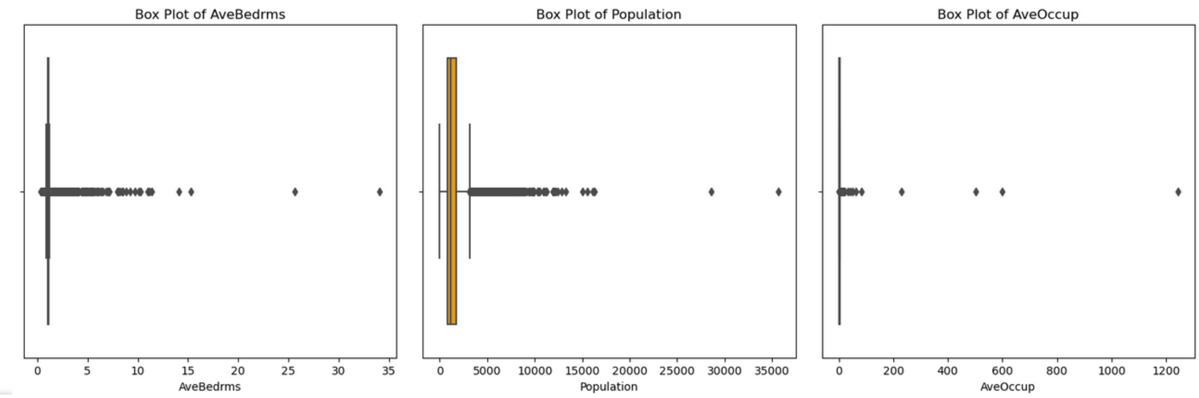
OUTPUT:

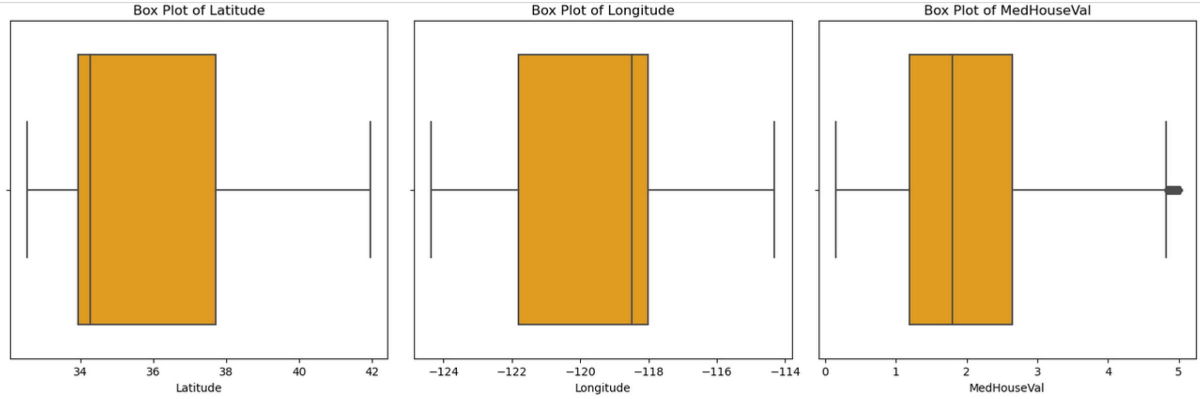

Distribution of MedInc
Count
MedInc
Distribution of HouseAge
Count
HouseAge
Distribution of AveRooms
Count
AveRooms


Distribution of AveBedrms
Count
AveBedrms
Distribution of Population
Count
Population
Distribution of AveOccup
Count
AveOccup


AveBedrms
Population
AveOccup
Distribution of Latitude
Count
Latitude
Distribution of Longitude
Count
Longitude
Distribution of MedHouseVal
Count
MedHouseVal


Box Plot of MedInc
MedInc
Box Plot of HouseAge
HouseAge
Box Plot of AveRooms
AveRooms






```
Outliers Detection:
MedInc: 681 outliers
HouseAge: 0 outliers
AveRooms: 511 outliers
AveBedrms: 1424 outliers
Population: 1196 outliers
AveOccup: 711 outliers
Latitude: 0 outliers
Longitude: 0 outliers
MedHouseVal: 1071 outliers

Dataset Summary:
             MedInc      HouseAge      AveRooms     AveBedrms    Population
count  20640.000000  20640.000000  20640.000000  20640.000000  20640.000000
mean       3.870671     28.639486      5.429000      1.096675   1425.476744
std        1.899822     12.585558      2.474173      0.473911   1132.462122
min        0.499900      1.000000      0.846154      0.333333      3.000000
25%        2.563400     18.000000      4.440716      1.006079    787.000000
50%        3.534800     29.000000      5.229129      1.048780   1166.000000
```

```
75%        4.743250    37.000000     6.052381     1.099526   1725.000000
max       15.000100    52.000000   141.909091    34.066667  35682.000000

            AveOccup     Latitude    Longitude  MedHouseVal
count   20640.000000 20640.000000 20640.000000 20640.000000
mean        3.070655    35.631861  -119.569704     2.068558
std        10.386050     2.135952     2.003532     1.153956
min         0.692308    32.540000  -124.350000     0.149990
25%         2.429741    33.930000  -121.800000     1.196000
50%         2.818116    34.260000  -118.490000     1.797000
75%         3.282261    37.710000  -118.010000     2.647250
max      1243.333333    41.950000  -114.310000     5.000010
```

2. **Develop a program to Compute the correlation matrix to understand the relationships between pairs of features. Visualize the correlation matrix using a heatmap to know which variables have strong positive/negative correlations. Create a pair plot to visualize pairwise relationships between features. Use California Housing dataset.**

```
import pandas as pd

import seaborn as sns

import matplotlib.pyplot as plt

from sklearn.datasets import fetch_california_housing


# Step 1: Load the California Housing Dataset

california_data = fetch_california_housing(as_frame=True)

data = california_data.frame


# Step 2: Compute the correlation matrix

correlation_matrix = data.corr()


# Step 3: Visualize the correlation matrix using a heatmap

plt.figure(figsize=(10, 8))

sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=0.5)

plt.title('Correlation Matrix of California Housing Features')

plt.show()
```

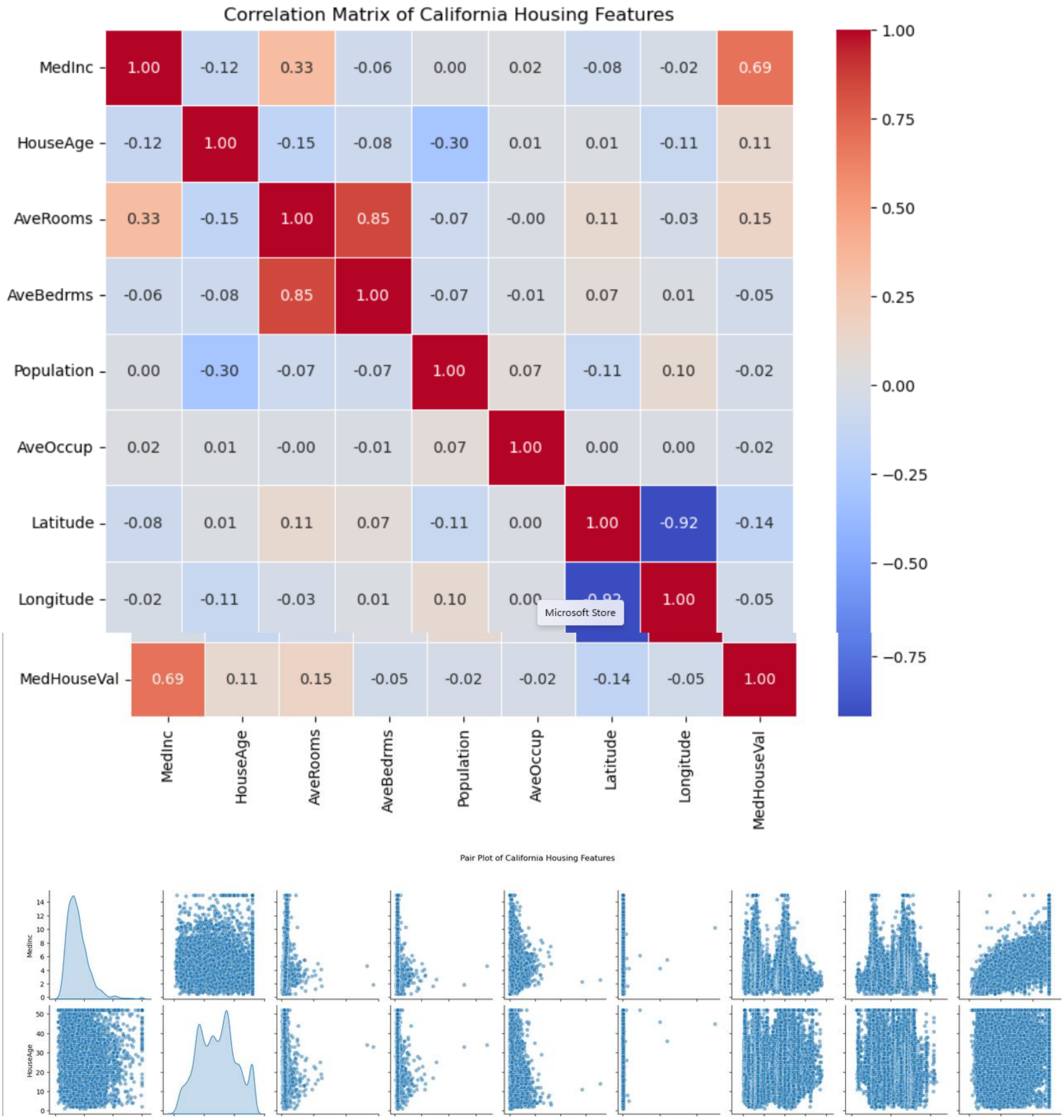
Step 4: Create a pair plot to visualize pairwise relationships

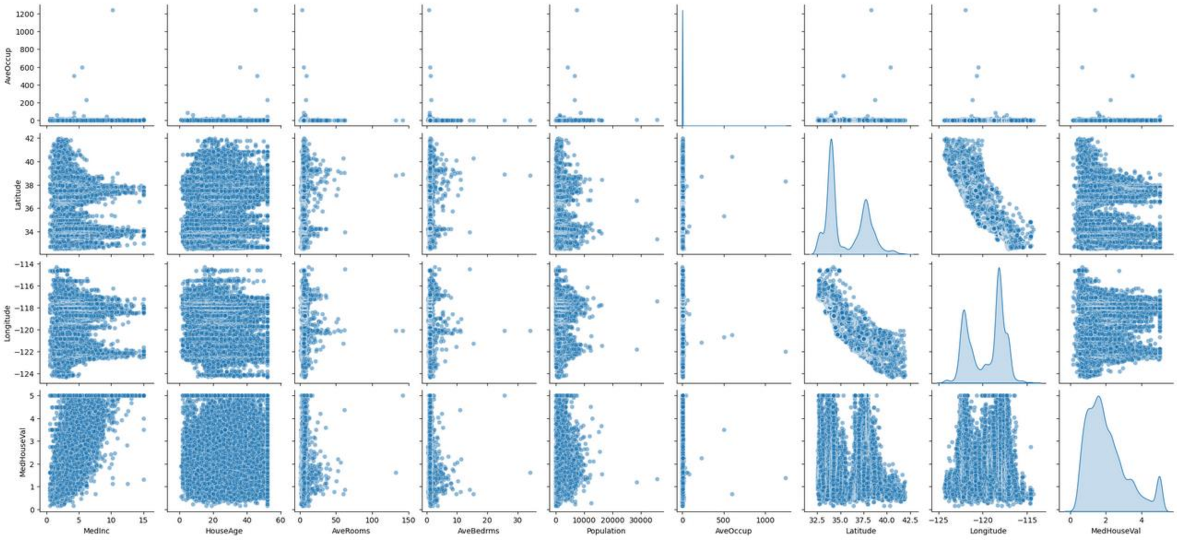
sns.pairplot(data, diag_kind='kde', plot_kws={'alpha': 0.5})

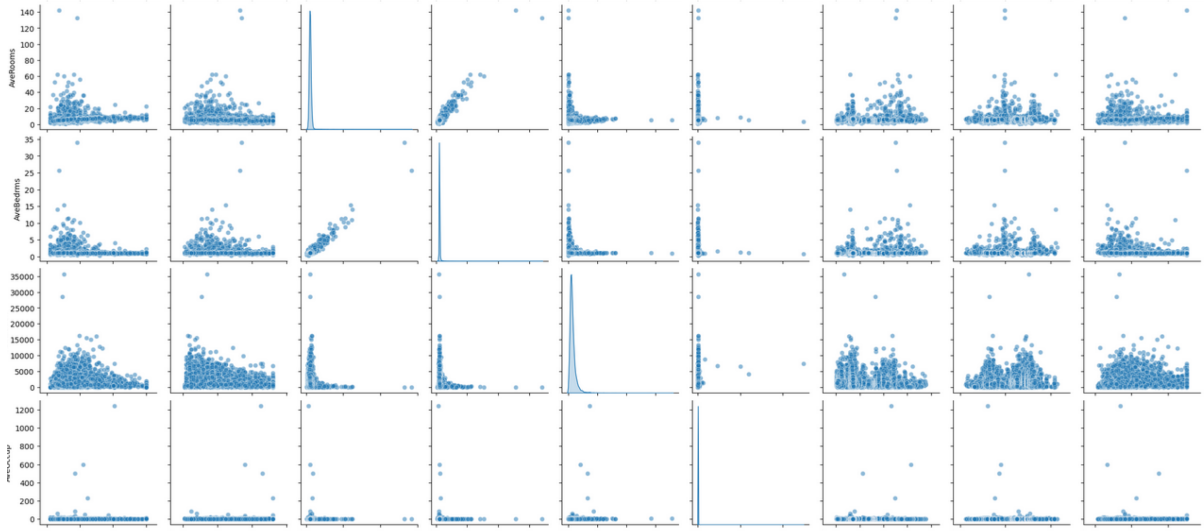
plt.suptitle('Pair Plot of California Housing Features', y=1.02)

plt.show()

OUTPUT:





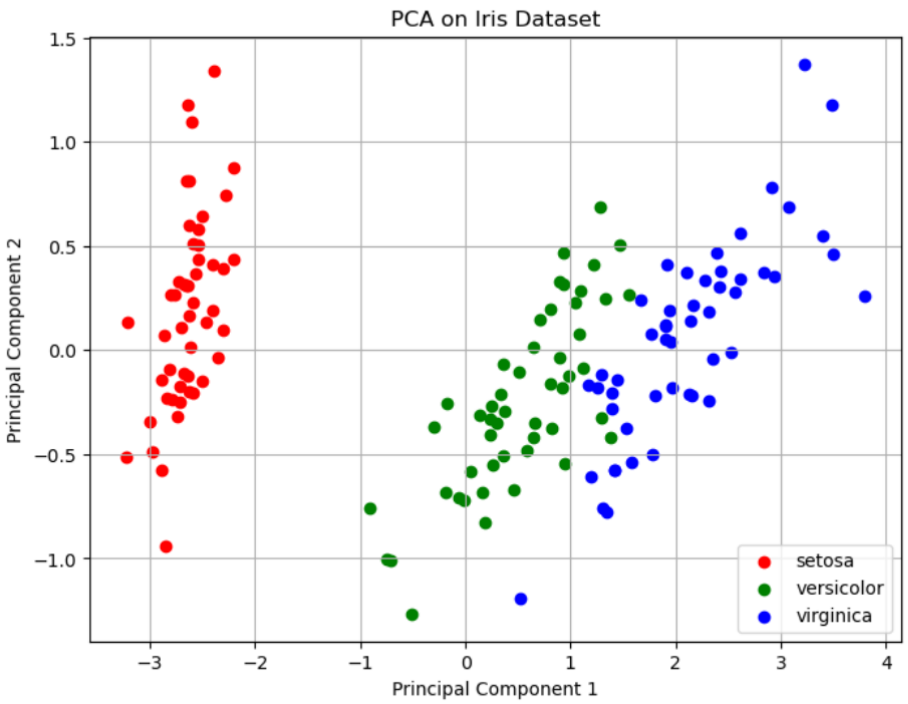


3. Develop a program to implement Principal Component Analysis (PCA) for reducing the dimensionality of the Iris dataset from 4 features to 2.

```
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = load_iris()
data = iris.data
labels = iris.target
label_names = iris.target_names

# Convert to a DataFrame for better visualization
iris_df = pd.DataFrame(data, columns=iris.feature_names)

# Perform PCA to reduce dimensionality to 2
```

```
pca = PCA(n_components=2)
data_reduced = pca.fit_transform(data)

# Create a DataFrame for the reduced data
reduced_df = pd.DataFrame(data_reduced, columns=['Principal Component 1', 'Principal
Component 2'])
reduced_df['Label'] = labels

# Plot the reduced data
plt.figure(figsize=(8, 6))
colors = ['r', 'g', 'b']
for i, label in enumerate(np.unique(labels)):
    plt.scatter(
        reduced_df[reduced_df['Label'] == label]['Principal Component 1'],
        reduced_df[reduced_df['Label'] == label]['Principal Component 2'],
        label=label_names[label],
        color=colors[i]
    )

plt.title('PCA on Iris Dataset')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend()
plt.grid()
plt.show()
```

OUTPUT:



4.For a given set of training data examples stored in a .CSV file, implement and demonstrate the Find-S algorithm to output a description of the set of all hypotheses consistent with the training examples.

```
import pandas as pd


def find_s_algorithm(file_path):
    data = pd.read_csv(file_path)

    print("Training data:")
    print(data)

    attributes = data.columns[:-1]
    class_label = data.columns[-1]

    hypothesis = ['?' for _ in attributes]

    for index, row in data.iterrows():
        if row[class_label] == 'Yes':
            for i, value in enumerate(row[attributes]):
                if hypothesis[i] == '?' or hypothesis[i] == value:
                    hypothesis[i] = value
                else:
                    hypothesis[i] = '?'

    return hypothesis


file_path = 'C:\\Users\\Admin\\Desktop\\training.csv'
hypothesis = find_s_algorithm(file_path)
print("\nThe final hypothesis is:", hypothesis)
```

<u>Output:</u>

Training data:

```
Training data:

    Outlook  Temperature  Humidity  Windy  PlayTennis
0     Sunny          Hot      High  False          No
1     Sunny          Hot      High   True          No
2  Overcast          Hot      High  False         Yes
3      Rain         Cold      High  False         Yes
4      Rain         Cold      High   True          No
5  Overcast          Hot      High   True         Yes
6     Sunny          Hot      High  False          No
```

```
The final hypothesis is: ['Overcast', 'Hot', 'High', '?']
```

5.Develop a program to implement k-Nearest Neighbour algorithm to classify the randomly generated 100 values of x in the range of [0,1]. Perform the following based on dataset generated.

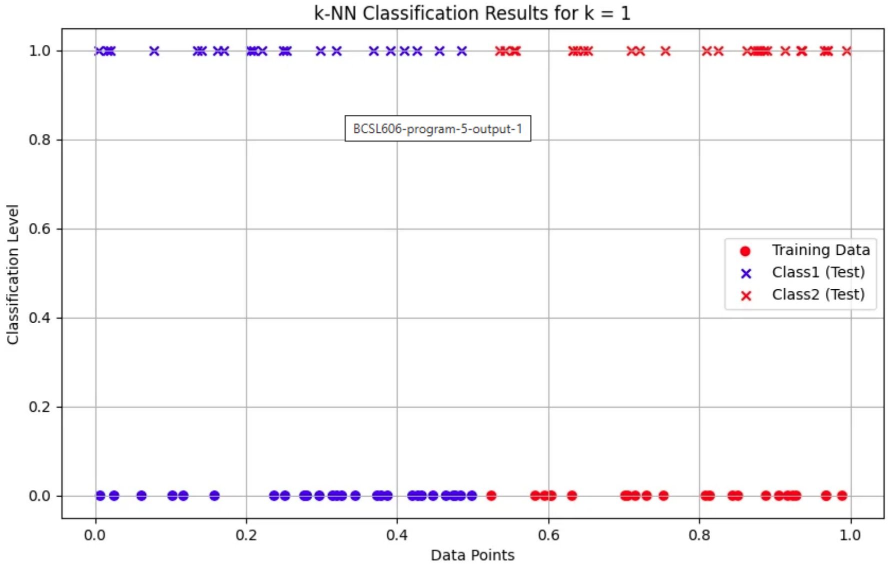
a) Label the first 50 points {x1,……,x50} as follows: if (xi ≤ 0.5), then xi ∊ Class1, else xi ∊ Class1
b) Classify the remaining points, x51,……,x100 using KNN. Perform this for k=1,2,3,4,5,20,30

```
import numpy as np

import matplotlib.pyplot as plt

from collections import Counter


data = np.random.rand(100)


labels = ["Class1" if x <= 0.5 else "Class2" for x in data[:50]]


def euclidean_distance(x1, x2):

    return abs(x1 - x2)


def knn_classifier(train_data, train_labels, test_point, k):

    distances = [(euclidean_distance(test_point, train_data[i]), train_labels[i]) for i in range(len(train_data))]


    distances.sort(key=lambda x: x[0])

    k_nearest_neighbors = distances[:k]


    k_nearest_labels = [label for _, label in k_nearest_neighbors]


    return Counter(k_nearest_labels).most_common(1)[0][0]
```

```
train_data = data[:50]
train_labels = labels

test_data = data[50:]

k_values = [1, 2, 3, 4, 5, 20, 30]

print("--- k-Nearest Neighbors Classification ---")
print("Training dataset: First 50 points labeled based on the rule (x <= 0.5 -> Class1, x > 0.5 -> Class2)")
print("Testing dataset: Remaining 50 points to be classified\n")

results = {}

for k in k_values:
    print(f"Results for k = {k}:")
    classified_labels = [knn_classifier(train_data, train_labels, test_point, k) for test_point in test_data]
    results[k] = classified_labels

    for i, label in enumerate(classified_labels, start=51):
        print(f"Point x{i} (value: {test_data[i - 51]:.4f}) is classified as {label}")
    print("\n")

print("Classification complete.\n")

for k in k_values:
    classified_labels = results[k]
    class1_points = [test_data[i] for i in range(len(test_data)) if classified_labels[i] == "Class1"]
```

```
class2_points = [test_data[i] for i in range(len(test_data)) if classified_labels[i] == "Class2"]


plt.figure(figsize=(10, 6))
plt.scatter(train_data, [0] * len(train_data), c=["blue" if label == "Class1" else "red" for label in train_labels],
            label="Training Data", marker="o")
plt.scatter(class1_points, [1] * len(class1_points), c="blue", label="Class1 (Test)", marker="x")
plt.scatter(class2_points, [1] * len(class2_points), c="red", label="Class2 (Test)", marker="x")


plt.title(f"k-NN Classification Results for k = {k}")
plt.xlabel("Data Points")
plt.ylabel("Classification Level")
plt.legend()
plt.grid(True)
plt.show()
```

Output:



--- k-Nearest Neighbors Classification ---

Training dataset: First 50 points labeled based on the rule (x <= 0.5 -> Class1, x > 0.5 -> Class2)

Testing dataset: Remaining 50 points to be classified

Results for k = 1:

Point x51 (value: 0.2059) is classified as Class1

Point x52 (value: 0.2535) is classified as Class1

Point x53 (value: 0.4856) is classified as Class1

Point x54 (value: 0.9651) is classified as Class2

Point x55 (value: 0.3906) is classified as Class1

Point x56 (value: 0.8903) is classified as Class2

Point x57 (value: 0.9695) is classified as Class2

Point x58 (value: 0.2206) is classified as Class1

Point x59 (value: 0.0203) is classified as Class1

Point x60 (value: 0.1619) is classified as Class1

Point x61 (value: 0.6461) is classified as Class2

Point x62 (value: 0.6523) is classified as Class2

Point x63 (value: 0.8728) is classified as Class2

Point x64 (value: 0.5435) is classified as Class2

Point x65 (value: 0.8246) is classified as Class2

Point x66 (value: 0.9347) is classified as Class2

Point x67 (value: 0.5361) is classified as Class2

Point x68 (value: 0.7215) is classified as Class2

Point x69 (value: 0.9703) is classified as Class2

Point x70 (value: 0.8764) is classified as Class2

Point x71 (value: 0.7543) is classified as Class2

Point x72 (value: 0.1406) is classified as Class1

Point x73 (value: 0.1349) is classified as Class1

Point x74 (value: 0.9705) is classified as Class2

Point x75 (value: 0.2985) is classified as Class1

Point x76 (value: 0.9948) is classified as Class2

Point x77 (value: 0.4551) is classified as Class1

Point x78 (value: 0.2101) is classified as Class1

Point x79 (value: 0.5542) is classified as Class2

Point x80 (value: 0.3202) is classified as Class1

Point x81 (value: 0.6325) is classified as Class2

Point x82 (value: 0.9345) is classified as Class2

Point x83 (value: 0.0156) is classified as Class1

Point x84 (value: 0.8859) is classified as Class2

Point x85 (value: 0.2495) is classified as Class1

Point x86 (value: 0.6380) is classified as Class2

Point x87 (value: 0.7095) is classified as Class2

Point x88 (value: 0.4259) is classified as Class1

Point x89 (value: 0.0052) is classified as Class1

Point x90 (value: 0.6322) is classified as Class2

Point x91 (value: 0.1701) is classified as Class1

Point x92 (value: 0.3693) is classified as Class1

Point x93 (value: 0.4087) is classified as Class1

Point x94 (value: 0.8103) is classified as Class2

Point x95 (value: 0.0773) is classified as Class1

Point x96 (value: 0.8792) is classified as Class2

Point x97 (value: 0.9138) is classified as Class2

Point x98 (value: 0.5567) is classified as Class2

Point x99 (value: 0.8625) is classified as Class2

Point x100 (value: 0.9363) is classified as Class2

Results for k = 2:

Point x51 (value: 0.2059) is classified as Class1

Point x52 (value: 0.2535) is classified as Class1

Point x53 (value: 0.4856) is classified as Class1

Point x54 (value: 0.9651) is classified as Class2

Point x55 (value: 0.3906) is classified as Class1

Point x56 (value: 0.8903) is classified as Class2

Point x57 (value: 0.9695) is classified as Class2

Point x58 (value: 0.2206) is classified as Class1

Point x59 (value: 0.0203) is classified as Class1

Point x60 (value: 0.1619) is classified as Class1

Point x61 (value: 0.6461) is classified as Class2

Point x62 (value: 0.6523) is classified as Class2

Point x63 (value: 0.8728) is classified as Class2

Point x64 (value: 0.5435) is classified as Class2

Point x65 (value: 0.8246) is classified as Class2

Point x66 (value: 0.9347) is classified as Class2

Point x67 (value: 0.5361) is classified as Class2

Point x68 (value: 0.7215) is classified as Class2

Point x69 (value: 0.9703) is classified as Class2

Point x70 (value: 0.8764) is classified as Class2

Point x71 (value: 0.7543) is classified as Class2

Point x72 (value: 0.1406) is classified as Class1

Point x73 (value: 0.1349) is classified as Class1

Point x74 (value: 0.9705) is classified as Class2

Point x75 (value: 0.2985) is classified as Class1

Point x76 (value: 0.9948) is classified as Class2

Point x77 (value: 0.4551) is classified as Class1

Point x78 (value: 0.2101) is classified as Class1

Point x79 (value: 0.5542) is classified as Class2

Point x80 (value: 0.3202) is classified as Class1

Point x81 (value: 0.6325) is classified as Class2

Point x82 (value: 0.9345) is classified as Class2

Point x83 (value: 0.0156) is classified as Class1

Point x84 (value: 0.8859) is classified as Class2

Point x85 (value: 0.2495) is classified as Class1

Point x86 (value: 0.6380) is classified as Class2

Point x87 (value: 0.7095) is classified as Class2

Point x88 (value: 0.4259) is classified as Class1

Point x89 (value: 0.0052) is classified as Class1

Point x90 (value: 0.6322) is classified as Class2

Point x91 (value: 0.1701) is classified as Class1

Point x92 (value: 0.3693) is classified as Class1

Point x93 (value: 0.4087) is classified as Class1

Point x94 (value: 0.8103) is classified as Class2

Point x95 (value: 0.0773) is classified as Class1

Point x96 (value: 0.8792) is classified as Class2

Point x97 (value: 0.9138) is classified as Class2

Point x98 (value: 0.5567) is classified as Class2

Point x99 (value: 0.8625) is classified as Class2

Point x100 (value: 0.9363) is classified as Class2

Results for k = 3:

Point x51 (value: 0.2059) is classified as Class1

Point x52 (value: 0.2535) is classified as Class1

Point x53 (value: 0.4856) is classified as Class1

Point x54 (value: 0.9651) is classified as Class2

Point x55 (value: 0.3906) is classified as Class1

Point x56 (value: 0.8903) is classified as Class2

Point x57 (value: 0.9695) is classified as Class2

Point x58 (value: 0.2206) is classified as Class1

Point x59 (value: 0.0203) is classified as Class1

Point x60 (value: 0.1619) is classified as Class1

Point x61 (value: 0.6461) is classified as Class2

Point x62 (value: 0.6523) is classified as Class2

Point x63 (value: 0.8728) is classified as Class2

Point x64 (value: 0.5435) is classified as Class2

Point x65 (value: 0.8246) is classified as Class2

Point x66 (value: 0.9347) is classified as Class2

Point x67 (value: 0.5361) is classified as Class2

Point x68 (value: 0.7215) is classified as Class2

Point x69 (value: 0.9703) is classified as Class2

Point x70 (value: 0.8764) is classified as Class2

Point x71 (value: 0.7543) is classified as Class2

Point x72 (value: 0.1406) is classified as Class1

Point x73 (value: 0.1349) is classified as Class1

Point x74 (value: 0.9705) is classified as Class2

Point x75 (value: 0.2985) is classified as Class1

Point x76 (value: 0.9948) is classified as Class2

Point x77 (value: 0.4551) is classified as Class1

Point x78 (value: 0.2101) is classified as Class1

Point x79 (value: 0.5542) is classified as Class2

Point x80 (value: 0.3202) is classified as Class1

Point x81 (value: 0.6325) is classified as Class2

Point x82 (value: 0.9345) is classified as Class2

Point x83 (value: 0.0156) is classified as Class1

Point x84 (value: 0.8859) is classified as Class2

Point x85 (value: 0.2495) is classified as Class1

Point x86 (value: 0.6380) is classified as Class2

Point x87 (value: 0.7095) is classified as Class2

Point x88 (value: 0.4259) is classified as Class1

Point x89 (value: 0.0052) is classified as Class1

Point x90 (value: 0.6322) is classified as Class2

Point x91 (value: 0.1701) is classified as Class1

Point x92 (value: 0.3693) is classified as Class1

Point x93 (value: 0.4087) is classified as Class1

Point x94 (value: 0.8103) is classified as Class2

Point x95 (value: 0.0773) is classified as Class1

Point x96 (value: 0.8792) is classified as Class2

Point x97 (value: 0.9138) is classified as Class2

Point x98 (value: 0.5567) is classified as Class2

Point x99 (value: 0.8625) is classified as Class2

Point x100 (value: 0.9363) is classified as Class2

Results for k = 4:

Point x51 (value: 0.2059) is classified as Class1

Point x52 (value: 0.2535) is classified as Class1

Point x53 (value: 0.4856) is classified as Class1

Point x54 (value: 0.9651) is classified as Class2

Point x55 (value: 0.3906) is classified as Class1

Point x56 (value: 0.8903) is classified as Class2

Point x57 (value: 0.9695) is classified as Class2

Point x58 (value: 0.2206) is classified as Class1

Point x59 (value: 0.0203) is classified as Class1

Point x60 (value: 0.1619) is classified as Class1

Point x61 (value: 0.6461) is classified as Class2

Point x62 (value: 0.6523) is classified as Class2

Point x63 (value: 0.8728) is classified as Class2

Point x64 (value: 0.5435) is classified as Class2

Point x65 (value: 0.8246) is classified as Class2

Point x66 (value: 0.9347) is classified as Class2

Point x67 (value: 0.5361) is classified as Class2

Point x68 (value: 0.7215) is classified as Class2

Point x69 (value: 0.9703) is classified as Class2

Point x70 (value: 0.8764) is classified as Class2

Point x71 (value: 0.7543) is classified as Class2

Point x72 (value: 0.1406) is classified as Class1

Point x73 (value: 0.1349) is classified as Class1

Point x74 (value: 0.9705) is classified as Class2

Point x75 (value: 0.2985) is classified as Class1

Point x76 (value: 0.9948) is classified as Class2

Point x77 (value: 0.4551) is classified as Class1

Point x78 (value: 0.2101) is classified as Class1

Point x79 (value: 0.5542) is classified as Class2

Point x80 (value: 0.3202) is classified as Class1

Point x81 (value: 0.6325) is classified as Class2

Point x82 (value: 0.9345) is classified as Class2

Point x83 (value: 0.0156) is classified as Class1

Point x84 (value: 0.8859) is classified as Class2

Point x85 (value: 0.2495) is classified as Class1

Point x86 (value: 0.6380) is classified as Class2

Point x87 (value: 0.7095) is classified as Class2

Point x88 (value: 0.4259) is classified as Class1

Point x89 (value: 0.0052) is classified as Class1

Point x90 (value: 0.6322) is classified as Class2

Point x91 (value: 0.1701) is classified as Class1

Point x92 (value: 0.3693) is classified as Class1

Point x93 (value: 0.4087) is classified as Class1

Point x94 (value: 0.8103) is classified as Class2

Point x95 (value: 0.0773) is classified as Class1

Point x96 (value: 0.8792) is classified as Class2

Point x97 (value: 0.9138) is classified as Class2

Point x98 (value: 0.5567) is classified as Class2

Point x99 (value: 0.8625) is classified as Class2

Point x100 (value: 0.9363) is classified as Class2

Results for k = 5:

Point x51 (value: 0.2059) is classified as Class1

Point x52 (value: 0.2535) is classified as Class1

Point x53 (value: 0.4856) is classified as Class1

Point x54 (value: 0.9651) is classified as Class2

Point x55 (value: 0.3906) is classified as Class1

Point x56 (value: 0.8903) is classified as Class2

Point x57 (value: 0.9695) is classified as Class2

Point x58 (value: 0.2206) is classified as Class1

Point x59 (value: 0.0203) is classified as Class1

Point x60 (value: 0.1619) is classified as Class1

Point x61 (value: 0.6461) is classified as Class2

Point x62 (value: 0.6523) is classified as Class2

Point x63 (value: 0.8728) is classified as Class2

Point x64 (value: 0.5435) is classified as Class2

Point x65 (value: 0.8246) is classified as Class2

Point x66 (value: 0.9347) is classified as Class2

Point x67 (value: 0.5361) is classified as Class1

Point x68 (value: 0.7215) is classified as Class2

Point x69 (value: 0.9703) is classified as Class2

Point x70 (value: 0.8764) is classified as Class2

Point x71 (value: 0.7543) is classified as Class2

Point x72 (value: 0.1406) is classified as Class1

Point x73 (value: 0.1349) is classified as Class1

Point x74 (value: 0.9705) is classified as Class2

Point x75 (value: 0.2985) is classified as Class1

Point x76 (value: 0.9948) is classified as Class2

Point x77 (value: 0.4551) is classified as Class1

Point x78 (value: 0.2101) is classified as Class1

Point x79 (value: 0.5542) is classified as Class2

Point x80 (value: 0.3202) is classified as Class1

Point x81 (value: 0.6325) is classified as Class2

Point x82 (value: 0.9345) is classified as Class2

Point x83 (value: 0.0156) is classified as Class1

Point x84 (value: 0.8859) is classified as Class2

Point x85 (value: 0.2495) is classified as Class1

Point x86 (value: 0.6380) is classified as Class2

Point x87 (value: 0.7095) is classified as Class2

Point x88 (value: 0.4259) is classified as Class1

Point x89 (value: 0.0052) is classified as Class1

Point x90 (value: 0.6322) is classified as Class2

Point x91 (value: 0.1701) is classified as Class1

Point x92 (value: 0.3693) is classified as Class1

Point x93 (value: 0.4087) is classified as Class1

Point x94 (value: 0.8103) is classified as Class2

Point x95 (value: 0.0773) is classified as Class1

Point x96 (value: 0.8792) is classified as Class2

Point x97 (value: 0.9138) is classified as Class2

Point x98 (value: 0.5567) is classified as Class2

Point x99 (value: 0.8625) is classified as Class2

Point x100 (value: 0.9363) is classified as Class2

Results for k = 20:

Point x51 (value: 0.2059) is classified as Class1

Point x52 (value: 0.2535) is classified as Class1

Point x53 (value: 0.4856) is classified as Class1

Point x54 (value: 0.9651) is classified as Class2

Point x55 (value: 0.3906) is classified as Class1

Point x56 (value: 0.8903) is classified as Class2

Point x57 (value: 0.9695) is classified as Class2

Point x58 (value: 0.2206) is classified as Class1

Point x59 (value: 0.0203) is classified as Class1

Point x60 (value: 0.1619) is classified as Class1

Point x61 (value: 0.6461) is classified as Class2

Point x62 (value: 0.6523) is classified as Class2

Point x63 (value: 0.8728) is classified as Class2

Point x64 (value: 0.5435) is classified as Class1

Point x65 (value: 0.8246) is classified as Class2

Point x66 (value: 0.9347) is classified as Class2

Point x67 (value: 0.5361) is classified as Class1

Point x68 (value: 0.7215) is classified as Class2

Point x69 (value: 0.9703) is classified as Class2

Point x70 (value: 0.8764) is classified as Class2

Point x71 (value: 0.7543) is classified as Class2

Point x72 (value: 0.1406) is classified as Class1

Point x73 (value: 0.1349) is classified as Class1

Point x74 (value: 0.9705) is classified as Class2

Point x75 (value: 0.2985) is classified as Class1

Point x76 (value: 0.9948) is classified as Class2

Point x77 (value: 0.4551) is classified as Class1

Point x78 (value: 0.2101) is classified as Class1

Point x79 (value: 0.5542) is classified as Class1

Point x80 (value: 0.3202) is classified as Class1

Point x81 (value: 0.6325) is classified as Class2

Point x82 (value: 0.9345) is classified as Class2

Point x83 (value: 0.0156) is classified as Class1

Point x84 (value: 0.8859) is classified as Class2

Point x85 (value: 0.2495) is classified as Class1

Point x86 (value: 0.6380) is classified as Class2

Point x87 (value: 0.7095) is classified as Class2

Point x88 (value: 0.4259) is classified as Class1

Point x89 (value: 0.0052) is classified as Class1

Point x90 (value: 0.6322) is classified as Class2

Point x91 (value: 0.1701) is classified as Class1

Point x92 (value: 0.3693) is classified as Class1

Point x93 (value: 0.4087) is classified as Class1

Point x94 (value: 0.8103) is classified as Class2

Point x95 (value: 0.0773) is classified as Class1

Point x96 (value: 0.8792) is classified as Class2

Point x97 (value: 0.9138) is classified as Class2

Point x98 (value: 0.5567) is classified as Class2

Point x99 (value: 0.8625) is classified as Class2

Point x100 (value: 0.9363) is classified as Class2

Results for k = 30:

Point x51 (value: 0.2059) is classified as Class1

Point x52 (value: 0.2535) is classified as Class1

Point x53 (value: 0.4856) is classified as Class1

Point x54 (value: 0.9651) is classified as Class2

Point x55 (value: 0.3906) is classified as Class1

Point x56 (value: 0.8903) is classified as Class2

Point x57 (value: 0.9695) is classified as Class2

Point x58 (value: 0.2206) is classified as Class1

Point x59 (value: 0.0203) is classified as Class1

Point x60 (value: 0.1619) is classified as Class1

Point x61 (value: 0.6461) is classified as Class2

Point x62 (value: 0.6523) is classified as Class2

Point x63 (value: 0.8728) is classified as Class2

Point x64 (value: 0.5435) is classified as Class1

Point x65 (value: 0.8246) is classified as Class2

Point x66 (value: 0.9347) is classified as Class2

Point x67 (value: 0.5361) is classified as Class1

Point x68 (value: 0.7215) is classified as Class2

Point x69 (value: 0.9703) is classified as Class2

Point x70 (value: 0.8764) is classified as Class2

Point x71 (value: 0.7543) is classified as Class2

Point x72 (value: 0.1406) is classified as Class1

Point x73 (value: 0.1349) is classified as Class1

Point x74 (value: 0.9705) is classified as Class2

Point x75 (value: 0.2985) is classified as Class1

Point x76 (value: 0.9948) is classified as Class2

Point x77 (value: 0.4551) is classified as Class1

Point x78 (value: 0.2101) is classified as Class1

Point x79 (value: 0.5542) is classified as Class1

Point x80 (value: 0.3202) is classified as Class1

Point x81 (value: 0.6325) is classified as Class2

Point x82 (value: 0.9345) is classified as Class2

Point x83 (value: 0.0156) is classified as Class1

Point x84 (value: 0.8859) is classified as Class2

Point x85 (value: 0.2495) is classified as Class1

Point x86 (value: 0.6380) is classified as Class2

Point x87 (value: 0.7095) is classified as Class2

Point x88 (value: 0.4259) is classified as Class1

Point x89 (value: 0.0052) is classified as Class1

Point x90 (value: 0.6322) is classified as Class2

Point x91 (value: 0.1701) is classified as Class1

Point x92 (value: 0.3693) is classified as Class1

Point x93 (value: 0.4087) is classified as Class1

Point x94 (value: 0.8103) is classified as Class2

Point x95 (value: 0.0773) is classified as Class1

Point x96 (value: 0.8792) is classified as Class2

Point x97 (value: 0.9138) is classified as Class2

Point x98 (value: 0.5567) is classified as Class1

Point x99 (value: 0.8625) is classified as Class2

Point x100 (value: 0.9363) is classified as Class2

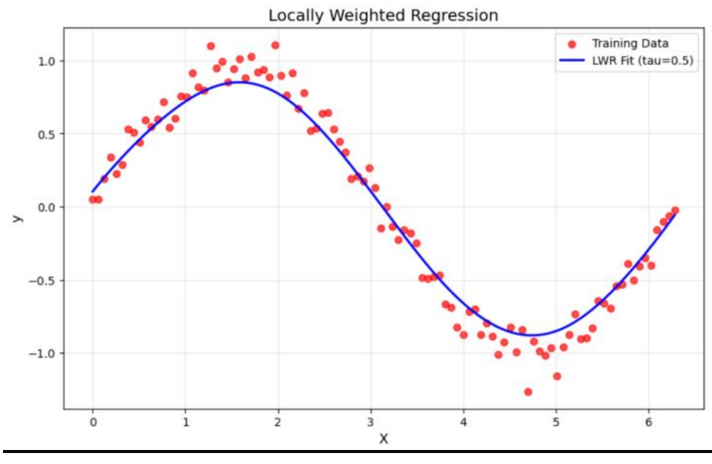
Classification complete.

6. Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs.

```
import numpy as np

import matplotlib.pyplot as plt



def gaussian_kernel(x, xi, tau):

    return np.exp(-np.sum((x - xi) ** 2) / (2 * tau ** 2))


def locally_weighted_regression(x, X, y, tau):

    m = X.shape[0]

    weights = np.array([gaussian_kernel(x, X[i], tau) for i in range(m)])

    W = np.diag(weights)

    X_transpose_W = X.T @ W

    theta = np.linalg.inv(X_transpose_W @ X) @ X_transpose_W @ y

    return x @ theta
```

```
np.random.seed(42)
X = np.linspace(0, 2 * np.pi, 100)
y = np.sin(X) + 0.1 * np.random.randn(100)
X_bias = np.c_[np.ones(X.shape), X]

x_test = np.linspace(0, 2 * np.pi, 200)
x_test_bias = np.c_[np.ones(x_test.shape), x_test]
tau = 0.5
y_pred = np.array([locally_weighted_regression(xi, X_bias, y, tau) for xi in x_test_bias])

plt.figure(figsize=(10, 6))
plt.scatter(X, y, color='red', label='Training Data', alpha=0.7)
plt.plot(x_test, y_pred, color='blue', label=f'LWR Fit (tau={tau})', linewidth=2)
plt.xlabel('X', fontsize=12)
plt.ylabel('y', fontsize=12)
plt.title('Locally Weighted Regression', fontsize=14)
plt.legend(fontsize=10)
plt.grid(alpha=0.3)
plt.show()
```

Output:



7. Develop a program to demonstrate the working of Linear Regression and Polynomial Regression. Use Boston Housing Dataset for Linear Regression and Auto MPG Dataset (for

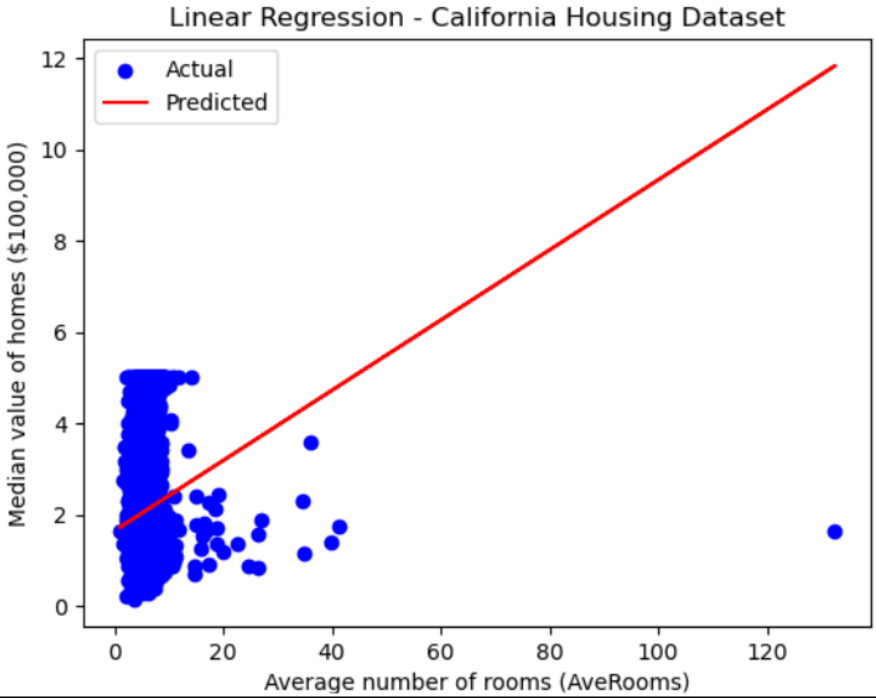
```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

from sklearn.datasets import fetch_california_housing

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LinearRegression

from sklearn.preprocessing import PolynomialFeatures, StandardScaler

from sklearn.pipeline import make_pipeline

from sklearn.metrics import mean_squared_error, r2_score


def linear_regression_california():

    housing = fetch_california_housing(as_frame=True)

    X = housing.data[["AveRooms"]]

    y = housing.target


    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)


    model = LinearRegression()

    model.fit(X_train, y_train)


    y_pred = model.predict(X_test)


    plt.scatter(X_test, y_test, color="blue", label="Actual")

    plt.plot(X_test, y_pred, color="red", label="Predicted")

    plt.xlabel("Average number of rooms (AveRooms)")

    plt.ylabel("Median value of homes ($100,000)")

    plt.title("Linear Regression - California Housing Dataset")
```

```
    plt.legend()
    plt.show()


    print("Linear Regression - California Housing Dataset")
    print("Mean Squared Error:", mean_squared_error(y_test, y_pred))
    print("R^2 Score:", r2_score(y_test, y_pred))



def polynomial_regression_auto_mpg():
    url = "https://archive.ics.uci.edu/ml/machine-learning-databases/auto-mpg/auto-mpg.data"
    column_names = ["mpg", "cylinders", "displacement", "horsepower", "weight", "acceleration",
"model_year", "origin"]
    data = pd.read_csv(url, sep='\s+', names=column_names, na_values="?")
    data = data.dropna()


    X = data["displacement"].values.reshape(-1, 1)
    y = data["mpg"].values


    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)


    poly_model = make_pipeline(PolynomialFeatures(degree=2), StandardScaler(),
LinearRegression())
    poly_model.fit(X_train, y_train)


    y_pred = poly_model.predict(X_test)


    plt.scatter(X_test, y_test, color="blue", label="Actual")
    plt.scatter(X_test, y_pred, color="red", label="Predicted")
    plt.xlabel("Displacement")
```

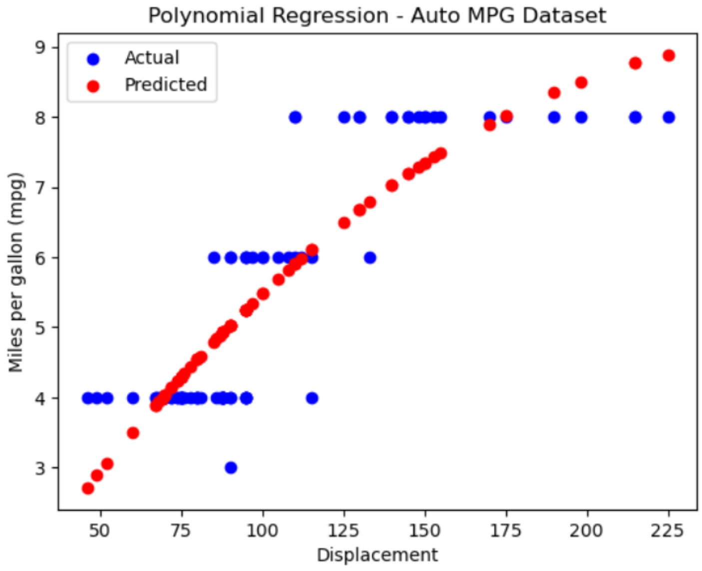
```
    plt.ylabel("Miles per gallon (mpg)")
    plt.title("Polynomial Regression - Auto MPG Dataset")
    plt.legend()
    plt.show()

    print("Polynomial Regression - Auto MPG Dataset")
    print("Mean Squared Error:", mean_squared_error(y_test, y_pred))
    print("R^2 Score:", r2_score(y_test, y_pred))


if __name__ == "__main__":
    print("Demonstrating Linear Regression and Polynomial Regression\n")
    linear_regression_california()
    polynomial_regression_auto_mpg()
```

Output:

```
Demonstrating Linear Regression and Polynomial Regression
```



```
Linear Regression - California Housing Dataset
Mean Squared Error: 1.2923314440807299
R^2 Score: 0.013795337532284901
```




```
Polynomial Regression - Auto MPG Dataset
Mean Squared Error: 0.7431490557205862
R^2 Score: 0.7505650609469626
```

8. Develop a program to demonstrate the working of the decision tree algorithm. Use Breast Cancer Data set for building the decision tree and apply this knowledge to classify a new sample.

9. Develop a program to implement the Naive Bayesian classifier considering Olivetti Face Data set for training. Compute the accuracy of the classifier, considering a few test data sets.

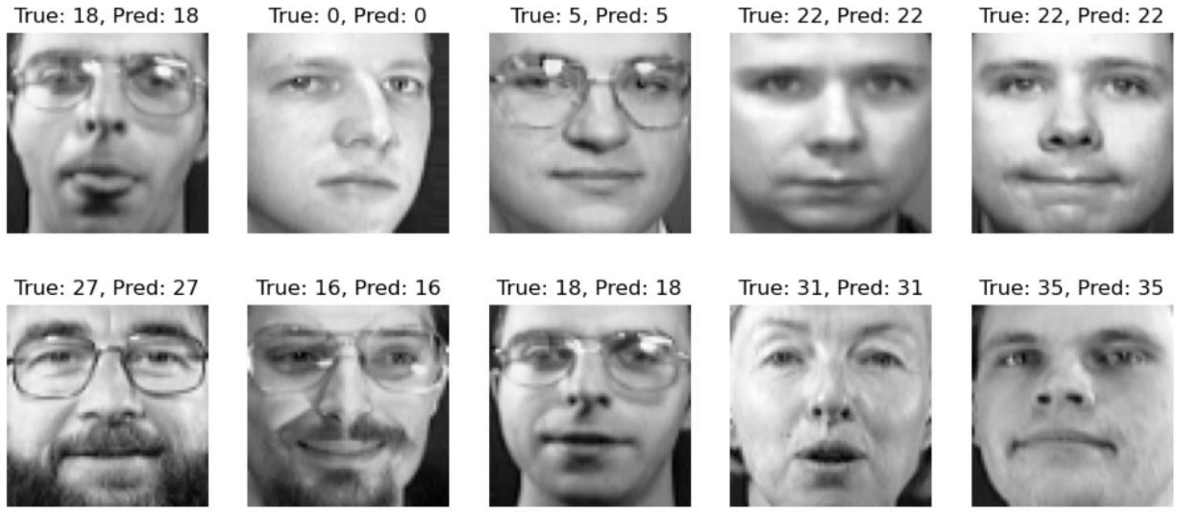
```
import numpy as np

from sklearn.datasets import fetch_olivetti_faces

from sklearn.model_selection import train_test_split, cross_val_score

from sklearn.naive_bayes import GaussianNB

from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

import matplotlib.pyplot as plt


data = fetch_olivetti_faces(shuffle=True, random_state=42)
```

```
X = data.data
y = data.target

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

gnb = GaussianNB()
gnb.fit(X_train, y_train)
y_pred = gnb.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy * 100:.2f}%')

print("\nClassification Report:")
print(classification_report(y_test, y_pred, zero_division=1))

print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred))

cross_val_accuracy = cross_val_score(gnb, X, y, cv=5, scoring='accuracy')
print(f'\nCross-validation accuracy: {cross_val_accuracy.mean() * 100:.2f}%')

fig, axes = plt.subplots(3, 5, figsize=(12, 8))
for ax, image, label, prediction in zip(axes.ravel(), X_test, y_test, y_pred):
    ax.imshow(image.reshape(64, 64), cmap=plt.cm.gray)
    ax.set_title(f"True: {label}, Pred: {prediction}")
    ax.axis('off')

plt.show()
```

Output:

```
downloading Olivetti faces from
https://ndownloader.figshare.com/files/5976027 to
C:\Users\Admin\scikit_learn_data
Accuracy: 80.83%

Classification Report:
              precision    recall  f1-score   support

           0       0.67      1.00      0.80         2
           1       1.00      1.00      1.00         2
           2       0.33      0.67      0.44         3
           3       1.00      0.00      0.00         5
           4       1.00      0.50      0.67         4
           5       1.00      1.00      1.00         2
           7       1.00      0.75      0.86         4
           8       1.00      0.67      0.80         3
           9       1.00      0.75      0.86         4
          10       1.00      1.00      1.00         3
          11       1.00      1.00      1.00         1
          12       0.40      1.00      0.57         4
          13       1.00      0.80      0.89         5
          14       1.00      0.40      0.57         5
          15       0.67      1.00      0.80         2
          16       1.00      0.67      0.80         3
          17       1.00      1.00      1.00         3
          18       1.00      1.00      1.00         3
          19       0.67      1.00      0.80         2
          20       1.00      1.00      1.00         3
          21       1.00      0.67      0.80         3
          22       1.00      0.60      0.75         5
          23       1.00      0.75      0.86         4
          24       1.00      1.00      1.00         3
          25       1.00      0.75      0.86         4
          26       1.00      1.00      1.00         2
          27       1.00      1.00      1.00         5
          28       0.50      1.00      0.67         2
          29       1.00      1.00      1.00         2
          30       1.00      1.00      1.00         2
          31       1.00      0.75      0.86         4
          32       1.00      1.00      1.00         2
          34       0.25      1.00      0.40         1
          35       1.00      1.00      1.00         5
          36       1.00      1.00      1.00         3
          37       1.00      1.00      1.00         1
          38       1.00      0.75      0.86         4
          39       0.50      1.00      0.67         5

    accuracy                           0.81       120
   macro avg       0.89      0.85      0.83       120
weighted avg       0.91      0.81      0.81       120


Confusion Matrix:
[[2 0 0 ... 0 0 0]
 [0 2 0 ... 0 0 0]
 [0 0 2 ... 0 0 1]
 ...
 [0 0 0 ... 1 0 0]
 [0 0 0 ... 0 3 0]
```

```
 [0 0 0 ... 0 0 5]]

Cross-validation accuracy: 87.25%
```



10. Develop a program to implement k-means clustering using Wisconsin Breast Cancer data set and visualize the clustering result.

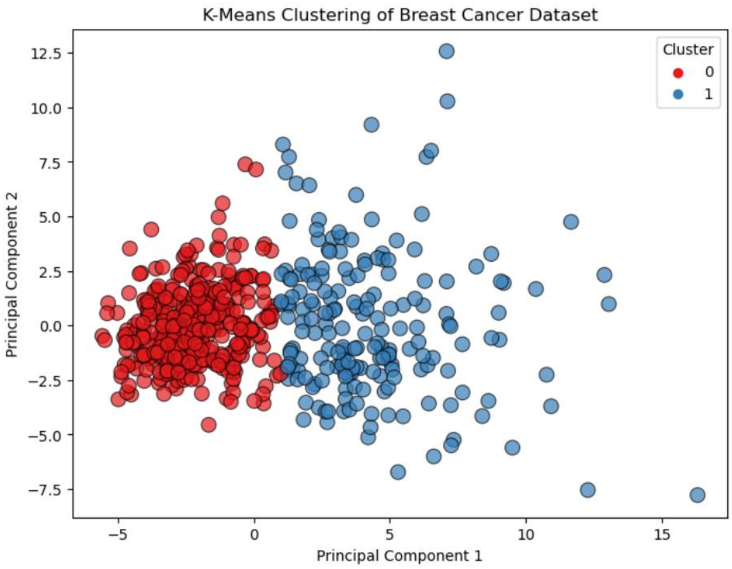
```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.datasets import load_breast_cancer

from sklearn.cluster import KMeans

from sklearn.preprocessing import StandardScaler

from sklearn.decomposition import PCA

from sklearn.metrics import confusion_matrix, classification_report


data = load_breast_cancer()
```

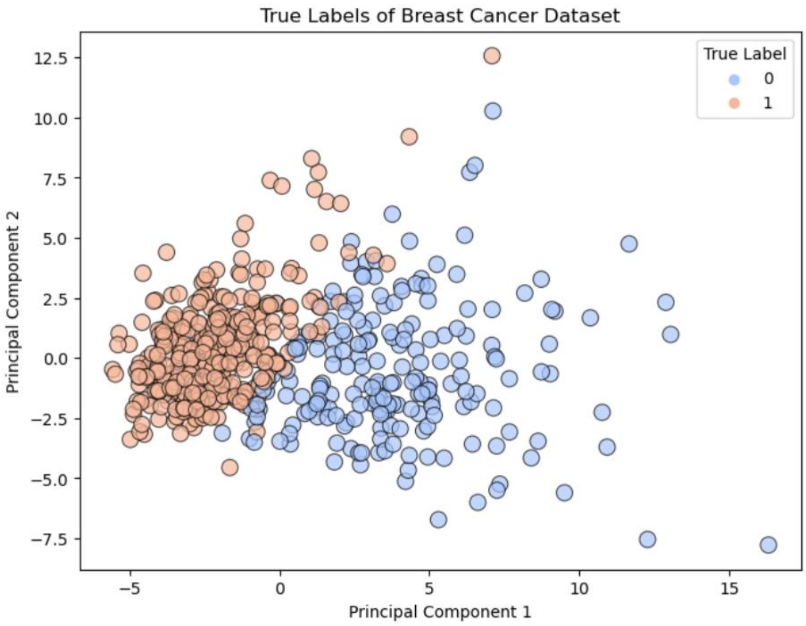
```
X = data.data

y = data.target


scaler = StandardScaler()

X_scaled = scaler.fit_transform(X)


kmeans = KMeans(n_clusters=2, random_state=42)

y_kmeans = kmeans.fit_predict(X_scaled)


print("Confusion Matrix:")

print(confusion_matrix(y, y_kmeans))

print("\nClassification Report:")

print(classification_report(y, y_kmeans))


pca = PCA(n_components=2)

X_pca = pca.fit_transform(X_scaled)


df = pd.DataFrame(X_pca, columns=['PC1', 'PC2'])

df['Cluster'] = y_kmeans

df['True Label'] = y


plt.figure(figsize=(8, 6))

sns.scatterplot(data=df, x='PC1', y='PC2', hue='Cluster', palette='Set1', s=100, edgecolor='black',
alpha=0.7)

plt.title('K-Means Clustering of Breast Cancer Dataset')

plt.xlabel('Principal Component 1')

plt.ylabel('Principal Component 2')

plt.legend(title="Cluster")

plt.show()
```

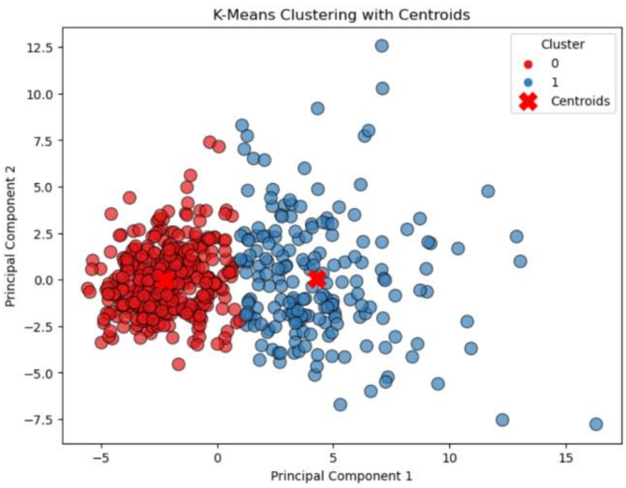
```
plt.figure(figsize=(8, 6))

sns.scatterplot(data=df, x='PC1', y='PC2', hue='True Label', palette='coolwarm', s=100, edgecolor='black', alpha=0.7)

plt.title('True Labels of Breast Cancer Dataset')

plt.xlabel('Principal Component 1')

plt.ylabel('Principal Component 2')

plt.legend(title="True Label")

plt.show()


plt.figure(figsize=(8, 6))

sns.scatterplot(data=df, x='PC1', y='PC2', hue='Cluster', palette='Set1', s=100, edgecolor='black', alpha=0.7)

centers = pca.transform(kmeans.cluster_centers_)

plt.scatter(centers[:, 0], centers[:, 1], s=200, c='red', marker='X', label='Centroids')

plt.title('K-Means Clustering with Centroids')

plt.xlabel('Principal Component 1')

plt.ylabel('Principal Component 2')

plt.legend(title="Cluster")

plt.show()
```

Output:

```
Confusion Matrix:
[[ 36 176]
 [339  18]]

Classification Report:
              precision    recall  f1-score   support

           0       0.10      0.17      0.12       212
           1       0.09      0.05      0.07       357

    accuracy                           0.09       569
   macro avg       0.09      0.11      0.09       569
weighted avg       0.09      0.09      0.09       569
```


K-Means Clustering of Breast Cancer Dataset
Cluster
0
1
Principal Component 2
Principal Component 1
12.5
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
−5
0
5
10
15


True Labels of Breast Cancer Dataset
True Label
0
1
Principal Component 2
Principal Component 1
12.5
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
−5
0
5
10
15


K-Means Clustering with Centroids
Cluster
0
1
Centroids
Principal Component 2
Principal Component 1
12.5
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
−5
0
5
10
15