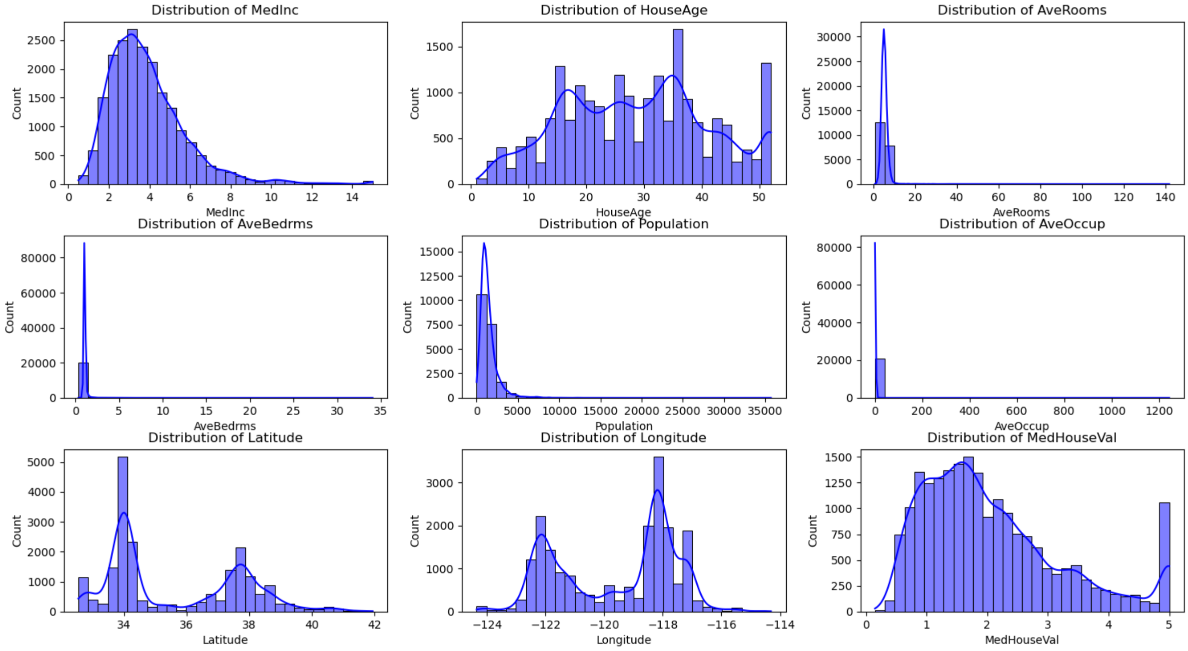
Machine Learning Lab Manual

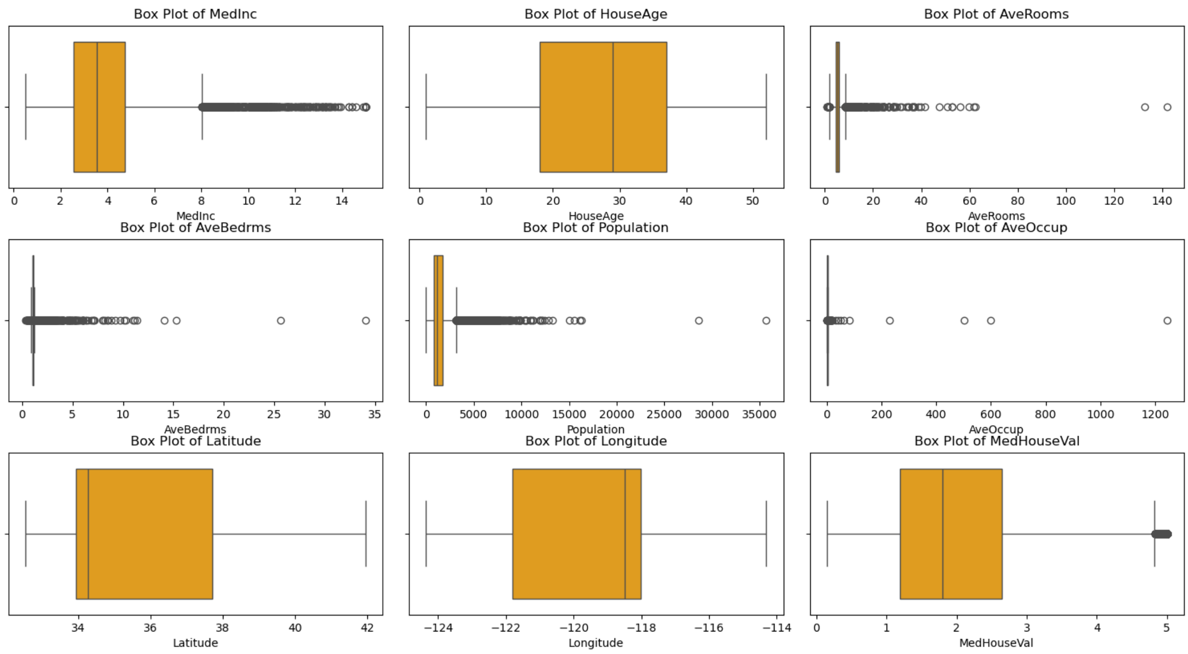
1. **Develop a program to create histograms for all numerical features and analyse the distribution of each feature. Generate box plots for all numerical features and identify any outliers. Use California Housing dataset.**

```
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

# Plot histograms
plt.figure(figsize=(15, 10))
for i, feature in enumerate(numerical_features):
plt.subplot(3, 3, 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, 10))
for i, feature in enumerate(numerical_features):
plt.subplot(3, 3, 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





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:

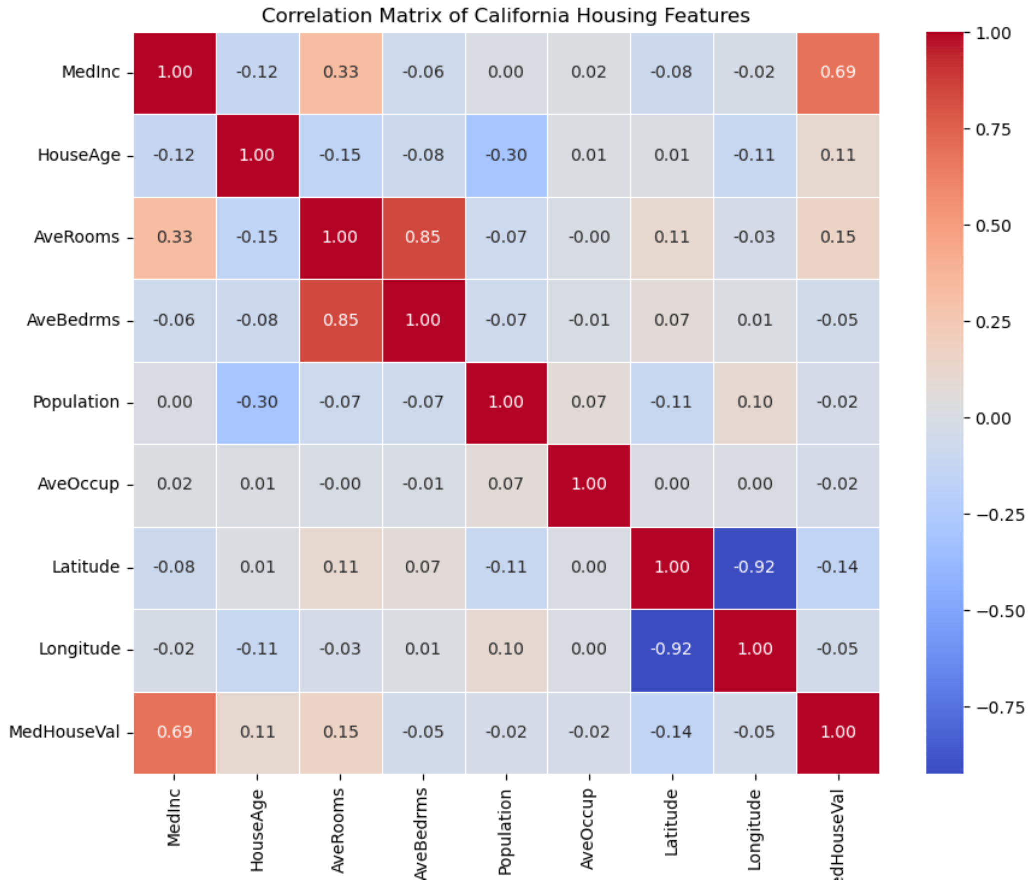
	MedInc	HouseAge	...	Longitude	MedHouseVal
count	20640.000000	20640.000000	...	20640.000000	20640.000000
mean	3.870671	28.639486	...	-119.569704	2.068558
std	1.899822	12.585558	...	2.003532	1.153956
min	0.499900	1.000000	...	-124.350000	0.149990
25%	2.563400	18.000000	...	-121.800000	1.196000
50%	3.534800	29.000000	...	-118.490000	1.797000
75%	4.743250	37.000000	...	-118.010000	2.647250
max	15.000100	52.000000	...	-114.310000	5.000010

[8 rows x 9 columns]

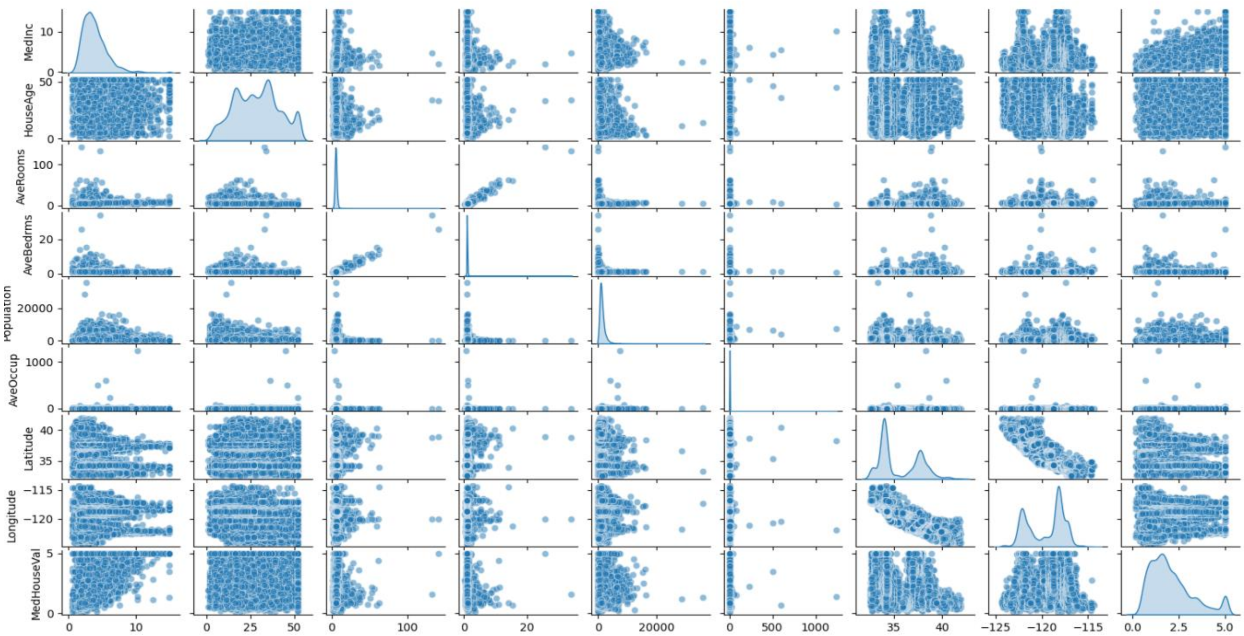
2. **Develop a program to Compute the correlation matrix to understand the relationships between pairs of features. Visualize the correlation matrix using a heatmap to know which variables have strong positive/negative correlations. Create a pair plot to visualize pairwise relationships between features.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

```
import 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



Correlation Matrix of California Housing Features
MedInc
HouseAge
AveRooms
AveBedrms
Population
AveOccup
Latitude
Longitude
MedHouseVal
1.00 -0.12 0.33 -0.06 0.00 0.02 -0.08 -0.02 0.69
-0.12 1.00 -0.15 -0.08 -0.30 0.01 0.01 -0.11 0.11
0.33 -0.15 1.00 0.85 -0.07 -0.00 0.11 -0.03 0.15
-0.06 -0.08 0.85 1.00 -0.07 -0.01 0.07 0.01 -0.05
0.00 -0.30 -0.07 -0.07 1.00 0.07 -0.11 0.10 -0.02
0.02 0.01 -0.00 -0.01 0.07 1.00 0.00 0.00 -0.02
-0.08 0.01 0.11 0.07 -0.11 0.00 1.00 -0.92 -0.14
-0.02 -0.11 -0.03 0.01 0.10 0.00 -0.92 1.00 -0.05
0.69 0.11 0.15 -0.05 -0.02 -0.02 -0.14 -0.05 1.00
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75

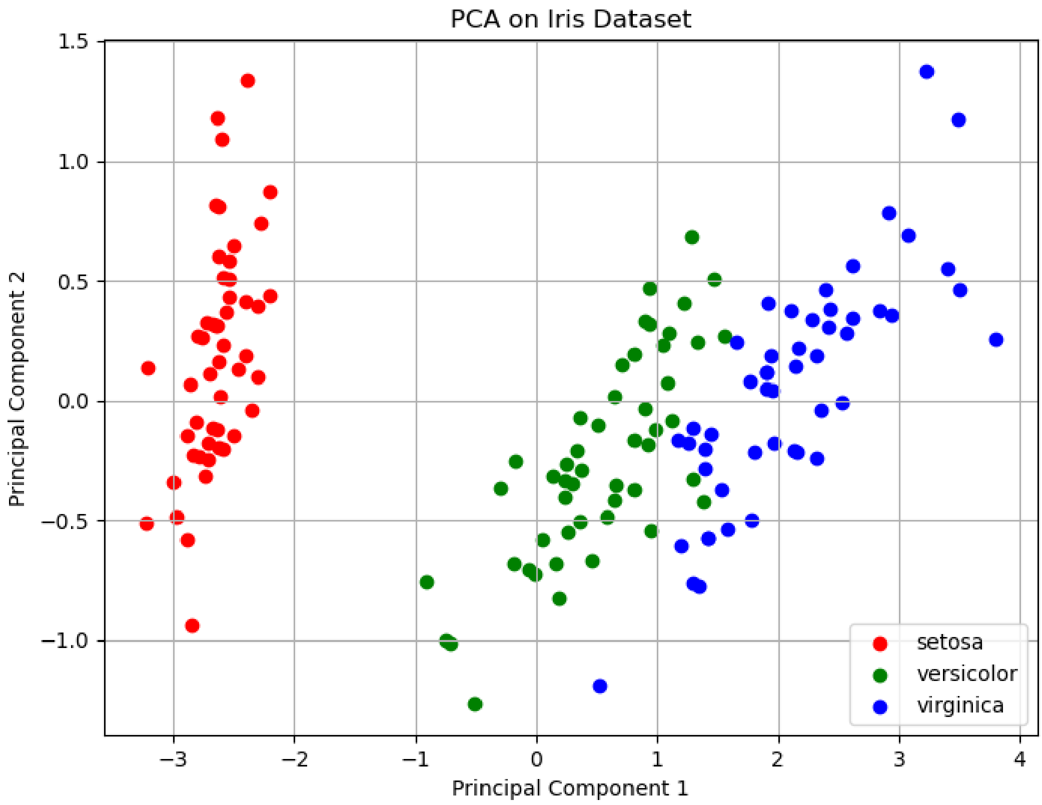


MedInc
HouseAge
AveRooms
AveBedrms
AveOccup
Latitude
Longitude
MedHouseVal

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



PCA on Iris Dataset
1.5
1.0
0.5
0.0
−0.5
−1.0
Principal Component 2
−3
−2
−1
0
1
2
3
4
Principal Component 1
setosa
versicolor
virginica

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.

download csv file click here

```
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 = 'training_data.csv'
hypothesis = find_s_algorithm(file_path)
print("\nThe final hypothesis is:", hypothesis)
```

OUTPUT

```
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', '?']
```

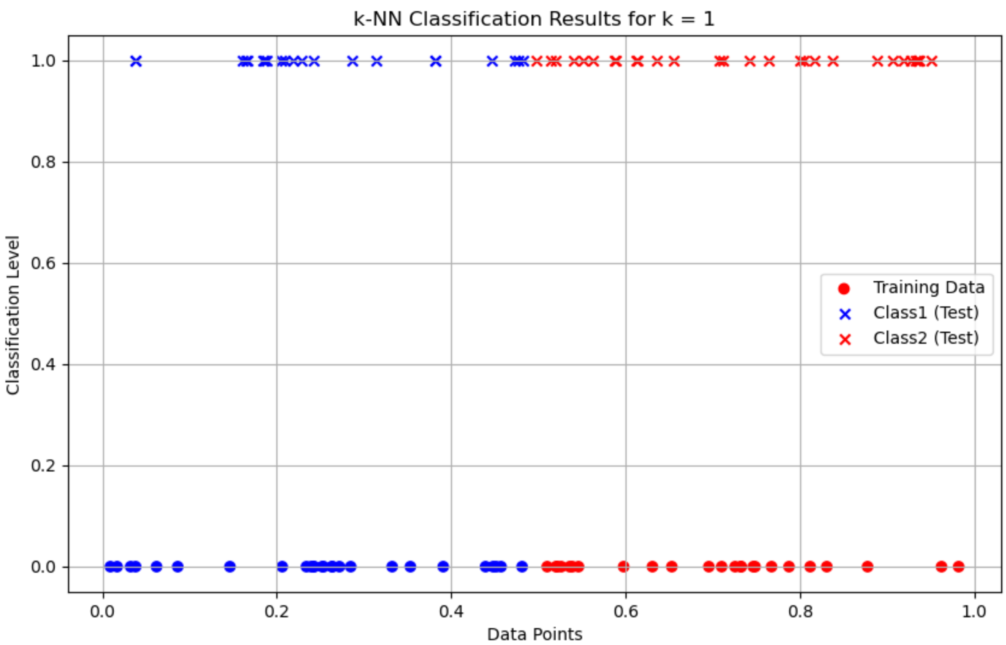
5. Develop a program to implement k-Nearest Neighbour algorithm to classify the randomly generated 100 values of x in the range of [0,1]. Perform the following based on dataset generated.

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: 0.3821) is classified as Class1
Point x52 (value: 0.8882) is classified as Class2
Point x53 (value: 0.1850) is classified as Class1
Point x54 (value: 0.9369) is classified as Class2
Point x55 (value: 0.6552) is classified as Class2
Point x56 (value: 0.2418) is classified as Class1
Point x57 (value: 0.5880) is classified as Class2
Point x58 (value: 0.9186) is classified as Class2
Point x59 (value: 0.2280) is classified as Class1
Point x60 (value: 0.3141) is classified as Class1
Point x61 (value: 0.5514) is classified as Class2

Point x62 (value: 0.2047) is classified as Class1
Point x63 (value: 0.8161) is classified as Class2
Point x64 (value: 0.0381) is classified as Class1
Point x65 (value: 0.5622) is classified as Class2
Point x66 (value: 0.2087) is classified as Class1
Point x67 (value: 0.6127) is classified as Class2
Point x68 (value: 0.5193) is classified as Class2
Point x69 (value: 0.8000) is classified as Class2
Point x70 (value: 0.2864) is classified as Class1
Point x71 (value: 0.4734) is classified as Class1
Point x72 (value: 0.2190) is classified as Class1
Point x73 (value: 0.8043) is classified as Class2
Point x74 (value: 0.9065) is classified as Class2
Point x75 (value: 0.4471) is classified as Class1
Point x76 (value: 0.1606) is classified as Class1
Point x77 (value: 0.7640) is classified as Class2
Point x78 (value: 0.9356) is classified as Class2
Point x79 (value: 0.5889) is classified as Class2
Point x80 (value: 0.7074) is classified as Class2
Point x81 (value: 0.7419) is classified as Class2
Point x82 (value: 0.6358) is classified as Class2
Point x83 (value: 0.6138) is classified as Class2
Point x84 (value: 0.8372) is classified as Class2
Point x85 (value: 0.9264) is classified as Class2
Point x86 (value: 0.7116) is classified as Class2
Point x87 (value: 0.4821) is classified as Class1
Point x88 (value: 0.9331) is classified as Class2
Point x89 (value: 0.9360) is classified as Class2
Point x90 (value: 0.9500) is classified as Class2
Point x91 (value: 0.0379) is classified as Class1
Point x92 (value: 0.4976) is classified as Class2
Point x93 (value: 0.1656) is classified as Class1
Point x94 (value: 0.5410) is classified as Class2
Point x95 (value: 0.1652) is classified as Class1
Point x96 (value: 0.3811) is classified as Class1
Point x97 (value: 0.1848) is classified as Class1
Point x98 (value: 0.5143) is classified as Class2
Point x99 (value: 0.1885) is classified as Class1
Point x100 (value: 0.4769) is classified as Class1

Results for k = 2:
Point x51 (value: 0.3821) is classified as Class1
Point x52 (value: 0.8882) is classified as Class2
Point x53 (value: 0.1850) is classified as Class1
Point x54 (value: 0.9369) is classified as Class2
Point x55 (value: 0.6552) is classified as Class2
Point x56 (value: 0.2418) is classified as Class1
Point x57 (value: 0.5880) is classified as Class2
Point x58 (value: 0.9186) is classified as Class2
Point x59 (value: 0.2280) is classified as Class1

Point x60 (value: 0.3141) is classified as Class1
Point x61 (value: 0.5514) is classified as Class2
Point x62 (value: 0.2047) is classified as Class1
Point x63 (value: 0.8161) is classified as Class2
Point x64 (value: 0.0381) is classified as Class1
Point x65 (value: 0.5622) is classified as Class2
Point x66 (value: 0.2087) is classified as Class1
Point x67 (value: 0.6127) is classified as Class2
Point x68 (value: 0.5193) is classified as Class2
Point x69 (value: 0.8000) is classified as Class2
Point x70 (value: 0.2864) is classified as Class1
Point x71 (value: 0.4734) is classified as Class1
Point x72 (value: 0.2190) is classified as Class1
Point x73 (value: 0.8043) is classified as Class2
Point x74 (value: 0.9065) is classified as Class2
Point x75 (value: 0.4471) is classified as Class1
Point x76 (value: 0.1606) is classified as Class1
Point x77 (value: 0.7640) is classified as Class2
Point x78 (value: 0.9356) is classified as Class2
Point x79 (value: 0.5889) is classified as Class2
Point x80 (value: 0.7074) is classified as Class2
Point x81 (value: 0.7419) is classified as Class2
Point x82 (value: 0.6358) is classified as Class2
Point x83 (value: 0.6138) is classified as Class2
Point x84 (value: 0.8372) is classified as Class2
Point x85 (value: 0.9264) is classified as Class2
Point x86 (value: 0.7116) is classified as Class2
Point x87 (value: 0.4821) is classified as Class1
Point x88 (value: 0.9331) is classified as Class2
Point x89 (value: 0.9360) is classified as Class2
Point x90 (value: 0.9500) is classified as Class2
Point x91 (value: 0.0379) is classified as Class1
Point x92 (value: 0.4976) is classified as Class2
Point x93 (value: 0.1656) is classified as Class1
Point x94 (value: 0.5410) is classified as Class2
Point x95 (value: 0.1652) is classified as Class1
Point x96 (value: 0.3811) is classified as Class1
Point x97 (value: 0.1848) is classified as Class1
Point x98 (value: 0.5143) is classified as Class2
Point x99 (value: 0.1885) is classified as Class1
Point x100 (value: 0.4769) is classified as Class1
.
.
Results for k = 30:
Point x51 (value: 0.3821) is classified as Class1
Point x52 (value: 0.8882) is classified as Class2
Point x53 (value: 0.1850) is classified as Class1
Point x54 (value: 0.9369) is classified as Class2
Point x55 (value: 0.6552) is classified as Class2
Point x56 (value: 0.2418) is classified as Class1

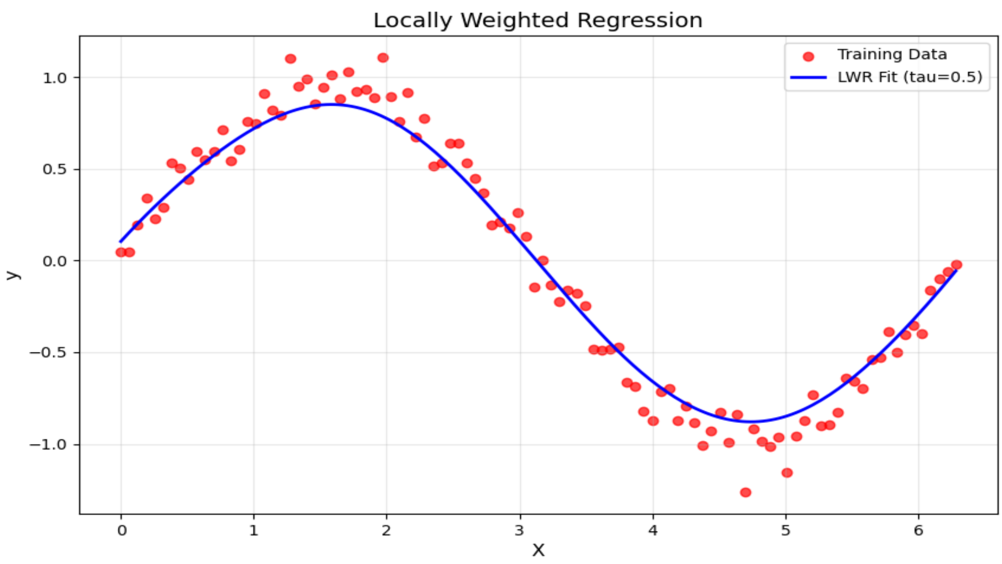
Point x57 (value: 0.5880) is classified as Class2
Point x58 (value: 0.9186) is classified as Class2
Point x59 (value: 0.2280) is classified as Class1
Point x60 (value: 0.3141) is classified as Class1
Point x61 (value: 0.5514) is classified as Class2
Point x62 (value: 0.2047) is classified as Class1
Point x63 (value: 0.8161) is classified as Class2
Point x64 (value: 0.0381) is classified as Class1
Point x65 (value: 0.5622) is classified as Class2
Point x66 (value: 0.2087) is classified as Class1
Point x67 (value: 0.6127) is classified as Class2
Point x68 (value: 0.5193) is classified as Class2
Point x69 (value: 0.8000) is classified as Class2
Point x70 (value: 0.2864) is classified as Class1
Point x71 (value: 0.4734) is classified as Class1
Point x72 (value: 0.2190) is classified as Class1
Point x73 (value: 0.8043) is classified as Class2
Point x74 (value: 0.9065) is classified as Class2
Point x75 (value: 0.4471) is classified as Class1
Point x76 (value: 0.1606) is classified as Class1
Point x77 (value: 0.7640) is classified as Class2
Point x78 (value: 0.9356) is classified as Class2
Point x79 (value: 0.5889) is classified as Class2
Point x80 (value: 0.7074) is classified as Class2
Point x81 (value: 0.7419) is classified as Class2
Point x82 (value: 0.6358) is classified as Class2
Point x83 (value: 0.6138) is classified as Class2
Point x84 (value: 0.8372) is classified as Class2
Point x85 (value: 0.9264) is classified as Class2
Point x86 (value: 0.7116) is classified as Class2
Point x87 (value: 0.4821) is classified as Class1
Point x88 (value: 0.9331) is classified as Class2
Point x89 (value: 0.9360) is classified as Class2
Point x90 (value: 0.9500) is classified as Class2
Point x91 (value: 0.0379) is classified as Class1
Point x92 (value: 0.4976) is classified as Class2
Point x93 (value: 0.1656) is classified as Class1
Point x94 (value: 0.5410) is classified as Class2
Point x95 (value: 0.1652) is classified as Class1
Point x96 (value: 0.3811) is classified as Class1
Point x97 (value: 0.1848) is classified as Class1
Point x98 (value: 0.5143) is classified as Class2
Point x99 (value: 0.1885) is classified as Class1
Point x100 (value: 0.4769) is classified as Class1

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

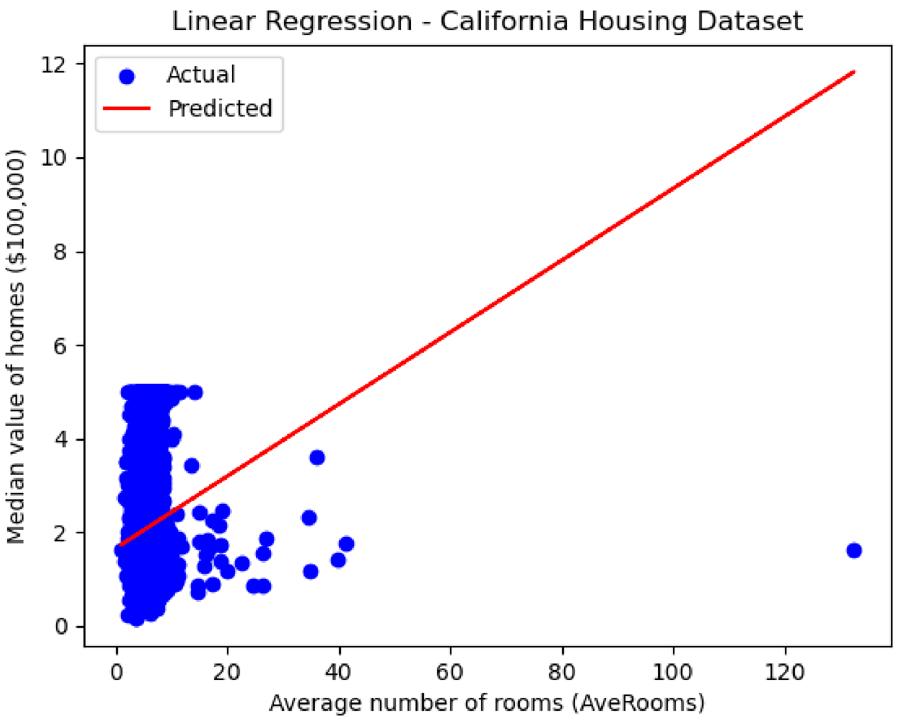


7. **Develop a program to demonstrate the working of Linear Regression and Polynomial Regression. Use Boston Housing Dataset for Linear Regression and Auto MPG Dataset (for vehicle fuel efficiency prediction) for Polynomial Regression**

```
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()
```

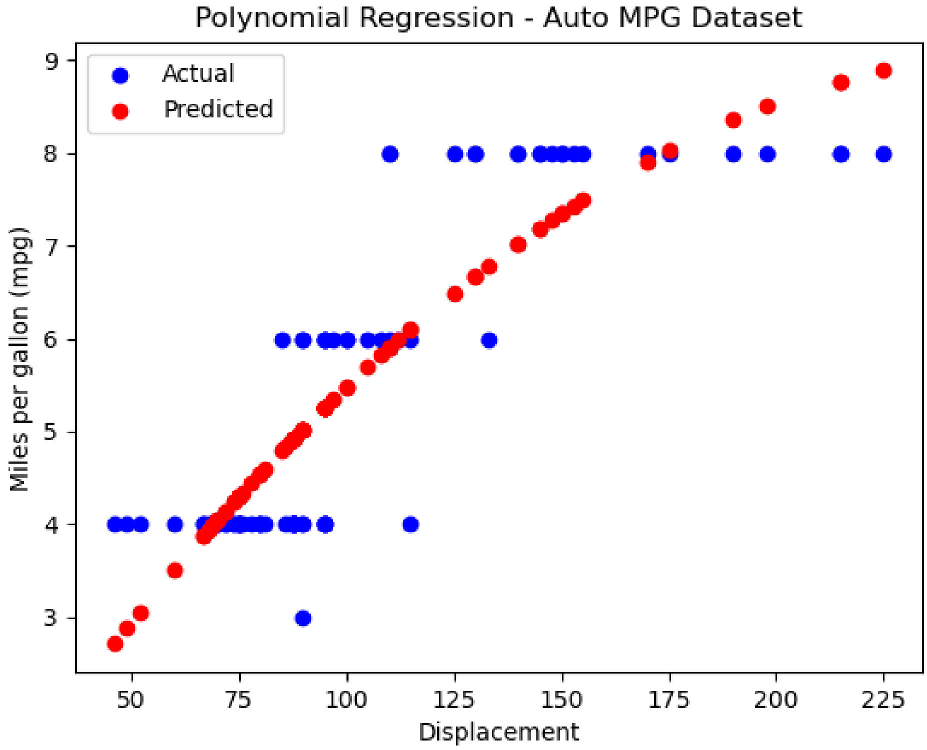
```
    plt.show()
    print("Polynomial Regression - Auto MPG Dataset")
    print("Mean Squared Error:", mean_squared_error(y_test, y_pred))
    print("R^2 Score:", r2_score(y_test, y_pred))
if __name__ == "__main__":
    print("Demonstrating Linear Regression and Polynomial Regression\n")
    linear_regression_california()
    polynomial_regression_auto_mpg()
```

OUTPUT



Demonstrating Linear Regression and Polynomial Regression

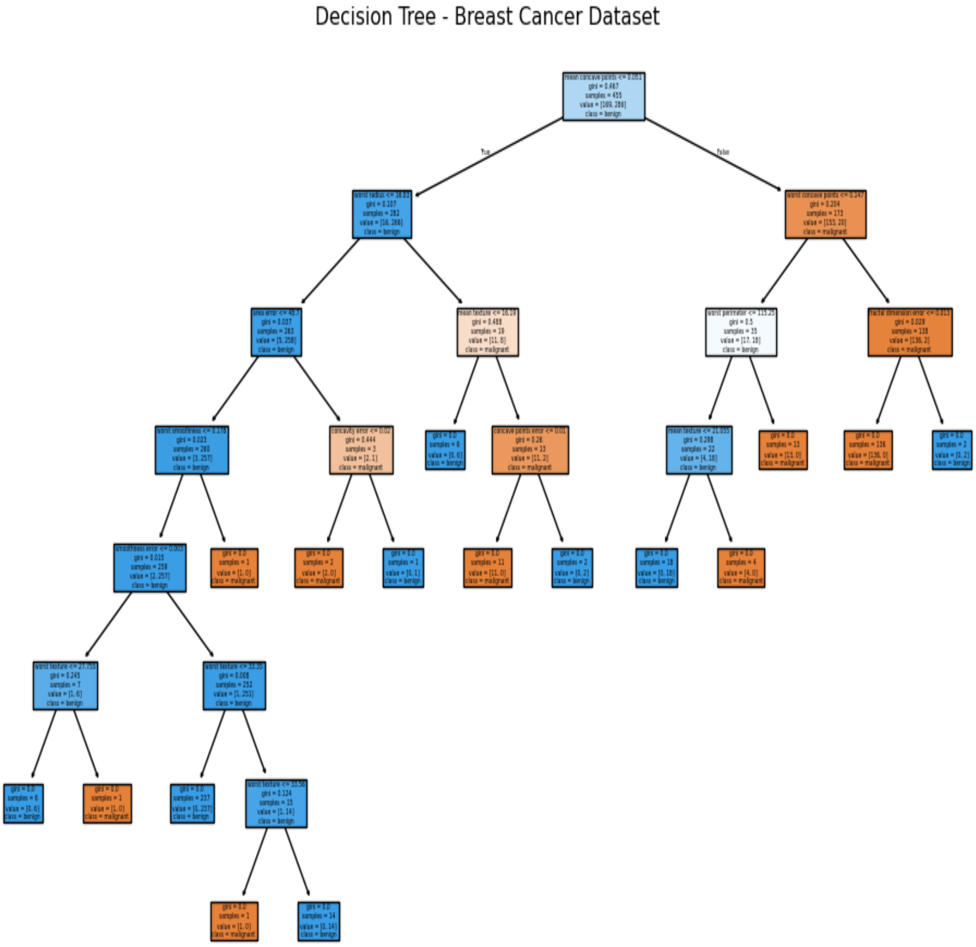
Linear Regression - California Housing Dataset
Mean Squared Error: 1.29233144408073
R^2 Score: 0.01379533753228468
Polynomial Regression - Auto MPG Dataset
Mean Squared Error: 0.743149055720586
R^2 Score: 0.7505650609469626


Polynomial Regression - Auto MPG Dataset
Actual
Predicted
Miles per gallon (mpg)
9
8
7
6
5
4
3
50
75
100
125
150
175
200
225
Displacement

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.

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn import tree
data = load_breast_cancer()
X = data.data
y = data.target
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
clf = DecisionTreeClassifier(random_state=42)
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Model Accuracy: {accuracy * 100:.2f}%")
new_sample = np.array([X_test[0]])
prediction = clf.predict(new_sample)
prediction_class = "Benign" if prediction == 1 else "Malignant"
print(f"Predicted Class for the new sample: {prediction_class}")
plt.figure(figsize=(12,8))
tree.plot_tree(clf, filled=True, feature_names=data.feature_names,
class_names=data.target_names)
plt.title("Decision Tree - Breast Cancer Dataset")
plt.show()
```

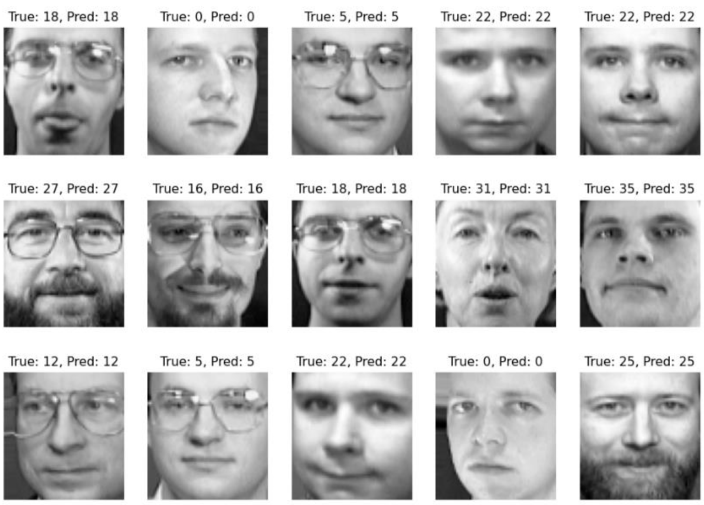
OUTPUT



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



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]]

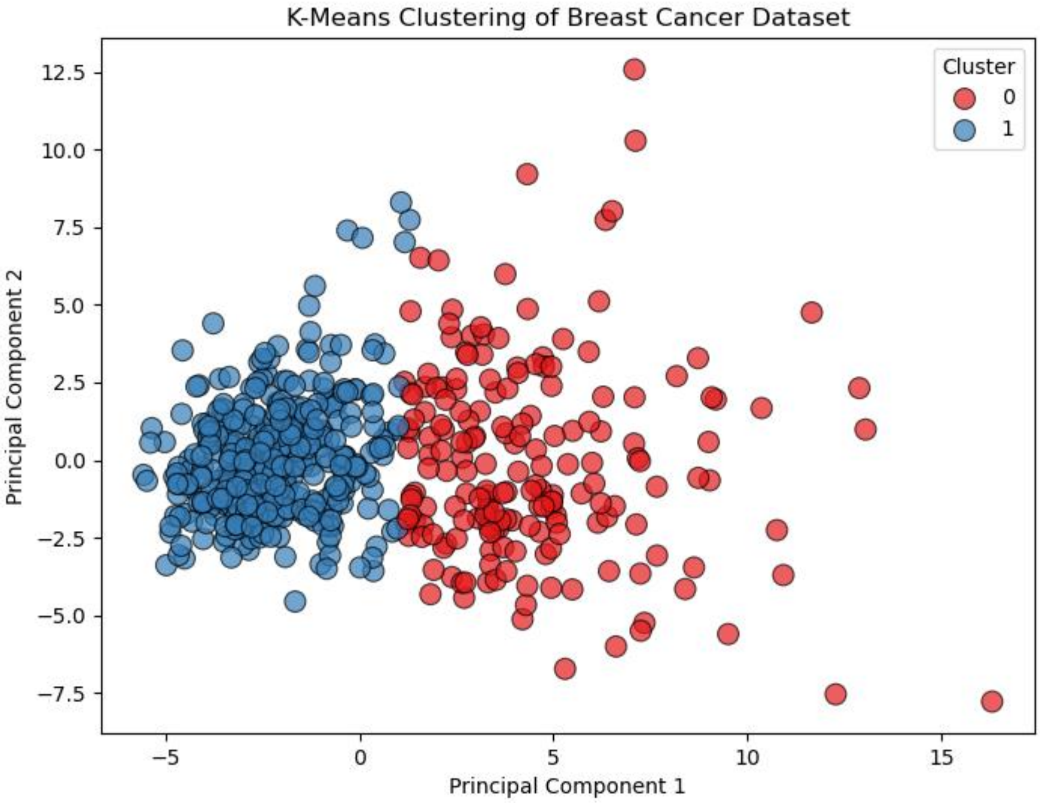
Cross-validation accuracy: 87.25%

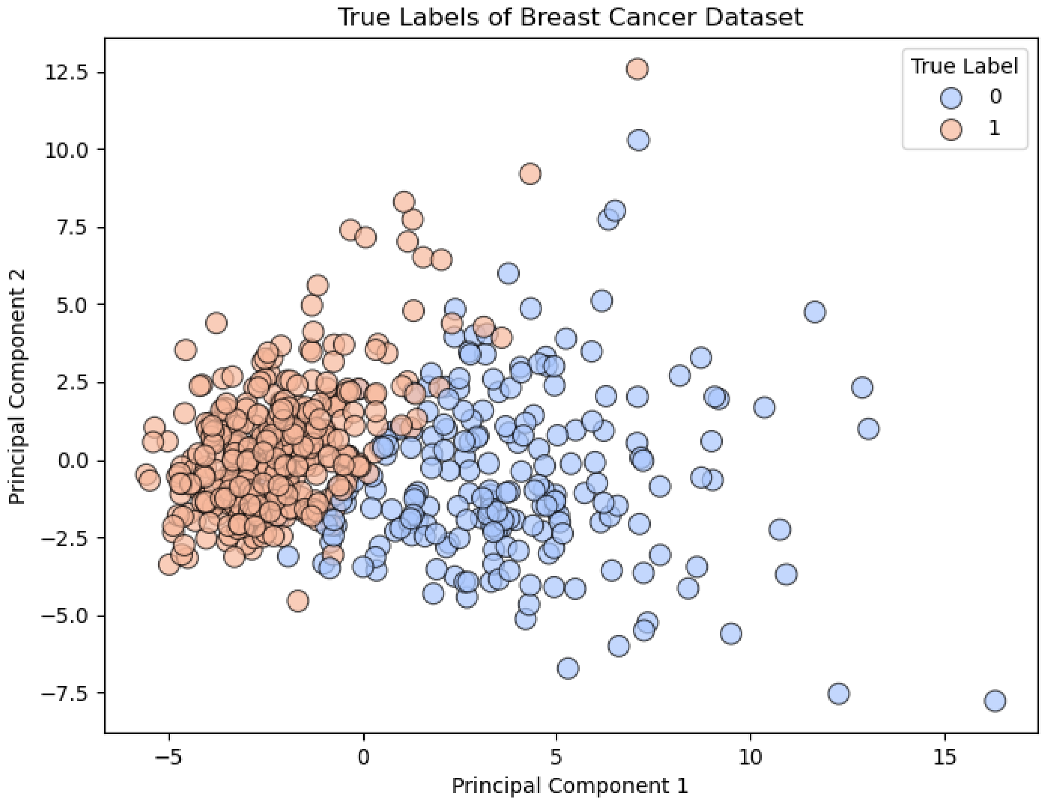
10. Develop a program to implement k-means clustering using Wisconsin Breast Cancer data set and visualize the clustering result.

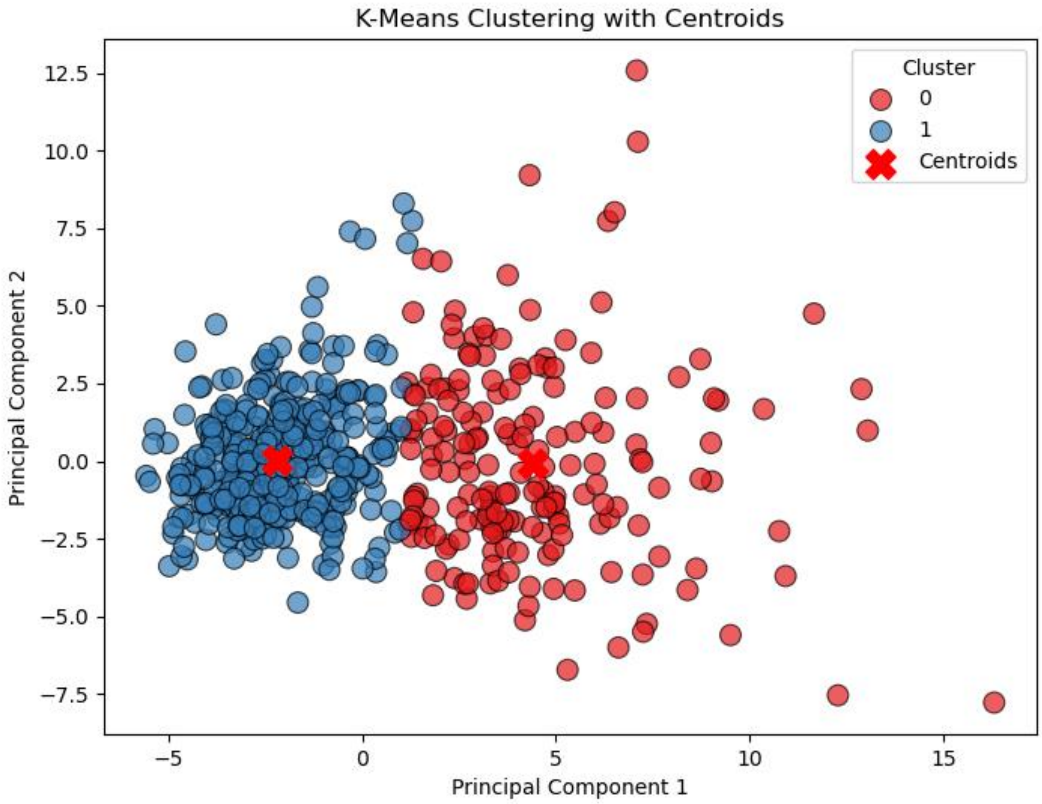
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import load_breast_cancer
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.metrics import confusion_matrix, classification_report
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




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

Confusion Matrix:

```
[[175  37]
 [ 13 344]]
```

Classification Report:

	precision	recall	f1-score	support
0	0.93	0.83	0.88	212
1	0.90	0.96	0.93	357
accuracy			0.91	569
macro avg	0.92	0.89	0.90	569
weighted avg	0.91	0.91	0.91	569