|| Jai Sri Gurudev ||
Sri Adichunchanagiri Shikshana Trust (R)

SJB Institute of Technology

An AUTONOMOUS INSTITUTION UNDER VISVESVARAYA TECHNOLOGICAL UNIVERSITY

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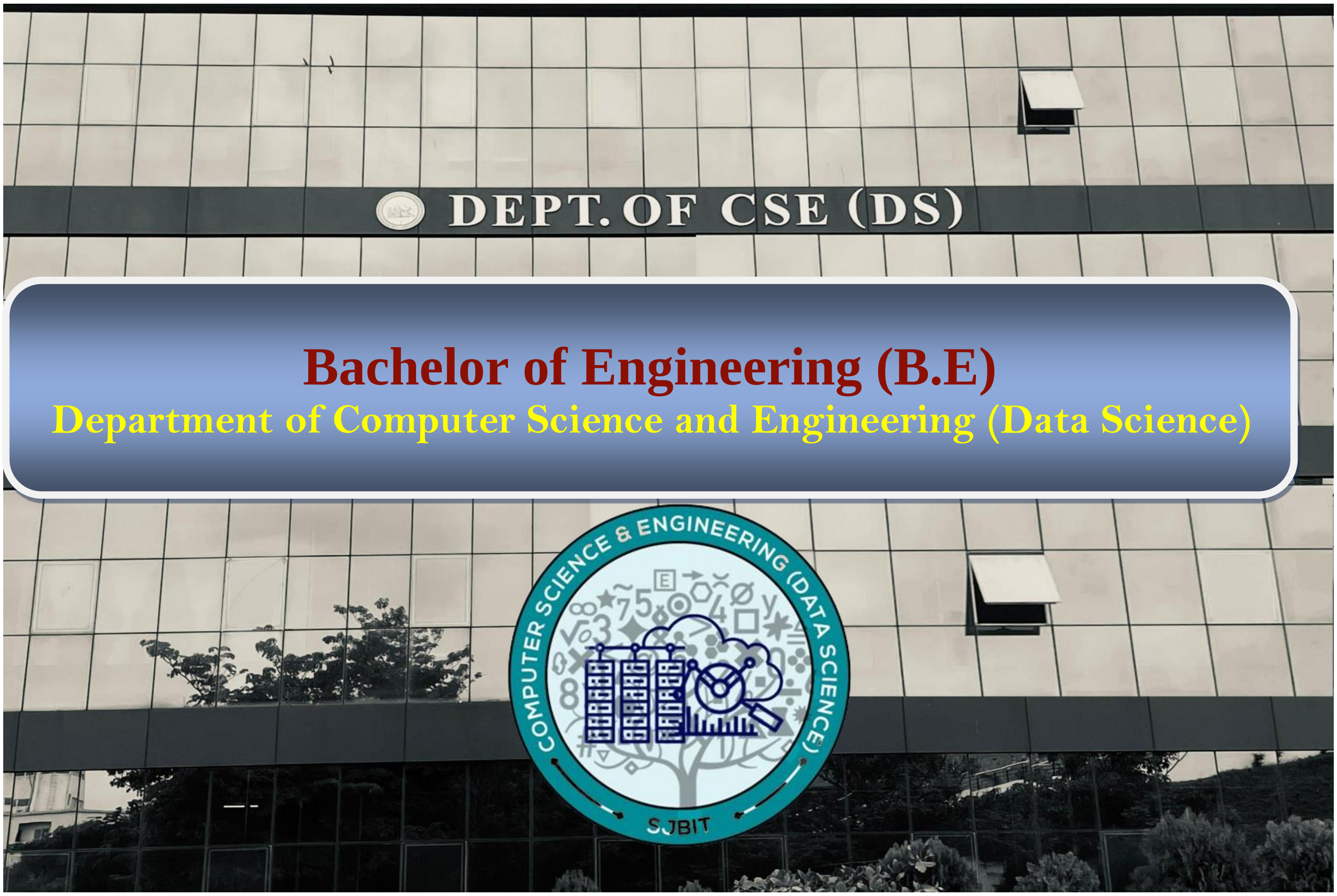

Bachelor of Engineering (B.E)

Department of Computer Science and Engineering (Data Science)

MACHINE LEARNING LABORATORY

(BCSL606)

(VTU Syllabus)

Prepared by:

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DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING (DATA SCIENCE)

2024-25

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING (DATA SCIENCE)

VISION

To enrich the next generation of young data practitioners, accomplish academic excellence and bring forward the Data Scientists

MISSION

M1: Grooming the students equipping with advanced technical knowledge to be industry-ready and globally competent.

M2: Facilitate quality data science education, enable students to become skilled professionals to solve real-time problems through industry collaboration.

M3: Encourage ethical value based transformation to serve the society with responsibility emphasizing on innovation and research methods

PROGRAM EDUCATIONAL OBJECTIVE

PEO 1: *Apply the structured statistical and mathematical methodology to process massive amounts of data to detect underlying patterns to make predictions under realistic constraints and to visualize the data.*

PEO 2: *Promote design, research, product implementation and services in the field of Data Science by using modern tools.*

Program Outcomes

1 **Engineering Knowledge**: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.
2 **Problem Analysis**: Identify, formulate, research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.
3 **Design/Development of Solutions**: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
4 **Conduct Investigations of Complex Problems**: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, andsynthesis of the information to provide valid conclusions.
5 **Modern Tool Usage**: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineeringactivities with an understanding of the limitations.
6 **The Engineer and Society**: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal, and cultural issues and the consequent responsibilitiesrelevant to the professional engineering practice
7 **Environment and Sustainability**: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.
8 **Ethics**: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
9 **Individual and Team Work**: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.s
10 **Communication**: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.
11 **Project Management and Finance**: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.
12 **Life-Long Learning:** Recognize the need for, and have the preparation and ability to engagein independent and life-long learning in the broadest context of technological change.

Program Specific Outcomes

PSO 1: Recognize the need for key changes in data organization, design analysis, and computer science principles in building intelligent systems for real-world problems using Artificial Intelligence and Machine Learning.

PSO 2: Develop an Intelligent system to solve a futuristic problem through project and experiential learning.

MACHINE LEARNING LABORATORY

Sub Code: BCSL606 **IA Marks: 50**

Hours/Week: 02

Machine Learning lab		Semester	6
Course Code	BCSL606	CIE Marks	50
Teaching Hours/Week (L:T:P: S)	0:0:2:0	SEE Marks	50
Credits	01	Exam Hours	100
Examination type (SEE)	Practical		

Course objectives:

1. To become familiar with data and visualize univariate, bivariate, and multivariate data using statistical techniques and dimensionality reduction.
2. To understand various machine learning algorithms such as similarity-based learning, regression, decision trees, and clustering.
3. To familiarize with learning theories, probability-based models and developing the skills required for decision-making in dynamic environments.

SLNO	Experiments
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. **Book 1: Chapter 2**
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. **Book 1: Chapter 2**
3	Develop a program to implement Principal Component Analysis (PCA) for reducing the dimensionality of the Iris dataset from 4 features to 2. **Book 1: Chapter 2**
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. **Book 1: Chapter 3**
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. 1. Label the first 50 points $\{x_1, \ldots\ldots, x_{50}\}$ as follows: if (xi ≤ 0.5), then $x_i \in Class_1$, else $x_i \in Class_1$ 2. Classify the remaining points, $x_{51}, \ldots\ldots, x_{100}$ using KNN. Perform this for *k=1,2,3,4,5,20,30* **Book 2: Chapter – 2**
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 **Book 1: Chapter – 4**
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. **Book 1: Chapter – 5**
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. **Book 2: Chapter – 3**

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. **Book 2: Chapter – 4**
10	Develop a program to implement k-means clustering using Wisconsin Breast Cancer data set and visualize the clustering result. **Book 2: Chapter – 4**

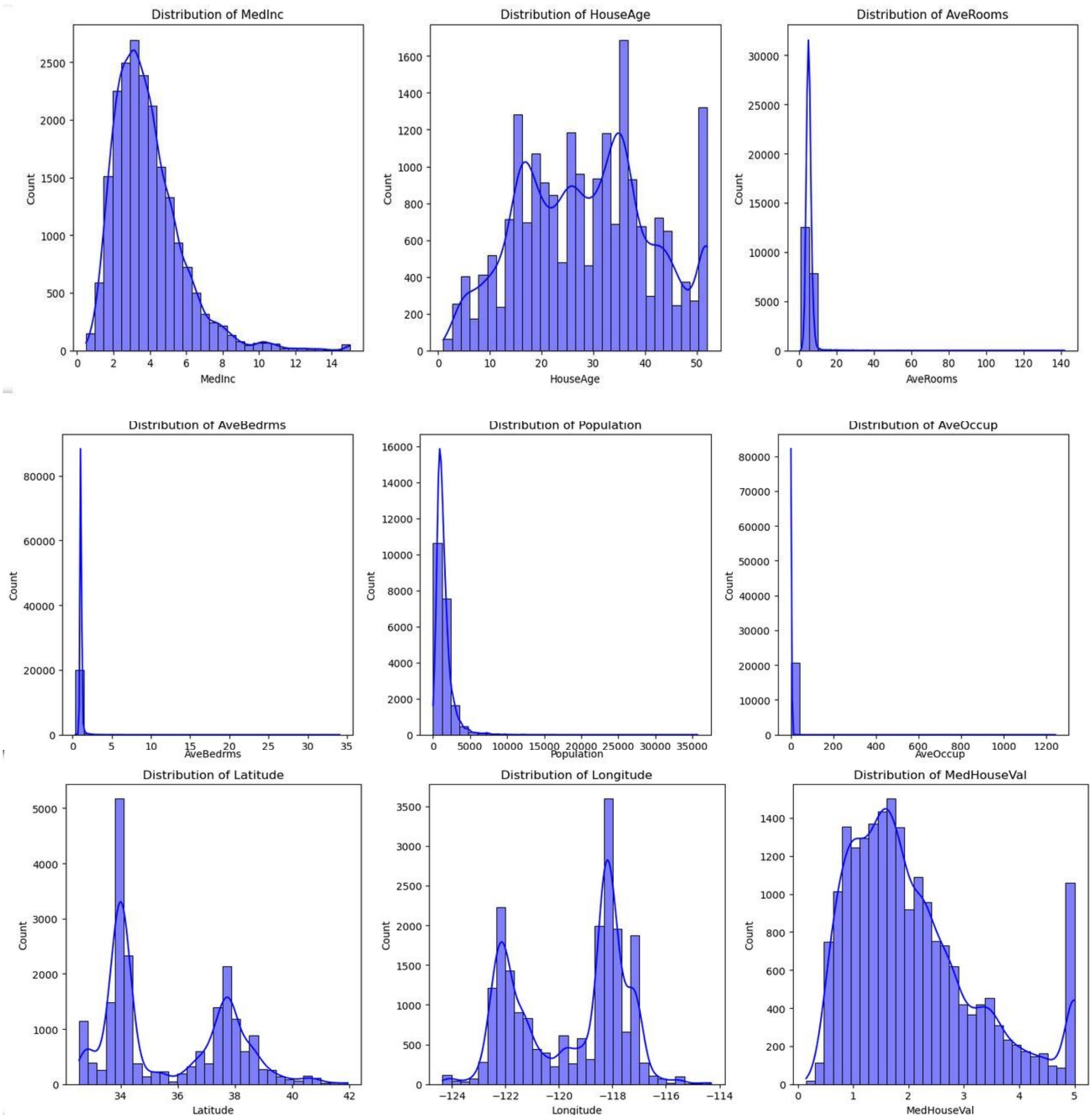
1. Develop a program to create histograms for all numerical features and analyze the distribution of each feature. Generate box plots for all numerical features and identify any outliers. Use California Housing dataset.

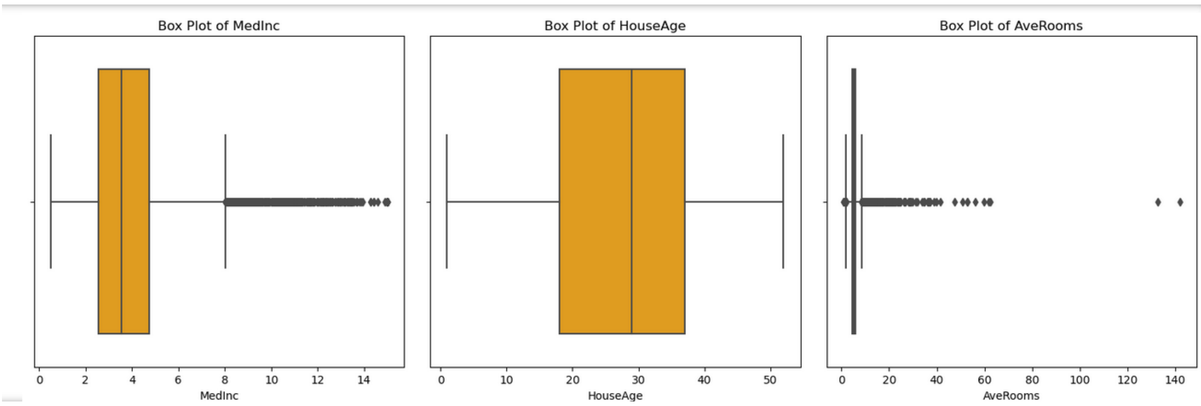
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.datasets import fetch_california_housing

# 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}')
```

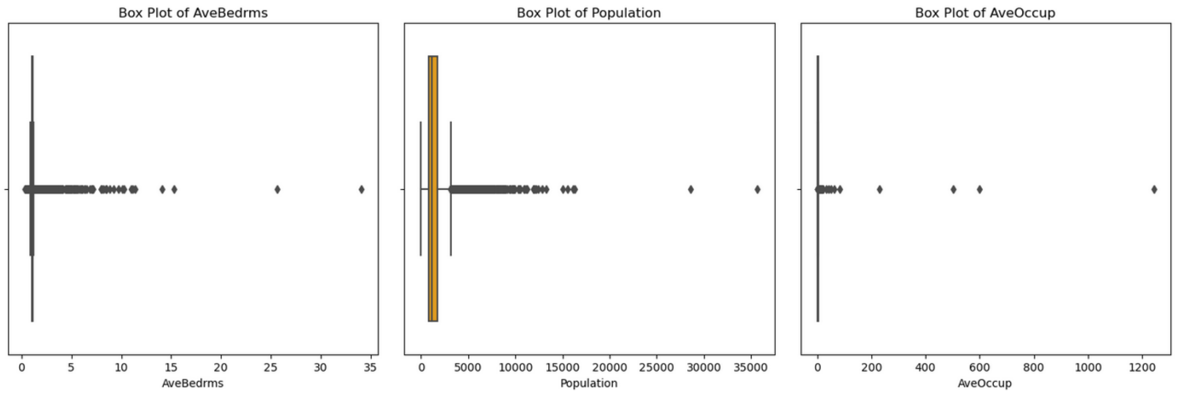
```
plt.tight_layout()

plt.show()
```

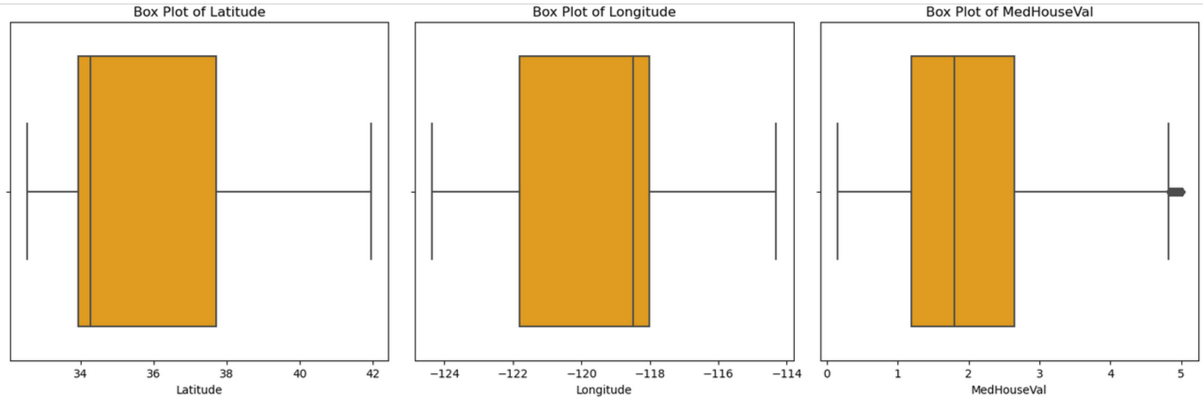
```
# Step 3: Generate box plots for numerical features
plt.figure(figsize=(15, 5 * n_rows))
for i, feature in enumerate(numerical_features):
    plt.subplot(n_rows, n_cols, i + 1)
    sns.boxplot(x=housing_df[feature], color='orange')
    plt.title(f'Box Plot of {feature}')
plt.tight_layout()
plt.show()

# 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
Distribution of HouseAge
Distribution of AveRooms
Distribution of AveBedrms
Distribution of Population
Distribution of AveOccup
Distribution of Latitude
Distribution of Longitude
Distribution of MedHouseVal
Count
MedInc
HouseAge
AveRooms
AveBedrms
Population
AveOccup
Latitude
Longitude
MedHouseVal


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

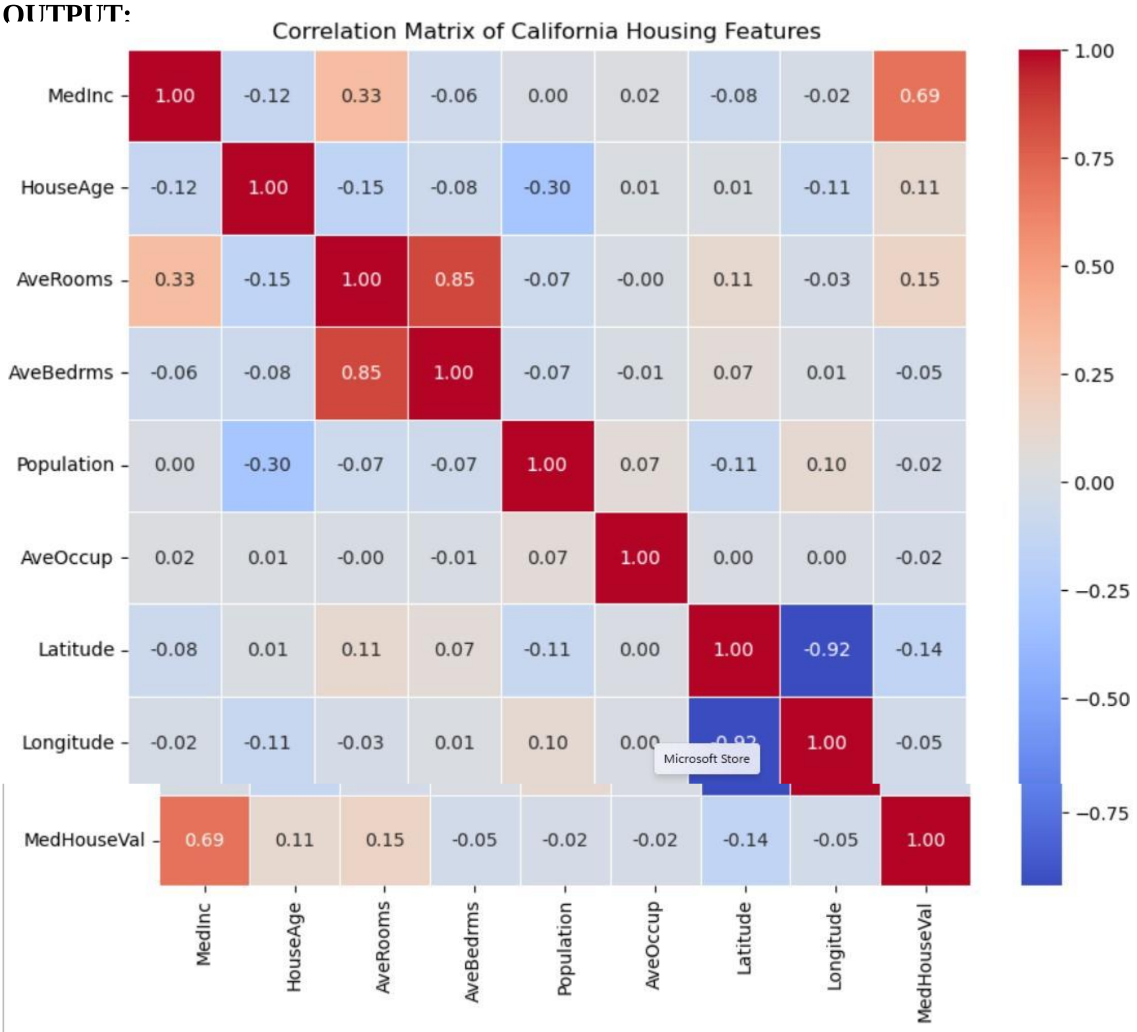
	AveOccup	Latitude	Longitude	MedHouseVal
count	20640.000000	20640.000000	20640.000000	20640.000000
mean	3.070655	35.631861	-119.569704	2.068558
std	10.386050	2.135952	2.003532	1.153956
min	0.692308	32.540000	-124.350000	0.149990
25%	2.429741	33.930000	-121.800000	1.196000
50%	2.818116	34.260000	-118.490000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

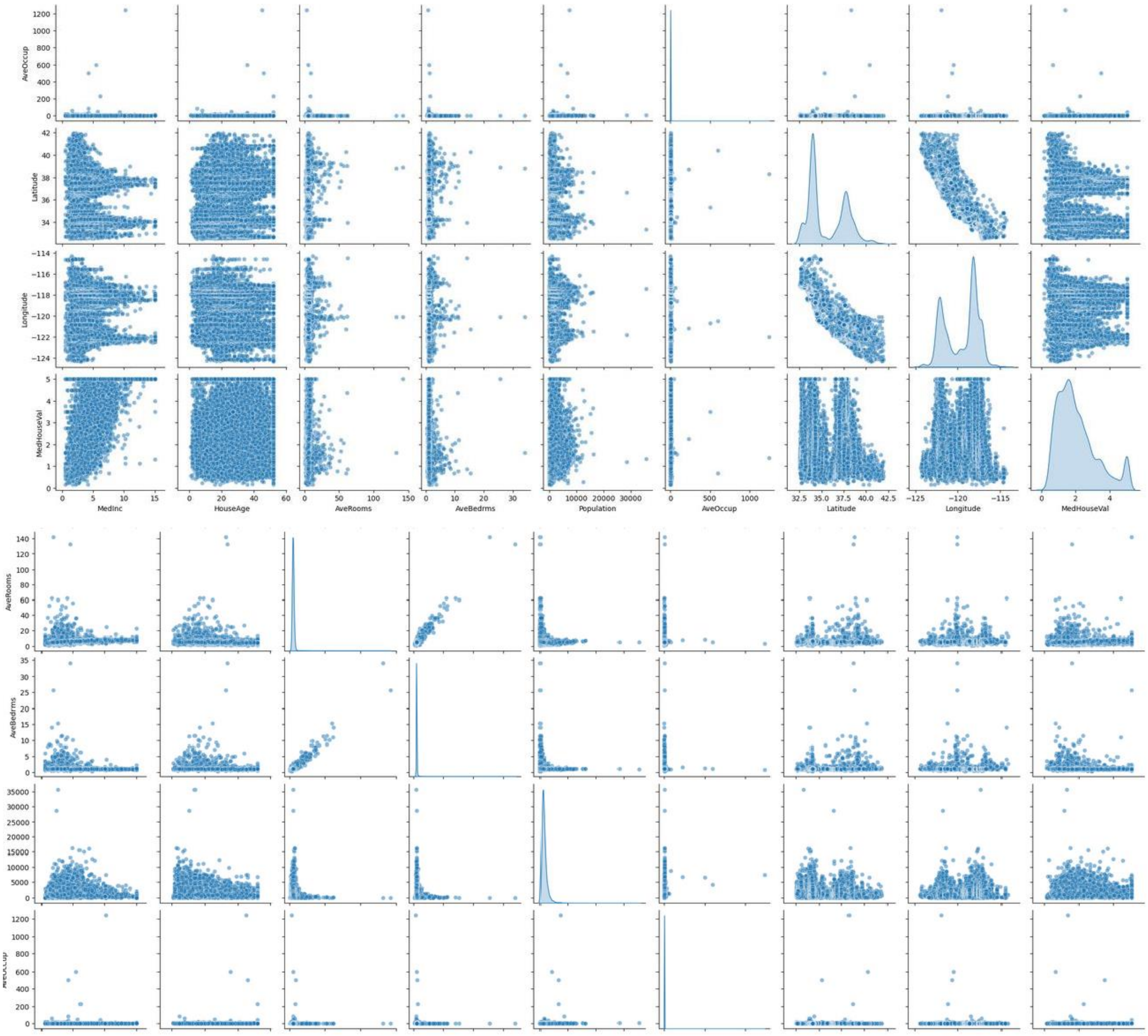
2. **Develop a program to Compute the correlation matrix to understand the relationships between pairs of features. Visualize the correlation matrix using a heatmap to know which variables have strong positive/negative correlations. Create a pair plot to visualize pairwise relationships between features.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





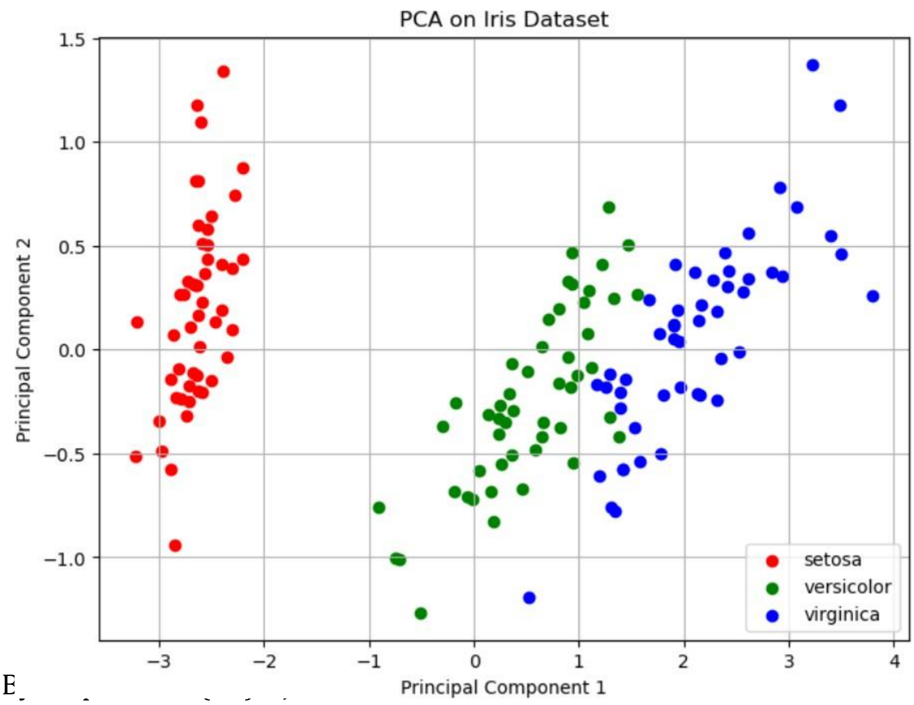
3. Develop a program to implement Principal Component Analysis (PCA) for reducing the dimensionality of the Iris dataset from 4 features to 2.

```
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

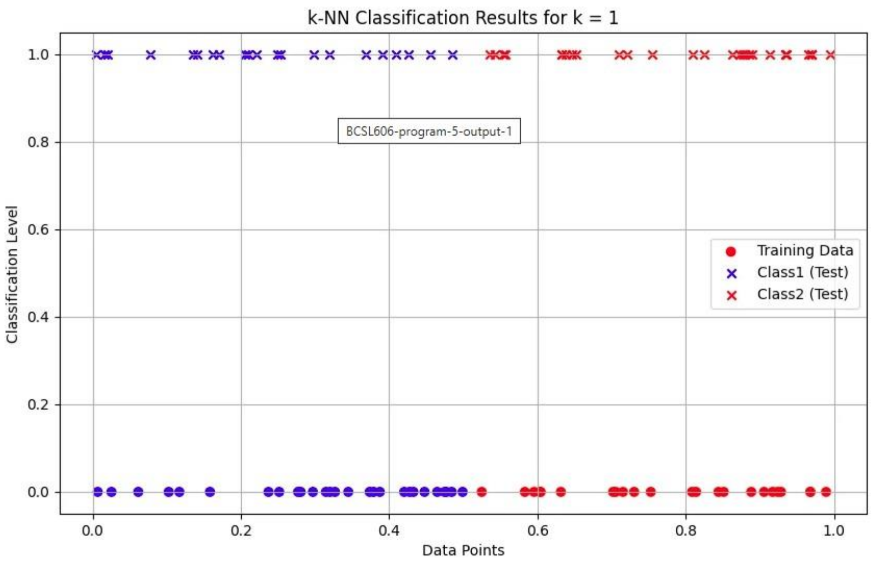
b) Classify the remaining points, x51,……,x100 using KNN. Perform this for k=1,2,3,4,5,20,30

```
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

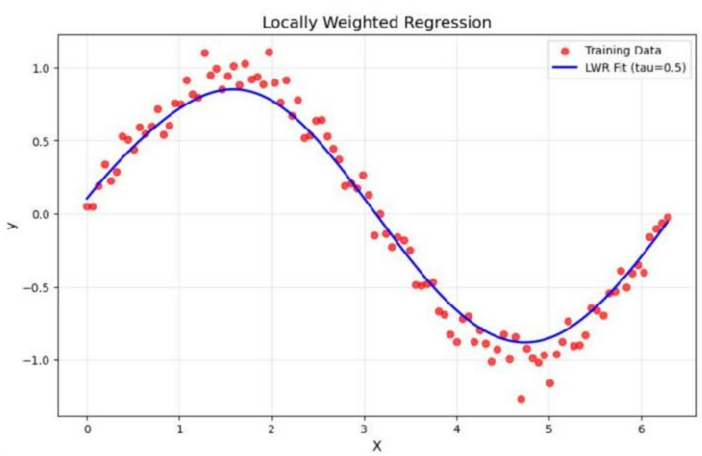
Classification complete.

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")
```

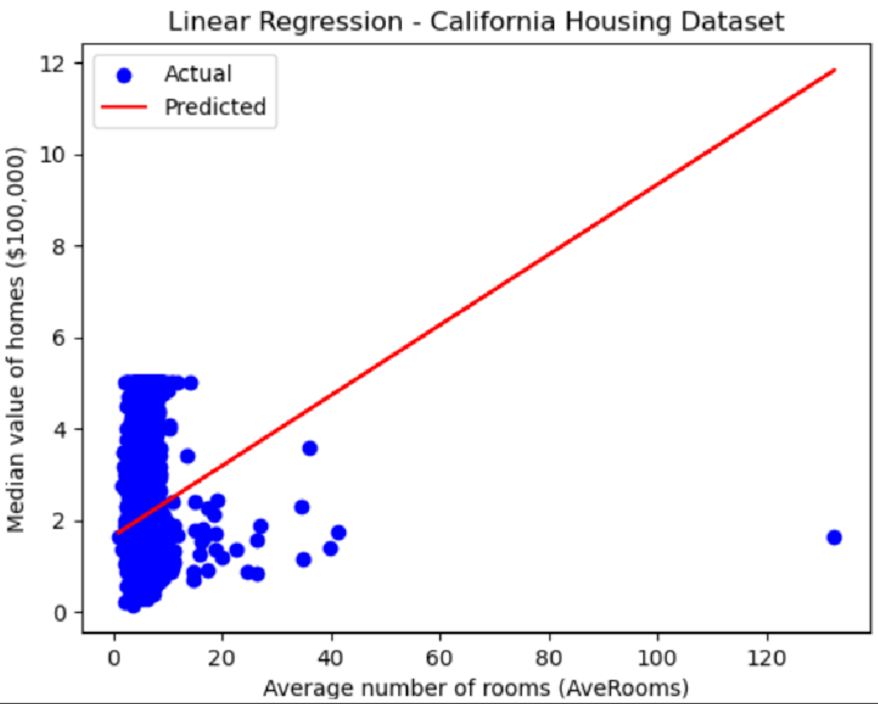
```
    plt.legend()
    plt.show()

    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")
```

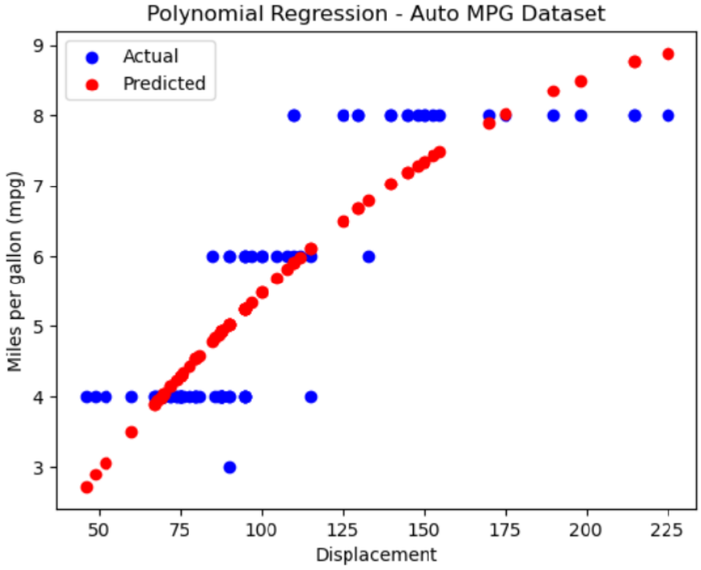
```
    plt.ylabel("Miles per gallon (mpg)")
    plt.title("Polynomial Regression - Auto MPG Dataset")
    plt.legend()
    plt.show()

    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:

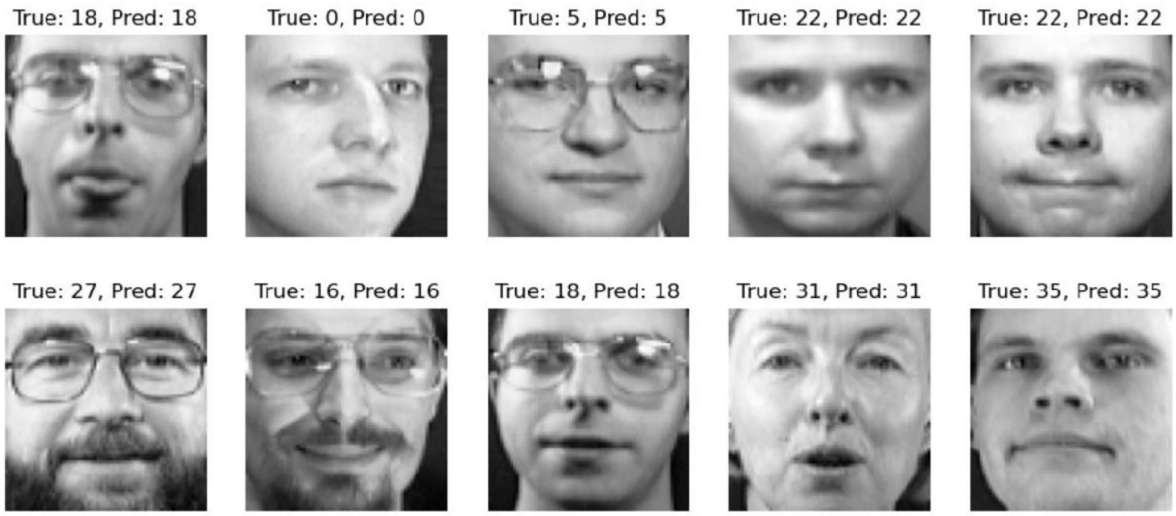
```
              precision    recall  f1-score   support

           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()
```

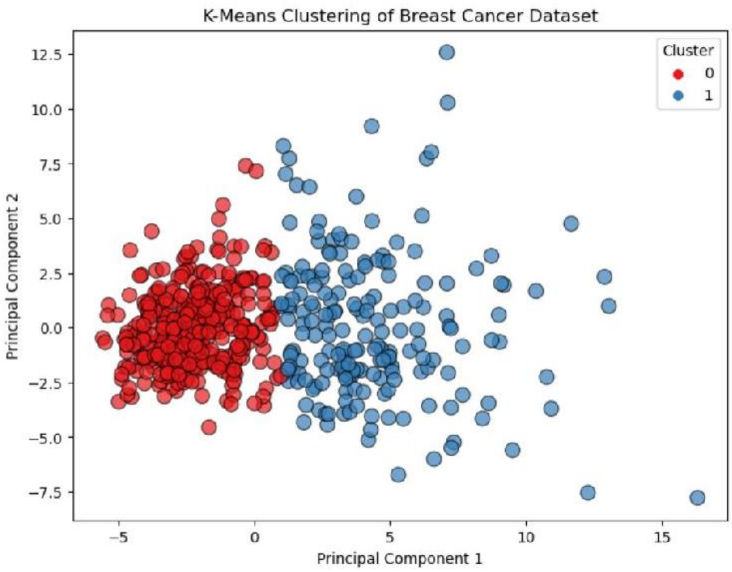
```
X = data.data
y = data.target

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")
```

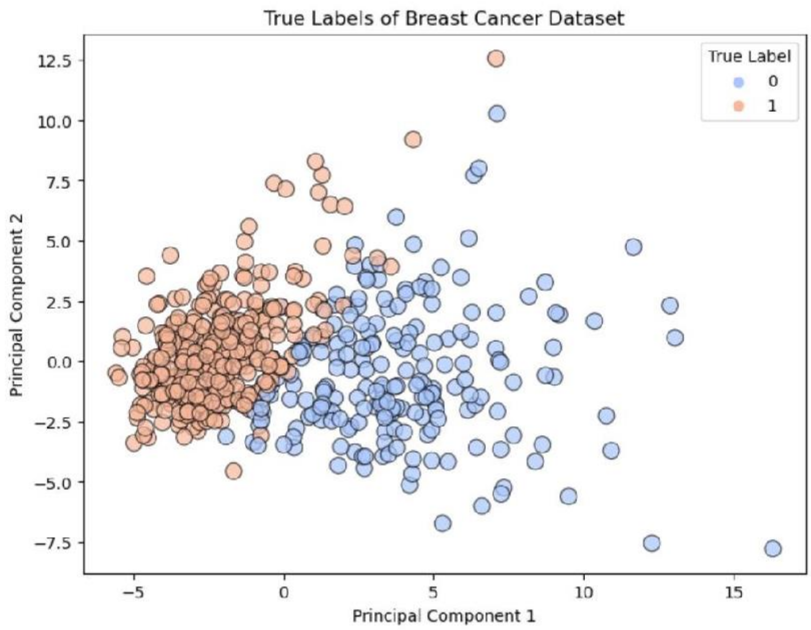
```
plt.show()
```

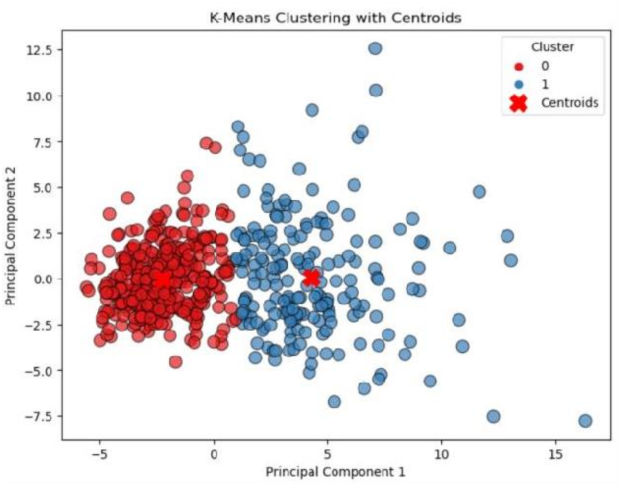
```
plt.figure(figsize=(8, 6))

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