Sri SAIRAM COLLEGE OF ENGINEERING
Anekal, Bengaluru

Accredited by NAAC
ISO 9001:2015 Certified Institution
Approved by AICTE, New Delhi
Affiliated to Visvesvaraya Technological University
www.sairamce.edu.in

Department of Computer Science and Engineering

LAB MANUAL

(2024-2025)

BCSL606

MACHINE LEARNING LAB

VI Semester

Prepared by:

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Vision of the Department

Transform students into professional, ethical engineers to meet global challenges through quality education.

Mission of the Department

M1. To impart quality education in Computer Science and Engineering with the strong industry institute partnership to develop technical & research skills.

M2. Enrich the technical ability of students to face the world with confidence, commitment and team-work in IT field.

M3. Provide a learning platform for interdisciplinary innovation, research and Self-learning.

M4. Encourage faculty and students to actively participate in holistic educational practices and to impart social values.

Program Educational Objectives (PEOs)

PEO 1 Graduates develop knowledge in the core areas of Computer Science Engineering and enhance technical and research skills for providing software solutions.

PEO 2 Graduates will pursue technical and managerial skills to analyze and develop problem solving abilities of Computer Science and Engineering through Mathematics,Science and Engineering to encounter industrial needs.

PEO 3 Graduates develop effective communication and management skills to interact effectively with stakeholders inthe field of Computer Science Engineering and develop innovative solutions for real time problems.

PEO 4 Graduate with lifelong learning, demonstrate skills and knowledge in the domain of computer programming and exhibit leadership qualities, teamwork,social and ethical values.

Program Specific Outcomes (PSOs)

PSO-1 The ability to understand, analyze and develop computer programs in the areas related to algorithms, system software, networking and embedded computing, web design, and data analytics for efficient design of computer-based systems.

PSO-2 The ability to understand the evolutionary changes in computing technologies, apply standard practices and strategies in software project development and testing using various programming environments to deliver a quality product for business, real world problems and meet the challenges of the future.

‘Instructions to the Candidates’

1. Students should come with thorough preparation for the experiment to be conducted.
2. Students will not be permitted to attend the laboratory unless they bring the practical record fully completed in all respects pertaining to the experiment conducted in the previous class.
3. Practical record should be neatly maintained.
4. They should obtain the signature of the staff-in-charge in the observation book after completing each experiment.
5. Theory regarding each experiment should be written in the practical record before procedure in your own words.
6. Ask lab technician for assistance if you have any problem.
7. Save your class work, assignments in system.
8. Do not download or install software without the assistance of the laboratory technician.
9. Do not alter the configuration of the system.
10. Turnoff the systems after use.

SYLLABUS

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.

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.

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

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 ε Class1, else xi ε Class1

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

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.

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.

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.

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

Experiment No:1

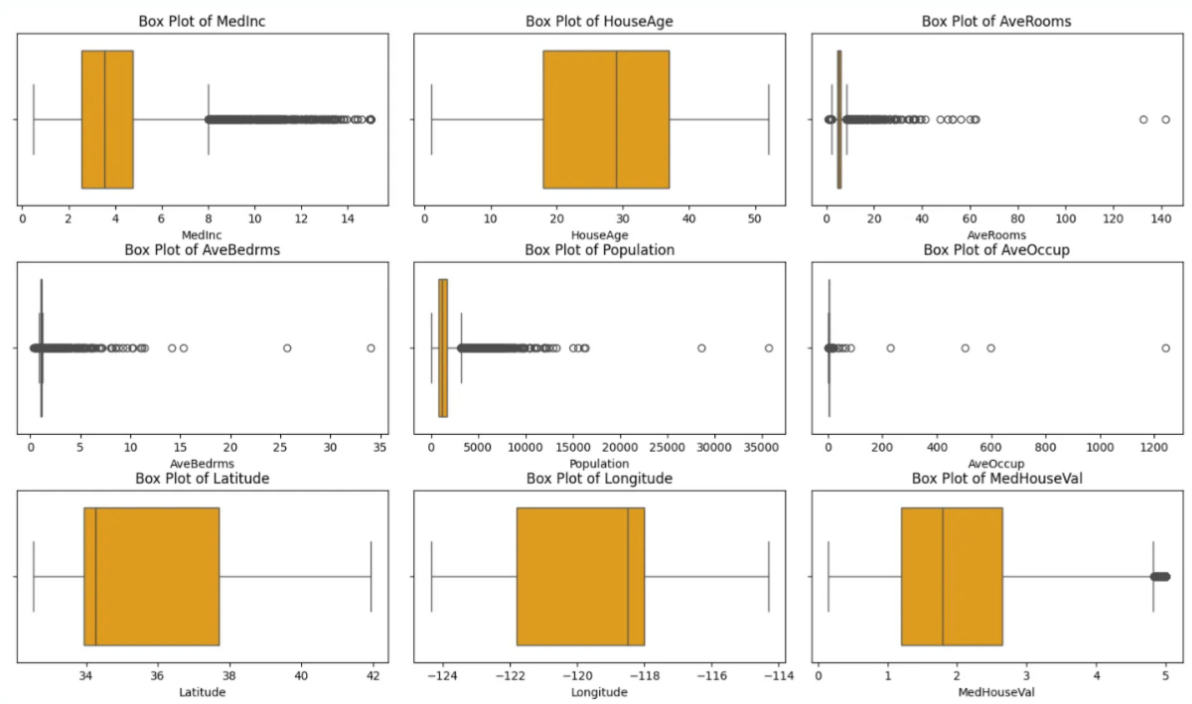
Develop a program to create histograms for all numerical features and analyze the distribution of each feature. Generate box plots for all numerical features and identify any outliers. Use California Housing dataset.

Program:

```
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

<u>Dataset Summary:</u>

	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]

Experiment No:2

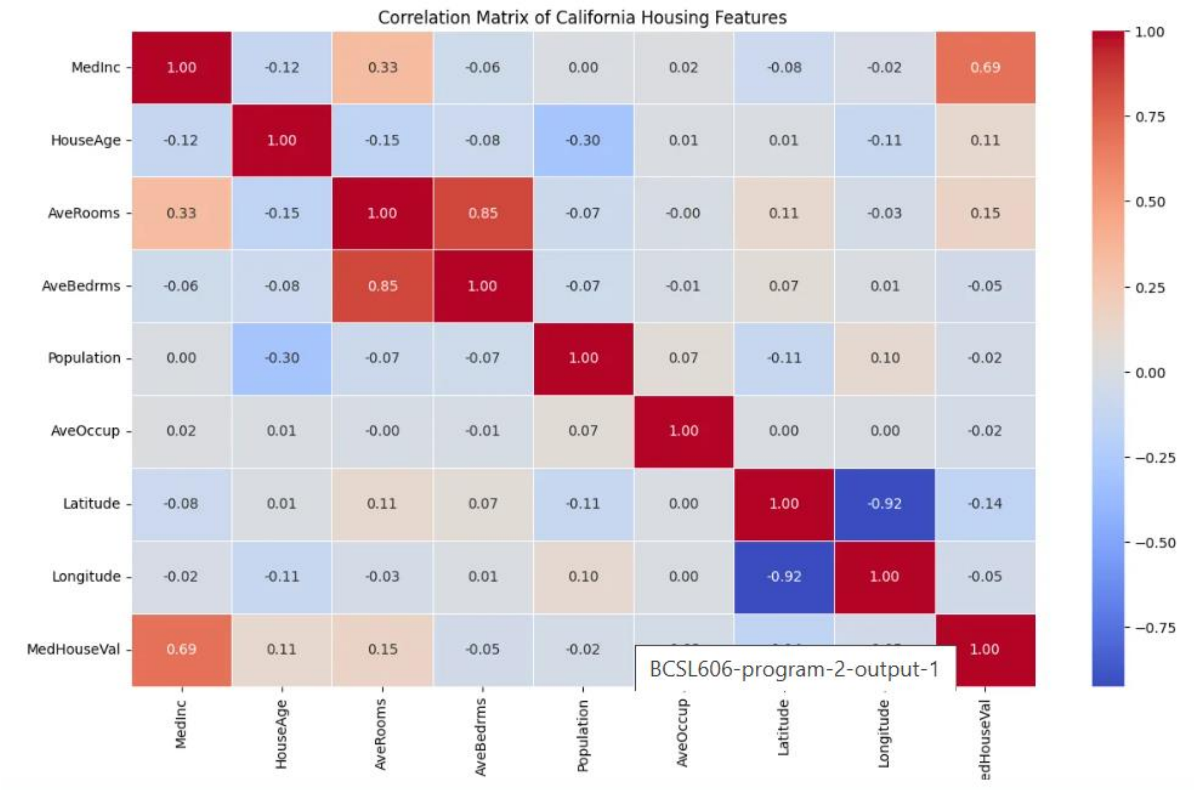
1. **Develop a program to Compute the correlation matrix to understand the relationships between pairs of features. Visualize the correlation matrix using a heatmap to know which variables have strong positive/negative correlations. Create a pair plot to visualize pairwise relationships between features.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

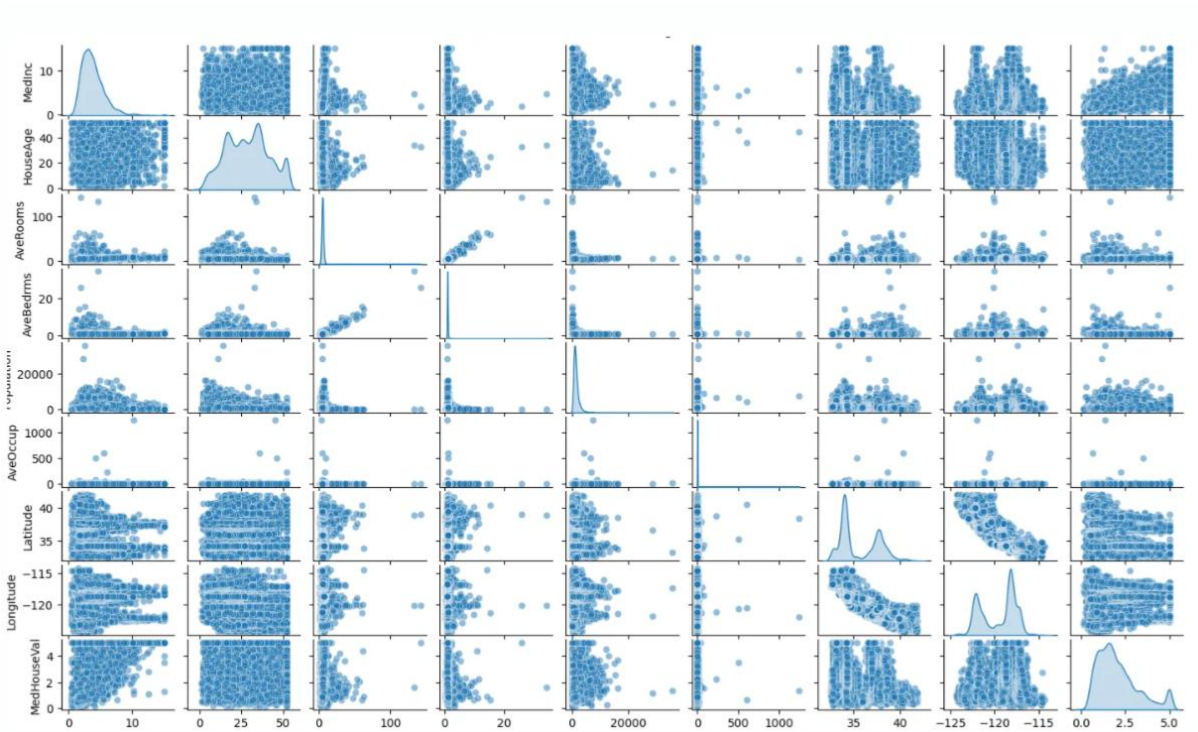
Program:

```
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:





Experiment No:3

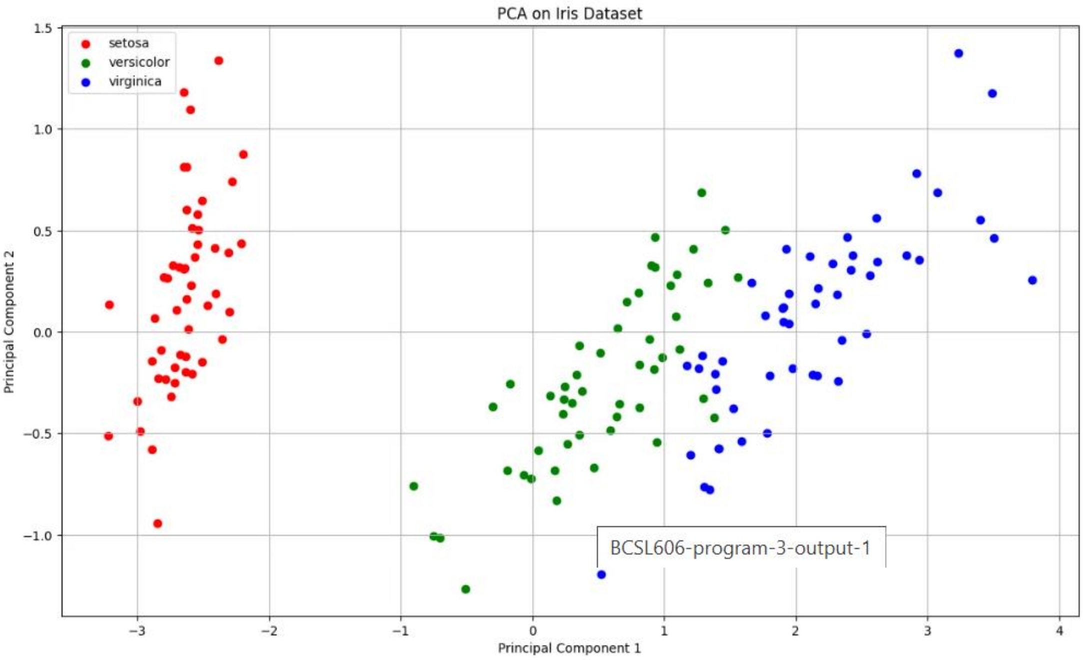
Develop a program to implement Principal Component Analysis (PCA) for reducing the dimensionality of the Iris dataset from 4 features to 2.

Program:

```
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:



Experiment No:4

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.

Program:

```
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', '?']

Experiment No:5

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

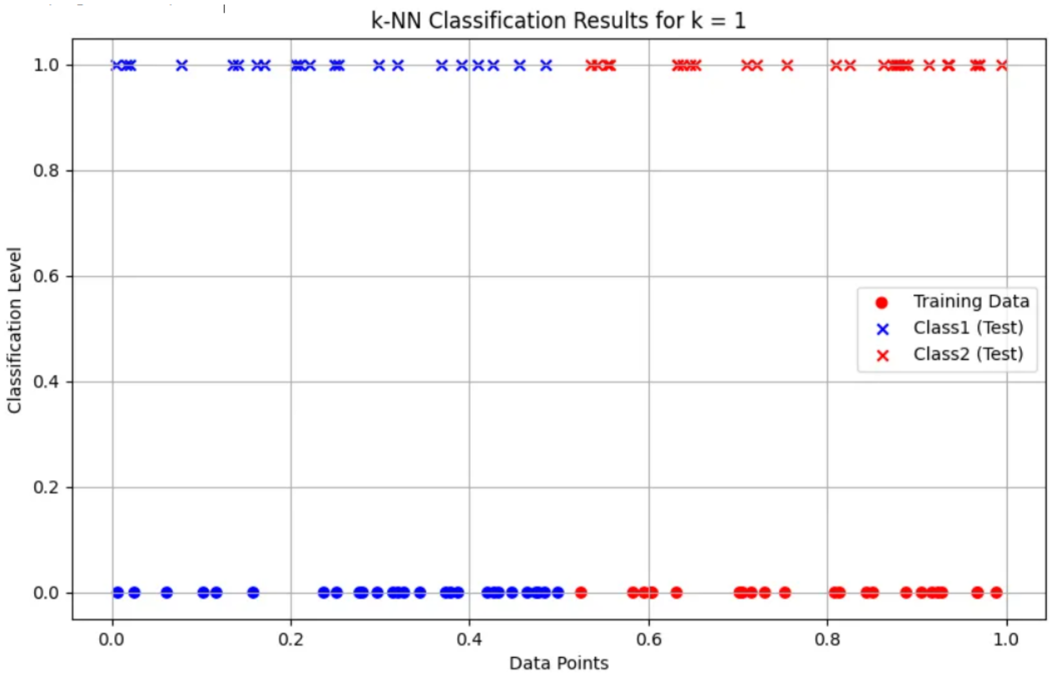
Program:

```
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:



Experiment No:6

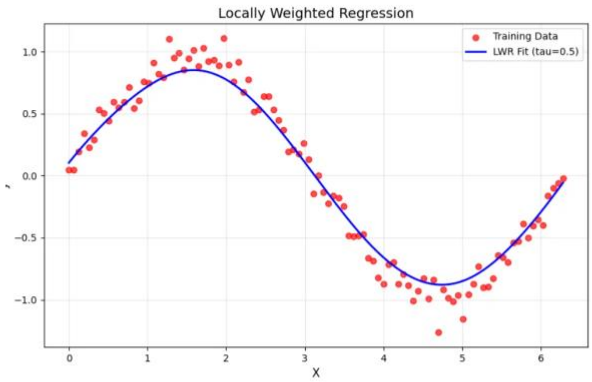
Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs.

Program:

```
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()
```

<u>Output:</u>



Experiment No: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.

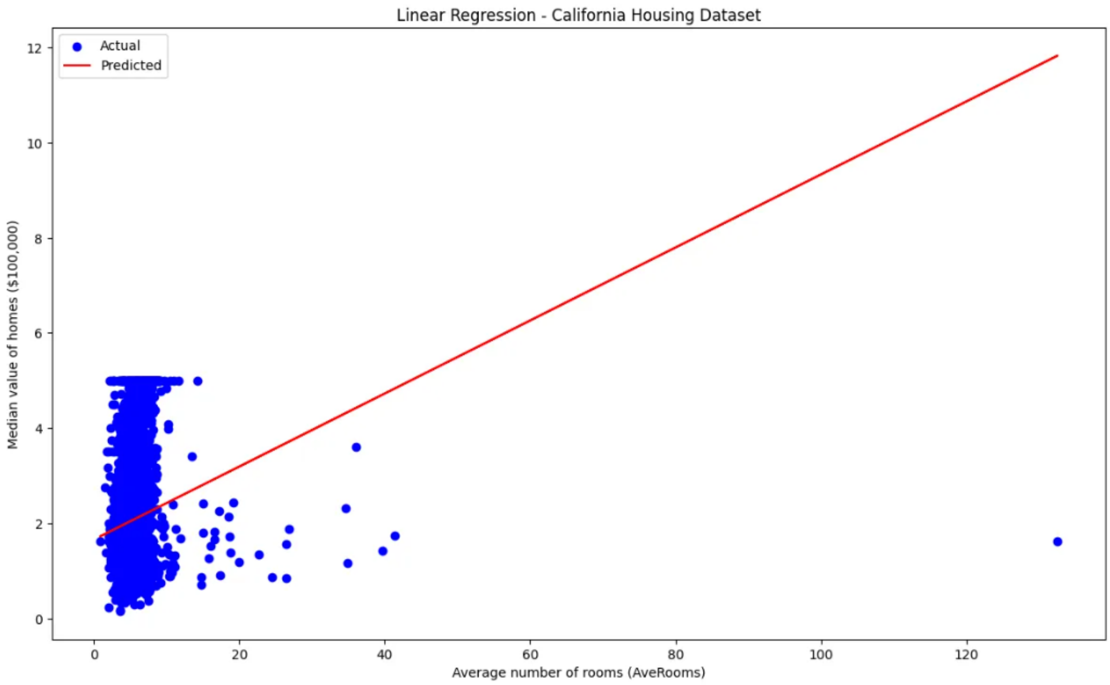
Program:

```
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:



Experiment No:8

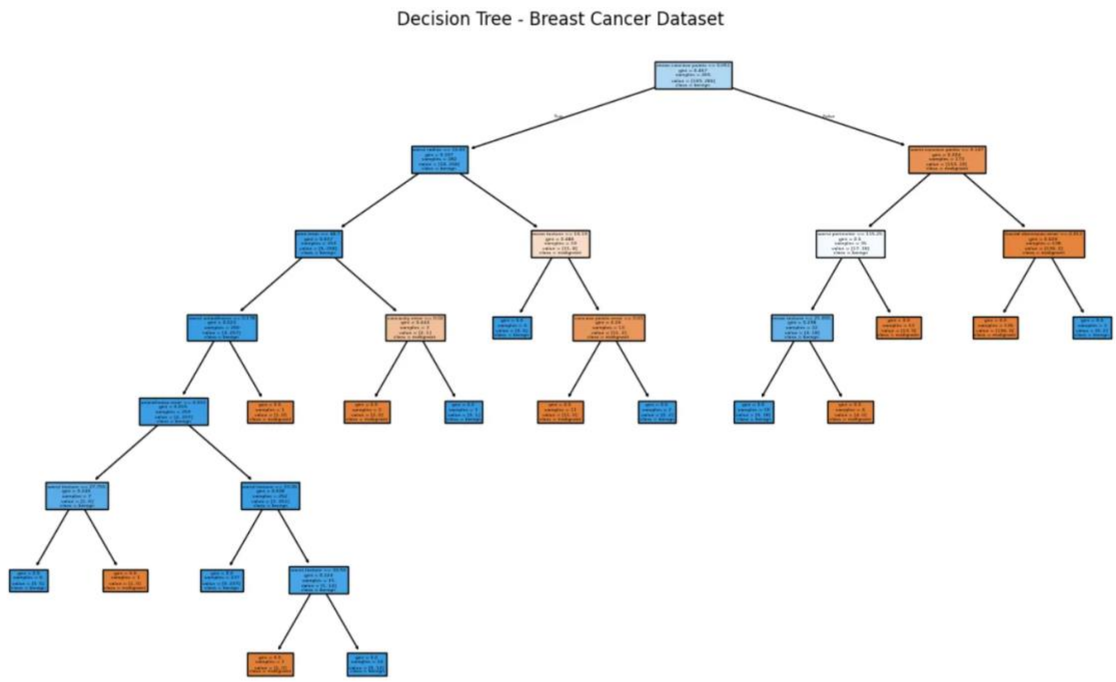
Develop a program to demonstrate the working of the decision tree algorithm. Use Breast Cancer Data set for building the decision tree and apply this knowledge to classify a new sample.

Program:

```
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:



Experiment No:9

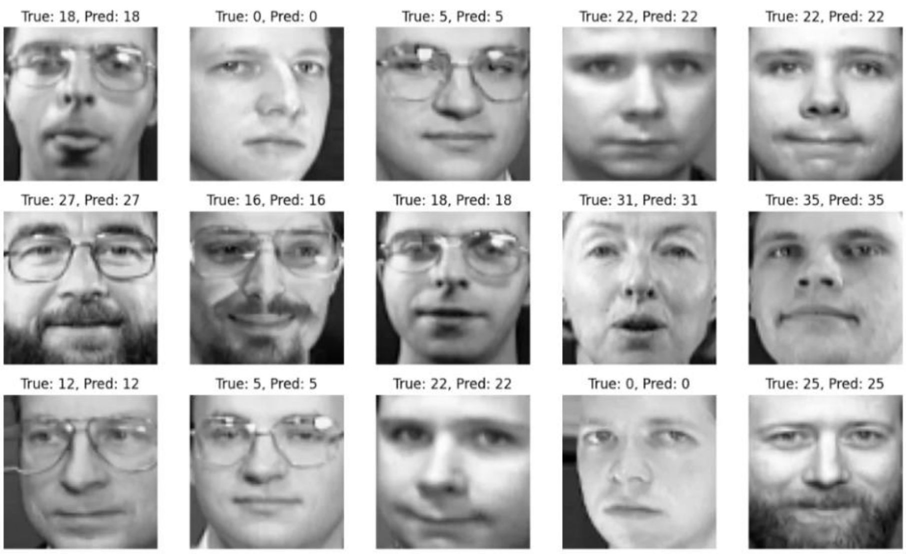
Develop a program to implement the Naive Bayesian classifier considering Olivetti Face Data set for training. Compute the accuracy of the classifier, considering a few test data sets.

Program:

```
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)

gb = 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()
```

<u>Output:</u>



Experiment No:10

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

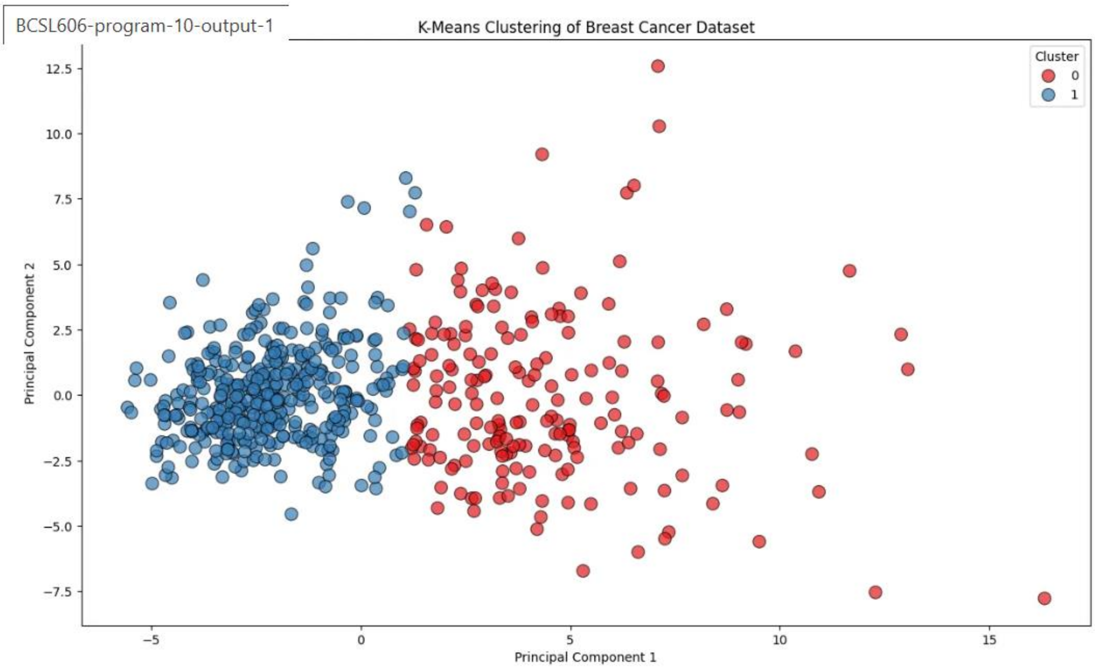
Program:

```
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)
```

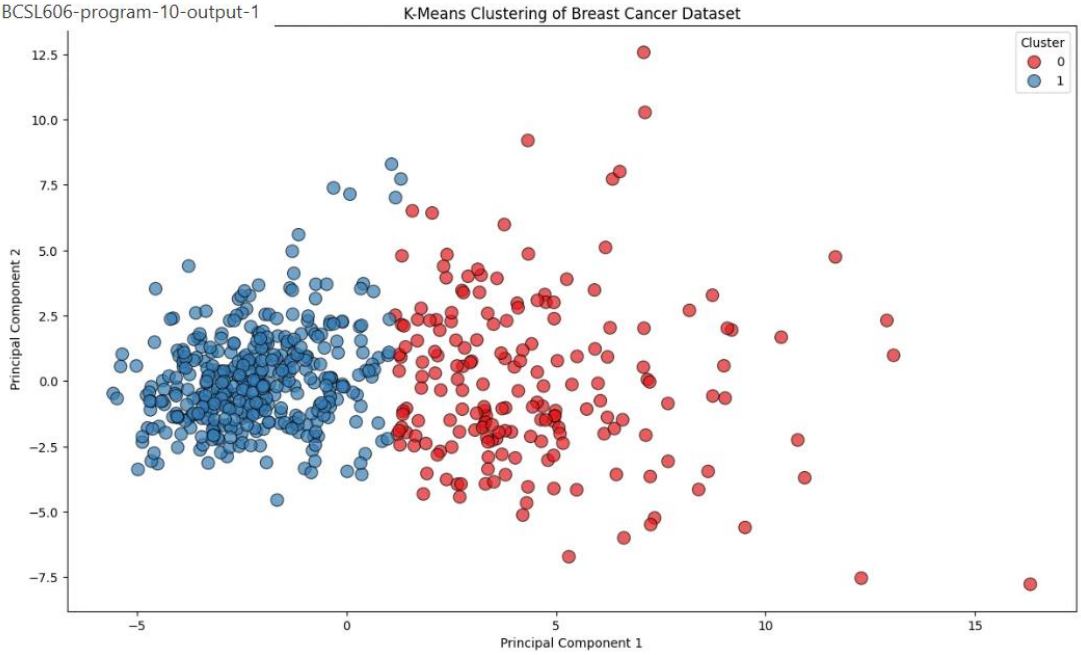
```
df = pd.DataFrame(X_pca, columns=['PC1', 'PC2'])

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")
```

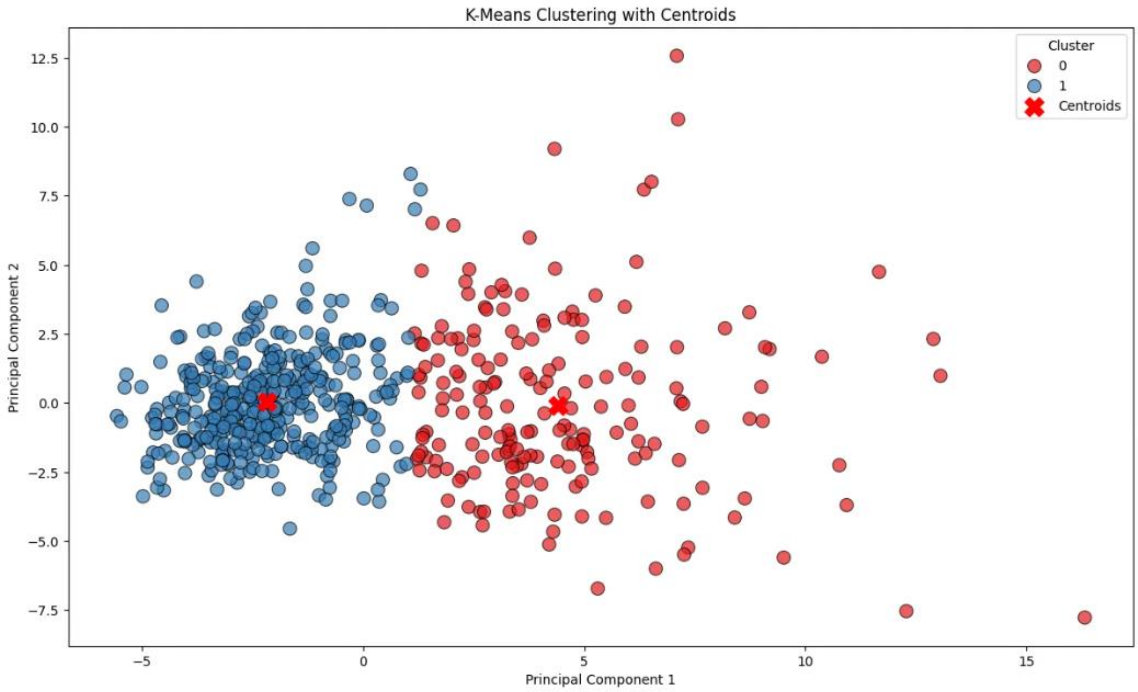
```
plt.show()
```

Output:



BCSL606-program-10-output-1





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