Assignment No. 5

Problem Statement: Implement and analyze the K-Nearest Neighbors (KNN) algorithm for classification and regression.

Objective: To understand and implement the KNN algorithm, analyze its performance, and evaluate how different parameters affect its accuracy in both classification and regression tasks.

Prerequisite :

1. A Python environment set up with libraries such as `numpy`, `pandas`, `matplotlib`, `seaborn`, and `sklearn`.
2. Internet connection (for fetching datasets if needed).
3. Basic knowledge of machine learning and KNN.

Theory :

K-Nearest Neighbors (KNN) Algorithm

KNN is a simple yet powerful supervised learning algorithm used for classification and regression. It makes predictions based on the similarity between a new data point and its closest neighbors in the feature space.

Working of KNN

1. Choose the value of **K** (number of nearest neighbors).
2. Calculate the distance (e.g., Euclidean, Manhattan) between the query instance and all training instances.
3. Select the **K** nearest neighbors.
4. For classification, assign the most frequent class among the neighbors.
5. For regression, compute the average (or weighted average) of the nearest neighbors' values.

Choosing the Right Value for K:

- A small K value (e.g., K=1) makes the model highly sensitive to noise.
- A large K value (e.g., K=20) results in a smoother decision boundary but may ignore local patterns.

Distance Metrics:

Euclidean Distance:

$$d = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

Manhattan Distance:

$$d = \sum_{i=1}^{n} |x_i - y_i|$$

Advantages of KNN:

- Simple and easy to implement.
- Works well for smaller datasets with fewer features.

Disadvantages of KNN:

- Computationally expensive for large datasets.
- Sensitive to irrelevant features and feature scaling.

Implementation Steps:

1. Understanding the Dataset

- Load the dataset using `pandas`.
- Check dataset dimensions using `.shape`.
- Display column data types using `.info()`.
- Check for missing values using `.isnull().sum()`.

2. Data Preprocessing

- Handle missing values (imputation or removal).
- Encode categorical features if necessary (`LabelEncoder`, `OneHotEncoder`).
- Normalize numerical features using **Min-Max Scaling** or **Standardization**.

3. Splitting Data into Training and Testing Sets

- Use `train_test_split` from `sklearn.model_selection`.
- Common split ratio: 80% training, 20% testing.

4. Implementing KNN for Classification

- Use `KNeighborsClassifier` from `sklearn.neighbors`.

- Train the model and make predictions.
- Evaluate performance using **accuracy, precision, recall, and confusion matrix**.

5. Implementing KNN for Regression

- Use `KNeighborsRegressor` from `sklearn.neighbors`.
- Train the model and make predictions.
- Evaluate performance using **Mean Squared Error (MSE) and R-squared Score**.

6. Hyperparameter Tuning

- Experiment with different K values to find the best one.
- Compare distance metrics (Euclidean, Manhattan, Minkowski).

7. Data Visualization

- **Plot decision boundaries** for classification.
- **Visualize the effect of K** on accuracy.
- **Plot actual vs. predicted values** for regression.

CODE & OUTPUT :

```
[3]: import numpy as np
     import pandas as pd
     import matplotlib.pyplot as plt
     import seaborn as sns
     from sklearn.model_selection import train_test_split
     from sklearn.preprocessing import StandardScaler
     from sklearn.neighbors import KNeighborsClassifier
     from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
     from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, precision_score, recall_score
```

```
•[4]: df = pd.read_csv('D:/ML/heart.csv')  # Load the heart disease dataset into a DataFrame
```

```
[5]: print(df.head(5))
```

```
   age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  slope  \
0   52    1   0       125   212    0        1      168      0      1.0      2
1   53    1   0       140   203    1        0      155      1      3.1      0
2   70    1   0       145   174    0        1      125      1      2.6      0
3   61    1   0       148   203    0        1      161      0      0.0      2
4   62    0   0       138   294    1        1      106      0      1.9      1

   ca  thal  target
0   2     3       0
1   0     3       0
2   0     3       0
3   1     3       0
4   3     2       0
```

```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1025 entries, 0 to 1024
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       1025 non-null   int64
 1   sex       1025 non-null   int64
 2   cp        1025 non-null   int64
 3   trestbps  1025 non-null   int64
 4   chol      1025 non-null   int64
 5   fbs       1025 non-null   int64
 6   restecg   1025 non-null   int64
 7   thalach   1025 non-null   int64
 8   exang     1025 non-null   int64
 9   oldpeak   1025 non-null   float64
 10  slope     1025 non-null   int64
 11  ca        1025 non-null   int64
 12  thal      1025 non-null   int64
 13  target    1025 non-null   int64
dtypes: float64(1), int64(13)
memory usage: 112.2 KB
None
```

```
print(df.describe())
```

```
              age          sex           cp     trestbps        chol  \
count  1025.000000  1025.000000  1025.000000  1025.000000  1025.00000
mean     54.434146     0.695610     0.942439   131.611707   246.00000
std       9.072290     0.460373     1.029641    17.516718    51.59251
min      29.000000     0.000000     0.000000    94.000000   126.00000
25%      48.000000     0.000000     0.000000   120.000000   211.00000
50%      56.000000     1.000000     1.000000   130.000000   240.00000
75%      61.000000     1.000000     2.000000   140.000000   275.00000
max      77.000000     1.000000     3.000000   200.000000   564.00000

              fbs      restecg      thalach        exang      oldpeak  \
count  1025.000000  1025.000000  1025.000000  1025.000000  1025.000000
mean      0.149268     0.529756   149.114146     0.336585     1.071512
std       0.356527     0.527878    23.005724     0.472772     1.175053
min       0.000000     0.000000    71.000000     0.000000     0.000000
25%       0.000000     0.000000   132.000000     0.000000     0.000000
50%       0.000000     1.000000   152.000000     0.000000     0.800000
75%       0.000000     1.000000   166.000000     1.000000     1.800000
max       1.000000     2.000000   202.000000     1.000000     6.200000

            slope           ca         thal       target
count  1025.000000  1025.000000  1025.000000  1025.000000
mean      1.385366     0.754146     2.323902     0.513171
std       0.617755     1.030798     0.620660     0.500070
min       0.000000     0.000000     0.000000     0.000000
25%       1.000000     0.000000     2.000000     0.000000
50%       1.000000     0.000000     2.000000     1.000000
75%       2.000000     1.000000     3.000000     1.000000
max       2.000000     4.000000     3.000000     1.000000
```

```
print(df.isnull().sum())
```

```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

```
# Check if the 'id' column exists in the dataset and drop it (to remove unnecessary identifiers)
if 'id' in df.columns:
    df.drop(columns=['id'], inplace=True)

# Check if the 'Unnamed: 32' column exists in the dataset and drop it (likely an extra unnamed column)
if 'Unnamed: 32' in df.columns:
    df.drop(columns=['Unnamed: 32'], inplace=True)
```

```python
# Separate the features (X) and target variable (y)
X = df.iloc[:, 1:]  # Select all columns except the first one as features
y = df.iloc[:, 0]   # Select the first column as the target variable

# Split the dataset into training and testing sets (80% training, 20% testing)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=2)
```

```python
# Create a K-Nearest Neighbors (KNN) classifier with k=3 (3 neighbors)
knn = KNeighborsClassifier(n_neighbors=3)

# Train the KNN classifier using the training data
knn.fit(X_train, y_train)
```

```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=3)
```

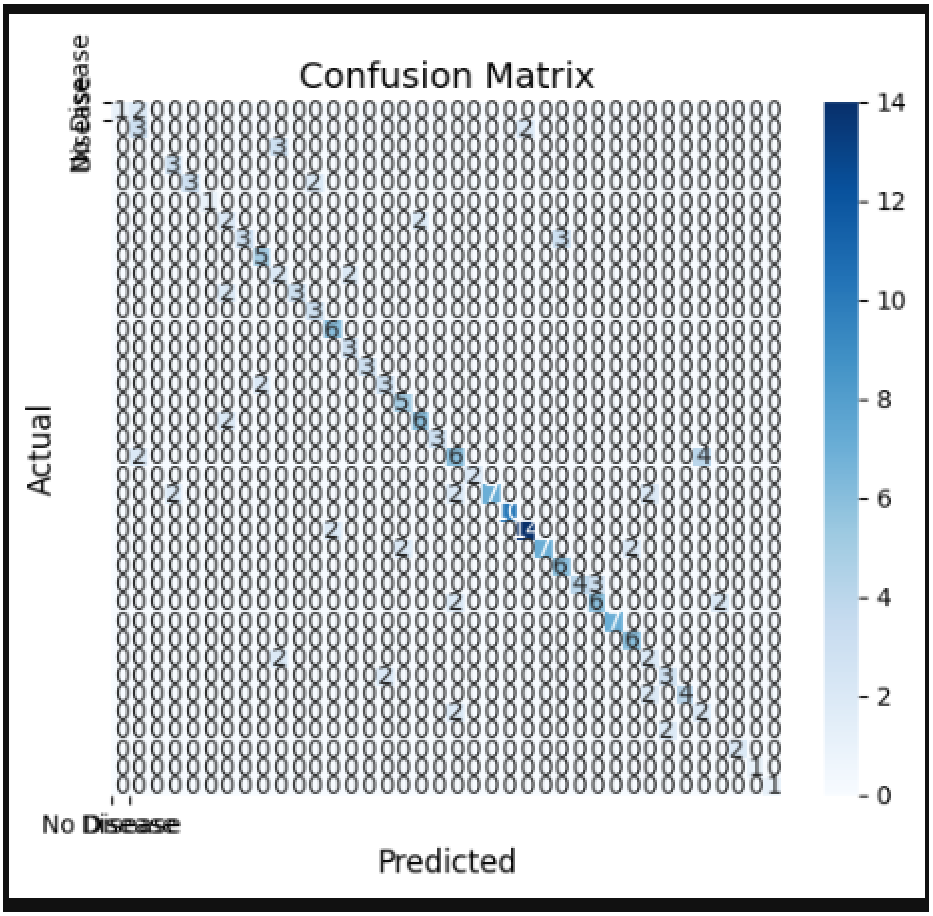
```python
# Predict the target values for the test dataset using the trained KNN model
y_pred = knn.predict(X_test)
```

```python
# Calculate the accuracy of the model (ratio of correct predictions to total predictions)
accuracy = accuracy_score(y_test, y_pred)

# Calculate the precision (ratio of correctly predicted positive observations to total predicted positives)
# 'macro' average computes the precision for each class and then takes the average
precision = precision_score(y_test, y_pred, average='macro', zero_division=1)

# Calculate recall (ratio of correctly predicted positive observations to all actual positives)
recall = recall_score(y_test, y_pred, average='macro', zero_division=1)

# Compute the confusion matrix (shows the number of TP, FP, TN, and FN)
cm = confusion_matrix(y_test, y_pred)

# Compute specificity (True Negative Rate): TN / (TN + FP)
specificity = cm[0,0] / (cm[0,0] + cm[0,1])  # Ensures we correctly classify negatives
```

```python
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("Specificity:", specificity)
print("Confusion Matrix:\n", cm)
print("Classification Report:\n", classification_report(y_test, y_pred))
```

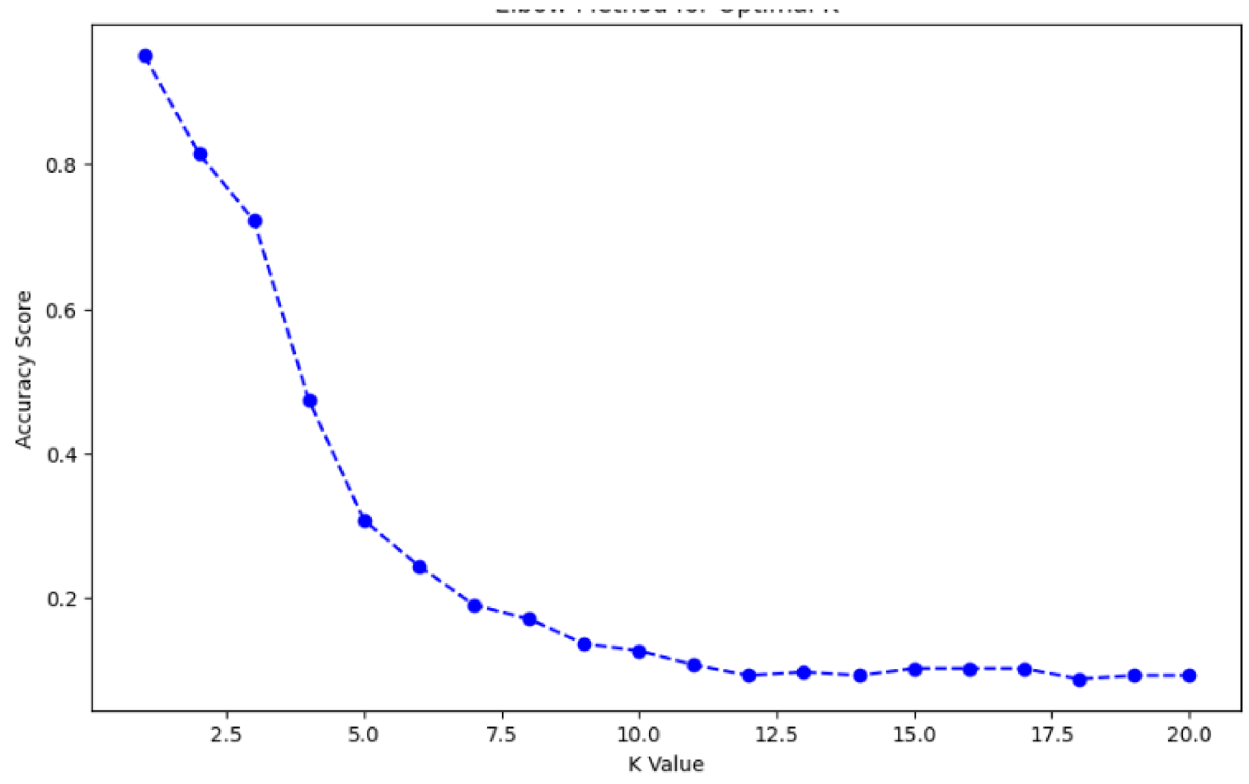
```
Accuracy: 0.7219512195121951
Precision: 0.7658208020050126
Recall: 0.7360856249014144
Specificity: 0.3333333333333333
Confusion Matrix:
 [[1 2 0 ... 0 0 0]
 [0 3 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 ...
 [0 0 0 ... 2 0 0]
 [0 0 0 ... 0 1 0]
 [0 0 0 ... 0 0 1]]
Classification Report:
              precision    recall  f1-score   support

          34       1.00      0.33      0.50         3
          35       0.43      0.60      0.50         5
          37       0.00      0.00      0.00         3
          38       0.60      1.00      0.75         3
          39       1.00      0.60      0.75         5
          40       1.00      1.00      1.00         1
          41       0.33      0.50      0.40         4
          42       1.00      0.50      0.67         6
          43       0.71      1.00      0.83         5
          44       0.29      0.50      0.36         4
          45       1.00      0.60      0.75         5
          46       0.60      1.00      0.75         3
          47       0.75      1.00      0.86         6
          48       0.60      1.00      0.75         3
          49       1.00      1.00      1.00         3
          50       0.60      0.60      0.60         5
          51       0.71      1.00      0.83         5
```

```python
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)

# Plot using seaborn
plt.figure(figsize=(6, 5))  # Set figure size
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", annot_kws={"size": 10})  # Reduce text size
plt.xlabel("Predicted", fontsize=12)
plt.ylabel("Actual", fontsize=12)
plt.title("Confusion Matrix", fontsize=14)
plt.xticks(ticks=[0, 1], labels=["No Disease", "Disease"], rotation=0, fontsize=10)
plt.yticks(ticks=[0, 1], labels=["No Disease", "Disease"], rotation=90, fontsize=10)
plt.show()
```




```python
scores = []
k_range = range(1, 21)  # Testing k from 1 to 20

for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    y_pred_k = knn.predict(X_test)
    scores.append(accuracy_score(y_test, y_pred_k))
```

```python
plt.figure(figsize=(10, 6))
plt.plot(k_range, scores, marker='o', linestyle='dashed', color='blue')
plt.xlabel('K Value')
plt.ylabel('Accuracy Score')
plt.title('Elbow Method for Optimal K')
plt.show()
```



Github : [**https://github.com/Vishalgodalkar/Machine-Learning**](https://github.com/Vishalgodalkar/Machine-Learning)

Conclusion:

This KNN implementation involved preprocessing the dataset, selecting optimal hyperparameters, and evaluating model performance. The impact of different values of k, distance metrics, and feature scaling techniques was analyzed. While the model performed well with an appropriate k, lower values of k led to overfitting, whereas higher values caused underfitting. Additionally, feature scaling significantly influenced distance calculations, affecting model accuracy. Careful selection of k and proper preprocessing ensured improved performance. Overall, the KNN model effectively classified/regressed data and demonstrated its strengths and limitations in various scenarios.