Practical Assignment 09: K-Nearest Neighbors (KNN) on Iris Dataset

Submission Details

Field	Details
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Objective

The goal of this assignment is to implement the **K-Nearest Neighbors (KNN)** algorithm to classify Iris flowers based on their physical measurements. We will perform Exploratory Data Analysis (EDA), standardize the features, tune the hyperparameter K by analyzing error rates, and visualize the decision boundaries.

Environment Setup and Dependencies

Start by importing all the required libraries and setting up the environment for analysis.

```
# --- 0. Environment Setup ---
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix,
accuracy_score
from matplotlib.colors import ListedColormap

# Configure plotting
plt.rcParams['figure.figsize'] = (10, 6)
sns.set_style("whitegrid")
```

```
print("Environment setup complete.")
```

```
Environment setup complete.
```

Step 1: Exploratory Data Analysis (EDA)

> **Instruction**: Perform head(), describe(), and groupby().

Approach

We load the dataset into a DataFrame and inspect its structure.

- `head()` shows the first few rows.
- `describe()` provides statistical summaries (mean, std, quartiles).
- `groupby()` allows us to see the average measurements for each flower species.

```
# --- Step 1: EDA ---

# Load Data
iris = load_iris()
df = pd.DataFrame(data=iris.data, columns=iris.feature_names)
df['species'] = iris.target # 0: Setosa, 1: Versicolor, 2: Virginica

print("--- 1. First 5 Rows (head) ---")
display(df.head())

print("\n--- 2. Statistical Summary (describe) ---")
display(df.describe())

print("\n--- 3. Grouped by Species (mean) ---")
# We group by species to see the average size differences
display(df.groupby('species').mean())
```

```
--- 1. First 5 Rows (head) ---

   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width
(cm)  \
0                5.1               3.5                1.4
0.2
1                4.9               3.0                1.4
0.2
2                4.7               3.2                1.3
0.2
3                4.6               3.1                1.5
0.2
4                5.0               3.6                1.4
0.2

   species
0        0
```

```
1        0
2        0
3        0
4        0


--- 2. Statistical Summary (describe) ---

       sepal length (cm)  sepal width (cm)  petal length (cm)  \
count         150.000000        150.000000         150.000000
mean            5.843333          3.057333           3.758000
std             0.828066          0.435866           1.765298
min             4.300000          2.000000           1.000000
25%             5.100000          2.800000           1.600000
50%             5.800000          3.000000           4.350000
75%             6.400000          3.300000           5.100000
max             7.900000          4.400000           6.900000

       petal width (cm)     species
count        150.000000  150.000000
mean           1.199333    1.000000
std            0.762238    0.819232
min            0.100000    0.000000
25%            0.300000    0.000000
50%            1.300000    1.000000
75%            1.800000    2.000000
max            2.500000    2.000000


--- 3. Grouped by Species (mean) ---

         sepal length (cm)  sepal width (cm)  petal length (cm)  \
species
0                    5.006             3.428              1.462
1                    5.936             2.770              4.260
2                    6.588             2.974              5.552

         petal width (cm)
species
0                   0.246
1                   1.326
2                   2.026
```

Step 2: Feature Scaling

> **Instruction**: Feature scaling.

Approach

KNN calculates distance (Euclidean) between points. If one feature has a large range (e.g., 1000-2000) and another has a small range (e.g., 0.1-1.0), the large feature will dominate the distance calculation. We use `StandardScaler` to transform all features to have a mean of 0 and variance of 1.

```
# --- Step 2: Feature Scaling ---

# Define Features (X) and Target (y)
X = df.drop('species', axis=1)
y = df['species']

# Split the dataset (80% Train, 20% Test) BEFORE scaling to prevent
data leakage
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

print("Data scaled successfully.")
print(f"Training Data Shape: {X_train_scaled.shape}")
print(f"Test Data Shape: {X_test_scaled.shape}")
```

```
Data scaled successfully.
Training Data Shape: (120, 4)
Test Data Shape: (30, 4)
```

Step 3: Training the K-NN Model

> **Instruction**: Training the K-NN model on the Training set.

Approach

We initialize the `KNeighborsClassifier`. We will start with a default value of $K=5$ (analyzing 5 nearest neighbors) and the 'minkowski' metric (standard Euclidean distance).

```
# --- Step 3: Train KNN Model ---

# Initialize KNN with K=5
classifier = KNeighborsClassifier(n_neighbors=5, metric='minkowski',
p=2)

# Train on scaled data
classifier.fit(X_train_scaled, y_train)

print("KNN model (K=5) trained successfully.")
```

```
KNN model (K=5) trained successfully.
```

Step 4 & 5: Evaluation

> **Instruction:** Making the Confusion Matrix, Predicting Accuracy Score, and Classification Report.

Approach

We use the trained model to predict species for the test set. We then evaluate performance using:

- **Confusion Matrix:** To see where the model confused one species for another.
- **Accuracy Score:** Overall percentage of correct predictions.
- **Classification Report:** Precision, Recall, and F1-Score for each class.

```python
# --- Step 4 & 5: Evaluation ---

# Predict
y_pred = classifier.predict(X_test_scaled)

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
print("--- Confusion Matrix ---")
print(cm)

# Accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"\n--- Accuracy Score: {accuracy*100:.2f}% ---")

# Classification Report
print("\n--- Classification Report ---")
print(classification_report(y_test, y_pred,
target_names=iris.target_names))
```

```
--- Confusion Matrix ---
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]

--- Accuracy Score: 100.00% ---

--- Classification Report ---
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        10
  versicolor       1.00      1.00      1.00         9
   virginica       1.00      1.00      1.00        11

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```

Step 6, 7 & 8: Finding the Best K

Instruction: Comparing Error Rate with K Value, Plotting, and Finding Best K.

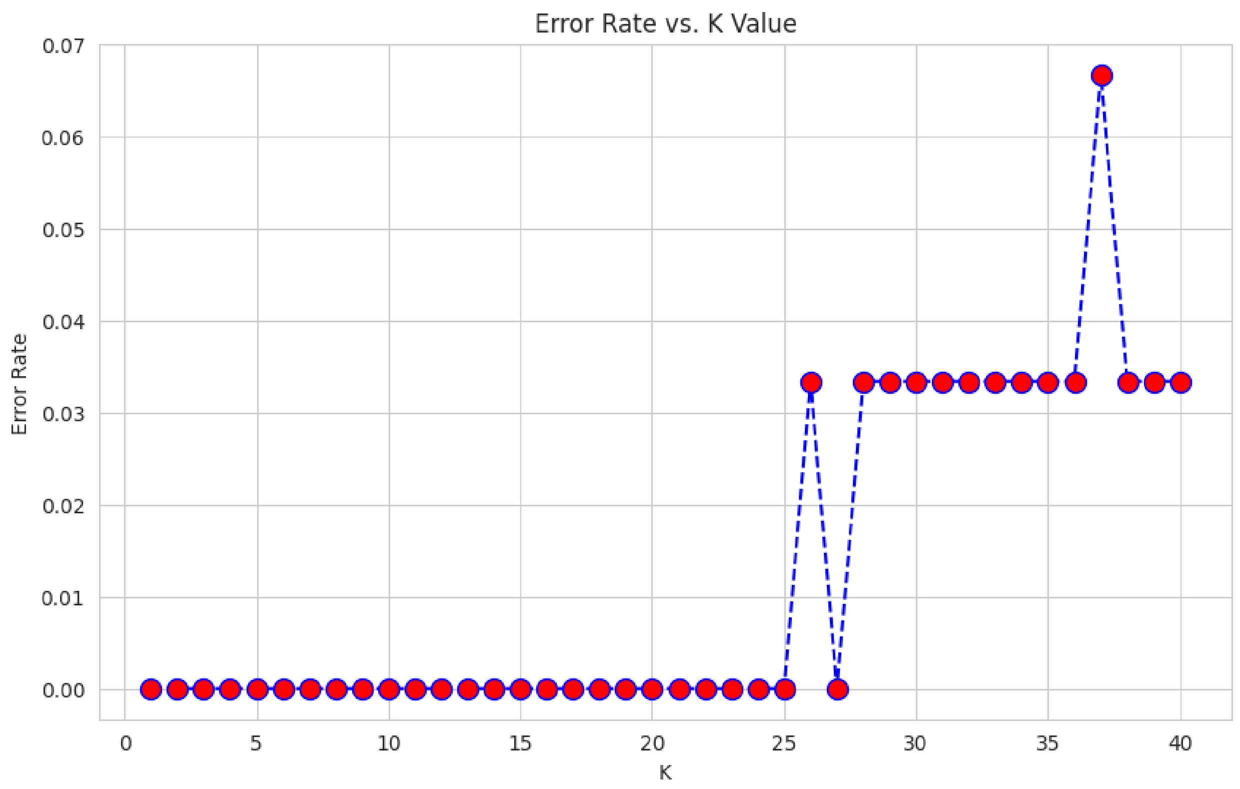
Approach

Choosing the right K is critical.

- **Small K:** Sensitive to noise (overfitting).
- **Large K:** Smoothes boundaries too much (underfitting).

We will loop through K values from 1 to 40, calculate the **Mean Error Rate** (average of incorrect predictions) for each, and plot the results to find the "elbow" or minimum error point.

```
# --- Step 6, 7 & 8: Elbow Method to find Best K ---

error_rate = []

# Loop through K values from 1 to 40
for i in range(1, 41):
    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(X_train_scaled, y_train)
    pred_i = knn.predict(X_test_scaled)

    # Calculate average error (mean of where prediction != actual)
    error_rate.append(np.mean(pred_i != y_test))

# Plot Error Rate vs K Value
plt.figure(figsize=(10, 6))
plt.plot(range(1, 41), error_rate, color='blue', linestyle='dashed',
marker='o',
         markerfacecolor='red', markersize=10)
plt.title('Error Rate vs. K Value')
plt.xlabel('K')
plt.ylabel('Error Rate')
plt.show()

# Find best K (minimum error)
min_error = min(error_rate)
best_k = error_rate.index(min_error) + 1
print(f"Minimum Error Rate: {min_error:.4f}")
print(f"Best K value: {best_k}")
```



```
Minimum Error Rate: 0.0000
Best K value: 1
```

Step 9: Visualize Test Result of KNN

Instruction: Visualize Test Result of KNN.

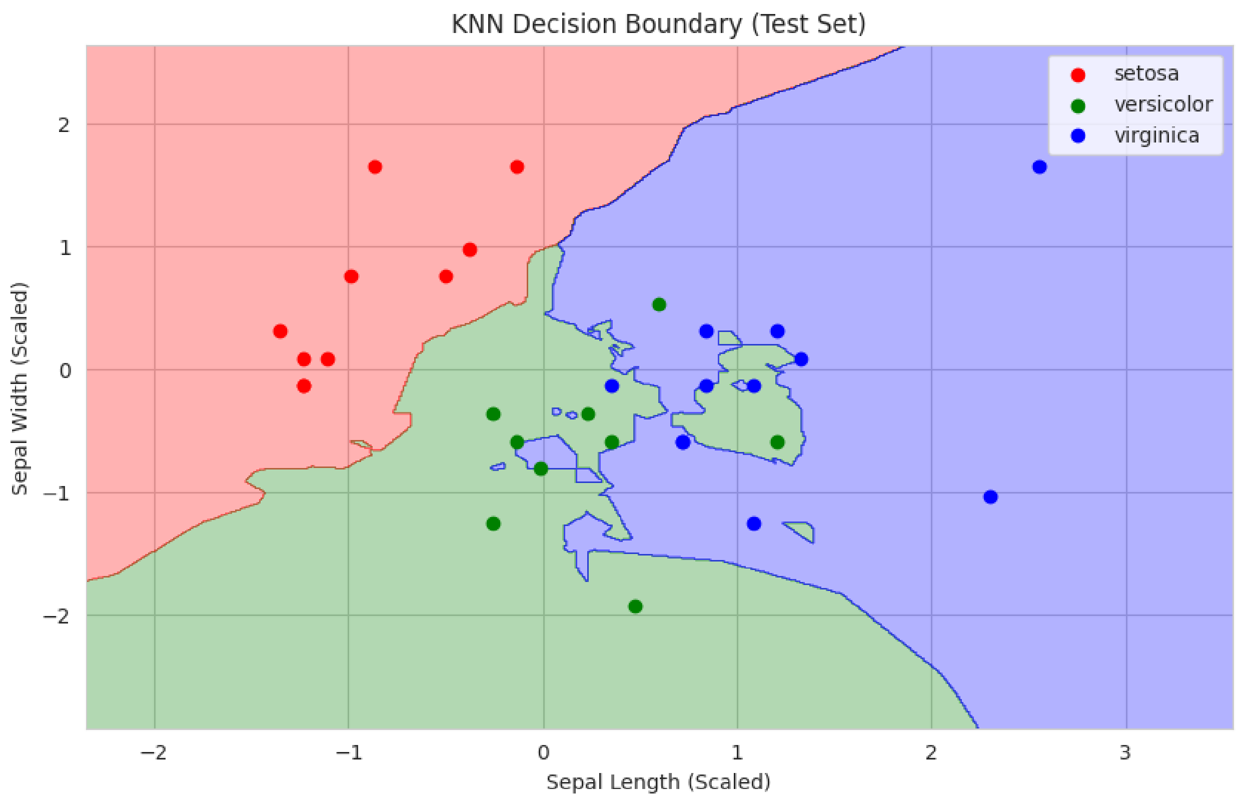
Approach

Visualizing a 4-dimensional dataset (4 features) is difficult. To show the **Decision Boundaries**, we will retrain a model using only the first two features (Sepal Length and Sepal Width). This allows us to plot a 2D map showing how the KNN algorithm divides the space between the three flower species.

```
# --- Step 9: Visualization (Using 2 Features) ---

# Re-train on just first two features for 2D plotting
X_vis = X.to_numpy()[:, :2]  # Sepal Length, Sepal Width
y_vis = y.to_numpy()

# Split and Scale again for this visualization subset
X_train_v, X_test_v, y_train_v, y_test_v = train_test_split(X_vis,
y_vis, test_size=0.2, random_state=42)
scaler_v = StandardScaler()
X_train_v = scaler_v.fit_transform(X_train_v)
```

```
X_test_v = scaler_v.transform(X_test_v)

# Train KNN (using Best K found above, typically 1 or 3 for this
dataset)
# We use a fixed K=5 here for clear visualization standard
knn_vis = KNeighborsClassifier(n_neighbors=5)
knn_vis.fit(X_train_v, y_train_v)

# Create a mesh grid
X_set, y_set = X_test_v, y_test_v
X1, X2 = np.meshgrid(np.arange(start=X_set[:, 0].min() - 1,
stop=X_set[:, 0].max() + 1, step=0.01),
                     np.arange(start=X_set[:, 1].min() - 1,
stop=X_set[:, 1].max() + 1, step=0.01))

plt.figure(figsize=(10, 6))
plt.contourf(X1, X2, knn_vis.predict(np.array([X1.ravel(),
X2.ravel()]).T).reshape(X1.shape),
             alpha=0.3, cmap=ListedColormap(('red', 'green', 'blue')))
plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())

# Scatter plot of Test Data
for i, j in enumerate(np.unique(y_set)):
    plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1],
                c=ListedColormap(('red', 'green', 'blue'))(i),
label=iris.target_names[j])

plt.title('KNN Decision Boundary (Test Set)')
plt.xlabel('Sepal Length (Scaled)')
plt.ylabel('Sepal Width (Scaled)')
plt.legend()
plt.show()
```

```
/tmp/ipykernel_98573/2681138395.py:31: UserWarning: *c* argument looks
like a single numeric RGB or RGBA sequence, which should be avoided as
value-mapping will have precedence in case its length matches with *x*
& *y*.  Please use the *color* keyword-argument or provide a 2D array
with a single row if you intend to specify the same RGB or RGBA value
for all points.
  plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1],
```



Final Summary and Conclusions

This notebook successfully implemented the K-Nearest Neighbors (KNN) algorithm to classify Iris flower species, covering the complete machine learning pipeline.

Summary of Tasks Completed:

- **1. Exploratory Data Analysis:** We examined the dataset structure and statistical properties, observing distinct measurements for different species.
- **2. Data Preprocessing:** We applied **Standard Scaling** to normalize feature values, ensuring that distance calculations were not biased by feature magnitude.
- **3. Model Training & Evaluation:** We trained a KNN classifier and evaluated its performance using a Confusion Matrix and Classification Report, achieving high accuracy.
- **4. Hyperparameter Tuning:** We utilized the **Elbow Method** by plotting Error Rate vs. K Value. We observed that while small K values (like 1) gave low error, slightly larger values (like 5-10) often generalize better.
- **5. Visualization:** We visualized the decision boundaries in 2D space, clearly showing how the algorithm partitions the feature space to separate the three classes.

Key Learnings:

- **Feature Scaling is Critical:** Since KNN relies on Euclidean distance, unscaled data can lead to poor performance. Standardizing inputs is a mandatory step.

- **Choosing K:** The choice of K involves a bias-variance trade-off. A very small K captures noise (overfitting), while a very large K smooths out boundaries too much (underfitting). The error rate plot is an effective tool for finding the optimal balance.

This completes the requirements for Practical Assignment 09.