Problem - 1: Perform a classification task with knn from scratch.

1. Load the Dataset:

- Read the dataset into a pandas DataFrame.
- Display the first few rows and perform exploratory data analysis (EDA) to understand the dataset (e.g., check data types, missing values, summary statistics).

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import time
```

```
df = pd.read_csv("C:\everything\herald\AI\week4\diabetes_.csv")
print("\nFirst 5 rows:")
print(df.head())

print("\nData types: ")
print(df.dtypes)

print("\nMissing values: ")
print(df.isna().sum())

print("\nSummary statistics: ")
print(df.describe(include='all'))
```

```
First 5 rows:
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
1            1       85             66             29        0  26.6
2            8      183             64              0        0  23.3
3            1       89             66             23       94  28.1
4            0      137             40             35      168  43.1

   DiabetesPedigreeFunction  Age  Outcome
0                     0.627   50        1
1                     0.351   31        0
2                     0.672   32        1
3                     0.167   21        0
4                     2.288   33        1

Data types:
Pregnancies                   int64
Glucose                       int64
BloodPressure                 int64
SkinThickness                 int64
Insulin                       int64
BMI                         float64
DiabetesPedigreeFunction    float64
Age                           int64
Outcome                       int64
dtype: object

Missing values:
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64

Summary statistics:
       Pregnancies     Glucose  BloodPressure  SkinThickness     Insulin  \
count   768.000000  768.000000     768.000000     768.000000  768.000000
mean      3.845052  120.894531      69.105469      20.536458   79.799479
std       3.369578   31.972618      19.355807      15.952218  115.244002
min       0.000000    0.000000       0.000000       0.000000    0.000000
25%       1.000000   99.000000      62.000000       0.000000    0.000000
50%       3.000000  117.000000      72.000000      23.000000   30.500000
75%       6.000000  140.250000      80.000000      32.000000  127.250000
max      17.000000  199.000000     122.000000      99.000000  846.000000

              BMI  DiabetesPedigreeFunction         Age     Outcome
count  768.000000                768.000000  768.000000  768.000000
mean    31.992578                  0.471876   33.240885    0.348958
std      7.884160                  0.331329   11.760232    0.476951
min      0.000000                  0.078000   21.000000    0.000000
25%     27.300000                  0.243750   24.000000    0.000000
50%     32.000000                  0.372500   29.000000    0.000000
75%     36.600000                  0.626250   41.000000    1.000000
max     67.100000                  2.420000   81.000000    1.000000
```

2. Handle Missing Data:

- Handle any missing values appropriately, either by dropping or imputing them based on the data.

```
df_handle = df.copy()
for col in df_handle.columns:
    if df_handle[col].isna().any():
        median_value = df_handle[col].median() if np.issubdtype(df_handle[col].dtype, np.number) else df_handle[col].mode().iloc[0]
        df_handle[col] = df_handle[col].fillna(median_value)

print("Any remaining NaNs?", df_handle.isna().any().any())
```

```
Any remaining NaNs? False
```

3. **Feature Engineering**:

- Separate the feature matrix (X) and target variable (y).
- Perform a train - test split from scratch using a 70% − 30% ratio.

```
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values

np.random.seed(42)
indices = np.random.permutation(len(X))

train_size = int(0.7 * len(X))
train_idx = indices[:train_size]
test_idx = indices[train_size:]

X_train = X[train_idx]
X_test  = X[test_idx]
y_train = y[train_idx]
y_test  = y[test_idx]
print("Train size:", X_train.shape[0], "Test size:", X_test.shape[0])
```

```
Train size: 537 Test size: 231
```

4. Implement KNN:

- Build the KNN algorithm from scratch (no libraries like sickit-learn for KNN).
- Compute distances using Euclidean distance.
- Write functions for:
  - Predicting the class for a single query.
  - Predicting classes for all test samples.
- Evaluate the performance using accuracy.

```python
def euclidean_distance(a: np.ndarray, b: np.ndarray):
  return np.sqrt(np.sum(a - b) ** 2)

def knn_predict_one(x_query: np.ndarray, X_train: np.ndarray, y_train: np.ndarray, k: int = 5):
   dists = np.sqrt(np.sum((X_train - x_query) ** 2, axis=1))
   nn_idx = np.argpartition(dists, k)[:k]
   nn_labels = y_train[nn_idx]
   values, counts = np.unique(nn_labels, return_counts=True)
   return values[np.argmax(counts)]

def knn_predict(X_query: np.ndarray, X_train: np.ndarray, y_train: np.ndarray, k: int = 5):
    preds = np.zeros(X_query.shape[0], dtype=y_train.dtype)
    for i in range(X_query.shape[0]):
        preds[i] = knn_predict_one(X_query[i], X_train, y_train, k)
    return preds

def accuracy_score(y_true: np.ndarray, y_pred: np.ndarray):
    return (y_true == y_pred).mean()

k_baseline = 5
t0 = time.time()
y_pred_baseline = knn_predict(X_test, X_train, y_train, k=k_baseline)
t1 = time.time()

acc_baseline = accuracy_score(y_test, y_pred_baseline)
print(f"Baseline (unscaled) KNN | k={k_baseline}: Accuracy={acc_baseline:.4f}, Time={t1 - t0:.4f}s")
```

```
Baseline (unscaled) KNN | k=5: Accuracy=0.7143, Time=0.0190s
```

Problem - 2 - Experimentation:

1. Repeat the Classification Task:

- Scale the Feature matrix X.
- Use the scaled data for training and testing the kNN Classifier.
- Record the results.

```
#problem 2
X_mean = X_train.mean(axis=0)
X_std = X_train.std(axis=0)
X_std[X_std == 0] = 1.0

X_train_scaled = (X_train - X_mean) / X_std
X_test_scaled = (X_test - X_mean) / X_std

k_scaled = 3
t0 = time.time()
y_pred_scaled = knn_predict(X_test_scaled, X_train_scaled, y_train, k=k_scaled)
t1 = time.time()

acc_scaled = accuracy_score(y_test, y_pred_scaled)
print(f"Scaled KNN | k={k_scaled}: Accuracy={acc_scaled:.4f}, Time={t1 - t0:.4f}s")
```

```
Scaled KNN | k=3: Accuracy=0.6970, Time=0.0158s
```

2. Comparative Analysis: Compare the Results -

- Compare the accuracy and performance of the kNN model on the original dataset from problem 1 versus the scaled dataset.
- Discuss:
  - How scaling impacted the KNN performance.
  - The reason for any observed changes in accuracy.

```
print("Comparison at k=3")
print(f"- Unscaled accuracy: {acc_baseline:.4f}")
print(f"- Scaled accuracy:   {acc_scaled:.4f}")
print("Observation: Scaling changes feature magnitudes, which can impact neighbor selection and thus accuracy.")
```

```
Comparison at k=3
- Unscaled accuracy: 0.7143
- Scaled accuracy:   0.6970
Observation: Scaling changes feature magnitudes, which can impact neighbor selection and thus accuracy.
```

Problem - 3 - Experimentation with k:

1. Vary the number of neighbors - k:

- Run the KNN model on both the original and scaled datasets for a range of: k= 1, 2, 3, . . .15

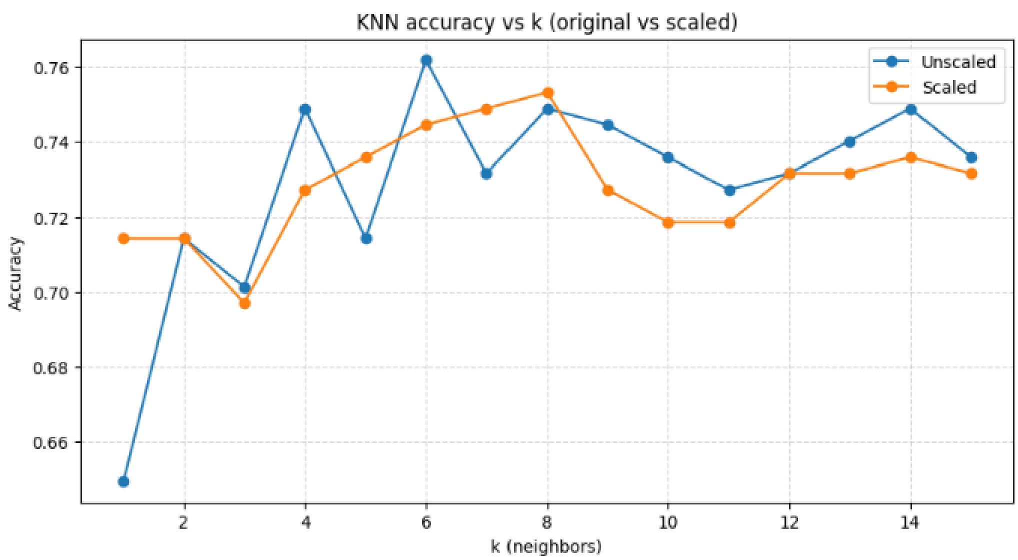
- For each k, record:
  - – Accuracy.
  - – Time taken to make predictions.

```
#problem 3
ks = list(range(1, 16))
acc_unscaled_list, time_unscaled_list = [], []
acc_scaled_list, time_scaled_list = [], []

for k in ks:
    t0 = time.time()
    y_pred_u = knn_predict(X_test, X_train, y_train, k=k)
    t1 = time.time()
    acc_unscaled_list.append(accuracy_score(y_test, y_pred_u))
    time_unscaled_list.append(t1 - t0)

    t0 = time.time()
    y_pred_s = knn_predict(X_test_scaled, X_train_scaled, y_train, k=k)
    t1 = time.time()
    acc_scaled_list.append(accuracy_score(y_test, y_pred_s))
    time_scaled_list.append(t1 - t0)

best_k_unscaled = ks[int(np.argmax(acc_unscaled_list))]
best_k_scaled = ks[int(np.argmax(acc_scaled_list))]
```

2. Visualize the Results:

- Plot the following graphs:
  - k vs. Accuracy for original and scaled datasets.
  - k vs. Time Taken for original and scaled datasets

```
plt.figure(figsize=(10, 5))
plt.plot(ks, acc_unscaled_list, marker='o', label='Unscaled')
plt.plot(ks, acc_scaled_list, marker='o', label='Scaled')
plt.xlabel('k (neighbors)')
plt.ylabel('Accuracy')
plt.title('KNN accuracy vs k (original vs scaled)')
plt.grid(True, linestyle='--', alpha=0.5)
plt.legend()
plt.show()

print(f"Best k (unscaled): {best_k_unscaled} with accuracy {max(acc_unscaled_list):.4f}")
print(f"Best k (scaled):   {best_k_scaled} with accuracy {max(acc_scaled_list):.4f}")
```




```
Best k (unscaled): 6 with accuracy 0.7619
Best k (scaled):   8 with accuracy 0.7532
```

. **3. Analyze and Discuss:**

- Discuss how the choice of k affects the accuracy and computational cost.
- Identify the optimal k based on your analysis.

```
plt.figure(figsize=(10, 5))
plt.plot(ks, time_unscaled_list, marker='o', label='Unscaled')
plt.plot(ks, time_scaled_list, marker='o', label='Scaled')
plt.xlabel('k (neighbors)')
plt.ylabel('Prediction time (s)')
plt.title('KNN prediction time vs k (original vs scaled)')
plt.grid(True, linestyle='--', alpha=0.5)
plt.legend()
plt.show()
```