5CS037 - Concepts and Technologies of AI.
Getting Started with Machine Learning Models.
Implementation of k-Nearest Neighbor from Scratch.

Prepared By: Siman Giri {Module Leader - 5CS037}

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1 Instructions

This worksheet contains programming exercises on building k-NN machine learning models based on the material discussed from the slides.This is a graded exercise and submission are mandatory.
Please answer the questions below using python in the Jupyter Notebook and follow the guidelines below:

- This worksheet must be completed individually.
- All the solutions must be written in Jupyter Notebook.
- Our Recommendation - Google Colaboratory.
- Dataset used for this session can be downloaded from shared drive.
- Complete the task only using core python library such as Numpy, pandsa, matplotlib etc.

Figure 1: Getting Started with Machine Learning.

——————– Here comes the Machine Learning!! ——————-

2 Building k-NN from Scratch.

1. k-NN Algorithm:

Algorithm 1 K-Nearest Neighbors (KNN) Algorithm

1: **Input:** Training dataset $\{(x_1,y_1),(x_2,y_2),...,(x_n,y_n)\}$, test data x_{test}, number of neighbors k
2: **Output:** Predicted label for x_{test}
3: **Step 1:** For each training sample x_i, compute the distance $d(x_{\text{test}},x_i)$ using Euclidean distance
4: **Step 2:** Sort the distances in ascending order and select the k nearest neighbors
5: **Step 3:** Find the majority class among the k nearest neighbors
6: **Step 4:** Return the majority class as the predicted label for x_{test}

2.1 Implementing k-NN Algorithm from scratch Step - step Guide:

Step - 1: Understanding Data: Example

Dataset: 'titanic.csv'.

1. Load Dataset: The following code loads a Titanic dataset, keeps only relevant columns, checks for missing data, and handles it by either filling with the mean (for columns with over 10% missing) or dropping rows (for columns with 10% or less missing).

Loading and Cleaning Data.

```
import pandas as pd import numpy as np
# Load the Titanic dataset data =
pd.read_csv("titanic.csv")
# Drop all categorical columns except 'Survived' categorical_columns =
data.select_dtypes(include=['object']).columns data = data.drop(columns=[col for col in
categorical_columns if col != 'Survived'])
# Check for missing values missing_info = data.isnull().sum() /
len(data) * 100
# Handle missing values for
column in data.columns:
    if missing_info[column] > 10: # If more than 10% missing data[column].fillna(data[column].mean(), inplace=True)
    else: # If less than 10% missing data.dropna(subset=[column], inplace=True)
# Display cleaned data print("Data after processing:\n", data.head())
print("\nMissing values after processing:\n", data.isnull().sum())
```

- **Importing Libraries:** We imported pandas as pd for data manipulation and numpy as np (though numpy is not used in this snippet).

- **Loading the Titanic Dataset:** We loaded a dataset about Titanic passengers from a given URL using pd.read_csv() and stored it in a variable called data.
- **Dropping Categorical Columns:** We selected columns with categorical data (text-based columns) and dropped all of them except the 'Survived' column. This means only the 'Survived' column is kept if it is of type object (e.g., text), and all others are removed from the data DataFrame.
- **Checking for Missing Values:** We calculated the percentage of missing values in each column using

$$\text{missing info} = \frac{\text{data.isnull().sum()}}{\text{len(data)}} \times 100$$

  to identify columns that have missing data and how much of it is missing as a percentage.
- **Handling Missing Values:** We iterated over each column in the data DataFrame:
  - If a column had more than 10% missing values, we filled those missing values with the mean of that column using:

```
data[column].fillna(data[column].mean(), inplace=True)
```

  - If a column had 10% or fewer missing values, we dropped any rows with missing values in that column using: data.dropna(subset=[column], inplace=True)
- **Displaying the Results:** We printed the first few rows of the cleaned data to see what it looks like after processing:

```
print("Data after processing:n", data.head())
```

  We also printed the count of missing values in each column after processing to confirm that the missing values were handled appropriately:

```
print("nMissing values after processing:n", data.isnull().sum())
```

2. Creating a Feature Matrix and Label Vector and Splitting Train - Test Split:This code separates the Titanic dataset into features (X) and target (y) and implements a custom train-test splitting function. It shuffles the data, splits it into training (70%) and testing (30%) sets, and verifies the output by displaying the shapes of the resulting datasets. This ensures that the model will have separate data for training and evaluation.

Feature Matrix and Label Vector with Train - Test Split:

```
import numpy as np
# Separate features (X) and target (y)
X = data.drop(columns=['Survived']).values # Convert features to NumPy array y =
data['Survived'].values # Convert target to NumPy array # Define a function for train-test split
from scratch def train_test_split_scratch(X, y, test_size=0.3, random_seed=42):
    """
    Splits dataset into train and test sets.
    Arguments:
    X : np.ndarray
        Feature matrix. y :
    np.ndarray
        Target array.
    test_size : float
        Proportion of the dataset to include in the test split (0 < test_size < 1).
    random_seed : int
        Seed for reproducibility.
    Returns:
    X_train, X_test, y_train, y_test : np.ndarray
        Training and testing splits of features and target.
    """
    np.random.seed(random_seed) indices =
    np.arange(X.shape[0]) np.random.shuffle(indices) # Shuffle
    the indices test_split_size = int(len(X) * test_size) test_indices
    = indices[:test_split_size] train_indices =
    indices[test_split_size:]
    X_train, X_test = X[train_indices], X[test_indices] y_train, y_test =
    y[train_indices], y[test_indices] return X_train, X_test, y_train, y_test
# Perform the train-test split
X_train, X_test, y_train, y_test = train_test_split_scratch(X, y, test_size=0.3)
# Output shapes to verify print("Shape of X_train:",
X_train.shape) print("Shape of X_test:",
X_test.shape) print("Shape of y_train:",
y_train.shape) print("Shape of y_test:",
y_test.shape)
```

- **Importing Required Library:** The numpy library was imported as np for numerical computations.
- **Separating Features and Target:**
  - X is created by dropping the 'Survived' column from the data DataFrame and converting the remaining features into a NumPy array.
  - y is created by extracting the 'Survived' column from the data DataFrame and converting it into a NumPy array. This column represents the target variable (whether a passenger survived or not).
- **Defining a Train-Test Split Function:** A custom function train test split scratch is defined to split the dataset into training and testing subsets:
  - **Arguments:**

  - ∗ X: The feature matrix.
  - ∗ y: The target array.
  - ∗ test size: The proportion of the dataset allocated to the test set (default is 0.3, meaning 30% of the data).
  - ∗ random _seed: A seed for reproducibility of random operations (default is 42).
- **Steps in the Function:**
  - ∗ Set the random seed using np.random.seed() for reproducibility.
  - ∗ Generate an array of indices (np.arange(X.shape[0])) corresponding to the rows of X.
  - ∗ Shuffle these indices randomly using np.random.shuffle().
  - ∗ Determine the number of samples in the test set as a proportion of the total dataset size:

$$\text{test split size} = \text{int}(\text{len}(X) * \text{test\_size})$$

  - ∗ Split the indices into test indices (first part) and train indices (remaining part).
  - ∗ Use the indices to split X and y into X _train, X test, y train, and y test.

- **Performing the Train-Test Split:** The custom function train test split _scratch is called with the feature matrix X, target array y, and a test size of 30%. The resulting training and testing datasets are stored in X _train, X test, y train, and y test.
- **Verifying the Results:** The shapes of the resulting datasets (X train, X test, y train, y test) are printed to verify the split.

Step - 2 - Computing Euclidean Distance Metrics:

1. The function ensures that the inputs are compatible and calculates the Euclidean distance using the formula. It is versatile for n-dimensional spaces and raises errors for incompatible inputs.

Implementation of Euclidean Distance:

```
def euclidean_distance(point1, point2): """
    Calculate the Euclidean distance between two points in n-dimensional space. Arguments:
    point1 : np.ndarray
        The first point as a numpy array. point2 :
    np.ndarray
        The second point as a numpy array.
    Returns: float
        The Euclidean distance between the two points.
    Raises:
    ValueError: If the input points do not have the same dimensionality.
    """
    # Check if the points are of the same dimension if point1.shape != point2.shape: raise ValueError("Points must have
    the same dimensions to calculate Euclidean distance.")
    # Calculate the Euclidean distance distance =
    np.sqrt(np.sum((point1 - point2) ** 2)) return distance
```

- **Function Purpose:** The euclidean distance function computes the straight-line distance between two points represented as NumPy arrays in any n-dimensional space.
- **Arguments:**
  - point1: A NumPy array representing the coordinates of the first point.
  - point2: A NumPy array representing the coordinates of the second point.
- **Return Value:** The function returns the Euclidean distance as a floating-point number.
- **Error Handling:**
  - If the dimensions of point1 and point2 do not match, the function raises a ValueError with the message:

    ”Points must have the same dimensions to calculate Euclidean distance.” •

Calculation: The Euclidean distance is calculated using the formula:

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

where x_i and y_i are the corresponding coordinates of point1 and point2.

- **Steps in the Function:**
  - Verify that point1 and point2 have the same dimensions:

    if point1.shape != point2.shape:

    If not, raise a ValueError.

- Compute the squared differences between corresponding elements, sum them, and take the square root:

distance = np.sqrt(np.sum((point1 - point2) ** 2)) Test Case for Euclidean Distance Computing Function:

```
# Test case for the function try:
    # Define two points point1 = np.array([3, 4]) point2 =
    np.array([0, 0]) # Calculate the distance result =
    euclidean_distance(point1, point2)
    # Check if the result matches the expected value (e.g., sqrt(3^2 + 4^2) = 5) expected_result = 5.0 assert
    np.isclose(result, expected_result), f"Expected {expected_result}, but got {result}" print("Test passed successfully!")
except ValueError as ve: print(f"ValueError: {ve}")
except AssertionError as ae:
    print(f"AssertionError: {ae}")
except Exception as e:
    print(f"An unexpected error occurred: {e}")
```

This code is a test case to validate the functionality of the euclidean distance function. The code helps:

- Computes distances accurately.
- Handles edge cases (e.g., mismatched dimensions) appropriately.
- Handles Errors:
  (a) ValueError: If the points have mismatched dimensions.
  (b) AssertionError: If the computed result does not match the expected value.
  (c) Other Exceptions: Catches unexpected errors.

Step - 3 - Implementation of core k-NN algorithm:

1. Predict the class label for a Single Query Point - knn predict single: This function implements the core logic of the K-Nearest Neighbors (KNN) algorithm for a single query point. It calculates the Euclidean distances from the query to all points in the training dataset, identifies the k nearest neighbors, and predicts the class label based on a majority vote among the neighbors. This function is useful for focused predictions on individual data points and acts as a modular building block for the generalized KNN algorithm.

Implementation of Core k-NN Algorithm:

```
# Function for KNN prediction for a single query def
knn_predict_single(query, X_train, y_train, k=3): """
    Predict the class label for a single query using the K-nearest neighbors algorithm. Arguments:
    query : np.ndarray
        The query point for which the prediction is to be made.
    X_train : np.ndarray
        The training feature matrix.
    y_train : np.ndarray
        The training labels.
    k : int, optional
        The number of nearest neighbors to consider (default is 3). Returns:
    int
        The predicted class label for the query.
    """ distances = [euclidean_distance(query, x) for x in X_train]
    sorted_indices = np.argsort(distances) nearest_indices = sorted_indices[:k]
    nearest_labels = y_train[nearest_indices] prediction =
    np.bincount(nearest_labels).argmax() return prediction
```

2. Predict Class Labels for All Test Samples - knn _predict: This function extends the KNN algorithm to handle multiple test samples simultaneously. By repeatedly calling knn predict single for each query in the test dataset, it predicts class labels for the entire test set. The function provides a streamlined interface to efficiently classify test points in bulk, leveraging the modularity of knn _predict _single.

Implementing kNN for whole Test Data set:

```
# Function to test KNN for all test samples def
knn_predict(X_test, X_train, y_train, k=3): """
    Predict the class labels for all test samples using the K-nearest neighbors algorithm. Arguments:
    X_test : np.ndarray
        The test feature matrix.
    X_train : np.ndarray
        The training feature matrix.
    y_train : np.ndarray
        The training labels.
    k : int, optional
        The number of nearest neighbors to consider (default is 3). Returns:

np.ndarray
    An array of predicted class labels for the test samples.
""" predictions = [knn_predict_single(x, X_train, y_train, k) for x in X_test] return
np.array(predictions)
```

3. Test Case for both above function: This test case verifies the functionality of the knn _predict function using a small subset of the test data. It predicts class labels for the subset and compares them to the actual labels. The test ensures that the predictions have the correct shape and raises an error if they do not. If successful, it confirms the function's correctness and prints both the predictions and the actual labels.

Test Function for knn _predict:

```
        # Test case for KNN on the Titanic dataset
# Assume X_train, X_test, y_train, and y_test have been prepared using the code above try:
    # Define the test set for the test case
    X_test_sample = X_test[:5] # Taking a small subset for testing y_test_sample = y_test[:5] #
    Corresponding labels for the subset
    # Make predictions predictions = knn_predict(X_test_sample, X_train, y_train,
    k=3)
    # Print test results print("Predictions:", predictions) print("Actual labels:", y_test_sample) # Check if predictions match
    expected format assert predictions.shape == y_test_sample.shape, "The shape of predictions does not match the shape
    of the actual labels."
    print("Test case passed successfully!")
except AssertionError as ae:
    print(f"AssertionError: {ae}")
except Exception as e:
    print(f"An unexpected error occurred: {e}")
```

Step - 4 - Computing Accuracy:

The compute accuracy function calculates the accuracy of predictions by comparing the true labels (y true) with the predicted labels (y pred). It computes the percentage of correct predictions out of the total predictions and returns the accuracy as a float value between 0 and 100.

Feature Matrix and Label Vector with Train - Test Split:

```
# Function to compute accuracy of predictions def
compute_accuracy(y_true, y_pred):
    """
    Compute the accuracy of predictions.
    Arguments:
    y_true : np.ndarray ; The true labels. y_pred :
    np.ndarray; The predicted labels.
    Returns:
    float : The accuracy as a percentage (0 to 100).
    """
    correct_predictions = np.sum(y_true == y_pred) total_predictions =
    len(y_true) accuracy = (correct_predictions / total_predictions) * 100
    return accuracy
```

The following code evaluates the KNN model's performance on the entire test set. It predicts the class labels for all test samples using the knn _predict function and calculates the model's accuracy with the compute accuracy function. The accuracy is then displayed as a percentage. Any errors during prediction or computation are caught and reported.

Feature Matrix and Label Vector with Train - Test Split:

```
 # Perform prediction on the entire test set try:
# Make predictions on the entire test set predictions =
knn_predict(X_test, X_train, y_train, k=3)
# Compute the accuracy accuracy =
compute_accuracy(y_test, predictions)
# Print the accuracy print(f"Accuracy of the KNN model on the test set:
{accuracy:.2f}%")
except Exception as e:
print(f"An unexpected error occurred during prediction or accuracy computation: {e}")
```

Step - 5 - Experiment with different values of k:

The function experiment _knn k values function evaluates the KNN algorithm's performance for various values of k (number of neighbors). It predicts test labels for each k using the knn predict function, computes the corresponding accuracy with compute accuracy, and stores the results in a dictionary. Finally, it plots k values against their respective accuracies, providing a visual analysis of how the choice of k affects the model's performance. The function also prints the accuracy for each k.

Experimenting with Various k values:

```
# Function to test KNN on different values of k and plot the accuracies import
matplotlib.pyplot as plt def experiment_knn_k_values(X_train, y_train, X_test, y_test,
k_values):
"""
Run KNN predictions for different values of k and plot the accuracies.

Arguments:
X_train : np.ndarray
    The training feature matrix.
y_train : np.ndarray
    The training labels.
X_test : np.ndarray
    The test feature matrix.
y_test : np.ndarray
    The test labels.
k_values : list of int
    A list of k values to experiment with.
Returns:
dict
    A dictionary with k values as keys and their corresponding accuracies as values.
""" accuracies = {} for k
in k_values:
    # Make predictions using the current value of k predictions =
    knn_predict(X_test, X_train, y_train, k=k)
    # Compute the accuracy accuracy =
    compute_accuracy(y_test, predictions) accuracies[k] =
    accuracy print(f"Accuracy for k={k}: {accuracy:.2f}%")
# Plot the accuracies plt.figure(figsize=(10, 5)) plt.plot(k_values,
list(accuracies.values()), marker='o') plt.xlabel('k (Number of
```

```
Neighbors)') plt.ylabel('Accuracy (%)') plt.title('Accuracy of KNN with
Different Values of k') plt.grid(True) plt.show() return accuracies
```

The following code sets up an experiment to test the KNN model's accuracy across a range of k values from 1 to 20 (modifiable range). It calls the experiment knn k values function to run predictions and accuracy calculations for each k and plots the results to show how accuracy varies with different numbers of neighbors. If an error occurs during the experiment, it is caught and reported. The output indicates the completion of the experiment and suggests checking the plot for trends in accuracy.

Test code for the Experiment:

```
# Define the range of k values to experiment with k_values = range(1, 21) #
You can adjust this range as needed
# Run the experiment try:
    accuracies = experiment_knn_k_values(X_train, y_train, X_test, y_test, k_values) print("Experiment completed. Check the
    plot for the accuracy trend.")
except Exception as e:
    print(f"An unexpected error occurred during the experiment: {e}")
```

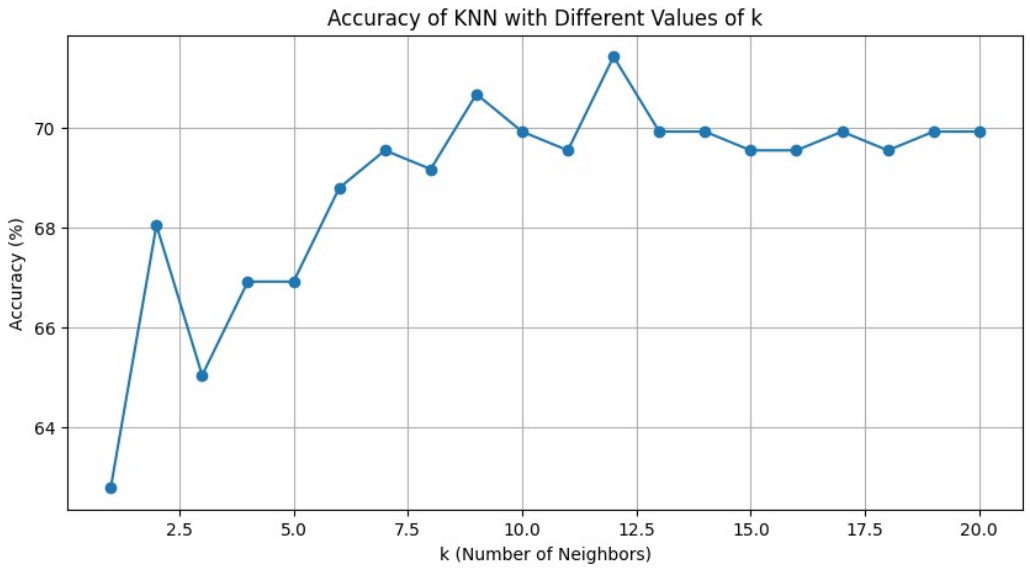


Figure 2: Experiment with different values of k.

3 To - Do Exercise:

For the provided dataset:

- diabetes.csv

Complete the following Problems.

Submission Instructions:

- Submit a single notebook containing:

    1. Clean and well-documented code.

2. Outputs and visualizations.
3. Detailed explanations and analysis for all steps.

- Ensure all cells are executed before submission.

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

2. 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).
3. Handle Missing Data:
   - Handle any missing values appropriately, either by dropping or imputing them based on the data.
4. Feature Engineering:
   - Separate the feature matrix (X) and target variable (y).
   - Perform a train - test split from scratch using a 70% − 30% ratio.
5. 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.

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

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

1.Load the Dataset: Read the dataset into a pandas DataFrame

```
df = pd.read_csv('/content/drive/MyDrive/Concept and Technologies of AI/diabetes_.csv');
df.head(3)
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1

Next steps: Generate code with df | New interactive sheet

• Display the first few rows and perform exploratory data analysis (EDA) to understand the dataset (e.g., check data types, missing values, summary statistics).

```
#  Finding all datas
print(df.info())

print()## for spaces

# Finding Missing values
print(df.isnull().sum())

print()

# Finding Summary statistics
print(df.describe(include="all"))

print()

# Finding Shape
print(df.shape)
```

```
# Finding Summary statistics
print(df.describe(include="all"))

print()

# Finding Shape
print(df.shape)

print()

# 6. finding names
print(df.columns)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               768 non-null    int64
 1   Glucose                   768 non-null    int64
 2   BloodPressure             768 non-null    int64
 3   SkinThickness             768 non-null    int64
 4   Insulin                   768 non-null    int64
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64
 8   Outcome                   768 non-null    int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
None

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

       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
```

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

	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

```
(768, 9)

Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

2.Handle Missing Data: • Handle any missing values appropriately, either by dropping or imputing them based on the data.

```
df.isnull().sum()#find missing data
```

	0
Pregnancies	0
Glucose	0
BloodPressure	0
SkinThickness	0
Insulin	0
BMI	0
DiabetesPedigreeFunction	0
Age	0
Outcome	0

dtype: int64

```python
# Clean column names
df.columns = df.columns.str.strip().str.lower()

# Drop unwanted columns safely
df = df.drop(
    columns=["bp.2s", "bp.2d", "location", "id", "chol", "stab.glu",
             "hdl", "glyhb", "bp.1s", "bp.1d", "time.ppn", "age"],
    errors="ignore"
)

# Handle frame column
if "frame" in df.columns:
    df["frame"] = df["frame"].fillna(df["frame"].mode()[0])
    df["frame"] = df["frame"].map({"small": 0, "medium": 1, "large": 2})

# Handle gender column
if "gender" in df.columns:
    df["gender"] = df["gender"].map({"male": 0, "female": 1})

# Fill numeric columns with median
num_cols = ["ratio", "height", "weight", "waist", "hip"]
for col in num_cols:
    if col in df.columns:
        df[col] = df[col].fillna(df[col].median())

df.head()
```

	pregnancies	glucose	bloodpressure	skinthickness	insulin	bmi	diabetespedigreefunction	outcome
0	6	148	72	35	0	33.6	0.627	1
1	1	85	66	29	0	26.6	0.351	0
2	8	183	64	0	0	23.3	0.672	1
3	1	89	66	23	94	28.1	0.167	0
4	0	137	40	35	168	43.1	2.288	1

Next steps: Generate code with df | New interactive sheet

```python
df.isnull().sum()
```

	0
pregnancies	0
glucose	0
bloodpressure	0
skinthickness	0
insulin	0
bmi	0
diabetespedigreefunction	0
outcome	0

dtype: int64

3.Feature Engineering: Separate the feature matrix (X) and target variable (y).

Perform a train - test split from scratch using a 70% – 30% ratio.

```python
import numpy as np
import pandas as pd

#1Clean column names (safe habit)
df.columns = (
    df.columns
      .str.strip()
      .str.lower()
      .str.replace(" ", "_")
)

print("Columns in dataset:")
print(df.columns.tolist())

# 2 Separate FEATURES (X) and TARGET (y)
X = df.drop(columns=["outcome"]).values
y = df["outcome"].values

print("X shape:", X.shape)
print("y shape:", y.shape)
```

```
Columns in dataset:
['pregnancies', 'glucose', 'bloodpressure', 'skinthickness', 'insulin', 'bmi', 'diabetespedigreefunction', 'outcome']
X shape: (768, 7)
y shape: (768,)
```

```python
def train_test_split_scratch(X, y, test_size=0.3, random_seed=42):
    """
    Splits dataset into train and test sets from scratch.
    """

    np.random.seed(random_seed)

    # Generate array of indices
    indices = np.arange(X.shape[0])
    np.random.shuffle(indices)

    # Determine test size
    test_count = int(len(X) * test_size)

    # Split indices
    test_idx = indices[:test_count]
    train_idx = indices[test_count:]

    # Create train and test sets
    X_train = X[train_idx]
    X_test = X[test_idx]
    y_train = y[train_idx]
    y_test = y[test_idx]

    #Printing the results
    print("X_train shape:", X_train.shape)
    print("X_test shape:", X_test.shape)
    print("y_train shape:", y_train.shape)
    print("y_test shape:", y_test.shape)

    return X_train, X_test, y_train, y_test

x_train, x_test, y_train, y_test = train_test_split_scratch(X, y)
```

```
X_train shape: (538, 7)
X_test shape: (230, 7)
y_train shape: (538,)
y_test shape: (230,)
```

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.

[49]

```python
def euclidean_distance(point1, point2):
    """
    Calculate the Euclidean distance between two points in n-dimensional space.

    Arguments:
    point1 : np.ndarray
        The first point as a numpy array.
    point2 : np.ndarray
        The second point as a numpy array.

    Returns:
    float
        The Euclidean distance between the two points.

    Raises:
    ValueError: If the input points do not have the same dimensionality.
    """

    if point1.shape != point2.shape:
        raise ValueError("Points must have the same dimensions to calculate Euclidean distance.")


    distance = np.sqrt(np.sum((point1 - point2) ** 2))
    return distance

euclidean_distance(x_train[0], x_train[1])
```

```
np.float64(41.84042083918373)
```

[50]

```python
try:

    point1 = np.array([3, 4])
    point2 = np.array([0, 0])


    result = euclidean_distance(point1, point2)


    expected_result = 5.0
    assert np.isclose(result, expected_result), f"Expected {expected_result}, but got {result}"

    print("Test passed successfully!")
```

```
        assert np.isclose(result, expected_result), f"Expected {expected_result}, but got {result}"

        print("Test passed successfully!")
    except ValueError as ve:
        print(f"ValueError: {ve}")
    except AssertionError as ae:
        print(f"AssertionError: {ae}")
    except Exception as e:
        print(f"An unexpected error occurred: {e}")
```

```
Test passed successfully!
```

```
def knn_predict_single(query, X_train, y_train, k=3):
    """
    Predict the class label for a single query using the K-nearest neighbors algorithm.

    Arguments:
    query : np.ndarray
        The query point for which the prediction is to be made.
    X_train : np.ndarray
        The training feature matrix.
    y_train : np.ndarray
        The training labels.
    k : int, optional
        The number of nearest neighbors to consider (default is 3).

    Returns:
    int
        The predicted class label for the query.
    """

    distances = [euclidean_distance(query, x) for x in X_train]


    sorted_indices = np.argsort(distances)


    nearest_indices = sorted_indices[:k]


    nearest_labels = y_train[nearest_indices]


    prediction = np.bincount(nearest_labels).argmax()

    return prediction
```

```
def knn_predict(X_test, X_train, y_train, k=3):
    """
    Predict the class labels for all test samples using the K-nearest neighbors algorithm.

    Arguments:
    X_test : np.ndarray
        The test feature matrix.
    X_train : np.ndarray
        The training feature matrix.
    y_train : np.ndarray
        The training labels.
    k : int, optional
        The number of nearest neighbors to consider (default is 3).

    Returns:
    np.ndarray
        An array of predicted class labels for the test samples.
    """

    predictions = [knn_predict_single(x, X_train, y_train, k) for x in X_test]
    return np.array(predictions)
```

```
try:

    X_test_sample = x_test[:5]
    y_test_sample = y_test[:5]


    predictions = knn_predict(X_test_sample, x_train, y_train, k=3)


    print("Predictions:", predictions)
    print("Actual labels:", y_test_sample)


    assert predictions.shape == y_test_sample.shape, (
        "The shape of predictions does not match the shape of the actual labels."
    )

    print("Test case passed successfully!")
except AssertionError as ae:
    print(f"AssertionError: {ae}")
except Exception as e:
    print(f"An unexpected error occurred: {e}")
```

```
Predictions: [0 1 0 0 1]
Actual labels: [0 0 0 0 0]
```

```
def compute_accuracy(y_true, y_pred):
    """
    Compute the accuracy of predictions.

    Arguments:
    y_true : np.ndarray
        The true labels.
    y_pred : np.ndarray
        The predicted labels.

    Returns:
    float
        The accuracy as a percentage (0 to 100).
    """
    correct_predictions = np.sum(y_true == y_pred)
    total_predictions = len(y_true)
    accuracy = (correct_predictions / total_predictions) * 100
    return accuracy



try:

    predictions = knn_predict(x_test, x_train, y_train, k=3)


    accuracy = compute_accuracy(y_test, predictions)


    print(f"Accuracy of the KNN model on the test set: {accuracy:.2f}%")
except Exception as e:
    print(f"An unexpected error occurred during prediction or accuracy computation: {e}")
```

```
Accuracy of the KNN model on the test set: 66.09%
```

```
for k in [1, 3, 5, 7, 9, 11,13,15,16,17,18,20]:
    preds = knn_predict(x_test, x_train, y_train, k)
    acc = np.mean(preds == y_test)
    print(f"k = {k} -> Accuracy = {acc*100:.2f}%")
```

```python
for k in [1, 3, 5, 7, 9, 11,13,15,16,17,18,20]:
    preds = knn_predict(x_test, x_train, y_train, k)
    acc = np.mean(preds == y_test)
    print(f"k = {k} -> Accuracy = {acc*100:.2f}%")
```

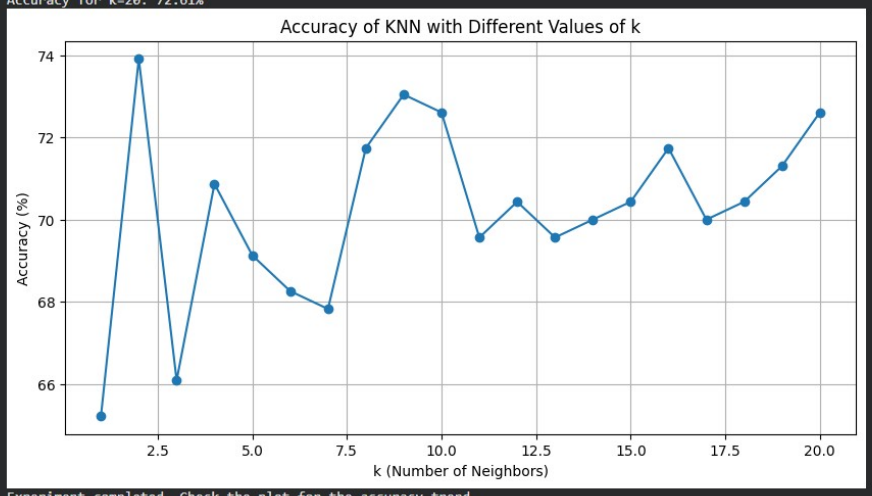
```
k = 1 -> Accuracy = 65.22%
k = 3 -> Accuracy = 66.09%
k = 5 -> Accuracy = 69.13%
k = 7 -> Accuracy = 67.83%
k = 9 -> Accuracy = 73.04%
k = 11 -> Accuracy = 69.57%
k = 13 -> Accuracy = 69.57%
k = 15 -> Accuracy = 70.43%
k = 16 -> Accuracy = 71.74%
k = 17 -> Accuracy = 70.00%
k = 18 -> Accuracy = 70.43%
k = 20 -> Accuracy = 72.61%
```

```python
def experiment_knn_k_values(X_train, y_train, X_test, y_test, k_values):
    """
    Run KNN predictions for different values of k and plot the accuracies.

    Arguments:
    X_train : np.ndarray
        The training feature matrix.
    y_train : np.ndarray
        The training labels.
    X_test : np.ndarray
        The test feature matrix.
    y_test : np.ndarray
        The test labels.
    k_values : list of int
        A list of k values to experiment with.

    Returns:
    dict
        A dictionary with k values as keys and their corresponding accuracies as values.
    """
    accuracies = {}

    for k in k_values:

        predictions = knn_predict(X_test, X_train, y_train, k=k)
        accuracy = compute_accuracy(y_test, predictions)
        accuracies[k] = accuracy
```

```
    """
    accuracies = {}

    for k in k_values:

        predictions = knn_predict(X_test, X_train, y_train, k=k)
        accuracy = compute_accuracy(y_test, predictions)
        accuracies[k] = accuracy

        print(f"Accuracy for k={k}: {accuracy:.2f}%")


    plt.figure(figsize=(10, 5))
    plt.plot(k_values, list(accuracies.values()), marker='o')
    plt.xlabel('k (Number of Neighbors)')
    plt.ylabel('Accuracy (%)')
    plt.title('Accuracy of KNN with Different Values of k')
    plt.grid(True)
    plt.show()

    return accuracies


k_values = range(1, 21)


try:
    accuracies = experiment_knn_k_values(x_train, y_train, x_test, y_test, k_values)
    print("Experiment completed. Check the plot for the accuracy trend.")
except Exception as e:
    print(f"An unexpected error occurred during the experiment: {e}")
```

```
Accuracy for k=1: 65.22%
Accuracy for k=2: 73.91%
Accuracy for k=3: 66.09%
Accuracy for k=4: 70.87%
Accuracy for k=5: 69.13%
Accuracy for k=6: 68.26%
Accuracy for k=7: 67.83%
Accuracy for k=8: 71.74%
Accuracy for k=9: 73.04%
Accuracy for k=10: 72.61%
Accuracy for k=11: 69.57%
Accuracy for k=12: 70.43%
Accuracy for k=13: 69.57%
Accuracy for k=14: 70.00%
Accuracy for k=15: 70.43%
Accuracy for k=16: 71.74%
Accuracy for k=17: 70.00%
```

```
Accuracy for k=1: 65.22%
Accuracy for k=2: 73.91%
Accuracy for k=3: 66.09%
Accuracy for k=4: 70.87%
Accuracy for k=5: 69.13%
Accuracy for k=6: 68.26%
Accuracy for k=7: 67.83%
Accuracy for k=8: 71.74%
Accuracy for k=9: 73.04%
Accuracy for k=10: 72.61%
Accuracy for k=11: 69.57%
Accuracy for k=12: 70.43%
Accuracy for k=13: 69.57%
Accuracy for k=14: 70.00%
Accuracy for k=15: 70.43%
Accuracy for k=16: 71.74%
Accuracy for k=17: 70.00%
Accuracy for k=18: 70.43%
Accuracy for k=19: 71.30%
Accuracy for k=20: 72.61%
```




```
Experiment completed. Check the plot for the accuracy trend.
```

Experiment completed. Check the plot for the accuracy trend. Problem - 2 - Experimentation:

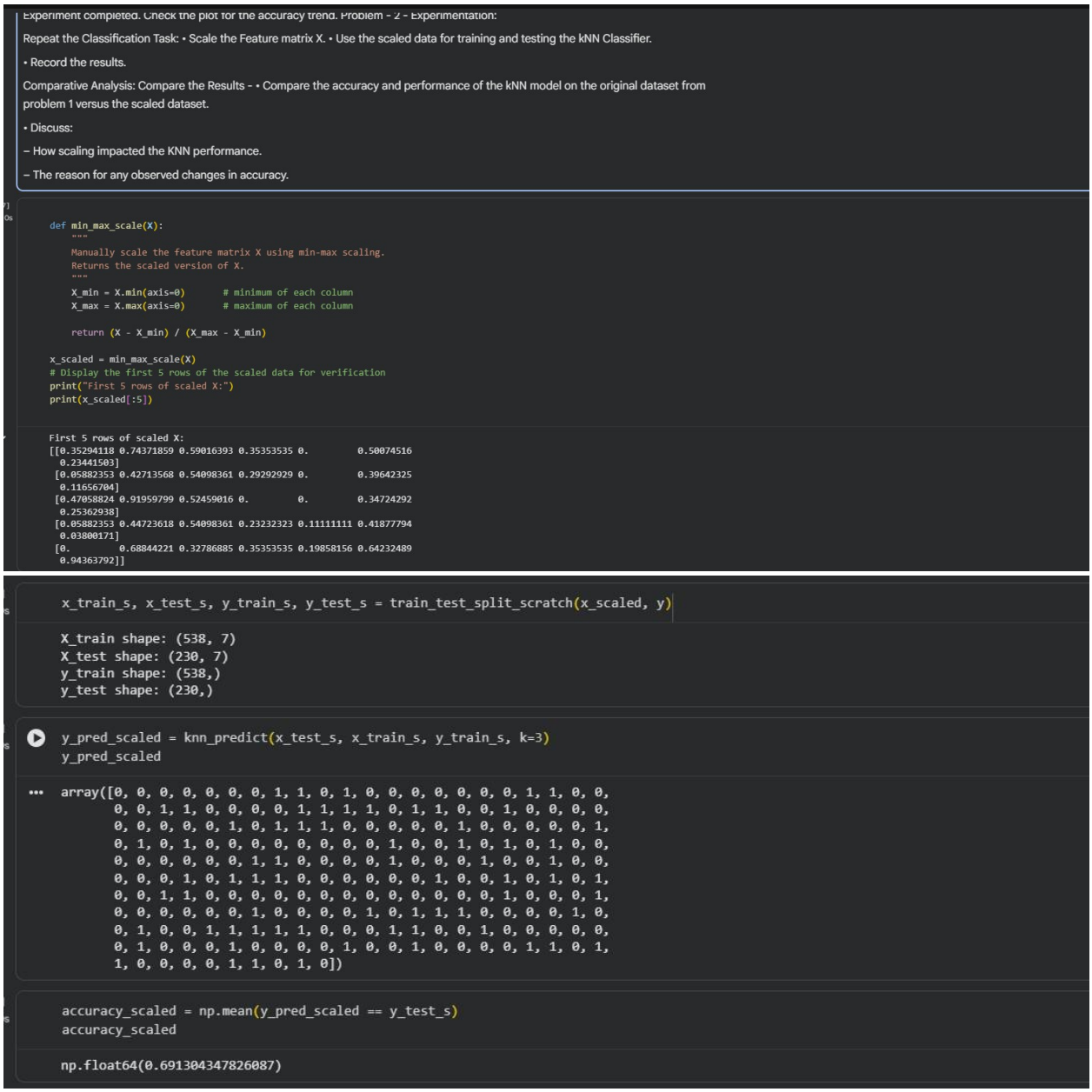
Problem - 2 - Experimentation:

1. Repeat the Classification Task:

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

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.



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.

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.

3. Analyze and Discuss:

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

Problem - 3 - Experimentation with k:

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.

Visualize the Results: • Plot the following graphs:

– k vs. Accuracy for original and scaled datasets.

– k vs. Time Taken for original and scaled datasets.

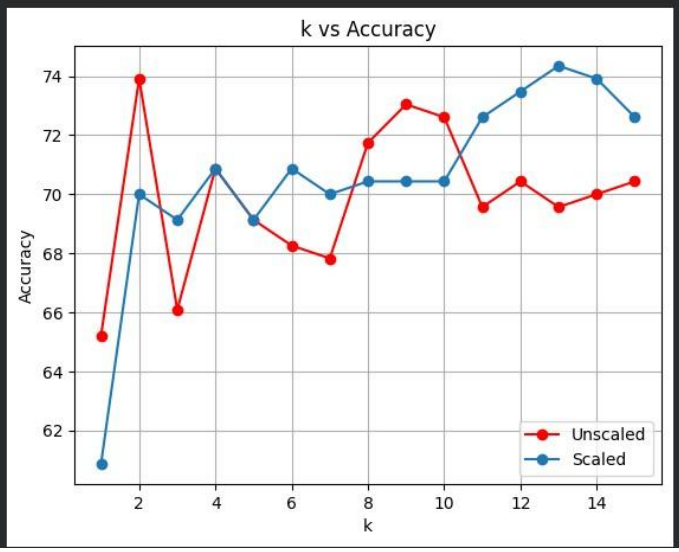
Analyze and Discuss: • Discuss how the choice of k affects the accuracy and computational cost.

• Identify the optimal k based on your analysis.

```
import time

k_values = range(1, 16)

scaled_accuracy = []
unscaled_accuracy = []
time_unscaled = []
time_scaled = []

for kk in k_values:
    # Unscaled
    start = time.time()
    unscaled_pred = knn_predict(x_test, x_train, y_train, kk)
    end = time.time()

    unscaled_accuracy.append(compute_accuracy(y_test, unscaled_pred))
    time_unscaled.append(end - start)
```

```
    time_unscaled.append(end - start)

    # Scaled
    start = time.time()
    scaled_pred = knn_predict(x_test_s, x_train_s, y_train, kk)
    end = time.time()

    scaled_accuracy.append(compute_accuracy(y_test, scaled_pred))
    time_scaled.append(end - start)
```

```
plt.plot(k_values, unscaled_accuracy, marker='o', label='Unscaled', color='red')
plt.plot(k_values, scaled_accuracy, marker='o', label='Scaled')
plt.xlabel('k')
plt.ylabel('Accuracy')
plt.title('k vs Accuracy')
plt.legend()
plt.grid(True)
plt.show()
```



Problem - 4 - Additional Questions {Optional - But Highly Recommended}:

- Discuss the challenges of using KNN for large datasets and high-dimensional data.
- Suggest strategies to improve the efficiency of KNN (e.g., approximate nearest neighbors, dimensionality reduction).

———————————– The - End ———————————-