IE7275 Data Mining in Engineering

Fall 2025 semester

-- STUDENT VERSION --

Guidelines for Completing and Submitting This Notebook

Please follow these instructions carefully. Completing all parts of this notebook is required to receive full credit:

You must:

- **Answer all questions** and reflection tasks using your own words.
- **Summarize every reflection task** clearly and completely.
- **Fill out all missing code cells** — do not leave any code blocks empty.
- **Run your notebook** to ensure that all outputs and visualizations are generated and visible.
- **Convert your completed notebook** to **PDF** or **HTML** format before submission.
- **Submit the file to Canvas** before the deadline.

Academic Integrity Reminder:

- You must complete this notebook individually.
- Do not copy answers or code from classmates, online sources, or use tools like **ChatGPT** or other **AI writing or code generation tools**.
- Keep in mind that if you use such tools, your answer may be **identical or highly similar** to others who do the same — in this case, we will treat it as copying and apply a **50% penalty** to your assignment grade.

By submitting this notebook, you confirm that all work is your own and that you have followed these guidelines.

Module 5: Supervised Learning – Classification Basics (Part 1)

Module 5.1: Introduction to Supervised Learning and Classification

Supervised learning is a fundamental branch of machine learning where models are trained using labeled data — meaning each input example is paired with a known output label. The goal is for the model to learn the relationship between input features and output labels so it can predict the labels for new, unseen data accurately.

In classification, the output labels are **discrete categories or classes**. For example, classifying emails as "spam" or "not spam," recognizing handwritten digits as 0-9, or diagnosing diseases based on symptoms. The task is to assign each input to one of the predefined classes.

Key points to understand:

- **Training data** consists of input features and known class labels.
- The model learns a mapping function from inputs to classes.
- Once trained, the model can predict the class of new data points.
- Classification can be binary (two classes) or multi-class (more than two classes).

Classification is widely used in real-world applications such as image recognition, natural language processing, fraud detection, and medical diagnosis.

Understanding the basics of supervised learning and classification prepares you for exploring various classification algorithms, evaluation techniques, and model optimization strategies in subsequent sub-modules.

Exercise 1: Exploring Labeled Data for Classification

Objective:
Understand the structure of supervised learning data by working with a labeled dataset and examining how features and class labels are used for classification tasks.

Instructions:

- Load a sample classification dataset such as the Iris dataset or Breast Cancer dataset from `sklearn.datasets`.
- Display the feature matrix (X) and target vector (y).
- Check the number of classes, sample distribution per class, and feature types.
- Plot basic visualizations such as:
  - Pairplot (if Iris) or correlation heatmap (if numeric features).
  - Class-wise distributions of selected features.
- Discuss why this dataset is suitable for a classification task.

Goal:
By the end of this exercise, you'll understand what labeled data looks like, how it is structured, and why classification is appropriate for such data.

In [67]:
```
# Step 1: Import libraries
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris

# Step 2: Load the Iris dataset
iris = load_iris()
X = pd.DataFrame(iris.data, columns=iris.feature_names)
y = pd.Series(iris.target, name='target')

# Step 3: Combine features and labels into one DataFrame
df = pd.concat([X, y], axis=1)
df['target_name'] = df['target'].map(dict(enumerate(iris.target_names)))
```

In [68]:
```
# Step 4: Display the first few rows
print("First five rows of the dataset:")
df.head()
```

```
First five rows of the dataset:
```

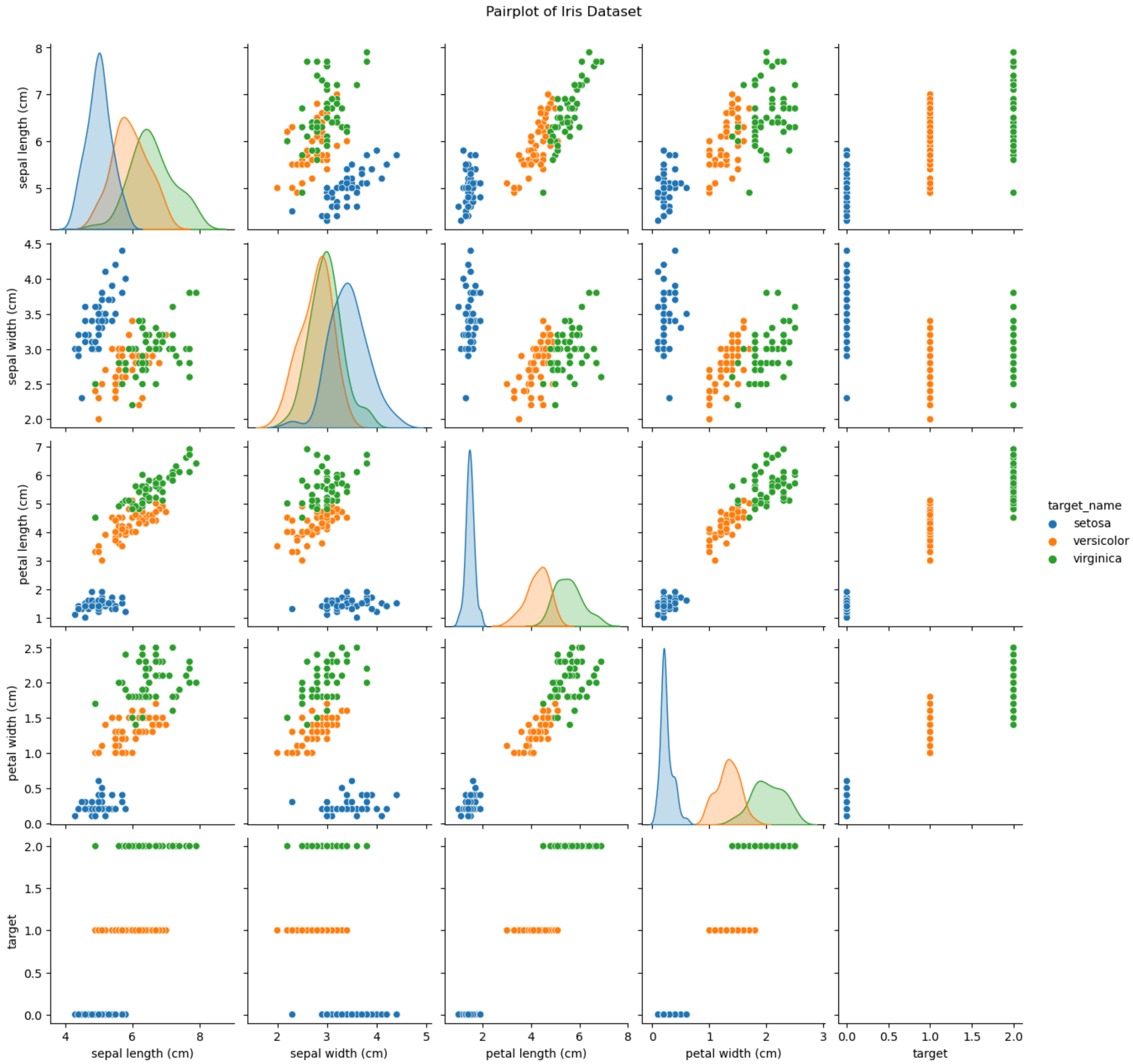
Out[68]:

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

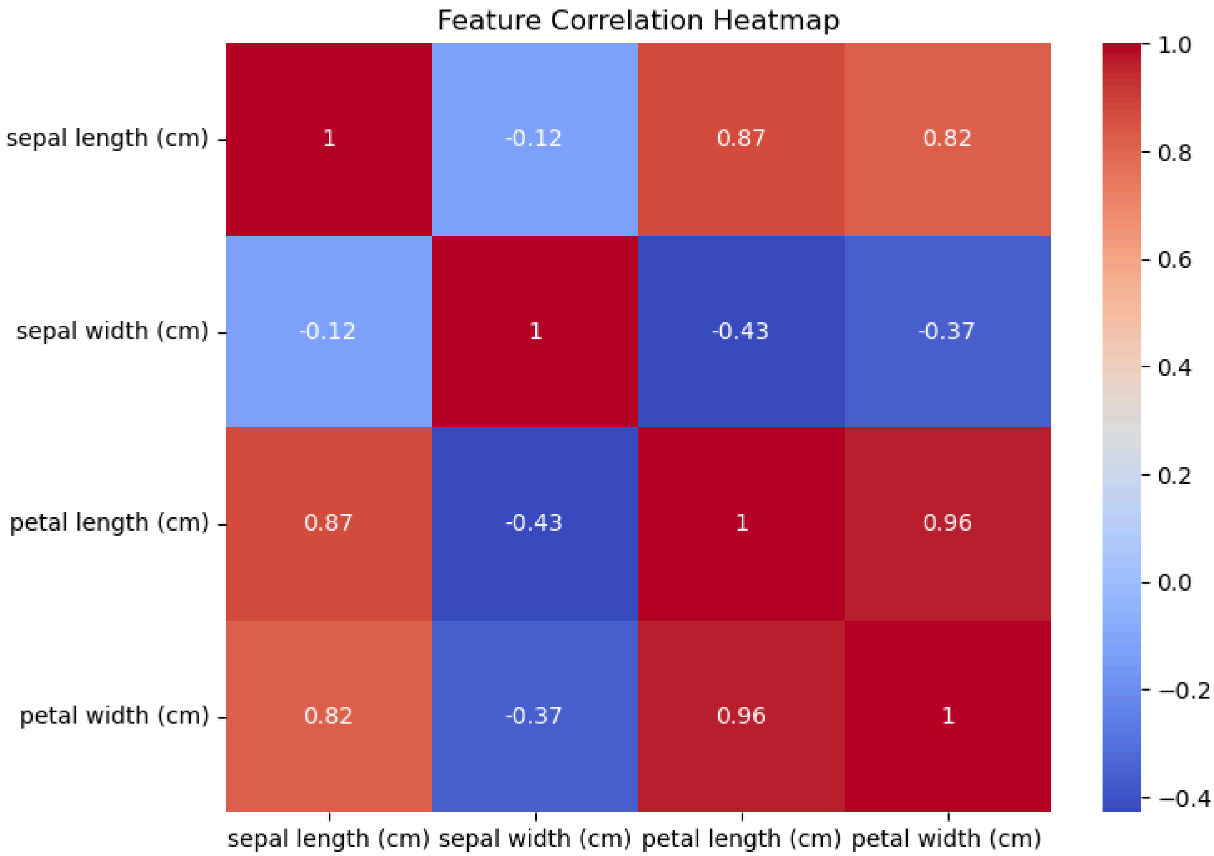
In [69]:
```
# Step 5: Check the number of classes and their distribution
print("\nClass distribution:")
print(df['target_name'].value_counts())
```

```
Class distribution:
setosa        50
versicolor    50
virginica     50
Name: target_name, dtype: int64
```

In [70]:
```
# Step 6: Plot pairplot to visualize class separation
sns.pairplot(df, hue='target_name')
plt.suptitle("Pairplot of Iris Dataset", y=1.02)
plt.show()
```



In [71]:
```
# Step 7: Correlation heatmap of features
plt.figure(figsize=(8, 6))
sns.heatmap(X.corr(), annot=True, cmap='coolwarm')
plt.title("Feature Correlation Heatmap")
plt.show()
```



In-Class Reflection: Exercise Summary

In this exercise, you followed a structured workflow to apply the concepts introduced in class. Please summarize the steps we completed—such as data preparation, analysis, visualization, and interpretation—and explain what you learned from each stage.

Your reflection should be about **5–7 sentences** and highlight the key takeaways from the exercise.

> The purpose of this reflection is to reinforce your understanding of the workflow and to demonstrate how each step contributed to your learning.

In this exercise we can see that we have loaded theiris daraser ,the separating the its features and the target labels for the analysis ,displaying the feature matrix and then checking the class distribution to understand the structure of the labelled data ,where the visualizations such as pairplot and correaltion heatmap ,it helps to illustrate the different classes that are distributed and separeated which is whithin the feature space ,here we learned how the labelled data provides mapping between inputs and desired outputs where it forms supervised classfication tasks ,this approach helps to understand the data and the representation before doing the modelling.

Exercise 2: Classification Task Setup with Train-Test Split

In this exercise, you'll take the next step in preparing a dataset for supervised learning — splitting it into training and test sets to evaluate model performance fairly.

Objective:
Understand how to prepare labeled data for supervised learning using the train-test split technique.

Instructions:

1. Load the Iris dataset using `sklearn.datasets.load_iris()` or directly from seaborn.
2. Separate the features (X) and target labels (y).
3. Use `train_test_split` from `sklearn.model_selection` to split the data:
   - 80% for training, 20% for testing.
   - Set a `random_state` for reproducibility.
4. Print the shape of the resulting training and test sets.
5. (Optional) Print the class distribution in each split to confirm balance.

This prepares the data for modeling and ensures that your model's performance is evaluated on data it hasn't seen during training.

In [72]:
```
# Step 1: Import necessary libraries
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
import pandas as pd
import numpy as np

# Step 2: Load the Iris dataset
iris = load_iris()
X = pd.DataFrame(iris.data, columns=iris.feature_names)
y = pd.Series(iris.target, name='species')
```

In [73]:
```
# Step 3: Perform train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)
```

In [74]:
```
# Step 4: Print the shape of the splits
print("Training Features Shape:", X_train.shape)
print("Test Features Shape:", X_test.shape)
print("Training Labels Shape:", y_train.shape)
print("Test Labels Shape:", y_test.shape)
```

```
Training Features Shape: (120, 4)
Test Features Shape: (30, 4)
Training Labels Shape: (120,)
Test Labels Shape: (30,)
```

In [75]:
```
# Step 5 (Optional): Print class distribution
print("\nClass distribution in training set:")
print(y_train.value_counts().sort_index())
```

```
print("\nClass distribution in test set:")
print(y_test.value_counts().sort_index())
```

```
Class distribution in training set:
0    40
1    40
2    40
Name: species, dtype: int64

Class distribution in test set:
0    10
1    10
2    10
Name: species, dtype: int64
```

In-Class Reflection: Exercise Summary

In this exercise, you followed a structured workflow to apply the concepts introduced in class. Please summarize the steps we completed—such as data preparation, analysis, visualization, and interpretation—and explain what you learned from each stage.

Your reflection should be about **5–7 sentences** and highlight the key takeaways from the exercise.

> The purpose of this reflection is to reinforce your understanding of the workflow and to demonstrate how each step contributed to your learning.

In this exercise ,we are splitting the iris dataset into the training and the test sets where we used the train test split function ,after loading and separating the data ,we then performed the split where it balances the class distribution .In this process it is learned that it is crucial to test a model on the unseen data ,where it ensures the evaluation of the performance ,where it helped in preventing data leakage and then preventing from the results being biased.

Module 5.2: Understanding the Classification Task

Framing a real-world problem as a classification task is an essential step in supervised learning. It involves defining the input features that describe each instance and the discrete target labels that represent the categories to predict.

In this sub-module, you will learn how to:

- Identify relevant **input features** that provide useful information for classification.
- Define the **target variable** clearly, ensuring it represents distinct classes.
- Understand the difference between **binary classification** (two classes) and **multi-class classification** (more than two classes).
- Recognize common challenges such as **class imbalance**, where some classes have many more examples than others, affecting model training and evaluation.

By properly framing the classification problem, you set the foundation for selecting appropriate models, evaluation metrics, and preprocessing steps tailored to your specific task.

Exercise 3: Framing the Problem as a Classification Task

In this exercise, you'll practice identifying input features and target labels for a classification problem using a real-world dataset.

Objective:
Understand how to structure a dataset for classification by clearly defining features and class labels.

Instructions:

1. Load the **Titanic dataset** from Seaborn or a CSV file.
2. Identify the **target variable** (`survived`) which indicates whether a passenger lived or died.
3. Select relevant **features** such as `pclass` , `sex` , `age` , and `fare` .
4. Clean the data:
   - Handle missing values (e.g., in `age`).
   - Encode categorical variables using label encoding or one-hot encoding.
5. Print the final dataset structure showing features and target labels.
6. Explain briefly why this is a binary classification problem.

This exercise helps you understand the importance of choosing the right variables and structuring them properly before training classification models.

In [76]:

```
# Exercise 3: Framing the Problem as a Classification Task

# Step 1: Load necessary libraries
import pandas as pd
import seaborn as sns
from sklearn.preprocessing import LabelEncoder

# Step 2: Load the Titanic dataset
df = sns.load_dataset("titanic")
df
```

Out[76]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_n
0	0	3	male	22.0	1	0	7.2500	S	Third	man	T
1	1	1	female	38.0	1	0	71.2833	C	First	woman	F
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	F
3	1	1	female	35.0	1	0	53.1000	S	First	woman	F
4	0	3	male	35.0	0	0	8.0500	S	Third	man	T
...	...	...	...	...	...	...	...	...	...	...	
886	0	2	male	27.0	0	0	13.0000	S	Second	man	T
887	1	1	female	19.0	0	0	30.0000	S	First	woman	F
888	0	3	female	NaN	1	2	23.4500	S	Third	woman	F
889	1	1	male	26.0	0	0	30.0000	C	First	man	T
890	0	3	male	32.0	0	0	7.7500	Q	Third	man	T

891 rows × 15 columns

In [77]:

```
# Step 3: Select target and feature columns
target = 'survived'
features = ['pclass', 'sex', 'age', 'fare']

# Step 4: Drop rows with missing values in selected columns
df = df[features + [target]].dropna()
df
```

Out[77]:

	pclass	sex	age	fare	survived
0	3	male	22.0	7.2500	0
1	1	female	38.0	71.2833	1
2	3	female	26.0	7.9250	1
3	1	female	35.0	53.1000	1
4	3	male	35.0	8.0500	0
...	...	...	...	...	...
885	3	female	39.0	29.1250	0
886	2	male	27.0	13.0000	0
887	1	female	19.0	30.0000	1
889	1	male	26.0	30.0000	1
890	3	male	32.0	7.7500	0

714 rows × 5 columns

In [78]:

```
# Step 5: Encode categorical variables
le = LabelEncoder()
```

```
df['sex'] = le.fit_transform(df['sex'])  # male=1, female=0
df
```

Out[78]:

	pclass	sex	age	fare	survived
0	3	1	22.0	7.2500	0
1	1	0	38.0	71.2833	1
2	3	0	26.0	7.9250	1
3	1	0	35.0	53.1000	1
4	3	1	35.0	8.0500	0
...	...	...	...	...	...
885	3	0	39.0	29.1250	0
886	2	1	27.0	13.0000	0
887	1	0	19.0	30.0000	1
889	1	1	26.0	30.0000	1
890	3	1	32.0	7.7500	0

714 rows × 5 columns

In [79]:

```
# Step 6: Separate input features and target
X = df[features]
y = df[target]

# Step 7: Print structure of final dataset
print("Input Features:\n", X.head())
print("\nTarget Labels:\n", y.head())

# Step 8: Explain classification type
print("\nThis is a binary classification task where:")
print("- Target value 'survived' has two classes: 0 = did not survive, 1 = surv
```

```
Input Features:
    pclass  sex   age     fare
0       3    1  22.0   7.2500
1       1    0  38.0  71.2833
2       3    0  26.0   7.9250
3       1    0  35.0  53.1000
4       3    1  35.0   8.0500

Target Labels:
 0    0
1    1
2    1
3    1
4    0
Name: survived, dtype: int64

This is a binary classification task where:
- Target value 'survived' has two classes: 0 = did not survive, 1 = survived.
```

In-Class Reflection: Exercise Summary

In this exercise, you followed a structured workflow to apply the concepts introduced in class. Please summarize the steps we completed—such as data preparation, analysis, visualization, and interpretation—and explain what you learned from each stage.

Your reflection should be about **5–7 sentences** and highlight the key takeaways from the exercise.

> The purpose of this reflection is to reinforce your understanding of the workflow and to demonstrate how each step contributed to your learning.

In this exercise ,titanic dataset was loaded where we had to identify the survived target variable ,where relevant input features were cleaned by handling the missinig values and also labelling the encoding for categorical features .The prepared dataset was inspected to confirm the correct organization and the binary perspective of the classification problem .Here it enhanced the understanding of the variable selection ,data cleaning and the structural definition before training the model .From this we can say that a model can be developed and interpretated according to the requirements.

Exercise 4: Exploring Binary vs. Multi-Class Classification

In this exercise, you'll compare how classification tasks differ when dealing with binary and multi-class labels.

Objective:
Understand the structural and modeling differences between binary and multi-class classification problems.

Instructions:

1. Load two datasets:
   - The **Titanic** dataset from `seaborn` (binary classification: survived vs. not).
   - The **Iris** dataset from `sklearn.datasets` or `seaborn` (multi-class classification: 3 flower species).
2. For each dataset:
   - Identify the target variable and count the number of unique classes.
   - Print the class distribution.
   - Comment on whether the classification task is **binary** or **multi-class**.
3. Visualize the class distribution using a bar plot.

By comparing these two datasets, you'll develop an intuition for identifying the type of classification problem and recognizing how this impacts algorithm selection, performance metrics, and model complexity.

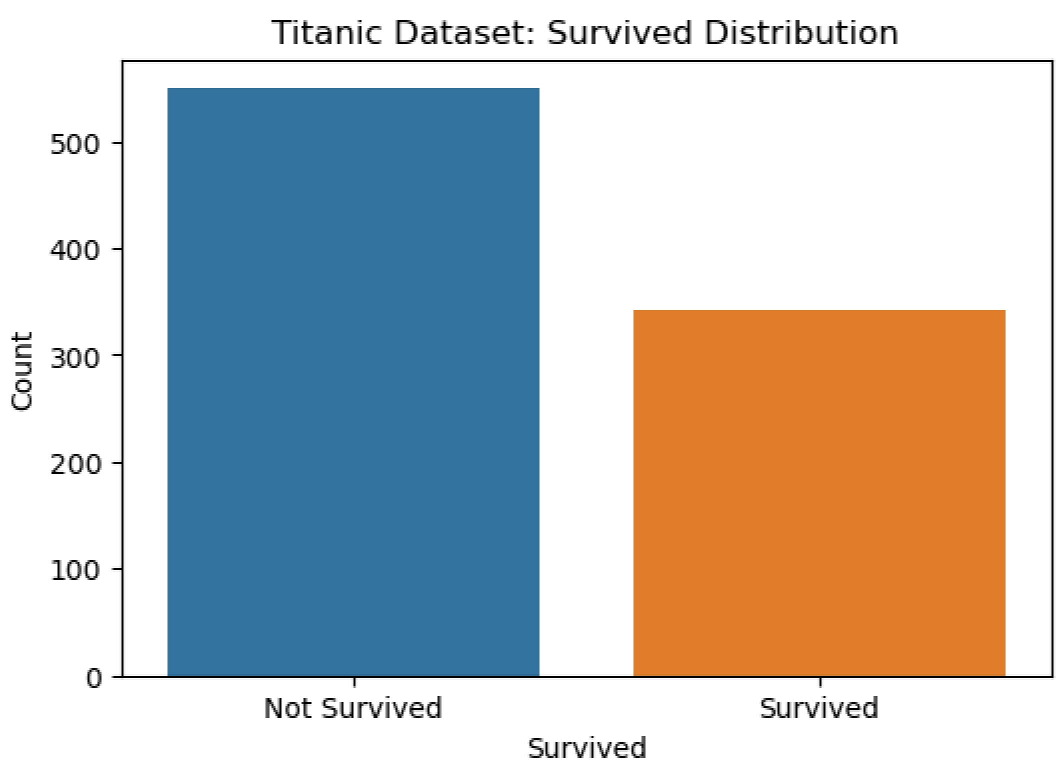
In [80]:
```
# Exercise 4: Exploring Binary vs. Multi-Class Classification
```

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris

# Load Titanic dataset (binary classification)
titanic = sns.load_dataset("titanic")
titanic_target = titanic["survived"]
titanic_classes = titanic_target.unique()

# Print details for Titanic
print("Titanic Dataset")
print("Target: Survived")
print("Unique Classes:", titanic_classes)
print("Class Distribution:\n", titanic_target.value_counts())
```

```
Titanic Dataset
Target: Survived
Unique Classes: [0 1]
Class Distribution:
 0    549
1    342
Name: survived, dtype: int64
```

In [81]:

```
# Plot class distribution for Titanic
plt.figure(figsize=(6, 4))
sns.countplot(x=titanic_target)
plt.title("Titanic Dataset: Survived Distribution")
plt.xlabel("Survived")
plt.ylabel("Count")
plt.xticks([0, 1], ['Not Survived', 'Survived'])
plt.show()
```



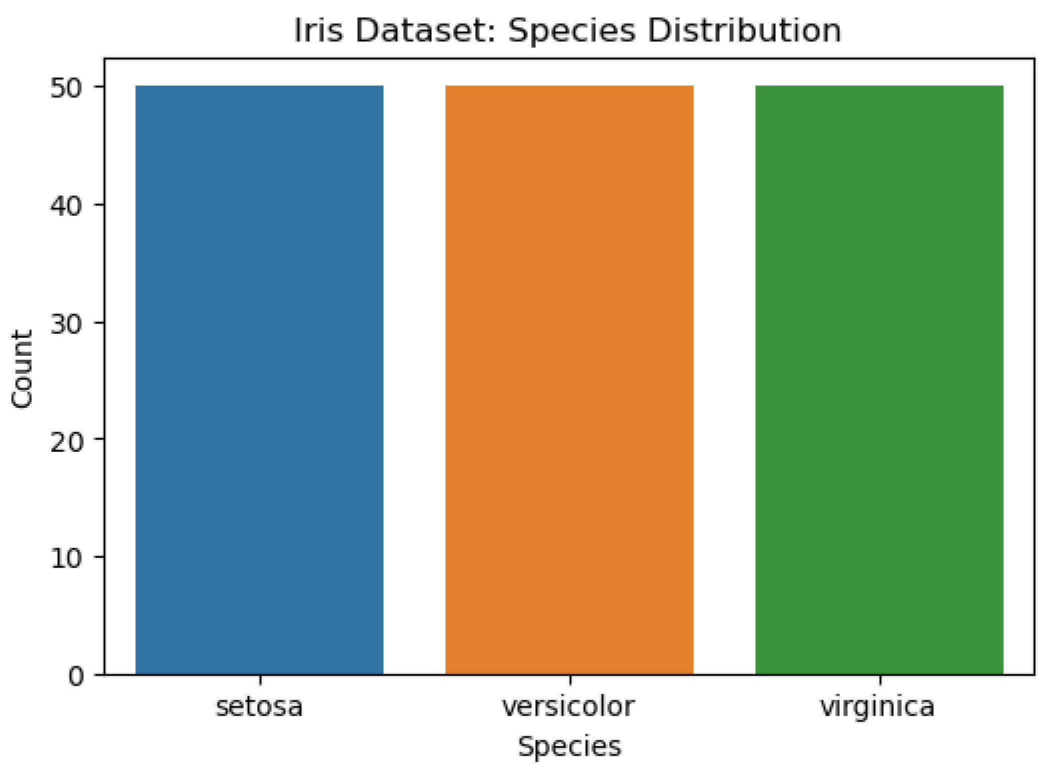
In [82]:

```
# Load Iris dataset (multi-class classification)
iris = load_iris(as_frame=True)
```

```
iris_target = iris.target
iris_classes = iris.target_names

# Print details for Iris
print("\nIris Dataset")
print("Target: Species")
print("Unique Classes:", iris_classes)
print("Class Distribution:\n", iris_target.value_counts())
```

```
Iris Dataset
Target: Species
Unique Classes: ['setosa' 'versicolor' 'virginica']
Class Distribution:
 0    50
1    50
2    50
Name: target, dtype: int64
```

In [83]:
```
# Plot class distribution for Iris
plt.figure(figsize=(6, 4))
sns.countplot(x=iris_target)
plt.title("Iris Dataset: Species Distribution")
plt.xlabel("Species")
plt.ylabel("Count")
plt.xticks([0, 1, 2], iris_classes)
plt.show()
```



In-Class Reflection: Exercise Summary

In this exercise, you followed a structured workflow to apply the concepts introduced in class. Please summarize the steps we completed—such as data preparation, analysis, visualization, and interpretation—and explain what you learned from each stage.

Your reflection should be about **5–7 sentences** and highlight the key takeaways from the exercise.

> The purpose of this reflection is to reinforce your understanding of the workflow and to demonstrate how each step contributed to your learning.

In thie exercise it seen that we have loaded both the titanic and iris datasets and identifyiing the target variables and the class counts,here we have seen the class distribution from the barpolots and compared the distribution and the structure requirements and the evaluation stepa for the each classification type,we cna understand the difference between the binary and multiclass distribution where we impact the class structure on modelling complexity .

Exercise 5: Identifying and Addressing Class Imbalance

In this exercise, you'll examine how class imbalance can affect classification tasks and explore simple techniques to detect and address it.

Objective:
Learn how to detect class imbalance and understand its impact on model performance.

Instructions:

1. Load an imbalanced dataset (e.g., the `sklearn.datasets.load_breast_cancer()` dataset).
2. Check the class distribution of the target variable using `value_counts()` or `np.bincount()`.
3. Visualize the imbalance using a `seaborn` or `matplotlib` bar chart.
4. Split the data into train and test sets using `train_test_split`.
5. Train a basic classifier (e.g., `LogisticRegression`) and evaluate accuracy.
6. Print a **classification report** using `classification_report` to show how imbalance affects precision and recall.

This exercise helps you recognize when class imbalance exists and shows how it can distort performance metrics like accuracy.

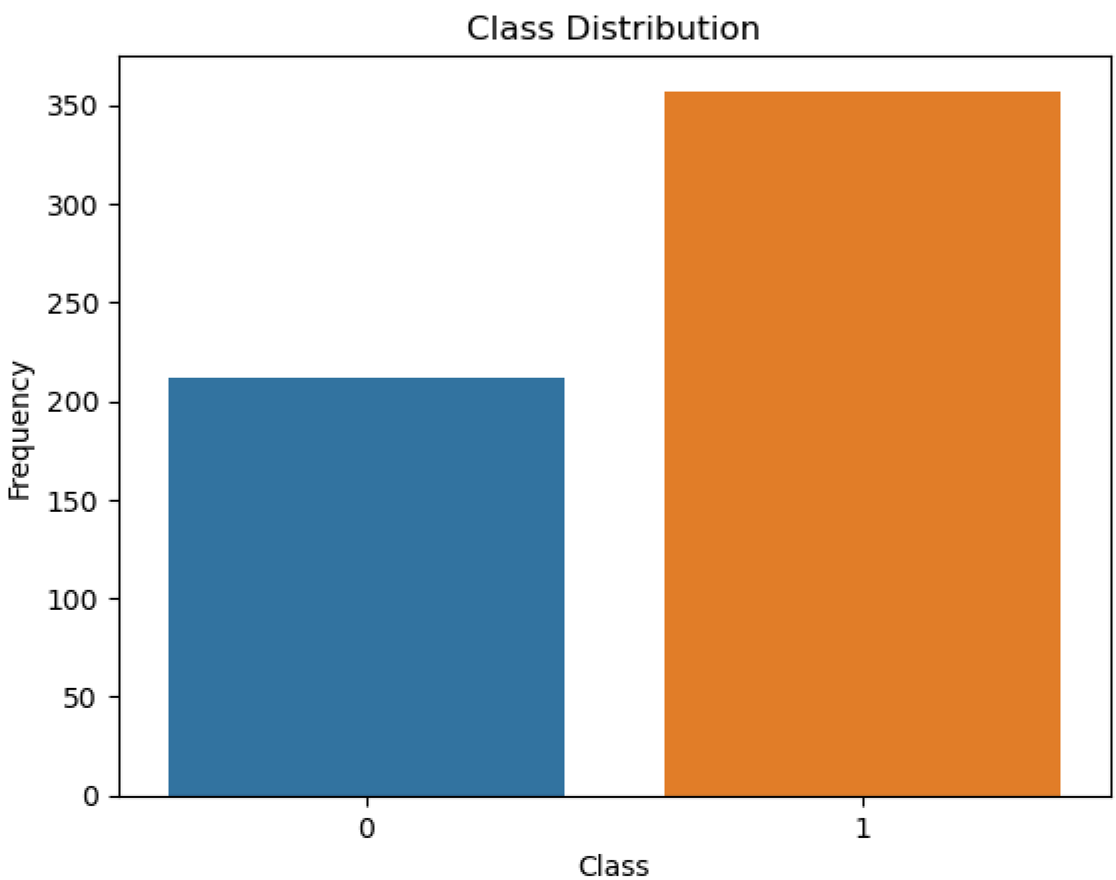
In [84]:
```
# Exercise 5: Identifying and Addressing Class Imbalance

# Step 1: Import necessary libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report
```

```
# Step 2: Load the dataset
data = load_breast_cancer()
X = pd.DataFrame(data.data, columns=data.feature_names)
y = pd.Series(data.target, name="target")
```

In [85]:
```
# Step 3: Check class distribution
print("Class distribution:")
print(y.value_counts())
```

```
Class distribution:
1    357
0    212
Name: target, dtype: int64
```

In [86]:
```
# Step 4: Visualize class imbalance
sns.countplot(x=y)
plt.title("Class Distribution")
plt.xlabel("Class")
plt.ylabel("Frequency")
plt.show()
```



In [87]:
```
# Step 5: Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, randor

# Step 6: Scale the data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 7: Train a classifier with more iterations
clf = LogisticRegression(max_iter=5000)
```

```
clf.fit(X_train_scaled, y_train)

# Step 8: Predict and evaluate
y_pred = clf.predict(X_test_scaled)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.98      0.95      0.96        43
           1       0.97      0.99      0.98        71

    accuracy                           0.97       114
   macro avg       0.97      0.97      0.97       114
weighted avg       0.97      0.97      0.97       114
```

In-Class Reflection: Exercise Summary

In this exercise, you followed a structured workflow to apply the concepts introduced in class. Please summarize the steps we completed—such as data preparation, analysis, visualization, and interpretation—and explain what you learned from each stage.

Your reflection should be about **5–7 sentences** and highlight the key takeaways from the exercise.

> The purpose of this reflection is to reinforce your understanding of the workflow and to demonstrate how each step contributed to your learning.

In this exercise,the imbalanced dataset was laoded where the target variable class distribution was visualized , After splitting the data ,the logistic regression classfier was trained and from the classification report was evaluated .The imbalance could be seen from the measures such as precision and recall ,even though the accuracy was more,the importance of checking the imbalance before the model evaluation ,hence the results was interpreted correctly.Fromm this the imbalance showed the performance in the classification tasks.

Exercise 6: Addressing Class Imbalance with Resampling Techniques

In this exercise, you'll learn how to handle class imbalance — a common challenge in classification tasks — by applying resampling techniques.

Objective:
Explore both **oversampling** and **undersampling** strategies to improve model performance on imbalanced datasets.

Instructions:

1. Load the **Breast Cancer dataset** from `sklearn.datasets`.
2. Split the dataset into features (X) and labels (y).

3. Perform a **train-test split** (80/20) using `train_test_split` with `random_state` for reproducibility.
4. Use `StandardScaler` to scale the features.
5. Apply one of the following resampling methods **on the training data**:
   - **RandomOverSampler** (from `imblearn.over_sampling`) to increase the number of minority class samples.
   - **RandomUnderSampler** (from `imblearn.under_sampling`) to reduce the number of majority class samples.
6. Fit a logistic regression model to the resampled training data.
7. Evaluate the model on the **original test set** using accuracy, confusion matrix, and classification report.
8. (Optional) Compare the results before and after resampling to assess the impact.

This exercise will help you understand how to mitigate the effects of class imbalance and improve model fairness and performance.

In [88]:
```python
# Exercise 6: Comparing Oversampling vs. Undersampling for Class Imbalance

# Step 1: Import libraries
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, accuracy_s
from imblearn.over_sampling import RandomOverSampler
from imblearn.under_sampling import RandomUnderSampler
import pandas as pd
import numpy as np

# Step 2: Load and prepare dataset
data = load_breast_cancer()
X = pd.DataFrame(data.data, columns=data.feature_names)
y = pd.Series(data.target)

# Step 3: Train-test split (with stratification to maintain class balance)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, randor

# Step 4: Scale features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [89]:
```python
# Step 5A: Oversampling the minority class
ros = RandomOverSampler(random_state=42)
X_ros, y_ros = ros.fit_resample(X_train_scaled, y_train)

model_ros = LogisticRegression(max_iter=1000, random_state=42)
model_ros.fit(X_ros, y_ros)
y_pred_ros = model_ros.predict(X_test_scaled)

print("=== Oversampling Evaluation ===")
print("Accuracy:", accuracy_score(y_test, y_pred_ros))
```

```
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_ros))
print("Classification Report:\n", classification_report(y_test, y_pred_ros))
```

```
=== Oversampling Evaluation ===
Accuracy: 0.9473684210526315
Confusion Matrix:
 [[41  1]
 [ 5 67]]
Classification Report:
               precision    recall  f1-score   support

           0       0.89      0.98      0.93        42
           1       0.99      0.93      0.96        72

    accuracy                           0.95       114
   macro avg       0.94      0.95      0.94       114
weighted avg       0.95      0.95      0.95       114
```

```
/opt/anaconda3/lib/python3.9/site-packages/sklearn/utils/deprecation.py:151: FutureWarning: 'force_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in 1.8.
  warnings.warn(
/opt/anaconda3/lib/python3.9/site-packages/sklearn/base.py:484: FutureWarning: `BaseEstimator._check_n_features` is deprecated in 1.6 and will be removed in 1.7. Use `sklearn.utils.validation._check_n_features` instead.
  warnings.warn(
/opt/anaconda3/lib/python3.9/site-packages/sklearn/base.py:493: FutureWarning: `BaseEstimator._check_feature_names` is deprecated in 1.6 and will be removed in 1.7. Use `sklearn.utils.validation._check_feature_names` instead.
  warnings.warn(
```

In [90]:

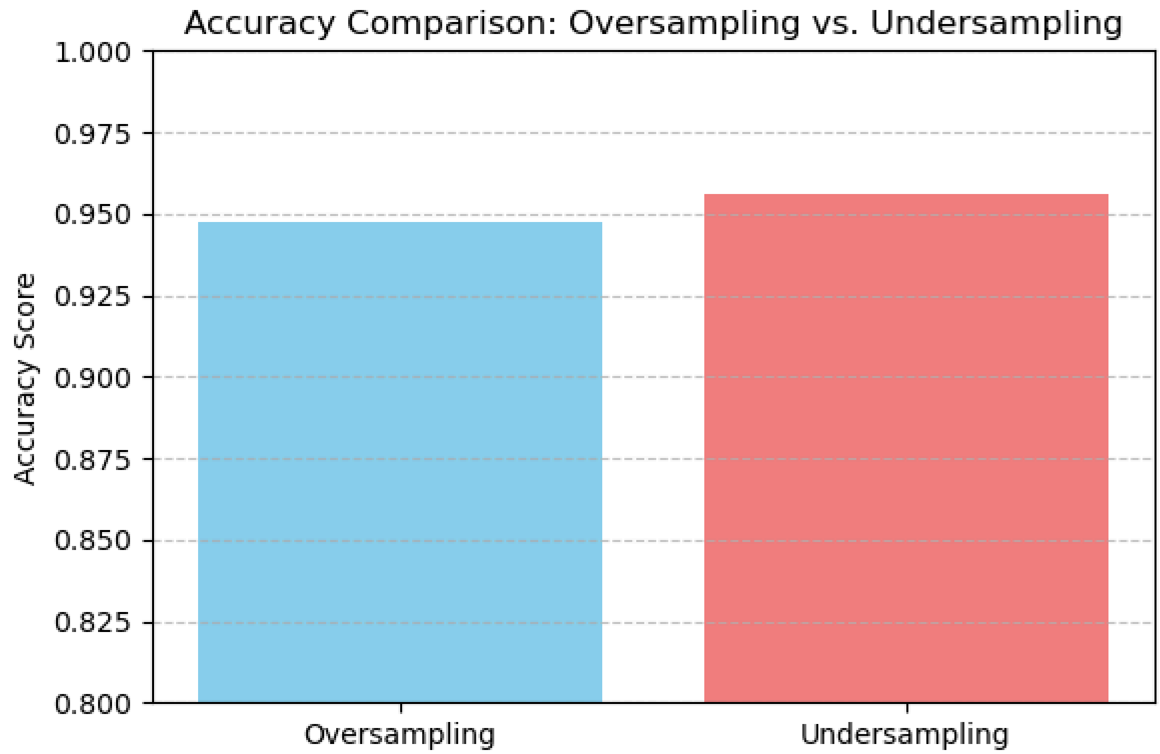
```
# Step 5B: Undersampling the majority class
rus = RandomUnderSampler(random_state=42)
X_rus, y_rus = rus.fit_resample(X_train_scaled, y_train)

model_rus = LogisticRegression(max_iter=1000, random_state=42)
model_rus.fit(X_rus, y_rus)
y_pred_rus = model_rus.predict(X_test_scaled)

print("\n=== Undersampling Evaluation ===")
print("Accuracy:", accuracy_score(y_test, y_pred_rus))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_rus))
print("Classification Report:\n", classification_report(y_test, y_pred_rus))
```

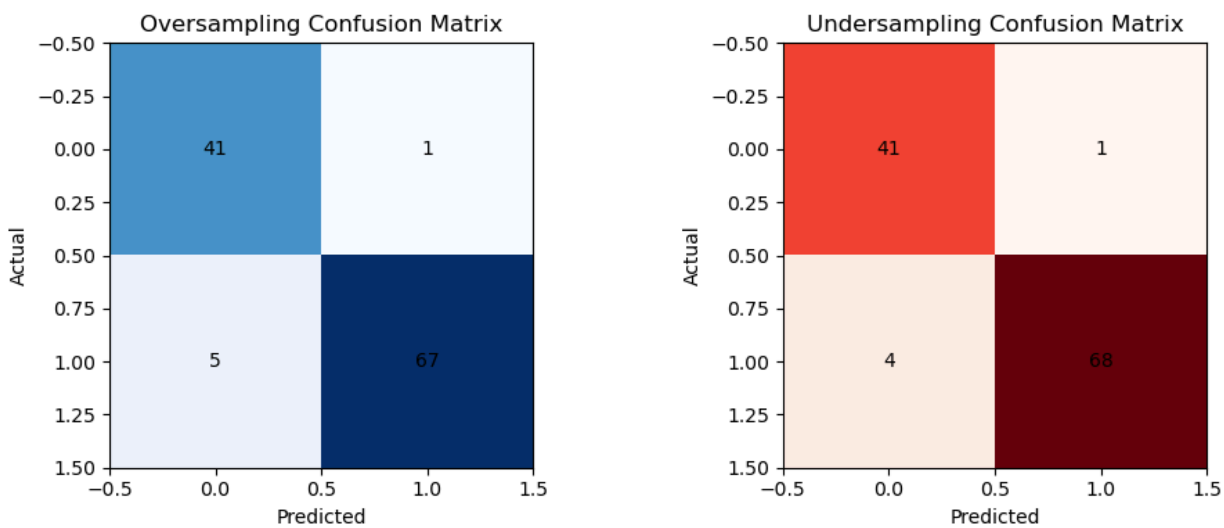
```
=== Undersampling Evaluation ===
Accuracy: 0.956140350877193
Confusion Matrix:
 [[41  1]
 [ 4 68]]
Classification Report:
               precision    recall  f1-score   support

           0       0.91      0.98      0.94        42
           1       0.99      0.94      0.96        72

    accuracy                           0.96       114
   macro avg       0.95      0.96      0.95       114
weighted avg       0.96      0.96      0.96       114
```

```
/opt/anaconda3/lib/python3.9/site-packages/sklearn/utils/deprecation.py:151: F
utureWarning: 'force_all_finite' was renamed to 'ensure_all_finite' in 1.6 and
will be removed in 1.8.
  warnings.warn(
/opt/anaconda3/lib/python3.9/site-packages/sklearn/base.py:484: FutureWarning:
`BaseEstimator._check_n_features` is deprecated in 1.6 and will be removed in
1.7. Use `sklearn.utils.validation._check_n_features` instead.
  warnings.warn(
/opt/anaconda3/lib/python3.9/site-packages/sklearn/base.py:493: FutureWarning:
`BaseEstimator._check_feature_names` is deprecated in 1.6 and will be removed
in 1.7. Use `sklearn.utils.validation._check_feature_names` instead.
  warnings.warn(
```

In [91]:

```python
# Step 6: Visual Comparison of Oversampling vs. Undersampling
import matplotlib.pyplot as plt

# Collect accuracy scores
accuracy_scores = {
    'Oversampling': accuracy_score(y_test, y_pred_ros),
    'Undersampling': accuracy_score(y_test, y_pred_rus)
}

# Create a bar plot for accuracy
plt.figure(figsize=(6, 4))
plt.bar(accuracy_scores.keys(), accuracy_scores.values(), color=['skyblue', 'l
plt.ylabel('Accuracy Score')
plt.title('Accuracy Comparison: Oversampling vs. Undersampling')
plt.ylim(0.8, 1.0)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()

# Optional: Plot Confusion Matrices side-by-side
fig, axes = plt.subplots(1, 2, figsize=(10, 4))

cm_ros = confusion_matrix(y_test, y_pred_ros)
cm_rus = confusion_matrix(y_test, y_pred_rus)

axes[0].imshow(cm_ros, cmap='Blues')
axes[0].set_title("Oversampling Confusion Matrix")
axes[0].set_xlabel("Predicted")
axes[0].set_ylabel("Actual")
for i in range(2):
    for j in range(2):
        axes[0].text(j, i, cm_ros[i, j], ha='center', va='center', color='blac

axes[1].imshow(cm_rus, cmap='Reds')
axes[1].set_title("Undersampling Confusion Matrix")
axes[1].set_xlabel("Predicted")
axes[1].set_ylabel("Actual")
for i in range(2):
    for j in range(2):
        axes[1].text(j, i, cm_rus[i, j], ha='center', va='center', color='blac

plt.tight_layout()
plt.show()
```





In-Class Reflection: Exercise Summary

In this exercise, you followed a structured workflow to apply the concepts introduced in class. Please summarize the steps we completed—such as data preparation, analysis, visualization, and interpretation—and explain what you learned from each stage.

Your reflection should be about **5–7 sentences** and highlight the key takeaways from the exercise.

> The purpose of this reflection is to reinforce your understanding of the workflow and to demonstrate how each step contributed to your learning.

Here in this exercise ,the datset was split into train ,test with the feature scaling ,here two methods of sampling is done oversampling and undersampling ,where we applied the training data to correct the class imbalance .Models were trained on each balanced set and evaluated using the accuracy ,confusion matrix and classification report .This approach we will be able to resample to timprove the fairness and performance on the imbalanced problems .Learning the practical strategies to balancing the data for the robust classification .

Module 5.3: Train-Test Split and Model Evaluation Setup

To build reliable classification models, it is crucial to evaluate their performance on data not seen during training. This is achieved by splitting the dataset into **training** and **testing** subsets.

In this sub-module, you will learn how to:

- Divide your data into **training and test sets** to assess generalization performance.
- Understand the importance of keeping the test set **completely separate** to avoid information leakage.
- Use common split ratios (e.g., 70% training, 30% testing) and stratified sampling to maintain class distributions.
- Prepare for more robust evaluation methods such as **cross-validation**, which further improves reliability by averaging results over multiple train-test splits.

Proper evaluation setup ensures that your model's performance estimates are realistic and helps prevent overfitting to training data.

Exercise 7: Stratified Train-Test Split for Balanced Evaluation

In this exercise, you'll perform a stratified train-test split to ensure that each class is represented proportionally in both training and test datasets.

Objective:
Learn how to split datasets while preserving class distribution.

Instructions:

1. Load the Iris dataset using `sklearn.datasets.load_iris()` or from Seaborn.
2. Separate the features (X) and target labels (y).
3. Use `train_test_split` with the `stratify=y` argument to ensure balanced class proportions.
4. Set the test size to 30% and specify `random_state` for reproducibility.
5. Print the class distribution in both training and test sets to confirm stratification.
6. (Optional) Visualize the class distributions using a bar chart.

This exercise shows how to maintain class balance in both training and testing data, which is especially important when working with imbalanced datasets.

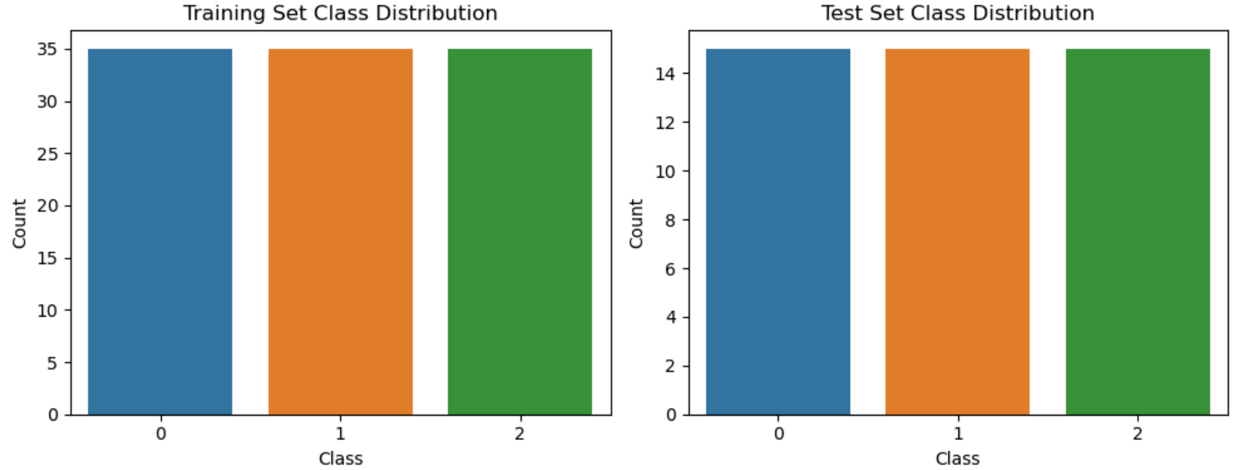
In [92]:
```
# Exercise 7: Stratified Train-Test Split for Balanced Evaluation

# Step 1: Import necessary libraries
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns

# Step 2: Load the Iris dataset
iris = load_iris()
X = pd.DataFrame(iris.data, columns=iris.feature_names)
y = pd.Series(iris.target, name='species')
```

In [93]:
```
# Step 3: Perform stratified train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, stratify=y, random_state=42
)
```

In [94]:
```
# Step 4: Display class distribution in training and test sets
train_dist = y_train.value_counts().sort_index()
test_dist = y_test.value_counts().sort_index()
print("Training set class distribution:")
print(train_dist)
print("\nTest set class distribution:")
print(test_dist)
```

```
Training set class distribution:
0    35
1    35
2    35
Name: species, dtype: int64

Test set class distribution:
0    15
1    15
2    15
Name: species, dtype: int64
```

In [95]:
```
# Step 5 (Optional): Visualize the class distribution
fig, ax = plt.subplots(1, 2, figsize=(10, 4))
sns.barplot(x=train_dist.index, y=train_dist.values, ax=ax[0])
ax[0].set_title('Training Set Class Distribution')
ax[0].set_xlabel('Class')
ax[0].set_ylabel('Count')

sns.barplot(x=test_dist.index, y=test_dist.values, ax=ax[1])
ax[1].set_title('Test Set Class Distribution')
ax[1].set_xlabel('Class')
ax[1].set_ylabel('Count')

plt.tight_layout()
plt.show()
```



In-Class Reflection: Exercise Summary

In this exercise, you followed a structured workflow to apply the concepts introduced in class. Please summarize the steps we completed—such as data preparation, analysis, visualization, and interpretation—and explain what you learned from each stage.

Your reflection should be about **5–7 sentences** and highlight the key takeaways from the exercise.

> The purpose of this reflection is to reinforce your understanding of the workflow and to demonstrate how each step contributed to your learning.

In this exercise we performed a stratified train test split on the iris dataset where the class proportions are constant in both training an dtest subsets .After visualizing the class distributions,we confirm that it is balanced ,since the datsets were imbalanced ,maintaining the stratification helps to eliminate the potential bias during the evaluation and promoting the performance comaprision,hence the significance of the data splitting is necessary for the model validation .

Exercise 8: Model Evaluation with Accuracy, Precision, Recall, and F1-Score

In this exercise, you'll learn how to evaluate the performance of a classification model using multiple metrics to get a comprehensive view of its effectiveness.

Objective:
Train a classification model and evaluate it using accuracy, precision, recall, and F1-score.

Instructions:

1. Load the **Iris dataset** and perform a stratified train-test split (80/20) as in the previous exercise.
2. Train a **Logistic Regression** model on the training set.

3. Use the trained model to make predictions on the test set.
4. Evaluate the model using the following metrics:
   - **Accuracy** – the overall percentage of correct predictions.
   - **Precision** – how many predicted positives were actually correct.
   - **Recall** – how many actual positives were correctly predicted.
   - **F1-score** – the harmonic mean of precision and recall.
5. Print the **classification report** using `classification_report` from `sklearn.metrics`.
6. (Optional) Visualize the confusion matrix for better insight into the types of errors.

This exercise helps you understand why multiple metrics are necessary to assess model performance, especially when class distributions or misclassification costs vary.

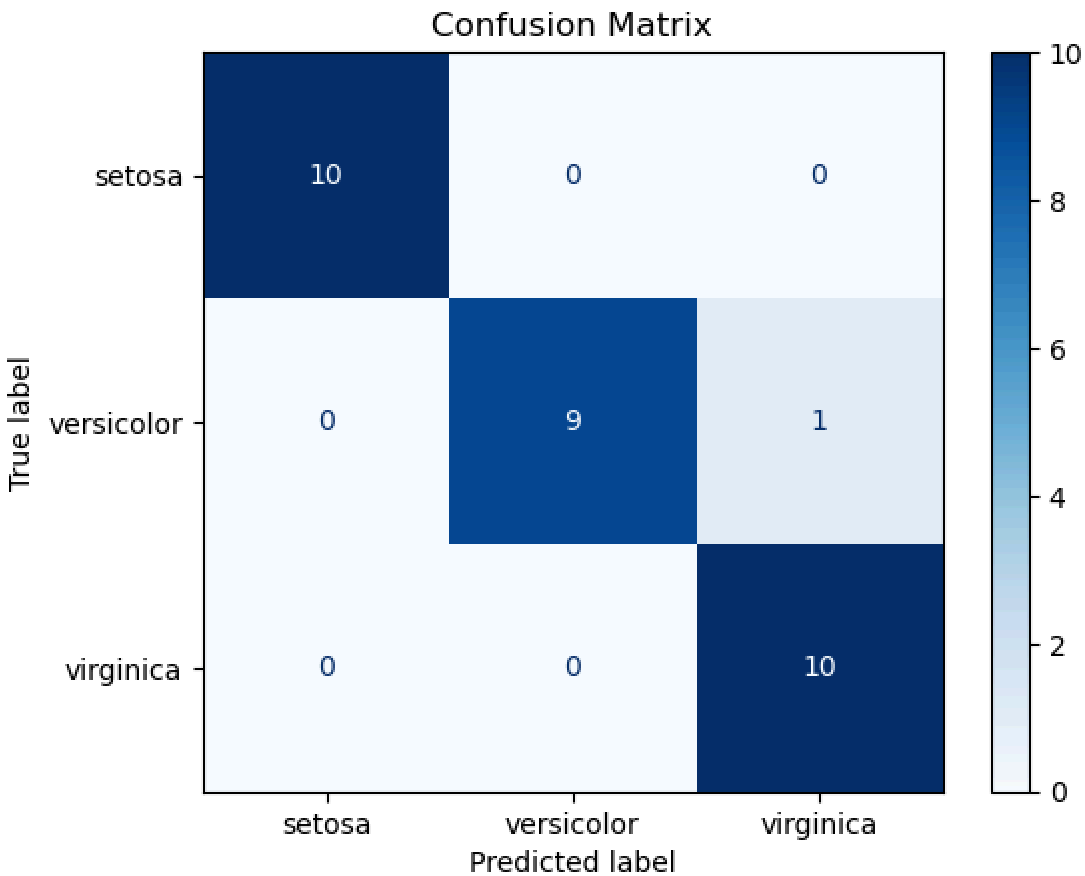
In [96]:
```
# Exercise 8: Model Evaluation with Accuracy, Precision, Recall, and F1-Score

# Step 1: Load the Iris dataset
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, Confusion
import matplotlib.pyplot as plt

# Load data
iris = load_iris()
X = iris.data
y = iris.target
```

In [97]:
```
# Step 2: Train-test split (stratified)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=42
)
```

In [98]:
```
# Step 3: Train the Logistic Regression model
model = LogisticRegression(max_iter=200)
model.fit(X_train, y_train)

# Step 4: Predict on the test set
y_pred = model.predict(X_test)
```

In [99]:
```
# Step 5: Print classification report
print("Classification Report:")
print(classification_report(y_test, y_pred, target_names=iris.target_names))

# Step 6: (Optional) Plot confusion matrix
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=iris.target_
disp.plot(cmap='Blues')
plt.title("Confusion Matrix")
plt.show()
```

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

      setosa       1.00      1.00      1.00        10
  versicolor       1.00      0.90      0.95        10
   virginica       0.91      1.00      0.95        10

    accuracy                           0.97        30
   macro avg       0.97      0.97      0.97        30
weighted avg       0.97      0.97      0.97        30
```



In-Class Reflection: Exercise Summary

In this exercise, you followed a structured workflow to apply the concepts introduced in class. Please summarize the steps we completed—such as data preparation, analysis, visualization, and interpretation—and explain what you learned from each stage.

Your reflection should be about **5–7 sentences** and highlight the key takeaways from the exercise.

> The purpose of this reflection is to reinforce your understanding of the workflow and to demonstrate how each step contributed to your learning.

In this exercise,the model was trained on the iris dataset where we follow the train test split in the ratio of 80-20 ,after the model is trained and predicted,and the model was evaluated using the accuracy ,precision,and recall and f2 score where it resulted in the classification report and the confusion matrix,from this is evaluated the model effectiveness which gives the accuracy to measure ,Considering the multiple metrics we can look into the deeper insight when dealing wirh the class imbalance or the missclassified values ,it highlights the need for the multidimensional evaluation for the classfication .

Module 5.4: Building a Baseline Classifier

Before applying complex models, it is important to establish a **baseline** performance using simple classifiers or rules. A baseline serves as a reference point to determine whether more sophisticated models provide meaningful improvements.

In this sub-module, you will learn how to:

- Use a **majority class classifier** that always predicts the most frequent class.
- Implement simple rule-based classifiers as baselines.
- Evaluate baseline performance using metrics like accuracy.
- Understand the limitations of baselines and the value of beating them with better models.

Building a baseline classifier helps you set realistic expectations and guides model development towards meaningful gains.

Exercise 9: Implementing a Majority Class Baseline

In this exercise, you'll build a simple baseline classifier that always predicts the most frequent class found in the training set. This approach is often used as a benchmark to determine whether a machine learning model provides real improvements.

Objective:
Establish a baseline accuracy using a majority class classifier and compare it to a trained model's performance.

Instructions:

1. Load the Iris dataset and split it into training and testing sets using `train_test_split`.
2. Identify the most frequent class in the training data.
3. Create a baseline predictor that always returns this class.
4. Evaluate the baseline using accuracy on the test set.
5. Optionally, compare this result to a Logistic Regression model to observe the improvement.

This helps highlight how much better a real model performs over a naive guess.

In [100…

```
# Exercise 9: Implementing a Majority Class Baseline

from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
import numpy as np
import pandas as pd

# Step 1: Load dataset
iris = load_iris()
X = iris.data
y = iris.target
class_names = iris.target_names

# Step 2: Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)
```

In [101…

```
# Step 3: Identify majority class in training data
majority_class = np.bincount(y_train).argmax()
```

In [102…

```
# Step 4: Predict using the majority class
y_pred_baseline = np.full_like(y_test, fill_value=majority_class)

# Step 5: Evaluate the baseline accuracy
baseline_accuracy = accuracy_score(y_test, y_pred_baseline)
print(f"Baseline Majority Class Accuracy: {baseline_accuracy:.2f}")

# Optional: Compare with Logistic Regression
clf = LogisticRegression(max_iter=200)
clf.fit(X_train, y_train)
y_pred_model = clf.predict(X_test)
model_accuracy = accuracy_score(y_test, y_pred_model)
print(f"Logistic Regression Accuracy: {model_accuracy:.2f}")
```

```
Baseline Majority Class Accuracy: 0.33
Logistic Regression Accuracy: 0.97
```

In-Class Reflection: Exercise Summary

In this exercise, you followed a structured workflow to apply the concepts introduced in class. Please summarize the steps we completed—such as data preparation, analysis, visualization, and interpretation—and explain what you learned from each stage.

Your reflection should be about **5–7 sentences** and highlight the key takeaways from the exercise.

> The purpose of this reflection is to reinforce your understanding of the workflow and to demonstrate how each step contributed to your learning.

In this exercise ,a simple baseline classfier was built to predict the most frequent class from the training set .The beseline was compared with the trained logistic regression model where it provides the reference ,such as the limitations of the prediction and th evalue of having the baseline to measure the model progress and for the further development of the model we can have the expectioons based on this.

Exercise 10: Build and Evaluate a Rule-Based Classifier

In this exercise, you'll implement a simple **rule-based classifier** that predicts a class based on one or two feature thresholds. This helps reinforce the intuition behind decision boundaries and feature importance.

Objective:
Understand how to create and evaluate a basic rule-based classifier as an interpretable baseline.

Instructions:

1. Load the Iris dataset and perform a train-test split.
2. Analyze feature distributions using visualizations (e.g., pairplots or histograms).
3. Manually define a simple rule using thresholds (e.g., if petal length < 2.5 → Setosa).
4. Apply the rule on the test set to make predictions.
5. Compare its accuracy to the majority class baseline and logistic regression model.
6. Discuss when rule-based models might be useful or preferable.

This exercise illustrates how human-readable decision rules can still perform reasonably well in certain domains and provides an intuitive stepping stone toward decision trees and more complex models.

In [103…

```
# Exercise 10: Build and Evaluate a Rule-Based Classifier

# Step 1: Load necessary libraries and dataset
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import pandas as pd
import numpy as np

# Load the dataset
iris = load_iris()
X = pd.DataFrame(iris.data, columns=iris.feature_names)
y = pd.Series(iris.target, name='species')

# Step 2: Split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)
```

In [104…

```
# Step 3: Define a simple rule-based classifier
# Example rule: if petal length < 2.5, predict Setosa (class 0)
```

```python
def rule_based_classifier(X):
    predictions = []
    for val in X['petal length (cm)']:
        if val < 2.5:
            predictions.append(0)  # Setosa
        else:
            predictions.append(1)  # Versicolor (assumption for simplicity)
    return np.array(predictions)

# Step 4: Apply rule-based classifier on the test set
rule_preds = rule_based_classifier(X_test)
```

In [105…

```python
# Step 5: Evaluate accuracy
rule_accuracy = accuracy_score(y_test, rule_preds)

# Step 6: Print result
print(f"Rule-Based Classifier Accuracy: {rule_accuracy:.2f}")
```

```
Rule-Based Classifier Accuracy: 0.67
```

In-Class Reflection: Exercise Summary

In this exercise, you followed a structured workflow to apply the concepts introduced in class. Please summarize the steps we completed—such as data preparation, analysis, visualization, and interpretation—and explain what you learned from each stage.

Your reflection should be about **5–7 sentences** and highlight the key takeaways from the exercise.

> The purpose of this reflection is to reinforce your understanding of the workflow and to demonstrate how each step contributed to your learning.

In this exercise,The classifier was implemented where we define the prediction rules based on the features thresholds ,the distribution analysis an dthe visualization that is been defined applied to the test set ,the accuracy is compared majority class baseline and the logistic regression .Here it demonstrates the interpretability and the utility of the rule based models where it relatives to the more flexible methods,it also includes the importance of the value to the progression to more complex algorithms.

Module 5.5: k-Nearest Neighbors (k-NN) Algorithm

The **k-Nearest Neighbors (k-NN)** algorithm is a simple yet powerful **non-parametric** classification and regression method. It classifies a new data point based on the **majority class** (for classification) or **average value** (for regression) among its (k) closest neighbors in the training set, where closeness is measured by a **distance metric**.

Why k-NN Matters

- **No explicit training**: k-NN is an **instance-based** or **lazy learning** algorithm. It stores the training data and makes predictions only when a query instance is provided.
- **Versatility**: Works for classification, regression, and even recommendation systems.
- **Interpretability**: Easy to understand and explain compared to more complex models.

How k-NN Works: Step-by-Step

1. **Choose** (k) — The number of neighbors to consider.
2. **Select a distance metric** — Common choices:
   - **Euclidean Distance**:
     $d(\mathbf{x}, \mathbf{y}) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$
   - **Manhattan Distance**:
     $d(\mathbf{x}, \mathbf{y}) = \sum_{i=1}^{n} |x_i - y_i|$
   - Others: Minkowski, cosine similarity, Hamming distance (for categorical data).
3. **Find the k nearest neighbors** — Measure the distance between the new point and all training points, then select the (k) smallest distances.
4. **Vote or Average**:
   - **Classification**: Assign the class with the majority vote among the neighbors.
   - **Regression**: Take the mean (or weighted mean) of neighbors' target values.
5. **Output the prediction**.

Choice of k and the Bias–Variance Trade-Off

- **Small k** (e.g., $(k = 1)$):
  - Low bias, high variance.
  - Sensitive to noise — a single mislabeled point can change the prediction.
- **Large k**:
  - Higher bias, lower variance.
  - Smoother decision boundaries, less sensitive to noise, but may overlook local patterns.
- (k) is often chosen via cross-validation to optimize performance.

Weighted k-NN

Rather than treating all neighbors equally, assign weights inversely proportional to their distance: $w_i = \frac{1}{d(\mathbf{x}_{\text{test}}, \mathbf{x}_i) + \epsilon}$ where (ϵ) is a small constant to avoid division by zero.
This gives **closer neighbors more influence** in the decision.

Strengths

- Simple to implement and interpret.
- Naturally supports multi-class classification.
- No assumptions about data distribution.

Limitations

- **Computational cost**: Prediction requires calculating distances to all training points ((O(n)) per query).
- **Memory usage**: Stores the entire training set.
- **Curse of dimensionality**: Performance degrades as the number of features grows — distances become less meaningful in high dimensions.
- Sensitive to feature scaling — normalization or standardization is recommended.

Important Considerations

- Always scale features before using distance-based methods.
- Use appropriate distance metrics for the type of data (continuous, categorical, mixed).
- Reduce dimensionality (e.g., PCA) when dealing with high-dimensional datasets to improve performance.

Exercise 11: Implementing Basic k-NN Classification

Objective:
Learn how to implement and evaluate a k-Nearest Neighbors classifier using the Iris dataset.

Instructions:

1. Load the Iris dataset and split it into training and test sets (80/20).
2. Use `StandardScaler` to normalize the feature values.
3. Apply `KNeighborsClassifier` from `sklearn.neighbors` with `k=3`.
4. Fit the model on the training data and predict on the test data.
5. Evaluate model performance using accuracy score and a classification report.
6. Visualize the decision boundaries (optional, using PCA for 2D).

This exercise introduces you to the basic k-NN classification pipeline and highlights the importance of data scaling before applying distance-based models.

In [106…

```python
# Exercise 11: Implementing Basic k-NN Classification

# Step 1: Import libraries
import pandas as pd
import numpy as np
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 accuracy_score, classification_report
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA

# Step 2: Load the Iris dataset
iris = load_iris()
```

```python
X = pd.DataFrame(iris.data, columns=iris.feature_names)
y = pd.Series(iris.target)
```

In [107…

```python
# Step 3: Split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, randor
```

In [108…

```python
# Step 4: Normalize the data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

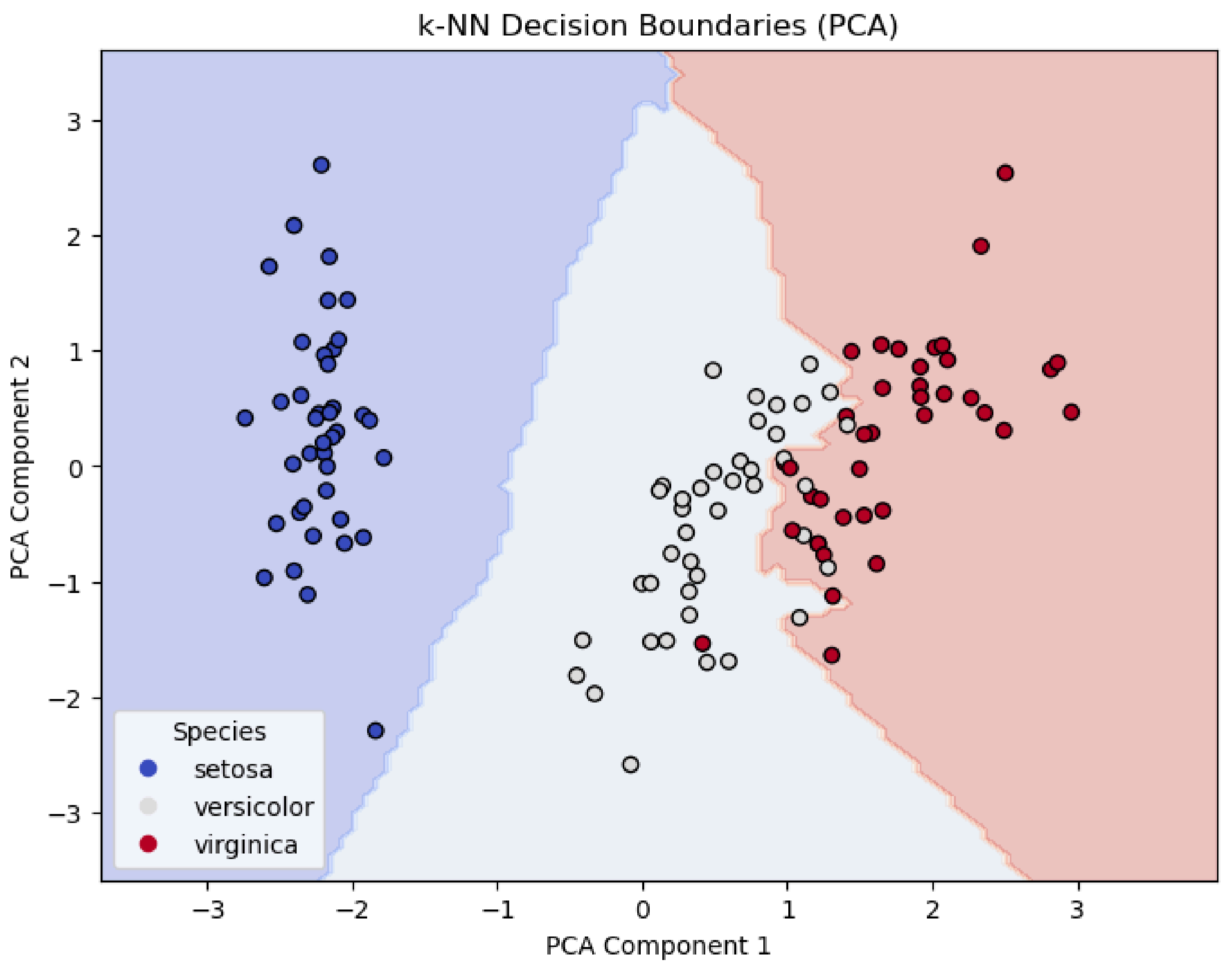
In [109…

```python
# Step 5: Apply k-NN classifier
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train_scaled, y_train)
y_pred = knn.predict(X_test_scaled)
```

In [110…

```python
# Step 6: Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred, target_names=iris.target_names)
print("Accuracy:", accuracy)
print(report)

# Step 7 (Optional): Visualize decision boundaries using PCA
pca = PCA(n_components=2)
X_train_pca = pca.fit_transform(X_train_scaled)
X_test_pca = pca.transform(X_test_scaled)

# Train k-NN on PCA-reduced data
knn_pca = KNeighborsClassifier(n_neighbors=3)
knn_pca.fit(X_train_pca, y_train)

# Create meshgrid for decision boundary
x_min, x_max = X_train_pca[:, 0].min() - 1, X_train_pca[:, 0].max() + 1
y_min, y_max = X_train_pca[:, 1].min() - 1, X_train_pca[:, 1].max() + 1
xx, yy = np.meshgrid(np.linspace(x_min, x_max, 100),
                     np.linspace(y_min, y_max, 100))
Z = knn_pca.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)

# Plot decision boundary and training points
plt.figure(figsize=(8, 6))
plt.contourf(xx, yy, Z, alpha=0.3, cmap=plt.cm.coolwarm)
scatter = plt.scatter(X_train_pca[:, 0], X_train_pca[:, 1], c=y_train, cmap=pl
plt.title("k-NN Decision Boundaries (PCA)")
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")

# Create custom legend
classes = np.unique(y_train)
handles = [
    plt.Line2D([], [], marker='o', linestyle='', color=plt.cm.coolwarm(i / 2),
               label=iris.target_names[i]) for i in classes
]
plt.legend(handles=handles, title="Species")
plt.show()
```

```
Accuracy: 1.0
              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
```



In-Class Reflection: Exercise Summary

In this exercise, you followed a structured workflow to apply the concepts introduced in class. Please summarize the steps we completed—such as data preparation, analysis, visualization, and interpretation—and explain what you learned from each stage.

Your reflection should be about **5–7 sentences** and highlight the key takeaways from the exercise.

> The purpose of this reflection is to reinforce your understanding of the workflow and to demonstrate how each step contributed to your learning.

In this exercise ,the K- nearest neighbors classifier was trained on the scaled iris dataset where k = 3 ,this included by fitting the model ,predicting the model and evaluating the model ,and also visualization of the decison boundaries with the PCA Here it also highlights the normalization is important in the distance based methods and also how knn is a simple technique for the classfication ,where step by step we can understand the k-nn it influences the data scaling on its results.

Exercise 12: Evaluating k-NN Performance with Different k Values

In this exercise, you'll explore how the choice of **k** (the number of neighbors) impacts the accuracy of the k-Nearest Neighbors (k-NN) classifier.

Objective:
Understand how model performance varies with different values of `k`, and how to choose the optimal value.

Instructions:

1. Load and split the Iris dataset into training and test sets.
2. Scale the feature values using `StandardScaler`.
3. Create a loop that trains a k-NN classifier for different `k` values (e.g., from 1 to 20).
4. Record the test accuracy for each value of `k`.
5. Plot `k` versus accuracy using `matplotlib` to visualize the trend.
6. Identify the value of `k` that gives the highest test accuracy.

This exercise helps you understand the **bias-variance tradeoff** and how parameter tuning affects classification performance.

In [111…

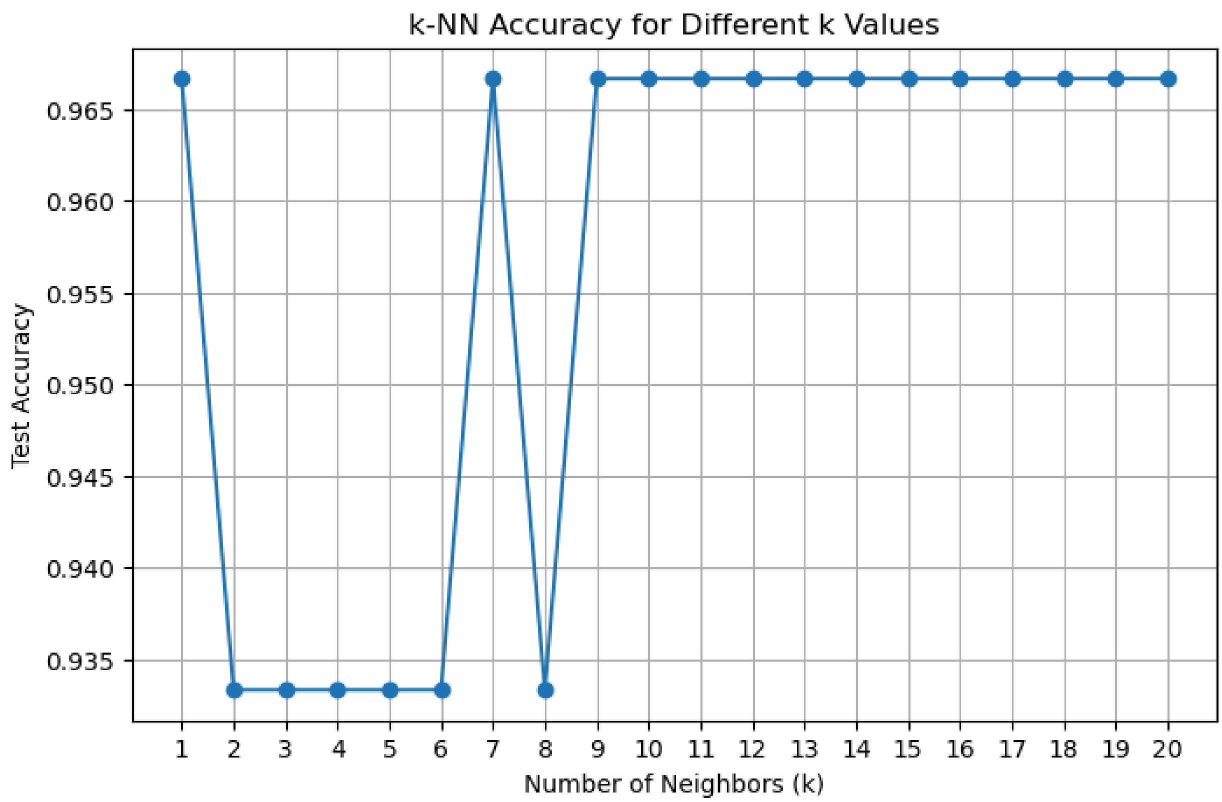
```
# Exercise 12: Evaluating k-NN Performance with Different k Values

import numpy as np
import matplotlib.pyplot as plt
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 accuracy_score

# Step 1: Load the dataset
iris = load_iris()
X = iris.data
y = iris.target

# Step 2: Split the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, randor

# Step 3: Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [112…

```
# Step 4: Loop through different k values and record accuracy
k_values = range(1, 21)
accuracies = []

for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train_scaled, y_train)
    y_pred = knn.predict(X_test_scaled)
    acc = accuracy_score(y_test, y_pred)
    accuracies.append(acc)
```

In [113…

```
# Step 5: Plot the accuracy vs k
plt.figure(figsize=(8, 5))
plt.plot(k_values, accuracies, marker='o')
plt.title("k-NN Accuracy for Different k Values")
plt.xlabel("Number of Neighbors (k)")
plt.ylabel("Test Accuracy")
plt.xticks(k_values)
plt.grid(True)
plt.show()
```



In-Class Reflection: Exercise Summary

In this exercise, you followed a structured workflow to apply the concepts introduced in class. Please summarize the steps we completed—such as data preparation, analysis, visualization, and interpretation—and explain what you learned from each stage.

Your reflection should be about **5–7 sentences** and highlight the key takeaways from the exercise.

> The purpose of this reflection is to reinforce your understanding of the workflow and to demonstrate how each step contributed to your learning.

In this exercise ,we understood that the optimization and its effects on the classification quality ,It also helps to understand the model performance of k-NN varies as k changes from 1 to 20 ,we try to record test accuracy for value ,where the results were plotted by identifying the optimal value visually,through this process ,the impact of the bias varinace tradeoff and the parameter tuning where the best classfier was interpretated.

Exercise 13: Comparing Distance Metrics in k-NN

In this exercise, you'll examine how different distance metrics impact the performance of the k-Nearest Neighbors (k-NN) classifier.

Objective:
Understand how the choice of distance metric (Euclidean, Manhattan, Minkowski) affects classification accuracy.

Instructions:

1. Load and split the Iris dataset (use train-test split with standardization).
2. For a fixed `k` value (e.g., 5), train k-NN models using the following distance metrics:
   - **Euclidean** (`metric='euclidean'`)
   - **Manhattan** (`metric='manhattan'`)
   - **Minkowski** (`metric='minkowski'` with `p=3`)
3. Record the test accuracy for each distance metric.
4. Plot a comparison bar chart showing the performance of each metric.
5. Summarize which distance metric performs best and under what conditions it might be preferred.

This exercise will help you evaluate how distance-based assumptions influence the behavior and accuracy of k-NN classifiers.

In [114…

```
# Exercise 13: Comparing Distance Metrics in k-NN

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

# Step 1: Load and split the data
iris = load_iris()
X = iris.data
y = iris.target
```

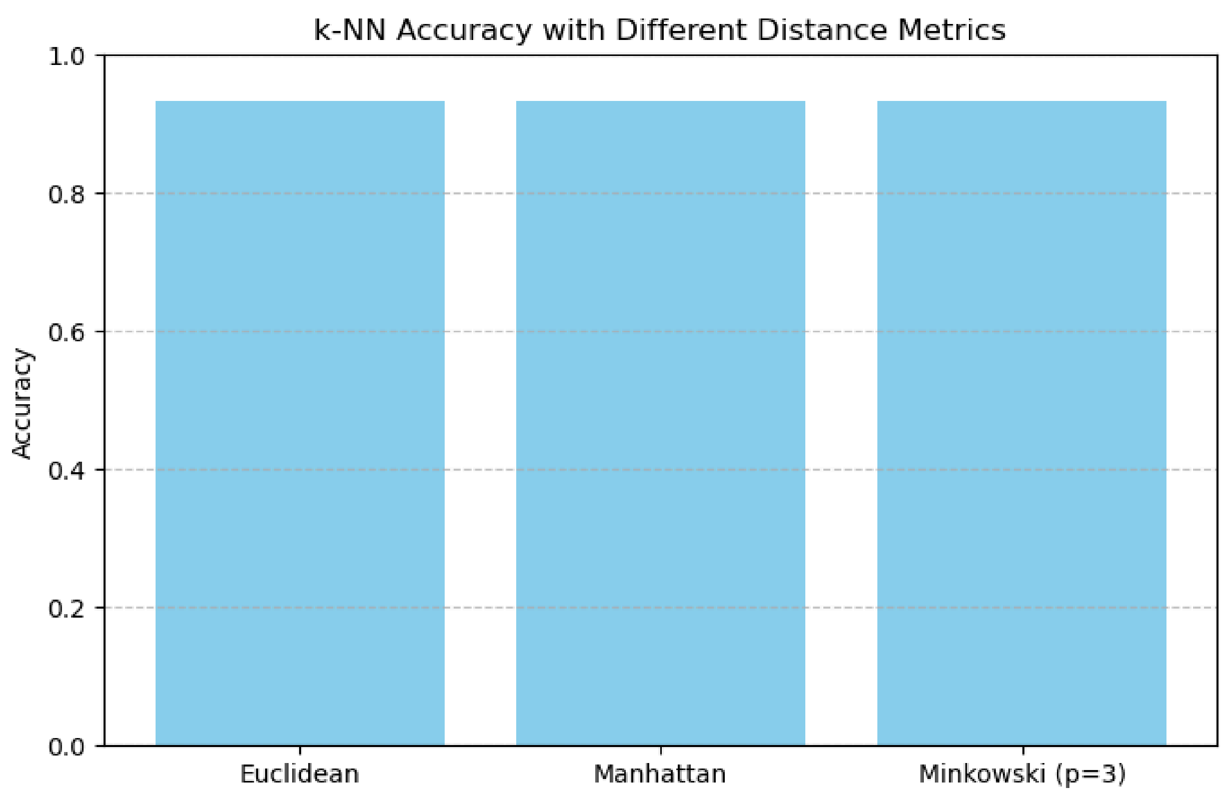
```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

# Step 2: Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [115…

```
# Step 3: Train k-NN classifiers with different distance metrics
metrics = {
    'Euclidean': {'metric': 'euclidean'},
    'Manhattan': {'metric': 'manhattan'},
    'Minkowski (p=3)': {'metric': 'minkowski', 'p': 3}
}

results = {}

for name, params in metrics.items():
    knn = KNeighborsClassifier(n_neighbors=5, **params)
    knn.fit(X_train_scaled, y_train)
    y_pred = knn.predict(X_test_scaled)
    accuracy = accuracy_score(y_test, y_pred)
    results[name] = accuracy
```

In [116…

```
# Step 4: Plot comparison
plt.figure(figsize=(8, 5))
plt.bar(results.keys(), results.values(), color='skyblue')
plt.title("k-NN Accuracy with Different Distance Metrics")
plt.ylabel("Accuracy")
plt.ylim(0, 1)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



In-Class Reflection: Exercise Summary

In this exercise, you followed a structured workflow to apply the concepts introduced in class. Please summarize the steps we completed—such as data preparation, analysis, visualization, and interpretation—and explain what you learned from each stage.

Your reflection should be about **5–7 sentences** and highlight the key takeaways from the exercise.

> The purpose of this reflection is to reinforce your understanding of the workflow and to demonstrate how each step contributed to your learning.

In this exercise ,it shows how the assumption can affect the model behaviour and its results.It involved the training k-NN models with the Euclidean ,Manhattan, and Minkowski distance mterics using the iris dataset and then comparing the dataset .A bar plot can help us to visulaize the results where it highlights the metric comparision ,it provides specific metrics on the feature type and the structure of the data .

Exercise 14: Choosing Optimal k in k-NN Using Cross-Validation

In this exercise, you'll learn how to select the best value for **k** in the k-NN algorithm using **cross-validation**, which helps you avoid overfitting or underfitting and improve generalization.

Objective:
Find the optimal number of neighbors (`k`) using cross-validation accuracy as the selection criterion.

Instructions:

1. Load and standardize the **Iris dataset**.
2. Use a loop to evaluate k values from 1 to 20.
3. For each k:
   - Use `KNeighborsClassifier(k)` and `cross_val_score` with `cv=5`.
   - Compute the average accuracy.
4. Plot the mean accuracy for each k value to visualize the best performing k.
5. Highlight the optimal k value on the plot.

This exercise will help you understand the impact of `k` on model performance and how to use cross-validation for hyperparameter tuning in classification tasks.

In [117…

```
# Exercise 14: Choosing Optimal k in k-NN Using Cross-Validation

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

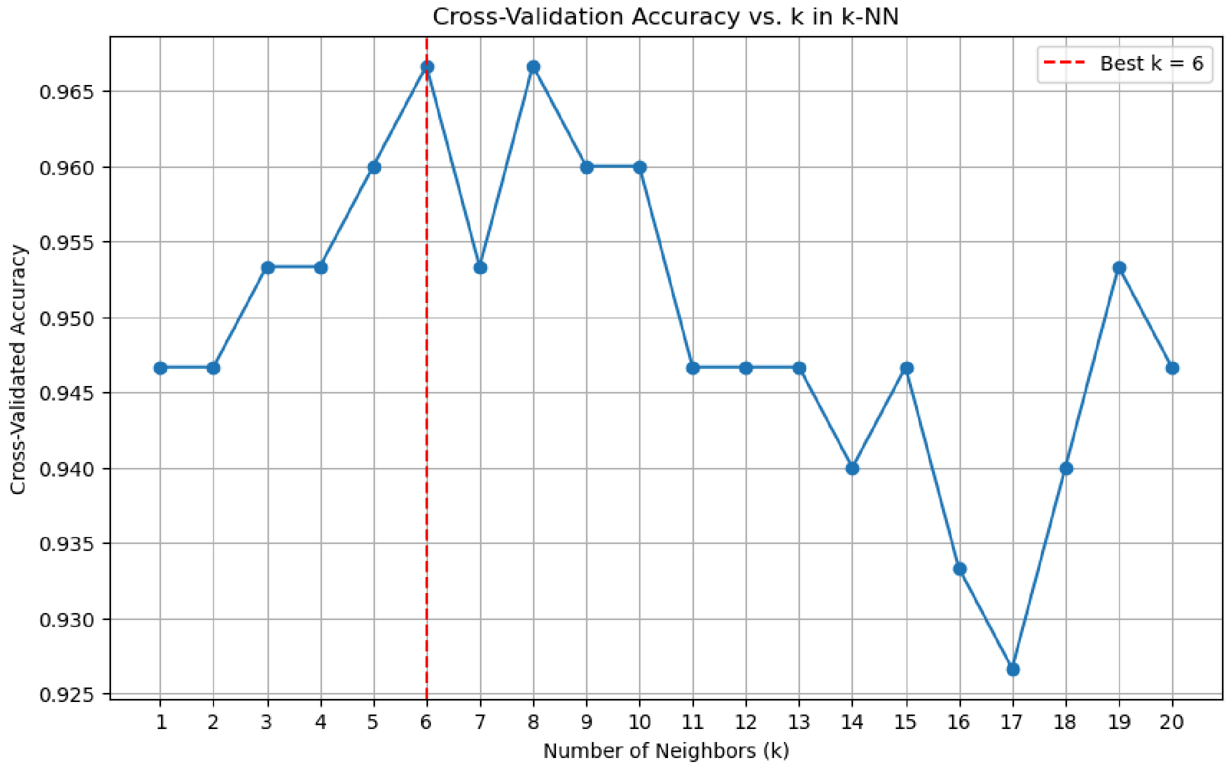
```python
from sklearn.datasets import load_iris
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score

# Step 1: Load and standardize the Iris dataset
iris = load_iris()
X, y = iris.data, iris.target
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [118…

```python
# Step 2–4: Evaluate k from 1 to 20 using 5-fold cross-validation
k_values = list(range(1, 21))
mean_scores = []

for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn, X_scaled, y, cv=5, scoring='accuracy')
    mean_scores.append(scores.mean())
```

In [119…

```python
# Step 5: Plot cross-validation accuracy for different k values
plt.figure(figsize=(10, 6))
plt.plot(k_values, mean_scores, marker='o')
plt.title("Cross-Validation Accuracy vs. k in k-NN")
plt.xlabel("Number of Neighbors (k)")
plt.ylabel("Cross-Validated Accuracy")
plt.xticks(k_values)
plt.grid(True)

# Highlight the best k
best_k = k_values[np.argmax(mean_scores)]
best_score = max(mean_scores)
plt.axvline(x=best_k, color='red', linestyle='--', label=f"Best k = {best_k}")
plt.legend()
plt.show()
```



In-Class Reflection: Exercise Summary

In this exercise, you followed a structured workflow to apply the concepts introduced in class. Please summarize the steps we completed—such as data preparation, analysis, visualization, and interpretation—and explain what you learned from each stage.

Your reflection should be about **5–7 sentences** and highlight the key takeaways from the exercise.

> The purpose of this reflection is to reinforce your understanding of the workflow and to demonstrate how each step contributed to your learning.

In this exercise ,we checked upon the optimization and comparitive accuracy as the key model development skills.It also find the cross validation to find the value that is optimal for k in k-NN by evaluating mean scoring over the values.We recorded the metric ,plotting the technique where we identify the best classfier having the best k minimal risk of overfitting ,applying the cross validation it helps in averaging performance across splits for the robust hyperparameter selction.Ihe comparative accuracy helped to serve aas a key model for the skills development.

Exercise 15: Implementing k-Nearest Neighbors from Scratch

In this exercise, you'll deepen your understanding of the k-Nearest Neighbors algorithm by building it from the ground up — without using `sklearn`. This will help you grasp the core logic behind distance-based classification and reinforce how predictions are made.

Objective:
Create a custom k-NN classifier that can classify new data points using Euclidean distance and majority voting.

Instructions:

1. Load the Iris dataset and split it into training and test sets.
2. Implement a function to calculate the **Euclidean distance** between two vectors.
3. For each test sample:
   - Calculate distances to all training samples.
   - Identify the k closest neighbors.
   - Perform **majority voting** to assign a class label.
4. Evaluate the custom classifier's accuracy by comparing predictions to the true test labels.
5. Compare your implementation's results with `sklearn`'s `KNeighborsClassifier` for validation.

This hands-on exercise reinforces your understanding of k-NN internals, distance calculations, and majority voting — key concepts in non-parametric learning.

In [120…

```
# Exercise 15: Implementing k-Nearest Neighbors from Scratch

import numpy as np
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from collections import Counter
from sklearn.metrics import accuracy_score

# Step 1: Load dataset and prepare data
iris = load_iris()
X = iris.data
y = iris.target

# Split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, randor
```

In [121…

```
# Step 2: Define Euclidean distance function
def euclidean_distance(x1, x2):
    return np.sqrt(np.sum((x1 - x2) ** 2))

# Step 3: Implement k-NN classifier
class KNNClassifier:
    def __init__(self, k=3):
        self.k = k

    def fit(self, X, y):
        self.X_train = X
        self.y_train = y

    def predict(self, X):
        predictions = [self._predict(x) for x in X]
        return np.array(predictions)
```

```
    def _predict(self, x):
        # Compute distances to all training points
        distances = [euclidean_distance(x, x_train) for x_train in self.X_trai
        
        # Get the k nearest samples and their labels
        k_indices = np.argsort(distances)[:self.k]
        k_nearest_labels = [self.y_train[i] for i in k_indices]
        
        # Majority voting
        most_common = Counter(k_nearest_labels).most_common(1)
        return most_common[0][0]
```

In [122…

```
# Step 4: Train and evaluate custom k-NN
knn = KNNClassifier(k=3)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)

# Step 5: Evaluate accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Custom k-NN Accuracy:", accuracy)
```

```
Custom k-NN Accuracy: 1.0
```

In [123…

```
# Step 6: Compare with sklearn's implementation
from sklearn.neighbors import KNeighborsClassifier
knn_sklearn = KNeighborsClassifier(n_neighbors=3)
knn_sklearn.fit(X_train, y_train)
y_pred_sklearn = knn_sklearn.predict(X_test)

accuracy_sklearn = accuracy_score(y_test, y_pred_sklearn)
print("sklearn k-NN Accuracy:", accuracy_sklearn)
```

```
sklearn k-NN Accuracy: 1.0
```

In-Class Reflection: Exercise Summary

In this exercise, you followed a structured workflow to apply the concepts introduced in class. Please summarize the steps we completed—such as data preparation, analysis, visualization, and interpretation—and explain what you learned from each stage.

Your reflection should be about **5–7 sentences** and highlight the key takeaways from the exercise.

> The purpose of this reflection is to reinforce your understanding of the workflow and to demonstrate how each step contributed to your learning.

In this exercise ,implemented k-NN classfier using the euclidean distance and understanding of k-NN internals,the implementation ,accuracy evaluation,and comparision to the sklearns k-NN reinforced foundational concepts of instance based learning,the step highlighted how the predictions are interpretated and help to understand the base algorithms where it is important in machine learning. We can compare the accuracy of both the knn implemenation and sklearn knn implementation.Hence it reinforces on the k -NN classifiers.

Revised: September 1, 2025

In [ ]: