Sri Sivasubramaniya Nadar College of Engineering, Chennai

(An Autonomous Institution Affiliated to Anna University)

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Subject Code & Name	ICS1512 – Machine Learning Algorithms Laboratory		
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Experiment #1: Exploring Python Libraries for Machine Learning

Aim:
To explore and understand the core functionalities of essential Python libraries — NumPy, Pandas, SciPy, Scikit-learn, and Matplotlib — for array manipulation, data preprocessing, machine learning workflows, and data visualization.

Libraries Used:

- `numpy`
- `pandas`
- `scipy`
- `scikit-learn`
- `matplotlib`
- `seaborn`

Objective:
To apply the core Python libraries on real-world datasets from UCI and Kaggle, demonstrate their features, and identify suitable machine learning models for different tasks.

Summary of Tasks:

- Performed numerical operations using NumPy: arrays, reshaping, broadcasting, statistics.
- Used Pandas for loading, cleaning, grouping, and aggregating tabular data.
- Applied SciPy functions for mathematical operations and statistical analysis.
- Built ML models with Scikit-learn: classification, regression, and feature selection.
- Visualized trends and distributions using Matplotlib and Seaborn.
- Worked with five datasets: Loan Prediction, Handwritten Digits, Spam Detection, Diabetes, and Iris.

Code Outputs and Screenshots:
(Refer attached Colab output)

ml-ex1

July 31, 2025

Aim: To explore and understand the core functionalities of essential Python libraries — NumPy, Pandas, SciPy, Scikit-learn, and Matplotlib — for performing array manipulation, data preprocessing, mathematical computing, machine learning workflows, and data visualization. Also, to apply these libraries on real-world datasets (from UCI and Kaggle) and identify suitable machine learning models and techniques based on the dataset characteristics.

1.Explore the various functions and methods available in the following Python libraries: Numpy, Pandas, Scipy, Scikit-learn, Matplotlib. Understand the key operations such as array manipulations, data preprocessing, mathematical computing, machine learning workflows, and data visualization

NumPy (Numerical Python):

What it is: The fundamental package for numerical computation in Python. It provides powerful N-dimensional array objects and sophisticated functions for working with these arrays. It's often referred to as the "scientific computing standard" for Python.

What it is used for: NumPy is the bedrock for most scientific and data-related libraries in Python. It's used for efficient numerical operations, mathematical computing, linear algebra, Fourier transforms, and random number generation. Its core strength lies in its ability to perform operations on entire arrays of data without explicit Python loops, leading to significantly faster execution times.

Key Operations/Features:

Array Creation: Functions like np.array(), np.zeros(), np.ones(), np.arange(), np.linspace() for generating arrays with various initializations and ranges.

Array Manipulation: Operations such as reshape(), concatenate(), stack(), split(), and transpose() to change the form or combine arrays.

Element-wise Operations: Fast arithmetic operations (+, -, *, /) applied directly to array elements, including broadcasting rules for arrays of different shapes.

Mathematical Functions: A vast collection of universal functions (ufuncs) for element-wise mathematical operations (e.g., np.sin(), np.exp(), np.sqrt()).

Linear Algebra: Functions for dot products (np.dot(), @), matrix multiplication, inverse, determinant, eigenvalues, and solving linear systems within the np.linalg submodule.

Statistical Operations: Methods like np.mean(), np.median(), np.std(), np.sum(), np.max(), np.min() for summarizing array data.

[17]:
```
# Import Numpy
import numpy as np
```

```python
# Creating basic arrays
arr = np.array([1, 2, 3, 4, 5])
print("Original 1D array:", arr)

# Array creation using various methods
a = np.array([1, 2, 3])
b = np.zeros((2, 2))
c = np.ones((3, 1))
d = np.arange(0, 10, 2)
e = np.linspace(0, 1, 5)

print("\nArray a (np.array):", a)
print("Array b (np.zeros):\n", b)
print("Array c (np.ones):\n", c)
print("Array d (np.arange):", d)
print("Array e (np.linspace):", e)

# Shape of arrays
print("\nShapes:")
print("a:", a.shape)
print("b:", b.shape)
print("c:", c.shape)
print("d:", d.shape)
print("e:", e.shape)

# Displaying data type
print("\nType of 'arr':", type(arr))         # object type
print("Data type of elements:", arr.dtype)  # data type of elements

# Creating 2D array
arr2 = np.array([[1, 2, 3], [4, 5, 6]])
print("\n2D Array:\n", arr2)

# Array dimensions
print("Dimensions of arr:", arr.ndim)
print("Dimensions of arr2:", arr2.ndim)

# Indexing (1D and 2D)
print("\n1D Indexing: arr[0] =", arr[0])
print("2D Indexing: 2nd element of 1st row =", arr2[0, 1])
print("Sum of arr[1] + arr[3] =", arr[1] + arr[3])

# Negative indexing
print("\nNegative indexing (last element):", arr[-1])

# Slicing
```

```python
print("\nSlicing arr[1:3]:", arr[1:3])
print("Slicing arr[1:]:", arr[1:])
print("Slicing arr[:3]:", arr[:3])
print("Negative slicing arr[-3:-1]:", arr[-3:-1])
print("Step slicing arr[1:5:2]:", arr[1:5:2])
print("Slicing 2D arr2[1,1:3]:", arr2[1, 1:3])

# Specific data type array
arr3 = np.array([1, 2, 3, 4, 5, 6], dtype='float')
print("\nArray with float dtype:", arr3)

# Changing data type
changedarr = arr3.astype('int')
print("Changed to int:", changedarr)
print("New dtype:", changedarr.dtype)

# Copy vs View
x = arr.copy()
print("\nOriginal array:", arr)
print("Copied array:", x)

a = np.array([1, 2, 3, 4])
b = a.view()
b[1] = 100
print("\nView after modifying b:", b)
print("Original a after modifying b:", a)  # reflects in a

# Reshaping
arr4 = np.array([1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12])
newarr = arr4.reshape(4, 3)
print("\nReshaped array:\n", newarr)

# Joining arrays
arr1 = np.array([1, 2, 3])
arr2 = np.array([4, 5, 6])

print("\nConcatenated:", np.concatenate([arr1, arr2]))
print("Horizontal Stack:", np.hstack([arr1, arr2]))
print("Vertical Stack:\n", np.vstack([arr1, arr2]))
print("Depth Stack:\n", np.dstack([arr1, arr2]))

# Splitting arrays
split_arr = np.array_split(arr4, 3)
print("\nSplitting arr4 into 3 parts:")
print("Part 1:", split_arr[0])
print("Part 2:", split_arr[1])
print("Part 3:", split_arr[2])
```

```python
# Sorting
arr = np.array([3, 2, 0, 1])
print("\nSorted array:", np.sort(arr))

# Random number generation
from numpy import random
print("\nRandom integer (0-100):", random.randint(100))

# Broadcasting example
print("\nBroadcasting:")
arr5 = np.array([1, 2, 3])
print("Original:", arr5)
print("After adding scalar 10:", arr5 + 10)  # scalar broadcast
arr6 = np.array([[1], [2], [3]])
print("Broadcast with compatible shapes:\n", arr6 + arr5)  # row + col

# Aggregate functions
print("\nAggregate Functions:")
print("Sum:", np.sum(a))
print("Mean:", np.mean(a))
print("Min:", np.min(a))
print("Max:", np.max(a))
print("Standard Deviation:", np.std(a))
print("Variance:", np.var(a))
print("Argmax (position of max):", np.argmax(a))
print("Argmin (position of min):", np.argmin(a))

# Mathematical operations
print("\nMath Operations:")
print("Dot product of a and a:", np.dot(a, a))
print("Exponent:", np.exp(a))
print("Square Root:", np.sqrt(a))
```

```
Original 1D array: [1 2 3 4 5]

Array a (np.array): [1 2 3]
Array b (np.zeros):
 [[0. 0.]
 [0. 0.]]
Array c (np.ones):
 [[1.]
 [1.]
 [1.]]
Array d (np.arange): [0 2 4 6 8]
Array e (np.linspace): [0.   0.25 0.5  0.75 1.  ]
```

```
Shapes:
a: (3,)
b: (2, 2)
c: (3, 1)
d: (5,)
e: (5,)

Type of 'arr': <class 'numpy.ndarray'>
Data type of elements: int64

2D Array:
 [[1 2 3]
 [4 5 6]]
Dimensions of arr: 1
Dimensions of arr2: 2

1D Indexing: arr[0] = 1
2D Indexing: 2nd element of 1st row = 2
Sum of arr[1] + arr[3] = 6

Negative indexing (last element): 5

Slicing arr[1:3]: [2 3]
Slicing arr[1:]: [2 3 4 5]
Slicing arr[:3]: [1 2 3]
Negative slicing arr[-3:-1]: [3 4]
Step slicing arr[1:5:2]: [2 4]
Slicing 2D arr2[1,1:3]: [5 6]

Array with float dtype: [1. 2. 3. 4. 5. 6.]
Changed to int: [1 2 3 4 5 6]
New dtype: int64

Original array: [1 2 3 4 5]
Copied array: [1 2 3 4 5]

View after modifying b: [  1 100   3   4]
Original a after modifying b: [  1 100   3   4]

Reshaped array:
 [[ 1  2  3]
 [ 4  5  6]
 [ 7  8  9]
 [10 11 12]]

Concatenated: [1 2 3 4 5 6]
Horizontal Stack: [1 2 3 4 5 6]
Vertical Stack:
```

```
 [[1 2 3]
 [4 5 6]]
Depth Stack:
 [[[1 4]
  [2 5]
  [3 6]]]

Splitting arr4 into 3 parts:
Part 1: [1 2 3 4]
Part 2: [5 6 7 8]
Part 3: [ 9 10 11 12]

Sorted array: [0 1 2 3]

Random integer (0-100): 31

Broadcasting:
Original: [1 2 3]
After adding scalar 10: [11 12 13]
Broadcast with compatible shapes:
 [[2 3 4]
 [3 4 5]
 [4 5 6]]

Aggregate Functions:
Sum: 108
Mean: 27.0
Min: 1
Max: 100
Standard Deviation: 42.16040796766559
Variance: 1777.5
Argmax (position of max): 1
Argmin (position of min): 0

Math Operations:
Dot product of a and a: 10026
Exponent: [2.71828183e+00 2.68811714e+43 2.00855369e+01 5.45981500e+01]
Square Root: [ 1.         10.          1.73205081  2.        ]
```

Pandas (Python Data Analysis Library):

What it is: A high-performance, easy-to-use data structures and data analysis tool. Its two primary data structures are Series (a one-dimensional labeled array) and DataFrame (a two-dimensional labeled data structure with columns of potentially different types, resembling a spreadsheet or SQL table).

What it is used for: Pandas is indispensable for data manipulation, cleaning, preparation, and analysis. It excels at handling tabular data, making it ideal for tasks like importing datasets from various formats (CSV, Excel, SQL), cleaning messy data (handling missing values, duplicates), transforming data (filtering, sorting, merging, grouping, pivoting), and performing exploratory data analysis (EDA) to understand data characteristics.

Key Operations/Features:

Data Input/Output: Functions like pd.read_csv(), pd.read_excel(), pd.read_sql() for loading data, and df.to_csv(), df.to_excel() for saving data.

Data Inspection: Methods like df.head(), df.tail(), df.info(), df.describe(), df.shape, df.columns for quickly understanding the data's structure and basic statistics.

Missing Data Handling: df.isnull().sum() to identify missing values, and df.dropna(), df.fillna() for removing or imputing them.

Data Selection and Indexing: Powerful ways to select data using labels (.loc[]), integer positions (.iloc[]), or boolean indexing (df[df['column'] > value]).

Data Transformation: df.apply(), df.map(), df.replace() for column-wise or element-wise transformations.

Grouping and Aggregation: The df.groupby() method combined with aggregation functions (e.g., mean(), sum(), count()) for summarizing data by categories.

Merging and Joining: pd.merge(), df.join() for combining DataFrames based on common columns or indices.

[18]:
```python
import pandas as pd

# create a simple Series (like a 1D array)
data = [10, 20, 30]
series = pd.Series(data)
print("Series:\n", series)

# Series with custom labels
series = pd.Series(data, index=['a', 'b', 'c'])
print("\nSeries with custom index:\n", series)

# create a basic DataFrame (like a table with rows and columns)
data = {
    "Name": ["Alice", "Bob", "Charlie", "David", "Eve"],
    "Age": [25, 30, 35, None, 25],
    "City": ["Delhi", "Mumbai", "Chennai", "Delhii", "Delhi"]
}
df = pd.DataFrame(data)
print("\nDataFrame:\n", df)

# read data from a CSV or JSON file (if you have those files)
# df_csv = pd.read_csv("data.csv")
# print("\nCSV Data:\n", df_csv.head())
# df_json = pd.read_json("data.json")
# print("\nJSON Data:\n", df_json.head())
```

```python
# look at the first and last few rows
print("\nFirst few rows:\n", df.head())
print("\nLast few rows:\n", df.tail())

# check column names and data types
print("\nColumn names:", df.columns)
print("\nData types:\n", df.dtypes)

# get basic statistics for numeric columns
print("\nSummary statistics:\n", df.describe())

# check for missing values
print("\nMissing values:\n", df.isnull())

# drop rows with missing data
df_cleaned = df.dropna()
print("\nAfter dropping missing values:\n", df_cleaned)

# or fill missing values with a default
df_filled = df.fillna("Unknown")
print("\nAfter filling missing values:\n", df_filled)

# fix formatting issues: convert 'Age' to numeric, invalid entries become NaN
df["Age"] = pd.to_numeric(df["Age"], errors='coerce')

# fix typos in 'City' column
df["City"] = df["City"].replace("Delhii", "Delhi")

# remove any duplicate rows
df = df.drop_duplicates()

# check correlation between numeric columns
print("\nCorrelation matrix:\n", df.select_dtypes(include='number').corr())

# group by a column and find average age in each group
grouped = df.groupby("City")["Age"].mean()
print("\nAverage age by city:\n", grouped)

# count how many times each city appears
print("\nCity counts:\n", df["City"].value_counts())

# sort the data by age
df_sorted = df.sort_values(by="Age")
print("\nSorted by age:\n", df_sorted)

# rename a column
df = df.rename(columns={"Name": "FullName"})
```

```python
print("\nAfter renaming column:\n", df)

# add a new column: Year of Birth
df["YearOfBirth"] = 2025 - df["Age"]
print("\nAfter adding YearOfBirth column:\n", df)

# drop a column
df = df.drop("YearOfBirth", axis=1)

# filter rows where age is greater than 25
adults = df[df["Age"] > 25]
print("\nRows where age > 25:\n", adults)
```

```
Series:
 0    10
1    20
2    30
dtype: int64

Series with custom index:
 a    10
b    20
c    30
dtype: int64

DataFrame:
       Name   Age     City
0    Alice  25.0    Delhi
1      Bob  30.0   Mumbai
2  Charlie  35.0  Chennai
3    David   NaN   Delhii
4      Eve  25.0    Delhi

First few rows:
       Name   Age     City
0    Alice  25.0    Delhi
1      Bob  30.0   Mumbai
2  Charlie  35.0  Chennai
3    David   NaN   Delhii
4      Eve  25.0    Delhi

Last few rows:
       Name   Age     City
0    Alice  25.0    Delhi
1      Bob  30.0   Mumbai
2  Charlie  35.0  Chennai
3    David   NaN   Delhii
```

```
4      Eve  25.0    Delhi

Column names: Index(['Name', 'Age', 'City'], dtype='object')

Data types:
 Name     object
Age     float64
City     object
dtype: object

Summary statistics:
              Age
count   4.000000
mean   28.750000
std     4.787136
min    25.000000
25%    25.000000
50%    27.500000
75%    31.250000
max    35.000000

Missing values:
     Name    Age   City
0  False  False  False
1  False  False  False
2  False  False  False
3  False   True  False
4  False  False  False

After dropping missing values:
       Name   Age     City
0    Alice  25.0    Delhi
1      Bob  30.0   Mumbai
2  Charlie  35.0  Chennai
4      Eve  25.0    Delhi

After filling missing values:
       Name      Age     City
0    Alice     25.0    Delhi
1      Bob     30.0   Mumbai
2  Charlie     35.0  Chennai
3    David  Unknown   Delhii
4      Eve     25.0    Delhi

Correlation matrix:
      Age
Age  1.0
```

```
Average age by city:
 City
Chennai    35.0
Delhi      25.0
Mumbai     30.0
Name: Age, dtype: float64

City counts:
 City
Delhi      3
Mumbai     1
Chennai    1
Name: count, dtype: int64

Sorted by age:
       Name   Age     City
0    Alice  25.0    Delhi
4      Eve  25.0    Delhi
1      Bob  30.0   Mumbai
2  Charlie  35.0  Chennai
3    David   NaN    Delhi

After renaming column:
   FullName   Age     City
0    Alice  25.0    Delhi
1      Bob  30.0   Mumbai
2  Charlie  35.0  Chennai
3    David   NaN    Delhi
4      Eve  25.0    Delhi

After adding YearOfBirth column:
   FullName   Age     City  YearOfBirth
0    Alice  25.0    Delhi       2000.0
1      Bob  30.0   Mumbai       1995.0
2  Charlie  35.0  Chennai       1990.0
3    David   NaN    Delhi          NaN
4      Eve  25.0    Delhi       2000.0

Rows where age > 25:
   FullName   Age     City
1      Bob  30.0   Mumbai
2  Charlie  35.0  Chennai
```

SciPy (Scientific Python):

What it is: A library that builds on NumPy and provides a vast collection of algorithms and mathematical tools for scientific and technical computing. It organizes its functionalities into sub-packages for specific domains.

What it is used for: SciPy is used for more advanced and specialized scientific computing tasks beyond the fundamental operations provided by NumPy. Its applications range from complex mathematical problem-solving in engineering, physics, and biology to advanced statistical analysis, signal processing, and image manipulation.

Key Operations/Features:

scipy.stats: Statistical functions for probability distributions (PDFs, CDFs), statistical tests (t-tests, ANOVA, chi-squared), and descriptive statistics.

scipy.optimize: Algorithms for minimization (e.g., minimize()), curve fitting, and root finding. Crucial for optimization problems in machine learning and data modeling.

scipy.interpolate: Tools for interpolation, allowing estimation of values between known data points (e.g., interp1d()).

scipy.linalg: More advanced linear algebra routines than NumPy, including specialized matrix operations and decompositions.

scipy.signal: Functions for signal processing, such as convolution, filtering, and spectral analysis.

scipy.special: A collection of special mathematical functions (e.g., Bessel functions, Gamma function).

scipy.spatial: Algorithms for spatial data structures and operations, like K-D trees and distance computations.

[19]:
```
import numpy as np
from scipy import constants, stats, optimize, interpolate, linalg, signal,␣
↪special, spatial

# constants
print("Speed of light (m/s):", constants.c)
print("Avogadro's number:", constants.N_A)
print()

# stats - probability distributions & tests
x = np.linspace(-3, 3, 100)
normal = stats.norm(loc=0, scale=1)
print("normal pdf(0):", normal.pdf(0))
print("normal cdf(0):", normal.cdf(0))
print("mean:", normal.mean(), "std:", normal.std())

# t-test
a = np.random.randn(20) + 0.5
b = np.random.randn(20)
t_stat, p_val = stats.ttest_ind(a, b)
print()
print("t-statistic:", t_stat)
print("p-value:", p_val)
```

```python
# chi-squared test
obs = np.array([10, 20, 30])
exp = np.array([15, 15, 30])
chi2, p = stats.chisquare(obs, f_exp=exp)
print()
print("chi2 value:", chi2)
print("p-value:", p)
print()

# optimize
root = optimize.root_scalar(lambda t: t**2 - 16, bracket=[0, 5]).root
print("Root of x^2 - 16:", root)

res = optimize.minimize(lambda t: (t-2)**2, x0=0)
print("Minimize (x-2)^2 result:", res.x)

def func(x, a, b): return a * np.exp(-b * x)
xp = np.linspace(0, 4, 50)
yp = func(xp, 2.5, 1.3) + 0.2 * np.random.normal(size=xp.size)
params, cov = optimize.curve_fit(func, xp, yp)
print("Fitted parameters (a, b):", params)
print()

# interpolate
f = interpolate.interp1d(xp, yp, kind='cubic')
print("Interpolated value at x=1.5:", f(1.5))
print()

# linalg
M = np.array([[3, 1], [1, 2]])
w, v = linalg.eig(M)
print("Eigenvalues:", w)
print("Inverse of matrix M:\n", linalg.inv(M))
print()

# signal
sig = np.sin(xp)
kernel = np.ones(5) / 5
smoothed = signal.convolve(sig, kernel, mode='same')
print("Smoothed signal (first 5 values):", smoothed[:5])
print()

# special
print("Bessel function J0(1):", special.j0(1))
print("Gamma function of 5:", special.gamma(5))
print()
```

```
# spatial
pts = np.random.rand(10, 2)
kdt = spatial.KDTree(pts)
dist, index = kdt.query(pts[0], k=2)
print("Distance to nearest neighbor:", dist[1])
print("Index of nearest neighbor:", index[1])
print()
```

```
Speed of light (m/s): 299792458.0
Avogadro's number: 6.02214076e+23

normal pdf(0): 0.3989422804014327
normal cdf(0): 0.5
mean: 0.0 std: 1.0

t-statistic: 1.8178532689200808
p-value: 0.07697707619624078

chi2 value: 3.3333333333333335
p-value: 0.1888756028375618

Root of x^2 - 16: 4.0
Minimize (x-2)^2 result: [1.99999998]
Fitted parameters (a, b): [2.44637921 1.24173072]

Interpolated value at x=1.5: 0.22041128436603624

Eigenvalues: [3.61803399+0.j 1.38196601+0.j]
Inverse of matrix M:
 [[ 0.4 -0.2]
 [-0.2  0.6]]

Smoothed signal (first 5 values): [0.04881659 0.09730806 0.16145984 0.24084467
0.31862543]

Bessel function J0(1): 0.7651976865579665
Gamma function of 5: 24.0

Distance to nearest neighbor: 0.3540393223995117
Index of nearest neighbor: 6
```

Scikit-learn (Sklearn):

What it is: A free software machine learning library for the Python programming language. It features various classification, regression and clustering algorithms including support vector machines, random forests, gradient boosting, k-means and DBSCAN, and is designed to interoperate with NumPy and SciPy.

What it is used for: Scikit-learn is the de-facto standard for implementing machine learning algorithms in Python for most common tasks. It's used for building predictive models, discovering patterns in data, and making data-driven decisions. Its consistent API across different models makes it highly user-friendly for experimenting with various algorithms.

Key Operations/Features:

sklearn.preprocessing: Essential for preparing data, including StandardScaler (standardization), MinMaxScaler (normalization), OneHotEncoder (for nominal categorical features), and LabelEncoder (for ordinal categorical features or target variables).

sklearn.model_selection: Tools for splitting data into training, testing, and validation sets (train_test_split), cross-validation techniques (KFold, StratifiedKFold), and hyperparameter tuning (GridSearchCV, RandomizedSearchCV).

sklearn.linear_model: Implementation of linear models like LinearRegression, LogisticRegression, Ridge, and Lasso.

sklearn.tree and sklearn.ensemble: Powerful tree-based models such as DecisionTreeClassifier, DecisionTreeRegressor, RandomForestClassifier, RandomForestRegressor, GradientBoostingClassifier, and AdaBoostClassifier.

sklearn.svm: Support Vector Machines (SVC for classification, SVR for regression) which are effective for high-dimensional data.

sklearn.neighbors:K-Nearest Neighbors (KNeighborsClassifier, KNeighborsRegressor) for instance-based learning.

sklearn.cluster: Unsupervised learning algorithms like KMeans, DBSCAN, and AgglomerativeClustering for grouping similar data points.

sklearn.metrics: A comprehensive suite of evaluation metrics for both supervised (accuracy_score, precision_score, recall_score, f1_score, roc_auc_score, mean_squared_error, r2_score, confusion_matrix) and unsupervised learning (silhouette_score).

[20]:
```
# importing all required libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, cross_val_score,␣
 ↪GridSearchCV
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪confusion_matrix
from sklearn.preprocessing import StandardScaler, MinMaxScaler, LabelEncoder,␣
 ↪Normalizer
from sklearn.linear_model import LinearRegression
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.metrics import silhouette_score, mean_squared_error, r2_score

# load iris dataset for classification
```

```python
iris = load_iris()
X = iris.data
y = iris.target

# split into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Random Forest Classification
clf = RandomForestClassifier()
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)

print("Random Forest Classification Accuracy:", accuracy_score(y_test, y_pred))
print()

print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print()

print("Classification Report:\n", classification_report(y_test, y_pred))
print()

# Standardization (Z-score normalization)
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
print("First 3 rows after standard scaling:\n", X_scaled[:3])
print()

# Normalization (scaling between 0 and 1)
normalizer = MinMaxScaler()
X_normalized = normalizer.fit_transform(X)
print("First 3 rows after normalization:\n", X_normalized[:3])
print()

# Encode target labels (though iris target is already encoded)
encoder = LabelEncoder()
y_encoded = encoder.fit_transform(y)
print("Encoded class labels:", y_encoded[:10])
print()

# Cross-validation
cv_scores = cross_val_score(clf, X, y, cv=5)
print("Cross-validation scores:", cv_scores)
print()
print("Mean cross-validation accuracy:", np.mean(cv_scores))
print()
```

```python
# GridSearchCV for best hyperparameter
params = {'n_estimators': [50, 100]}
grid = GridSearchCV(RandomForestClassifier(), param_grid=params, cv=3)
grid.fit(X_train, y_train)
print("Best parameters from GridSearch:", grid.best_params_)
print()

# KMeans clustering (unsupervised)
kmeans = KMeans(n_clusters=3, random_state=42)
kmeans.fit(X[:, :2])  # use first 2 features for simplicity
print("KMeans cluster centers:\n", kmeans.cluster_centers_)
print()

print("KMeans Silhouette Score:", silhouette_score(X[:, :2], kmeans.labels_))
print()

# PCA dimensionality reduction
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)
print("PCA reduced shape:", X_pca.shape)
print()
```

```
Random Forest Classification Accuracy: 1.0

Confusion Matrix:
 [[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]

Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       1.00      1.00      1.00         9
           2       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


First 3 rows after standard scaling:
 [[-0.90068117  1.01900435 -1.34022653 -1.3154443 ]
 [-1.14301691 -0.13197948 -1.34022653 -1.3154443 ]
 [-1.38535265  0.32841405 -1.39706395 -1.3154443 ]]

First 3 rows after normalization:
```

```
 [[0.22222222 0.625      0.06779661 0.04166667]
 [0.16666667 0.41666667 0.06779661 0.04166667]
 [0.11111111 0.5        0.05084746 0.04166667]]

Encoded class labels: [0 0 0 0 0 0 0 0 0 0]

Cross-validation scores: [0.96666667 0.96666667 0.93333333 0.96666667 1.
]

Mean cross-validation accuracy: 0.9666666666666668

Best parameters from GridSearch: {'n_estimators': 50}

KMeans cluster centers:
 [[6.81276596 3.07446809]
 [5.77358491 2.69245283]
 [5.006      3.428     ]]

KMeans Silhouette Score: 0.4450525692083638

PCA reduced shape: (150, 2)
```

Matplotlib:

What it is: A comprehensive library for creating static, animated, and interactive visualizations in Python. It provides an object-oriented API for embedding plots into applications using general-purpose GUI toolkits like Tkinter, wxPython, Qt, or GTK.

What it is used for: Matplotlib is the foundation for creating almost any type of 2D plot, and some 3D plots. It's extensively used for exploratory data analysis to visualize data distributions, relationships between variables, and to present the results of data analysis and machine learning models in a clear and understandable manner. Its fine-grained control allows for highly customized and publication-quality figures.

Key Operations/Features:

Core Plotting Functions: plt.plot() for line plots, plt.scatter() for scatter plots, plt.hist() for histograms, plt.bar() for bar charts, plt.boxplot() for box plots, and plt.imshow() for image displays/heatmaps.

Figure and Axes Management: plt.figure() to create a new figure, and plt.subplot() or plt.subplots() to create multiple plots within a single figure.

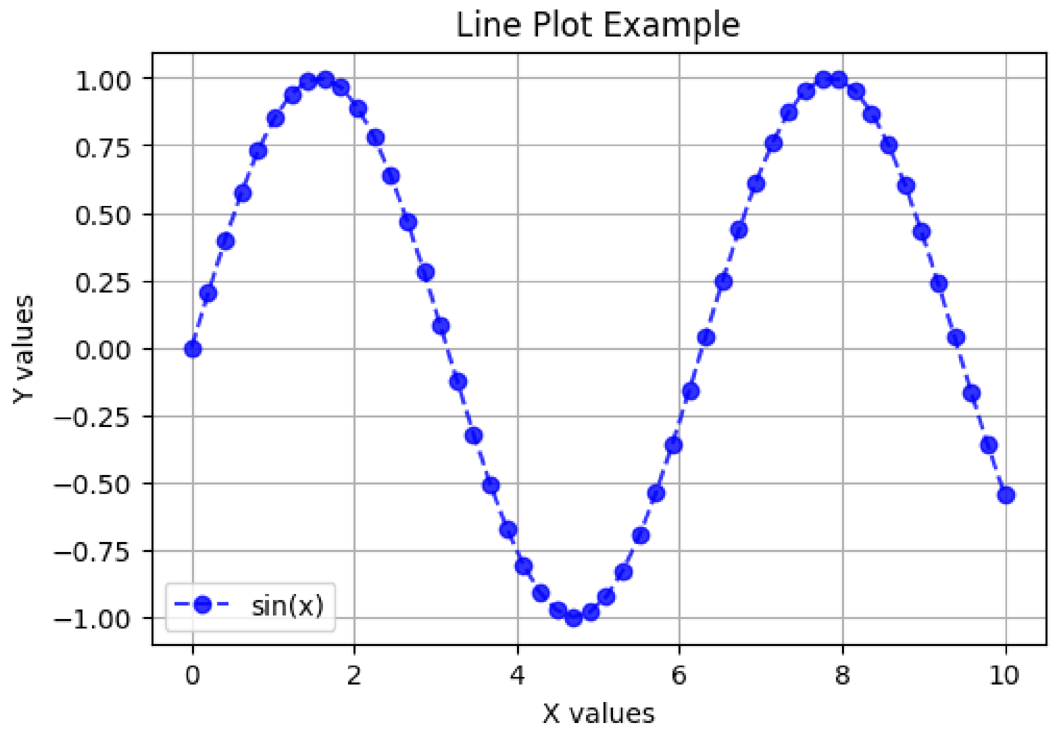
Customization: Extensive options for customizing plot elements including plt.xlabel(), plt.ylabel(), plt.title() for labels and titles; plt.legend() for plot legends; plt.grid() for grid lines; setting colors, line styles, markers, and transparency (alpha).

Saving Plots: plt.savefig() to save plots in various formats (PNG, JPG, PDF, SVG).

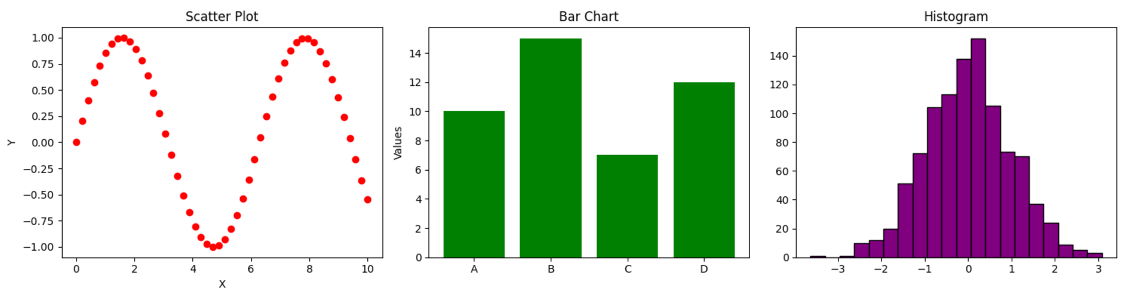
Integration with Pandas and Seaborn: Pandas DataFrames have a built-in .plot() method that uses Matplotlib. Seaborn, another popular visualization library, is built on Matplotlib and provides a high-level interface for drawing attractive and informative statistical graphics.

[5]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns

# Sample data
x = np.linspace(0, 10, 50)
y = np.sin(x)
categories = ['A', 'B', 'C', 'D']
values = [10, 15, 7, 12]
data = np.random.randn(1000)

# Line plot with customization
plt.figure(figsize=(6, 4))
plt.plot(x, y, color='blue', linestyle='--', marker='o', label='sin(x)',␣
 ↪alpha=0.8)
plt.title('Line Plot Example')
plt.xlabel('X values')
plt.ylabel('Y values')
plt.grid(True)
plt.legend()
plt.savefig("line_plot.png")  # Save the plot
plt.show()

# Scatter, Bar, Histogram as subplots
fig, axs = plt.subplots(1, 3, figsize=(15, 4))

# Scatter
axs[0].scatter(x, y, color='red')
axs[0].set_title('Scatter Plot')
axs[0].set_xlabel('X')
axs[0].set_ylabel('Y')

# Bar chart
axs[1].bar(categories, values, color='green')
axs[1].set_title('Bar Chart')
axs[1].set_ylabel('Values')

# Histogram
axs[2].hist(data, bins=20, color='purple', edgecolor='black')
axs[2].set_title('Histogram')

plt.tight_layout()
plt.savefig("subplot_visuals.png")
plt.show()
```

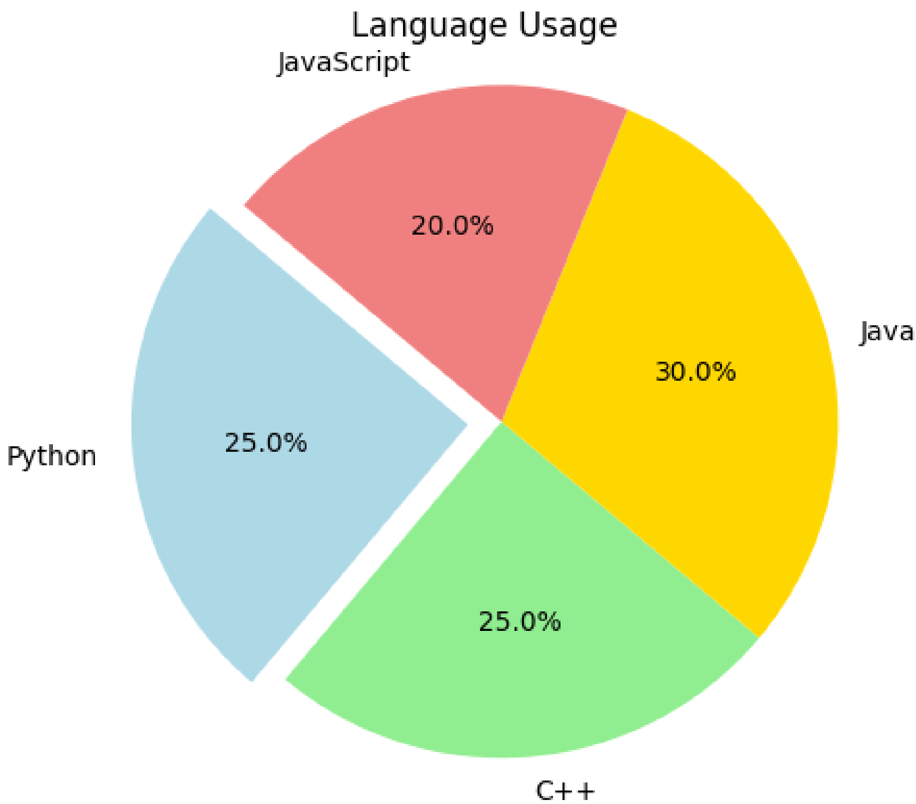
```
# Pie chart
sizes = [25, 25, 30, 20]
labels = ['Python', 'C++', 'Java', 'JavaScript']
colors = ['lightblue', 'lightgreen', 'gold', 'lightcoral']
explode = [0.1, 0, 0, 0]

plt.figure(figsize=(5, 5))
plt.pie(sizes, labels=labels, colors=colors, explode=explode, autopct='%1.
  ↪1f%%', startangle=140)
plt.title("Language Usage")
plt.axis('equal')
plt.savefig("pie_chart.png")
plt.show()

# Box plot
data_box = np.random.normal(100, 10, 200)
plt.boxplot(data_box)
plt.title("Box Plot")
plt.ylabel("Values")
plt.savefig("box_plot.png")
plt.show()

# Heatmap using imshow()
matrix = np.random.rand(5, 5)
plt.imshow(matrix, cmap='viridis', interpolation='nearest')
plt.colorbar()
plt.title("Heatmap with imshow()")
plt.savefig("heatmap.png")
plt.show()

# Integration with Pandas
df = pd.DataFrame({
    'x': np.arange(10),
    'y': np.random.rand(10)
})
df.plot(x='x', y='y', kind='line', title="Pandas Line Plot")
plt.savefig("pandas_plot.png")
plt.show()

# Seaborn integration
iris = sns.load_dataset("iris")
sns.scatterplot(data=iris, x='sepal_length', y='sepal_width', hue='species')
plt.title("Seaborn Scatterplot - Iris Dataset")
plt.savefig("seaborn_scatter.png")
plt.show()
```

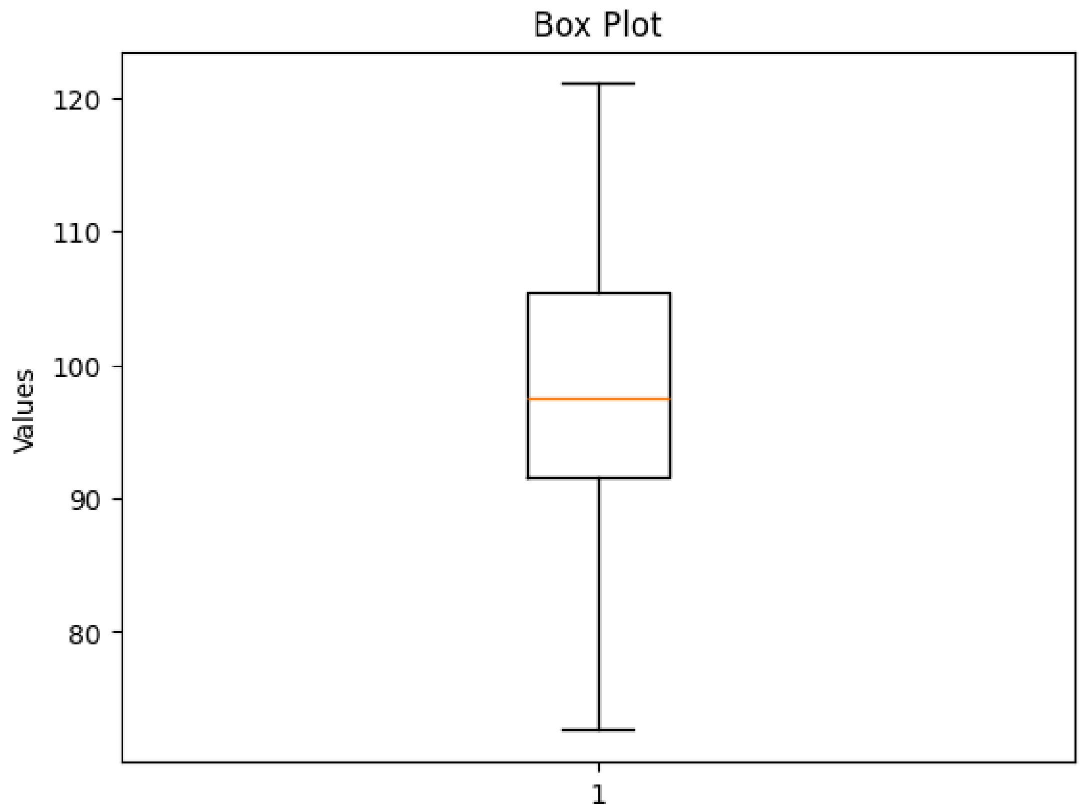


Line Plot Example
Y values
X values
sin(x)
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
2
4
6
8
10

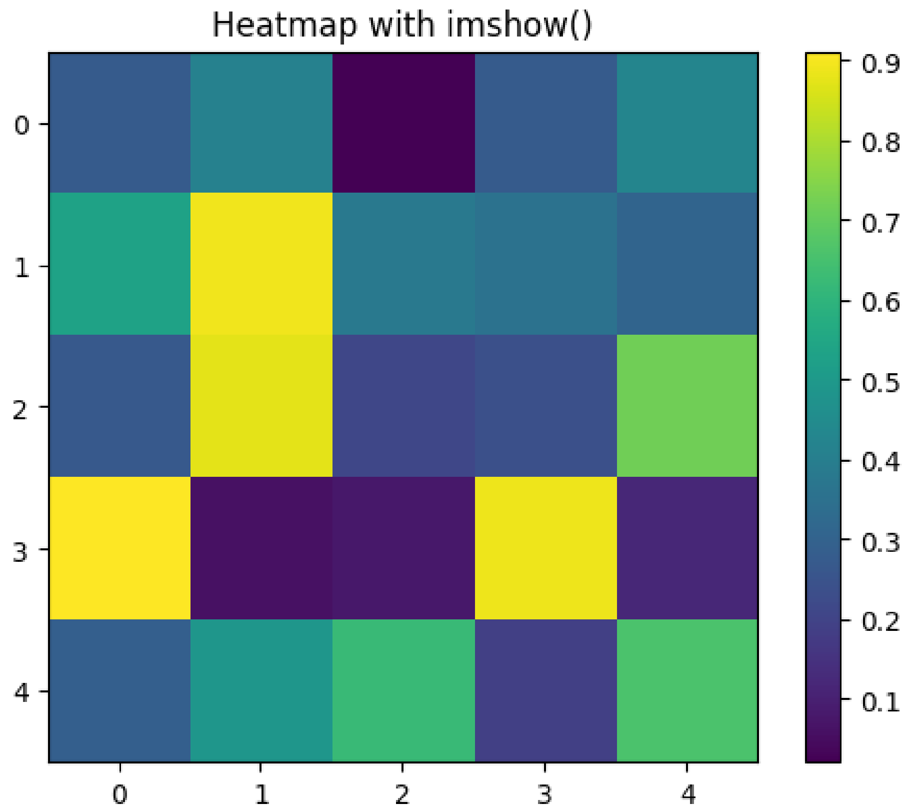


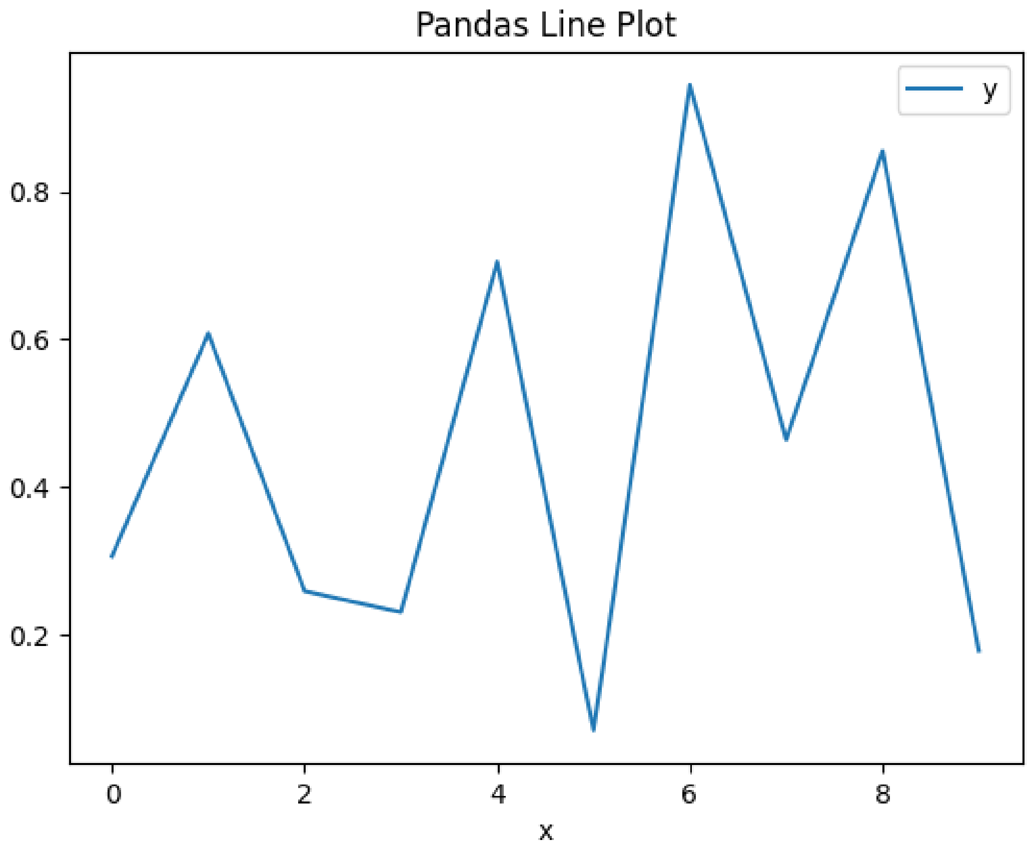
Scatter Plot
Y
X
Bar Chart
Values
A
B
C
D
Histogram

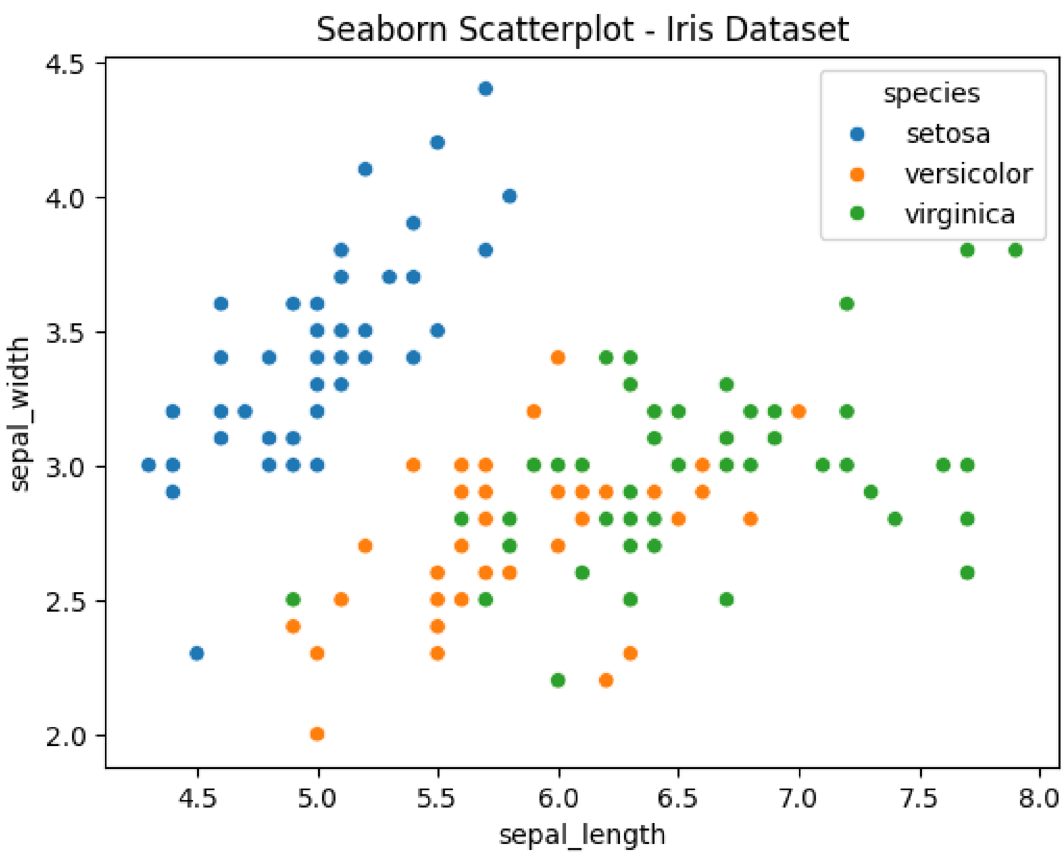

Language Usage
JavaScript
20.0%
Java
30.0%
Python
25.0%
25.0%
C++



Box Plot
Values
120
110
100
90
80
1


Heatmap with imshow()
0
1
2
3
4
0
1
2
3
4
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1


Pandas Line Plot
y
0.2
0.4
0.6
0.8
0
2
4
6
8
x



2. Explore public repositories such as the UCI Machine Learning Repository (UCI Repository) and Kaggle Datasets. Download the following datasets and identify the appropriate machine learning model to be used (e.g., Supervised, Unsupervised, Semi-supervised, Regression, Classification) [CO1, K3].
   i.) Loan amount prediction
   ii.) Handwritten character recognition
   iii.) Classification of Email spam and MNIST data
   iv.) Predicting Diabetes
   v.) Iris Dataset

[6]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

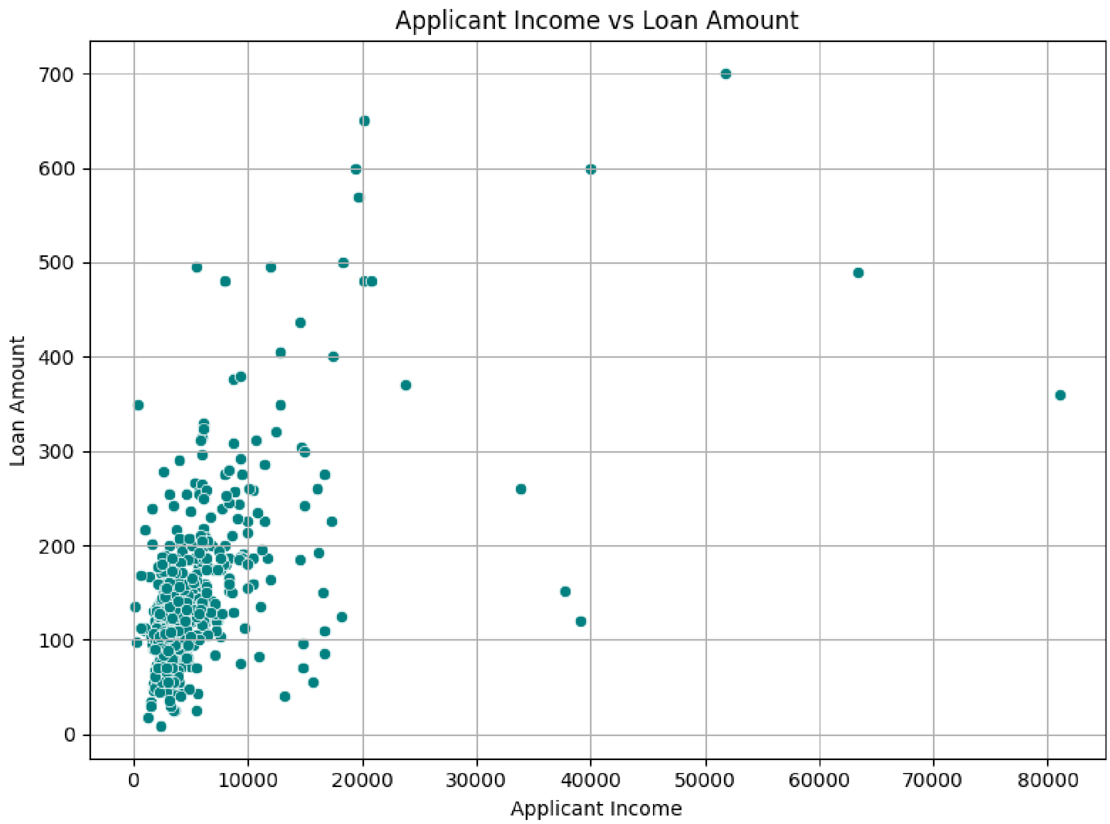
i) Loan Amount Prediction Model Type:

Supervised Learning – Regression

Justification: Loan amount prediction involves predicting a continuous numeric value (loan amount) based on other features such as income, employment status, credit history, etc. Since the dataset contains both the input features and the actual loan amount as output, this is a supervised learning problem. And because the target is a numeric value, regression is the right approach.

[7]:
```python
# 1. Import libraries
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from google.colab import drive

# 2. Mount Google Drive and load dataset
drive.mount('/content/drive')
df = pd.read_csv('/content/drive/MyDrive/loan_prediction.csv')

# 3. Display correlation between LoanAmount and incomes
print("Correlation Matrix:")
print(df[['LoanAmount', 'ApplicantIncome', 'CoapplicantIncome']].corr())

# 4. Scatterplot of ApplicantIncome vs LoanAmount
plt.figure(figsize=(8,6))
sns.scatterplot(x='ApplicantIncome', y='LoanAmount', data=df, color='teal')
plt.title("Applicant Income vs Loan Amount")
plt.xlabel("Applicant Income")
plt.ylabel("Loan Amount")
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
Correlation Matrix:
                   LoanAmount  ApplicantIncome  CoapplicantIncome
LoanAmount           1.000000         0.570909           0.188619
ApplicantIncome      0.570909         1.000000          -0.116605
CoapplicantIncome    0.188619        -0.116605           1.000000
```



ii) Handwritten Character Recognition Model Type:

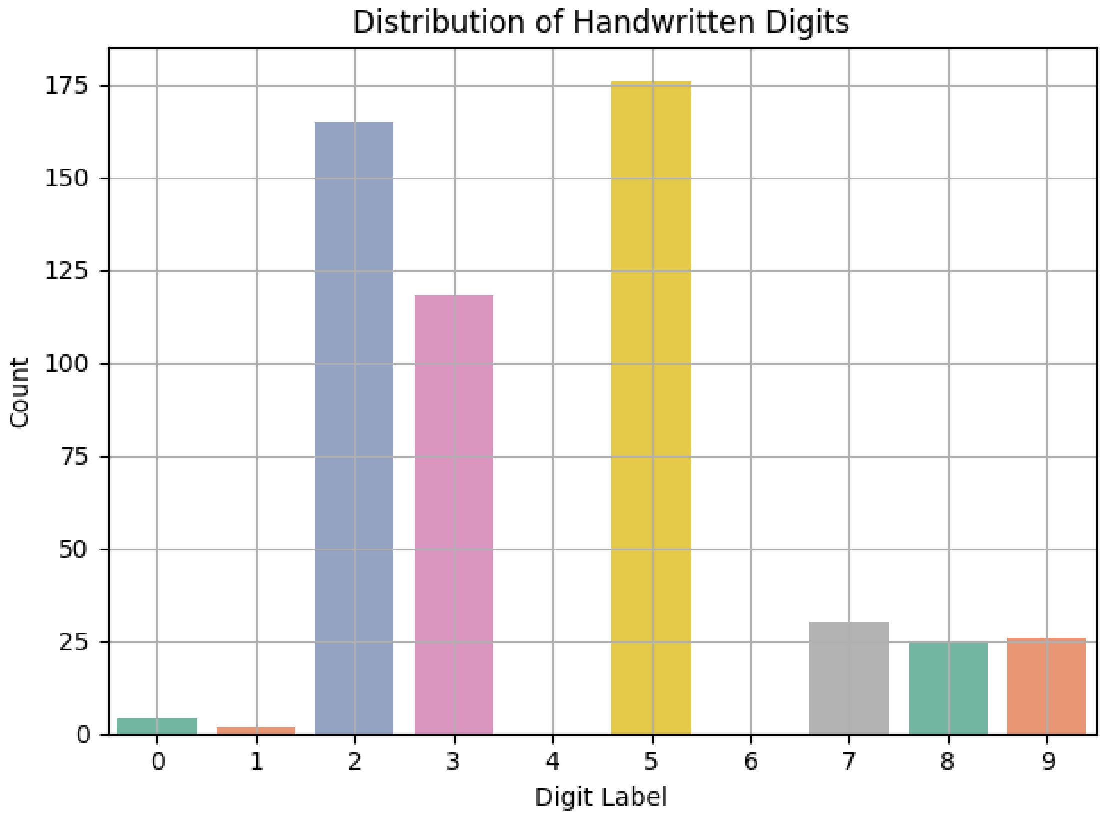
Supervised Learning – Classification

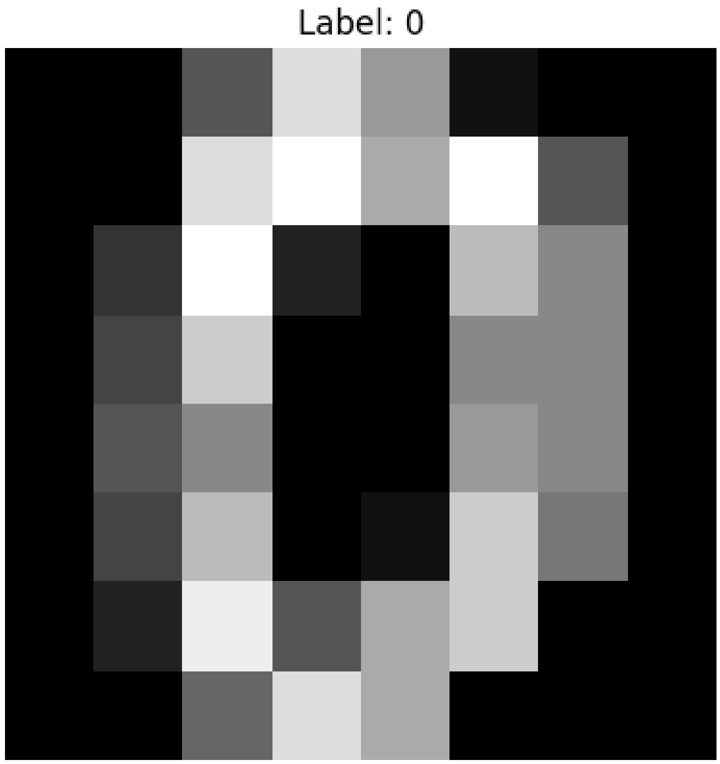
Justification: In handwritten character recognition, each input is an image (or pixel array) of a character and it is labeled with the actual character (like 'A', 'B', 'C'). This means the model learns to classify images into one of several categories. Since labels are given, it's a supervised classification problem.

[21]:
```
# 1. Import libraries
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.datasets import load_digits
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

# 2. Load dataset
digits = load_digits()
X = digits.data
y = digits.target
```

```python
# 3. Convert to DataFrame for visualization
df = pd.DataFrame(X)
df['label'] = y

# 4. Show class distribution
sns.countplot(x='label', data=df, palette='Set2')
plt.title("Distribution of Handwritten Digits")
plt.xlabel("Digit Label")
plt.ylabel("Count")
plt.grid(True)
plt.tight_layout()
plt.show()

# 5. Display a sample digit image
plt.imshow(digits.images[0], cmap='gray')
plt.title(f'Label: {digits.target[0]}')
plt.axis('off')
plt.show()

# 6. Split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)

# 7. Train the model
model = LogisticRegression(max_iter=3000)
model.fit(X_train, y_train)

# 8. Evaluate the model
y_pred = model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
/tmp/ipython-input-1457417528.py:20: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(x='label', data=df, palette='Set2')
```


Distribution of Handwritten Digits
Count
Digit Label
0
25
50
75
100
125
150
175
0
1
2
3
4
5
6
7
8
9




```
Accuracy: 0.9685185185185186

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        53
           1       0.96      0.94      0.95        50
           2       0.96      1.00      0.98        47
           3       0.98      0.96      0.97        54
           4       1.00      0.97      0.98        60
           5       0.94      0.95      0.95        66
           6       0.96      0.98      0.97        53
           7       1.00      0.96      0.98        55
           8       0.91      0.98      0.94        43
           9       0.97      0.95      0.96        59

    accuracy                           0.97       540
   macro avg       0.97      0.97      0.97       540
weighted avg       0.97      0.97      0.97       540
```

iii) Classification of Email Spam and MNIST Data Model Type:

Supervised Learning – Classification

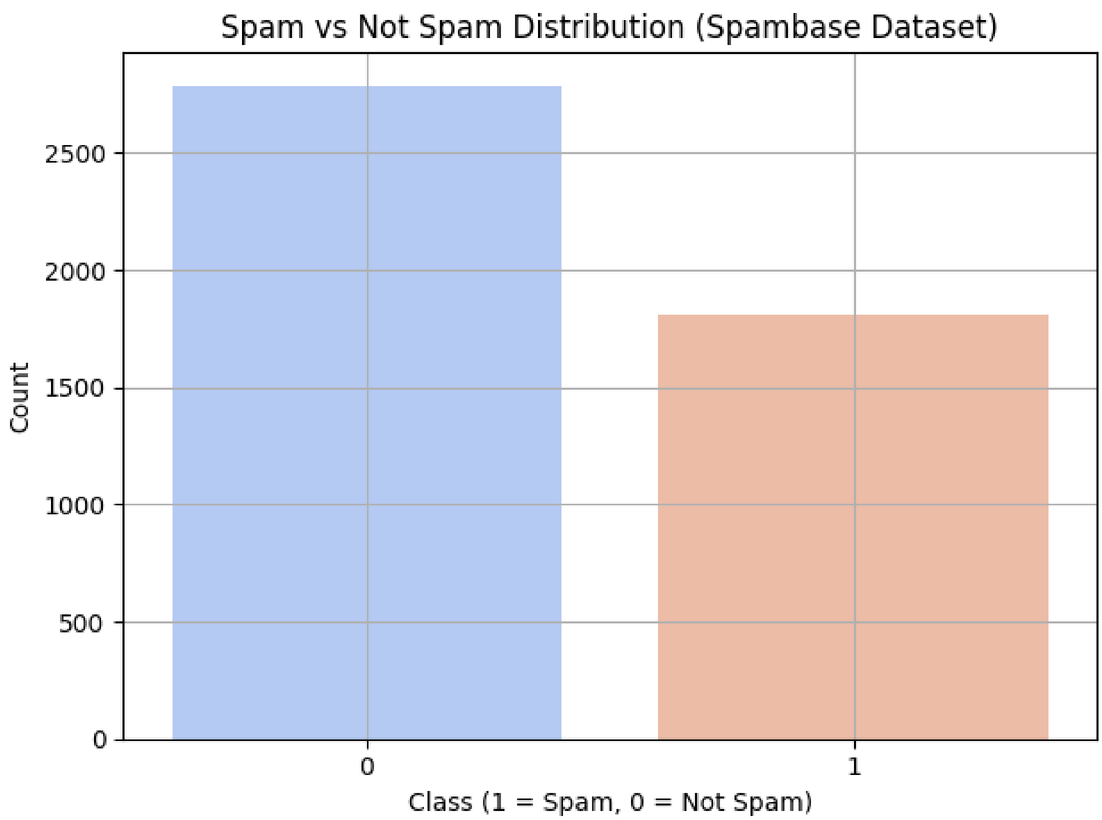
Justification: Both email spam detection and MNIST are classic examples of classification. In spam detection, each email is labeled as "spam" or "not spam". In MNIST, each image is labeled with a digit (0-9). Since the correct class is known for every example, both are supervised classification tasks.

[22]:
```
# 1. Install ucimlrepo
!pip install ucimlrepo

# 2. Import libraries
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from ucimlrepo import fetch_ucirepo
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, classification_report

# 3. Load dataset from UCI
spambase = fetch_ucirepo(id=94)

# 4. Extract features and target
X = spambase.data.features
y = spambase.data.targets

# 5. Combine features and target for visualization
df = pd.concat([X, y], axis=1)
target_col = y.columns[0]  # Usually 'class' or 'target'

# 6. Visualize class distribution
sns.countplot(x=target_col, data=df, palette="coolwarm")
plt.title("Spam vs Not Spam Distribution (Spambase Dataset)")
plt.xlabel(f"{target_col} (1 = Spam, 0 = Not Spam)")
plt.ylabel("Count")
plt.grid(True)
plt.tight_layout()
plt.show()

# 7. Split dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y[target_col],␣
↪test_size=0.2, random_state=0)

# 8. Train Naive Bayes model
model = GaussianNB()
model.fit(X_train, y_train)

# 9. Evaluate model
```

```python
y_pred = model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Requirement already satisfied: ucimlrepo in /usr/local/lib/python3.11/dist-
packages (0.0.7)
Requirement already satisfied: pandas>=1.0.0 in /usr/local/lib/python3.11/dist-
packages (from ucimlrepo) (2.2.2)
Requirement already satisfied: certifi>=2020.12.5 in
/usr/local/lib/python3.11/dist-packages (from ucimlrepo) (2025.7.14)
Requirement already satisfied: numpy>=1.23.2 in /usr/local/lib/python3.11/dist-
packages (from pandas>=1.0.0->ucimlrepo) (2.0.2)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.11/dist-packages (from pandas>=1.0.0->ucimlrepo)
(2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-
packages (from pandas>=1.0.0->ucimlrepo) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-
packages (from pandas>=1.0.0->ucimlrepo) (2025.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-
packages (from python-dateutil>=2.8.2->pandas>=1.0.0->ucimlrepo) (1.17.0)
```

```
/tmp/ipython-input-3789337961.py:25: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(x=target_col, data=df, palette="coolwarm")
```




```
Accuracy: 0.8067318132464713

Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.72      0.81       538
           1       0.70      0.93      0.80       383

    accuracy                           0.81       921
   macro avg       0.82      0.82      0.81       921
weighted avg       0.84      0.81      0.81       921
```

iv) Predicting Diabetes Model Type:

Supervised Learning – Classification

Justification: The diabetes dataset contains health-related features for patients and a label indicating whether or not the person has diabetes. The goal is to classify whether a person has diabetes or not — making it a binary classification task under supervised learning.

[23]:

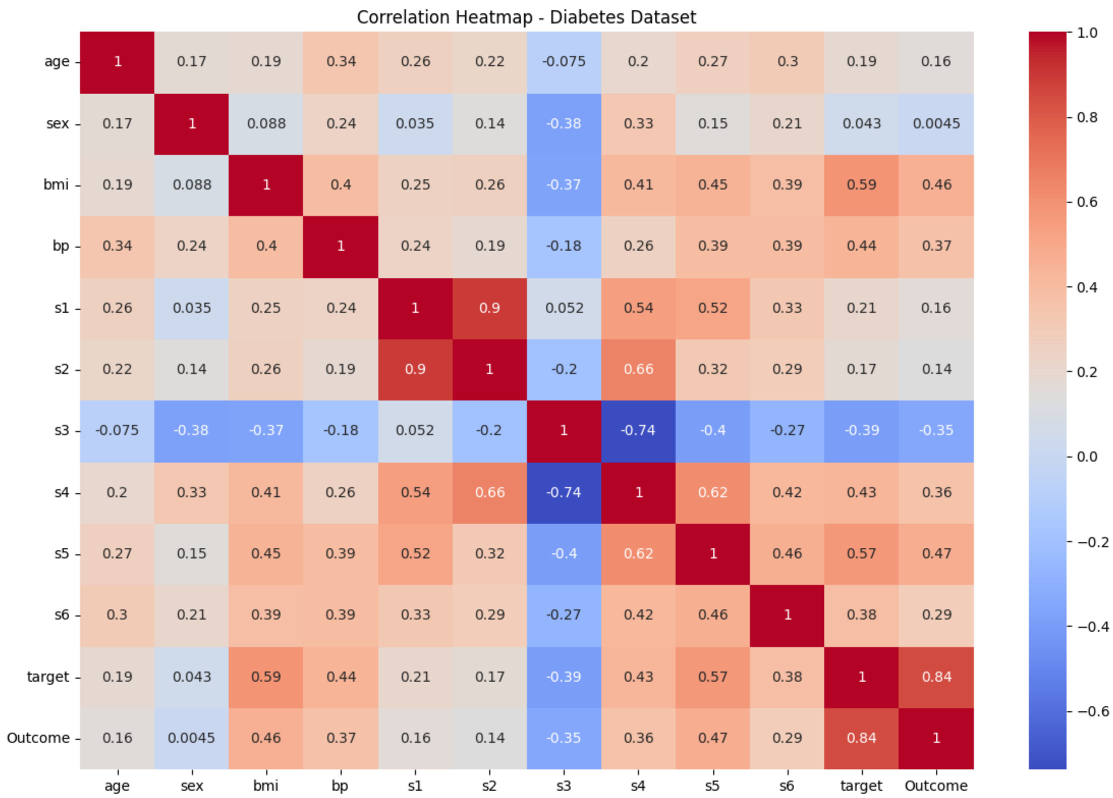
```python
# 1. Import libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.datasets import load_diabetes
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, accuracy_score,␣
↪confusion_matrix, roc_curve, auc

# 2. Load diabetes dataset from sklearn
data = load_diabetes(as_frame=True)
df = data.frame

# 3. EDA - Show info and description
print(df.info())
print(df.describe())

# 4. Convert continuous target into binary Outcome (0 = low, 1 = high)
df['Outcome'] = (df['target'] > df['target'].median()).astype(int)

# 5. Correlation heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
plt.title("Correlation Heatmap - Diabetes Dataset")
plt.tight_layout()
plt.show()

# 6. Class distribution
sns.countplot(x='Outcome', data=df, palette='Set2')
plt.title("Diabetes Outcome Distribution (0 = Low, 1 = High)")
plt.xlabel("Outcome")
plt.ylabel("Count")
plt.grid(True)
plt.tight_layout()
plt.show()

# 7. Preprocessing
X = df.drop(columns=['target', 'Outcome'])
y = df['Outcome']
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# 8. Train-test split
```

```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.
 ↪25, random_state=42)

# 9. Train Random Forest model
clf = RandomForestClassifier()
clf.fit(X_train, y_train)

# 10. Evaluation
y_pred = clf.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))

# 11. Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=["Low", "High"], yticklabels=["Low", "High"])
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.tight_layout()
plt.show()

# 12. Feature Importance
feature_names = X.columns
importances = clf.feature_importances_
indices = np.argsort(importances)[::-1]
plt.figure(figsize=(10, 6))
sns.barplot(x=importances[indices], y=feature_names[indices])
plt.title("Feature Importances (Random Forest)")
plt.xlabel("Importance")
plt.ylabel("Features")
plt.tight_layout()
plt.show()

# 13. ROC Curve
y_proba = clf.predict_proba(X_test)[:, 1]
fpr, tpr, _ = roc_curve(y_test, y_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(6, 5))
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (AUC = %0.2f)' %␣
 ↪roc_auc)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlim([-0.01, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
```

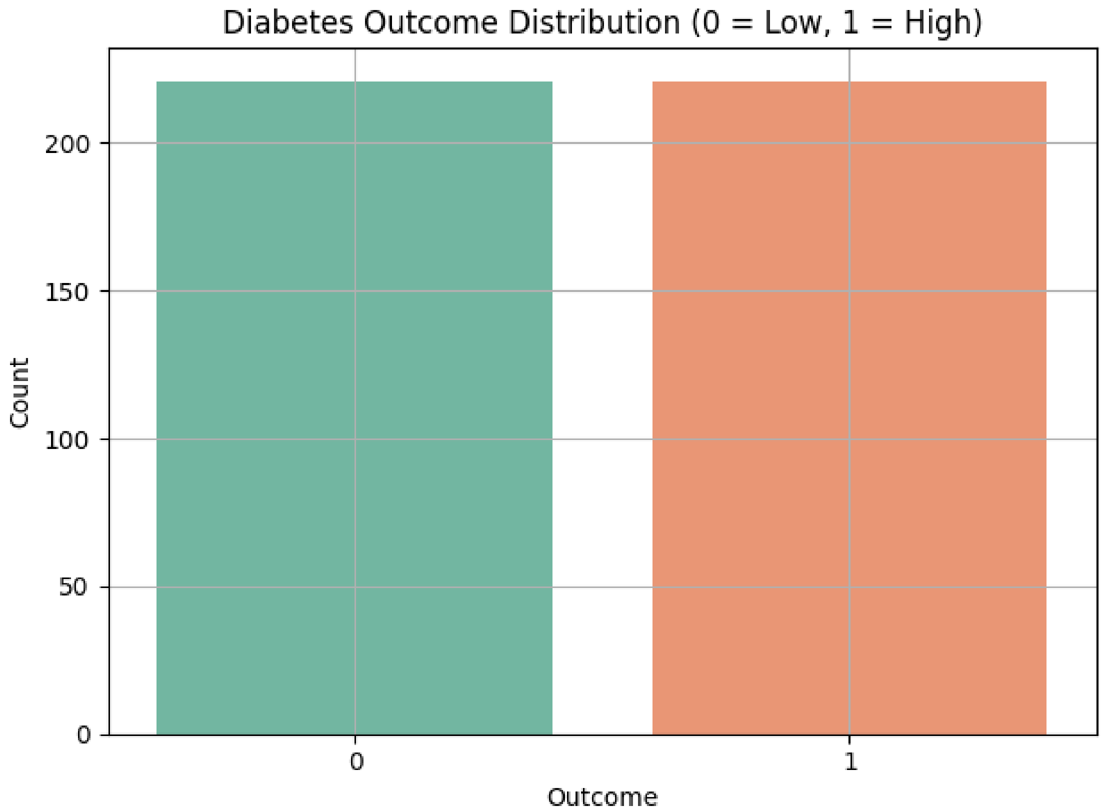
```python
plt.ylabel("True Positive Rate")
plt.title("Receiver Operating Characteristic")
plt.legend(loc="lower right")
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 442 entries, 0 to 441
Data columns (total 11 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   age     442 non-null    float64
 1   sex     442 non-null    float64
 2   bmi     442 non-null    float64
 3   bp      442 non-null    float64
 4   s1      442 non-null    float64
 5   s2      442 non-null    float64
 6   s3      442 non-null    float64
 7   s4      442 non-null    float64
 8   s5      442 non-null    float64
 9   s6      442 non-null    float64
 10  target  442 non-null    float64
dtypes: float64(11)
memory usage: 38.1 KB
None
                age           sex           bmi            bp            s1  \
count  4.420000e+02  4.420000e+02  4.420000e+02  4.420000e+02  4.420000e+02
mean  -2.511817e-19  1.230790e-17 -2.245564e-16 -4.797570e-17 -1.381499e-17
std    4.761905e-02  4.761905e-02  4.761905e-02  4.761905e-02  4.761905e-02
min   -1.072256e-01 -4.464164e-02 -9.027530e-02 -1.123988e-01 -1.267807e-01
25%   -3.729927e-02 -4.464164e-02 -3.422907e-02 -3.665608e-02 -3.424784e-02
50%    5.383060e-03 -4.464164e-02 -7.283766e-03 -5.670422e-03 -4.320866e-03
75%    3.807591e-02  5.068012e-02  3.124802e-02  3.564379e-02  2.835801e-02
max    1.107267e-01  5.068012e-02  1.705552e-01  1.320436e-01  1.539137e-01

                 s2            s3            s4            s5            s6  \
count  4.420000e+02  4.420000e+02  4.420000e+02  4.420000e+02  4.420000e+02
mean   3.918434e-17 -5.777179e-18 -9.042540e-18  9.293722e-17  1.130318e-17
std    4.761905e-02  4.761905e-02  4.761905e-02  4.761905e-02  4.761905e-02
min   -1.156131e-01 -1.023071e-01 -7.639450e-02 -1.260971e-01 -1.377672e-01
25%   -3.035840e-02 -3.511716e-02 -3.949338e-02 -3.324559e-02 -3.317903e-02
50%   -3.819065e-03 -6.584468e-03 -2.592262e-03 -1.947171e-03 -1.077698e-03
75%    2.984439e-02  2.931150e-02  3.430886e-02  3.243232e-02  2.791705e-02
max    1.987880e-01  1.811791e-01  1.852344e-01  1.335973e-01  1.356118e-01

           target
```

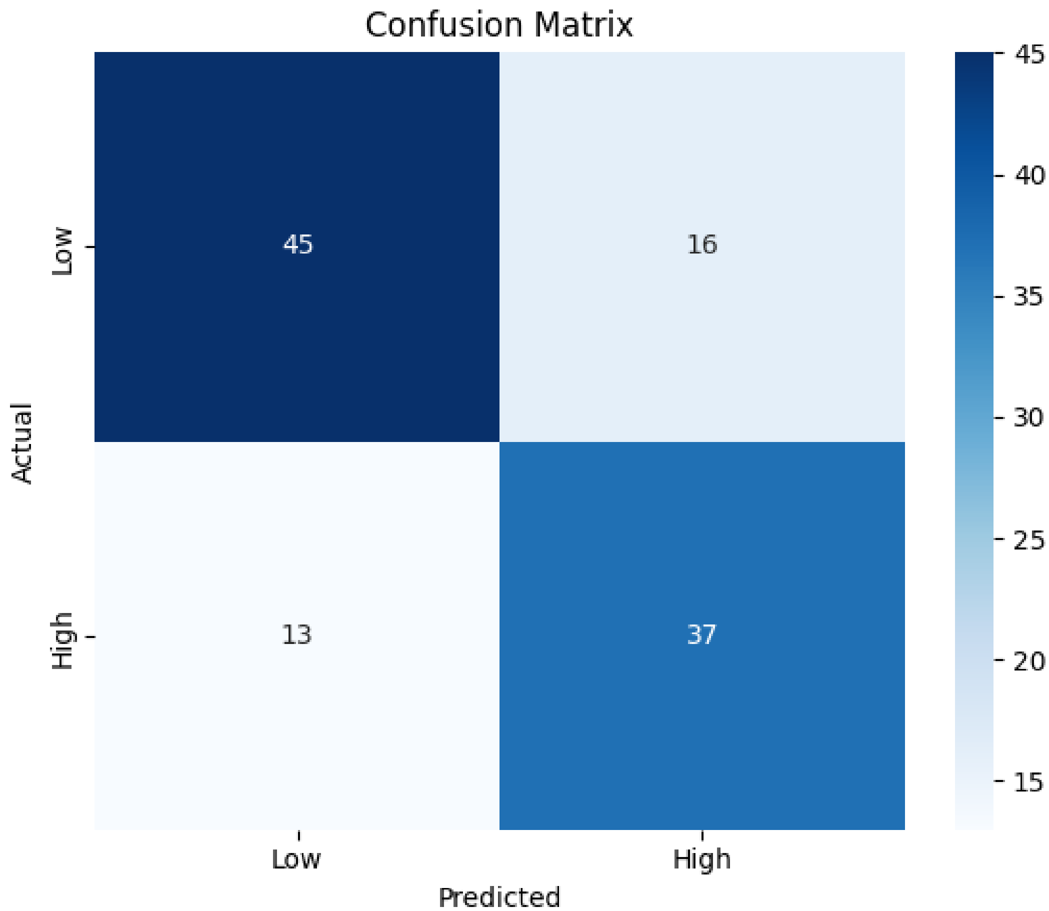
```
count   442.000000
mean    152.133484
std      77.093005
min      25.000000
25%      87.000000
50%     140.500000
75%     211.500000
max     346.000000
```



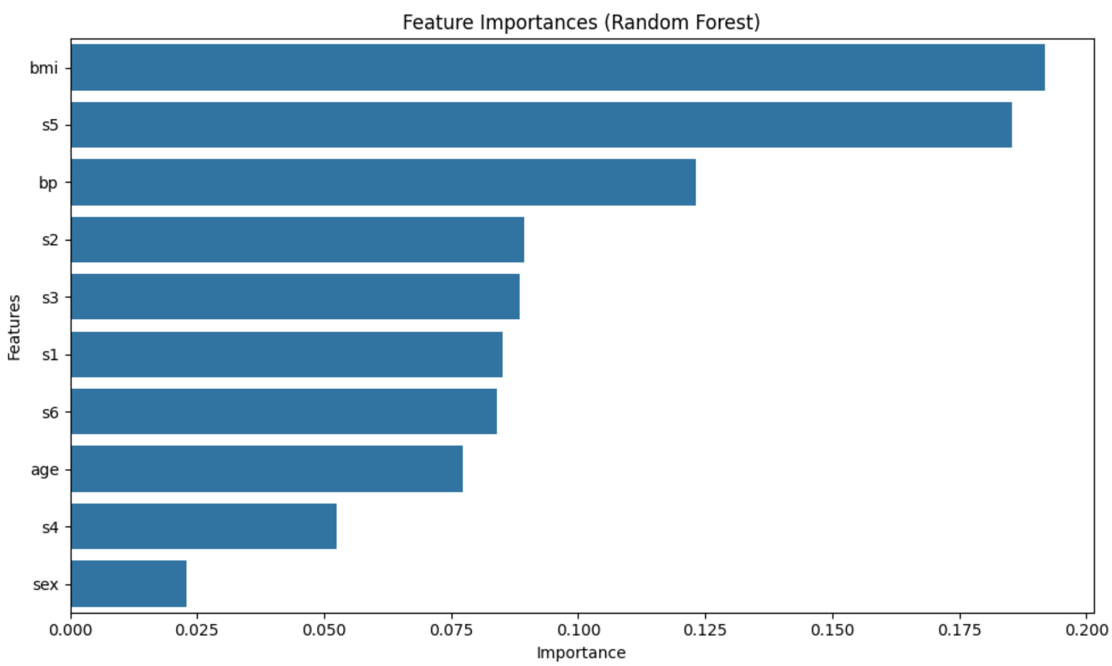

```
/tmp/ipython-input-3132952514.py:31: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(x='Outcome', data=df, palette='Set2')
```



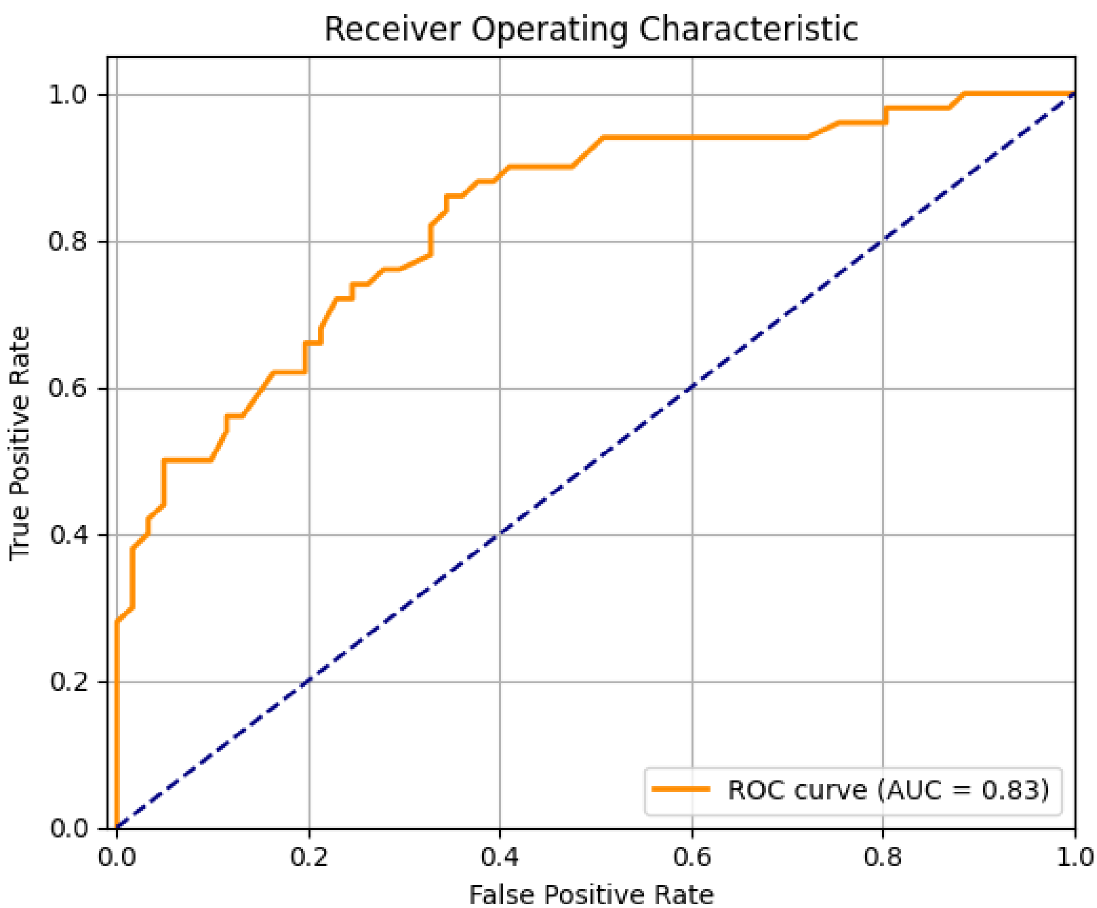

```
Accuracy: 0.7387387387387387

Classification Report:
              precision    recall  f1-score   support

           0       0.78      0.74      0.76        61
           1       0.70      0.74      0.72        50

    accuracy                           0.74       111
   macro avg       0.74      0.74      0.74       111
weighted avg       0.74      0.74      0.74       111
```



Confusion Matrix
45
16
13
37
Low
High
Actual
Predicted
45
40
35
30
25
20
15



Feature Importances (Random Forest)
bmi
s5
bp
s2
s3
s1
s6
age
s4
sex
Features
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200
Importance



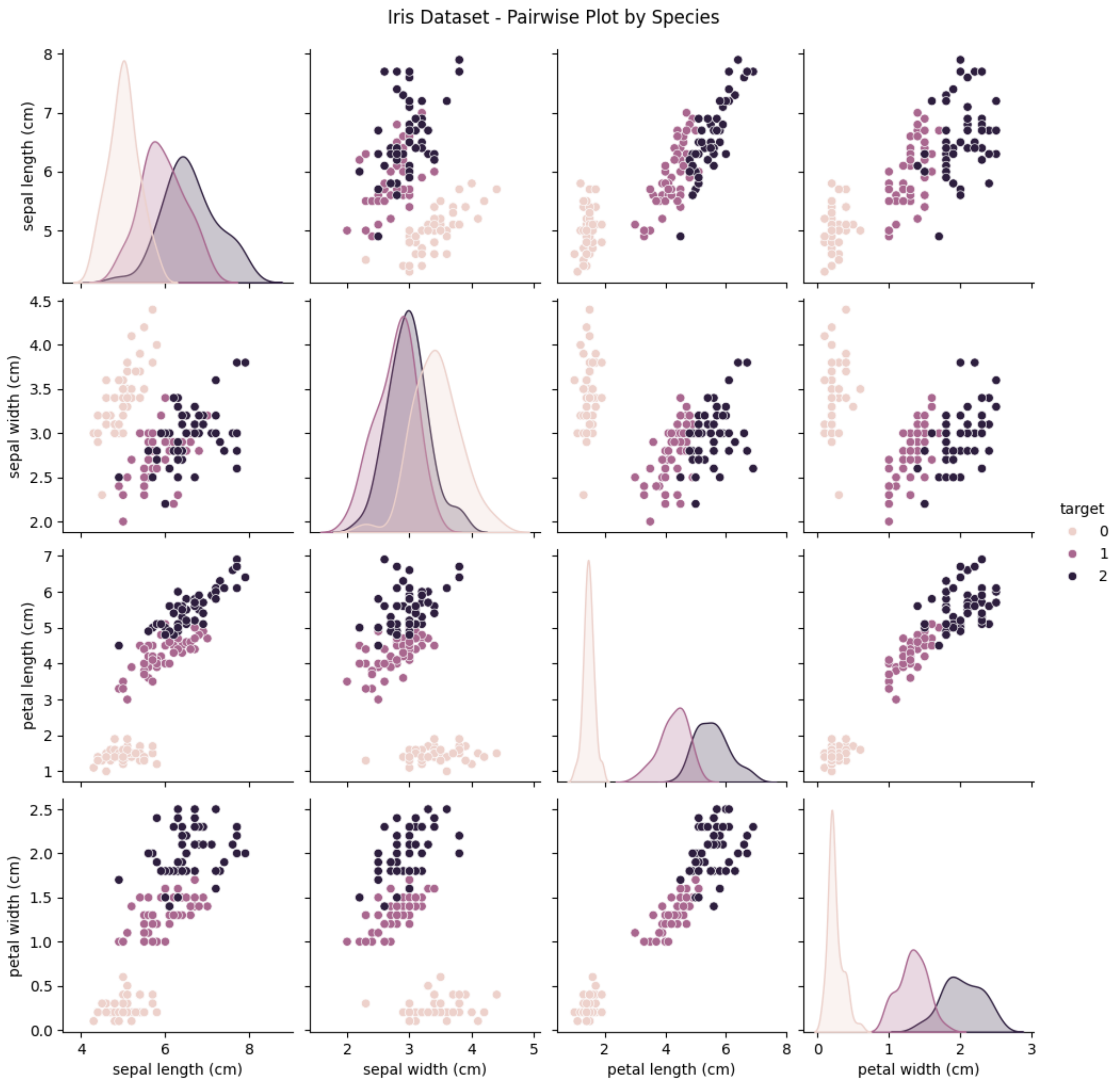
v) Iris Dataset Model Type:

Supervised Learning – Classification

Justification: The Iris dataset has measurements of flower parts (sepal and petal lengths/widths) and a label indicating the flower species (Setosa, Versicolor, Virginica). Since the target is a category and labels are known, this is a supervised classification problem.

[11]:
```
import seaborn as sns
from sklearn.datasets import load_iris
import pandas as pd
import matplotlib.pyplot as plt

iris = load_iris(as_frame=True)
df = iris.frame

sns.pairplot(df, hue='target')
```

```
plt.suptitle("Iris Dataset - Pairwise Plot by Species", y=1.02)
plt.show()
```



Dataset	Type of ML Task	Feature Selection Technique	Suitable ML Algorithm
Predicting Diabetes	Classification	SelectKBest (f_regression)	Linear Regression, Random Forest
Classification of Email Spam	Classification	SelectKBest (chi2)	Naive Bayes, Logistic Regression
Iris Dataset	Classification	SelectKBest (chi2)	KNN, Decision Tree
Loan Amount Prediction	Regression	SelectKBest (f_regression)	Linear Regression, XGBoost

Dataset	**Type of ML Task**	**Feature Selection Technique**	**Suitable ML Algorithm**
Handwritten Character Recognition	Classification (Multi)	SelectKBest (chi2)	KNN, SVM

Inference Table:

Dataset	ML Task	Model / Technique
Loan Amount Prediction	Regression (Supervised)	Linear Regression
Handwritten Digit Recognition	Classification (Supervised)	Logistic Regression
Spam Detection	Classification (Supervised)	Logistic Regression with Chi-square Feature Selection
Diabetes Prediction	Classification (Supervised)	Linear Regression with SelectKBest
Iris Dataset	Classification	Random Forest, PCA, KMeans (for clustering)

Learning Outcomes:

- Understood the usage of key ML libraries in Python.
- Learned how to clean, preprocess, and visualize datasets.
- Explored different ML models and their evaluation techniques.
- Identified suitable algorithms for various ML problems.