

## CODE

```
# Import required libraries
```

```
import pandas as pd
```

```
from sklearn.model_selection import train_test_split
```

```
from sklearn.ensemble import RandomForestClassifier
```

```
from sklearn.metrics import accuracy_score, classification_report
```

```
import seaborn as sns
```

```
import matplotlib.pyplot as plt
```

```
# Step 1: Load the Dataset from CSV
```

```
df = pd.read_csv('iris_is.csv', encoding='ISO-8859-1') # Load the dataset
```

```
print(df)
```

```
# Step 2: Perform Basic EDA
```

```
def basic_eda(data):
```

```
    """
```

```
    Basic EDA functions to check the data info, head, description, and missing values
```

```
    """
```

```
    print("First 5 rows of the dataset:\n", data.head())
```

```
    print("\nInfo about the dataset:\n", data.info())
```

```
    print("\nStatistical description of the dataset:\n", data.describe())
```

```
    # Checking for missing values
```

```
    print("\nMissing values in each column:\n", data.isnull().sum())
```

```
# Step 3: Handle Missing Values (if any)
```

```
def handle_missing_values(data):
```

```
    """
```

Handle missing values by filling them with the mean (for numeric columns)

```
"""
```

```
# Select only numeric columns (excluding 'species' column)
```

```
numeric_columns = data.select_dtypes(include=['float64', 'int64']).columns
```

```
data[numeric_columns] = data[numeric_columns].fillna(data[numeric_columns].mean())
```

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

```
return data
```

# Step 4: Data Visualization (Exploratory Data Analysis)

```
def plot_eda(data):
```

```
    """
```

```
    Visualize relationships between features using pairplot and heatmap
```

```
    """
```

```
# Pairplot to see relationships between the features
```

```
sns.pairplot(data, hue='species')
```

```
plt.title("Pairplot of Iris Dataset")
```

```
plt.show()
```

```
# Correlation Heatmap (exclude the 'species' column)
```

```
correlation_matrix = data.drop(columns='species').corr()
```

```
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
```

```
plt.title("Correlation Heatmap")
```

```
plt.show()
```

# Step 5: Data Preprocessing and Model Training

```
def train_model(data):
```

```
    """
```

```
    Function to train a Random Forest model for Iris classification
```

```

"""

# Define features and target variable
X = data.drop(columns=['species'])
y = data['species']

# Split the data into train and test sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create the RandomForestClassifier model
model = RandomForestClassifier(random_state=42)

# Train the model
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# Evaluate the model
print(f"Accuracy: {accuracy_score(y_test, y_pred)}")
print("\nClassification Report:\n", classification_report(y_test, y_pred))

return model, X_train, X_test, y_train, y_test, y_pred

# Step 6: Predicting for New Data
def predict_new_data(model, new_data, feature_names):
    """
    Predict the species of a new Iris flower based on its measurements.
    Ensure new data has the same feature names as the trained model.
    """

```

```
# Convert the new data to a DataFrame with the correct feature names
new_data_df = pd.DataFrame(new_data, columns=feature_names)

# Make the prediction
prediction = model.predict(new_data_df)
print("\nPredicted species for the new flower:", prediction[0])

# Main function to execute the steps
if __name__ == "__main__":
    # Load the data (already done at the top)
    data = df # Using the DataFrame directly since it is already loaded

    # Perform basic EDA
    basic_eda(data)

    # Handle missing values (if any)
    data = handle_missing_values(data)

    # Visualize the data with pairplot and heatmap
    plot_eda(data)

    # Train the model and evaluate
    model, X_train, X_test, y_train, y_test, y_pred = train_model(data)

    # Get the feature names (columns) from the training data
    feature_names = X_train.columns

    # Example: Predicting a new flower's species
    new_flower = [[5.1, 3.5, 1.4, 0.2]] # Sepal length, Sepal width, Petal length, Petal width
```

```
predict_new_data(model, new_flower, feature_names)
```

## OUTPUT

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa
..	...	...	...	...	...
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

[150 rows x 5 columns]

First 5 rows of the dataset:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 150 entries, 0 to 149

Data columns (total 5 columns):

#	Column	Non-Null Count	Dtype
---	--------	----------------	-------

```

--- -----
0  sepal_length  150 non-null  float64
1  sepal_width   150 non-null  float64
2  petal_length  150 non-null  float64
3  petal_width   150 non-null  float64
4  species       150 non-null  object
dtypes: float64(4), object(1)
memory usage: 6.0+ KB

```

Info about the dataset:

None

Statistical description of the dataset:

	sepal_length	sepal_width	petal_length	petal_width
count	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.054000	3.758667	1.198667
std	0.828066	0.433594	1.764420	0.763161
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.350000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

Missing values in each column:

```

sepal_length  0
sepal_width   0
petal_length  0
petal_width   0
species       0

```

dtype: int64

Missing values after handling:

sepal\_length 0

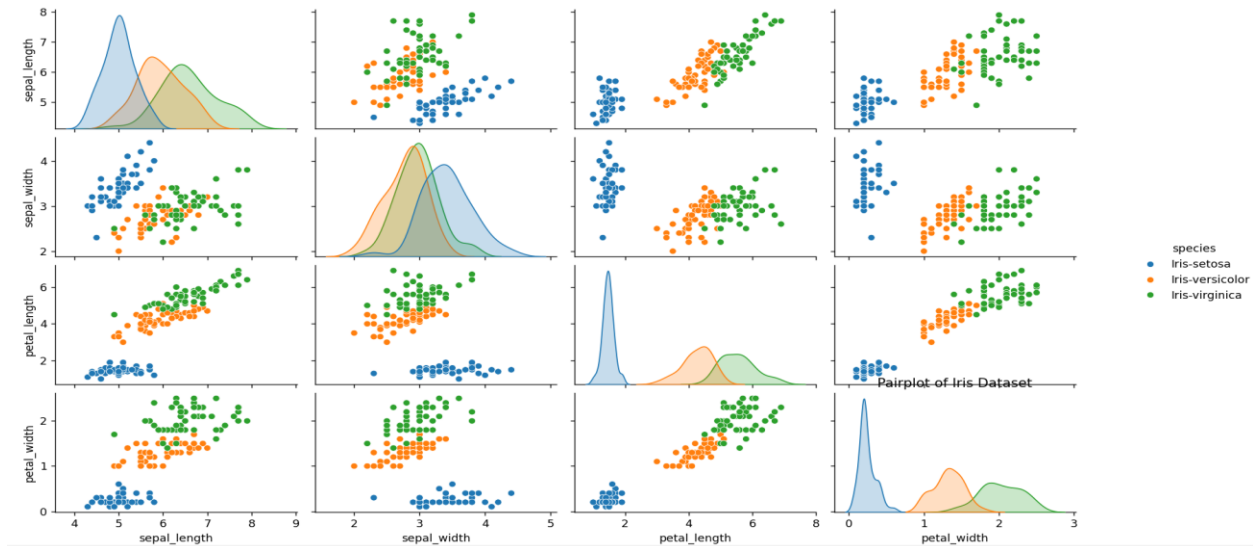
sepal\_width 0

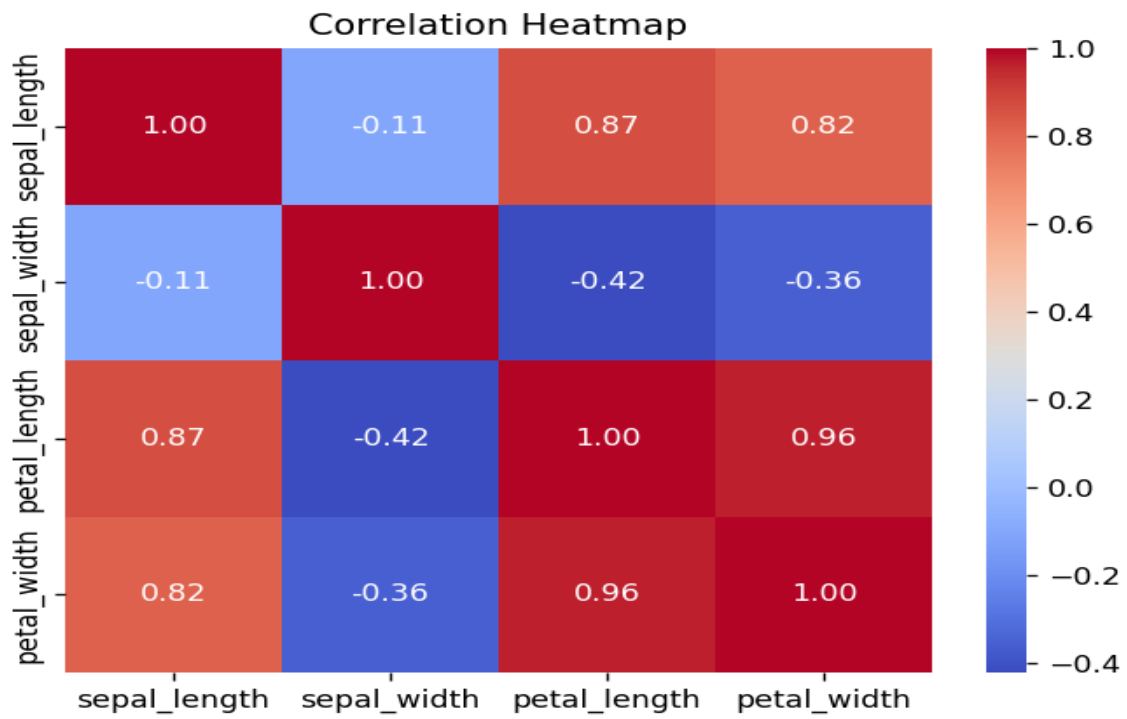
petal\_length 0

petal\_width 0

species 0

dtype: int64





Accuracy: 1.0

Classification Report:

	precision	recall	f1-score	support
Iris-setosa	1.00	1.00	1.00	10
Iris-versicolor	1.00	1.00	1.00	9
Iris-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

Predicted species for the new flower: Iris-setosa