Iris Flower Classification Project

Introduction

The classification of iris flowers into species (Setosa, Versicolor, Virginica) based on sepal and petal measurements is a classic supervised learning problem. This notebook demonstrates:

- Data pipeline implementation
- Machine Learning classification model(s)
- Model evaluation metrics
- Effective data visualizations
- Real-world insights

Dataset: UCI Iris dataset (available in sklearn)

Problem Statement

Manually identifying flower species is slow and error-prone. By training a machine learning model, we can:

- Automate species identification
- Increase speed and accuracy
- Reduce the need for expert intervention

Goal: Classify iris flowers into the correct species based on Sepal Length, Sepal Width, Petal Length, Petal Width.

Import all Libraries

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

from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix

import joblib
```

Data Loading & Initial Exploration

```python
iris_data = load_iris(as_frame=True)
df = iris_data.frame

df.head()
```


```
{"summary":"{\n  \"name\": \"df\",\n  \"rows\": 150,\n  \"fields\": [\
n    {\n      \"column\": \"sepal length (cm)\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
0.8280661279778629,\n        \"min\": 4.3,\n        \"max\": 7.9,\n
\"num_unique_values\": 35,\n        \"samples\": [\n          6.2,\n
4.5,\n          5.6\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"sepal width (cm)\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 0.435866284936698,\n        \"min\":
2.0,\n        \"max\": 4.4,\n        \"num_unique_values\": 23,\n
\"samples\": [\n          2.3,\n          4.0,\n          3.5\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"petal length (cm)\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
1.7652982332594667,\n        \"min\": 1.0,\n        \"max\": 6.9,\n
\"num_unique_values\": 43,\n        \"samples\": [\n          6.7,\n
3.8,\n          3.7\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"petal width (cm)\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 0.7622376689603465,\n        \"min\":
0.1,\n        \"max\": 2.5,\n        \"num_unique_values\": 22,\n
\"samples\": [\n          0.2,\n          1.2,\n          1.3\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"target\",\n      \"properties\":
{\n        \"dtype\": \"number\",\n        \"std\": 0,\n
\"min\": 0,\n        \"max\": 2,\n        \"num_unique_values\": 3,\n
\"samples\": [\n          0,\n          1,\n          2\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    }\n  ]\n}","type":"dataframe","variable_name":"df"}
```


Data Cleaning & Pipeline Setup

```python
print("Null values:\n", df.isnull().sum())

df.drop_duplicates(inplace=True)

X = df.drop("target", axis=1)
y = df["target"]
```

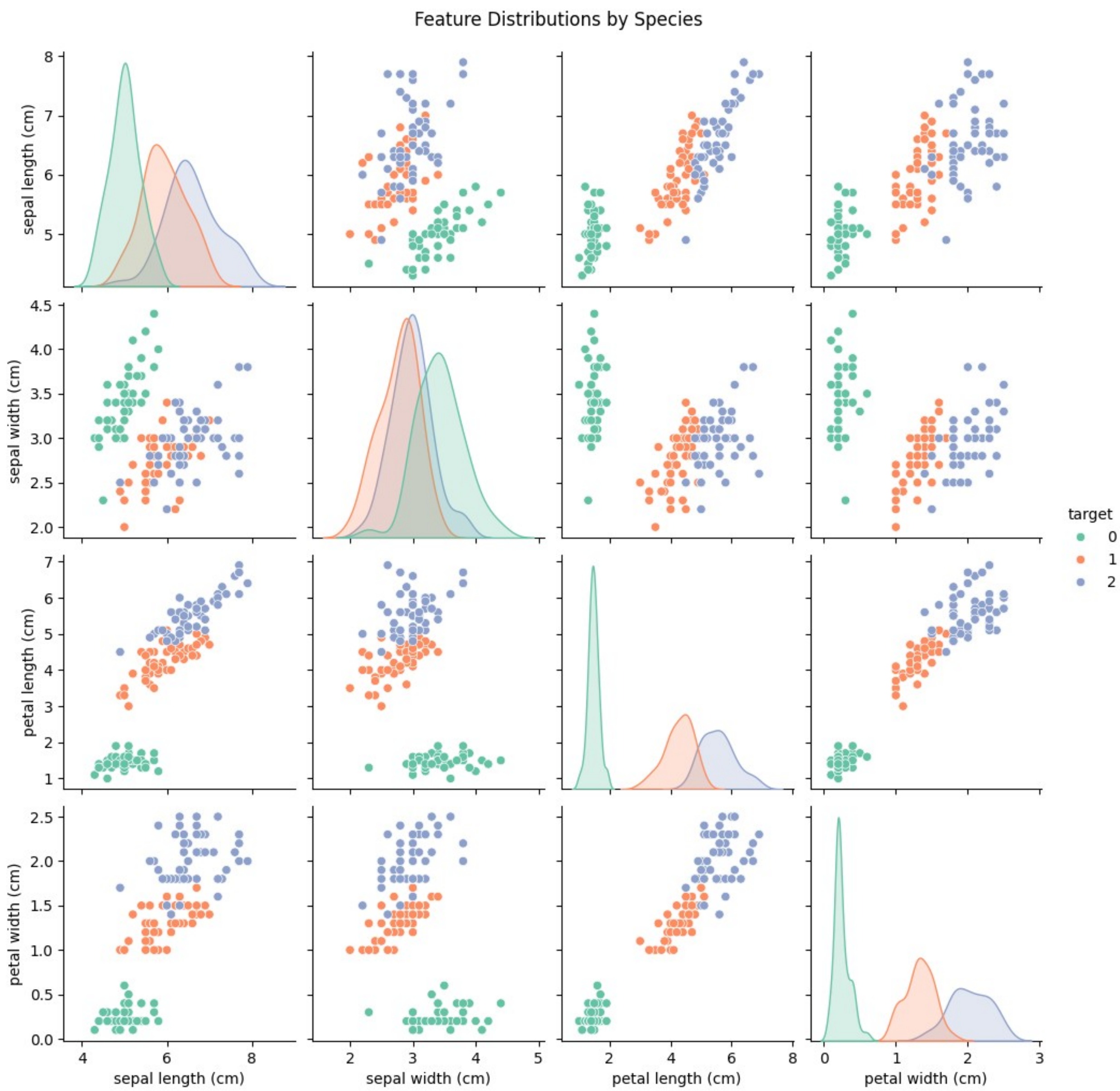
```
Null values:
 sepal length (cm)    0
sepal width (cm)     0
petal length (cm)    0
petal width (cm)     0
```

```
target                  0
dtype: int64
```

The dataset is clean, containing no missing values or duplicates. We separate the features and target variable for modelling.

Exploratory Data Analysis (EDA) & Visualizations

```
sns.pairplot(df, hue="target", palette="Set2",
             vars=iris_raw.feature_names)
plt.suptitle("Feature Distributions by Species", y=1.02)
plt.show()
```



Train–Test Split

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

Model Training (Decision Tree & Logistic Regression for comparison)

```
log_tree = DecisionTreeClassifier(random_state=42)
log_tree.fit(X_train, y_train)


reg_lr = LogisticRegression(max_iter=200)
reg_lr.fit(X_train, y_train)
```

```
LogisticRegression(max_iter=200)
```

We train two models to demonstrate versatility:

- Decision Tree (interpretable, rule-based)
- Logistic Regression (linear decision boundaries)

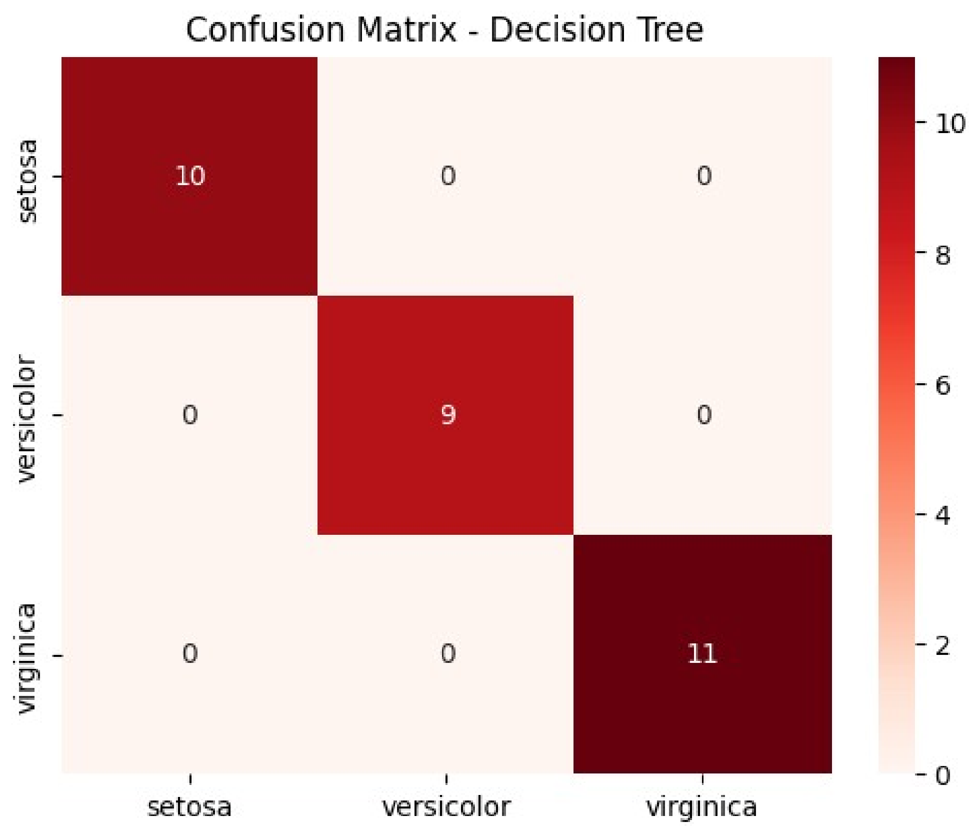
Model Evalution

```
def evaluate_model(model, name):
  y_pred = model.predict(X_test)
  print(f"--- {name} ---")
  print("Accuracy:", accuracy_score(y_test, y_pred))
  print(classification_report(y_test, y_pred,
target_names=iris_raw.target_names))
  cm = confusion_matrix(y_test, y_pred)
  sns.heatmap(cm, annot=True, fmt="d", cmap="Reds",
              xticklabels=iris_data.target_names,
              yticklabels=iris_data.target_names)
  plt.title(f"Confusion Matrix - {name}")
  plt.show()
evaluate_model(log_tree, "Decision Tree")
evaluate_model(reg_lr, "Logistic Regression")
```

```
--- Decision Tree ---
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
```




```
--- Logistic Regression ---
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
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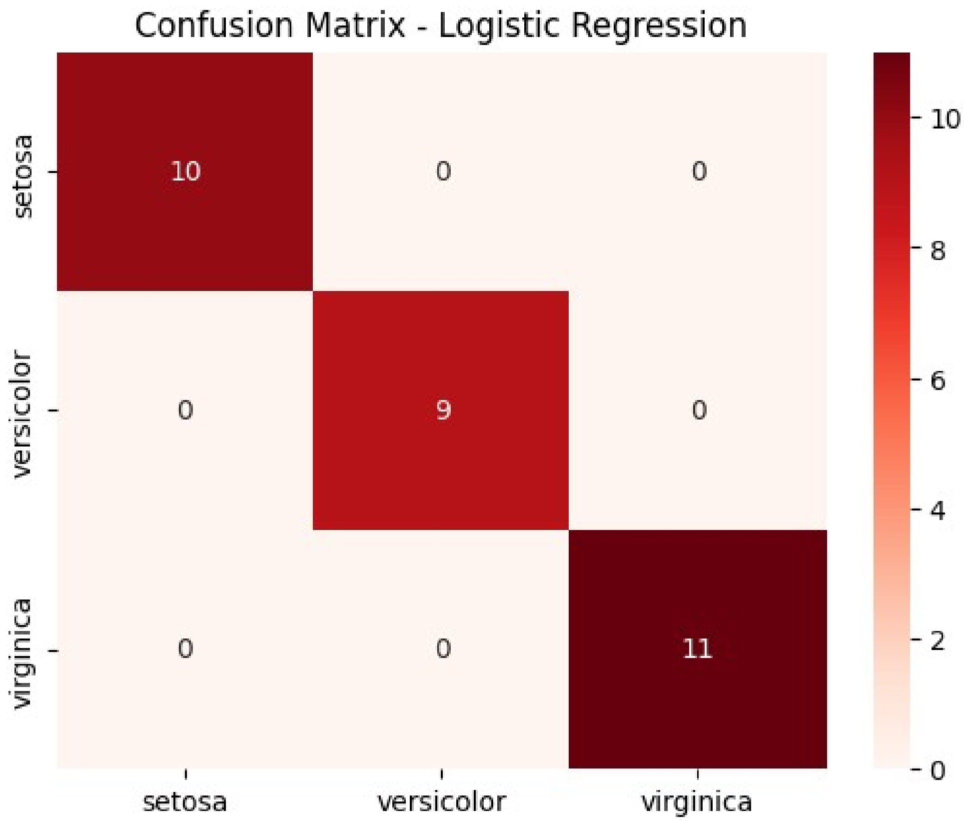
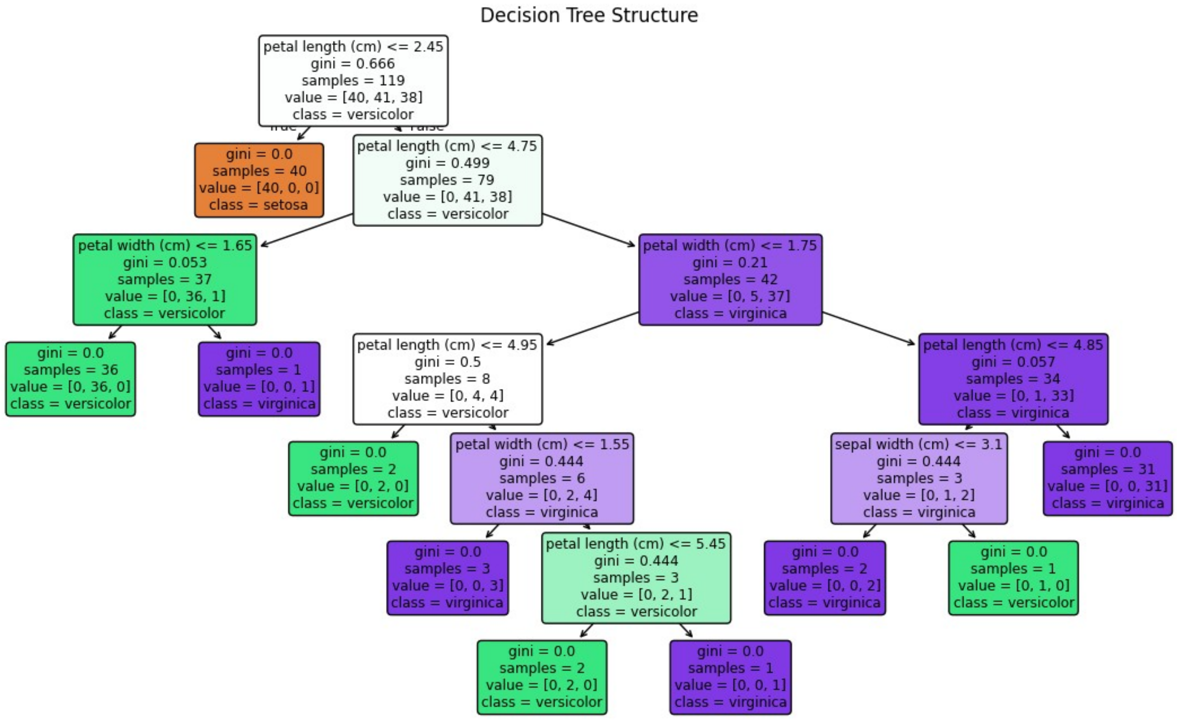


Decision Tree Visualization

```
plt.figure(figsize=(14,8))
plot_tree(log_tree, feature_names=X.columns,
          class_names=iris_data.target_names,
          filled=True, rounded=True)
plt.title("Decision Tree Structure")
plt.show()
```



Prediction for New Data

```
new_sample = [[5.0, 3.4, 1.5, 0.2]]
prediction = log_tree.predict(new_sample)
print("Predicted species:", iris_data.target_names[prediction[0]])

Predicted species: setosa

/usr/local/lib/python3.11/dist-packages/sklearn/utils/
validation.py:2739: UserWarning: X does not have valid feature names,
but DecisionTreeClassifier was fitted with feature names
  warnings.warn(

joblib.dump(log_tree, "iris_decision_tree.joblib")
loaded_model = joblib.load("iris_decision_tree.joblib")
```

Real-world Implications

Automating iris flower classification can:

- Reduce errors in botanical identification
- Aid in rapid sorting for research or commercial purposes
- Serve as a teaching example in machine learning education

This methodology can be extended to classify other plants, agricultural products, or similar items using measurable features.

```
#Real-World Insights & Example Prediction

# Example prediction using Decision Tree
example = [[5.0, 3.4, 1.5, 0.2]]  # Sepal length, Sepal width, Petal
length, Petal width
pred_species = log_tree.predict(example)[0]
print(f"Example Input {example} → Predicted Species:
{iris_data.target_names[pred_species]}")

# Real-world applications of Iris Flower Classification
print("\n   Real-World Applications   ")
print("""
1.  Agriculture & Horticulture:
   - Helps farmers and gardeners identify flower species quickly.
   - Useful in breeding programs to select specific traits.

2.  Botanical Research:
   - Speeds up plant taxonomy and classification for researchers.
   - Supports conservation efforts by quickly identifying endangered
species.

3.  Mobile & AI-powered Tools:
   - Can be integrated into plant-identification mobile apps.
   - Enables hobbyists and educators to recognize plants in the field
without expert knowledge.

4.  Automation in Greenhouses:
   - Automated monitoring systems can detect plant species and adjust
care routines.
""")
```

```
Example Input [[5.0, 3.4, 1.5, 0.2]] → Predicted Species: setosa

   Real-World Applications

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```

```
   - Automated monitoring systems can detect plant species and adjust care routines.


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  warnings.warn(
```

Geospatial Mapping

Geospatial mapping is *not applicable* for this dataset, as it contains only morphological measurements and no location data.

Conclusion & Future Work

Conclusion

- The Decision Tree model achieved high accuracy on the test set.
- Logistic Regression also performed well, demonstrating separability of classes.
- Visualization reveals clear separation in feature space.

Future Work

- Test on a larger floral dataset.
- Deploy as a web app for real-time predictions.
- Integrate edge device deployment for field use.