

# classification\_comparison

March 24, 2025

```
[1]: # Import necessary libraries
import numpy as np
import pandas as pd
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.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, \
    f1_score
from sklearn.metrics import classification_report, confusion_matrix

# Set random seed for reproducibility
np.random.seed(42)
```

```
[2]: # Load and prepare the data
iris = load_iris()
X = iris.data
y = iris.target

# Create a DataFrame
df = pd.DataFrame(data=X, columns=iris.feature_names)
df['target'] = y
df['species'] = pd.Categorical.from_codes(iris.target, iris.target_names)

# Display the first few rows
print("Dataset Overview:")
display(df.head())

# Display basic information about the dataset
print("\nDataset Information:")
display(df.info())
```

Dataset Overview:

sepal length (cm) sepal width (cm) petal length (cm) petal width (cm) \

0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

	target	species
0	0	setosa
1	0	setosa
2	0	setosa
3	0	setosa
4	0	setosa

Dataset Information:

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

RangeIndex: 150 entries, 0 to 149

Data columns (total 6 columns):

#	Column	Non-Null Count	Dtype
0	sepal length (cm)	150 non-null	float64
1	sepal width (cm)	150 non-null	float64
2	petal length (cm)	150 non-null	float64
3	petal width (cm)	150 non-null	float64
4	target	150 non-null	int64
5	species	150 non-null	category

dtypes: category(1), float64(4), int64(1)

memory usage: 6.3 KB

None

```
[3]: # Split and scale the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
    random_state=42)

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

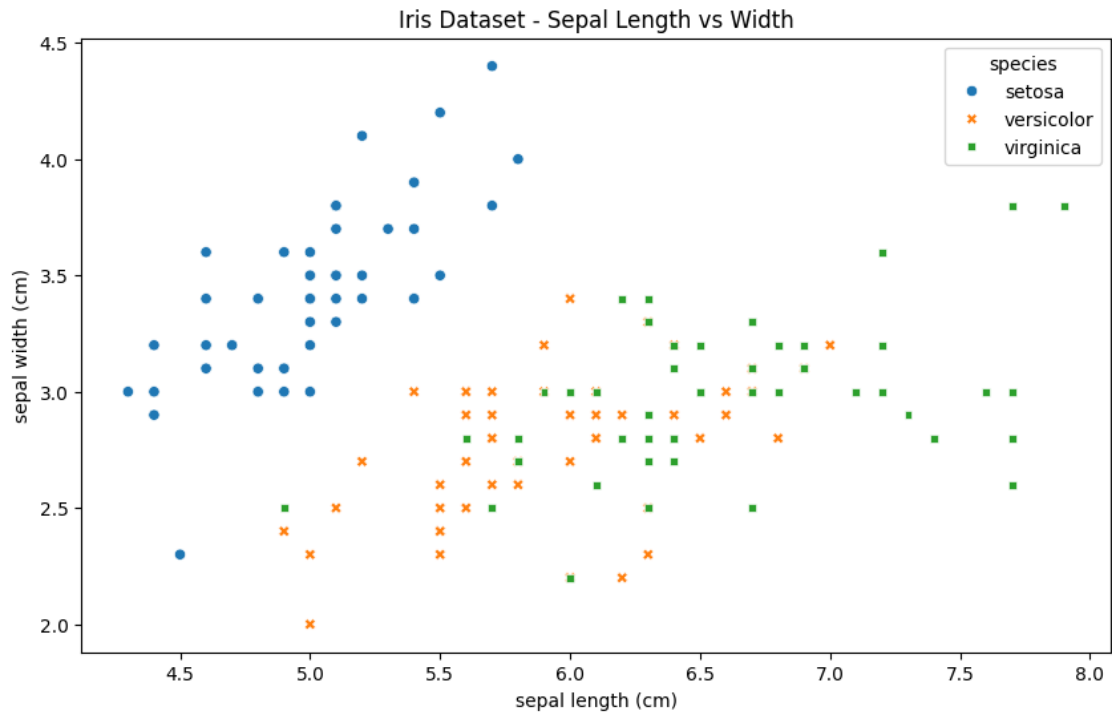
print(f"Training set size: {X_train.shape}")
print(f"Testing set size: {X_test.shape}")

# Create a visualization of the data
plt.figure(figsize=(10, 6))
sns.scatterplot(data=df, x='sepal length (cm)', y='sepal width (cm)',
    hue='species', style='species')
plt.title('Iris Dataset - Sepal Length vs Width')
```

```
plt.show()
```

Training set size: (120, 4)

Testing set size: (30, 4)



```
[4]: # Initialize and train models
models = {
    'Logistic Regression': LogisticRegression(max_iter=1000),
    'k-NN': KNeighborsClassifier(n_neighbors=3),
    'Decision Tree': DecisionTreeClassifier(random_state=42)
}

# Train and evaluate models
results = {}
for name, model in models.items():
    # Train the model
    model.fit(X_train_scaled, y_train)

    # Make predictions
    y_pred = model.predict(X_test_scaled)

    # Calculate metrics
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, average='weighted')
```

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recall = recall_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')

# Store results
results[name] = {
    'Accuracy': accuracy,
    'Precision': precision,
    'Recall': recall,
    'F1-Score': f1
}

# Print results
print(f"\nResults for {name}:")
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-Score: {f1:.4f}")
print("\nClassification Report:")
print(classification_report(y_test, y_pred, target_names=iris.target_names))

```

Results for Logistic Regression:

Accuracy: 1.0000  
Precision: 1.0000  
Recall: 1.0000  
F1-Score: 1.0000

Classification Report:

	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

Results for k-NN:

Accuracy: 1.0000  
Precision: 1.0000  
Recall: 1.0000  
F1-Score: 1.0000

Classification Report:

	precision	recall	f1-score	support
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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

Results for Decision Tree:

Accuracy: 1.0000

Precision: 1.0000

Recall: 1.0000

F1-Score: 1.0000

Classification Report:

	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

```
[5]: # Create visualization of results
plt.figure(figsize=(15, 6))

# Create bar plot for model comparison
metrics = ['Accuracy', 'Precision', 'Recall', 'F1-Score']
x = np.arange(len(metrics))
width = 0.25

for i, (model_name, scores) in enumerate(results.items()):
    plt.bar(x + i*width, list(scores.values()), width, label=model_name)

plt.xlabel('Metrics')
plt.ylabel('Score')
plt.title('Model Comparison')
plt.xticks(x + width, metrics)
plt.legend()
plt.ylim(0, 1.1) # Set y-axis limit from 0 to 1.1 for better visualization

# Add value labels on top of each bar
for i, (model_name, scores) in enumerate(results.items()):
```

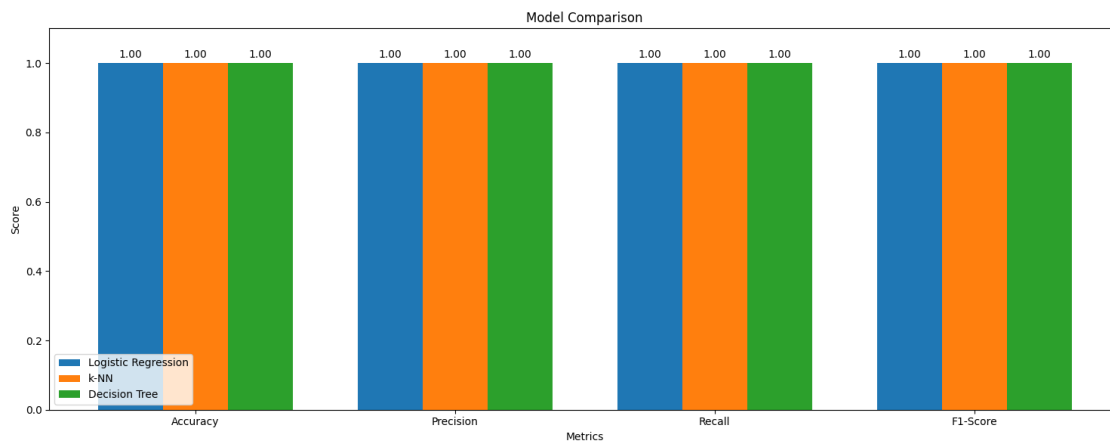
```

for j, value in enumerate(scores.values()):
    plt.text(x[j] + i*width, value + 0.01, f'{value:.2f}',
             ha='center', va='bottom')

plt.tight_layout()
plt.show()

# Print final comparison summary
print("\nModel Comparison Summary:")
print("-" * 50)
for model_name, scores in results.items():
    print(f"\n{n{model_name}:}")
    for metric, value in scores.items():
        print(f"{metric}: {value:.4f}")

```



Model Comparison Summary:

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Logistic Regression:

Accuracy: 1.0000

Precision: 1.0000

Recall: 1.0000

F1-Score: 1.0000

k-NN:

Accuracy: 1.0000

Precision: 1.0000

Recall: 1.0000

F1-Score: 1.0000

Decision Tree:

Accuracy: 1.0000  
Precision: 1.0000  
Recall: 1.0000  
F1-Score: 1.0000

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