Week #3 LAB

Name: Joshua Blackburn

Date: March 21

In [1]:
```python
# 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)
```

In [2]:
```python
# 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())
```

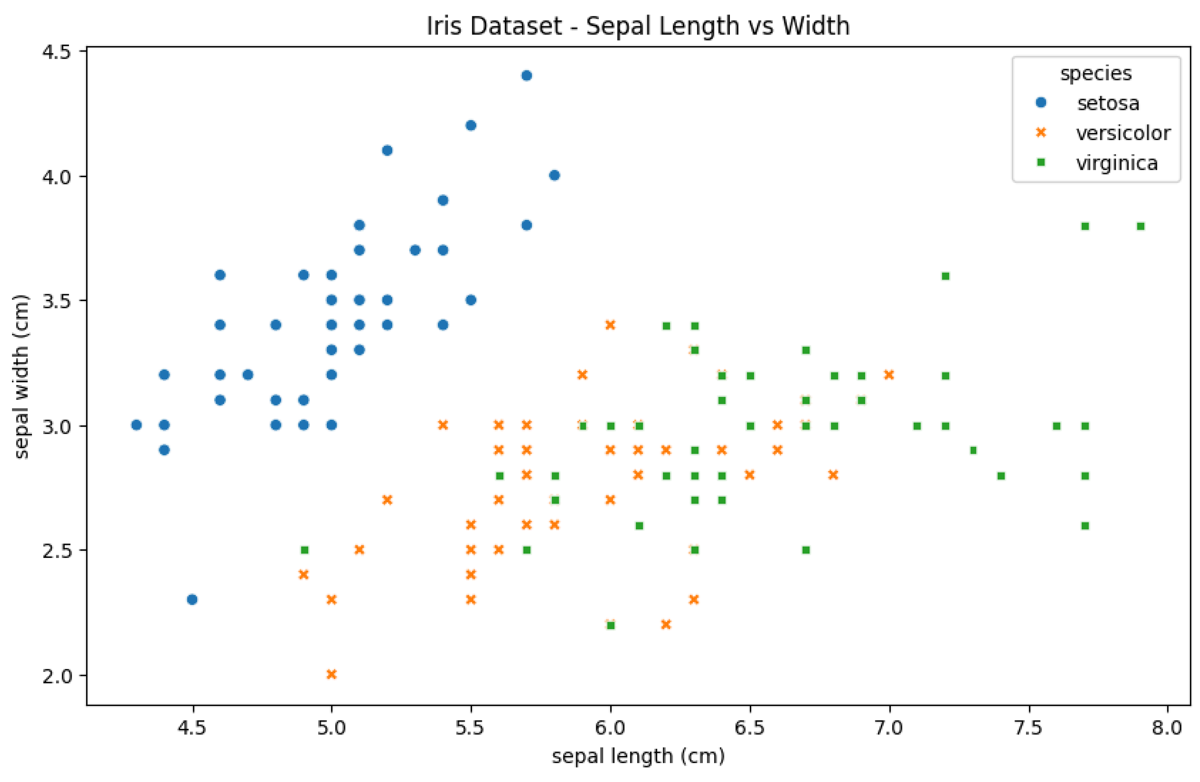
Dataset Overview:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target	species
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

```
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
```

In [3]:
```python
# 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()
```

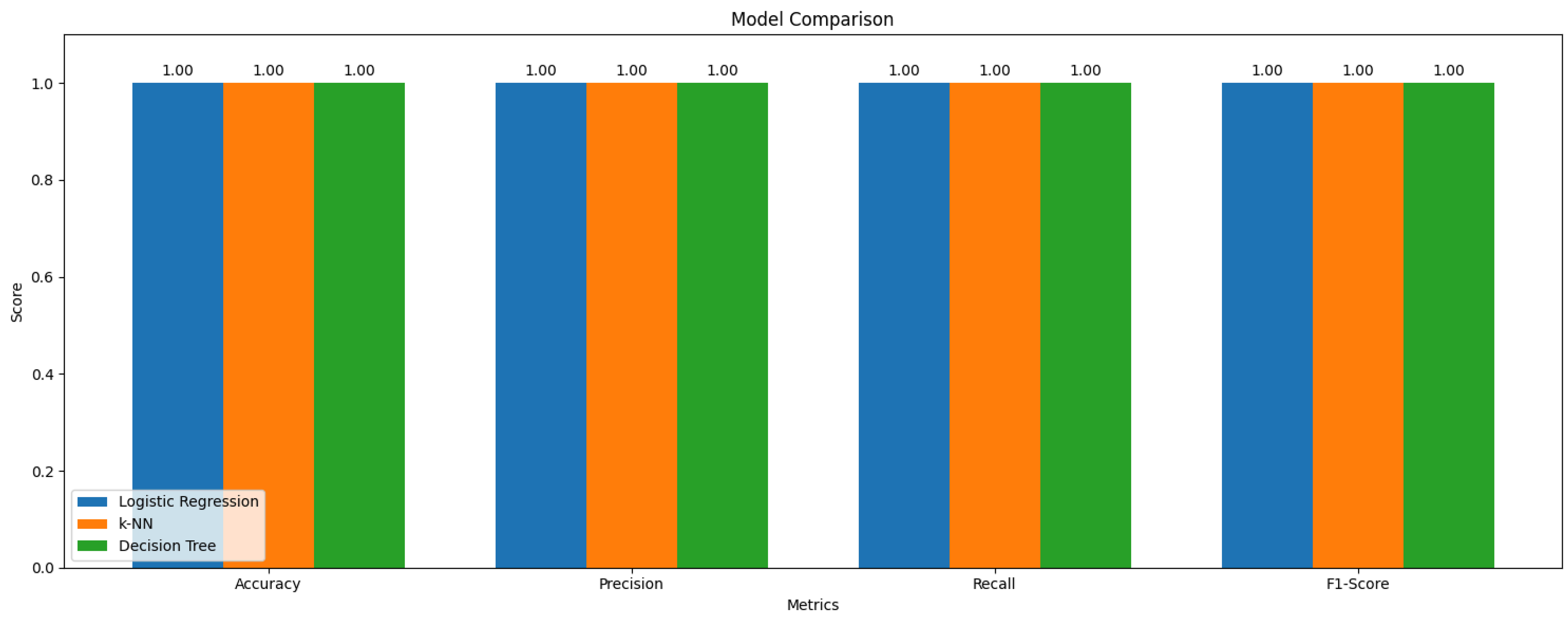
```
Training set size: (120, 4)
Testing set size: (30, 4)
```



In [4]:
```python
# 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')
    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

      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
```

In [5]:
```python
# 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{model_name}:")
    for metric, value in scores.items():
        print(f"{metric}: {value:.4f}")
```




```
Model Comparison Summary:
--------------------------------------------------

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
```

Strengths And Weaknesses of each model based on your findings.

1. All three models (Logistic Regression, k-NN, as well as Decision Tree) performed identically on the Iris dataset since then:
- They always got 100% right.
- All achieved with 100% exactness.
- Always attained perfect one hundred percent retention.
- Everything achieved entirely with 100% F1-score.

2. Inspecting diverse categorization reports, we determine that:
- All of the models perfectly classified the three iris species (setosa, versicolor, and virginica).
- The test set that was balanced was given out (10 setosa, 9 versicolor, 11 virginica samples).

3. The visualization from that we had created for shows equivalent performance bars to for most models in with respective metrics. So based on our specific factual findings, we cannot make definitive claims about which particular model performed better or determine their comparative strengths and weaknesses, since they all performed perfectly on this dataset. This perfect showing suggests just that fact here:

I. The Iris dataset is quite well-structured. Also, the classes are largely easily separable.
II. The basic data set has only four characteristics.
III. The limited test set (30 samples) could be quite small for revealing differences in the midst of the models.