TASK 3

IRIS FLOWER CLASSIFICATION

In [16]:
```
# IRIS flower classification

import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import classification_report, confusion_matrix, ConfusionMa
from sklearn.ensemble import RandomForestClassifier
```

In [17]:
```
df = pd.read_csv("IRIS.csv")
```

In [18]:
```
df.head()
```

Out[18]:

	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

In [19]:
```
print("\nClass Distribution:")
print(df['species'].value_counts())
```

```
Class Distribution:
species
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name: count, dtype: int64
```

In [20]:
```
df.info()
```

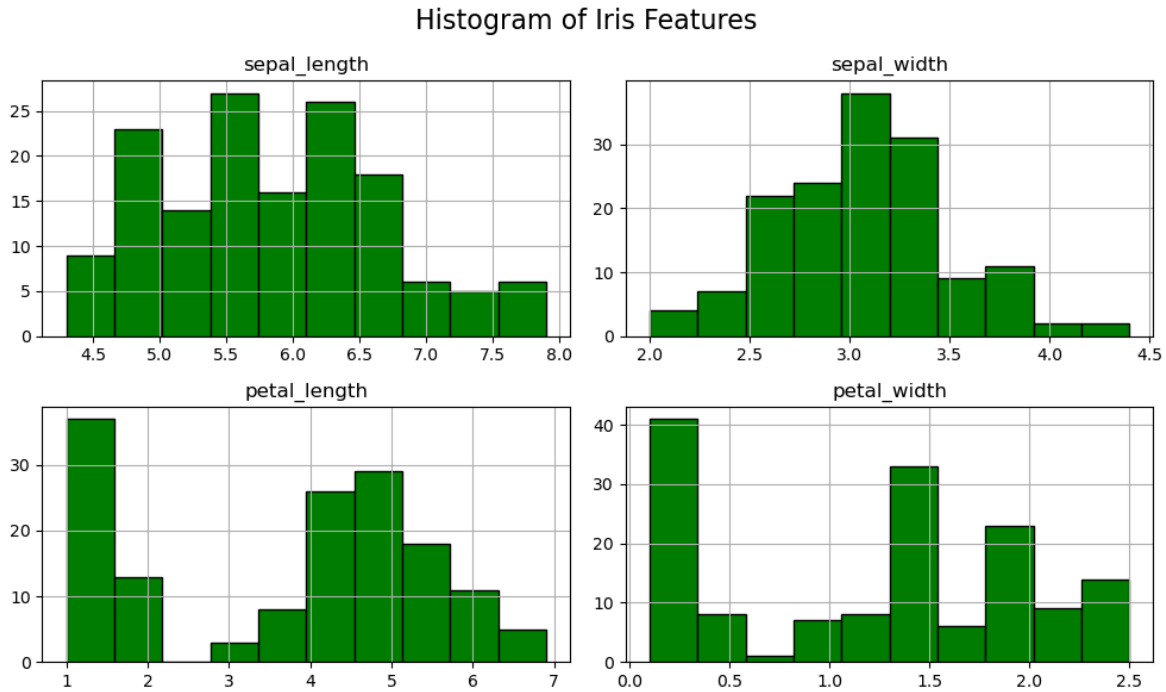
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   sepal_length  150 non-null    float64
 1   sepal_width   150 non-null    float64
 2   petal_length  150 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
```

In [21]:
```
df.describe()
```

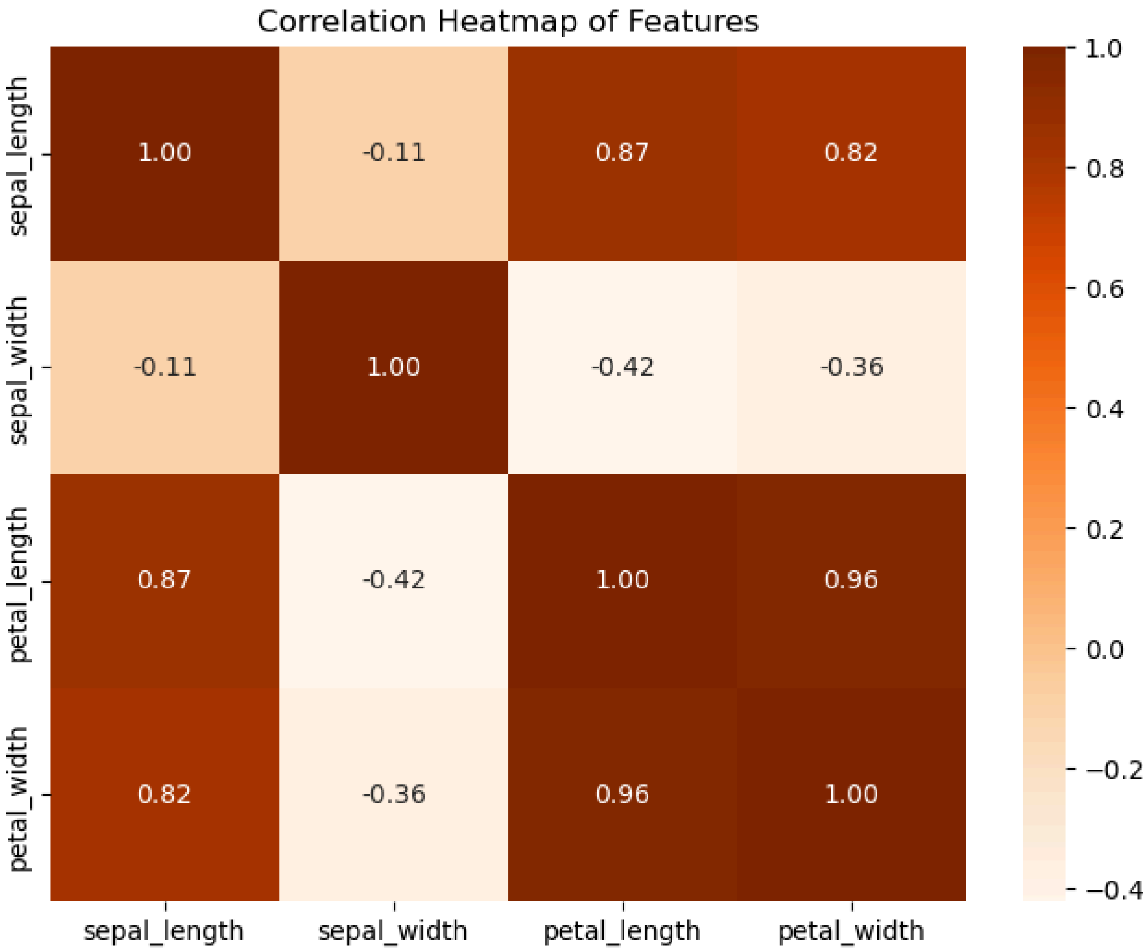
Out[21]:

	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

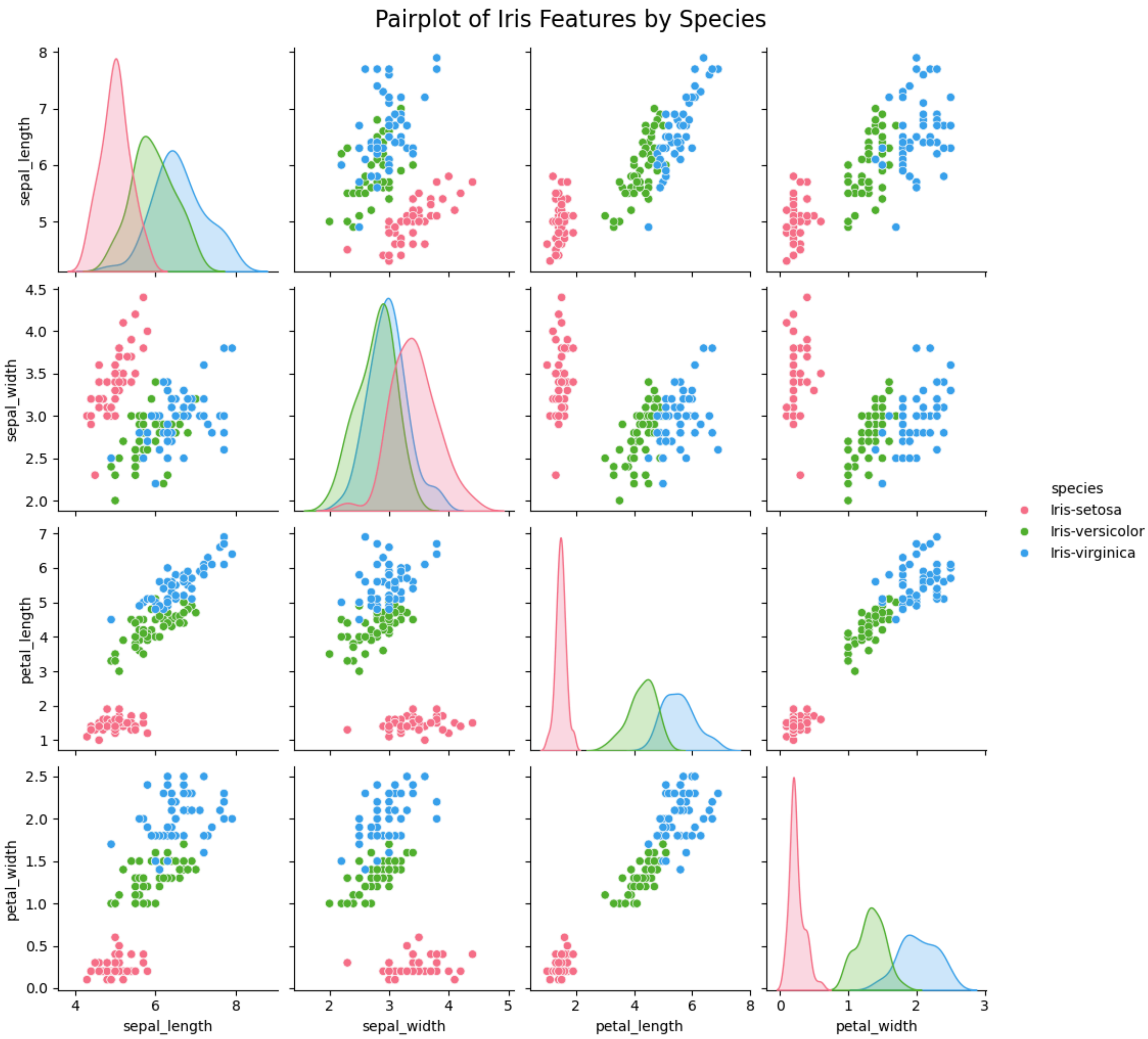
In [22]:
```
df.hist(figsize=(10, 6), edgecolor='black', color='green')
plt.suptitle("Histogram of Iris Features", fontsize=16)
plt.tight_layout()
plt.show()
```



In [33]:
```
plt.figure(figsize=(8, 6))
sns.heatmap(df.drop('species', axis=1).corr(), annot=True, cmap='Oranges', fmt="
plt.title("Correlation Heatmap of Features")
plt.show()
```



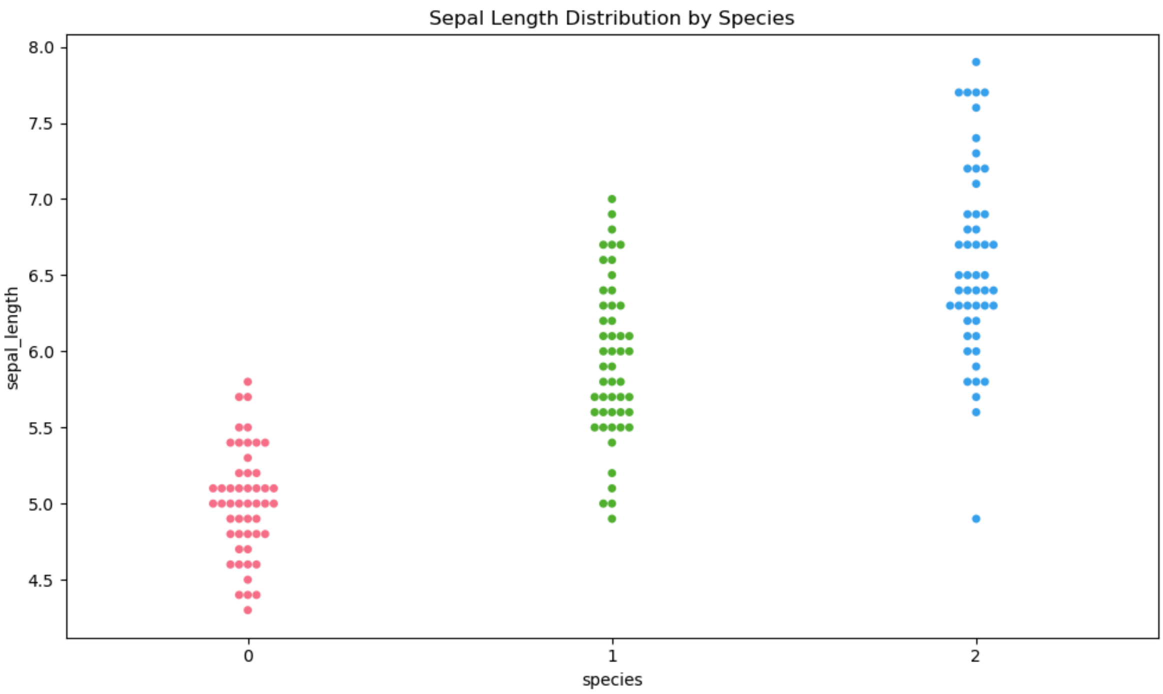
In [24]:
```
sns.pairplot(df, hue='species', palette='husl')
plt.suptitle("Pairplot of Iris Features by Species", y=1.02, fontsize=16)
plt.show()
```



In [37]:

```
plt.figure(figsize=(10, 6))
sns.swarmplot(data=df, x='species', y='sepal_length', palette='husl')
plt.title("Sepal Length Distribution by Species")
plt.tight_layout()
plt.show()
```

```
C:\Users\gonda\AppData\Local\Temp\ipykernel_2628\3458291229.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v
0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effe
ct.

  sns.swarmplot(data=df, x='species', y='sepal_length', palette='husl')
```

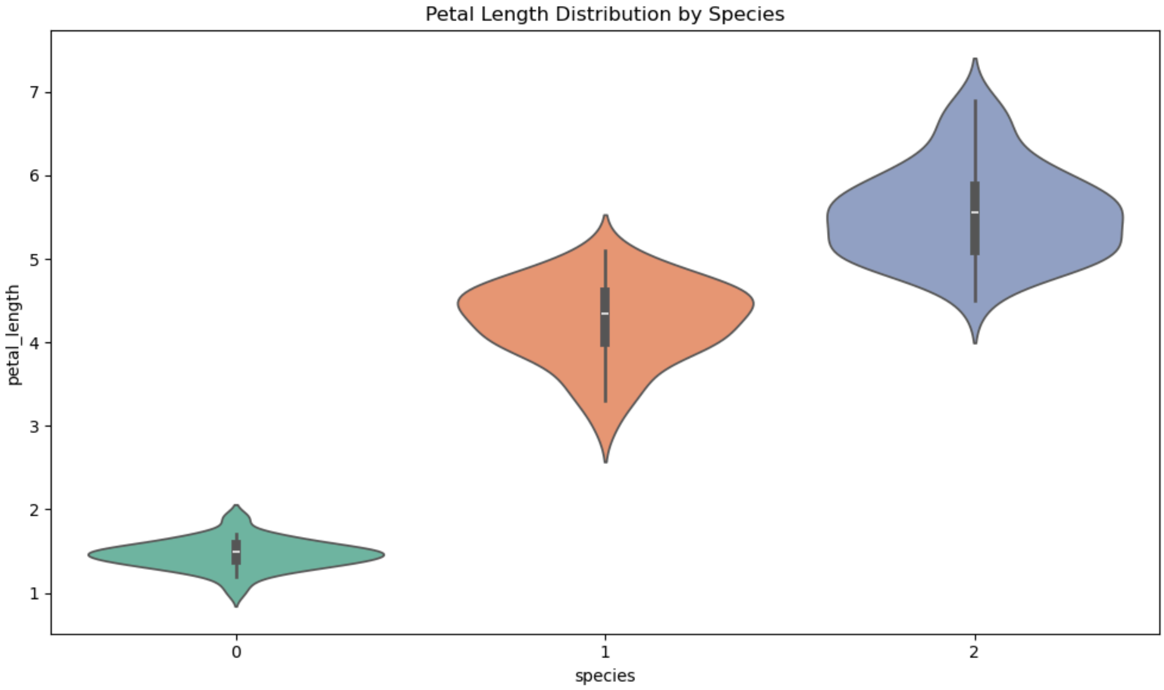


In [38]:
```
sns.countplot(data=df, x='species', palette='Set1')
plt.title("Class Distribution of Iris Species")
plt.tight_layout()
plt.show()
```

```
C:\Users\gonda\AppData\Local\Temp\ipykernel_2628\3854417594.py:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v
0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effe
ct.

  sns.countplot(data=df, x='species', palette='Set1')
```

In [40]:
```
plt.figure(figsize=(10, 6))
sns.violinplot(data=df, x='species', y='petal_length', palette='Set2')
plt.title("Petal Length Distribution by Species")
plt.tight_layout()
plt.show()
```

```
C:\Users\gonda\AppData\Local\Temp\ipykernel_2628\2535030879.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v
0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effe
ct.

  sns.violinplot(data=df, x='species', y='petal_length', palette='Set2')
```



In [25]:
```
le = LabelEncoder()
df['species'] = le.fit_transform(df['species'])
```

In [26]:
```
X = df.drop('species', axis=1)
y = df['species']
```

In [27]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
```

In [28]:
```
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)
```

Out[28]:

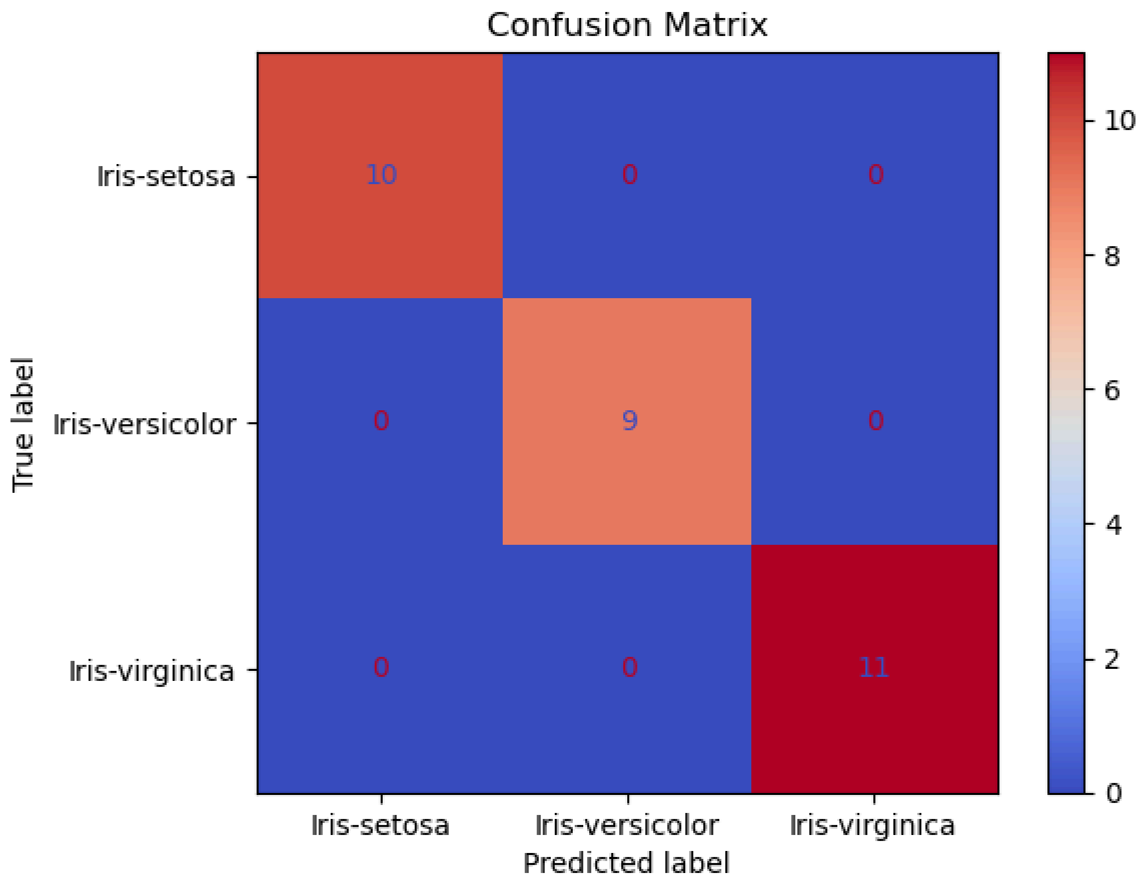
```
▾ RandomForestClassifier
RandomForestClassifier(random_state=42)
```

In [29]:
```
y_pred = model.predict(X_test)
```

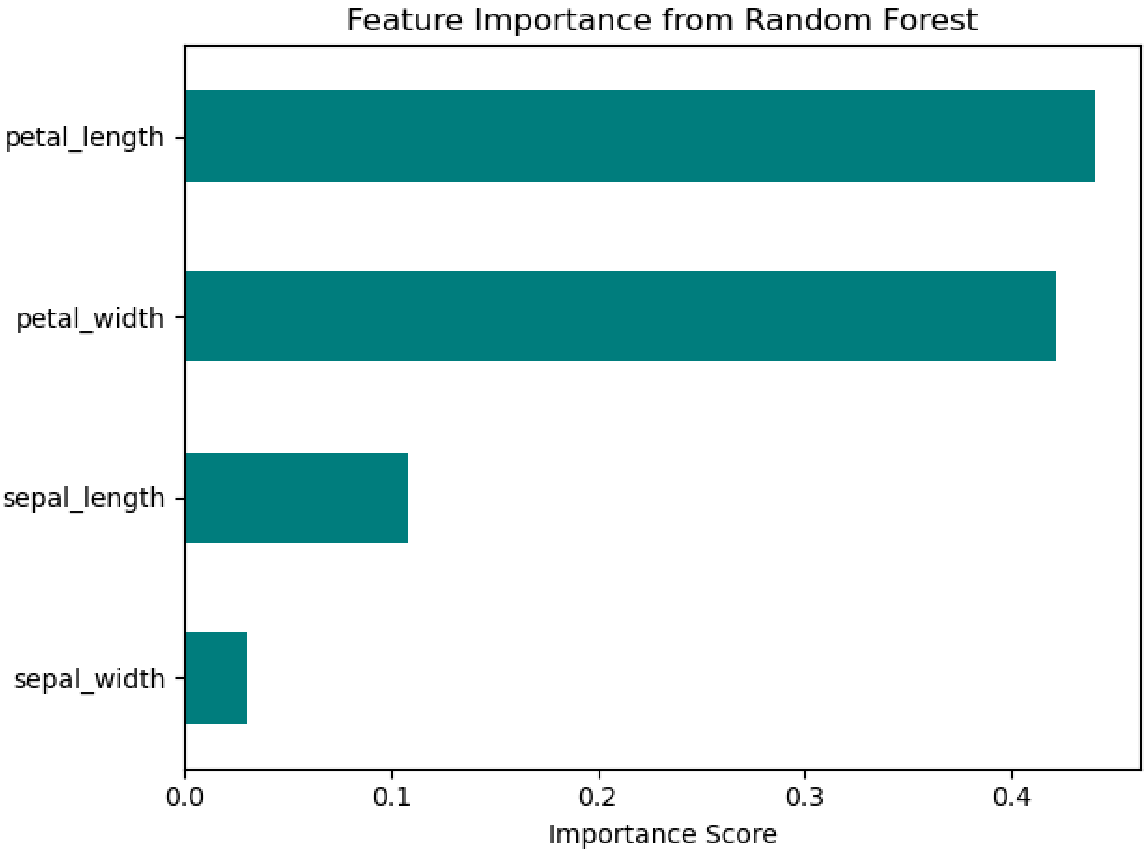
In [30]:
```
print("\nClassification Report:")
print(classification_report(y_test, y_pred, target_names=le.classes_))
```

```
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
```

In [31]:
```python
conf_mat = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=conf_mat, display_labels=le.class
disp.plot(cmap='coolwarm')
plt.title("Confusion Matrix")
plt.show()
```



In [32]:
```python
feature_importance = pd.Series(model.feature_importances_, index=X.columns)
feature_importance.sort_values().plot(kind='barh', color='teal')  # Color change
plt.title("Feature Importance from Random Forest")
plt.xlabel("Importance Score")
plt.tight_layout()
plt.show()
```


Feature Importance from Random Forest
petal_length
petal_width
sepal_length
sepal_width
0.0
0.1
0.2
0.3
0.4
Importance Score

```
In [ ]:
```