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Course: Bil470

Importing the Dependincies

In [39]:
```
import numpy as np
import pandas as pd
from sklearn import svm
from sklearn import metrics
from sklearn.metrics import accuracy_score, precision_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_recall_fscore_support
from sklearn.metrics import classification_report
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from dt import DecisionTreeClassifier
from tabulate import tabulate
from sklearn.model_selection import learning_curve
```

Exploratory Data Analysis (EDA) for IRIS

In [2]:
```
iris_data = pd.read_csv('Iris.csv')
iris_data.head()
```

Out[2]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

In [3]:
```
iris_data = iris_data.drop('Id',axis=1)
```

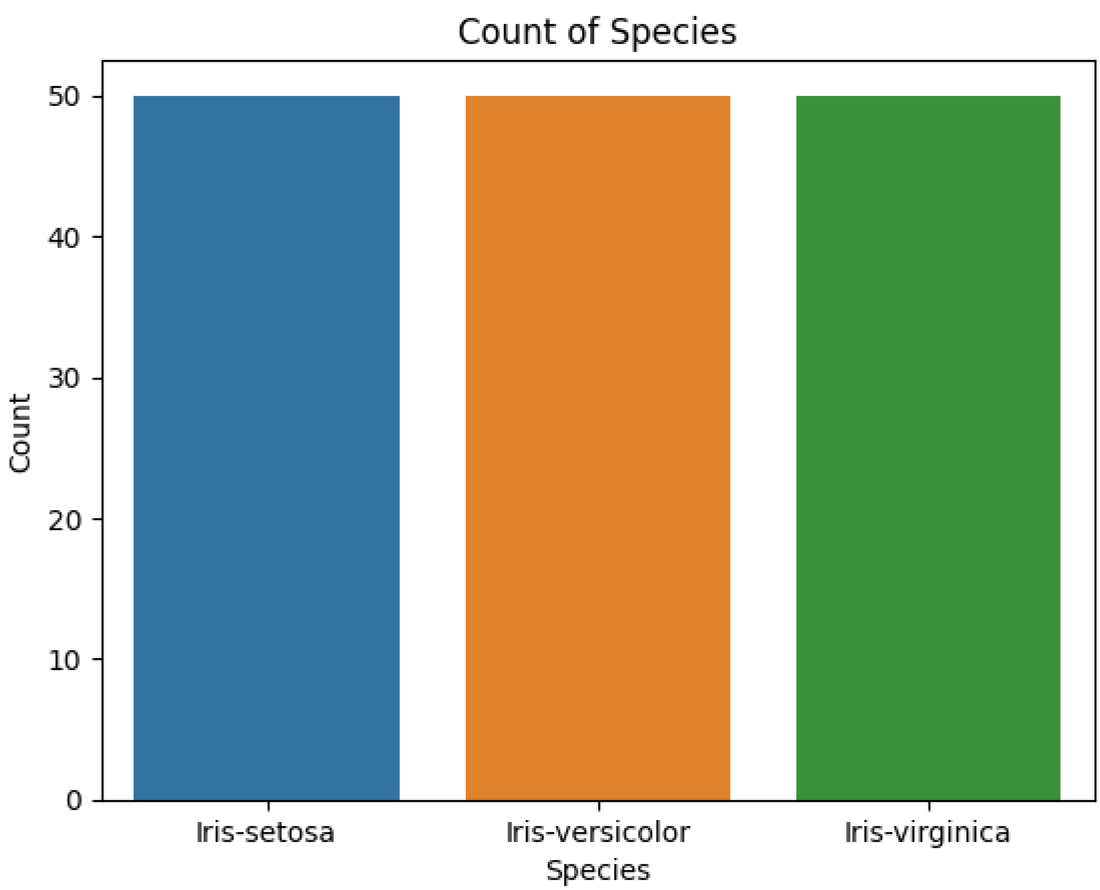
In [4]:
```
iris_data.describe()
```

Out[4]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
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 [5]:

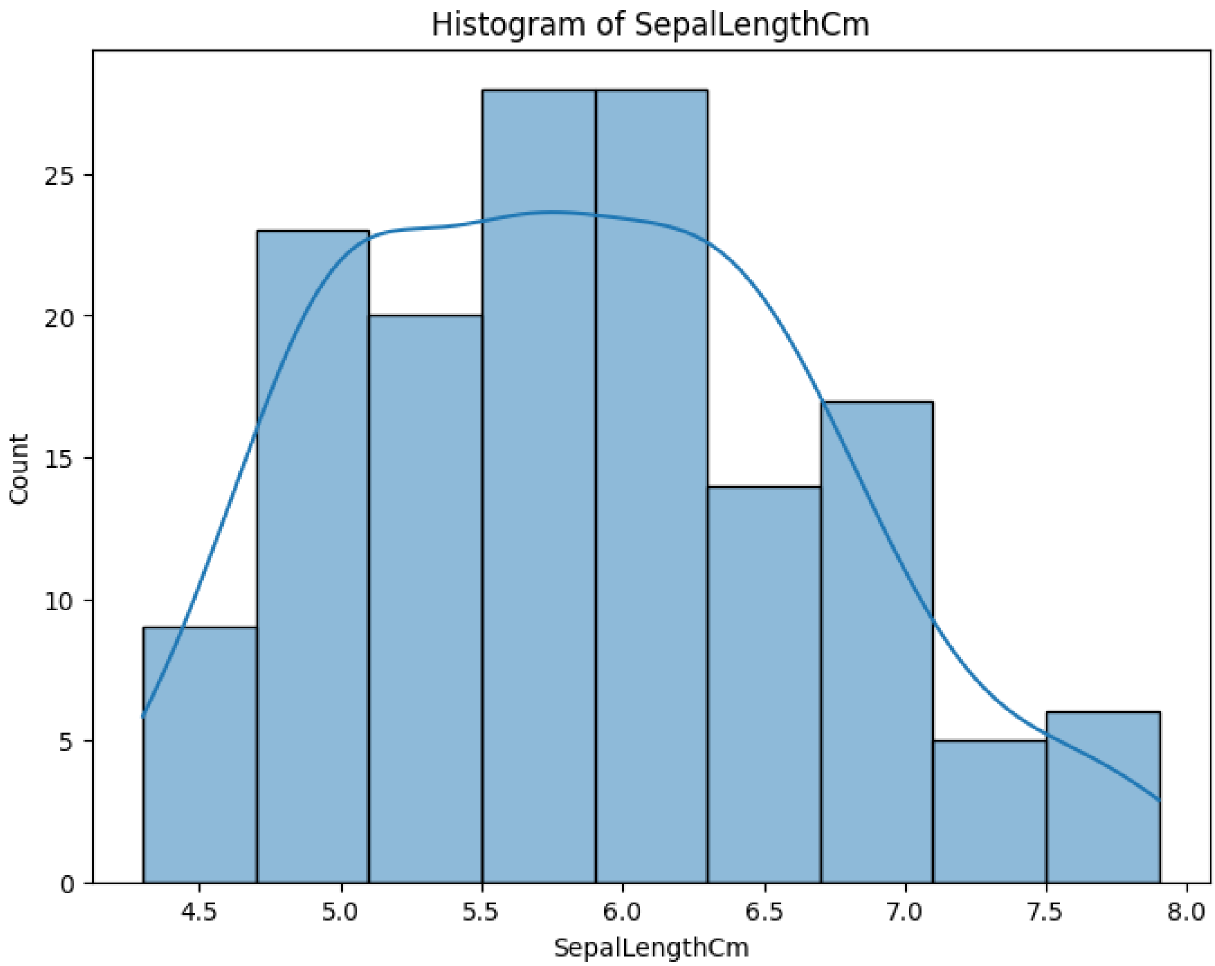
```
sns.countplot(data=iris_data, x='Species')
plt.xlabel('Species')
plt.ylabel('Count')
plt.title('Count of Species')
plt.show()
```

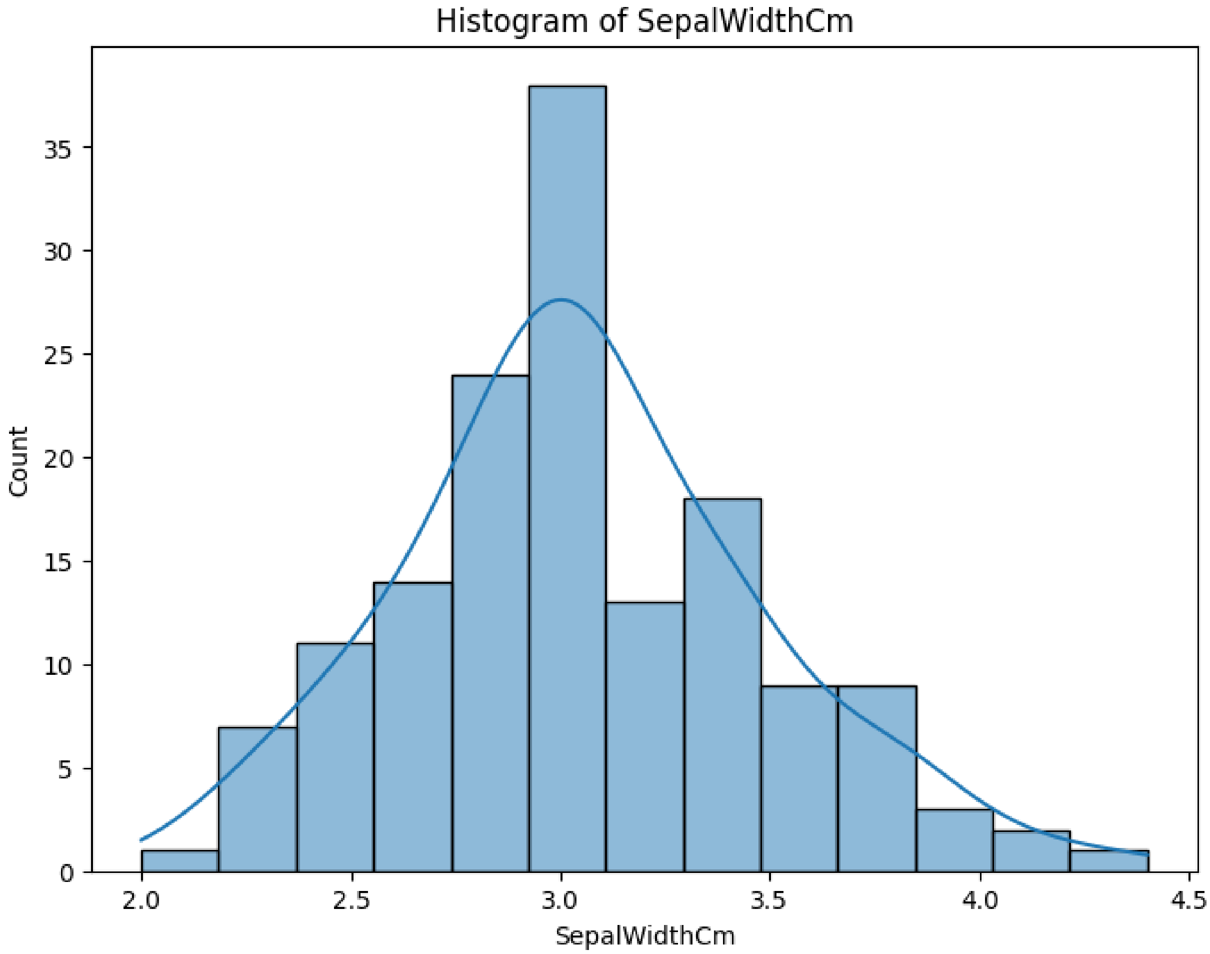


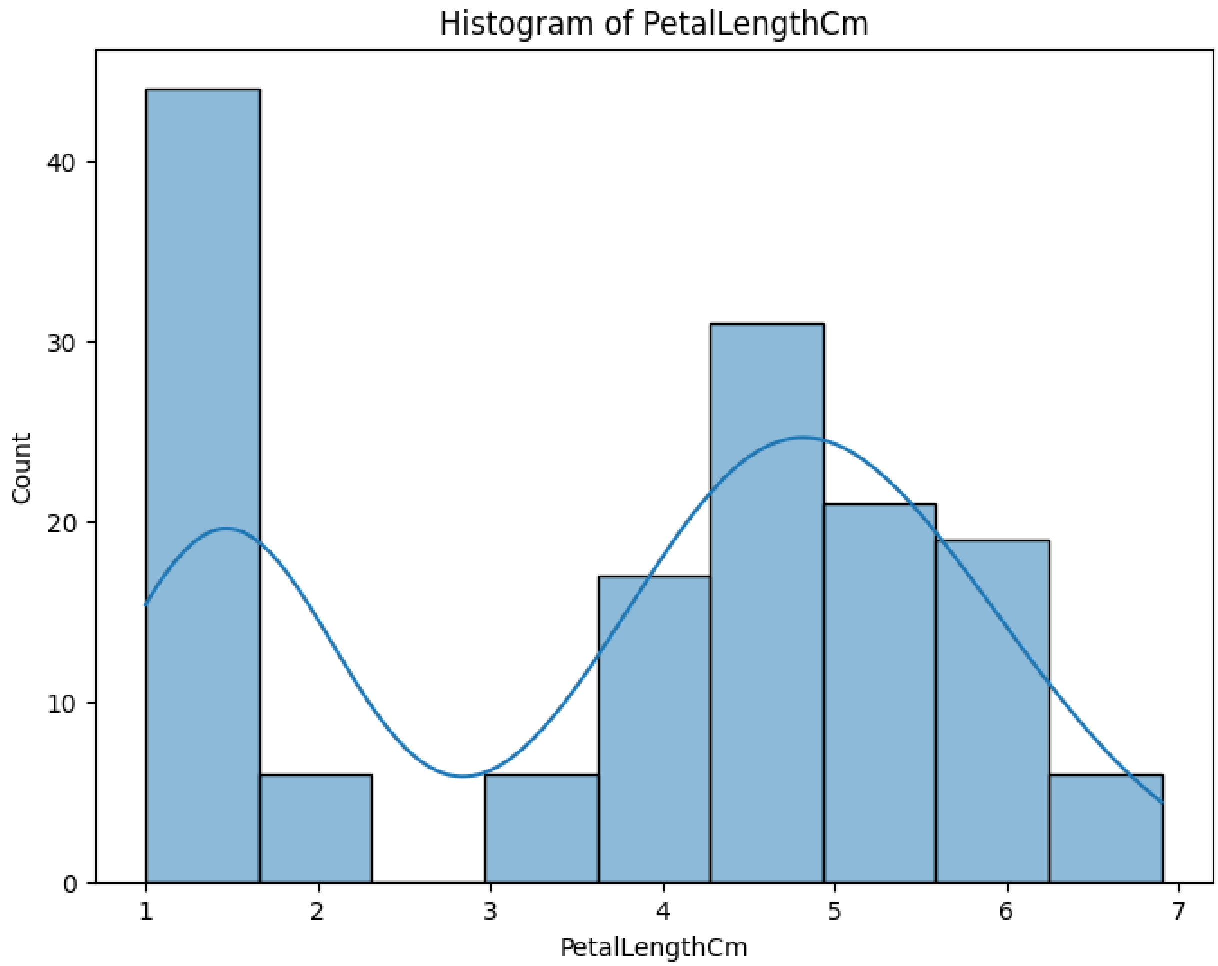
In [6]:

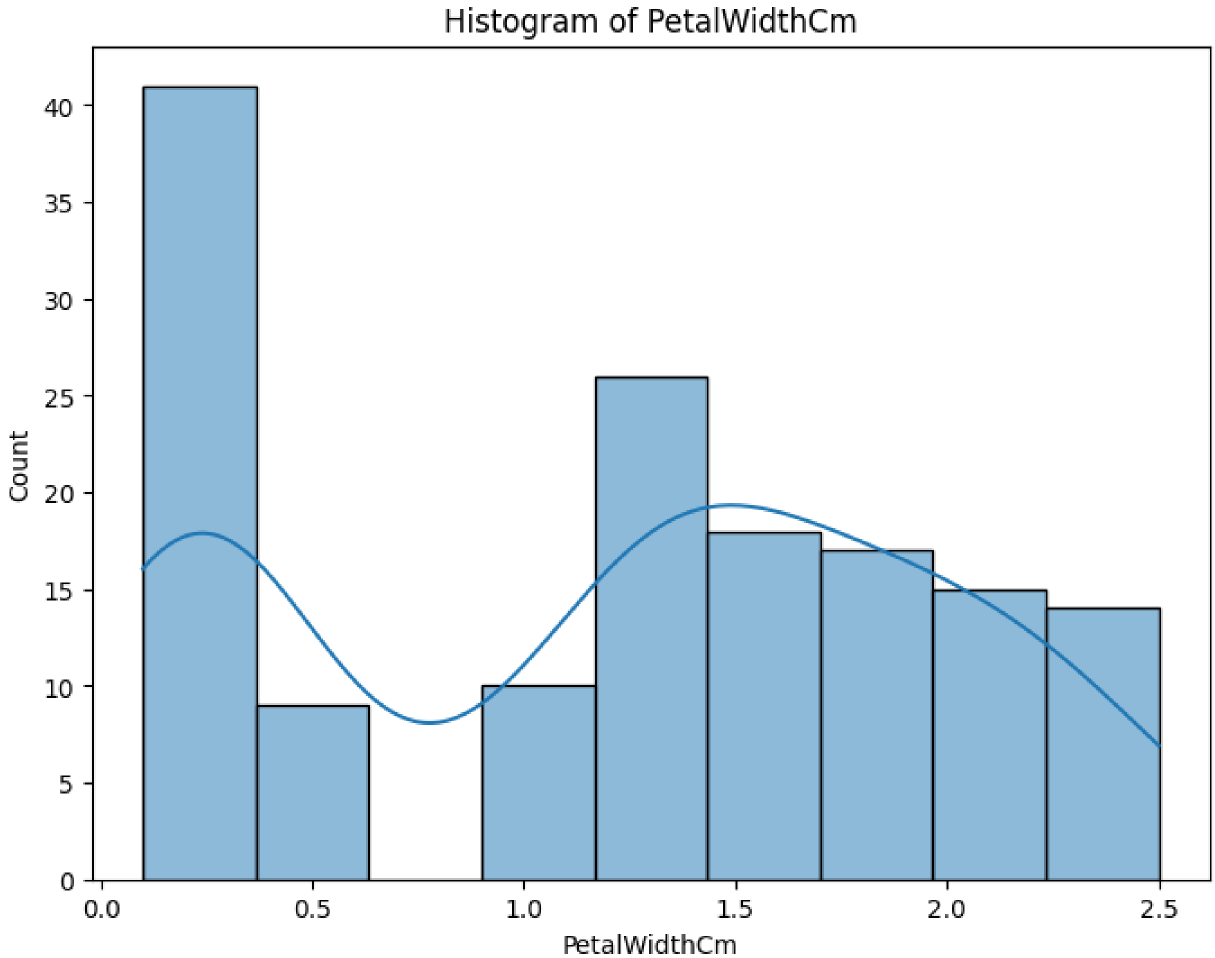
```
features = iris_data.columns[:-1]

for feature in features:
    plt.figure(figsize=(8, 6))
    sns.histplot(data= iris_data, x=feature, kde=True) #kde is density
    plt.xlabel(feature)
    plt.ylabel('Count')
    plt.title(f'Histogram of {feature}')
```

```
plt.show()
```

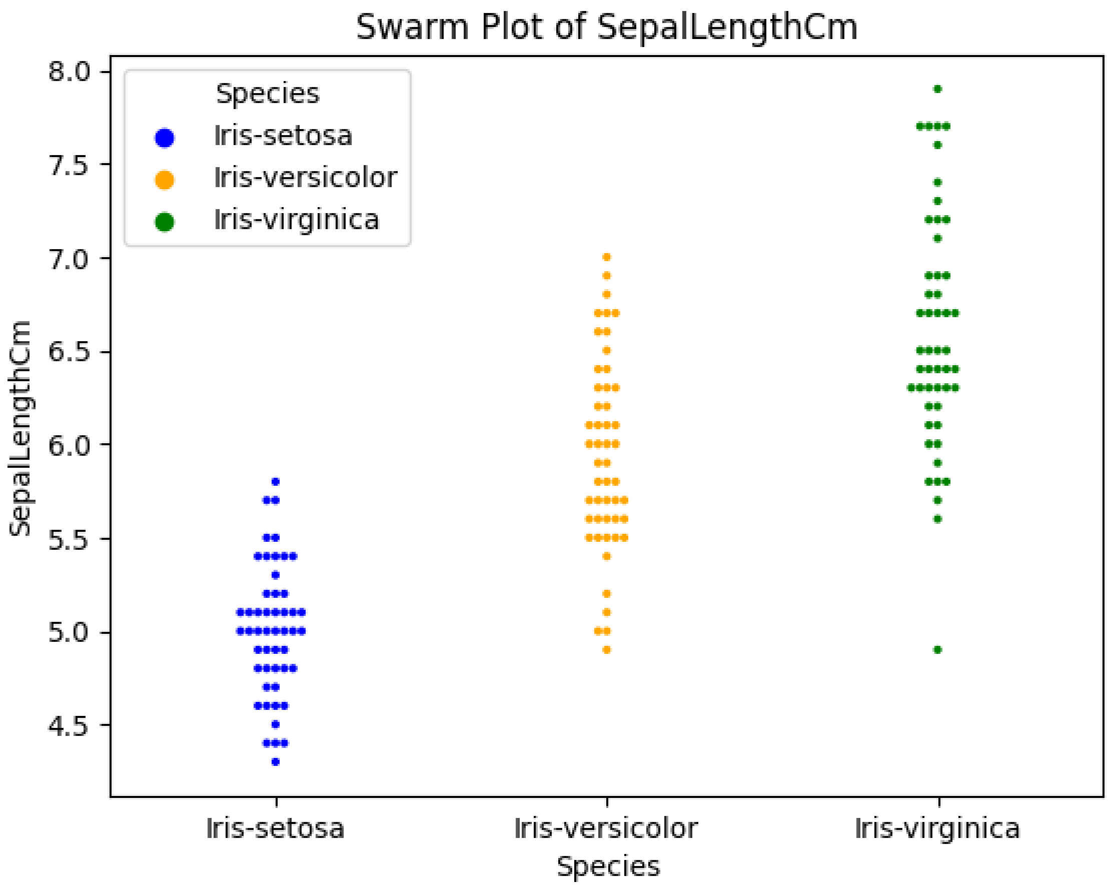

Histogram of SepalLengthCm
Count
SepalLengthCm
0
5
10
15
20
25
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0

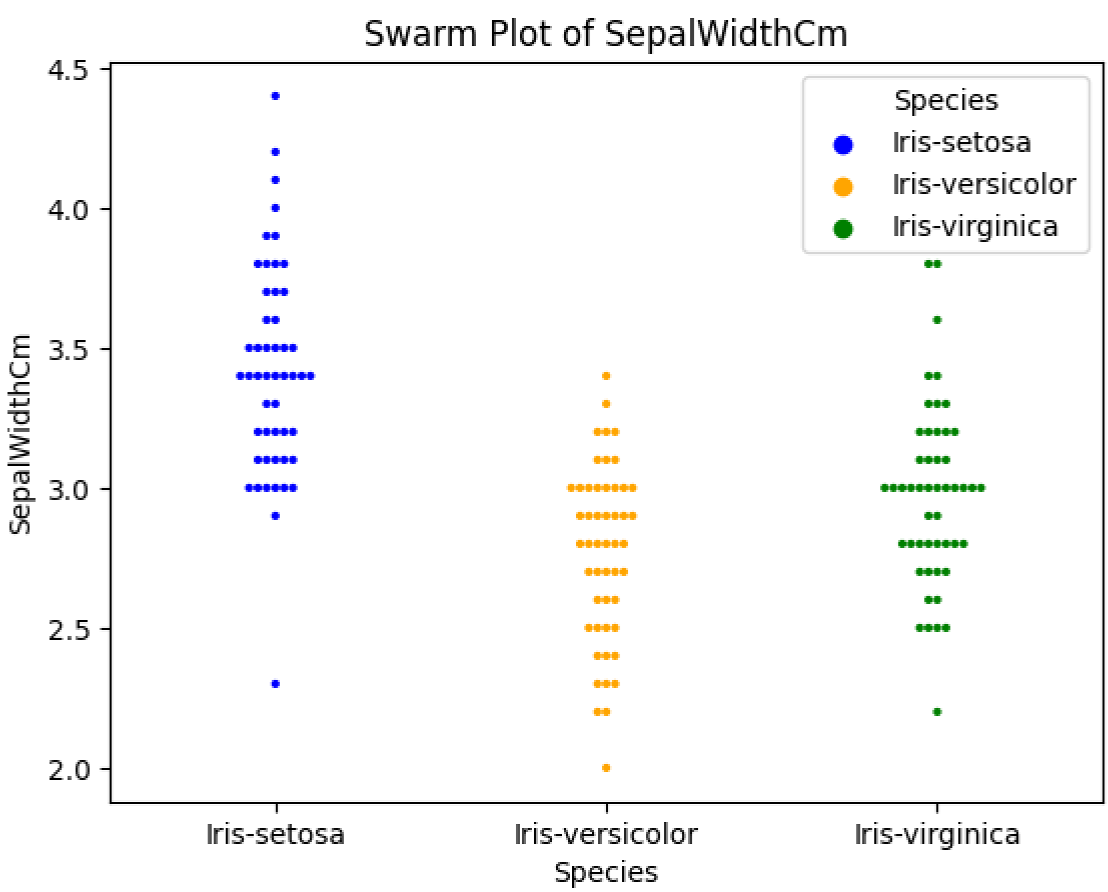

Histogram of SepalWidthCm
Count
SepalWidthCm
0
5
10
15
20
25
30
35
2.0
2.5
3.0
3.5
4.0
4.5

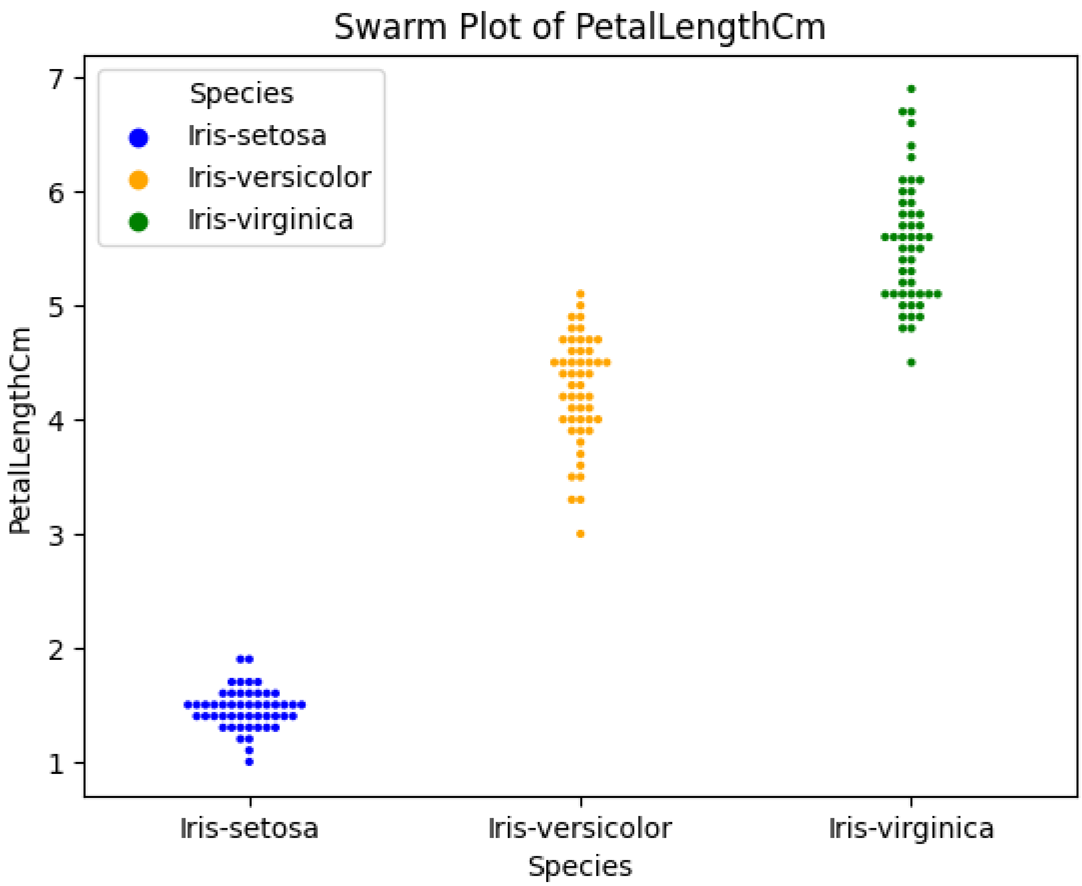

Histogram of PetalLengthCm
Count
PetalLengthCm
0
10
20
30
40
1
2
3
4
5
6
7

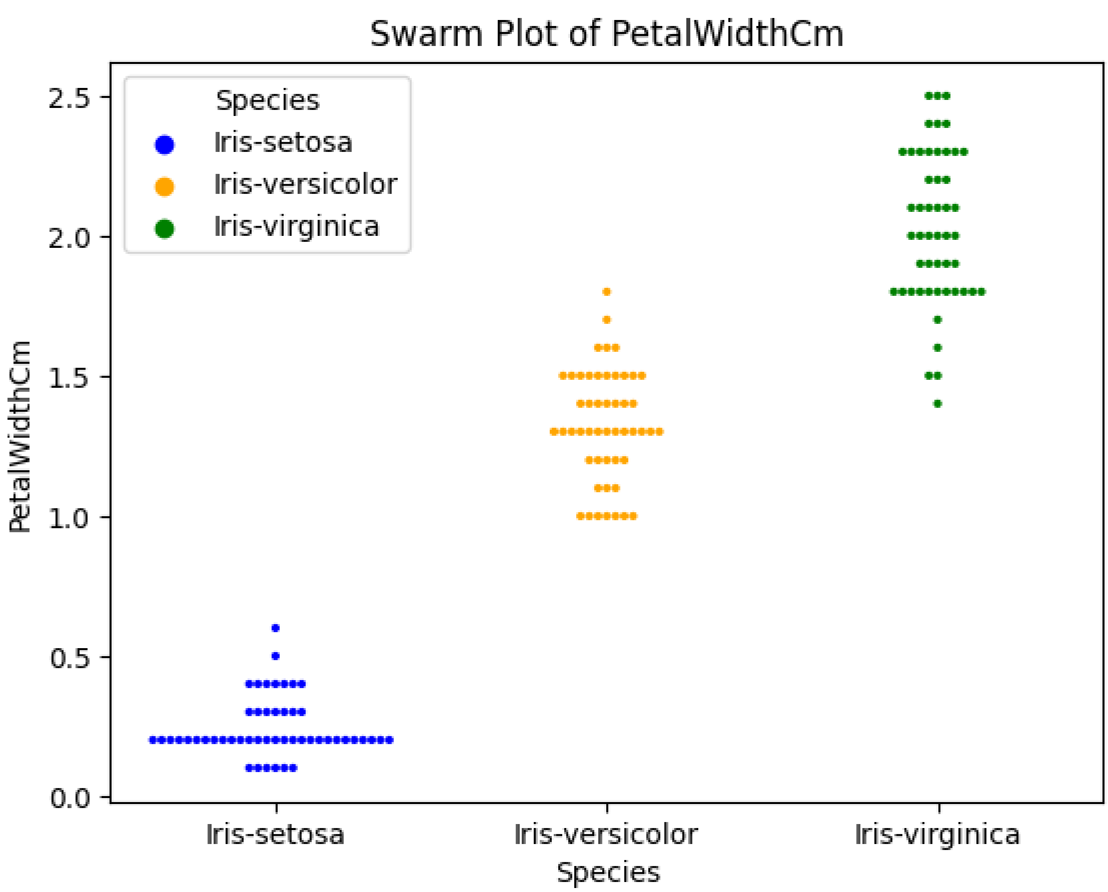


In [7]:
```
species_colors = {'setosa': 'blue', 'versicolor': 'orange', 'virginica': 'green'}

for feature in features:
    plt.figure()
    sns.swarmplot(data=iris_data, x='Species', y=feature, hue='Species', palette=speci
    plt.xlabel('Species')
    plt.ylabel(feature)
    plt.title(f'Swarm Plot of {feature}')
    plt.show()
```


Swarm Plot of SepalLengthCm
Species
Iris-setosa
Iris-versicolor
Iris-virginica
SepalLengthCm
8.0
7.5
7.0
6.5
6.0
5.5
5.0
4.5
Iris-setosa
Iris-versicolor
Iris-virginica
Species

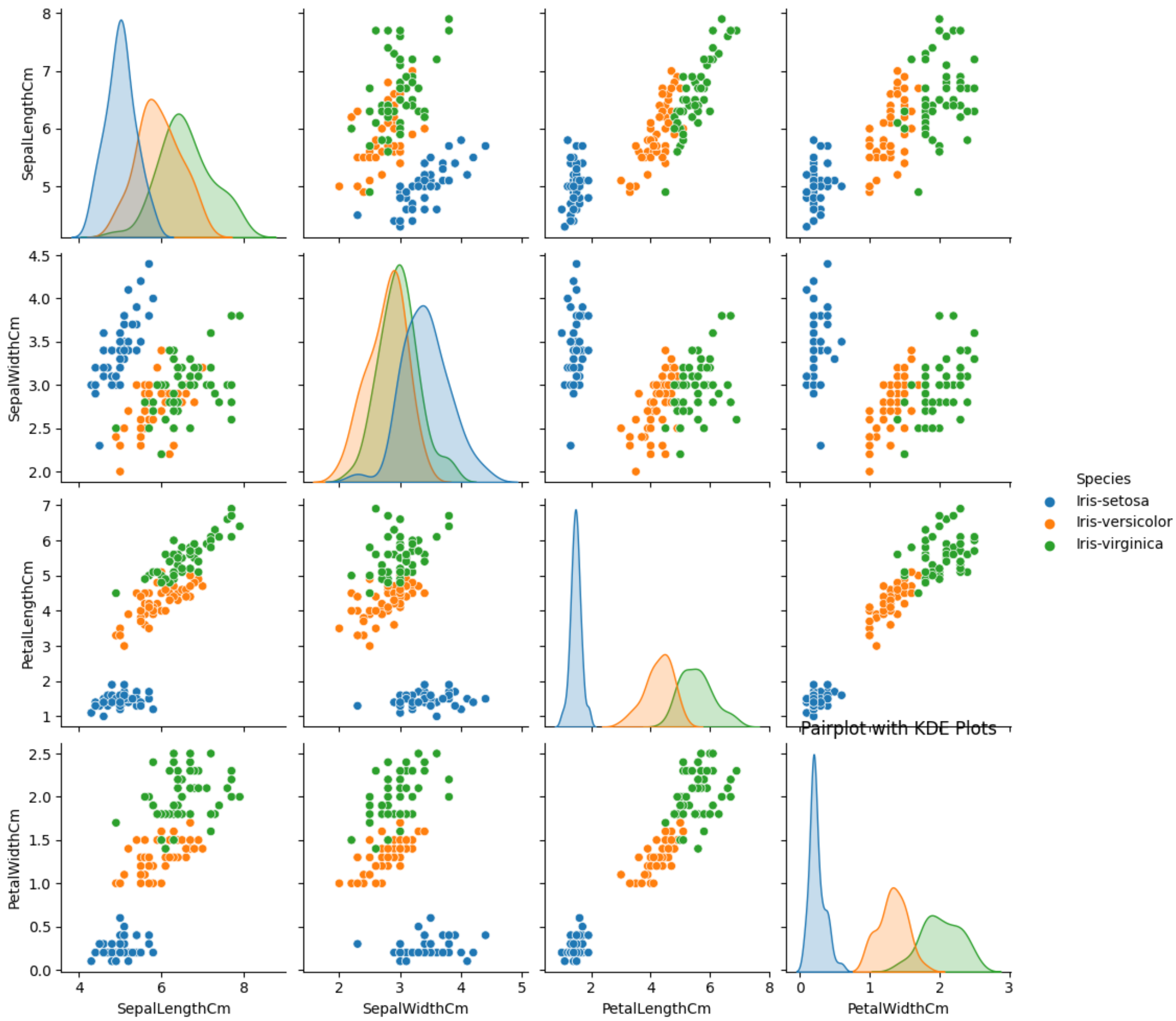

Swarm Plot of SepalWidthCm
Species
Iris-setosa
Iris-versicolor
Iris-virginica
SepalWidthCm
4.5
4.0
3.5
3.0
2.5
2.0
Iris-setosa
Iris-versicolor
Iris-virginica
Species





In [8]:
```
sns.pairplot(data=iris_data, hue='Species', diag_kind='kde')
plt.title('Pairplot with KDE Plots')
```

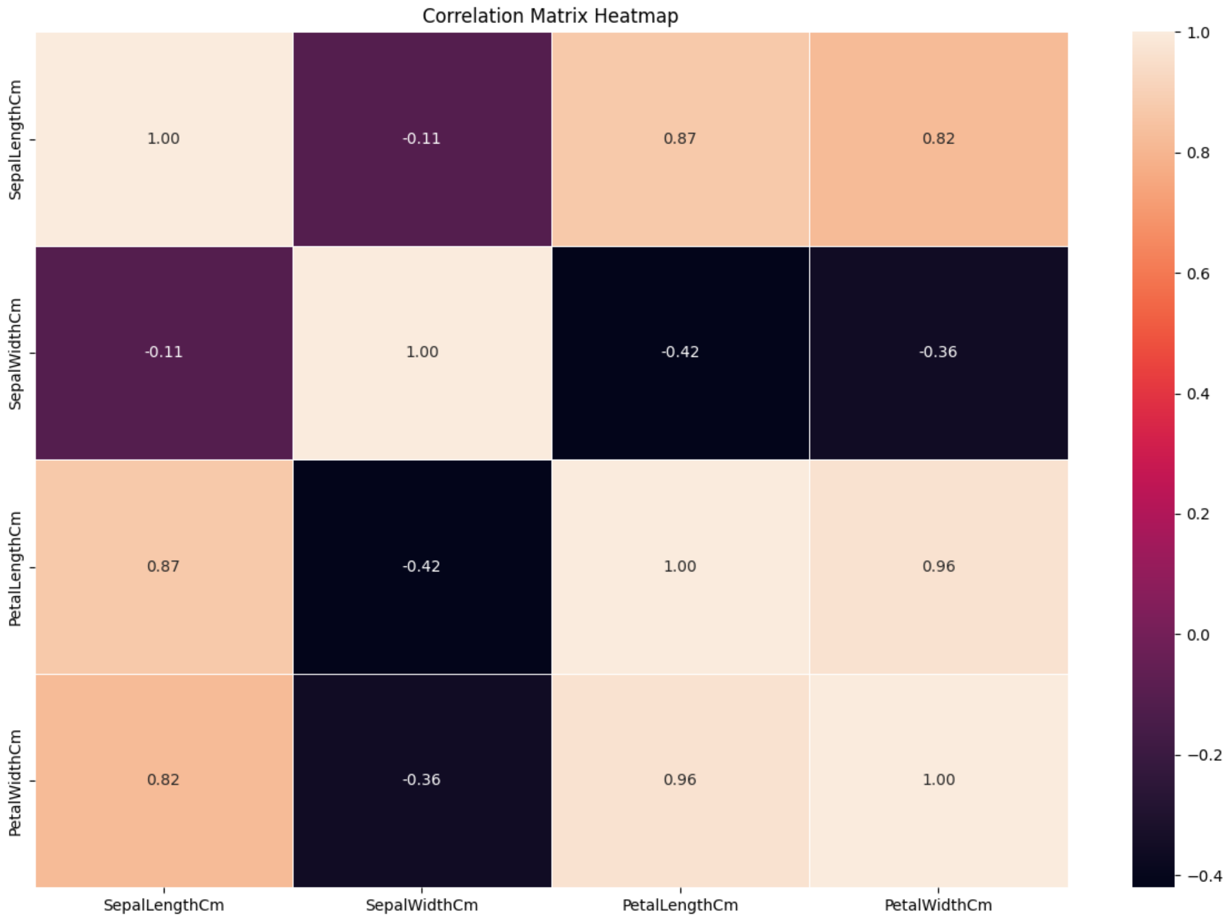
```
plt.show()
```



In [9]:

```
correlation_matrix = iris_data.corr()

plt.figure(figsize=(15, 10))
sns.heatmap(correlation_matrix, annot=True, linewidths=0.5, fmt='.2f')
plt.title("Correlation Matrix Heatmap")
plt.show()
```

```
C:\Users\Berkay\AppData\Local\Temp\ipykernel_16236\2869641057.py:1: FutureWarning: 
e default value of numeric_only in DataFrame.corr is deprecated. In a future version,
it will default to False. Select only valid columns or specify the value of numeric_o
nly to silence this warning.
  correlation_matrix = iris_data.corr()
```



In [10]:
```
labels = LabelEncoder().fit_transform(iris_data.Species)
print(labels)
```

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2]
```

In [11]:
```
iris_data['Target'] = labels
```

Train the classifier

In [12]:
```
clf = DecisionTreeClassifier(max_depth=5)
```

In [13]:
```
X = iris_data.drop(['Species','Target'], axis=1)
Y = iris_data['Target']
```

In [14]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2, shuffle
```

In [15]:
```
X_train_list = X_train.values.tolist()
Y_train_list = Y_train.values.tolist()
```

In [16]:
```
clf.fit(X_train_list,Y_train_list)
```

Out[16]:
```
<dt.Node at 0x12e8b76e860>
```

In [17]:
```python
clf.print_tree()
```

```
X_2 <= 1.9 ? 0.32464769647696473
 left:0
 right:X_3 <= 1.7 ? 0.3870826209910089
  left:X_2 <= 4.9 ? 0.06530864197530856
    left:X_3 <= 1.6 ? 0.04875000000000007
        left:1
        right:2
    right:X_3 <= 1.5 ? 0.21333333333333332
        left:2
        right:X_0 <= 6.7 ? 0.4444444444444444
                left:1
                right:2
  right:X_2 <= 4.8 ? 0.016557097638178662
    left:X_0 <= 5.9 ? 0.4444444444444444
        left:1
        right:2
    right:2
```

Predict Class of Train values

In [18]:
```python
print(Y_train.values.tolist())
predictOfTrain = clf.predict(X_train.values.tolist())
print(predictOfTrain)
```

```
[1, 0, 0, 2, 1, 2, 2, 1, 2, 1, 1, 2, 0, 0, 2, 1, 2, 0, 2, 1, 2, 1, 0, 2, 1, 0, 0, 0
2, 1, 1, 2, 1, 0, 0, 0, 2, 1, 1, 0, 0, 0, 2, 2, 1, 2, 2, 1, 1, 1, 2, 1, 0, 0, 2, 0,
1, 2, 1, 0, 2, 0, 1, 2, 1, 0, 1, 2, 0, 1, 2, 1, 2, 1, 0, 2, 2, 0, 2, 0, 1, 2, 1, 0,
2, 1, 2, 1, 0, 1, 2, 2, 2, 0, 0, 1, 1, 1, 1, 0, 2, 2, 0, 1, 0, 0, 1, 1, 0, 0, 0, 2,
2, 1, 2, 2, 0, 1, 0, 1]
[1, 0, 0, 2, 1, 2, 2, 1, 2, 1, 1, 2, 0, 0, 2, 1, 2, 0, 2, 1, 2, 1, 0, 2, 1, 0, 0, 0,
2, 1, 1, 2, 1, 0, 0, 0, 2, 1, 1, 0, 0, 0, 2, 2, 1, 2, 2, 1, 1, 1, 2, 1, 0, 0, 2, 0,
1, 2, 1, 0, 2, 0, 1, 2, 1, 0, 1, 2, 0, 1, 2, 1, 2, 1, 0, 2, 2, 0, 2, 0, 1, 2, 1, 0,
2, 1, 2, 1, 0, 1, 2, 2, 2, 0, 0, 1, 1, 1, 1, 0, 2, 2, 0, 1, 0, 0, 1, 1, 0, 0, 0, 2,
2, 1, 2, 2, 0, 1, 0, 1]
```

In [19]:
```python
differences = [y_true != y_pred for y_true, y_pred in zip(Y_train, predictOfTrain)
difference_rate = sum(differences) / len(Y_train)
print(difference_rate)
```

```
0.0
```

Predict Class of Test values

In [20]:
```python
print(Y_test.values.tolist())
predictOfTest = clf.predict(X_test.values.tolist())
print(predictOfTest)
```

```
[0, 1, 2, 2, 2, 1, 2, 2, 1, 2, 0, 0, 2, 0, 2, 0, 0, 0, 2, 1, 1, 0, 0, 1, 0, 1, 2, 1
0, 0]
[0, 1, 2, 2, 2, 1, 2, 2, 1, 2, 0, 0, 2, 0, 2, 0, 0, 0, 2, 1, 1, 0, 0, 1, 0, 1, 2, 1,
0, 0]
```

In [21]:
```python
differences = [y_true != y_pred for y_true, y_pred in zip(Y_test, predictOfTest)]
difference_rate = sum(differences) / len(Y_train)
```

```
print(difference_rate)
```

```
0.0
```

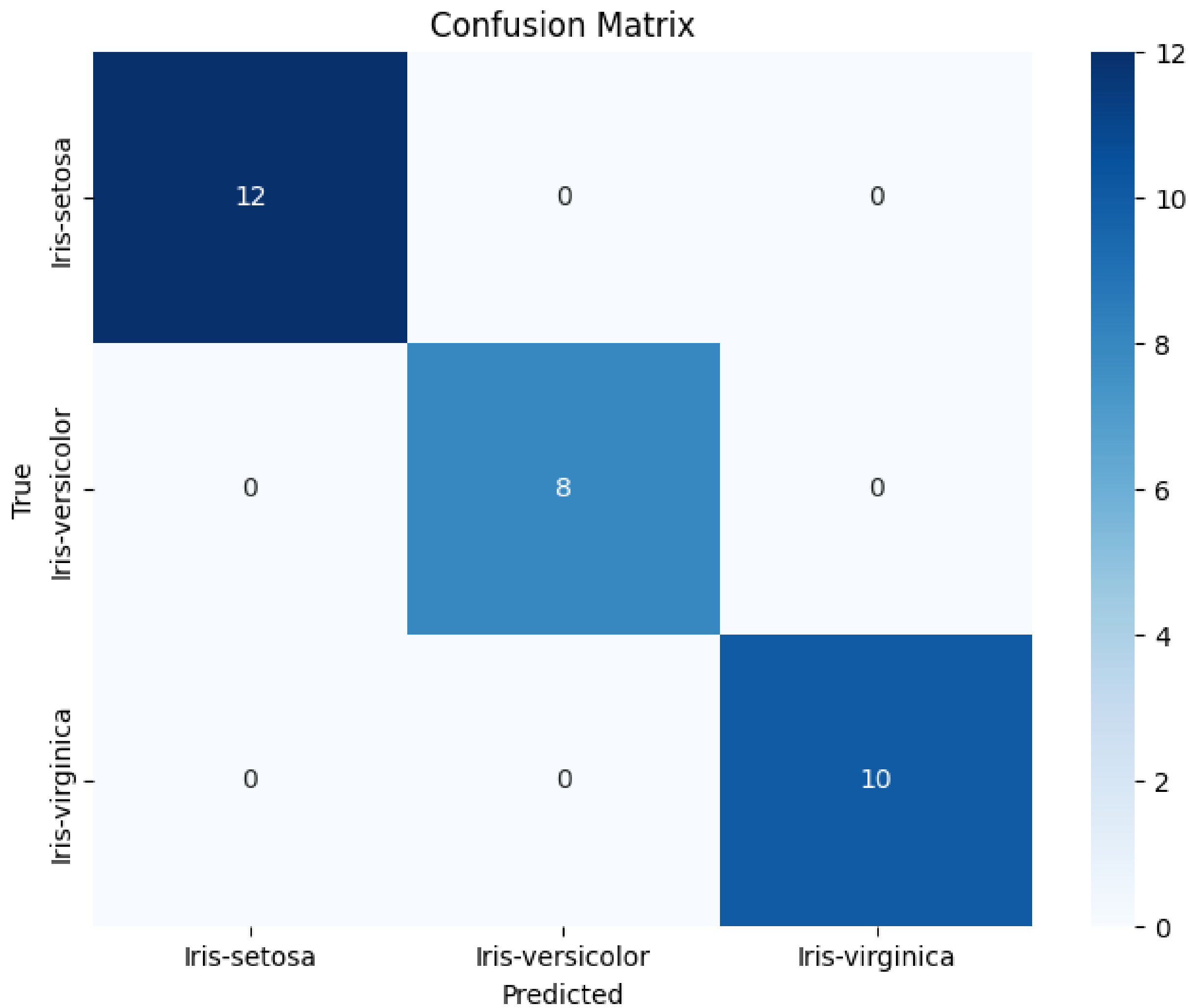
Results

Confusion Matrix of Test

In [22]:
```
cm = confusion_matrix(Y_test.values.tolist(), predictOfTest)

# Print the confusion matrix
print("Confusion Matrix:")
print(cm)
```

```
Confusion Matrix:
[[12  0  0]
 [ 0  8  0]
 [ 0  0 10]]
```

In [23]:
```
class_labels = list(LabelEncoder().fit(iris_data.Species).classes_)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, cmap='Blues', fmt='d', xticklabels=class_labels, ytickla
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

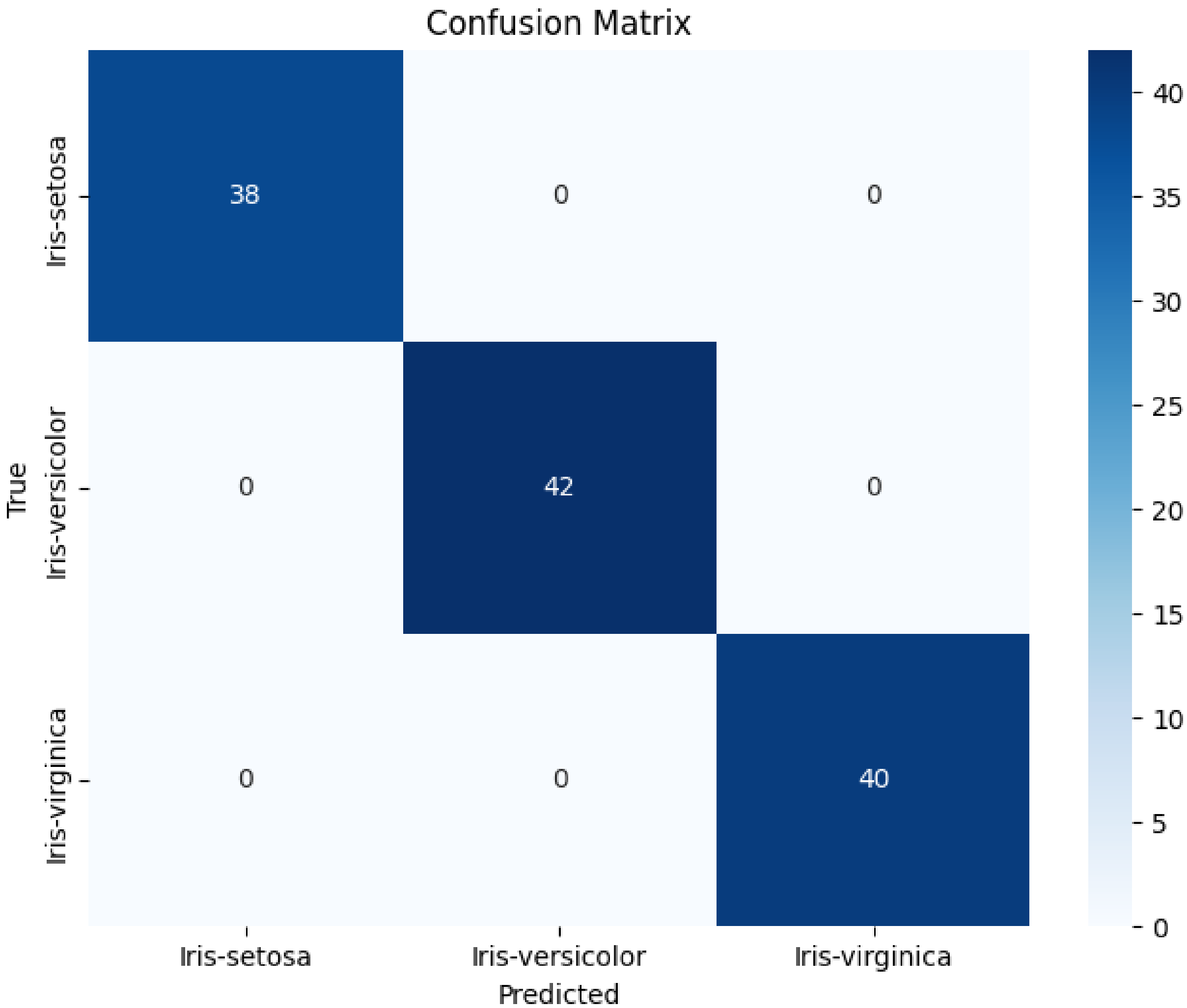


Confusion Matrix of Train

In [24]:
```
cm = confusion_matrix(Y_train.values.tolist(), predictOfTrain)

# Print the confusion matrix
print("Confusion Matrix:")
print(cm)
```

```
Confusion Matrix:
[[38  0  0]
 [ 0 42  0]
 [ 0  0 40]]
```

In [25]:
```
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, cmap='Blues', fmt='d', xticklabels=class_labels, yticklabe
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```



F1-Score

In [26]:
```
report = classification_report(Y_train.values.tolist(), predictOfTrain, target_nam

print("Classification Report:")
print("-" * 60)
print(report)
```

```
Classification Report:
------------------------------------------------------------
                 precision    recall  f1-score   support

    Iris-setosa      1.000     1.000     1.000        38
Iris-versicolor      1.000     1.000     1.000        42
 Iris-virginica      1.000     1.000     1.000        40

       accuracy                          1.000       120
      macro avg      1.000     1.000     1.000       120
   weighted avg      1.000     1.000     1.000       120
```

F1-Score,Precision,Recall and Accuracy of Train

In [27]:
```
precision, recall, f1, support = precision_recall_fscore_support(Y_train, predictO
accuracy = accuracy_score(Y_train, predictOfTrain)

for i, label in enumerate(class_labels):
    print(f"Class: {label}")
    print(f"Precision: {precision[i]:.2f}")
    print(f"Recall: {recall[i]:.2f}")
    print(f"F1-Score: {f1[i]:.2f}")
    print("")

print(f"Overall Accuracy: {accuracy:.2f}")
```

```
Class: Iris-setosa
Precision: 1.00
Recall: 1.00
F1-Score: 1.00

Class: Iris-versicolor
Precision: 1.00
Recall: 1.00
F1-Score: 1.00

Class: Iris-virginica
Precision: 1.00
Recall: 1.00
F1-Score: 1.00

Overall Accuracy: 1.00
```

F1-Score,Precision,Recall and Accuracy of Train

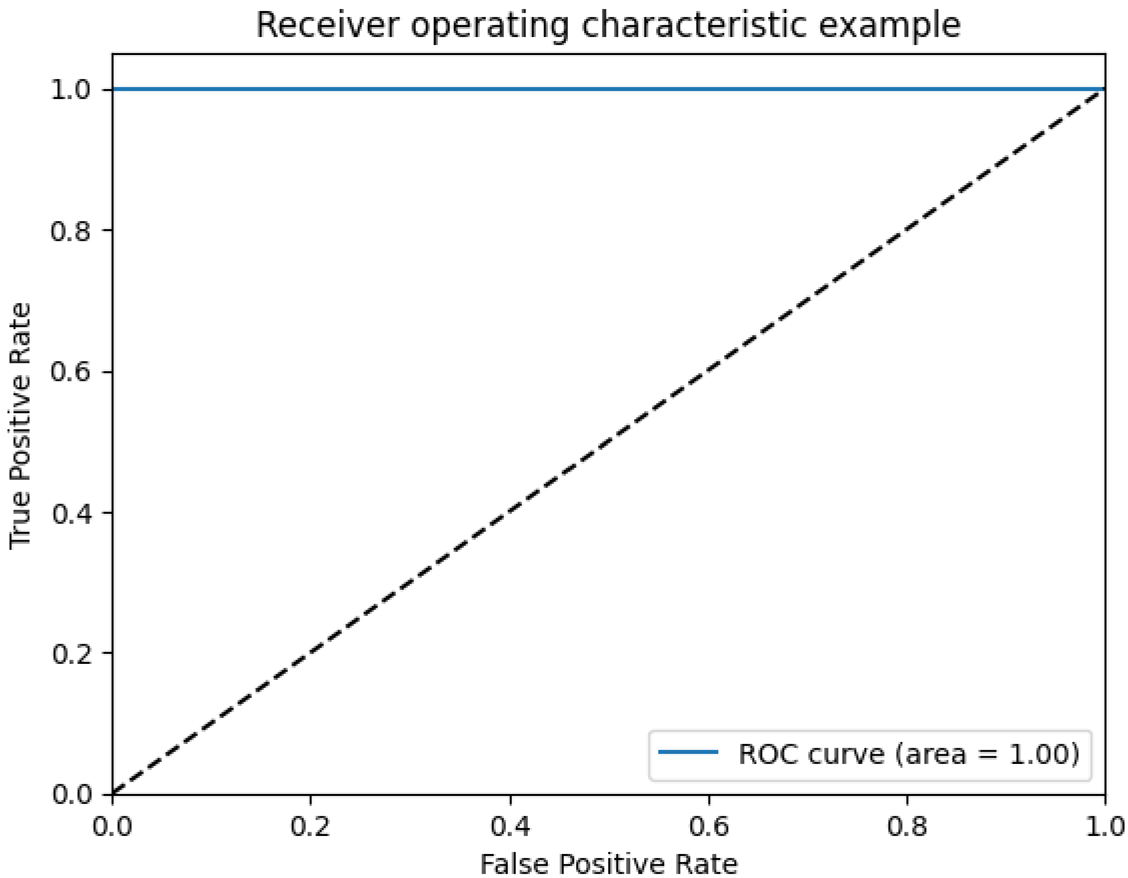
In [28]:
```
precision, recall, f1, support = precision_recall_fscore_support(Y_test, predictOf
accuracy = accuracy_score(Y_train, predictOfTrain)

for i, label in enumerate(class_labels):
    print(f"Class: {label}")
    print(f"Precision: {precision[i]:.2f}")
    print(f"Recall: {recall[i]:.2f}")
    print(f"F1-Score: {f1[i]:.2f}")
    print("")

print(f"Overall Accuracy: {accuracy:.2f}")
```

```
Class: Iris-setosa
Precision: 1.00
Recall: 1.00
F1-Score: 1.00

Class: Iris-versicolor
Precision: 1.00
Recall: 1.00
F1-Score: 1.00

Class: Iris-virginica
Precision: 1.00
Recall: 1.00
F1-Score: 1.00

Overall Accuracy: 1.00
```

Plot of ROC Curve (Test/Train) and Value of AUC (Test/Train)

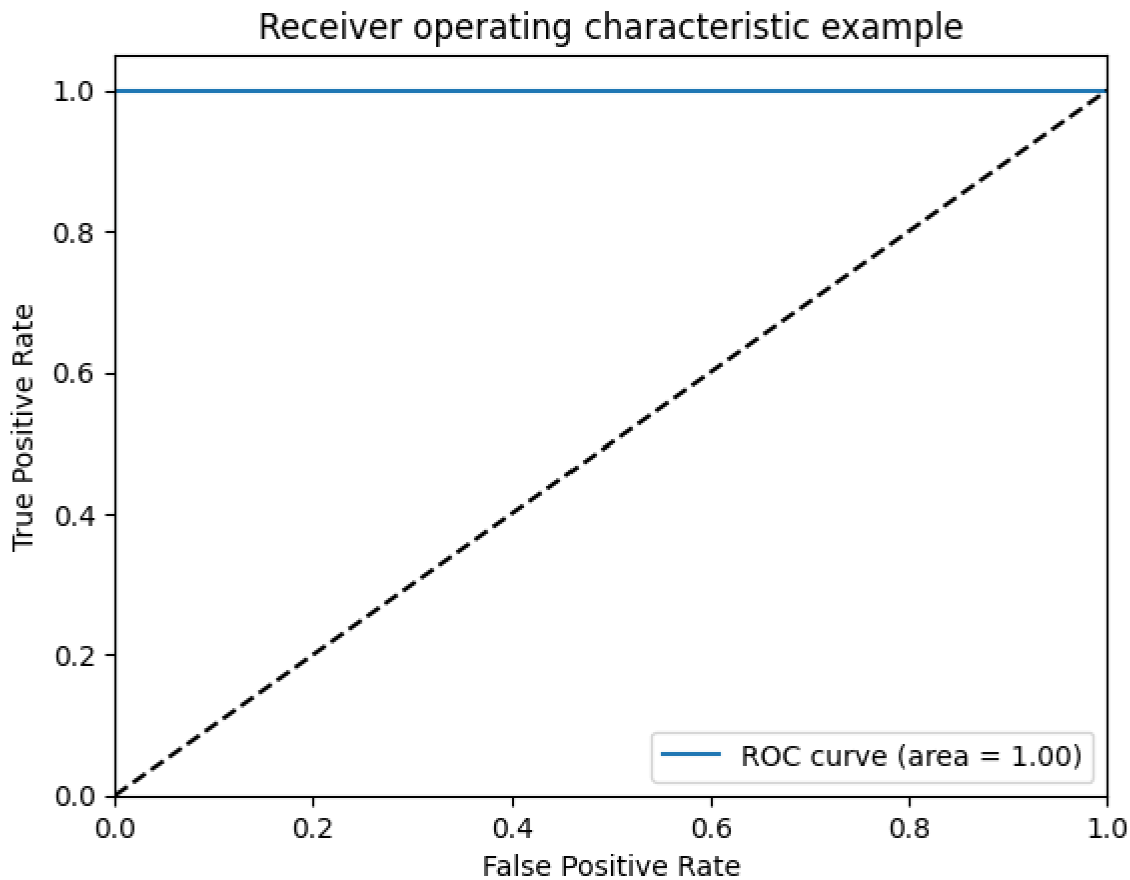
In [29]:

```
y = label_binarize(pd.Series(Y_test.values.tolist()), classes=[0, 1, 2])
y2 = label_binarize(pd.Series(predictOfTest), classes=[0, 1, 2])
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(3):
 fpr[i], tpr[i], _ = roc_curve(y[:, i], y2[:, i])
 roc_auc[i] = auc(fpr[i], tpr[i])
fpr["micro"], tpr["micro"], _ = roc_curve(y.ravel(), y2.ravel())
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])
plt.figure()
plt.plot(fpr[2], tpr[2], label='ROC curve (area = %0.2f)' % roc_auc[2])
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
```



In [30]:

```
y = label_binarize(pd.Series(Y_train.values.tolist()), classes=[0, 1, 2])
y2 = label_binarize(pd.Series(predictOfTrain), classes=[0, 1, 2])
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(3):
 fpr[i], tpr[i], _ = roc_curve(y[:, i], y2[:, i])
 roc_auc[i] = auc(fpr[i], tpr[i])
fpr["micro"], tpr["micro"], _ = roc_curve(y.ravel(), y2.ravel())
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])
plt.figure()
plt.plot(fpr[2], tpr[2], label='ROC curve (area = %0.2f)' % roc_auc[2])
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
```



Evaluation

Kendi yazdığım karar ağacı modelinin üzerinden eğittiğim iris data seti test ve train verileri üzerinde hatasız çalışmıştır. Bu hatasız çalışmanın sebepleri arasında verinin kolayca ayırt edilebilen özelliklere sahip olması ve yüksek performans elde etmek mümkün olması, train veri setinin overfitlenmiş olabilmesi ve test veri setinin çok büyük olmaması sonucu ayırt edilememiş olması veya modelin bu eğitimde tam doğru noktalardan karar ağacını ayırması olabilir.

Ideal Depth for DT

Kendi modelimdeki derinlik 5, bu değeri öylesine seçmiştim fakat aşağıdaki grafikte de görüldüğü üzere ideal derinlik 2 çıktı. Grafiğe bakıldığında görebileceğimiz gibi derinlik 2'den sonra daima aynı. Bu gibi durumlarda (aynı performansı gösteren) en basit modeli seçmek en mantıklıdır.

In [34]:
```
clf.print_tree()
```

```
X_2 <= 1.9 ? 0.32464769647696473
 left:0
 right:X_3 <= 1.7 ? 0.3870826209910089
  left:X_2 <= 4.9 ? 0.06530864197530856
    left:X_3 <= 1.6 ? 0.04875000000000007
        left:1
        right:2
    right:X_3 <= 1.5 ? 0.21333333333333332
        left:2
        right:X_0 <= 6.7 ? 0.4444444444444444
                left:1
                right:2
  right:X_2 <= 4.8 ? 0.016557097638178662
    left:X_0 <= 5.9 ? 0.4444444444444444
        left:1
        right:2
    right:2
```

Level 0: Root node (X_2 <= 1.9)

Level 1: Left branch (0.32464769647696473)

Level 1: Right branch (X_3 <= 1.7)

Level 2: Left branch (X_2 <= 4.9)

Level 3: Left branch (X_3 <= 1.6)

Level 4: Left branch (1)

Level 4: Right branch (2)

Level 3: Right branch (X_3 <= 1.5)

Level 4: Left branch (2)

Level 4: Right branch (X_0 <= 6.7)

Level 5: Left branch (1)

Level 5: Right branch (2)

Level 2: Right branch (X_2 <= 4.8)

Level 3: Left branch (X_0 <= 5.9)

Level 4: Left branch (1)

Level 4: Right branch (2)

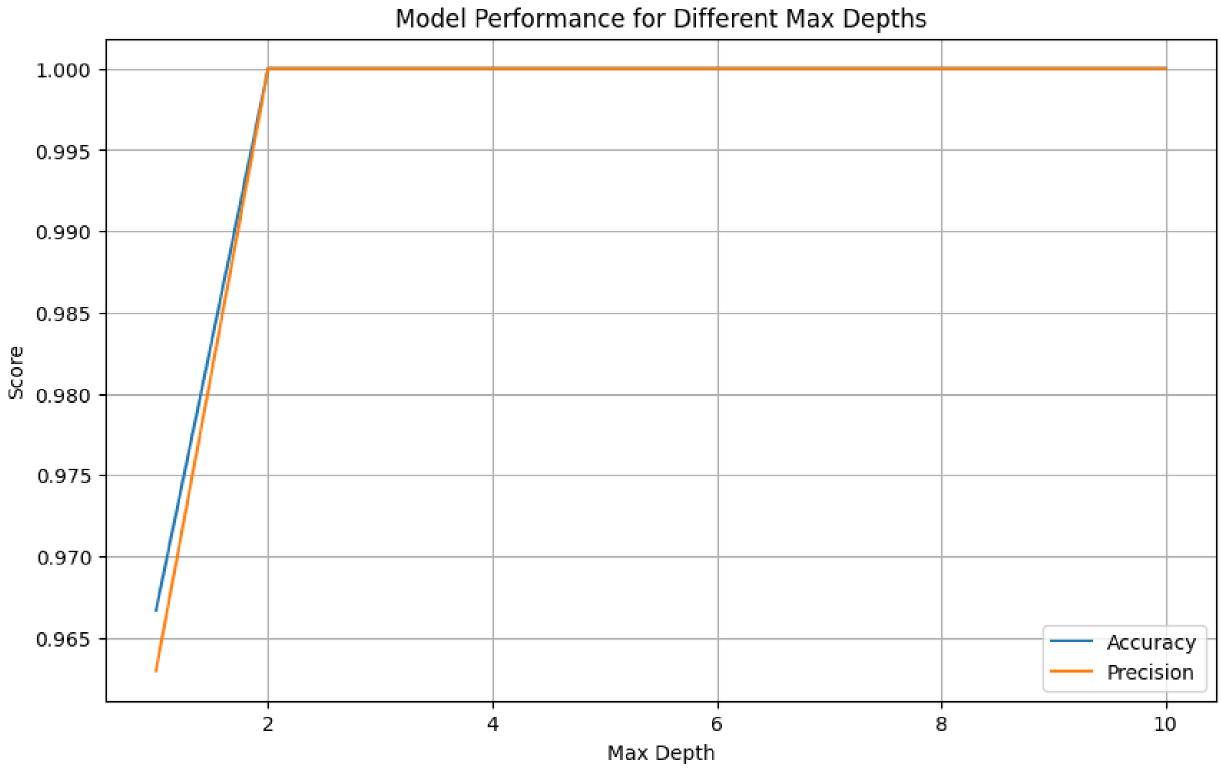
Level 3: Right branch (2)

```
Level 0: X_2 <= 1.9
        |
```

```
                              ------------------------------
                            |                               |
                   Level 1: 0.3246             Level 1: X_3 <= 1.7
                                                            |
                               ---------------------------------------------
                             |                                              |
                 Level 2: X_2 <= 4.9                          Level 2: X_2 <= 4.8
                             |                                              |
           ------------------------                           --------------------
        -----
          |                         |                   |
        |
        Level 3: X_3 <= 1.6    Level 3: X_3 <= 1.5    Level 3: X_0 <= 5.9
        Level 3: 2
          |                         |                   |
        Level 4: 1                Level 4: 2          ------------------------
        -
                                                         |
        |
                                                  Level 4: 1

        Level 4: 2
```

In [40]:

```python
depth_values = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
accuracy_scores = []
precision_scores = []

for depth in depth_values:
    model = DecisionTreeClassifier(max_depth=depth)
    model.fit(X_train.values.tolist(), Y_train.values.tolist())
    y_pred = model.predict(X_test.values.tolist())
    accuracy = accuracy_score(Y_test, y_pred)
    precision = precision_score(Y_test, y_pred, average='macro')
    accuracy_scores.append(accuracy)
    precision_scores.append(precision)

plt.figure(figsize=(10, 6))
plt.plot(depth_values, accuracy_scores, label='Accuracy')
plt.plot(depth_values, precision_scores, label='Precision')
plt.xlabel('Max Depth')
plt.ylabel('Score')
plt.title('Model Performance for Different Max Depths')
plt.legend()
plt.grid(True)
plt.show()
```



Model Performance for Different Max Depths
Score
1.000
0.995
0.990
0.985
0.980
0.975
0.970
0.965
Max Depth
2
4
6
8
10
Accuracy
Precision