iris-poc

January 10, 2024

- IRIS FLOWER CLASSIFICATION

Task 1

** Iris flower has three species; setosa, versicolor, and virginica, which differs according to their measurements. Now assume that you have the measurements of the iris flowers according to their species, and here your task is to train a machine learning model that can learn from the measurements of the iris species and classify them.

#Description

###Sources:

- Classify iris plants into three species in this classic dataset
- **Dataset Link:**https://www.kaggle.com/datasets/saurabh00007/iriscsv

0.0.1 Problem Statement:

- This is a multiple-classification problem.I built a logistic regression, decision tree classification, and random forest classification, Support Vector Machine" (SVM). The goal is to predict what Species.

###About Dataset

- The Iris dataset was used in R.A. Fisher's classic 1936 paper, The Use of Multiple Measurements in Taxonomic Problems, and can also be found on the UCI Machine Learning Repository.
- It includes three iris species with 50 samples each as well as some properties about each flower. One flower species is linearly separable from the other two, but the other two are not linearly separable from each other.

###The columns in this dataset are:

- Id
- SepalLengthCm
- SepalWidthCm
- PetalLengthCm
- PetalWidthCm
- Species

1 sepal

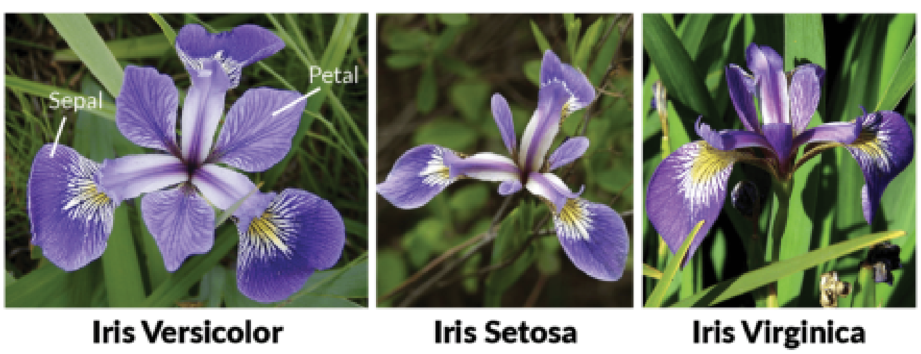
- **Iris setosa** has sepal length not greater than 6.0 cm and sepal width not less than 2.3 cm.

- **Iris versicolor** has sepal length not less than 5.0 cm and sepal width not greater than 3.4 cm.
- **Iris virginica** has sepal length not less than 6.0 cm and sepal width not greater than 3.8 cm.

2 Import necessary libraries

[53]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import␣
↪confusion_matrix,accuracy_score,classification_report
```

[54]:
```
# image file
image = 'iris.png'

# Load and display the image
img = plt.imread(image)
plt.imshow(img)
plt.axis('off')  # Turn off axis labels
plt.show()
```



[55]:
```
# Load the Iris dataset
df=pd.read_csv('Iris.csv')
```

#Exploratory data analysis(EDA)

[56]:
```
#shallow copy
df2=df.copy()
```

[57]:
```
print('The shape of a DataFrame:',df.shape)
```

```
The shape of a DataFrame: (150, 6)
```

[58]:
```
print('Display all columns:\n',df.columns)
```

```
Display all columns:
 Index(['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm',
       'Species'],
      dtype='object')
```

[59]:
```
# display top 5 on dataset
df.head()
```

[59]:

	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

[60]:
```
# Display the bottom rows
df.tail()
```

[60]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	\
145	146	6.7	3.0	5.2	2.3	
146	147	6.3	2.5	5.0	1.9	
147	148	6.5	3.0	5.2	2.0	
148	149	6.2	3.4	5.4	2.3	
149	150	5.9	3.0	5.1	1.8	

	Species
145	Iris-virginica
146	Iris-virginica
147	Iris-virginica
148	Iris-virginica
149	Iris-virginica

[61]:
```
# specific rows of a DataFrame ( "integer location" Method)
df.iloc[100:200]
```

[61]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	\
100	101	6.3	3.3	6.0	2.5	
101	102	5.8	2.7	5.1	1.9	

102	103	7.1	3.0	5.9	2.1
103	104	6.3	2.9	5.6	1.8
104	105	6.5	3.0	5.8	2.2
105	106	7.6	3.0	6.6	2.1
106	107	4.9	2.5	4.5	1.7
107	108	7.3	2.9	6.3	1.8
108	109	6.7	2.5	5.8	1.8
109	110	7.2	3.6	6.1	2.5
110	111	6.5	3.2	5.1	2.0
111	112	6.4	2.7	5.3	1.9
112	113	6.8	3.0	5.5	2.1
113	114	5.7	2.5	5.0	2.0
114	115	5.8	2.8	5.1	2.4
115	116	6.4	3.2	5.3	2.3
116	117	6.5	3.0	5.5	1.8
117	118	7.7	3.8	6.7	2.2
118	119	7.7	2.6	6.9	2.3
119	120	6.0	2.2	5.0	1.5
120	121	6.9	3.2	5.7	2.3
121	122	5.6	2.8	4.9	2.0
122	123	7.7	2.8	6.7	2.0
123	124	6.3	2.7	4.9	1.8
124	125	6.7	3.3	5.7	2.1
125	126	7.2	3.2	6.0	1.8
126	127	6.2	2.8	4.8	1.8
127	128	6.1	3.0	4.9	1.8
128	129	6.4	2.8	5.6	2.1
129	130	7.2	3.0	5.8	1.6
130	131	7.4	2.8	6.1	1.9
131	132	7.9	3.8	6.4	2.0
132	133	6.4	2.8	5.6	2.2
133	134	6.3	2.8	5.1	1.5
134	135	6.1	2.6	5.6	1.4
135	136	7.7	3.0	6.1	2.3
136	137	6.3	3.4	5.6	2.4
137	138	6.4	3.1	5.5	1.8
138	139	6.0	3.0	4.8	1.8
139	140	6.9	3.1	5.4	2.1
140	141	6.7	3.1	5.6	2.4
141	142	6.9	3.1	5.1	2.3
142	143	5.8	2.7	5.1	1.9
143	144	6.8	3.2	5.9	2.3
144	145	6.7	3.3	5.7	2.5
145	146	6.7	3.0	5.2	2.3
146	147	6.3	2.5	5.0	1.9
147	148	6.5	3.0	5.2	2.0
148	149	6.2	3.4	5.4	2.3

```
149  150           5.9           3.0           5.1           1.8

             Species
100  Iris-virginica
101  Iris-virginica
102  Iris-virginica
103  Iris-virginica
104  Iris-virginica
105  Iris-virginica
106  Iris-virginica
107  Iris-virginica
108  Iris-virginica
109  Iris-virginica
110  Iris-virginica
111  Iris-virginica
112  Iris-virginica
113  Iris-virginica
114  Iris-virginica
115  Iris-virginica
116  Iris-virginica
117  Iris-virginica
118  Iris-virginica
119  Iris-virginica
120  Iris-virginica
121  Iris-virginica
122  Iris-virginica
123  Iris-virginica
124  Iris-virginica
125  Iris-virginica
126  Iris-virginica
127  Iris-virginica
128  Iris-virginica
129  Iris-virginica
130  Iris-virginica
131  Iris-virginica
132  Iris-virginica
133  Iris-virginica
134  Iris-virginica
135  Iris-virginica
136  Iris-virginica
137  Iris-virginica
138  Iris-virginica
139  Iris-virginica
140  Iris-virginica
141  Iris-virginica
142  Iris-virginica
143  Iris-virginica
```

```
144   Iris-virginica
145   Iris-virginica
146   Iris-virginica
147   Iris-virginica
148   Iris-virginica
149   Iris-virginica
```

[62]:
```
# prints information about the DataFrame.
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             150 non-null    int64
 1   SepalLengthCm  150 non-null    float64
 2   SepalWidthCm   150 non-null    float64
 3   PetalLengthCm  150 non-null    float64
 4   PetalWidthCm   150 non-null    float64
 5   Species        150 non-null    object
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
None
```

[63]:
```
# Display summary statistics for numerical columns in  DataFrame.
df.describe().T
```

[63]:

	count	mean	std	min	25%	50%	75%	max
Id	150.0	75.500000	43.445368	1.0	38.25	75.50	112.75	150.0
SepalLengthCm	150.0	5.843333	0.828066	4.3	5.10	5.80	6.40	7.9
SepalWidthCm	150.0	3.054000	0.433594	2.0	2.80	3.00	3.30	4.4
PetalLengthCm	150.0	3.758667	1.764420	1.0	1.60	4.35	5.10	6.9
PetalWidthCm	150.0	1.198667	0.763161	0.1	0.30	1.30	1.80	2.5

[64]:
```
# Dispaly (string) columns in the summary statistics.
df.describe(include=object)
```

[64]:

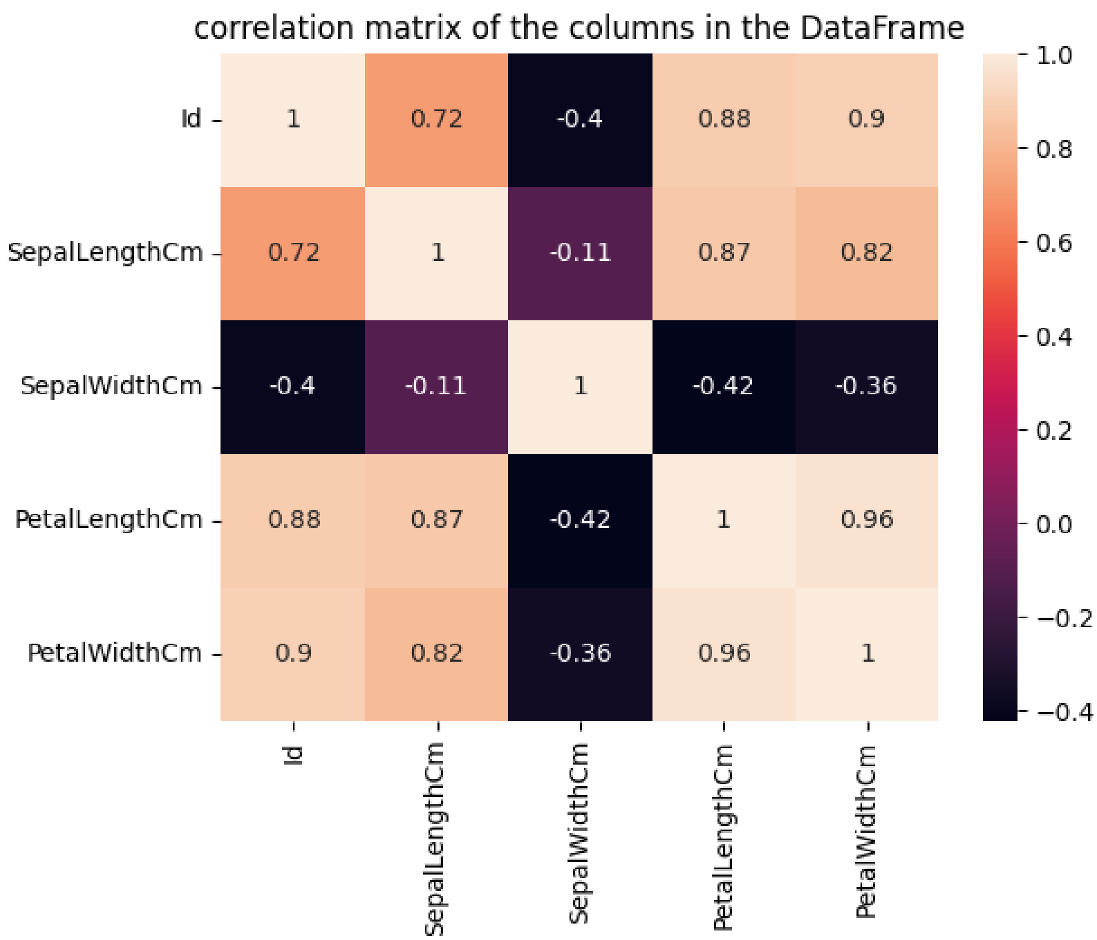
	Species
count	150
unique	3
top	Iris-setosa
freq	50

[65]:
```
sns.heatmap(df.corr(),annot=True)
plt.title('correlation matrix of the columns in the DataFrame')
```

```
<ipython-input-65-145c8a9e783a>:1: FutureWarning: The 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_only
to silence this warning.
  sns.heatmap(df.corr(),annot=True)
```

[65]:
```
Text(0.5, 1.0, 'correlation matrix of the columns in the DataFrame')
```



3 Data cleaning

[66]:
```python
# Drop the 'Id' column
df=df.drop(columns=['Id'])
```

[67]:
```python
print('To check for duplicate values in a DataFrame:',df.duplicated().sum())
```

```
To check for duplicate values in a DataFrame: 3
```

[68]:
```
#remove duplication
df=df.drop_duplicates()
```

[69]:
```
print('check after remove dulpication :',df.duplicated().sum())
```

```
check after remove dulpication : 0
```

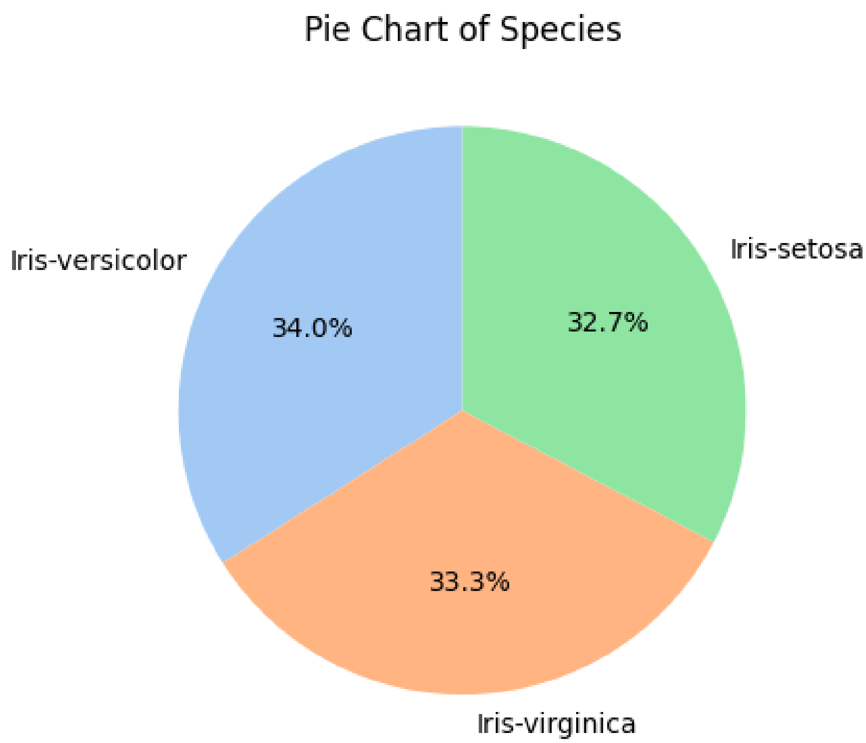
[70]:
```
print('The Number f Missing Values in The df: \n',df.isnull().sum())
```

```
The Number f Missing Values in The df:
 SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

4 Visualization

[71]:
```
# Get value counts for the 'Species' column
species_counts = df['Species'].value_counts()

# Create a pie chart
plt.pie(species_counts, labels=species_counts.index, autopct='%1.1f%%',␣
↪startangle=90, colors=sns.color_palette('pastel'))
plt.title('Pie Chart of Species')
```

[71]:
```
Text(0.5, 1.0, 'Pie Chart of Species')
```

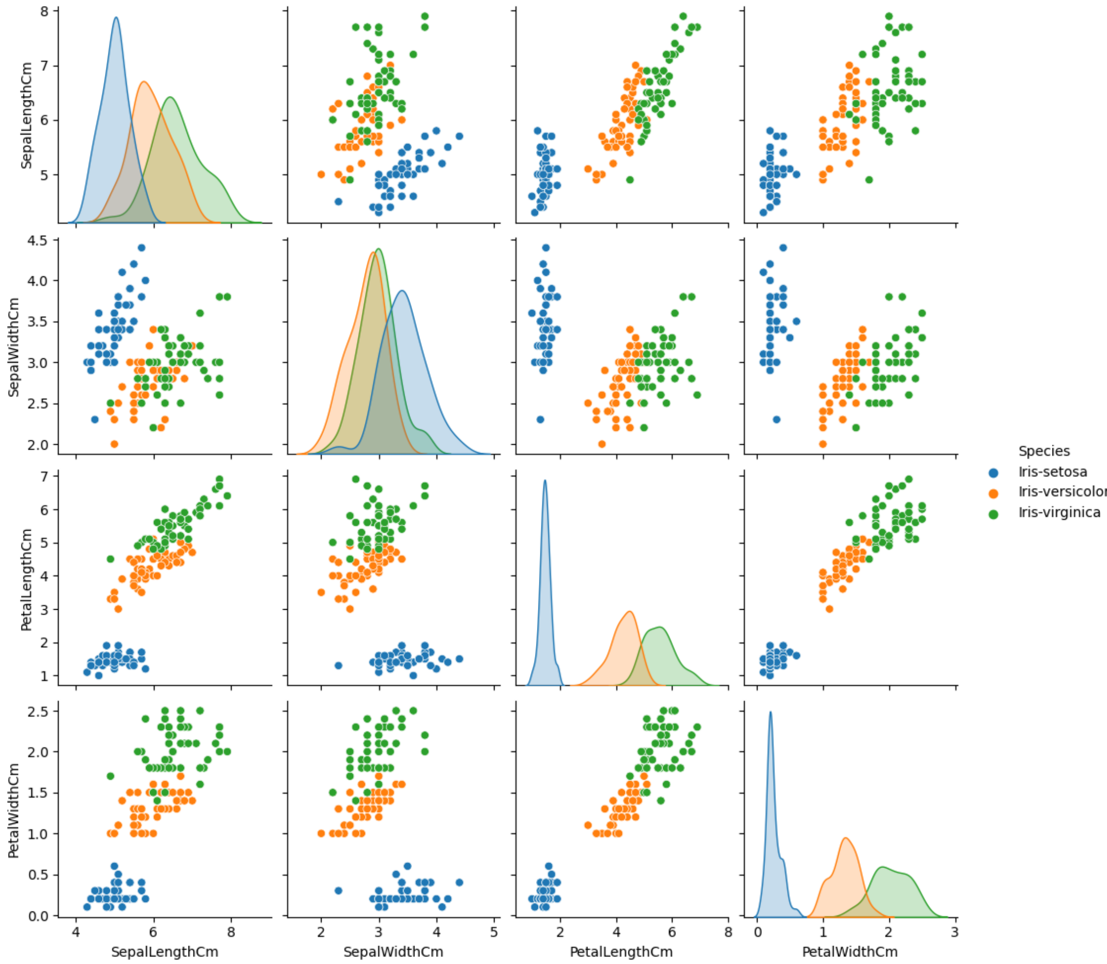


[72]:
```
df['Species'].value_counts()
```

[72]:
```
Iris-versicolor    50
Iris-virginica     49
Iris-setosa        48
Name: Species, dtype: int64
```

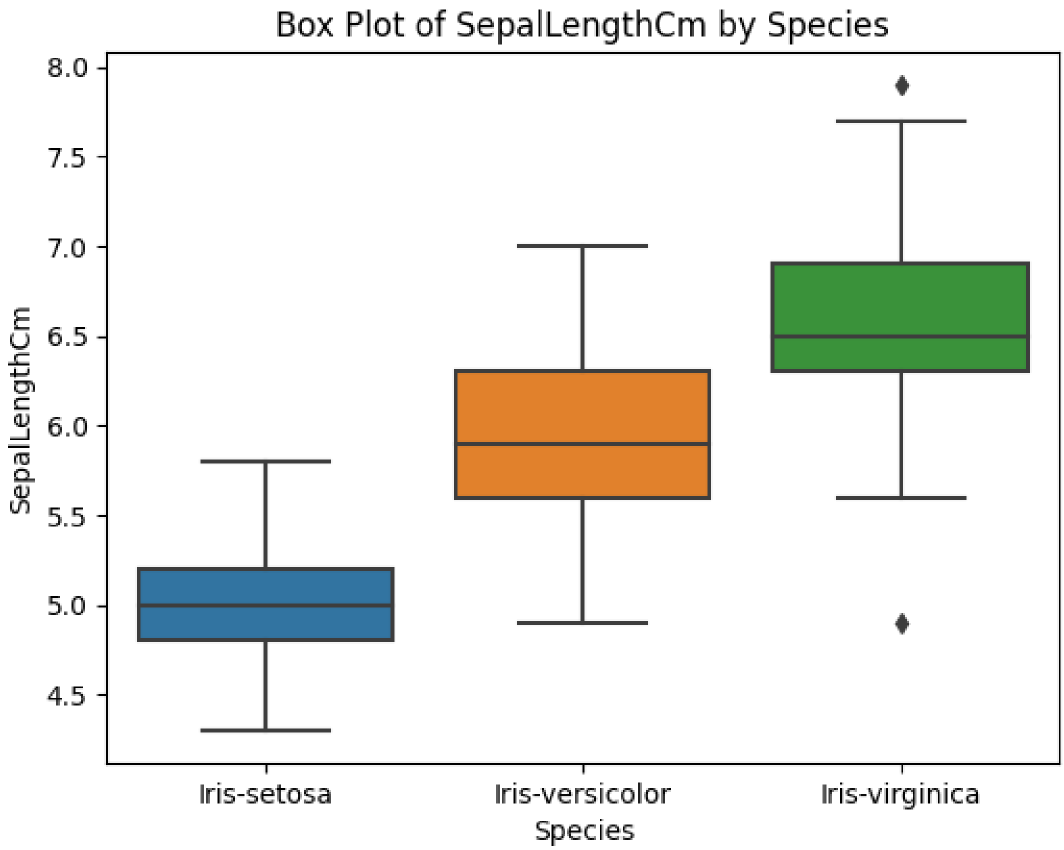
[73]:
```
# Pair Plot of Iris Dataset by Species
plt.figure(figsize=(10,6))
sns.pairplot(df,hue='Species')
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```



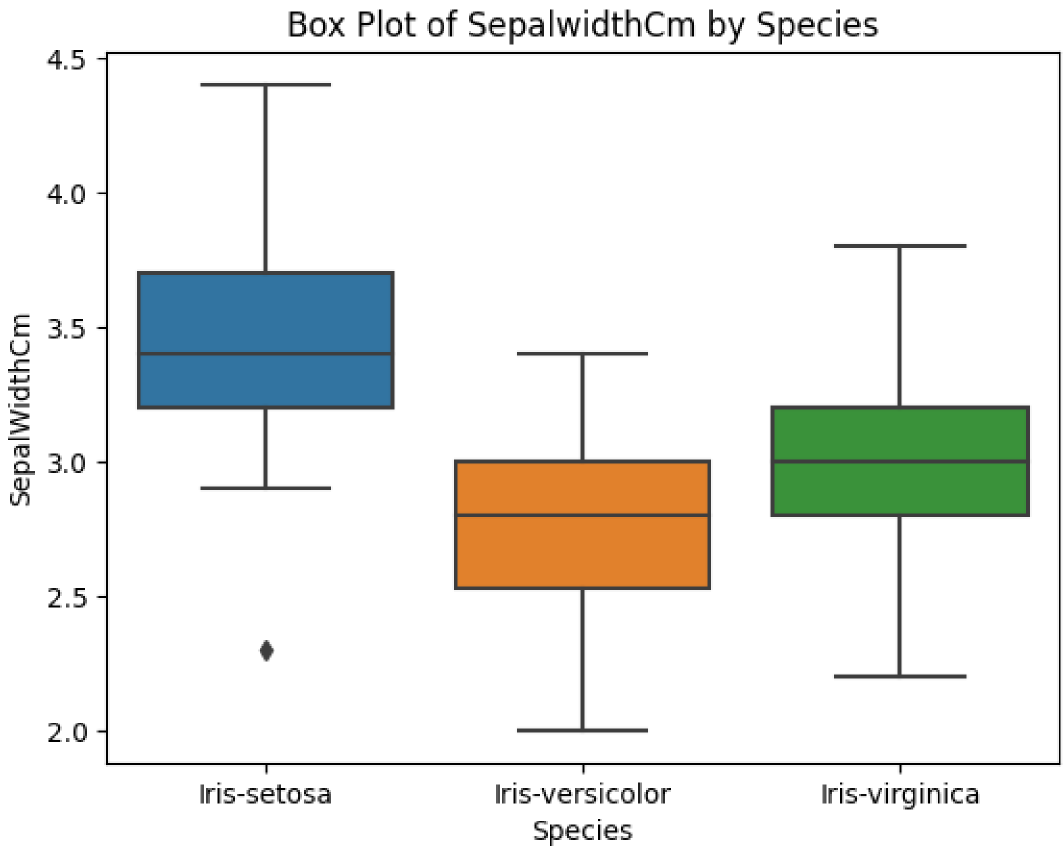
[74]:
```
sns.boxplot(x=df['Species'], y=df['SepalLengthCm'])
plt.title(f'Box Plot of SepalLengthCm by Species')
```

[74]: Text(0.5, 1.0, 'Box Plot of SepalLengthCm by Species')



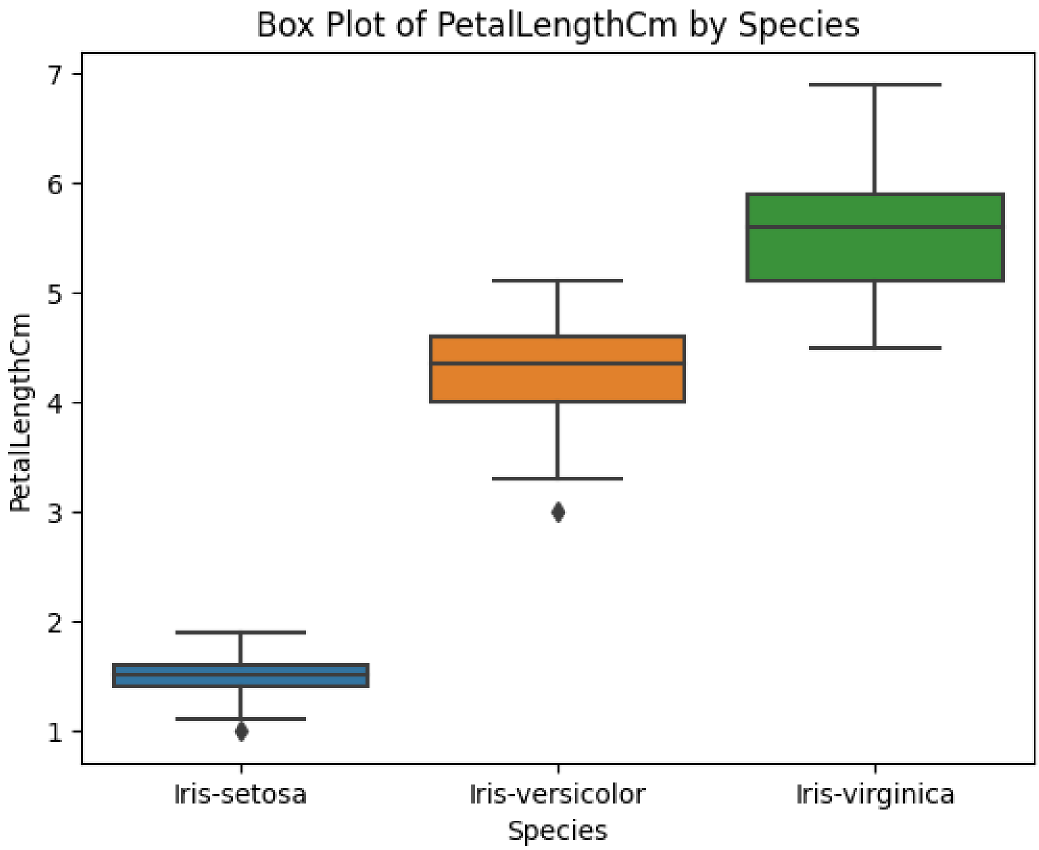
[75]:
```
sns.boxplot(x=df['Species'], y=df['SepalWidthCm'])
plt.title('Box Plot of SepalwidthCm by Species')
```

[75]: Text(0.5, 1.0, 'Box Plot of SepalwidthCm by Species')



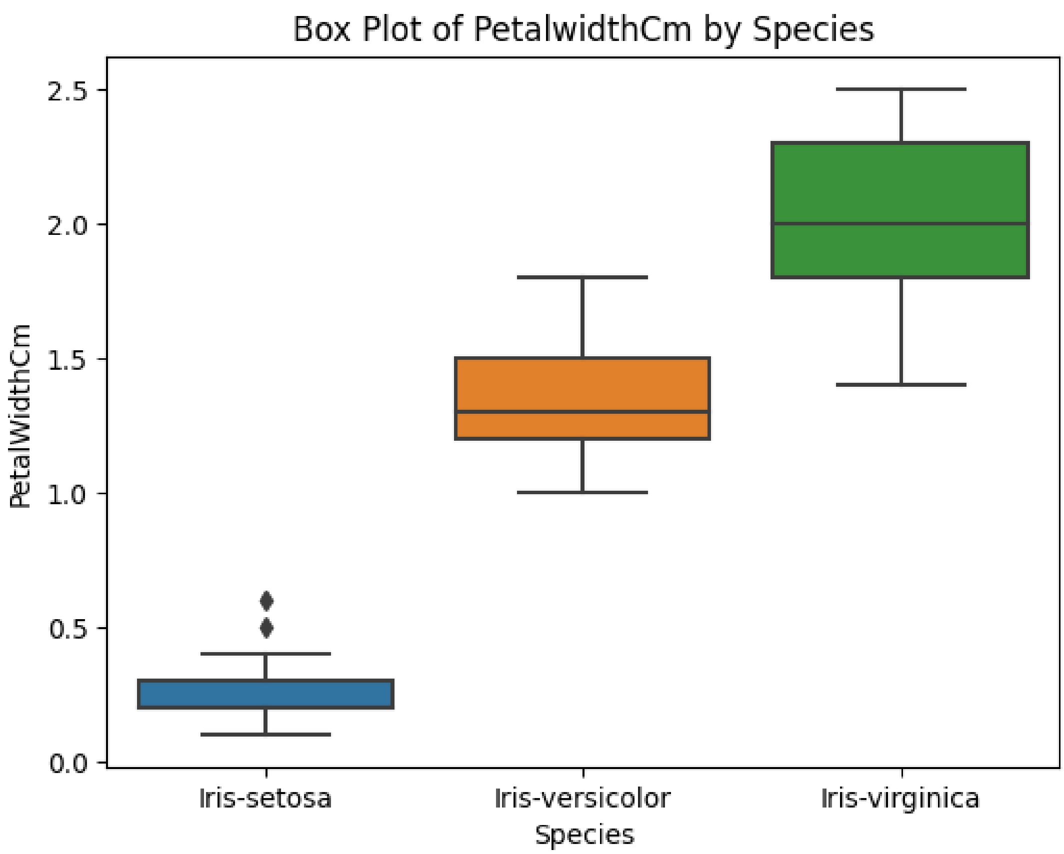
[76]:
```
sns.boxplot(x=df['Species'], y=df['PetalLengthCm'])
plt.title('Box Plot of PetalLengthCm by Species')
```

[76]: Text(0.5, 1.0, 'Box Plot of PetalLengthCm by Species')



[77]:
```
sns.boxplot(x=df['Species'], y=df['PetalWidthCm'])
plt.title('Box Plot of PetalwidthCm by Species')
```

[77]: Text(0.5, 1.0, 'Box Plot of PetalwidthCm by Species')



[78]:
```
df.shape
```

[78]: (147, 5)

#Outliers

[79]:
```
# Calculate IQR
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1

# Define a threshold for outliers
threshold = 1.5

# Identify outliers
outliers = df[~((df < (Q1 - threshold * IQR)) | (df > (Q3 + threshold * IQR))).
 ↪any(axis=1)]

# Print or handle outliers as needed
print("Outliers:")
```

```
outliers.describe()
```

```
Outliers:

<ipython-input-79-7ff41e04d6be>:2: FutureWarning: The default value of
numeric_only in DataFrame.quantile is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  Q1 = df.quantile(0.25)
<ipython-input-79-7ff41e04d6be>:3: FutureWarning: The default value of
numeric_only in DataFrame.quantile is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  Q3 = df.quantile(0.75)
<ipython-input-79-7ff41e04d6be>:10: FutureWarning: Automatic reindexing on
DataFrame vs Series comparisons is deprecated and will raise ValueError in a
future version. Do `left, right = left.align(right, axis=1, copy=False)` before
e.g. `left == right`
  outliers = df[~((df < (Q1 - threshold * IQR)) | (df > (Q3 + threshold *
IQR))).any(axis=1)]
```

[79]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	143.000000	143.000000	143.000000	143.000000
mean	5.870629	3.038462	3.830769	1.230769
std	0.835045	0.398222	1.750824	0.754538
min	4.300000	2.200000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.400000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.000000	6.900000	2.500000

[80]:
```
df=outliers
```

[81]:
```
df.isnull().sum()
```

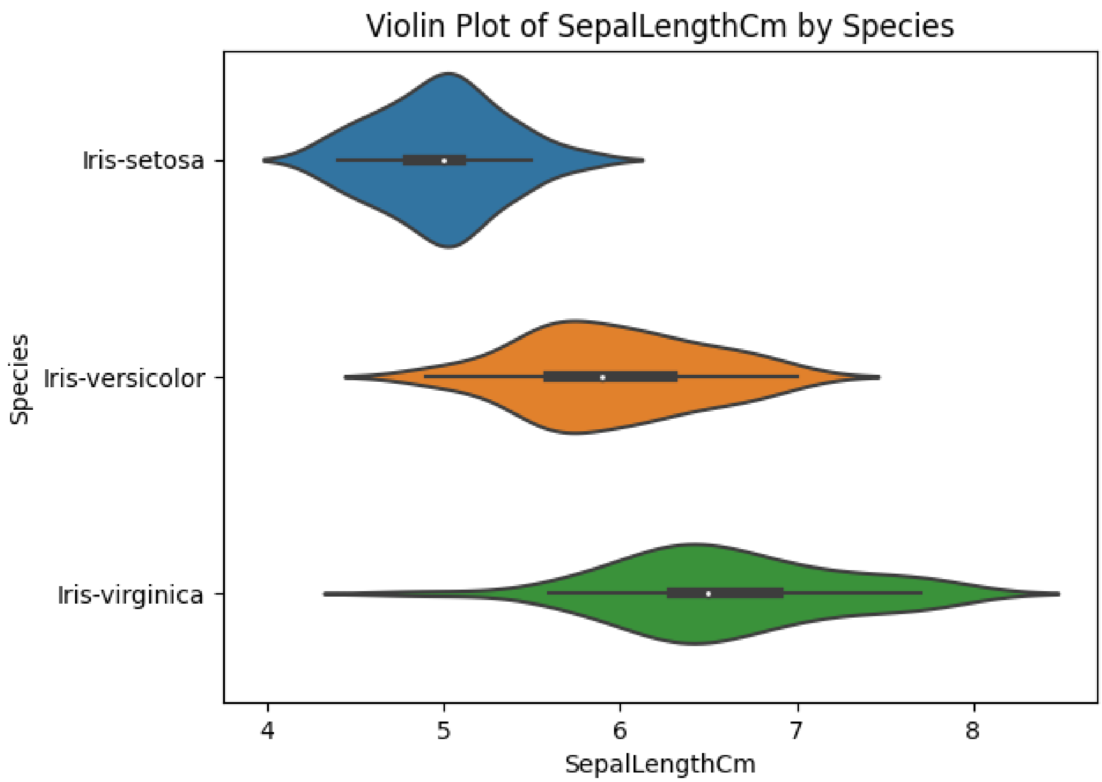
[81]:
```
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

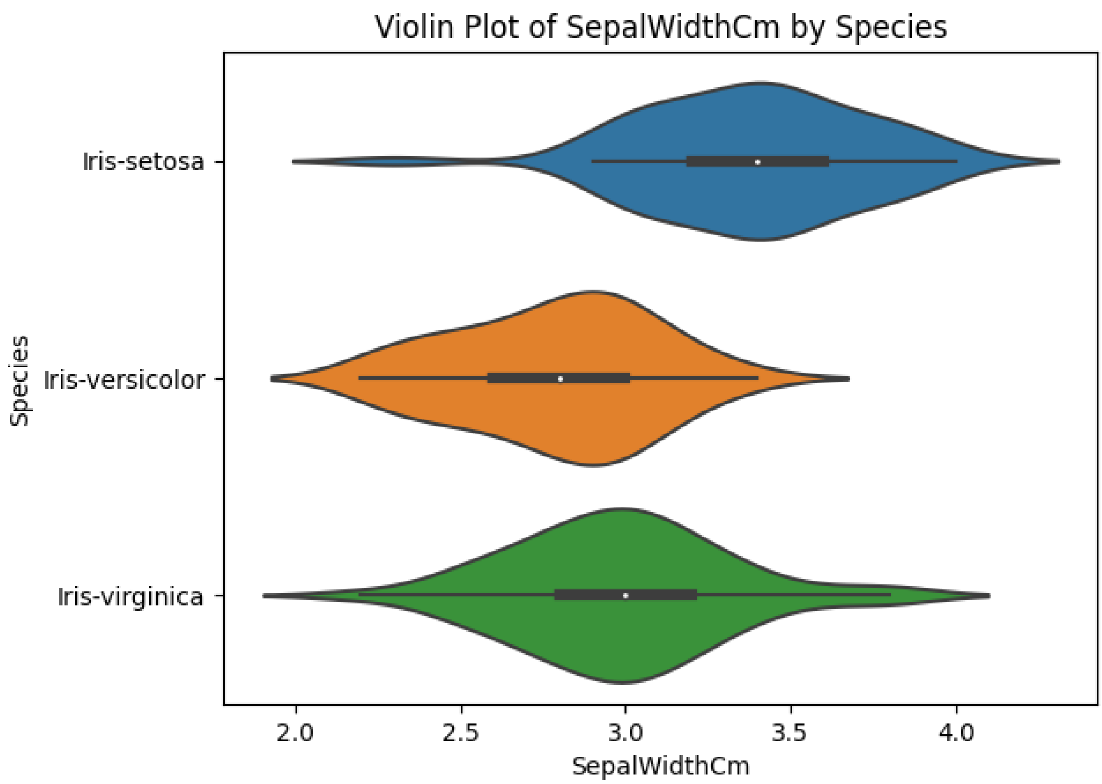
[82]:
```
df.shape
```

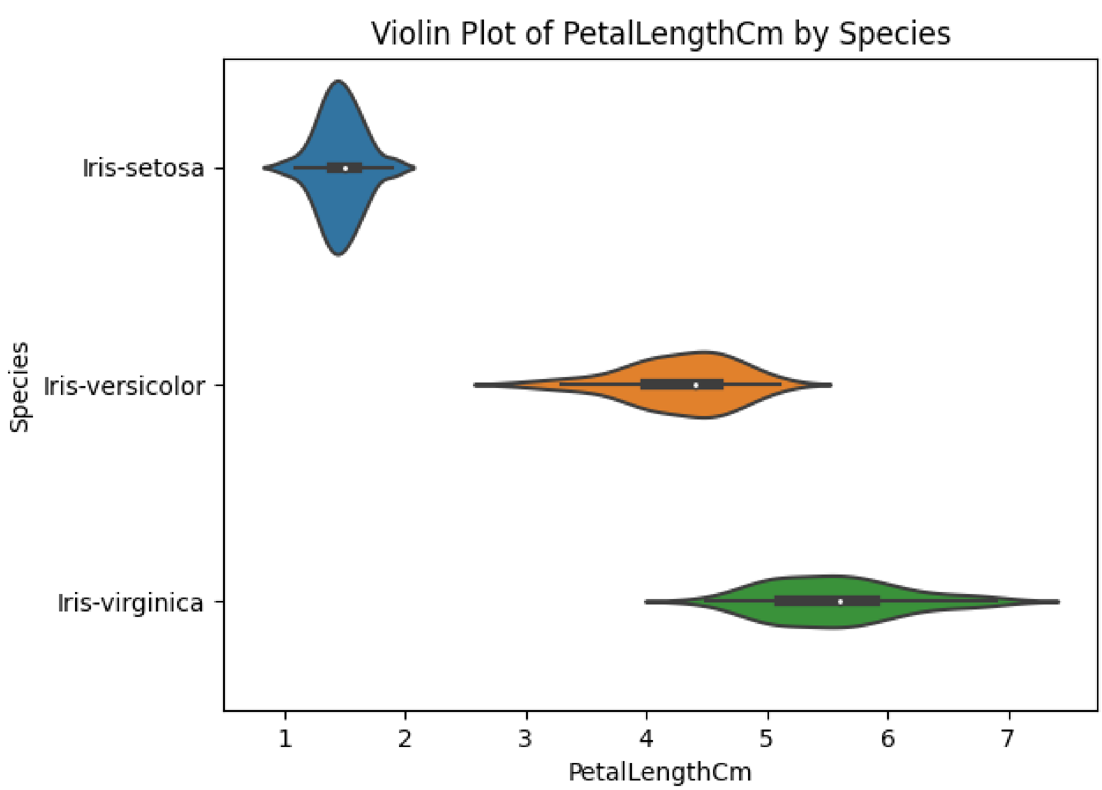
[82]:
```
(143, 5)
```

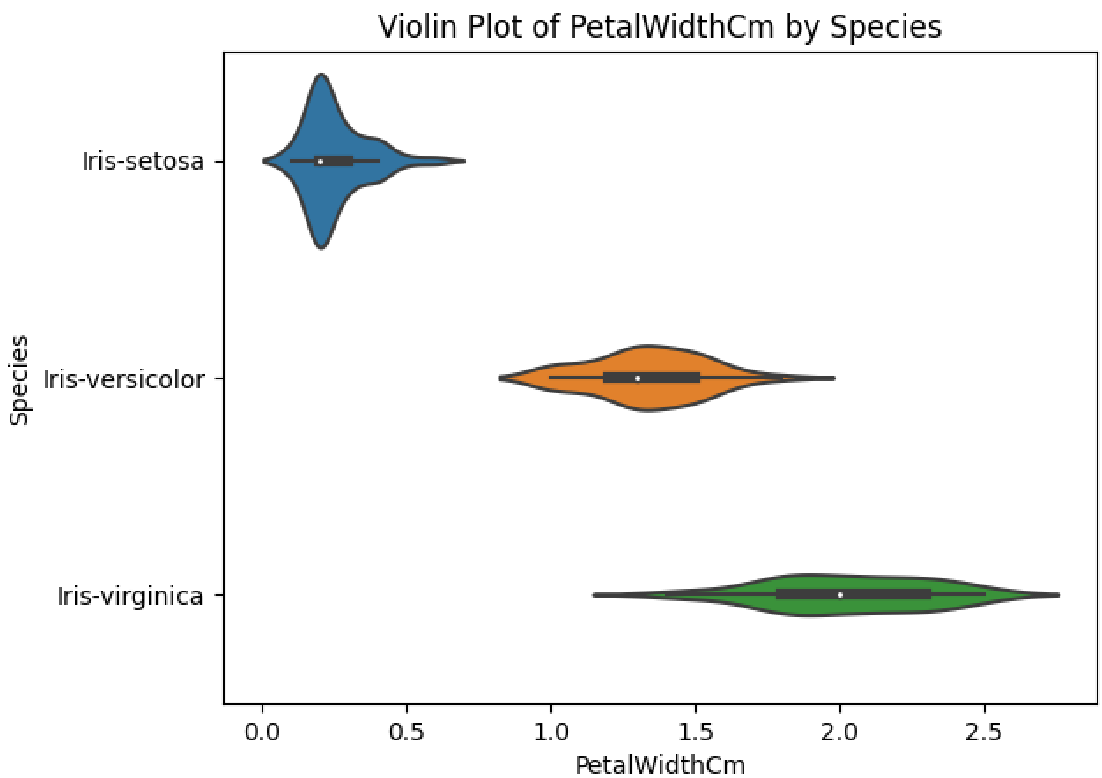
[83]:

```
for i in df.columns[:-1]:
  sns.violinplot(y=df['Species'],x=df[i])
  plt.title(f'Violin Plot of {i} by Species')
  plt.show()
```

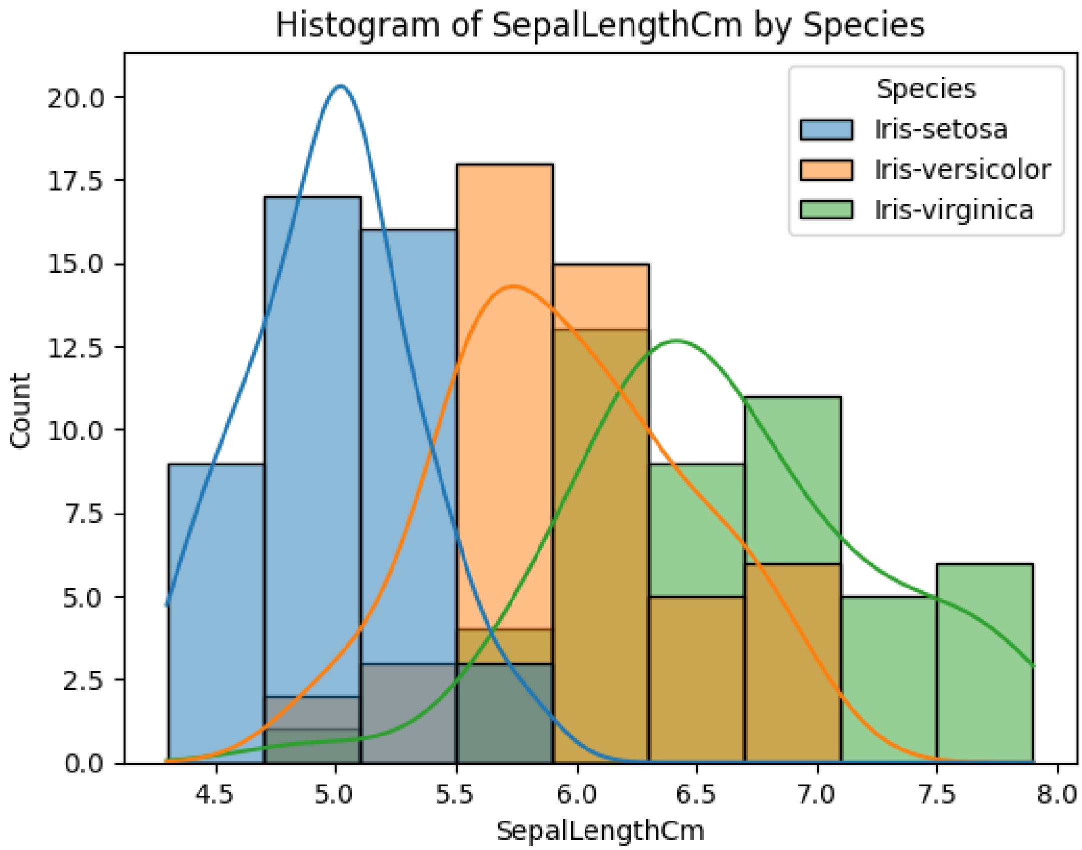


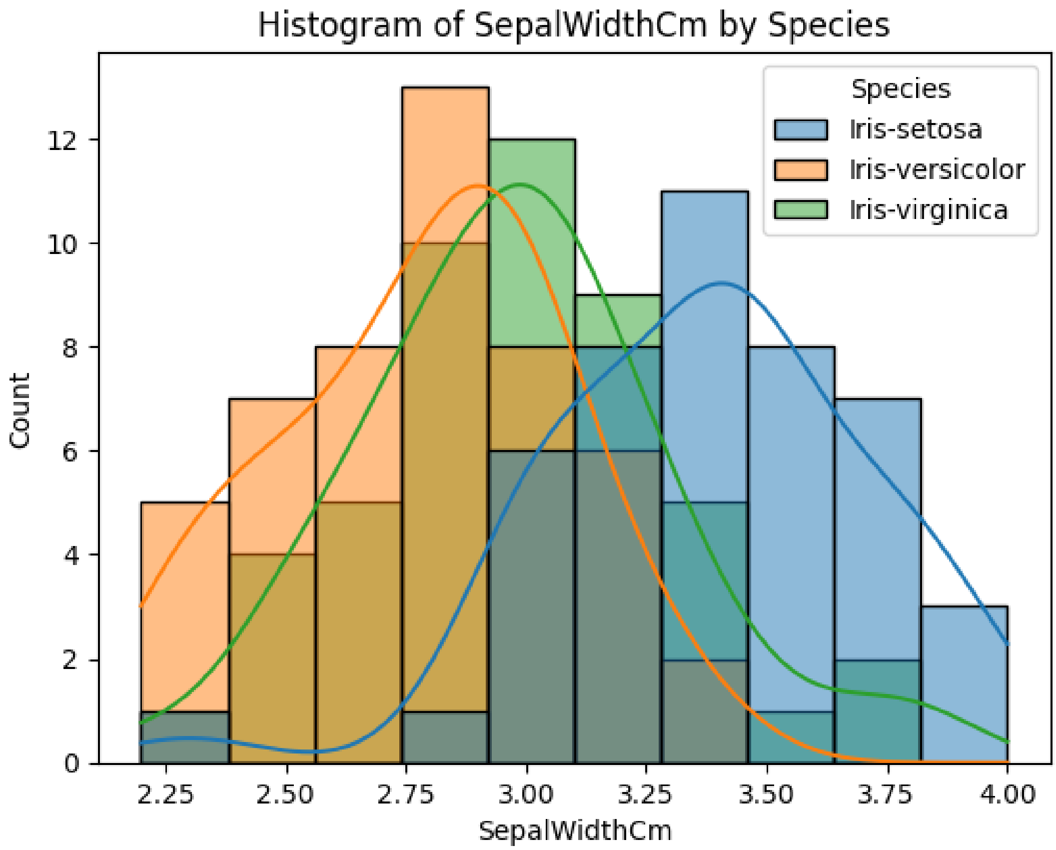

Violin Plot of SepalWidthCm by Species
Iris-setosa
Iris-versicolor
Iris-virginica
Species
2.0
2.5
3.0
3.5
4.0
SepalWidthCm

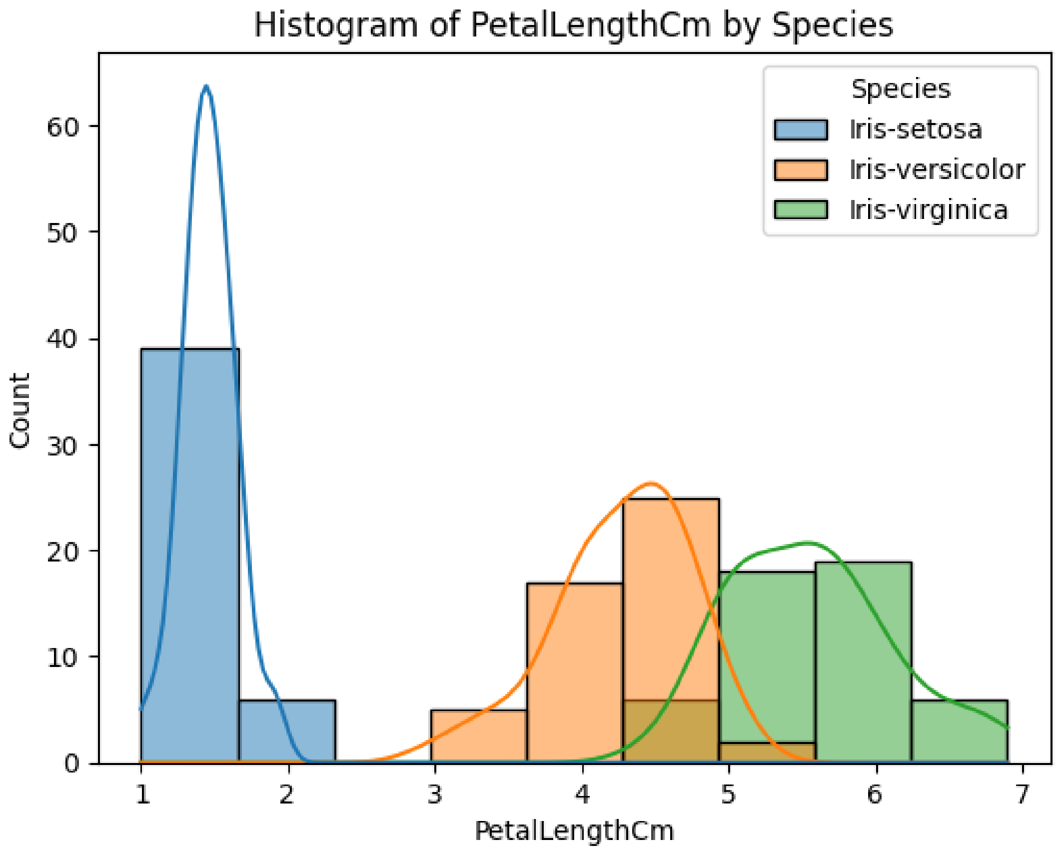

Violin Plot of PetalLengthCm by Species
Iris-setosa
Iris-versicolor
Iris-virginica
Species
1
2
3
4
5
6
7
PetalLengthCm

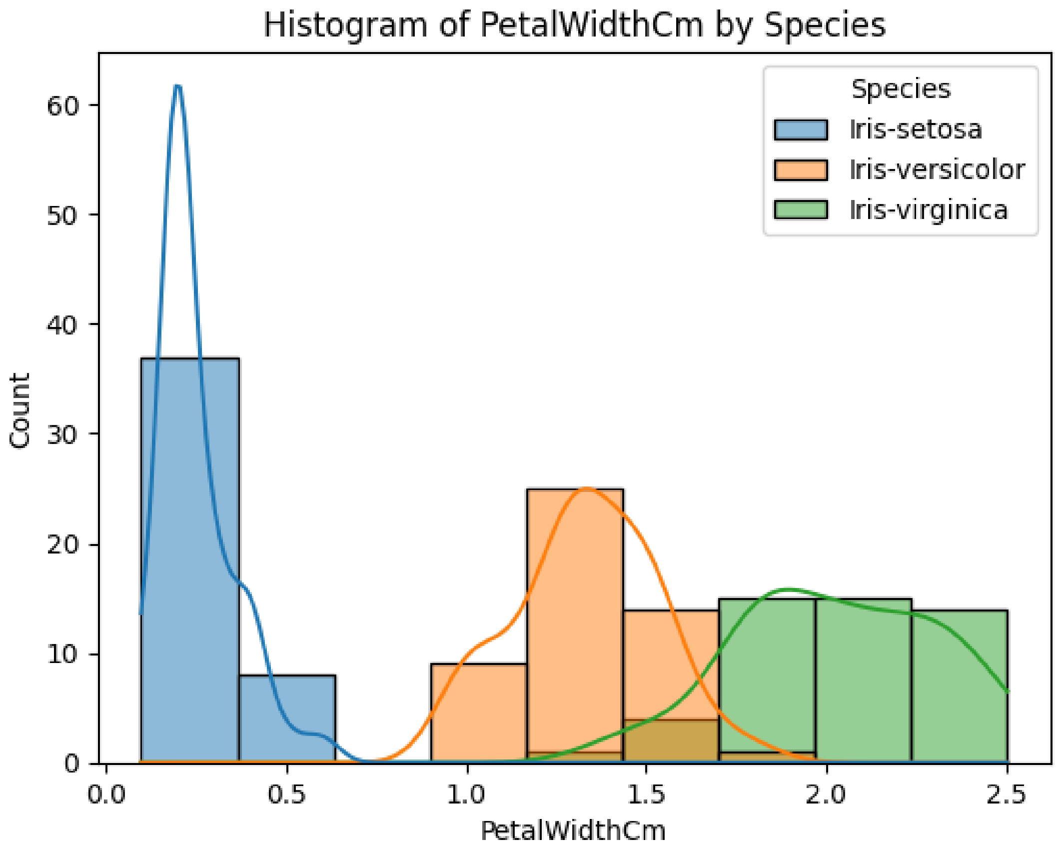


[84]:
```
for i in df.columns[:-1]:
    sns.histplot(data=df, x=i, hue='Species', kde=True)
    plt.title(f'Histogram of {i} by Species')
    plt.show()
```


Histogram of SepalLengthCm by Species
Species
Iris-setosa
Iris-versicolor
Iris-virginica
Count
SepalLengthCm
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0


Histogram of SepalWidthCm by Species
Species
Iris-setosa
Iris-versicolor
Iris-virginica
Count
0
2
4
6
8
10
12
2.25
2.50
2.75
3.00
3.25
3.50
3.75
4.00
SepalWidthCm


Histogram of PetalLengthCm by Species
Species
Iris-setosa
Iris-versicolor
Iris-virginica
Count
60
50
40
30
20
10
0
1
2
3
4
5
6
7
PetalLengthCm



#LabelEncoder

[85]:
```
lb=LabelEncoder()
```

[86]:
```
df['Species']=lb.fit_transform(df['Species'])
```

5 Split x and y

[87]:
```
# Split the data into features (X) and target variable (y)
```

[88]:
```
x=df.iloc[ : , : -1]
y=df.iloc[ : , -1]
```

Display the shape of X and y

[89]:
```
x.shape
```

[89]: (143, 4)

[90]:
```
y.shape
```

[90]:
```
(143,)
```

6 split training and testing

[91]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.
↪2,random_state=42)
```

7 Train_and_Evaluate_Model

[92]:
```
def train_and_evaluate_model(X_TRAIN,X_TEST,Y_TRAIN,Y_TEST,MODEL):
  MODEL.fit(X_TRAIN,Y_TRAIN)
  Y_PRED_MODEL=MODEL.predict(X_TEST)
  print('classification_report:\n',classification_report(Y_TEST,Y_PRED_MODEL))
  ACCURACY=accuracy_score(Y_TEST,Y_PRED_MODEL)*100
  print('accuracy_score:',ACCURACY)
  print('ERROR Values:',np.mean(Y_PRED_MODEL!=Y_TEST)*100)
  print('confusion_matrix:\n',confusion_matrix(Y_TEST,Y_PRED_MODEL))
  return ACCURACY
```

##LogisticRegression()

[93]:
```
lg=LogisticRegression()
```

[94]:
```
lg_accuracy=train_and_evaluate_model(x_train,x_test,y_train,y_test,lg)
```

```
classification_report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         8
           1       0.83      0.91      0.87        11
           2       0.89      0.80      0.84        10

    accuracy                           0.90        29
   macro avg       0.91      0.90      0.90        29
weighted avg       0.90      0.90      0.90        29

accuracy_score: 89.65517241379311
ERROR Values: 10.344827586206897
confusion_matrix:
 [[ 8  0  0]
 [ 0 10  1]
 [ 0  2  8]]
```

##Support vector machine

- Support Vector Machines are a type of supervised machine learning algorithm used for classification and regression. Here's a basic overview of how SVMs work:

1. Input Data:

- SVMs are used for classification and regression tasks. Given a set of labeled training data (input features and corresponding labels), SVM aims to find a hyperplane that best separates the data into different classes.

2. Hyperplane:

- In a binary classification task, the hyperplane is a decision boundary that maximally separates the instances of different classes. The goal is to find the hyperplane with the maximum margin, i.e., the maximum distance between the hyperplane and the nearest data point from each class.

3. Support Vectors:

- The data points that are closest to the hyperplane and have the most influence on its position are called support vectors.

4. Kernel Trick:

- SVMs can handle non-linear decision boundaries by using a kernel function. The kernel function implicitly maps the input data into a higher-dimensional space, making it possible to find a linear hyperplane in that space.

5. Training:

- The training process involves finding the optimal parameters (weights and biases) that define the hyperplane, considering the margin and minimizing classification errors.

6. Prediction:

- Once the SVM is trained, it can be used to classify new, unseen data by determining which side of the hyperplane the data point falls on.

[95]:
```
svm=SVC(kernel='linear')
```

[96]:
```
svm_accuracy=train_and_evaluate_model(x_train,x_test,y_train,y_test,svm)
```

```
classification_report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00         8
           1       1.00      0.91      0.95        11
           2       0.91      1.00      0.95        10

    accuracy                           0.97        29
   macro avg       0.97      0.97      0.97        29
weighted avg       0.97      0.97      0.97        29

accuracy_score: 96.55172413793103
ERROR Values: 3.4482758620689653
```

```
confusion_matrix:
 [[ 8  0  0]
 [ 0 10  1]
 [ 0  0 10]]
```

##DecisionTreeClassifier

- Step-1: Begin the tree with the root node, says S, which contains the complete dataset.
- Step-2: Find the best attribute in the dataset using Attribute Selection Measure (ASM).
- Step-3: Divide the S into subsets that contains possible values for the best attributes.
- Step-4: Generate the decision tree node, which contains the best attribute.
- Step-5: Recursively make new decision trees using the subsets of the dataset created in step -3. Continue this process until a stage is reached where you cannot further classify the nodes and called the final node as a leaf node.

[97]:
```
dt=DecisionTreeClassifier(random_state=42)
```

[98]:
```
dt_accuracy=train_and_evaluate_model(x_train,x_test,y_train,y_test,dt)
```

```
classification_report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00         8
           1       0.83      0.91      0.87        11
           2       0.89      0.80      0.84        10

    accuracy                           0.90        29
   macro avg       0.91      0.90      0.90        29
weighted avg       0.90      0.90      0.90        29

accuracy_score: 89.65517241379311
ERROR Values: 10.344827586206897
confusion_matrix:
 [[ 8  0  0]
 [ 0 10  1]
 [ 0  2  8]]
```

##RandomForestClassifier

[99]:
```
rf=RandomForestClassifier(n_estimators=100,random_state=42)
```

[100]:
```
rt_accuracy=train_and_evaluate_model(x_train,x_test,y_train,y_test,rf)
```

```
classification_report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00         8
           1       0.83      0.91      0.87        11
           2       0.89      0.80      0.84        10
```

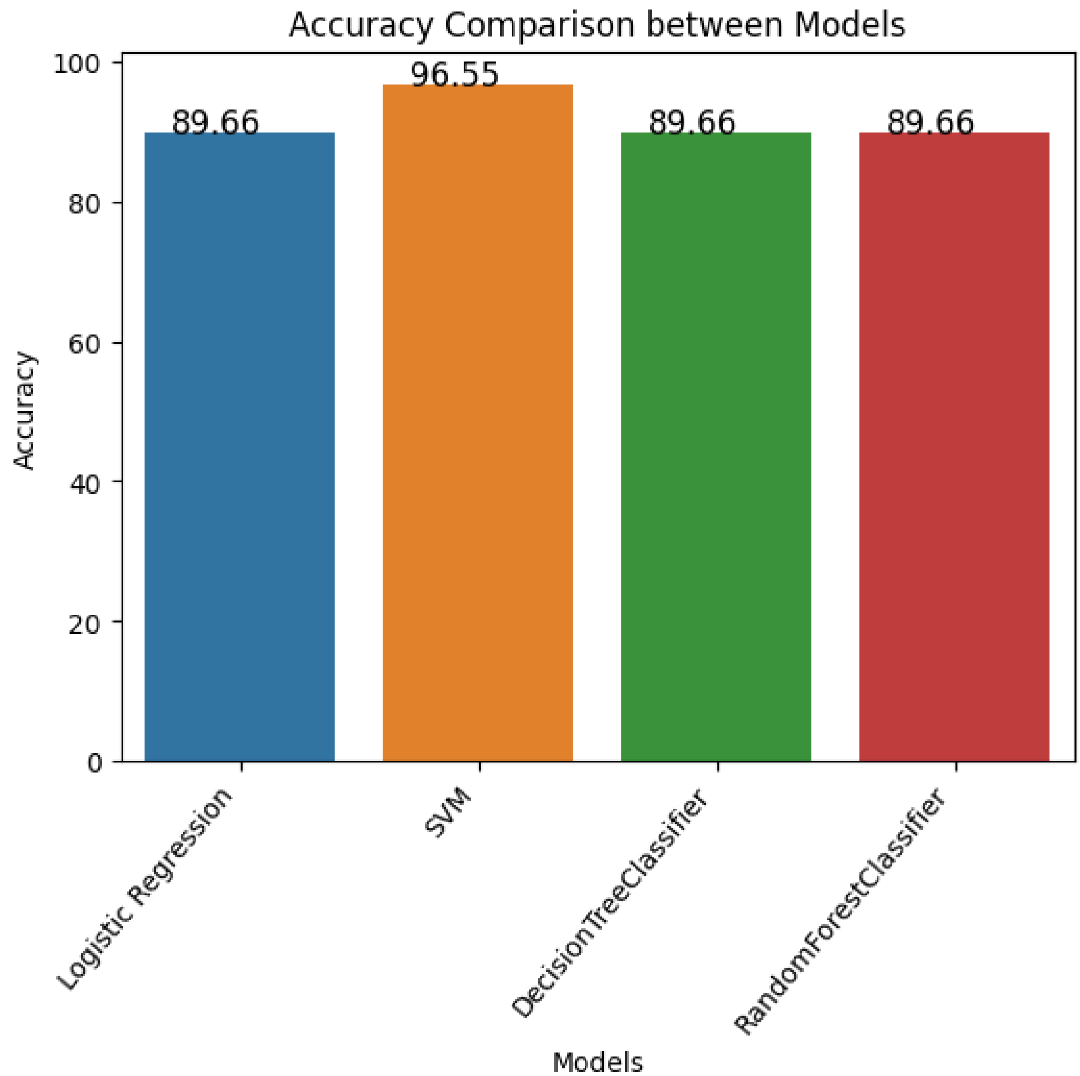
```
    accuracy                           0.90        29
   macro avg       0.91      0.90      0.90        29
weighted avg       0.90      0.90      0.90        29

accuracy_score: 89.65517241379311
ERROR Values: 10.344827586206897
confusion_matrix:
 [[ 8  0  0]
 [ 0 10  1]
 [ 0  2  8]]
```

#Comparison of Model Accuracies

[101]:
```
# Create an accuracy comparison graph
models = ['Logistic Regression',␣
↪'SVM','DecisionTreeClassifier','RandomForestClassifier']
accuracies = [lg_accuracy, svm_accuracy,dt_accuracy,rt_accuracy]

for name, score in zip(models,accuracies):
  print(f'{name} Accuracy: {score:.2f}')

# Create a bar plot
bars = sns.barplot(x=models, y=accuracies)

# Add text annotations on top of each bar
for bar, score in zip(bars.patches, accuracies):
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2 - 0.1, height + 0.01, f'{score:.
↪2f}', ha='center', fontsize=12)

# Customize plot
plt.xlabel('Models')
plt.ylabel('Accuracy')
plt.xticks(rotation=50, ha='right')
plt.title('Accuracy Comparison between Models')
```

```
Logistic Regression Accuracy: 89.66
SVM Accuracy: 96.55
DecisionTreeClassifier Accuracy: 89.66
RandomForestClassifier Accuracy: 89.66
```

[101]:
```
Text(0.5, 1.0, 'Accuracy Comparison between Models')
```


Accuracy Comparison between Models
Accuracy
Models
100
80
60
40
20
0
89.66
96.55
89.66
89.66
Logistic Regression
SVM
DecisionTreeClassifier
RandomForestClassifier