Oasis_Infobyte_Task_1

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1 OASIS INFOBYTE INTERNSHIP

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3 TASK-1 IRIS FLOWER CLASSIFICATION

4 Problem Statement -

Develop a machine learning model to classify iris flowers into different species based on their measurements. The goal is to accurately predict the species of an iris flower given its sepal length, sepal width, petal length, and petal width.

5 Import Libraries:

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import joblib
import pickle
import matplotlib_inline

from sklearn.datasets import load_iris
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score, confusion_matrix

import warnings
```

```
warnings.filterwarnings('ignore')
```

6 Load the Dataset

[2]:
```
from sklearn.datasets import load_iris
```

[3]:
```
iris = pd.read_csv('Iris.csv')
```

[4]:
```
iris
```

[4]:
```
      Id  SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm  \
0      1            5.1           3.5            1.4           0.2
1      2            4.9           3.0            1.4           0.2
2      3            4.7           3.2            1.3           0.2
3      4            4.6           3.1            1.5           0.2
4      5            5.0           3.6            1.4           0.2
..   …            …           …            …           …
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
0       Iris-setosa
1       Iris-setosa
2       Iris-setosa
3       Iris-setosa
4       Iris-setosa
..              …
145  Iris-virginica
146  Iris-virginica
147  Iris-virginica
148  Iris-virginica
149  Iris-virginica

[150 rows x 6 columns]
```

[5]:
```
#shows top 5 rows
iris.head()
```

[5]:
```
   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
```

[6]:
```
#shows last 5 rows
iris.tail()
```

[6]:
```
      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
```

7 Explore Dataset

[7]:
```
#all dataset information
iris.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
```

[8]:
```
#size of the dataset
iris.shape
```

[8]: (150, 6)

[9]:
```
#summary statistics of the numerical columns
iris.describe()
```

[9]:
```
               Id  SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm
count  150.000000     150.000000    150.000000     150.000000    150.000000
mean    75.500000       5.843333      3.054000       3.758667      1.198667
```

std	43.445368	0.828066	0.433594	1.764420	0.763161
min	1.000000	4.300000	2.000000	1.000000	0.100000
25%	38.250000	5.100000	2.800000	1.600000	0.300000
50%	75.500000	5.800000	3.000000	4.350000	1.300000
75%	112.750000	6.400000	3.300000	5.100000	1.800000
max	150.000000	7.900000	4.400000	6.900000	2.500000

[10]:
```
#checking all dtypes
iris.dtypes
```

[10]:
```
Id                 int64
SepalLengthCm    float64
SepalWidthCm     float64
PetalLengthCm    float64
PetalWidthCm     float64
Species           object
dtype: object
```

[11]:
```
#checking null values
iris.isna().sum()
```

[11]:
```
Id               0
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

8 Preprocess Dataset

[12]:
```
#Drop the Id column from data set because no need of Id feature model building.
iris.drop('Id',axis=1, inplace=True)
```

[13]:
```
#cheking duplicates values
iris.duplicated().sum()
```

[13]: 3

[14]:
```
iris[iris.duplicated(keep=False)]
```

[14]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
9	4.9	3.1	1.5	0.1	Iris-setosa
34	4.9	3.1	1.5	0.1	Iris-setosa
37	4.9	3.1	1.5	0.1	Iris-setosa
101	5.8	2.7	5.1	1.9	Iris-virginica
142	5.8	2.7	5.1	1.9	Iris-virginica

[15]:
```
iris.drop_duplicates(inplace=True)
```

[16]:
```
#unique values for each features
iris.nunique()
```

[16]:
```
SepalLengthCm    35
SepalWidthCm     23
PetalLengthCm    43
PetalWidthCm     22
Species           3
dtype: int64
```

[17]:
```
new_column_names ={'SepalLengthCm':'Sepal Length(cm)','SepalWidthCm':'Sepal␣
↪Width(cm)','PetalLengthCm':'Petal Length(cm)','PetalWidthCm':'Petal␣
↪Width(cm)'}
iris = iris.rename(columns=new_column_names)
iris.head()
```

[17]:
```
   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

       Species
0  Iris-setosa
1  Iris-setosa
2  Iris-setosa
3  Iris-setosa
4  Iris-setosa
```

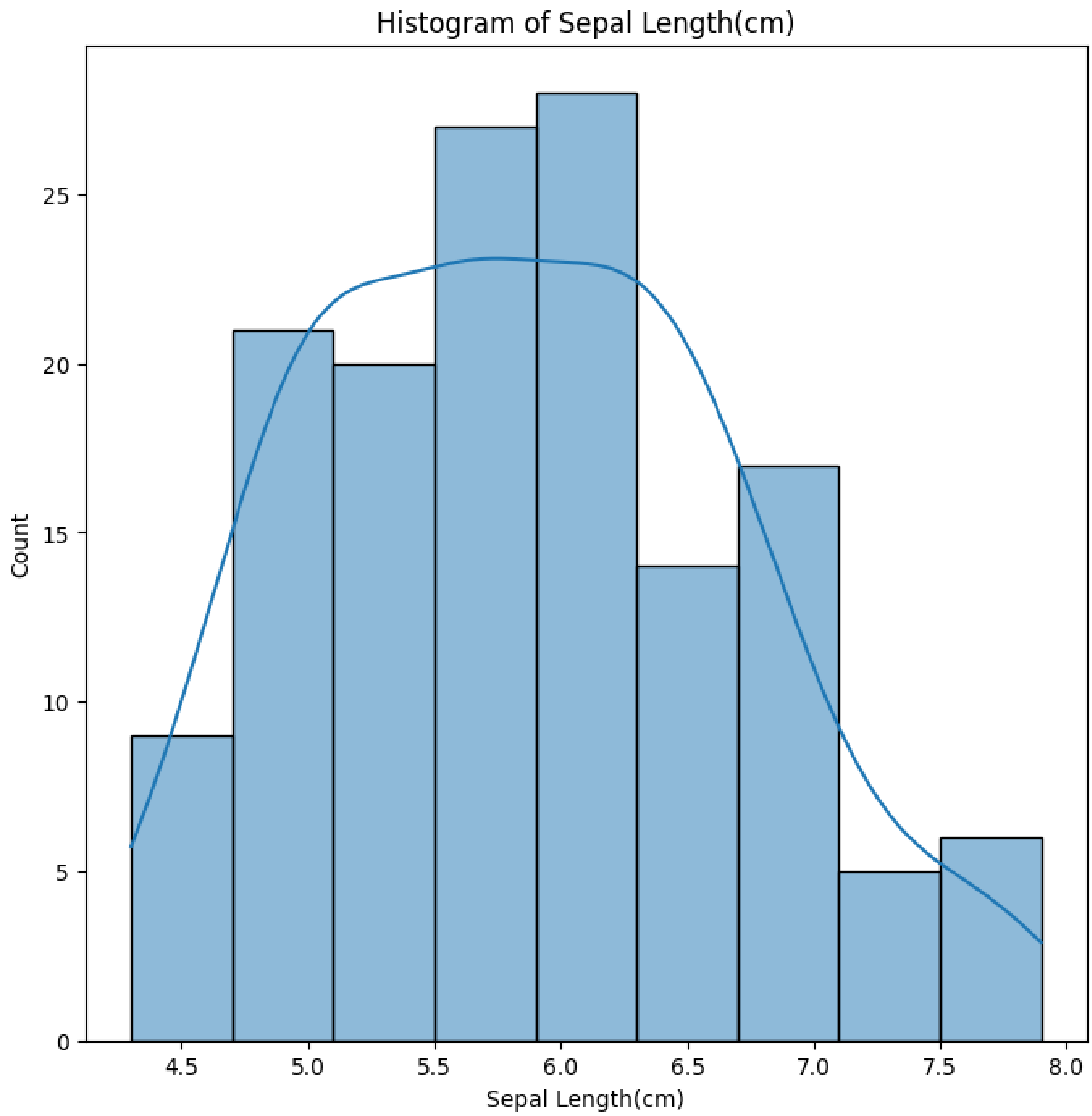
[18]:
```
iris.columns
```

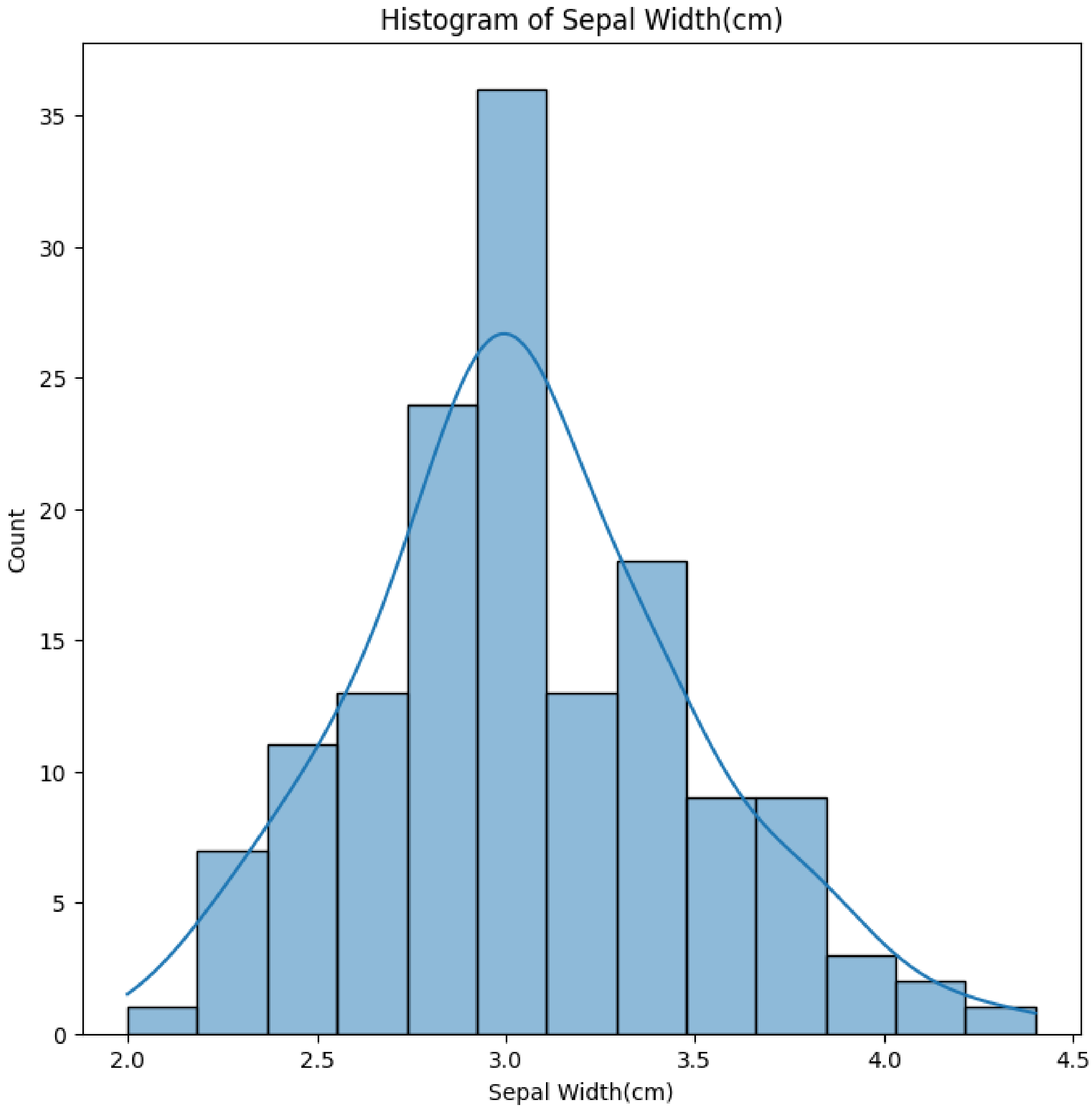
[18]:
```
Index(['Sepal Length(cm)', 'Sepal Width(cm)', 'Petal Length(cm)',
       'Petal Width(cm)', 'Species'],
      dtype='object')
```

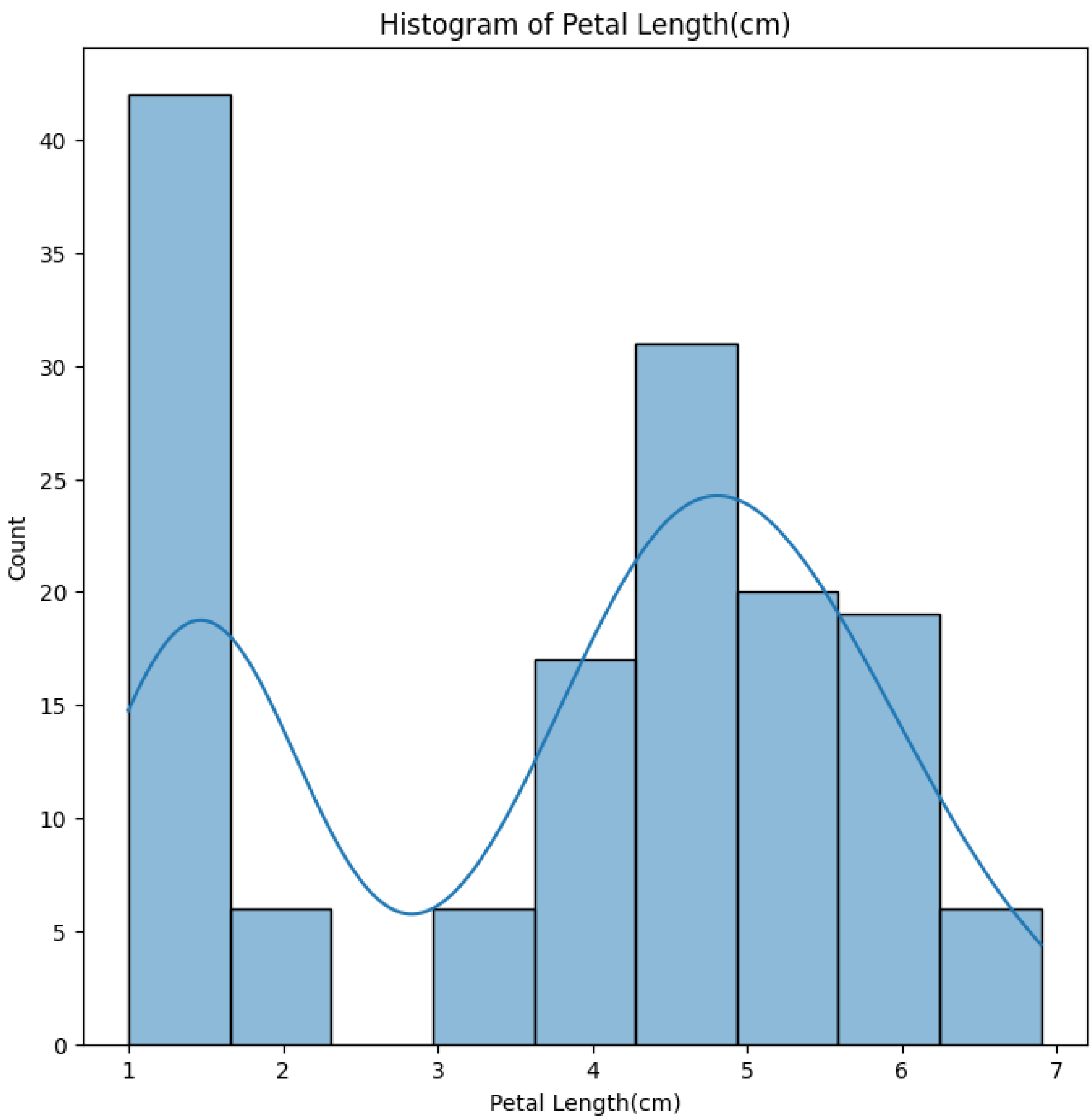
[19]:
```
features = ['Sepal Length(cm)', 'Sepal Width(cm)', 'Petal Length(cm)', 'Petal␣
↪Width(cm)','Species']
```

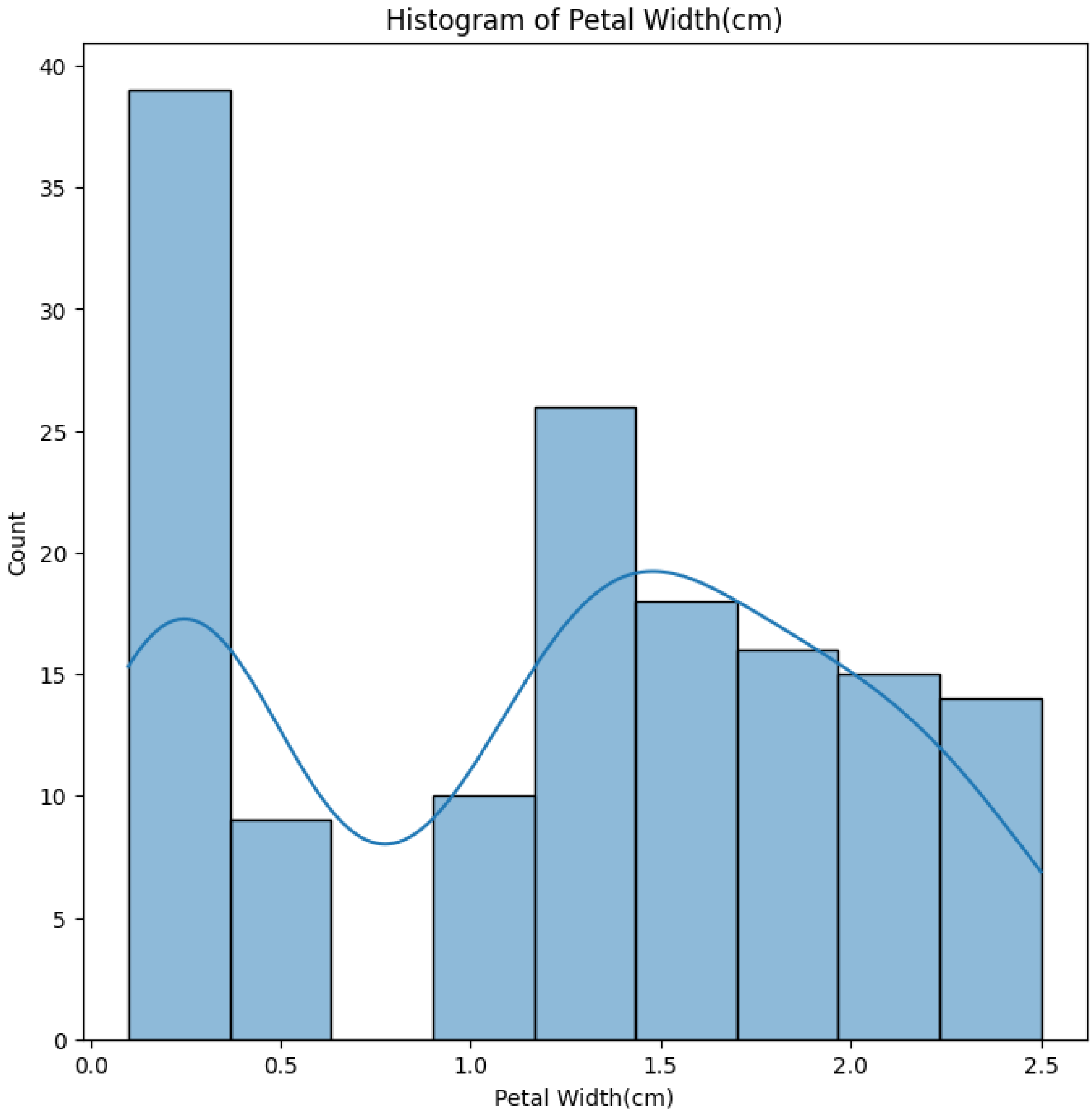
[20]:
```
#To visualize the distribution of each feature, create histograms using␣
↪Matplotlib
for feature in features:
    plt.figure(figsize=(8,8))
    sns.histplot(iris[feature],kde =True)
    plt.xlabel(feature)
```

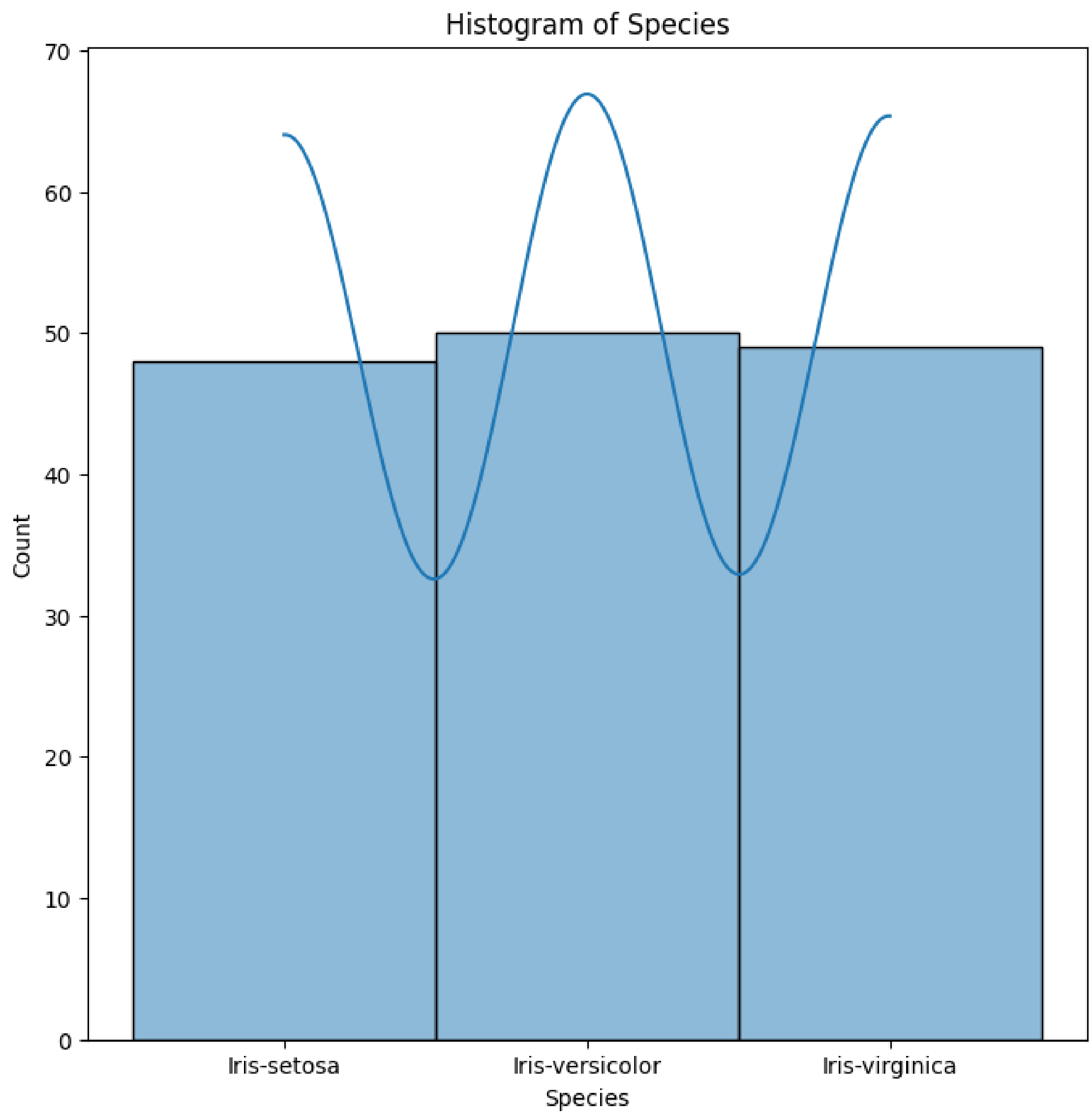
```
    plt.ylabel('Count')
    plt.title(f'Histogram of {feature}')
    plt.show()
```




Histogram of Sepal Width(cm)
Count
Sepal Width(cm)
0
5
10
15
20
25
30
35
2.0
2.5
3.0
3.5
4.0
4.5

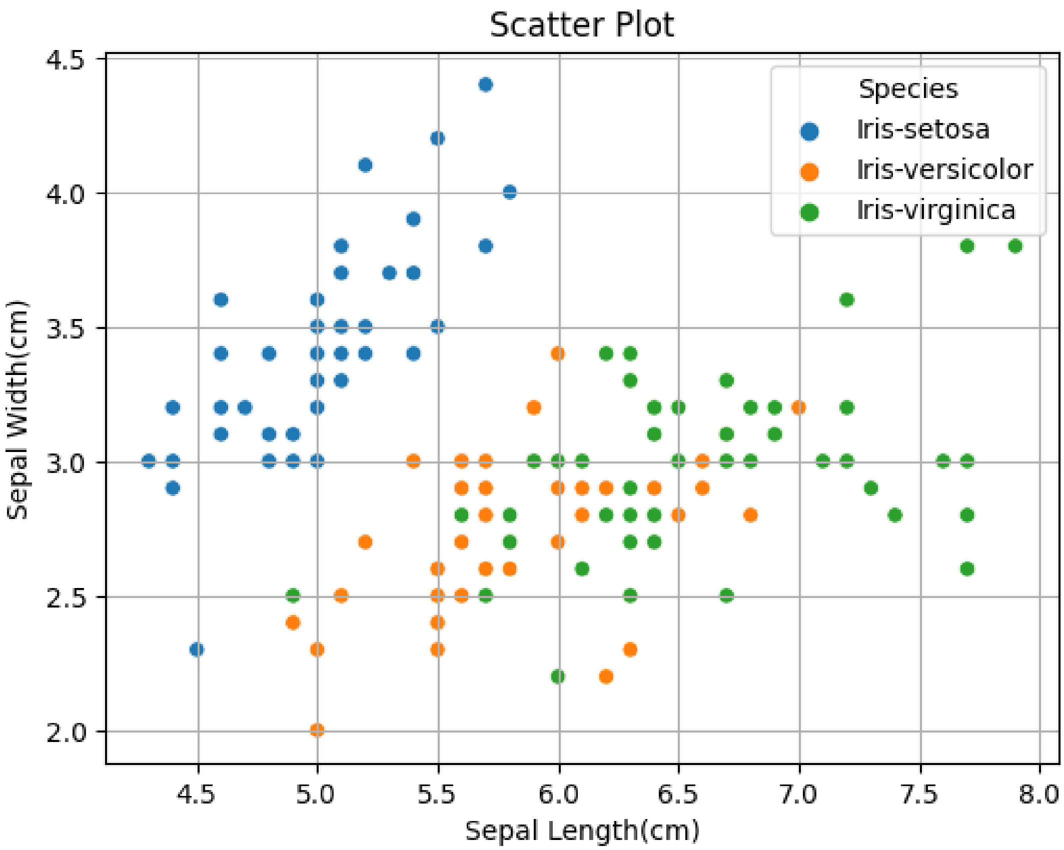

Histogram of Petal Length(cm)
Count
Petal Length(cm)
0
5
10
15
20
25
30
35
40
1
2
3
4
5
6
7


Histogram of Petal Width(cm)
Count
Petal Width(cm)
0
5
10
15
20
25
30
35
40
0.0
0.5
1.0
1.5
2.0
2.5



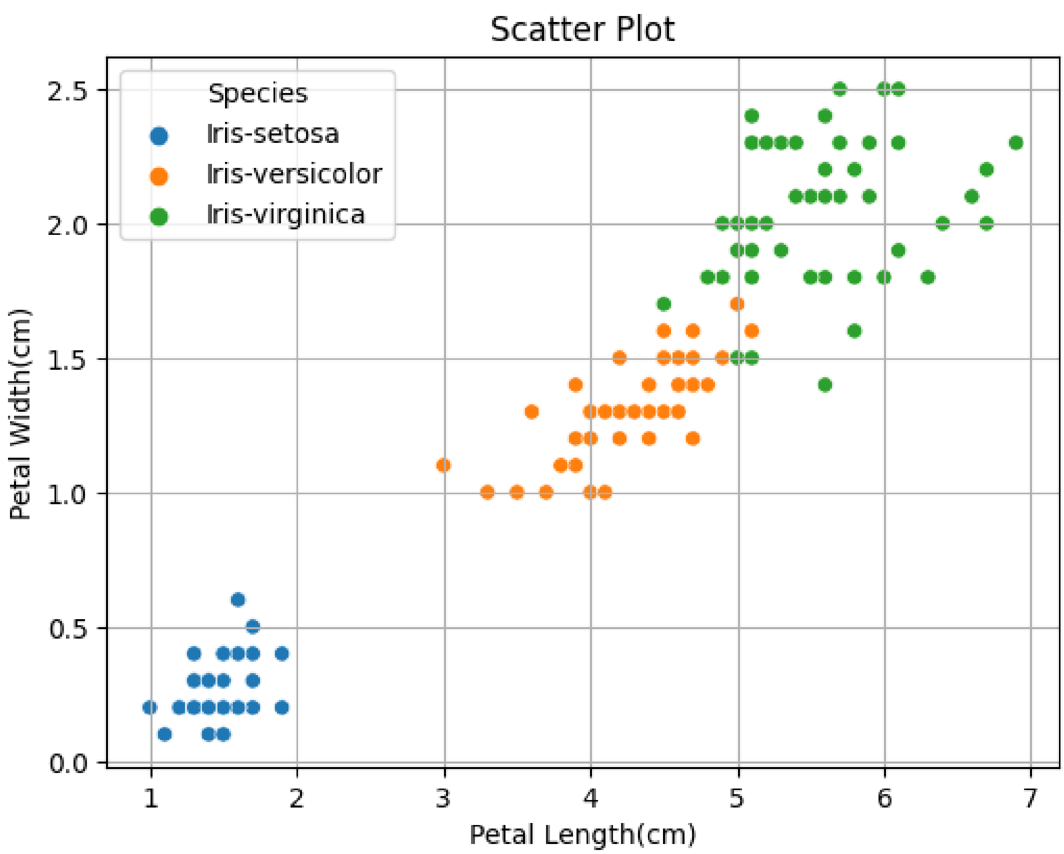
[21]:
```
y = iris['Species']
```

[22]:
```
#to visualize the relationships between features, you can create scatter plots␣
↪using Matplotlib
sns.scatterplot(data=iris,x ='Sepal Length(cm)',y='Sepal␣
↪Width(cm)',hue='Species')
plt.xlabel('Sepal Length(cm)')
plt.ylabel('Sepal Width(cm)')
plt.title('Scatter Plot')
plt.grid(True)
plt.show()
```

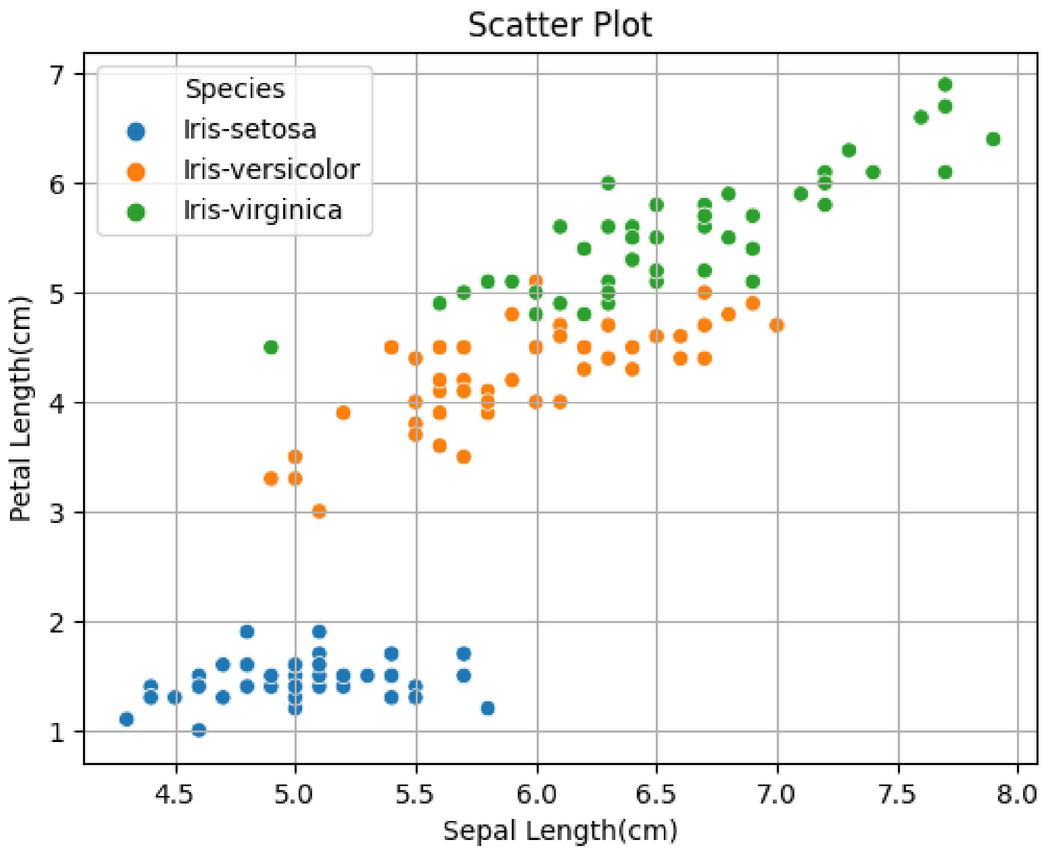


[23]:

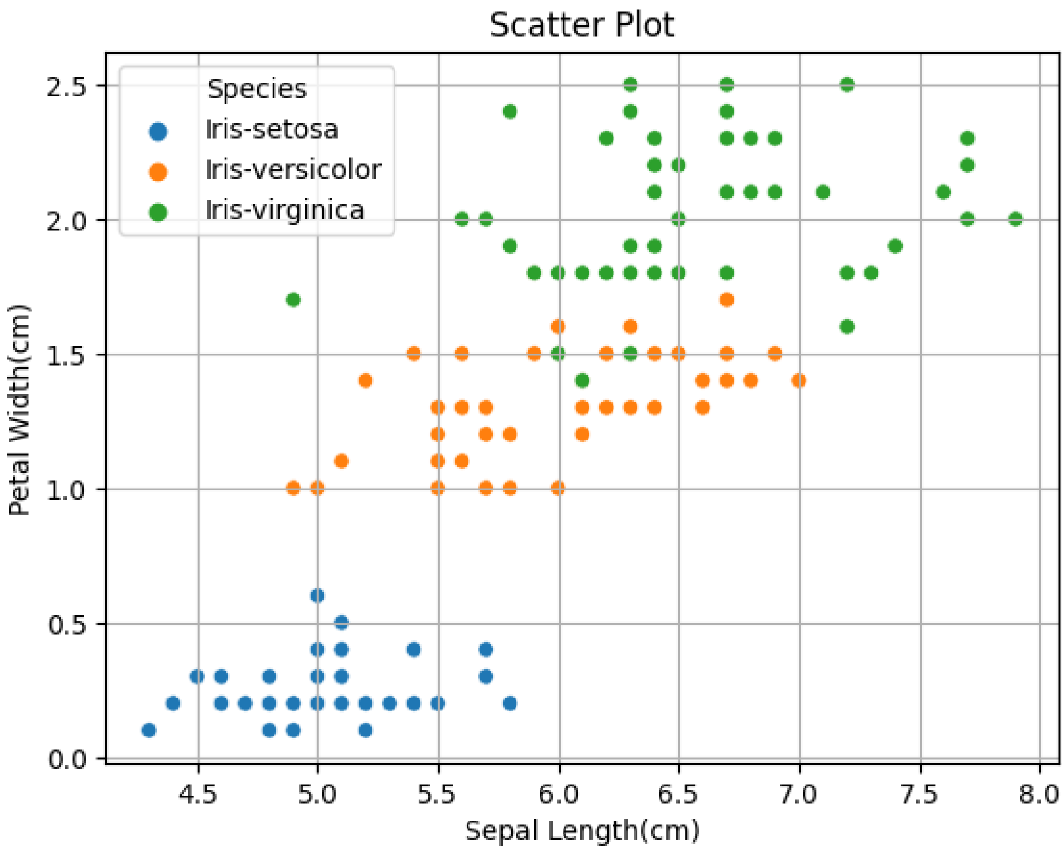
```
sns.scatterplot(data=iris,x ='Petal Length(cm)',y='Petal␣
↪Width(cm)',hue='Species')
plt.xlabel('Petal Length(cm)')
plt.ylabel('Petal Width(cm)')
plt.title('Scatter Plot')
plt.grid(True)
plt.show()
```



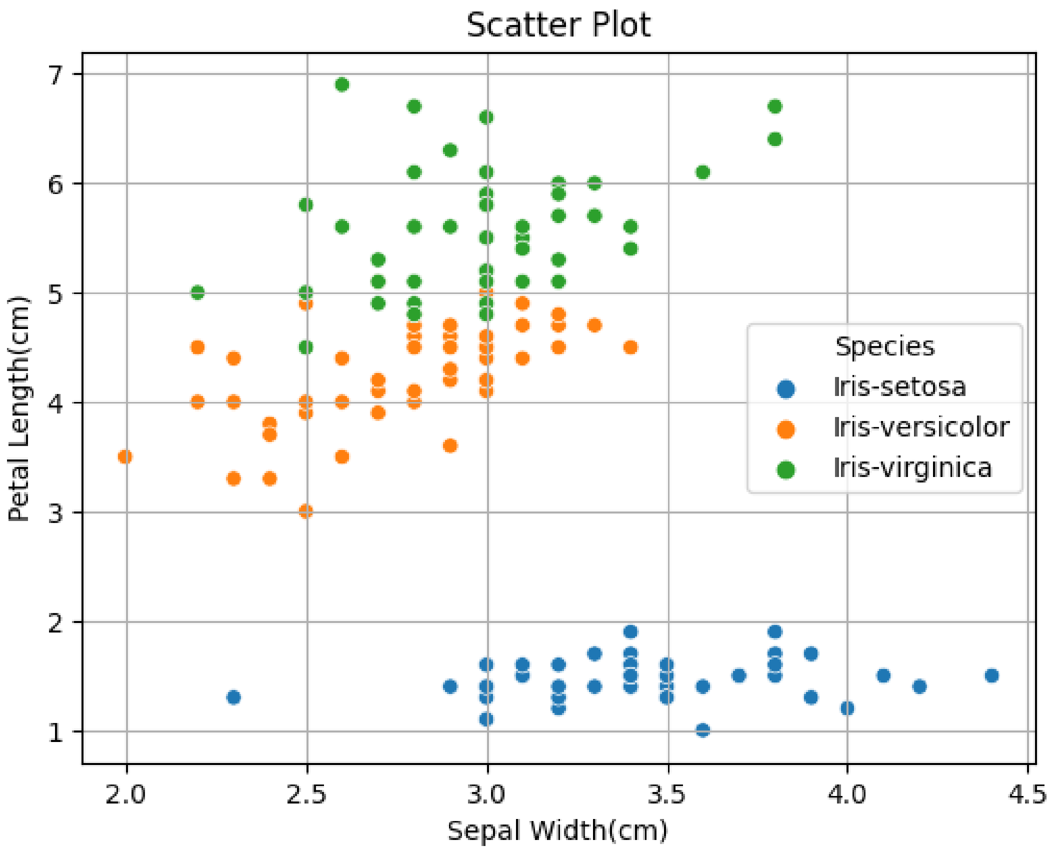
[24]:
```
sns.scatterplot(data=iris,x ='Sepal Length(cm)',y='Petal␣
↪Length(cm)',hue='Species')
plt.xlabel('Sepal Length(cm)')
plt.ylabel('Petal Length(cm)')
plt.title('Scatter Plot')
plt.grid(True)
plt.show()
```



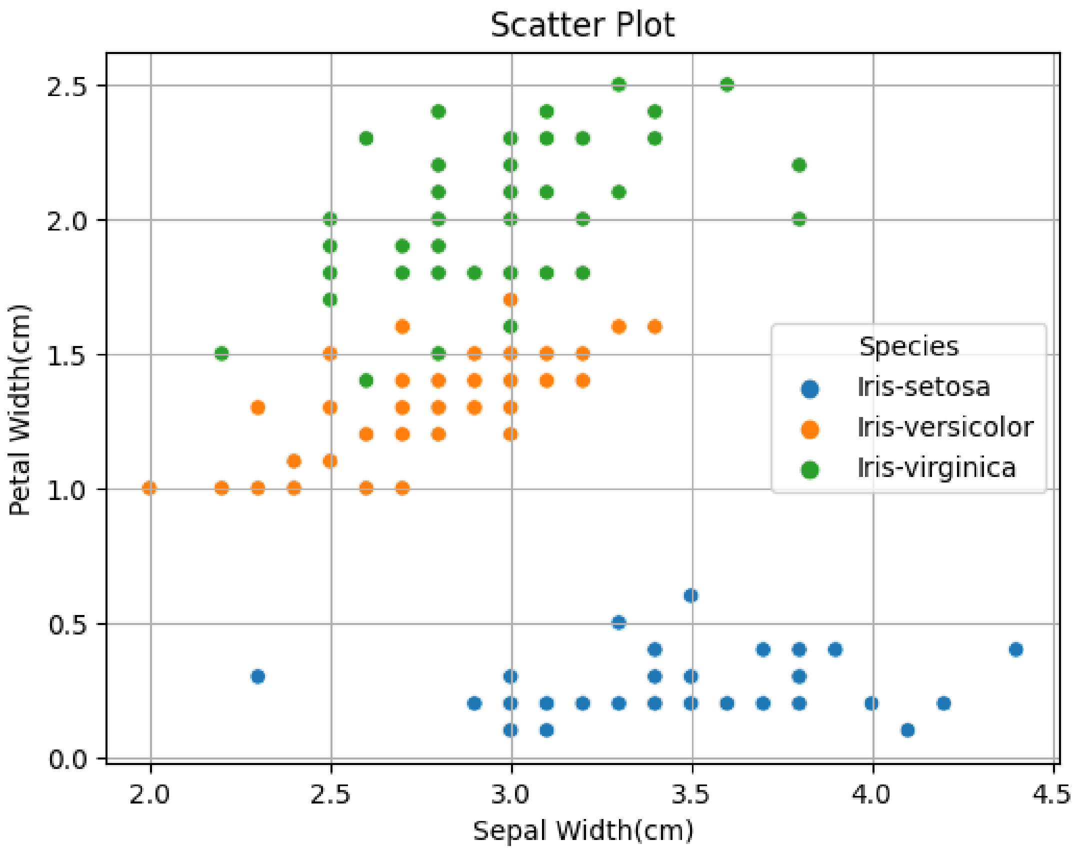
[25]:
```
sns.scatterplot(data=iris,x ='Sepal Length(cm)',y='Petal␣
↪Width(cm)',hue='Species')
plt.xlabel('Sepal Length(cm)')
plt.ylabel('Petal Width(cm)')
plt.title('Scatter Plot')
plt.grid(True)
plt.show()
```



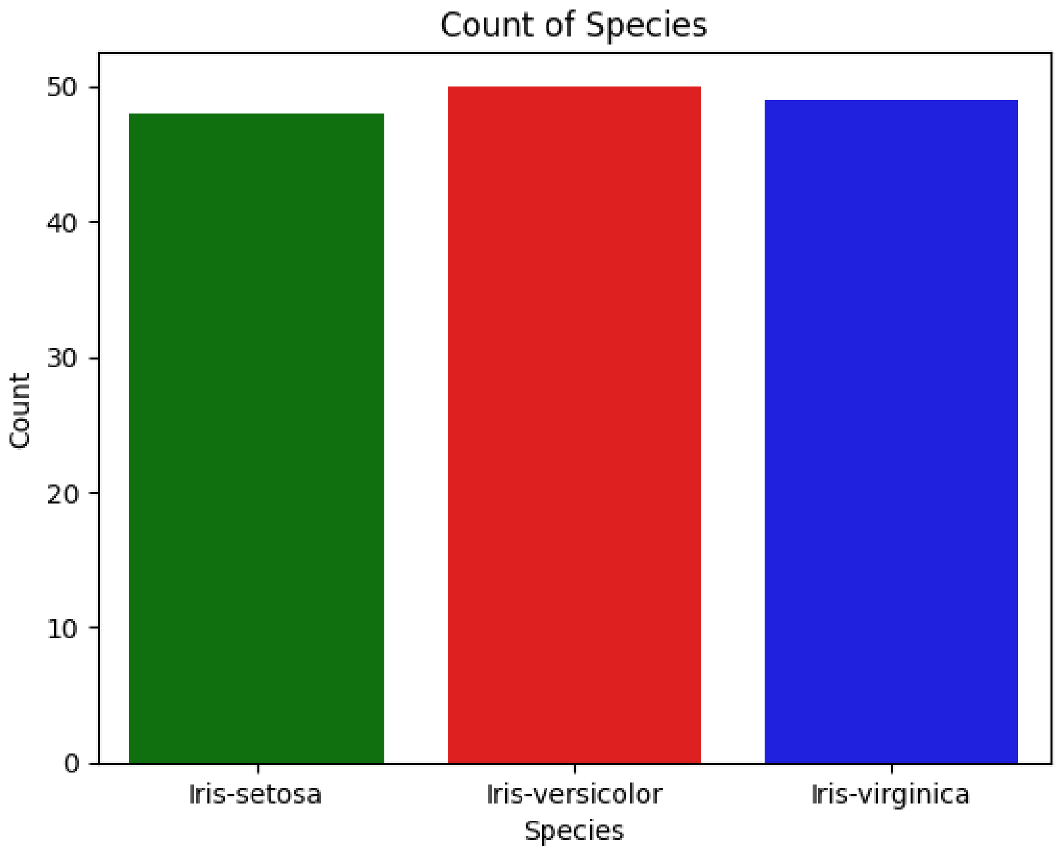
[26]:
```
sns.scatterplot(data=iris,x ='Sepal Width(cm)',y='Petal␣
↪Length(cm)',hue='Species')
plt.xlabel('Sepal Width(cm)')
plt.ylabel('Petal Length(cm)')
plt.title('Scatter Plot')
plt.grid(True)
plt.show()
```



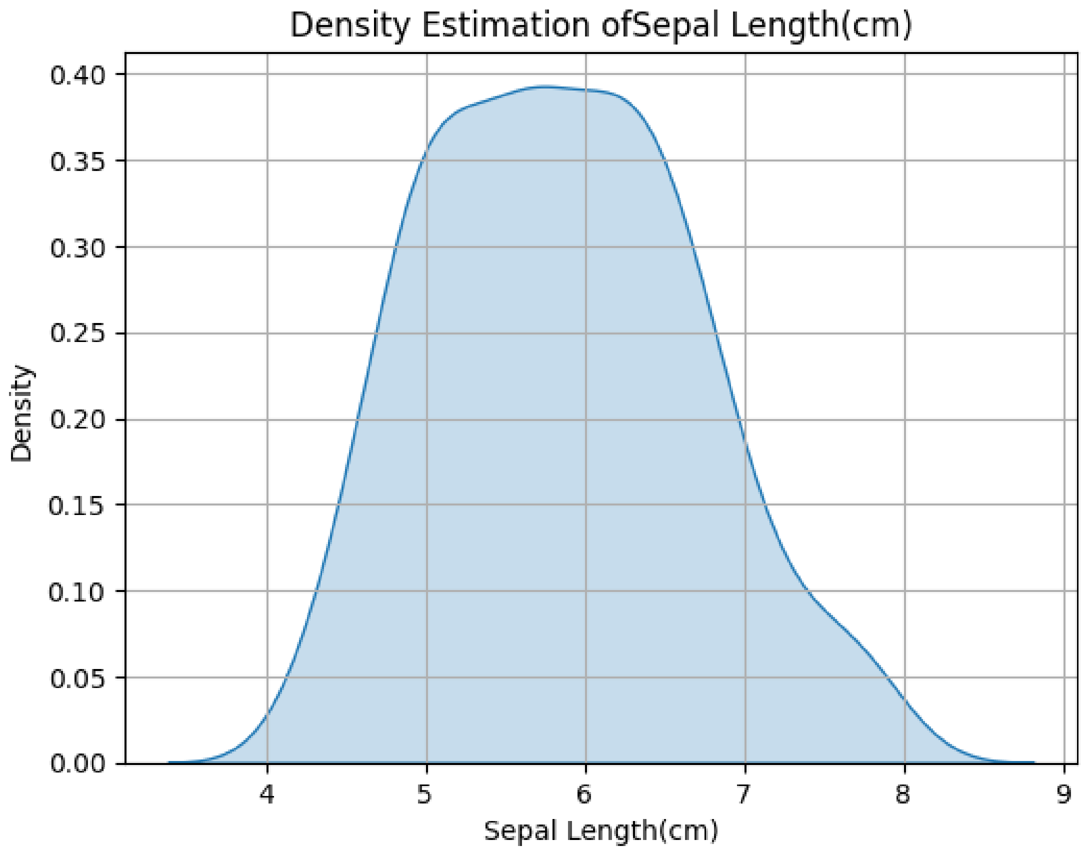
[27]:
```
sns.scatterplot(data=iris,x ='Sepal Width(cm)',y='Petal␣
↪Width(cm)',hue='Species')
plt.xlabel('Sepal Width(cm)')
plt.ylabel('Petal Width(cm)')
plt.title('Scatter Plot')
plt.grid(True)
plt.show()
```

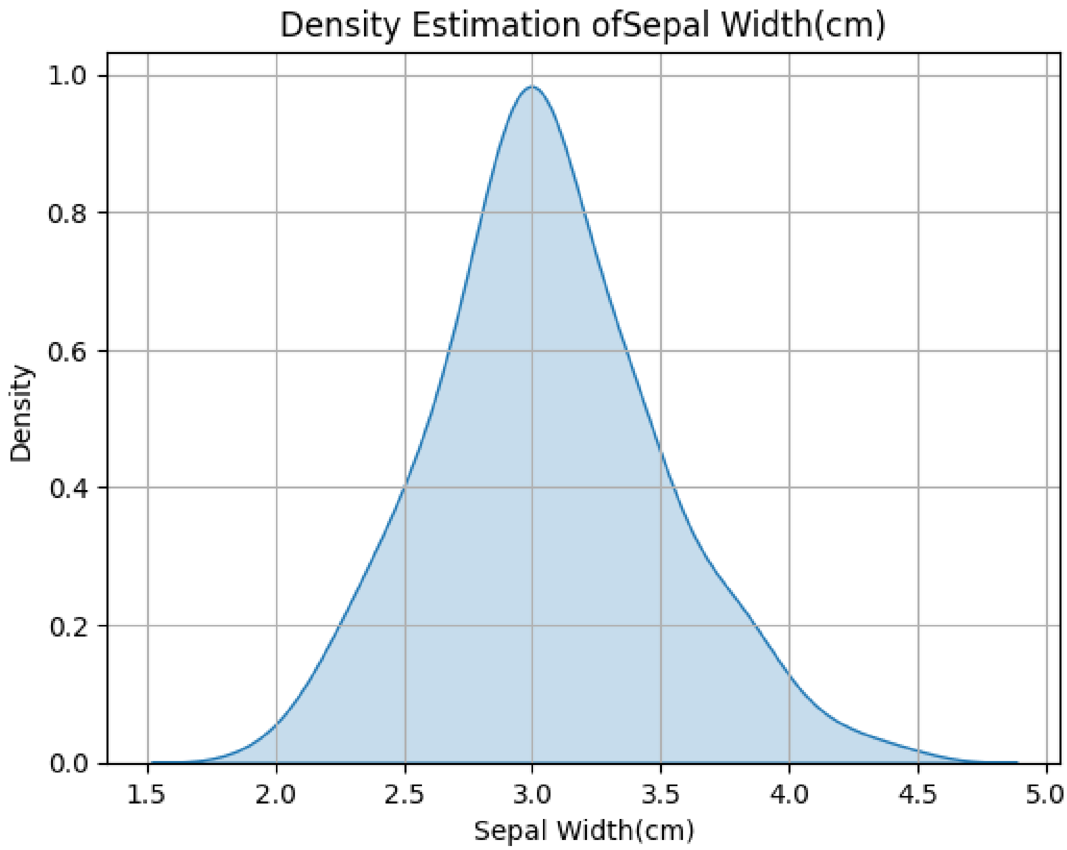


[28]:
```
#countplot for species
color_pallete = ['Green','Red','Blue']
sns.countplot(data=iris,x = y,palette=color_pallete)
plt.xlabel('Species')
plt.ylabel('Count')
plt.title('Count of Species')
plt.show()
```

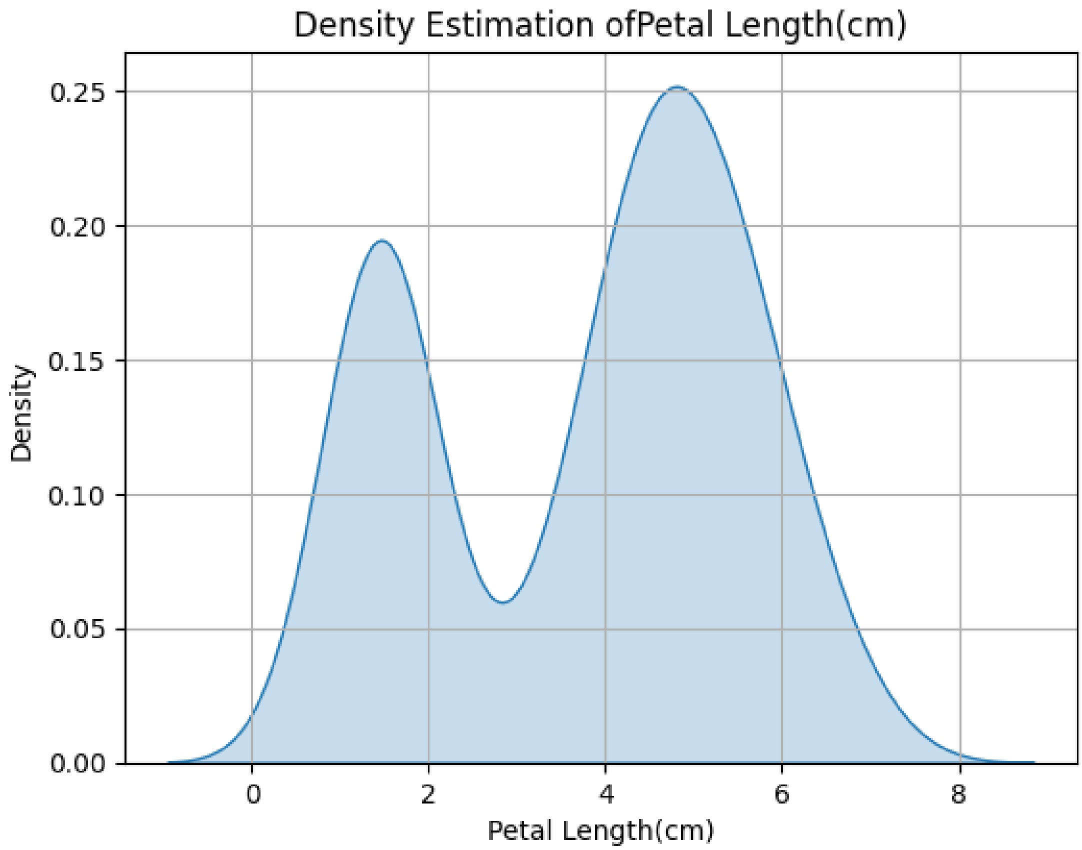


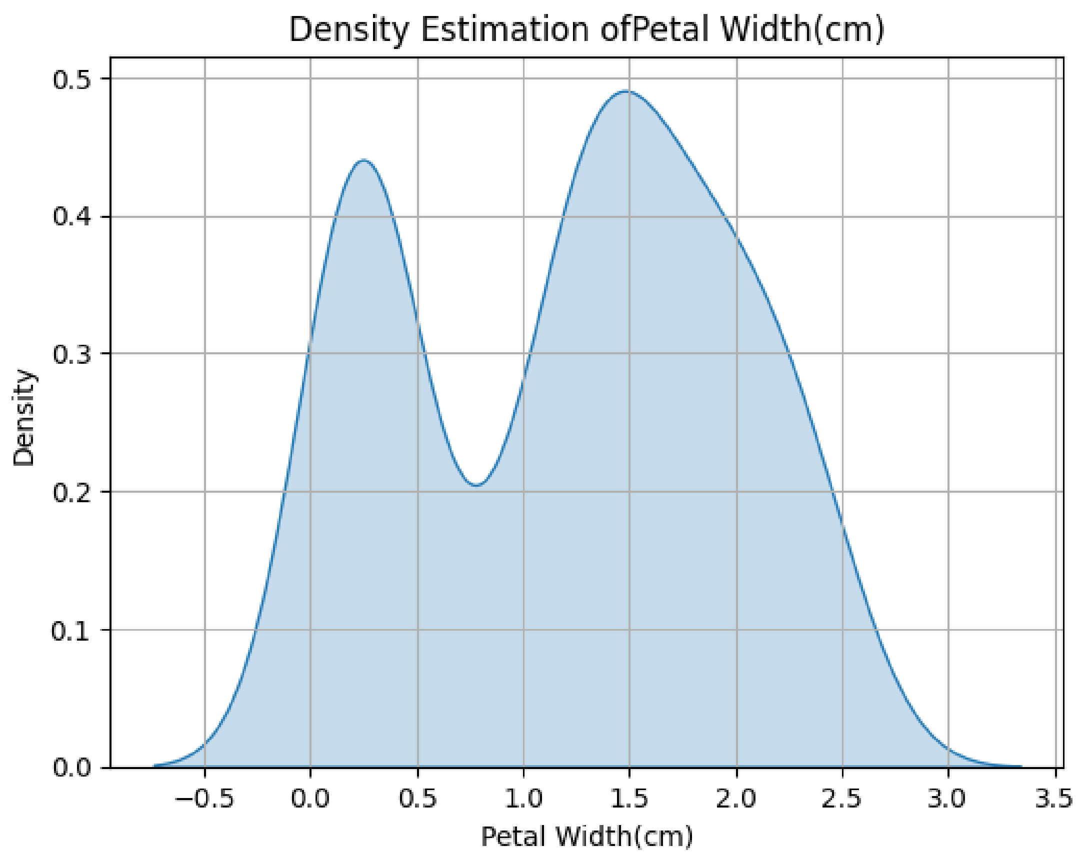
[29]:
```
#Iterate over each column
for feature in iris.columns[:-1]:
    sns.kdeplot(data=iris,x = feature,fill=True,shade=True)
    plt.xlabel(feature)
    plt.ylabel('Density')
    plt.title(f'Density Estimation of{feature}')
    plt.grid(True)
    plt.show()
```


Density Estimation ofSepal Length(cm)
Density
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
4
5
6
7
8
9
Sepal Length(cm)



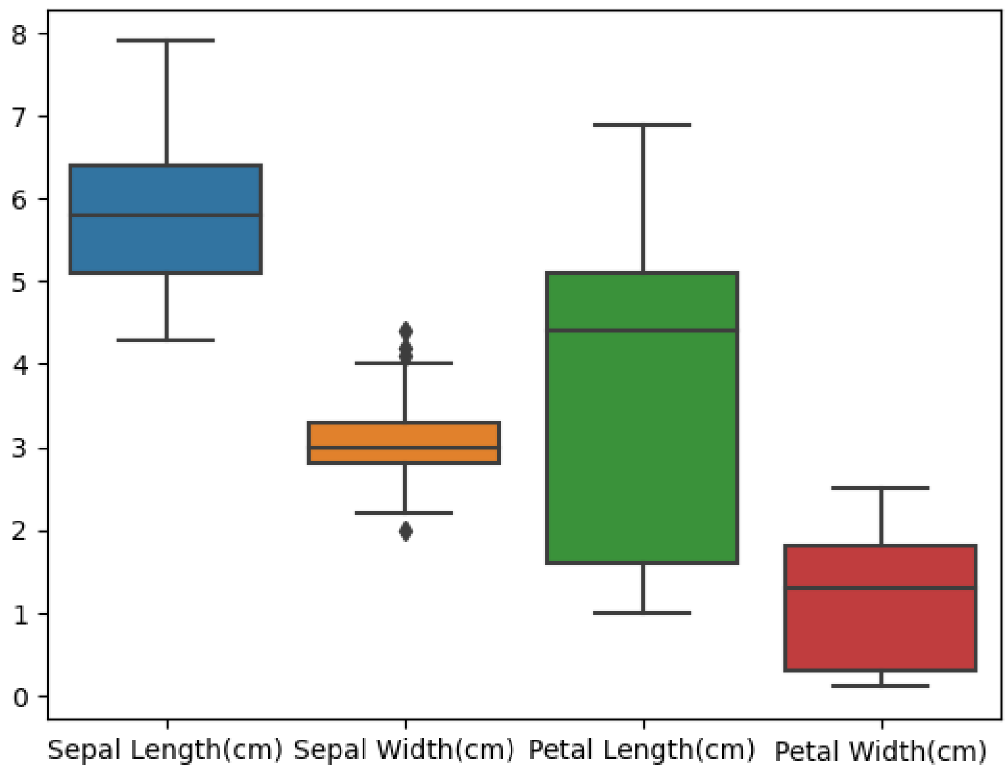
Density Estimation ofSepal Width(cm)
Density
Sepal Width(cm)
1.0
0.8
0.6
0.4
0.2
0.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0


Density Estimation ofPetal Length(cm)
Density
0.00
0.05
0.10
0.15
0.20
0.25
0
2
4
6
8
Petal Length(cm)



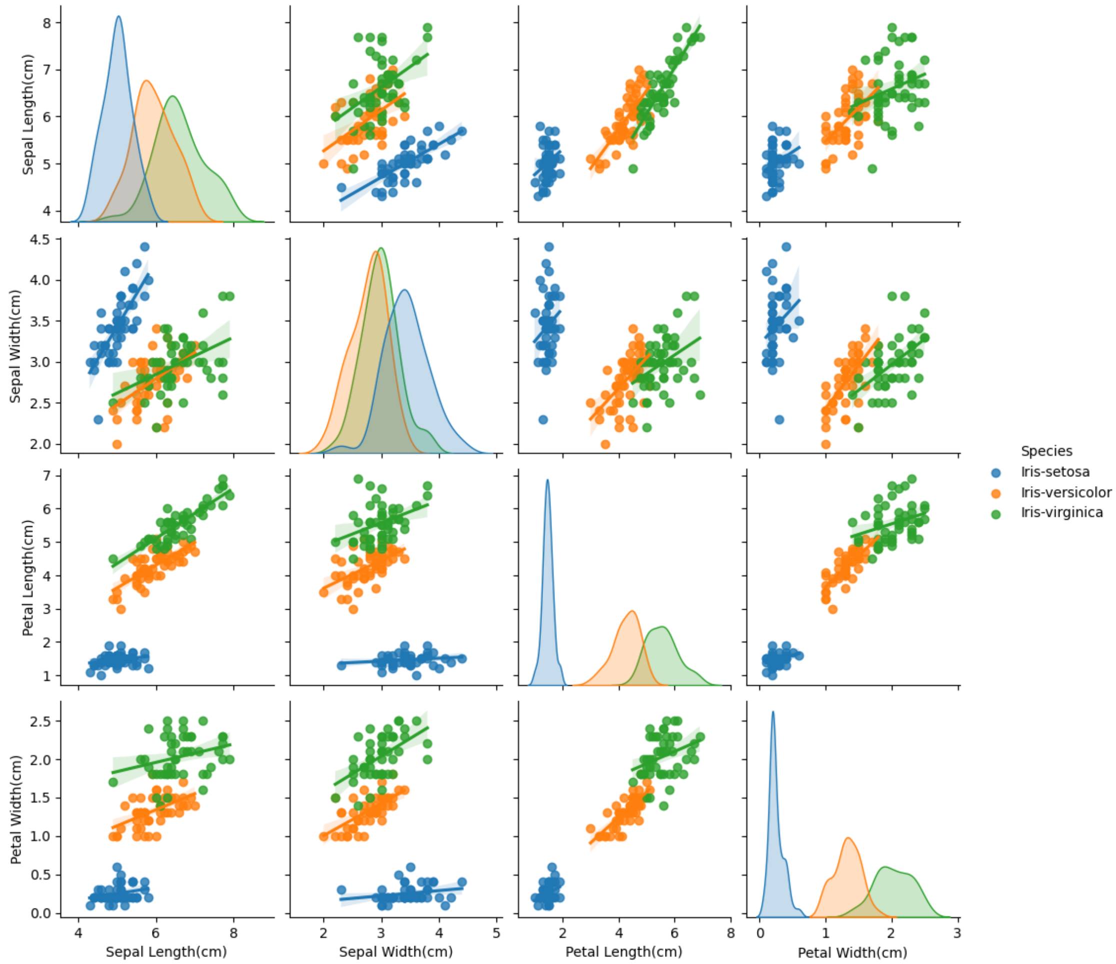
[30]:
```
sns.boxplot(data=iris)
```

[30]: <Axes: >



[31]:
```
sns.pairplot(data=iris,hue='Species',kind='reg')
```

[31]: <seaborn.axisgrid.PairGrid at 0x22ba71fefb0>



[32]:
```
#Correlation
```

[33]:
```
correlation = iris.corr()
correlation
```

[33]:
```
                  Sepal Length(cm)  Sepal Width(cm)  Petal Length(cm)  \
Sepal Length(cm)          1.000000        -0.109321          0.871305
Sepal Width(cm)          -0.109321         1.000000         -0.421057
Petal Length(cm)          0.871305        -0.421057          1.000000
Petal Width(cm)           0.817058        -0.356376          0.961883

                  Petal Width(cm)
Sepal Length(cm)         0.817058
Sepal Width(cm)         -0.356376
Petal Length(cm)         0.961883
Petal Width(cm)          1.000000
```

```
[34]: plt.figure(figsize=(10,5))
      sns.heatmap(correlation,annot=True,cmap='viridis')
```

```
[34]: <Axes: >
```


```
[35]: iris.head()
```

```
[35]:    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

             Species
      0  Iris-setosa
      1  Iris-setosa
      2  Iris-setosa
      3  Iris-setosa
      4  Iris-setosa
```

```
[36]: #Label Encoding
      y=iris['Species']
```

```
[37]: from sklearn.preprocessing import LabelEncoder
      le = LabelEncoder()
      y_labled = le.fit_transform(y)
      y_labled
```

[37]:
```
array([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, 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])
```

[38]:
```
iris['Species'] = y_labled
iris
```

[38]:
```
     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
..                …              …                …               …
145               6.7              3.0               5.2              2.3
146               6.3              2.5               5.0              1.9
147               6.5              3.0               5.2              2.0
148               6.2              3.4               5.4              2.3
149               5.9              3.0               5.1              1.8

     Species
0          0
1          0
2          0
3          0
4          0
..       …
145        2
146        2
147        2
148        2
149        2

[147 rows x 5 columns]
```

9 Splitting Data

[39]:
```
from sklearn.model_selection import train_test_split
```

[40]:
```
X = iris.iloc[:,:-1]
y = iris.iloc[:,-1]
```

[41]:
```
xtrain,xtest,ytrain,ytest = train_test_split(X,y,test_size=0.25,random_state=1)
```

[42]:
```
xtrain.head()
```

[42]:

	Sepal Length(cm)	Sepal Width(cm)	Petal Length(cm)	Petal Width(cm)
120	6.9	3.2	5.7	2.3
17	5.1	3.5	1.4	0.3
113	5.7	2.5	5.0	2.0
80	5.5	2.4	3.8	1.1
71	6.1	2.8	4.0	1.3

[43]:
```
xtest.head()
```

[43]:

	Sepal Length(cm)	Sepal Width(cm)	Petal Length(cm)	Petal Width(cm)
101	5.8	2.7	5.1	1.9
95	5.7	3.0	4.2	1.2
56	6.3	3.3	4.7	1.6
105	7.6	3.0	6.6	2.1
100	6.3	3.3	6.0	2.5

[44]:
```
ytrain.head()
```

[44]:
```
120    2
17     0
113    2
80     1
71     1
Name: Species, dtype: int32
```

[45]:
```
ytest.head()
```

[45]:
```
101    2
95     1
56     1
105    2
100    2
Name: Species, dtype: int32
```

10 Model Building

11 1) Logistic Regression

[46]:
```
from sklearn.linear_model import LogisticRegression
#choose the model
model_1 = LogisticRegression()
```

[47]:
```
#train the model
model_1.fit(xtrain,ytrain)
```

[47]: LogisticRegression()

[48]:
```
#evaluate
y_pred = model_1.predict(xtest)
```

[49]:
```
accuracy = accuracy_score(ytest,y_pred)
print(f"Accuracy: ",accuracy*100)

precision = precision_score(ytest,y_pred,average='weighted')
print(f"Precision: ",precision*100)

recall = recall_score(ytest,y_pred,average='weighted')
print(f"Recall: ",recall*100)

F1_score = f1_score(ytest,y_pred,average='weighted')
print(f"F1_score: ",F1_score*100)
```

```
Accuracy:  94.5945945945946
Precision:  94.5945945945946
Recall:  94.5945945945946
F1_score:  94.5945945945946
```

12 2) Random Forest Classifier

[50]:
```
from sklearn.ensemble import RandomForestClassifier
```

[51]:
```
model_2 = RandomForestClassifier()
```

[52]:
```
model_2.fit(xtrain,ytrain)
```

[52]: RandomForestClassifier()

[53]:
```
y_pred = model_2.predict(xtest)
```

[54]:
```
accuracy = accuracy_score(ytest,y_pred)
print(f"Accuracy: ",accuracy*100)

precision = precision_score(ytest,y_pred,average='weighted')
print(f"Precision: ",precision*100)

recall = recall_score(ytest,y_pred,average='weighted')
print(f"Recall: ",recall*100)

F1_score = f1_score(ytest,y_pred,average='weighted')
print(f"F1_score: ",F1_score*100)
```

```
Accuracy:  91.8918918918919
Precision:  92.03229203229203
```

```
Recall:  91.8918918918919
F1_score:  91.86577882230058
```

13 3) KNN Classifier

[55]:
```python
from sklearn.neighbors import KNeighborsClassifier
```

[56]:
```python
model_3 = KNeighborsClassifier()
```

[57]:
```python
model_3.fit(xtrain,ytrain)
```

[57]:
```
KNeighborsClassifier()
```

[58]:
```python
y_pred = model_3.predict(xtest)
```

[59]:
```python
accuracy = accuracy_score(ytest,y_pred)
print(f"Accuracy: ",accuracy*100)

precision = precision_score(ytest,y_pred,average='weighted')
print(f"Precision: ",precision*100)

recall = recall_score(ytest,y_pred,average='weighted')
print(f"Recall: ",recall*100)

F1_score = f1_score(ytest,y_pred,average='weighted')
print(f"F1_score: ",F1_score*100)
```

```
Accuracy:  97.2972972972973
Precision:  97.50519750519751
Recall:  97.2972972972973
F1_score:  97.2972972972973
```

14 4) Decision Tree Classifier

[60]:
```python
from sklearn.tree import DecisionTreeClassifier
```

[61]:
```python
model_4 = DecisionTreeClassifier()
```

[62]:
```python
model_4.fit(xtrain,ytrain)
```

[62]:
```
DecisionTreeClassifier()
```

[63]:
```python
y_pred = model_4.predict(xtest)
```

[64]:
```python
accuracy = accuracy_score(ytest,y_pred)
print(f"Accuracy: ",accuracy*100)
```

```
precision = precision_score(ytest,y_pred,average='weighted')
print(f"Precision: ",precision*100)

recall = recall_score(ytest,y_pred,average='weighted')
print(f"Recall: ",recall*100)

F1_score = f1_score(ytest,y_pred,average='weighted')
print(f"F1_score: ",F1_score*100)
```

```
Accuracy:  91.8918918918919
Precision:  92.03229203229203
Recall:  91.8918918918919
F1_score:  91.86577882230058
```

15 5) SVC

[65]:
```
from sklearn.svm import SVC
```

[66]:
```
model_5 = SVC()
```

[67]:
```
model_5.fit(xtrain,ytrain)
```

[67]: SVC()

[68]:
```
y_pred = model_5.predict(xtest)
```

[69]:
```
accuracy = accuracy_score(ytest,y_pred)
print(f"Accuracy: ",accuracy*100)

precision = precision_score(ytest,y_pred,average='weighted')
print(f"Precision: ",precision*100)

recall = recall_score(ytest,y_pred,average='weighted')
print(f"Recall: ",recall*100)

F1_score = f1_score(ytest,y_pred,average='weighted')
print(f"F1_score: ",F1_score*100)
```

```
Accuracy:  94.5945945945946
Precision:  94.5945945945946
Recall:  94.5945945945946
F1_score:  94.5945945945946
```

16 Model Comparison

[70]:
```
models = [
    ('Logistic Regression',LogisticRegression()),
    ('Random Forest Classifier',RandomForestClassifier()),
    ('K-Nearest Neighbors',KNeighborsClassifier()),
    ('Decision Tree Classifier',DecisionTreeClassifier()),
    ('SVM',SVC())]
```

[71]:
```
results = []
for name, model in models:
    model.fit(xtrain, ytrain)
    y_pred = model.predict(xtest)
    accuracy = accuracy_score(ytest, y_pred)
    results.append((name, accuracy))
```

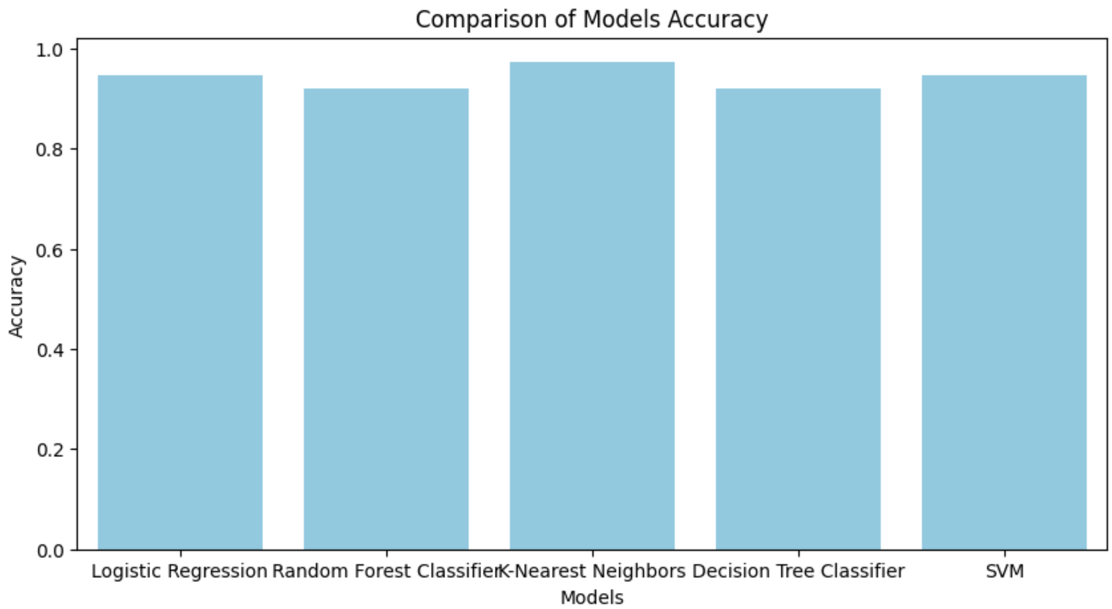
[72]:
```
df_result = pd.DataFrame(results,columns=['Models','Accuracy'])
```

[73]:
```
df_result
```

[73]:

	Models	Accuracy
0	Logistic Regression	0.945946
1	Random Forest Classifier	0.918919
2	K-Nearest Neighbors	0.972973
3	Decision Tree Classifier	0.918919
4	SVM	0.945946

[74]:
```
#Visualize Models Accuracy
plt.figure(figsize=(10,5))
sns.barplot(y='Accuracy',x='Models',data=df_result,color='skyblue')
plt.xlabel('Models')
plt.ylabel('Accuracy')
plt.title('Comparison of Models Accuracy')
plt.show()
```



17 Hypertunning

[75]:
```
grid ={'n_neighbors': [1, 3, 5, 7, 9], 'weights': ['uniform', 'distance'], 'p':␣
↪[1, 2]}
grid_search = GridSearchCV(estimator=model_3, param_grid=grid, cv=5)
grid_search.fit(xtrain, ytrain)
```

[75]:
```
GridSearchCV(cv=5, estimator=KNeighborsClassifier(),
             param_grid={'n_neighbors': [1, 3, 5, 7, 9], 'p': [1, 2],
                         'weights': ['uniform', 'distance']})
```

[76]:
```
# Print the best hyperparameters and the corresponding accuracy score
print("Best Hyperparameters:", grid_search.best_params_)
best_model = grid_search.best_estimator_
y_pred = best_model.predict(xtest)
accuracy = accuracy_score(ytest, y_pred)
print("Accuracy:", accuracy)
```

```
Best Hyperparameters: {'n_neighbors': 5, 'p': 2, 'weights': 'uniform'}
Accuracy: 0.972972972972973
```

18 Predicition on New Unseen Data

[77]:
```
# Example unseen data
new_data = [[5.1, 3.5, 1.4, 0.2], [6.2, 2.8, 4.8, 1.8], [7.3, 2.9, 6.3, 1.8]]
```

[78]:
```
#make prediction on new data
predictions = model_3.predict(new_data)
```

[79]:
```
# Map the predicted labels to target names
target_names = iris['Species']
predicted_species = [target_names[prediction] for prediction in predictions]

# Print the predicted species
for data, species in zip(new_data, predicted_species):
    print(f"Data: {data} --> Predicted Species: {species}")
```

```
Data: [5.1, 3.5, 1.4, 0.2] --> Predicted Species: 0
Data: [6.2, 2.8, 4.8, 1.8] --> Predicted Species: 0
Data: [7.3, 2.9, 6.3, 1.8] --> Predicted Species: 0
```

19 Model Saving

[80]:
```
import joblib
```

[81]:
```
joblib.dump(model_3, 'knn.pkl')
```

[81]:
```
['knn.pkl']
```

20 Thank You!