Step 1 – Load the data:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt


from warnings import filterwarnings
filterwarnings(action='ignore')


iris=pd.read_csv("iris.csv")
print(iris)
```

```
      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]
```

```
print(iris.shape)
```

```
(150, 6)
```

```
print(iris.describe())
```

```
               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
```

Step 2 – Analyze and visualize the dataset:

```
#Checking for null values
print(iris.isna().sum())
print(iris.describe())
```

```
Id               0
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
               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
```

```
iris.head()
```

	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

```
iris.head(150)
```

	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
...	...	...	...	...	...	...
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 6 columns

```
iris.tail(100)
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
50	51	7.0	3.2	4.7	1.4	Iris-versicolor
51	52	6.4	3.2	4.5	1.5	Iris-versicolor
52	53	6.9	3.1	4.9	1.5	Iris-versicolor
53	54	5.5	2.3	4.0	1.3	Iris-versicolor
54	55	6.5	2.8	4.6	1.5	Iris-versicolor
...	...	...	...	...	...	...
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

100 rows × 6 columns

```
n = len(iris[iris['Species'] == 'Iris-versicolor'])
print("No of Versicolor in Dataset:",n)
```

```
No of Versicolor in Dataset: 50
```

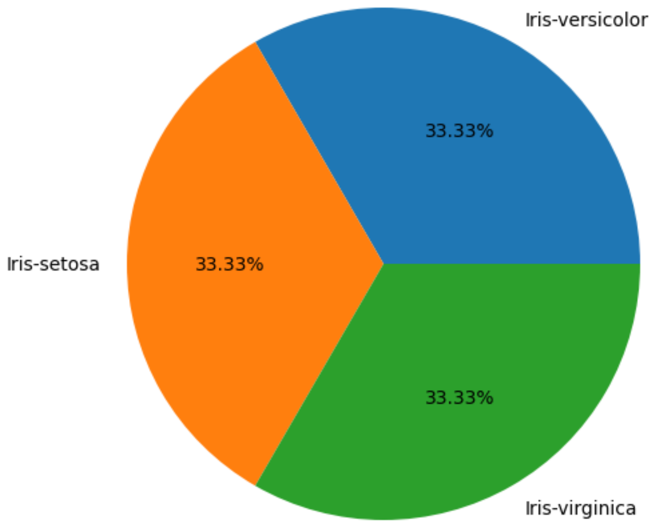
```
n1 = len(iris[iris['Species'] == 'Iris-virginica'])
print("No of Virginica in Dataset:",n1)
```

```
No of Virginica in Dataset: 50
```

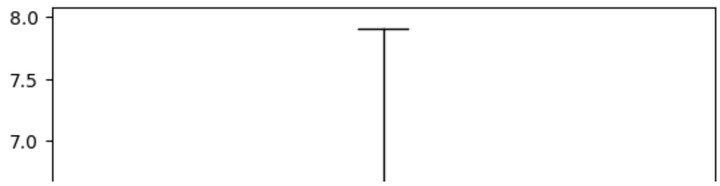
```
n2 = len(iris[iris['Species'] == 'Iris-setosa'])
print("No of Setosa in Dataset:",n2)
```

```
No of Setosa in Dataset: 50
```

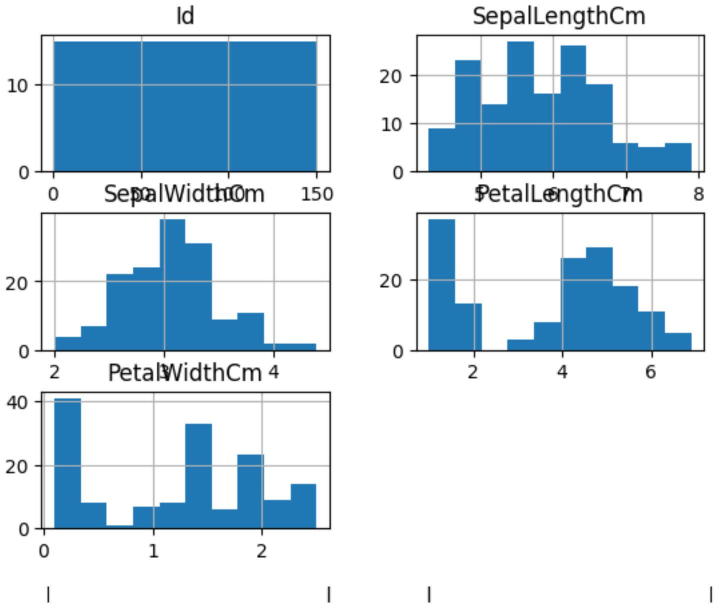
```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.axis('equal')
l = ['Iris-versicolor', 'Iris-setosa', 'Iris-virginica']
s = [50,50,50]
ax.pie(s, labels = l,autopct='%1.2f%%')
plt.show()
```




```
#Checking for outliars
import matplotlib.pyplot as plt
plt.figure(1)
plt.boxplot([iris['SepalLengthCm']])
plt.figure(2)
plt.boxplot([iris['SepalWidthCm']])
plt.show()
```

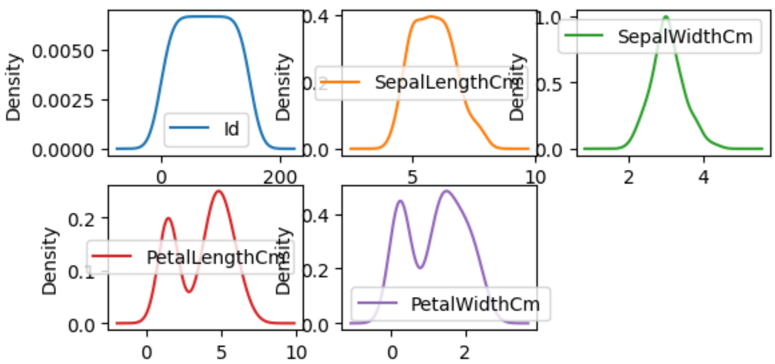


```
iris.hist()
plt.show()
```



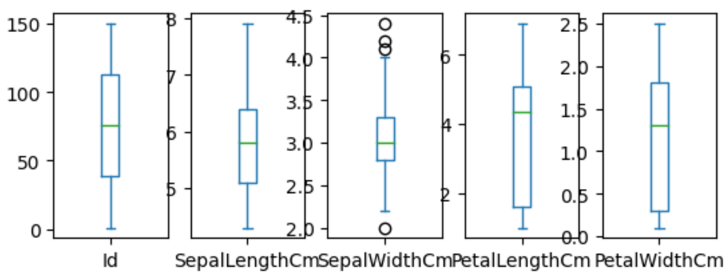

```
iris.plot(kind ='density',subplots = True, layout =(3,3),sharex = False)
```

```
array([[<Axes: ylabel='Density'>, <Axes: ylabel='Density'>,
        <Axes: ylabel='Density'>],
       [<Axes: ylabel='Density'>, <Axes: ylabel='Density'>,
        <Axes: ylabel='Density'>],
       [<Axes: ylabel='Density'>, <Axes: ylabel='Density'>,
        <Axes: ylabel='Density'>]], dtype=object)
```




```
iris.plot(kind ='box',subplots = True, layout =(2,5),sharex = False)
```

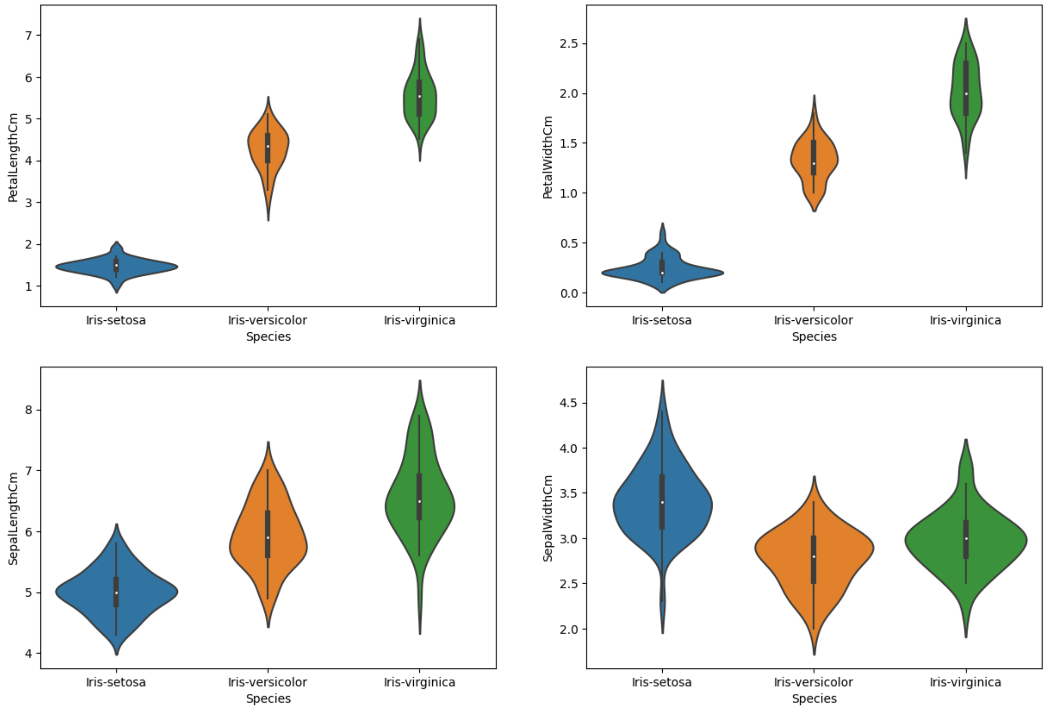
```
Id                  Axes(0.125,0.53;0.133621x0.35)
SepalLengthCm    Axes(0.285345,0.53;0.133621x0.35)
SepalWidthCm      Axes(0.44569,0.53;0.133621x0.35)
PetalLengthCm    Axes(0.606034,0.53;0.133621x0.35)
PetalWidthCm     Axes(0.766379,0.53;0.133621x0.35)
dtype: object
```




```
plt.figure(figsize=(15,10))
plt.subplot(2,2,1)
```

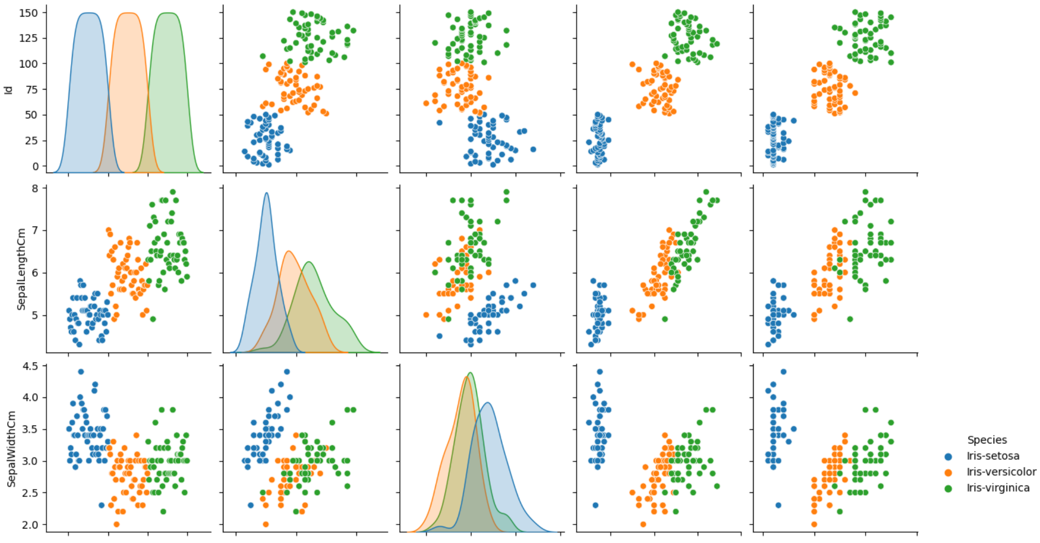
```
sns.violinplot(x='Species',y='PetalLengthCm',data=iris)
plt.subplot(2,2,2)
sns.violinplot(x='Species',y='PetalWidthCm',data=iris)
plt.subplot(2,2,3)
sns.violinplot(x='Species',y='SepalLengthCm',data=iris)
plt.subplot(2,2,4)
sns.violinplot(x='Species',y='SepalWidthCm',data=iris)
```

```
<Axes: xlabel='Species', ylabel='SepalWidthCm'>
```

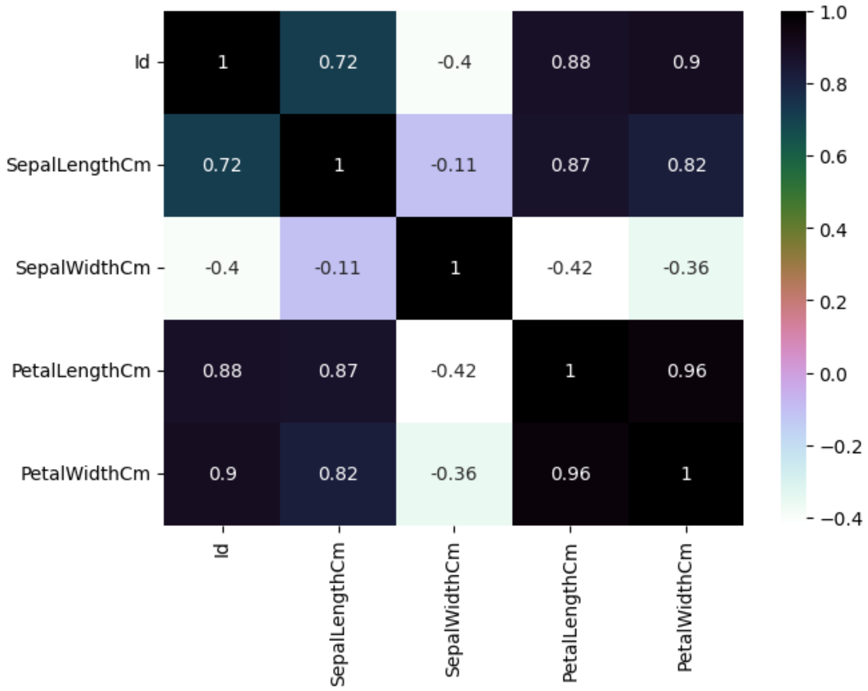



```
sns.pairplot(iris,hue='Species')
```

```
<seaborn.axisgrid.PairGrid at 0x7f1c8a186470>
```




```
plt.figure(figsize=(7,5))
sns.heatmap(iris.corr(), annot=True, cmap='cubehelix_r')
plt.show()
```




```
X = iris['SepalLengthCm'].values.reshape(-1,1)
print(X)
```

```
[[5.1]
 [4.9]
 [4.7]
 [4.6]
 [5. ]
 [5.4]
 [4.6]
 [5. ]
 [4.4]
 [4.9]
 [5.4]
 [4.8]
 [4.8]
 [4.3]
 [5.8]
 [5.7]
 [5.4]
 [5.1]
 [5.7]
 [5.1]
 [5.4]
 [5.1]
 [4.6]
 [5.1]
```

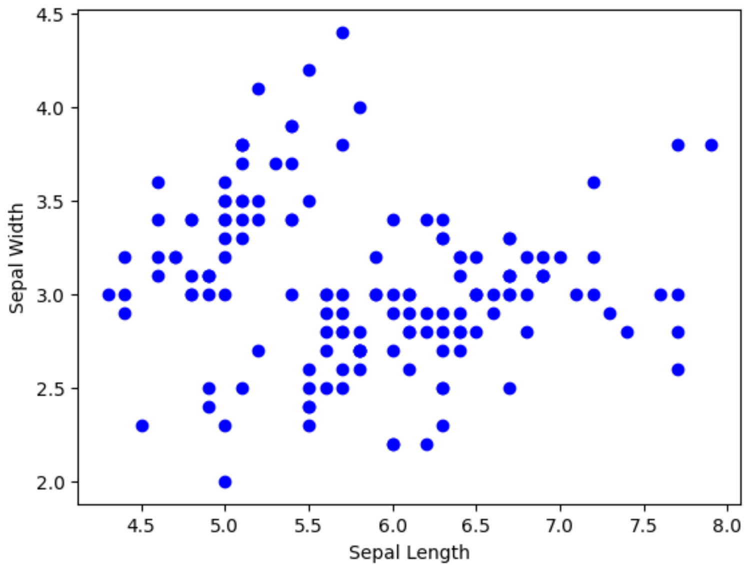
```
 [4.8]
 [5. ]
 [5. ]
 [5.2]
 [5.2]
 [4.7]
 [4.8]
 [5.4]
 [5.2]
 [5.5]
 [4.9]
 [5. ]
 [5.5]
 [4.9]
 [4.4]
 [5.1]
 [5. ]
 [4.5]
 [4.4]
 [5. ]
 [5.1]
 [4.8]
 [5.1]
 [4.6]
 [5.3]
 [5. ]
 [7. ]
 [6.4]
 [6.9]
 [5.5]
 [6.5]
 [5.7]
 [6.3]
```

```
Y = iris['SepalWidthCm'].values.reshape(-1,1)
print(Y)
```

```
[[3.5]
 [3. ]
 [3.2]
 [3.1]
 [3.6]
 [3.9]
 [3.4]
 [3.4]
 [2.9]
 [3.1]
 [3.7]
 [3.4]
 [3. ]
 [3. ]
 [4. ]
 [4.4]
 [3.9]
 [3.5]
 [3.8]
 [3.8]
 [3.4]
 [3.7]
 [3.6]
 [3.3]
 [3.4]
 [3. ]
 [3.4]
 [3.5]
 [3.4]
 [3.2]
 [3.1]
 [3.4]
 [4.1]
 [4.2]
 [3.1]
 [3.2]
 [3.5]
 [3.1]
 [3. ]
 [3.4]
 [3.5]
 [2.3]
 [3.2]
 [3.5]
 [3.8]
 [3. ]
 [3.8]
 [3.2]
 [3.7]
 [3.3]
 [3.2]
 [3.2]
```

```
[3.1]
[2.3]
[2.8]
[2.8]
[3.3]
[2.4]
```

```
plt.xlabel("Sepal Length")
plt.ylabel("Sepal Width")
plt.scatter(X,Y,color='b')
plt.show()
```




```
#Correlation
corr_mat = iris.corr()
print(corr_mat)
```

```
                     Id  SepalLengthCm  SepalWidthCm  PetalLengthCm  \
Id             1.000000       0.716676     -0.397729       0.882747
SepalLengthCm  0.716676       1.000000     -0.109369       0.871754
SepalWidthCm  -0.397729      -0.109369      1.000000      -0.420516
PetalLengthCm  0.882747       0.871754     -0.420516       1.000000
PetalWidthCm   0.899759       0.817954     -0.356544       0.962757

               PetalWidthCm
Id                 0.899759
SepalLengthCm      0.817954
SepalWidthCm      -0.356544
PetalLengthCm      0.962757
PetalWidthCm       1.000000
```

Step 3 – Model training:

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn import svm
from sklearn import metrics
from sklearn.tree import DecisionTreeClassifier
```

```
train, test = train_test_split(iris, test_size = 0.25)
print(train.shape)
print(test.shape)
```

```
(112, 6)
(38, 6)
```

```
train_X = train[['SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm',
                 'PetalWidthCm']]
train_y = train.Species

test_X = test[['SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm',
                 'PetalWidthCm']]
test_y = test.Species
```

```
train_X.head()
```

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
57	4.9	2.4	3.3	1.0
14	5.8	4.0	1.2	0.2
3	4.6	3.1	1.5	0.2
37	4.9	3.1	1.5	0.1
118	7.7	2.6	6.9	2.3

```
test_y.head()
```

```
11        Iris-setosa
18        Iris-setosa
67    Iris-versicolor
74    Iris-versicolor
61    Iris-versicolor
Name: Species, dtype: object
```

Step 4 – Model Evaluation:

```
#Using LogisticRegression
model = LogisticRegression()
model.fit(train_X, train_y)
prediction = model.predict(test_X)
print('Accuracy:',metrics.accuracy_score(prediction,test_y))
```

```
Accuracy: 0.9210526315789473
```

```
#Confusion matrix
from sklearn.metrics import confusion_matrix,classification_report
confusion_mat = confusion_matrix(test_y,prediction)
print("Confusion matrix: \n",confusion_mat)
print(classification_report(test_y,prediction))
```

```
Confusion matrix:
 [[12  0  0]
 [ 0 14  1]
 [ 0  2  9]]
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        12
Iris-versicolor       0.88      0.93      0.90        15
 Iris-virginica       0.90      0.82      0.86        11

       accuracy                           0.92        38
      macro avg       0.92      0.92      0.92        38
   weighted avg       0.92      0.92      0.92        38
```

```
#Using Support Vector
from sklearn.svm import SVC
model1 = SVC()
model1.fit(train_X,train_y)

pred_y = model1.predict(test_X)

from sklearn.metrics import accuracy_score
print("Acc=",accuracy_score(test_y,pred_y))
```

```
Acc= 0.9473684210526315
```

```
#Using KNN Neighbors
from sklearn.neighbors import KNeighborsClassifier
model2 = KNeighborsClassifier(n_neighbors=5)
model2.fit(train_X,train_y)
y_pred2 = model2.predict(test_X)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(test_y,y_pred2))
```

```
Accuracy Score: 0.9473684210526315
```

```
#Using GaussianNB
from sklearn.naive_bayes import GaussianNB
```

```
model3 = GaussianNB()
model3.fit(train_X,train_y)
y_pred3 = model3.predict(test_X)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(test_y,y_pred3))
```

```
Accuracy Score: 0.9473684210526315
```

```
#Using Decision Tree
from sklearn.tree import DecisionTreeClassifier
model4 = DecisionTreeClassifier(criterion='entropy',random_state=7)
model4.fit(train_X,train_y)
y_pred4 = model4.predict(test_X)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(test_y,y_pred4))
```

```
Accuracy Score: 0.9210526315789473
```

```
results = pd.DataFrame({
    'Model': ['Logistic Regression','Support Vector Machines', 'Naive Bayes','KNN' ,'Decision Tree'],
    'Score': [0.947,0.947,0.947,0.947,0.921]})

result_df = results.sort_values(by='Score', ascending=False)
result_df = result_df.set_index('Score')
result_df.head(9)
```

	Model
Score	
0.947	Logistic Regression
0.947	Support Vector Machines
0.947	Naive Bayes
0.947	KNN
0.921	Decision Tree

Step 5 – Testing the model:

```
X_new = np.array([[3, 2, 1, 0.2], [  4.9, 2.2, 3.8, 1.1 ], [  5.3, 2.5, 4.6, 1.9 ]])
#Prediction of the species from the input vector
prediction = model.predict(X_new)
print("Prediction of Species: {}".format(prediction))
```

```
Prediction of Species: ['Iris-setosa' 'Iris-versicolor' 'Iris-virginica']
```