Git_publishing iris

December 20, 2021

INTRODUCTION TO DATA SCIENCE - IRIS

Importing libraries

[73]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[74]:
```
data = pd.read_csv(r'/Users/balajir/Documents/MSC/Sem 2/Introduction to Data␣
↪Science/Assignment/Iris.csv')
```

Analysing Dataset

[75]:
```
data.head()
```

[75]:

	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

[76]:
```
data.describe()
```

[76]:

	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

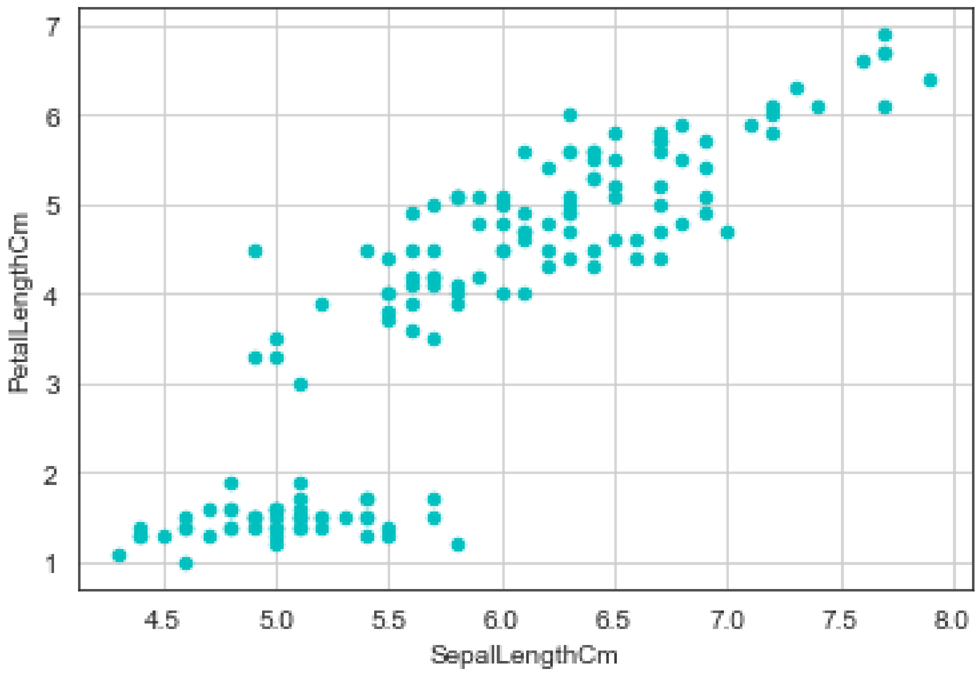
[77]:
```
data.info()
```

```
<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
```

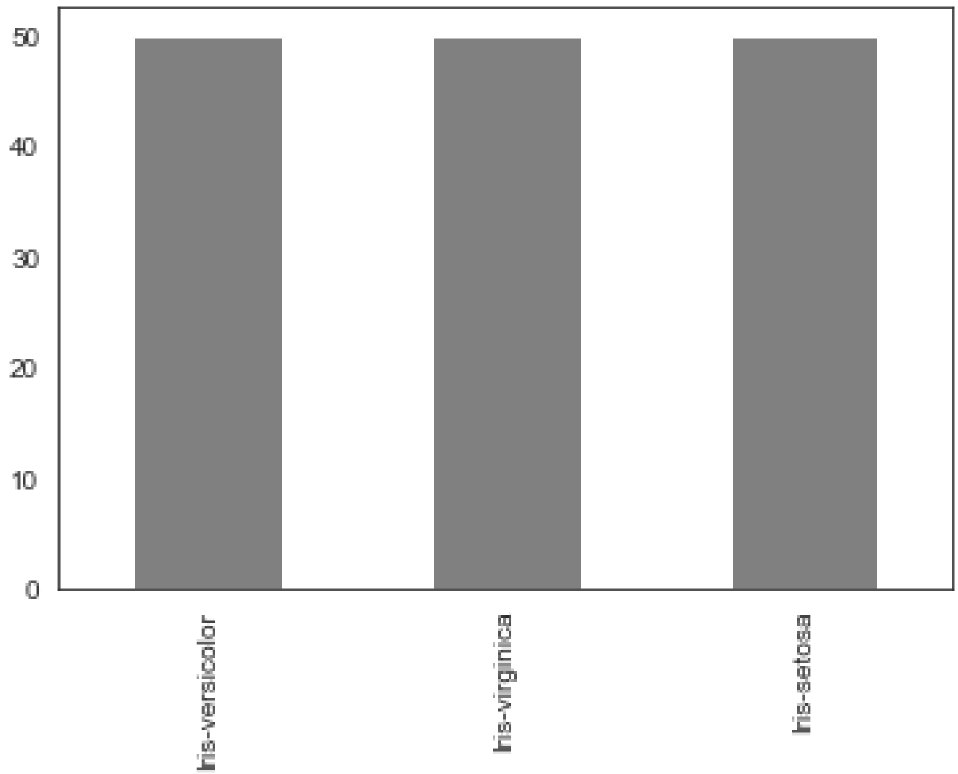
Scatter Plots

[78]:
```
data.plot(kind ="scatter",
          x ='SepalLengthCm',
          y ='PetalLengthCm',c = 'c')
plt.grid()
plt.savefig('Analysis1.pdf')
```

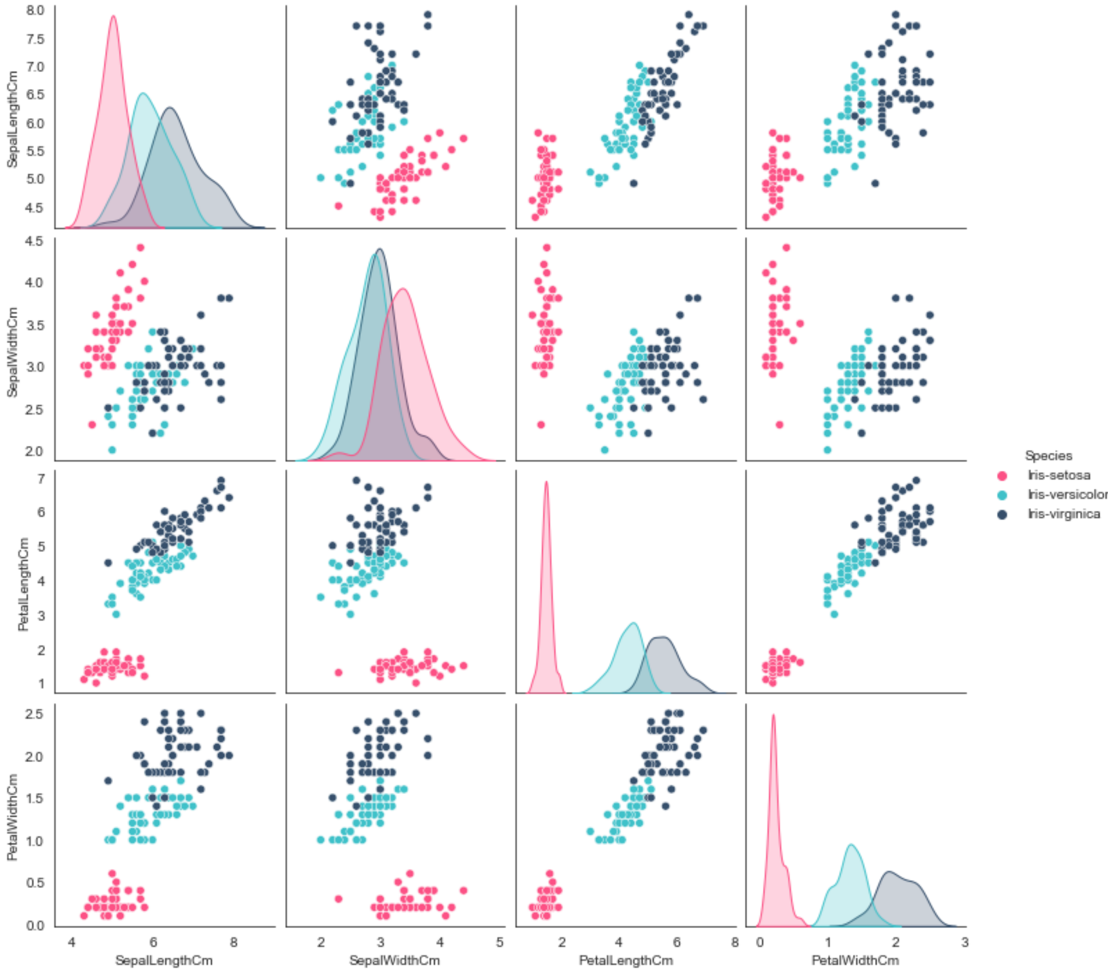


[79]:
```
data['Species'].value_counts().plot(kind='bar', color = 'Grey')
```

[79]:
```
<AxesSubplot:>
```



[80]:
```
color_pallete = ['#fc5185', '#3fc1c9', '#364f6b']
sns.set_palette(color_pallete)
sns.set_style("white")
sns.pairplot(data.drop(['Id'],axis=1),hue='Species')
plt.savefig('Analysis.pdf')
plt.show()
```



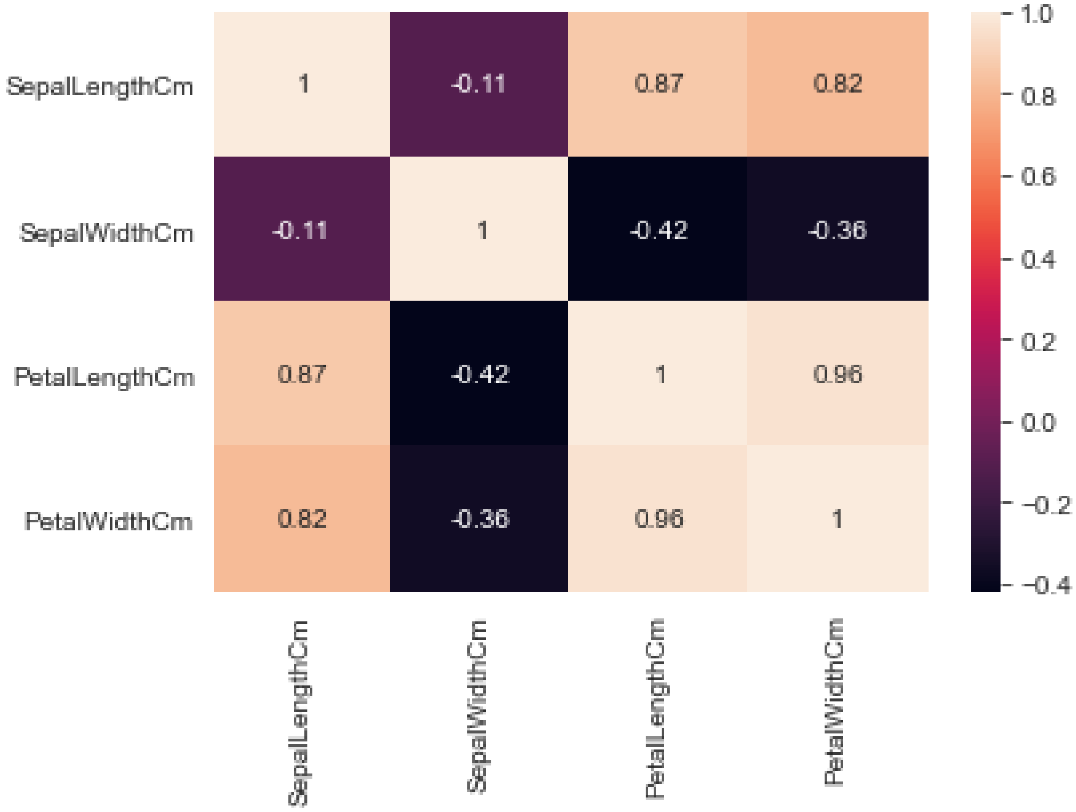
Correlation within dataset

[81]:
```
data1= data.iloc[:,1:5]

data1.corr()
```

[81]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
SepalLengthCm	1.000000	-0.109369	0.871754	0.817954
SepalWidthCm	-0.109369	1.000000	-0.420516	-0.356544
PetalLengthCm	0.871754	-0.420516	1.000000	0.962757
PetalWidthCm	0.817954	-0.356544	0.962757	1.000000

[82]:
```
plt.figure()
sns.heatmap(data1.corr(),annot=True)

plt.savefig('correl.pdf')
plt.show()
```



Assigning x & y variables

[83]:
```
x = data.iloc[:,1:5]
y = data.iloc[:,5]
```

Data split

[84]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.30,␣
↪random_state=10)
```

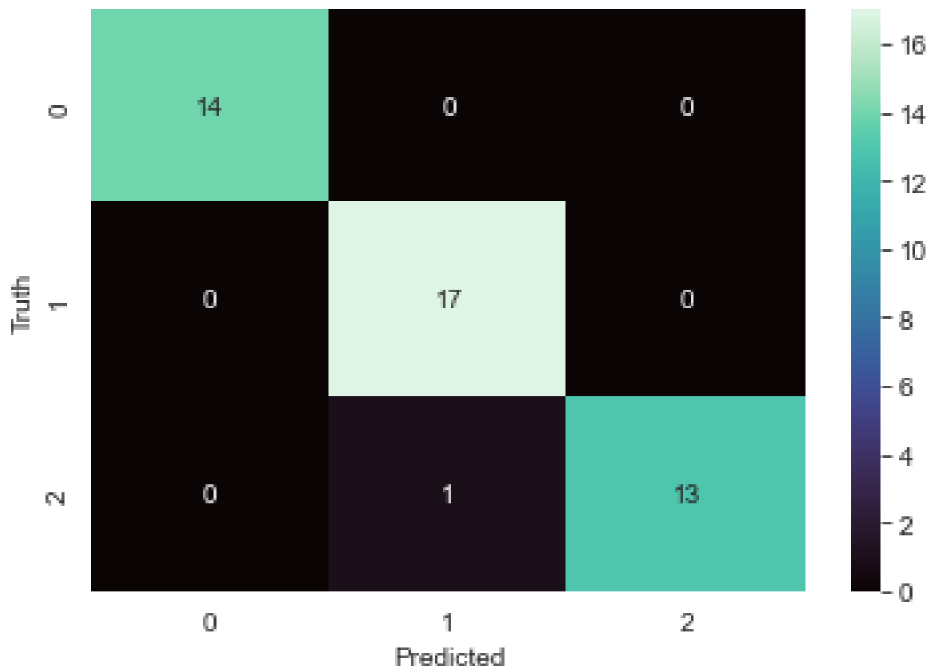
Decision Tree

[85]:
```
from sklearn import tree
dt= tree.DecisionTreeClassifier()
dt.fit(X_train,y_train)
y_pred = dt.predict(X_test)
dt.score(X_test,y_test)
```

[85]:
```
0.9777777777777777
```

Confusion matrix - Decision Tree

[86]:
```python
from sklearn import metrics
from sklearn.metrics import confusion_matrix , classification_report
cfdt = metrics.confusion_matrix(y_test,y_pred)
sns.heatmap(cfdt, annot=True,cmap="mako")
plt.xlabel('Predicted')
plt.ylabel('Truth')
plt.savefig('DT_CF.pdf')
```



Cross validation - Decision Tree (10 fold)

[87]:
```python
from sklearn.model_selection import cross_val_score
scores_dt = cross_val_score(dt, X_train, y_train, cv=10)
print("Mean:", scores_dt.mean())
scores_dt
```

```
Mean: 0.9045454545454545
```

[87]:
```
array([0.81818182, 0.90909091, 0.90909091, 0.90909091, 1.        ,
       1.        , 0.6       , 1.        , 0.9       , 1.        ])
```

Precision, recall, F1score - Decision tree

[88]:
```python
print(classification_report(y_test, y_pred))
```

```
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        14
```

```
Iris-versicolor       0.94      1.00      0.97        17
 Iris-virginica       1.00      0.93      0.96        14

       accuracy                           0.98        45
      macro avg       0.98      0.98      0.98        45
   weighted avg       0.98      0.98      0.98        45
```

Logistic regression

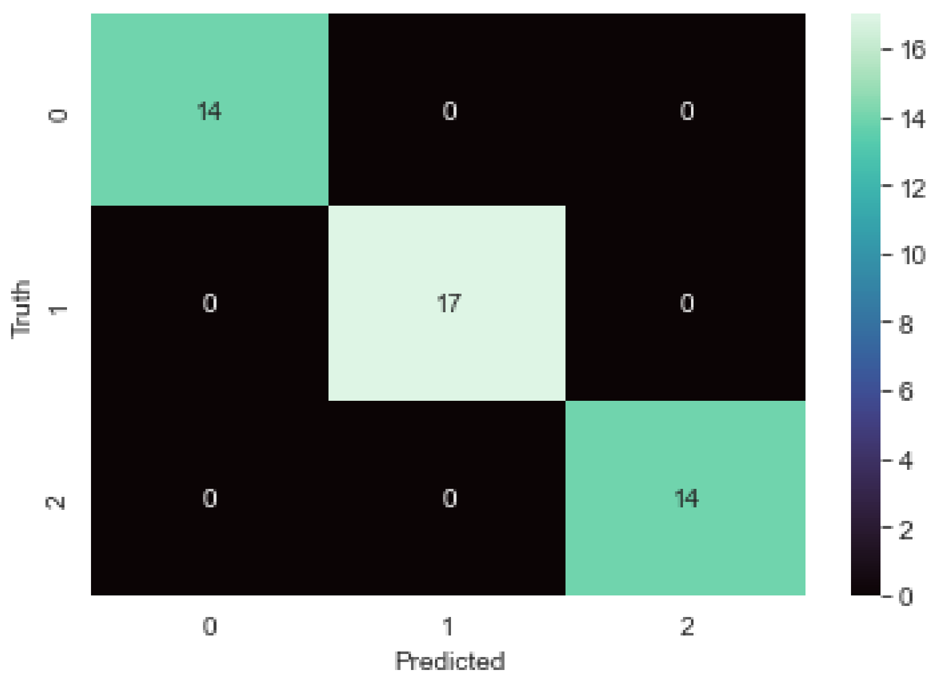
[89]:
```
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression(max_iter= 1000)
lr.fit(X_train,y_train)
lr.score(X_test,y_test)
```

[89]: 1.0

[90]:
```
y_pred_lr = lr.predict(X_test)
```

Confusion matrix - Logistic regression

[91]:
```
cflr= metrics.confusion_matrix(y_test,y_pred_lr)
sns.heatmap(cflr, annot=True,cmap="mako")
plt.xlabel('Predicted')
plt.ylabel('Truth')
plt.savefig('LR_CF.pdf')
```



Precision, recall, F1score - Logistic regression

[92]:
```
print(classification_report(y_test, y_pred_lr))
```

```
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        14
Iris-versicolor       1.00      1.00      1.00        17
 Iris-virginica       1.00      1.00      1.00        14

       accuracy                           1.00        45
      macro avg       1.00      1.00      1.00        45
   weighted avg       1.00      1.00      1.00        45
```

Cross validation - Logistic Regression (10 fold)

[93]:
```
scores_lr = cross_val_score(lr, X_train, y_train, cv=10)
print("Mean:", scores_lr.mean())
scores_lr
```

```
Mean: 0.9527272727272728
```

[93]:
```
array([0.90909091, 0.90909091, 1.        , 0.90909091, 1.        ,
       1.        , 0.9       , 1.        , 0.9       , 1.        ])
```

Random Forest

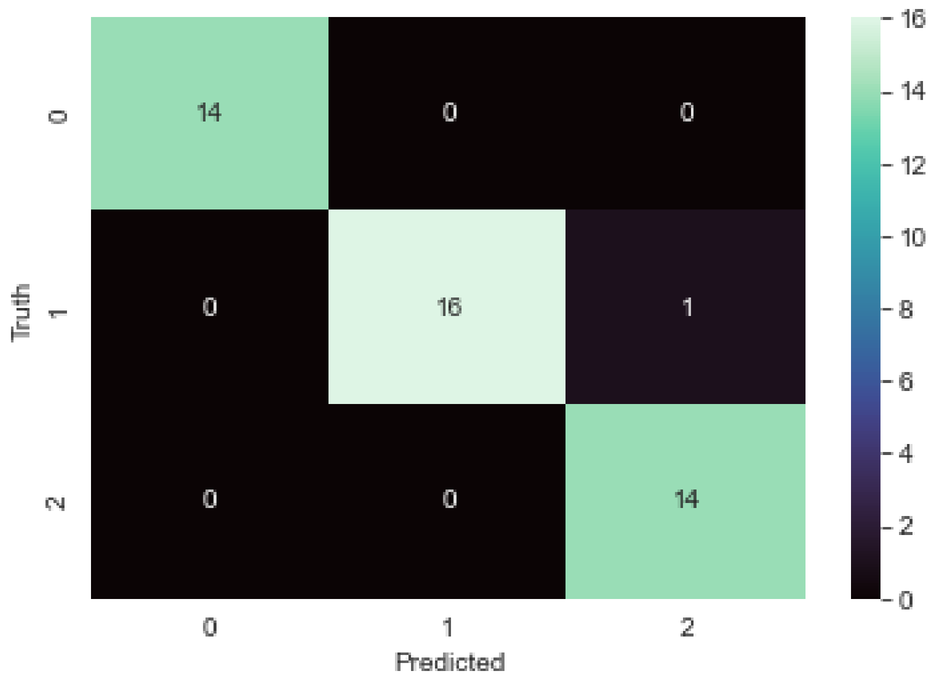
[94]:
```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier()
rf.fit(X_train, y_train)
rf.score(X_test,y_test)
```

[94]:
```
0.9777777777777777
```

[95]:
```
y_pred_rf = rf.predict(X_test)
```

Confusion matrix - Random Forest

[96]:
```
cfrf= metrics.confusion_matrix(y_test,y_pred_rf)
sns.heatmap(cfrf, annot=True,cmap="mako")
plt.xlabel('Predicted')
plt.ylabel('Truth')
plt.savefig('RF_CF.pdf')
```



Precision, recall, F1score - Linear regression

[97]:
```
print(classification_report(y_test, y_pred_rf))
```

```
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        14
Iris-versicolor       1.00      0.94      0.97        17
 Iris-virginica       0.93      1.00      0.97        14

       accuracy                           0.98        45
      macro avg       0.98      0.98      0.98        45
   weighted avg       0.98      0.98      0.98        45
```

Cross validation - Random forest (10 fold)

[98]:
```
scores_rf = cross_val_score(rf, X_train, y_train, cv=10)
print("Mean:", scores_rf.mean())
scores_rf
```

```
Mean: 0.9236363636363636
```

[98]:
```
array([0.90909091, 0.90909091, 0.90909091, 0.90909091, 1.        ,
       0.9       , 0.8       , 1.        , 0.9       , 1.        ])
```

Converting Precision, recall, f1score to Data frame

[99]:
```
rf_clas = classification_report(y_test, y_pred_rf, output_dict= True)
rf_clas_df = pd.DataFrame(rf_clas).transpose()
dt_clas = classification_report(y_test, y_pred, output_dict= True)
dt_clas_df = pd.DataFrame(dt_clas).transpose()
lr_clas = classification_report(y_test, y_pred_lr, output_dict= True)
lr_clas_df = pd.DataFrame(lr_clas).transpose()
lr_clas_df
```

[99]:

	precision	recall	f1-score	support
Iris-setosa	1.0	1.0	1.0	14.0
Iris-versicolor	1.0	1.0	1.0	17.0
Iris-virginica	1.0	1.0	1.0	14.0
accuracy	1.0	1.0	1.0	1.0
macro avg	1.0	1.0	1.0	45.0
weighted avg	1.0	1.0	1.0	45.0

Final scores

[100]:
```
class_report = (rf_clas_df.iloc[4,0:3],lr_clas_df.iloc[4,0:3],dt_clas_df.
 ↪iloc[4,0:3])
class_report1= pd.DataFrame(class_report)
new_header =['Random Forest','Logistic Regression','Decsion Tree']
class_report1['Classifier'] = new_header
class_report1 = class_report1.
 ↪reindex(columns=['Classifier','precision','recall','f1-score'])
class_report1
```

[100]:

	Classifier	precision	recall	f1-score
macro avg	Random Forest	0.977778	0.980392	0.978405
macro avg	Logistic Regression	1.000000	1.000000	1.000000
macro avg	Decsion Tree	0.981481	0.976190	0.978131

all classifier scores

[101]:
```
Classifier_scores = pd.DataFrame({
    'Model': ['Decision Tree','LogisticRegression','Random Forest'],
    'Score': [dt.score(X_test,y_test),lr.score(X_test,y_test),rf.
 ↪score(X_test,y_test)]})
Classifier_scores.sort_values(by='Score', ascending=False)
```

[101]:

	Model	Score
1	LogisticRegression	1.000000
0	Decision Tree	0.977778
2	Random Forest	0.977778

Cross validation ranking

[102]:
```
Classifier_cv = pd.DataFrame({
    'Model': ['Decision Tree','LogisticRegression','Random Forest'],
```

```
    'cv_Score': [scores_rf.mean(),scores_lr.mean(),scores_dt.mean()]})
Classifier_cv.sort_values(by='cv_Score', ascending=False)
```

[102]:

	Model	cv_Score
1	LogisticRegression	0.952727
0	Decision Tree	0.923636
2	Random Forest	0.904545

By the above scores and models Logistic regression is the best classifier.