MACHINE LEARNING LAB
ASSIGNMENT 1

Name - Pritesh Kumar Sahani
Roll - 001811001005
Department - Information Technology
Year - 4th
Semester - 7th

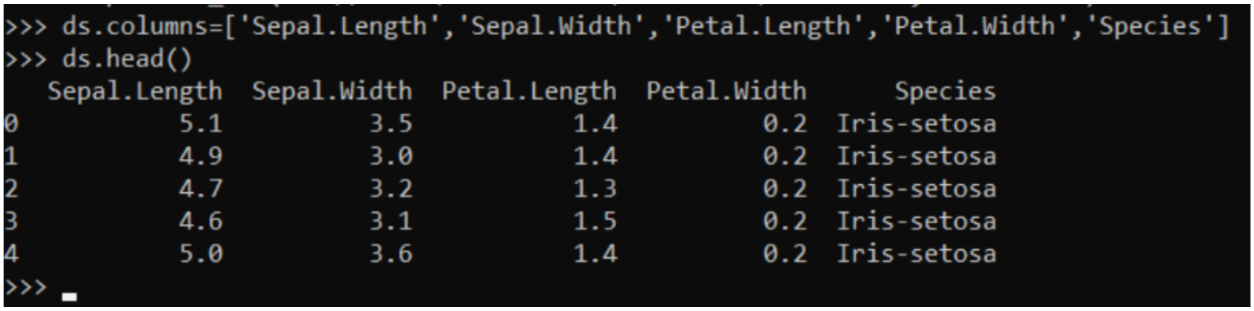
IRIS PLANT DATASET

- Decision Tree classifier

First we will import some packages like numpy,pandas and matplotlib for variety of mathematical operations.

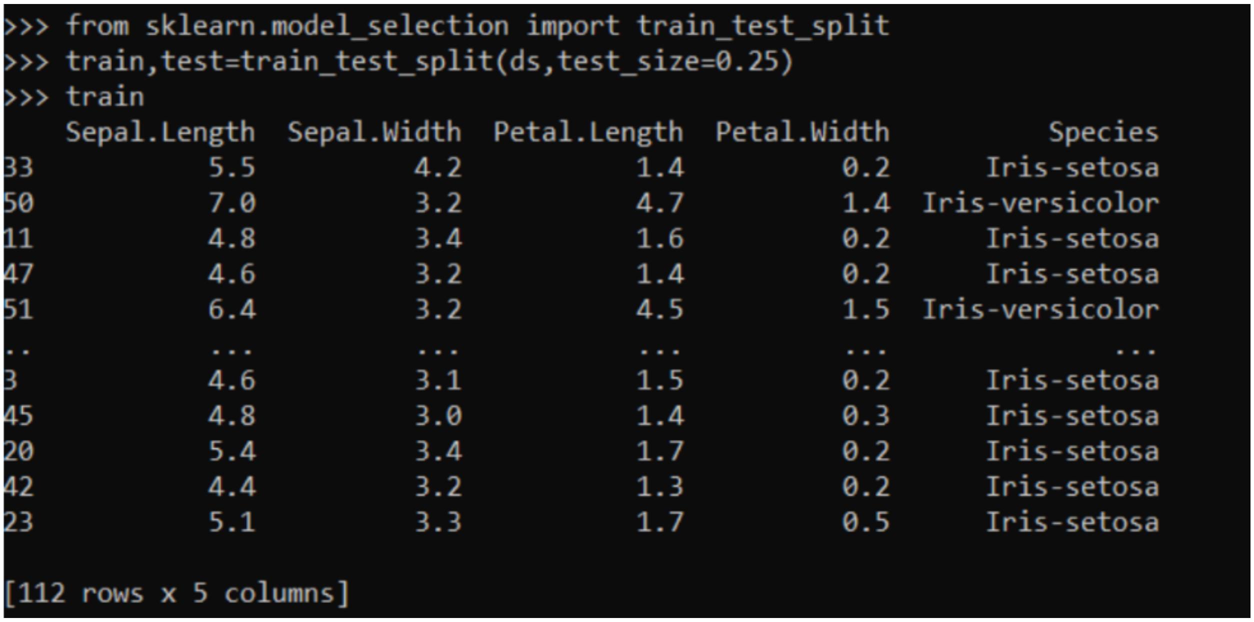
Then we will read the iris data which I have downloaded from below website
https://archive.ics.uci.edu/ml/datasets/Iris/

After that we read the iris.data without header and then we will add (using ds.columns) header for our further operation.



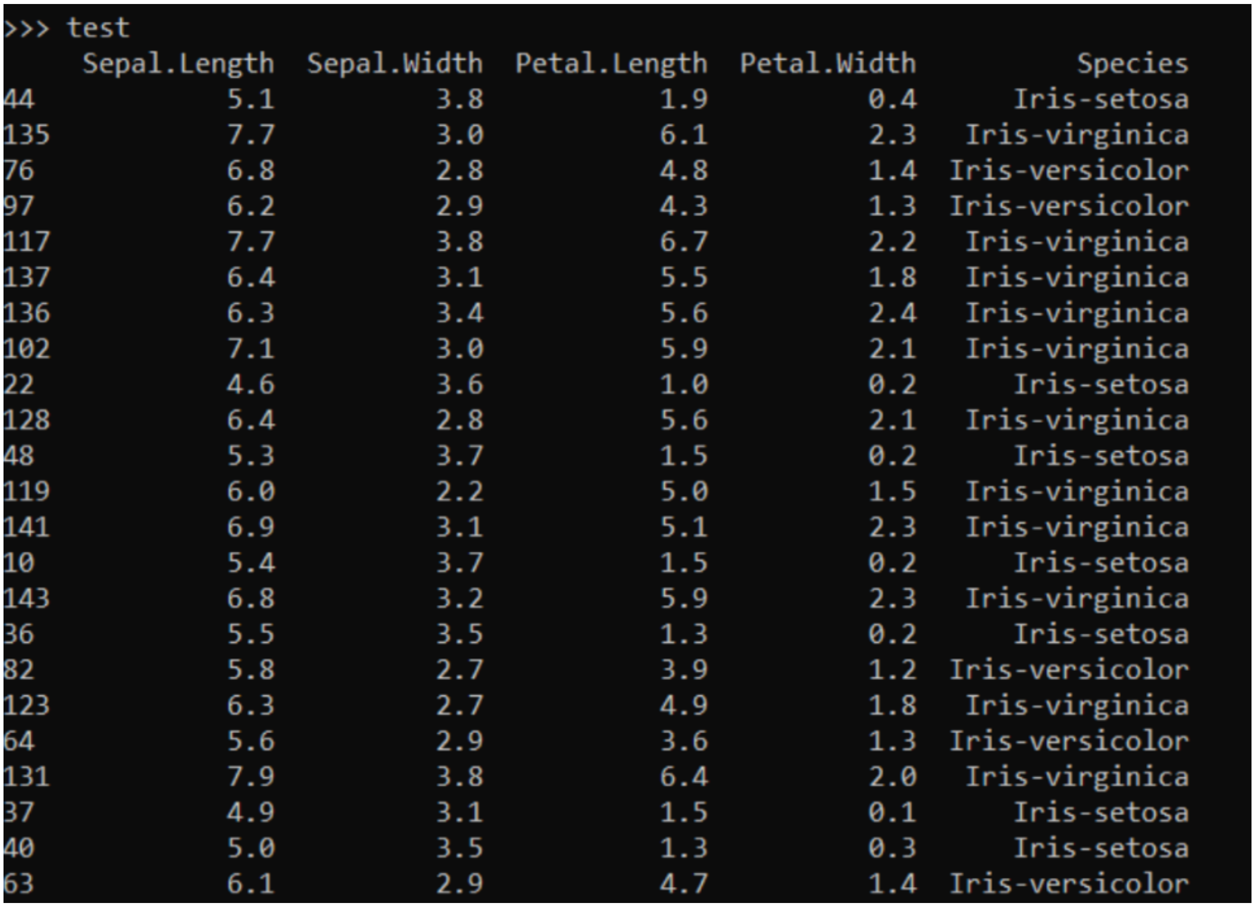
```
>>> ds.columns=['Sepal.Length','Sepal.Width','Petal.Length','Petal.Width','Species']
>>> ds.head()
   Sepal.Length  Sepal.Width  Petal.Length  Petal.Width      Species
0           5.1          3.5           1.4          0.2  Iris-setosa
1           4.9          3.0           1.4          0.2  Iris-setosa
2           4.7          3.2           1.3          0.2  Iris-setosa
3           4.6          3.1           1.5          0.2  Iris-setosa
4           5.0          3.6           1.4          0.2  Iris-setosa
>>>
```

Then we will divide the dataset as test data 25% and train data 75% by writing size=0.25



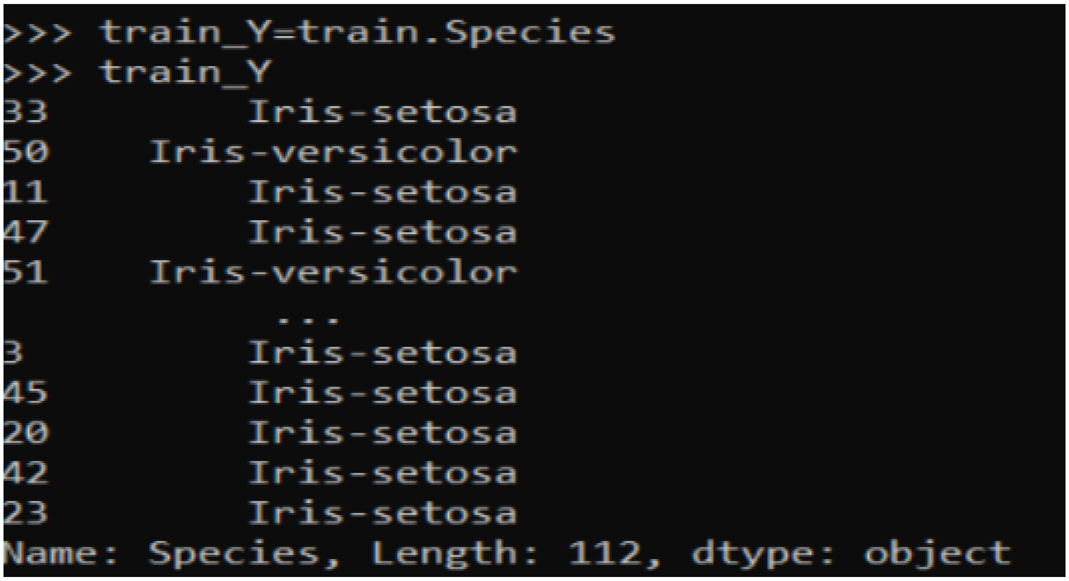
```
>>> from sklearn.model_selection import train_test_split
>>> train,test=train_test_split(ds,test_size=0.25)
>>> train
    Sepal.Length  Sepal.Width  Petal.Length  Petal.Width          Species
33           5.5          4.2           1.4          0.2      Iris-setosa
50           7.0          3.2           4.7          1.4  Iris-versicolor
11           4.8          3.4           1.6          0.2      Iris-setosa
47           4.6          3.2           1.4          0.2      Iris-setosa
51           6.4          3.2           4.5          1.5  Iris-versicolor
..           ...          ...           ...          ...              ...
3            4.6          3.1           1.5          0.2      Iris-setosa
45           4.8          3.0           1.4          0.3      Iris-setosa
20           5.4          3.4           1.7          0.2      Iris-setosa
42           4.4          3.2           1.3          0.2      Iris-setosa
23           5.1          3.3           1.7          0.5      Iris-setosa

[112 rows x 5 columns]
```

Above picture data is train data and below picture data is test data

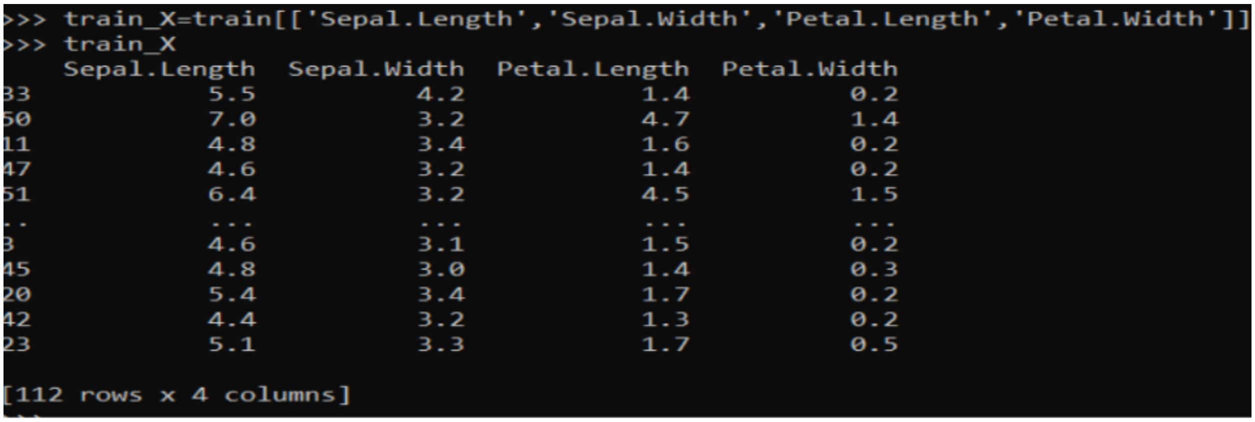


```
>>> test
     Sepal.Length  Sepal.Width  Petal.Length  Petal.Width          Species
44            5.1          3.8           1.9          0.4      Iris-setosa
135           7.7          3.0           6.1          2.3   Iris-virginica
76            6.8          2.8           4.8          1.4  Iris-versicolor
97            6.2          2.9           4.3          1.3  Iris-versicolor
117           7.7          3.8           6.7          2.2   Iris-virginica
137           6.4          3.1           5.5          1.8   Iris-virginica
136           6.3          3.4           5.6          2.4   Iris-virginica
102           7.1          3.0           5.9          2.1   Iris-virginica
22            4.6          3.6           1.0          0.2      Iris-setosa
128           6.4          2.8           5.6          2.1   Iris-virginica
48            5.3          3.7           1.5          0.2      Iris-setosa
119           6.0          2.2           5.0          1.5   Iris-virginica
141           6.9          3.1           5.1          2.3   Iris-virginica
10            5.4          3.7           1.5          0.2      Iris-setosa
143           6.8          3.2           5.9          2.3   Iris-virginica
36            5.5          3.5           1.3          0.2      Iris-setosa
82            5.8          2.7           3.9          1.2  Iris-versicolor
123           6.3          2.7           4.9          1.8   Iris-virginica
64            5.6          2.9           3.6          1.3  Iris-versicolor
131           7.9          3.8           6.4          2.0   Iris-virginica
37            4.9          3.1           1.5          0.1      Iris-setosa
40            5.0          3.5           1.3          0.3      Iris-setosa
63            6.1          2.9           4.7          1.4  Iris-versicolor
```

After that We will divide some column as test_X and one column as test_Y for effective mapping.

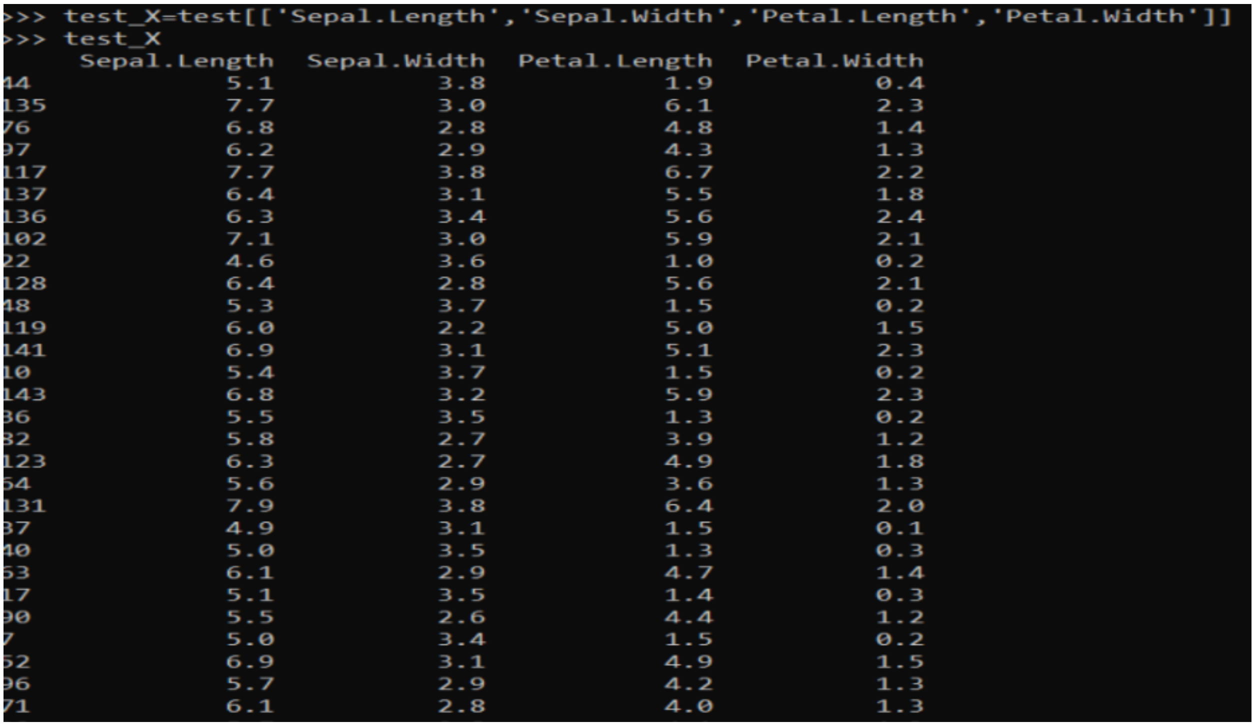


```
>>> train_Y=train.Species
>>> train_Y
33        Iris-setosa
50    Iris-versicolor
11        Iris-setosa
47        Iris-setosa
51    Iris-versicolor
           ...
3         Iris-setosa
45        Iris-setosa
20        Iris-setosa
42        Iris-setosa
23        Iris-setosa
Name: Species, Length: 112, dtype: object
```

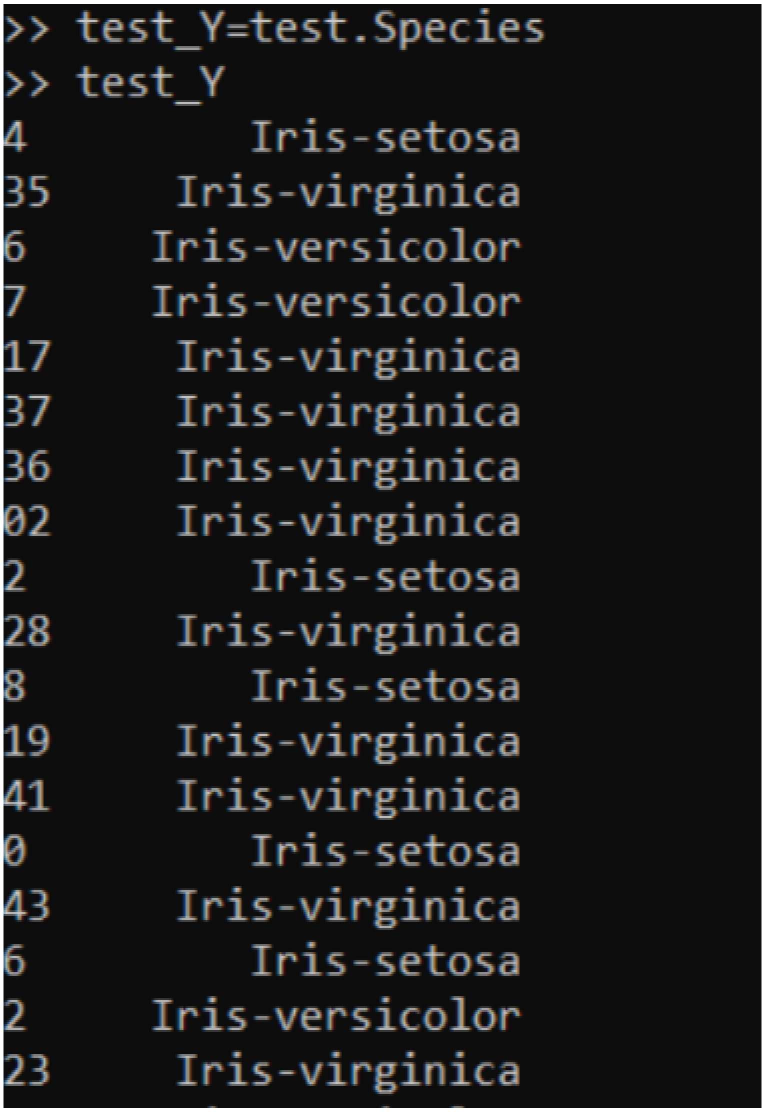


```
>>> train_X=train[['Sepal.Length','Sepal.Width','Petal.Length','Petal.Width']]
>>> train_X
    Sepal.Length  Sepal.Width  Petal.Length  Petal.Width
33           5.5          4.2           1.4          0.2
50           7.0          3.2           4.7          1.4
11           4.8          3.4           1.6          0.2
47           4.6          3.2           1.4          0.2
51           6.4          3.2           4.5          1.5
..           ...          ...           ...          ...
3            4.6          3.1           1.5          0.2
45           4.8          3.0           1.4          0.3
20           5.4          3.4           1.7          0.2
42           4.4          3.2           1.3          0.2
23           5.1          3.3           1.7          0.5

[112 rows x 4 columns]
```

Similarly we will divide test data as test_X and test_Y .We will give test data to the train model and match it with test_Y data .So that we can analyze the output.

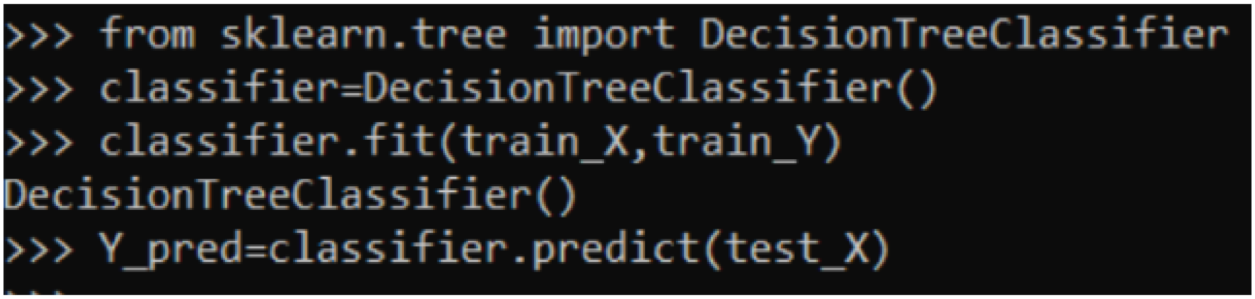


```
>>> test_X=test[['Sepal.Length','Sepal.Width','Petal.Length','Petal.Width']]
>>> test_X
     Sepal.Length  Sepal.Width  Petal.Length  Petal.Width
44            5.1          3.8           1.9          0.4
135           7.7          3.0           6.1          2.3
76            6.8          2.8           4.8          1.4
97            6.2          2.9           4.3          1.3
117           7.7          3.8           6.7          2.2
137           6.4          3.1           5.5          1.8
136           6.3          3.4           5.6          2.4
102           7.1          3.0           5.9          2.1
22            4.6          3.6           1.0          0.2
128           6.4          2.8           5.6          2.1
48            5.3          3.7           1.5          0.2
119           6.0          2.2           5.0          1.5
141           6.9          3.1           5.1          2.3
10            5.4          3.7           1.5          0.2
143           6.8          3.2           5.9          2.3
36            5.5          3.5           1.3          0.2
82            5.8          2.7           3.9          1.2
123           6.3          2.7           4.9          1.8
64            5.6          2.9           3.6          1.3
131           7.9          3.8           6.4          2.0
37            4.9          3.1           1.5          0.1
40            5.0          3.5           1.3          0.3
63            6.1          2.9           4.7          1.4
17            5.1          3.5           1.4          0.3
90            5.5          2.6           4.4          1.2
7             5.0          3.4           1.5          0.2
52            6.9          3.1           4.9          1.5
96            5.7          2.9           4.2          1.3
71            6.1          2.8           4.0          1.3
```



```
>> test_Y=test.Species
>> test_Y
4        Iris-setosa
35    Iris-virginica
6    Iris-versicolor
7    Iris-versicolor
17    Iris-virginica
37    Iris-virginica
36    Iris-virginica
02    Iris-virginica
2        Iris-setosa
28    Iris-virginica
8        Iris-setosa
19    Iris-virginica
41    Iris-virginica
0        Iris-setosa
43    Iris-virginica
6        Iris-setosa
2    Iris-versicolor
23    Iris-virginica
```

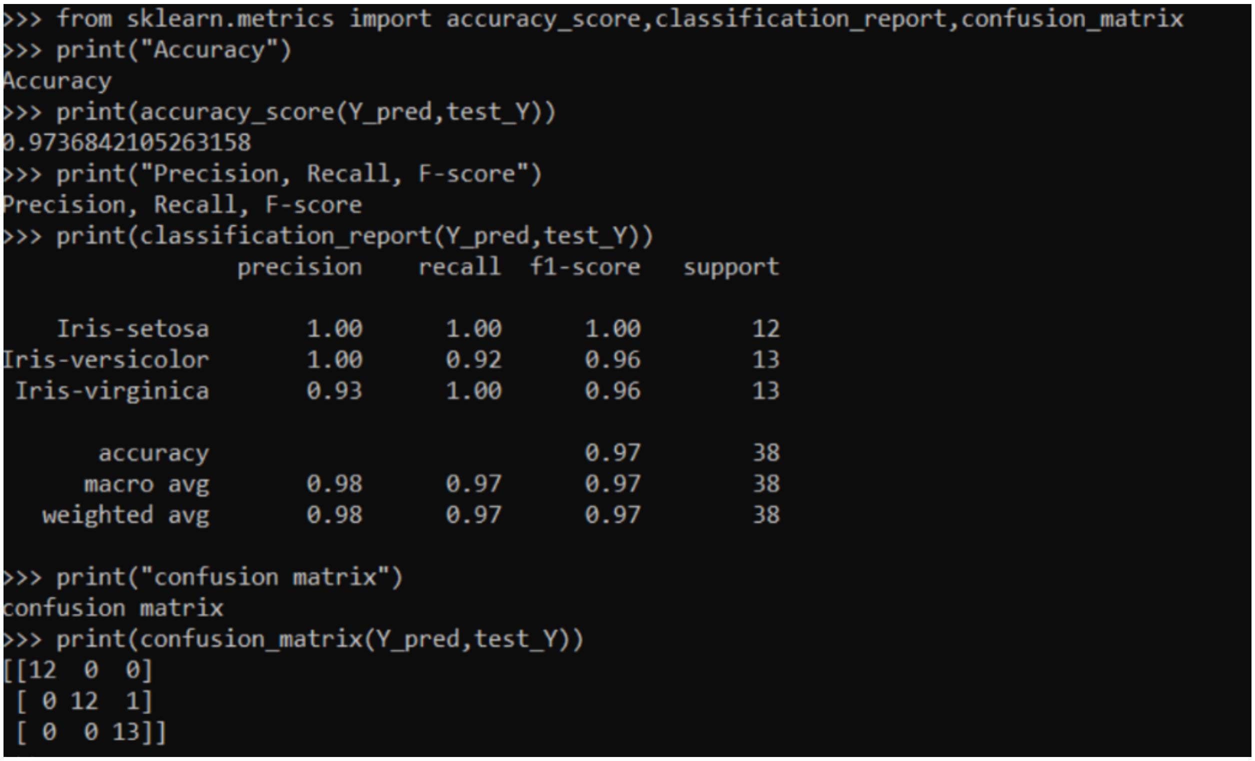
In this example we use DecisionTreeClassifier without parameter tuning and use train_ X data and train_Y data to train the model. After that we will get the corresponding output by giving test_X date and that will store in Y_pred.



```
>>> from sklearn.tree import DecisionTreeClassifier
>>> classifier=DecisionTreeClassifier()
>>> classifier.fit(train_X,train_Y)
DecisionTreeClassifier()
>>> Y_pred=classifier.predict(test_X)
```

OUTPUT WITHOUT PARAMETER TUNING:

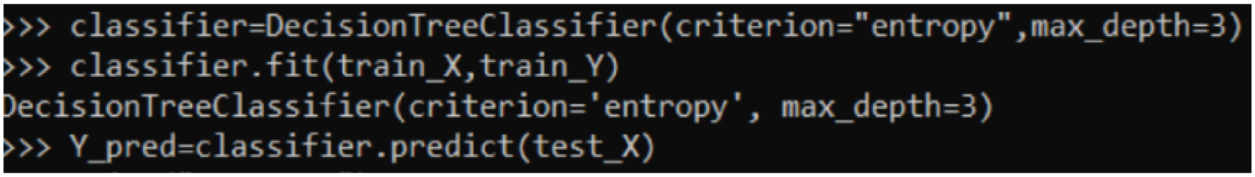
Then we will check the performance of the model by analysis the Accuracy, Precision, Recall, F-score, confusion matrix output.



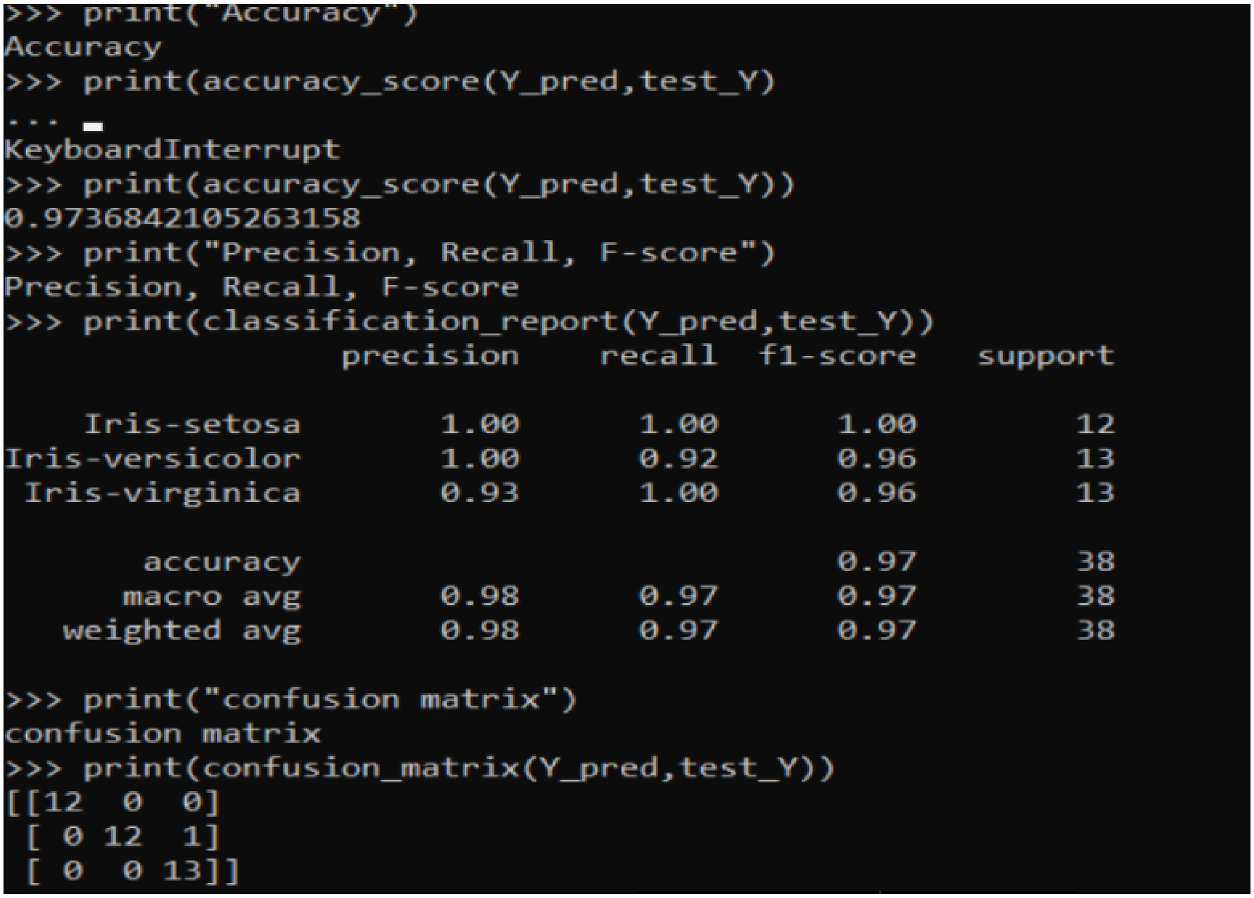
```
>>> from sklearn.metrics import accuracy_score,classification_report,confusion_matrix
>>> print("Accuracy")
Accuracy
>>> print(accuracy_score(Y_pred,test_Y))
0.9736842105263158
>>> print("Precision, Recall, F-score")
Precision, Recall, F-score
>>> print(classification_report(Y_pred,test_Y))
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        12
Iris-versicolor       1.00      0.92      0.96        13
 Iris-virginica       0.93      1.00      0.96        13

       accuracy                           0.97        38
      macro avg       0.98      0.97      0.97        38
   weighted avg       0.98      0.97      0.97        38

>>> print("confusion matrix")
confusion matrix
>>> print(confusion_matrix(Y_pred,test_Y))
[[12  0  0]
 [ 0 12  1]
 [ 0  0 13]]
```

OUTPUT WITH PARAMETER TUNING:

Here we will pass the parameter criterion =”entropy”(default “gini”) Max_depth=3

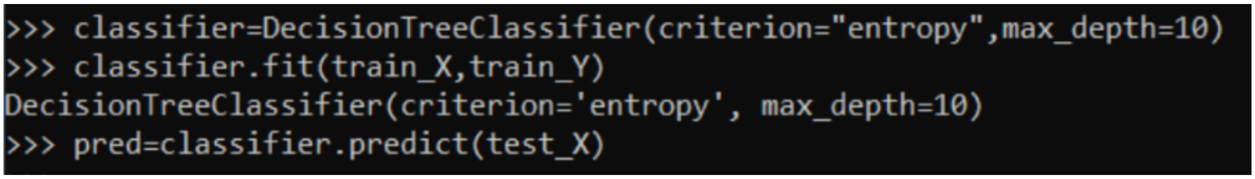


```
>>> classifier=DecisionTreeClassifier(criterion="entropy",max_depth=3)
>>> classifier.fit(train_X,train_Y)
DecisionTreeClassifier(criterion='entropy', max_depth=3)
>>> Y_pred=classifier.predict(test_X)
```

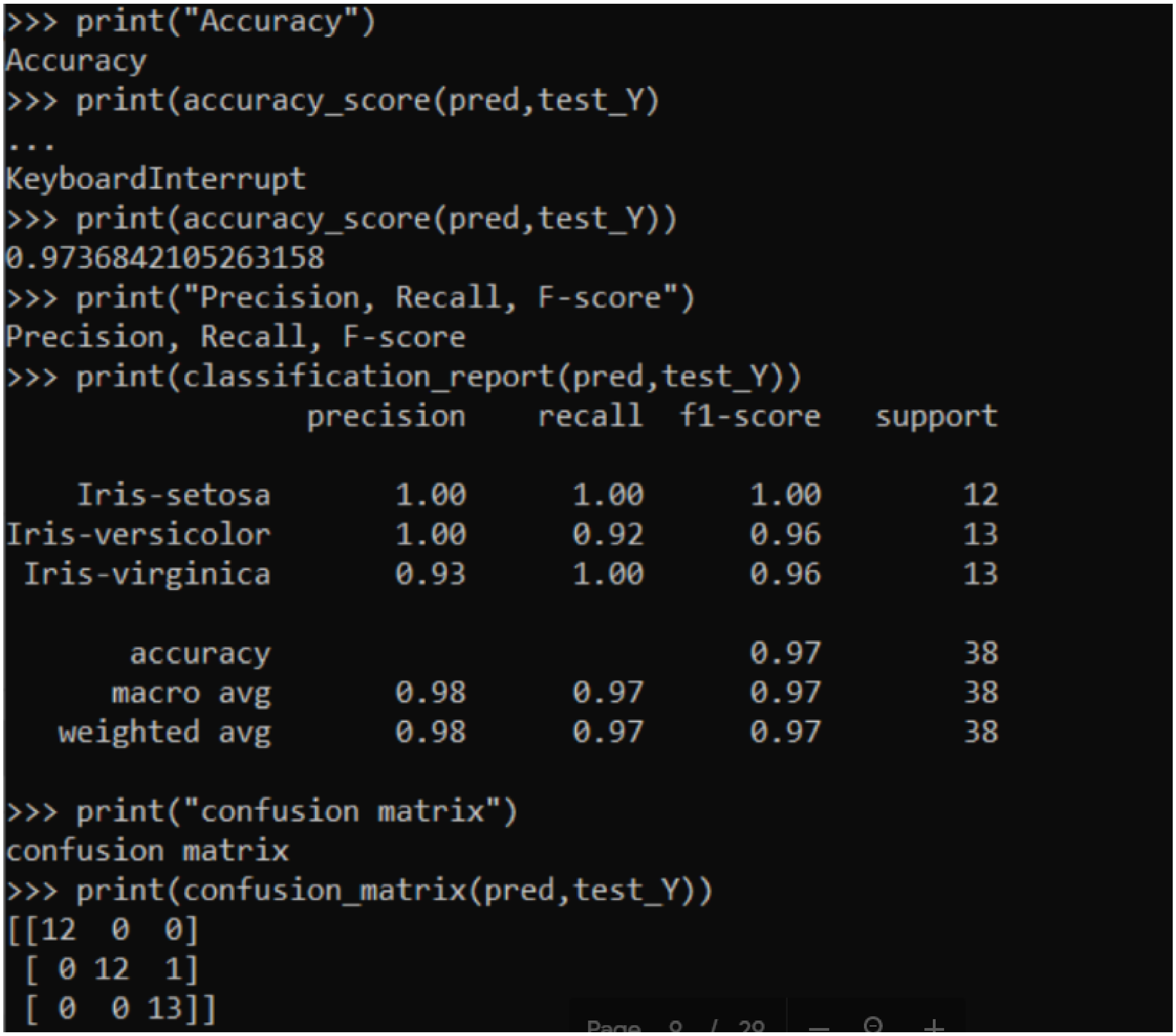


```
>>> print("Accuracy")
Accuracy
>>> print(accuracy_score(Y_pred,test_Y)
... 
KeyboardInterrupt
>>> print(accuracy_score(Y_pred,test_Y))
0.9736842105263158
>>> print("Precision, Recall, F-score")
Precision, Recall, F-score
>>> print(classification_report(Y_pred,test_Y))
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        12
Iris-versicolor       1.00      0.92      0.96        13
 Iris-virginica       0.93      1.00      0.96        13

       accuracy                           0.97        38
      macro avg       0.98      0.97      0.97        38
   weighted avg       0.98      0.97      0.97        38

>>> print("confusion matrix")
confusion matrix
>>> print(confusion_matrix(Y_pred,test_Y))
[[12  0  0]
 [ 0 12  1]
 [ 0  0 13]]
```

Here we will pass the parameter criterion =”entropy”(default “gini”)
Max_depth=10

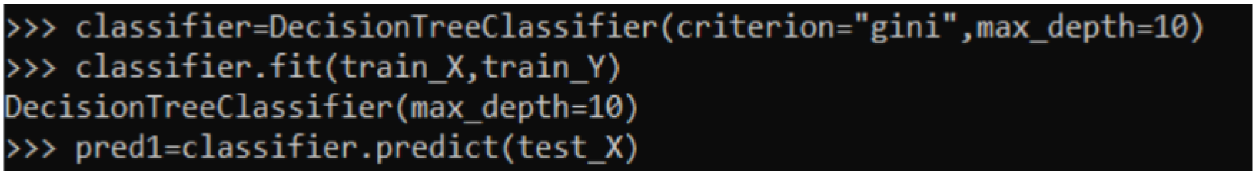


```
>>> classifier=DecisionTreeClassifier(criterion="entropy",max_depth=10)
>>> classifier.fit(train_X,train_Y)
DecisionTreeClassifier(criterion='entropy', max_depth=10)
>>> pred=classifier.predict(test_X)
```

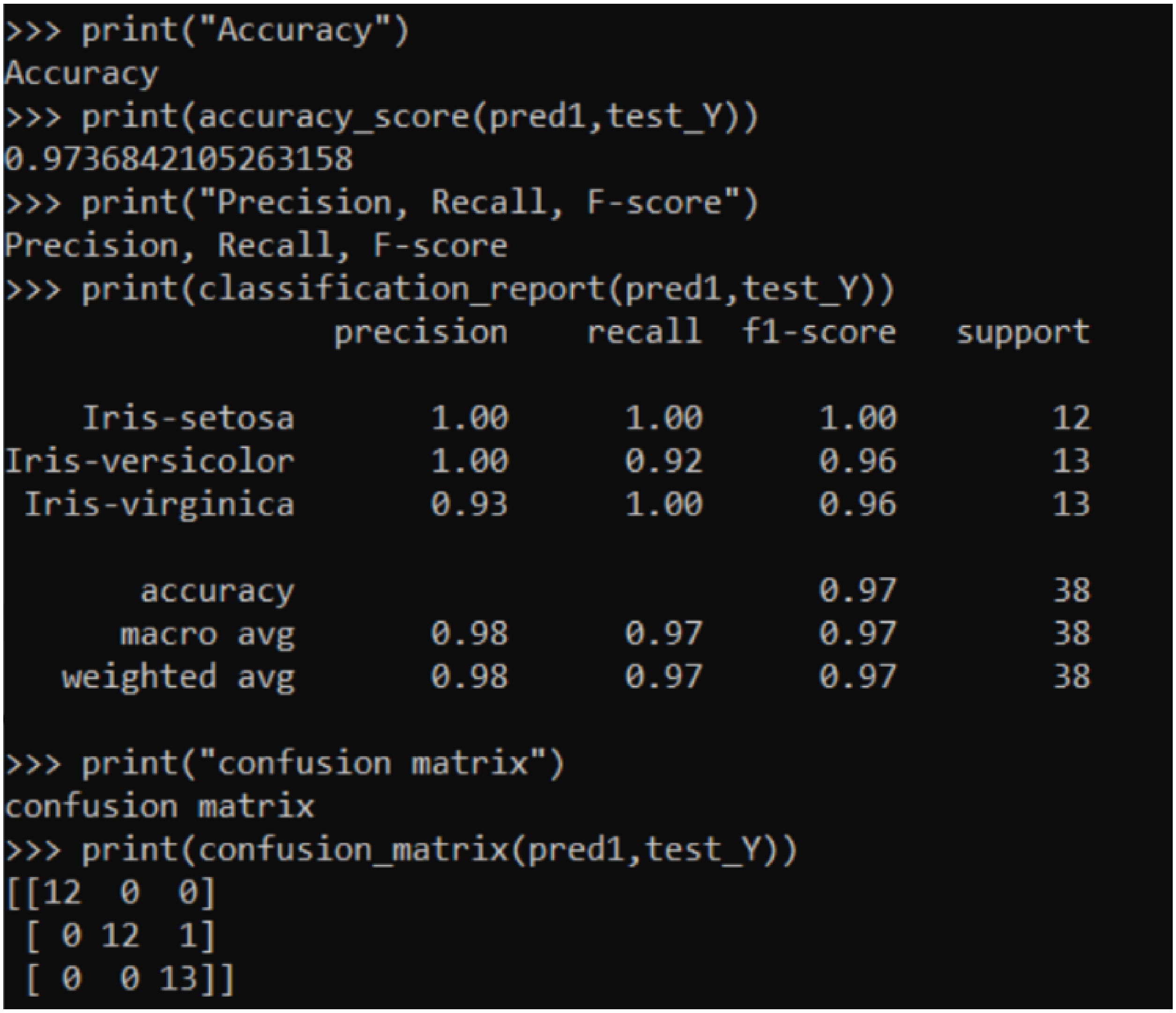


```
>>> print("Accuracy")
Accuracy
>>> print(accuracy_score(pred,test_Y)
...
KeyboardInterrupt
>>> print(accuracy_score(pred,test_Y))
0.9736842105263158
>>> print("Precision, Recall, F-score")
Precision, Recall, F-score
>>> print(classification_report(pred,test_Y))
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        12
Iris-versicolor       1.00      0.92      0.96        13
 Iris-virginica       0.93      1.00      0.96        13

       accuracy                           0.97        38
      macro avg       0.98      0.97      0.97        38
   weighted avg       0.98      0.97      0.97        38

>>> print("confusion matrix")
confusion matrix
>>> print(confusion_matrix(pred,test_Y))
[[12  0  0]
 [ 0 12  1]
 [ 0  0 13]]
```

Here we will pass the parameter criterion =“gini” Max_depth=10.

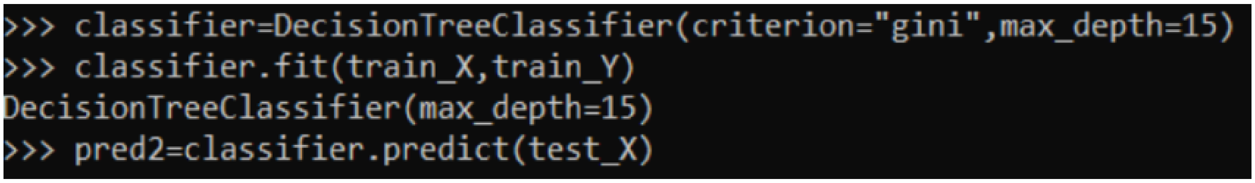


```
>>> classifier=DecisionTreeClassifier(criterion="gini",max_depth=10)
>>> classifier.fit(train_X,train_Y)
DecisionTreeClassifier(max_depth=10)
>>> pred1=classifier.predict(test_X)
```

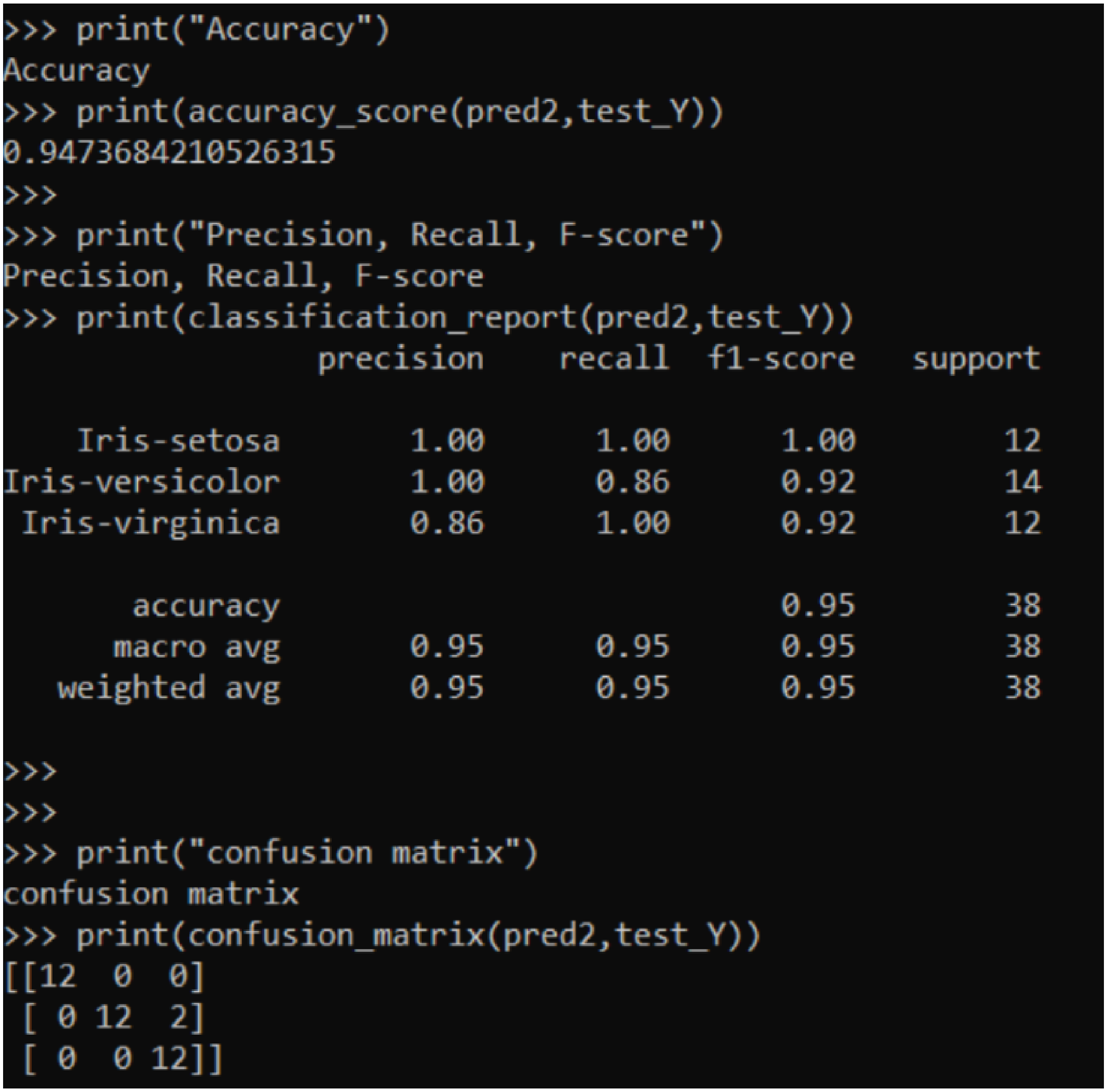


```
>>> print("Accuracy")
Accuracy
>>> print(accuracy_score(pred1,test_Y))
0.9736842105263158
>>> print("Precision, Recall, F-score")
Precision, Recall, F-score
>>> print(classification_report(pred1,test_Y))
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        12
Iris-versicolor       1.00      0.92      0.96        13
 Iris-virginica       0.93      1.00      0.96        13

       accuracy                           0.97        38
      macro avg       0.98      0.97      0.97        38
   weighted avg       0.98      0.97      0.97        38

>>> print("confusion matrix")
confusion matrix
>>> print(confusion_matrix(pred1,test_Y))
[[12  0  0]
 [ 0 12  1]
 [ 0  0 13]]
```

Here we will pass the parameter criterion = “gini” Max_depth=15



```
>>> classifier=DecisionTreeClassifier(criterion="gini",max_depth=15)
>>> classifier.fit(train_X,train_Y)
DecisionTreeClassifier(max_depth=15)
>>> pred2=classifier.predict(test_X)
```

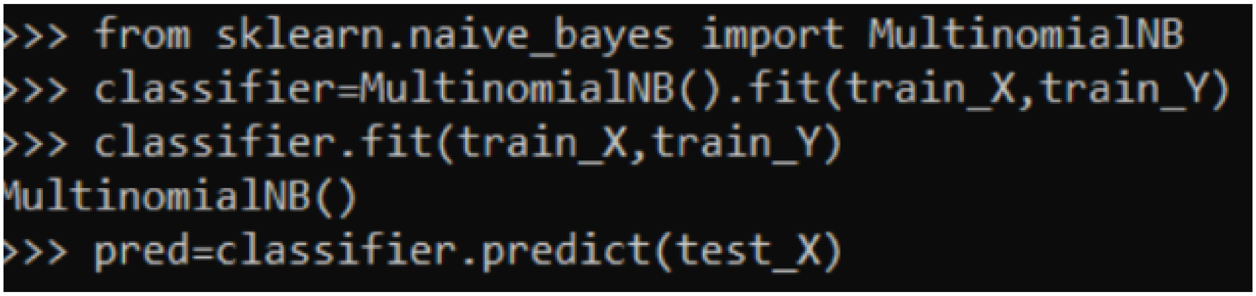


```
>>> print("Accuracy")
Accuracy
>>> print(accuracy_score(pred2,test_Y))
0.9473684210526315
>>>
>>> print("Precision, Recall, F-score")
Precision, Recall, F-score
>>> print(classification_report(pred2,test_Y))
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        12
Iris-versicolor       1.00      0.86      0.92        14
 Iris-virginica       0.86      1.00      0.92        12

       accuracy                           0.95        38
      macro avg       0.95      0.95      0.95        38
   weighted avg       0.95      0.95      0.95        38

>>>
>>>
>>> print("confusion matrix")
confusion matrix
>>> print(confusion_matrix(pred2,test_Y))
[[12  0  0]
 [ 0 12  2]
 [ 0  0 12]]
```

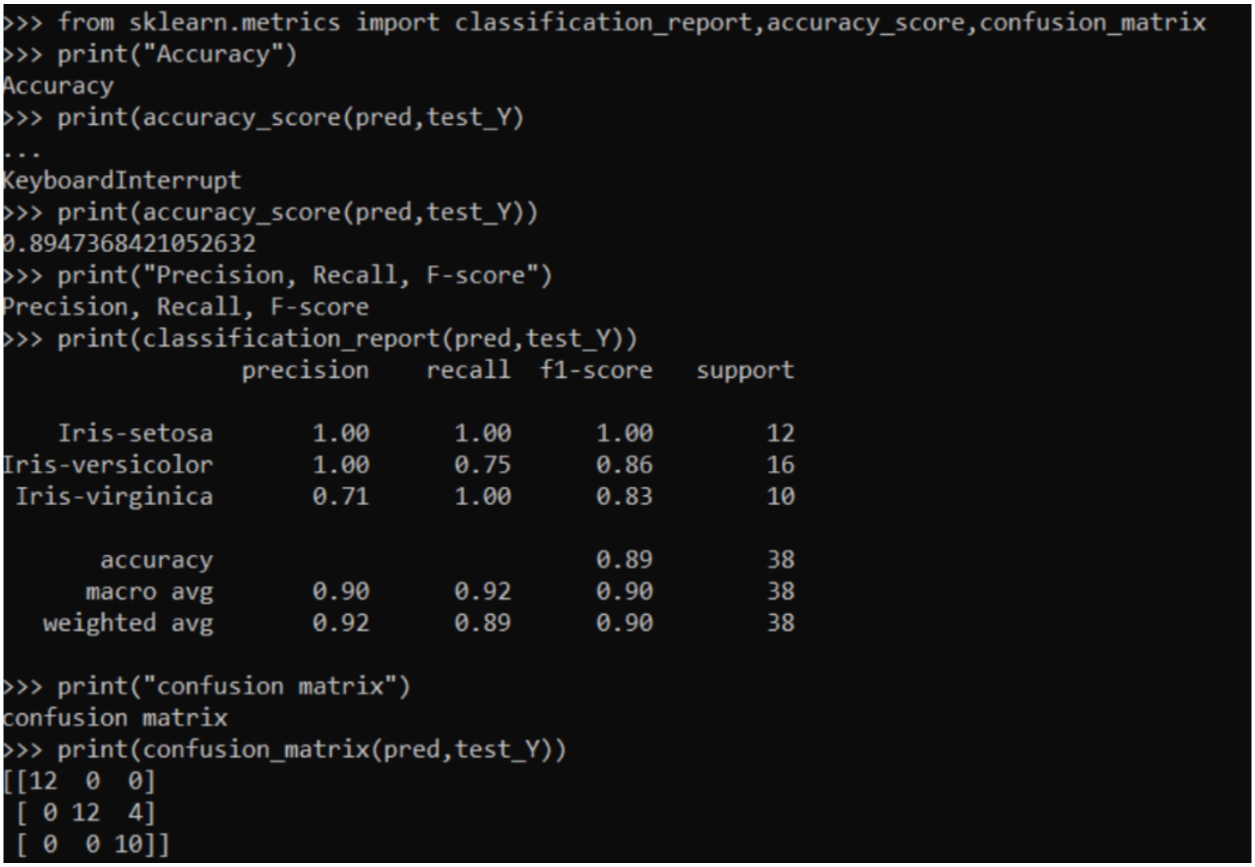
1.Naive Bayes:

There are three types of Naïve Bayes model under the scikit-learn Library.

1. Here first we will use the MultinomialNB classifier and calculate Accuracy, Precision, Recall, F-score, confusion matrix without parameter tuning.

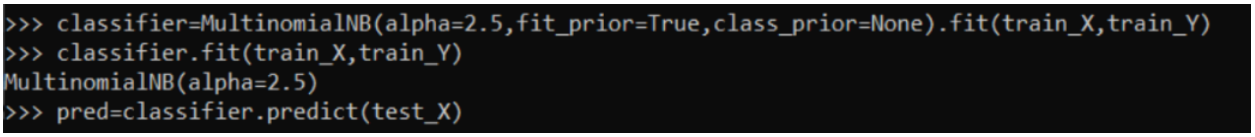


```
>>> from sklearn.naive_bayes import MultinomialNB
>>> classifier=MultinomialNB().fit(train_X,train_Y)
>>> classifier.fit(train_X,train_Y)
MultinomialNB()
>>> pred=classifier.predict(test_X)
```

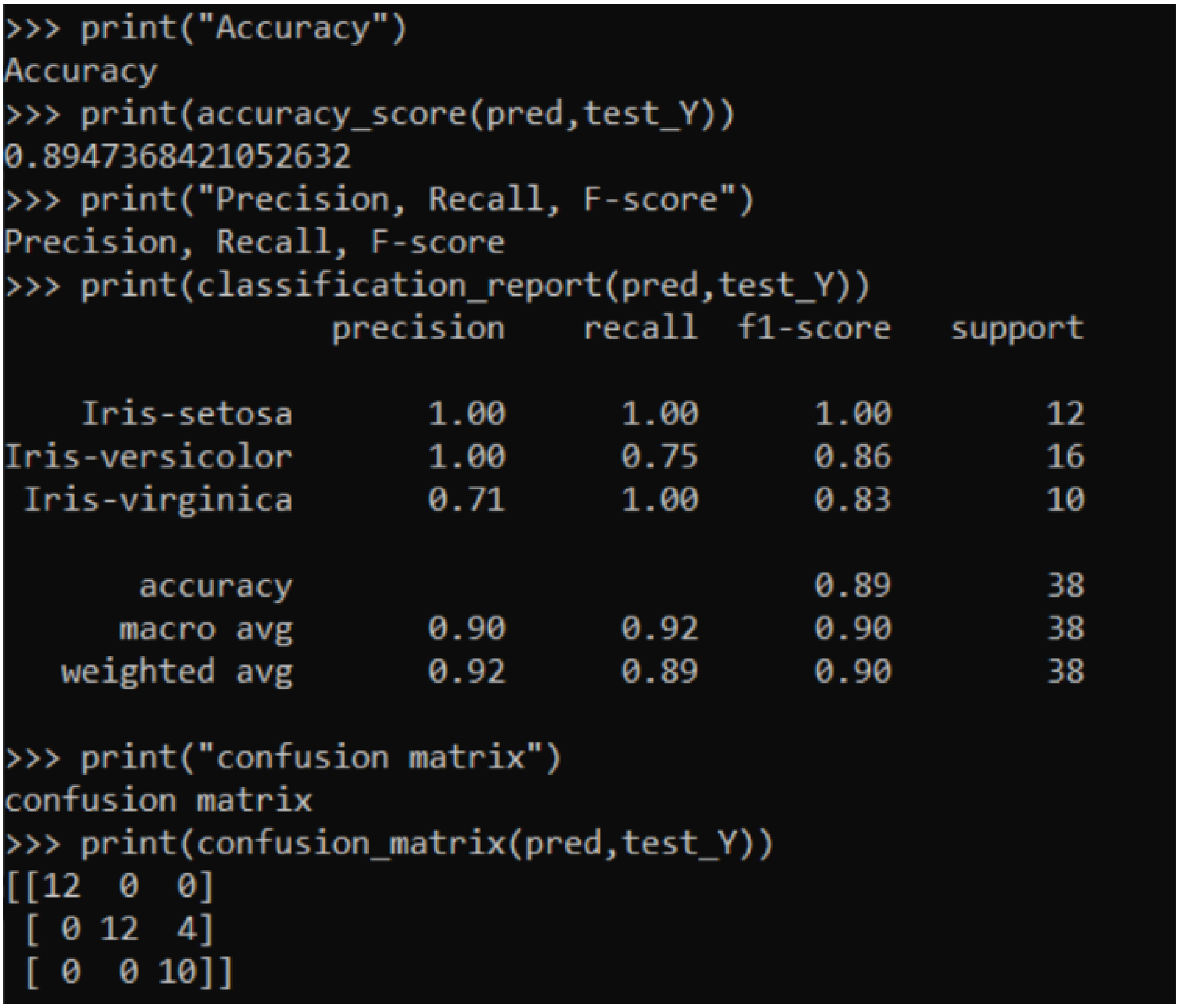


```
>>> from sklearn.metrics import classification_report,accuracy_score,confusion_matrix
>>> print("Accuracy")
Accuracy
>>> print(accuracy_score(pred,test_Y)
...
KeyboardInterrupt
>>> print(accuracy_score(pred,test_Y))
0.8947368421052632
>>> print("Precision, Recall, F-score")
Precision, Recall, F-score
>>> print(classification_report(pred,test_Y))
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        12
Iris-versicolor       1.00      0.75      0.86        16
 Iris-virginica       0.71      1.00      0.83        10

       accuracy                           0.89        38
      macro avg       0.90      0.92      0.90        38
   weighted avg       0.92      0.89      0.90        38

>>> print("confusion matrix")
confusion matrix
>>> print(confusion_matrix(pred,test_Y))
[[12  0  0]
 [ 0 12  4]
 [ 0  0 10]]
```

Output of MultinomialNB classifier with parameter tuning.

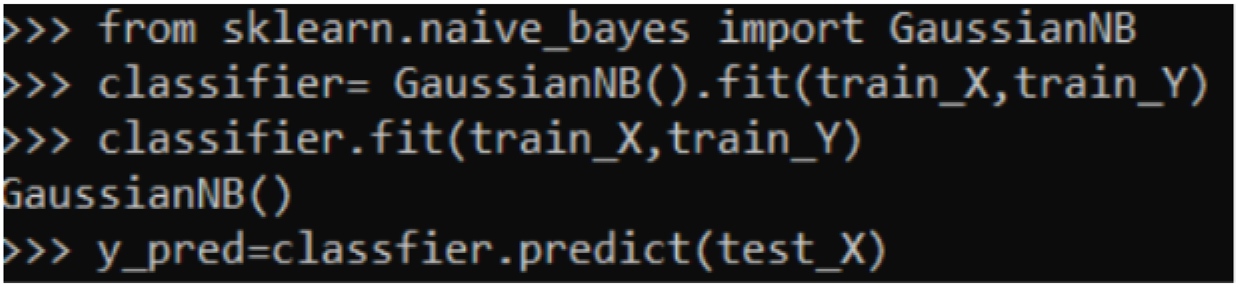


```
>>> classifier=MultinomialNB(alpha=2.5,fit_prior=True,class_prior=None).fit(train_X,train_Y)
>>> classifier.fit(train_X,train_Y)
MultinomialNB(alpha=2.5)
>>> pred=classifier.predict(test_X)
```



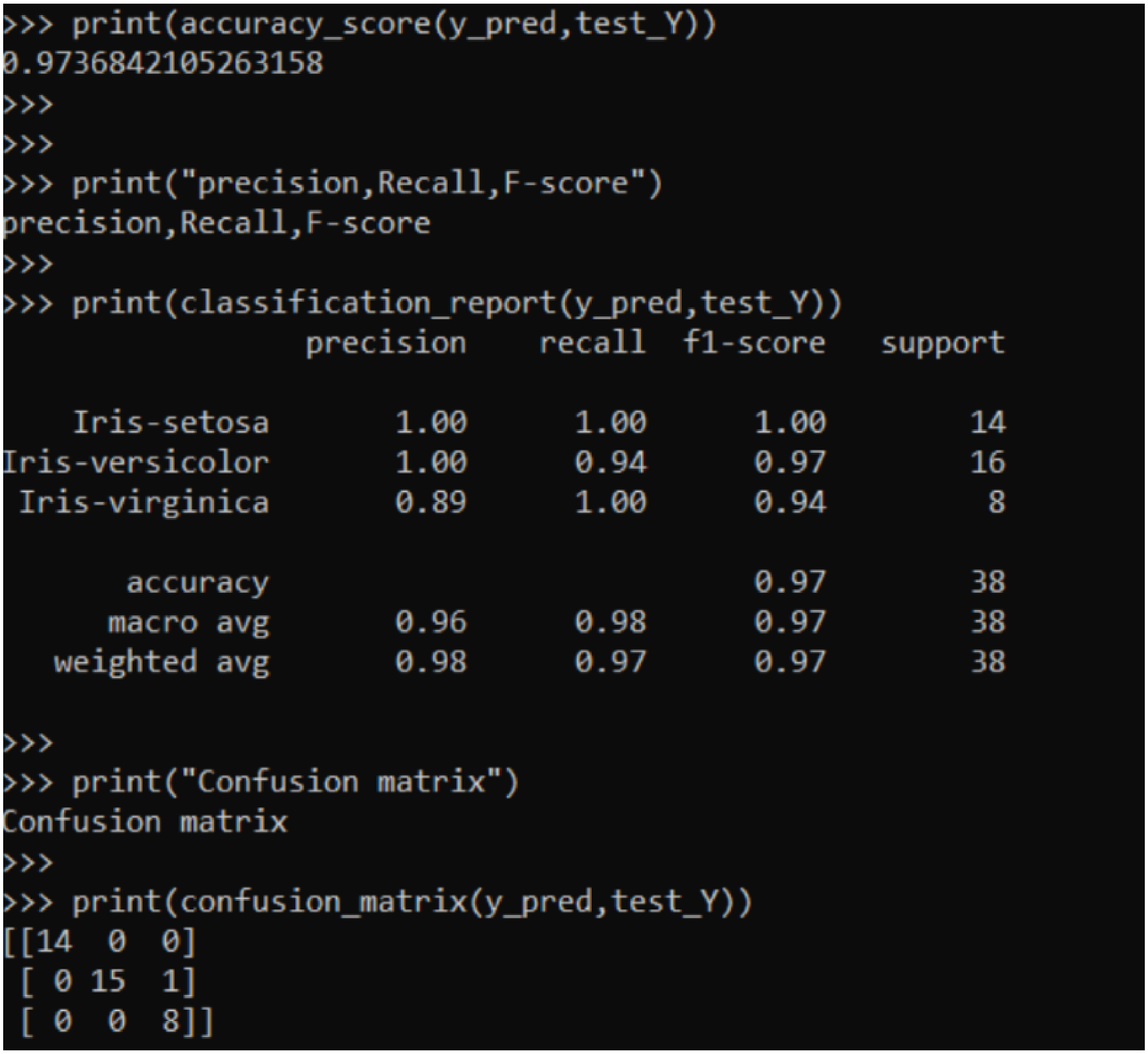
```
>>> print("Accuracy")
Accuracy
>>> print(accuracy_score(pred,test_Y))
0.8947368421052632
>>> print("Precision, Recall, F-score")
Precision, Recall, F-score
>>> print(classification_report(pred,test_Y))
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        12
Iris-versicolor       1.00      0.75      0.86        16
 Iris-virginica       0.71      1.00      0.83        10

       accuracy                           0.89        38
      macro avg       0.90      0.92      0.90        38
   weighted avg       0.92      0.89      0.90        38

>>> print("confusion matrix")
confusion matrix
>>> print(confusion_matrix(pred,test_Y))
[[12  0  0]
 [ 0 12  4]
 [ 0  0 10]]
```

2. Now second type of classifier that we will use GaussianNB classifier and calculate Accuracy, Precision, Recall, F-score, confusion matrix without parameter tuning.



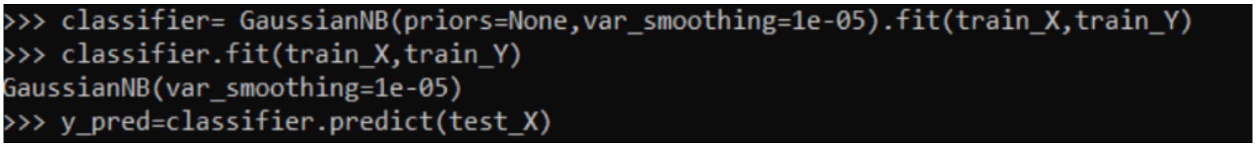
```
>>> from sklearn.naive_bayes import GaussianNB
>>> classifier= GaussianNB().fit(train_X,train_Y)
>>> classifier.fit(train_X,train_Y)
GaussianNB()
>>> y_pred=classfier.predict(test_X)
```

Output of GaussianNB classifier without parameter tuning

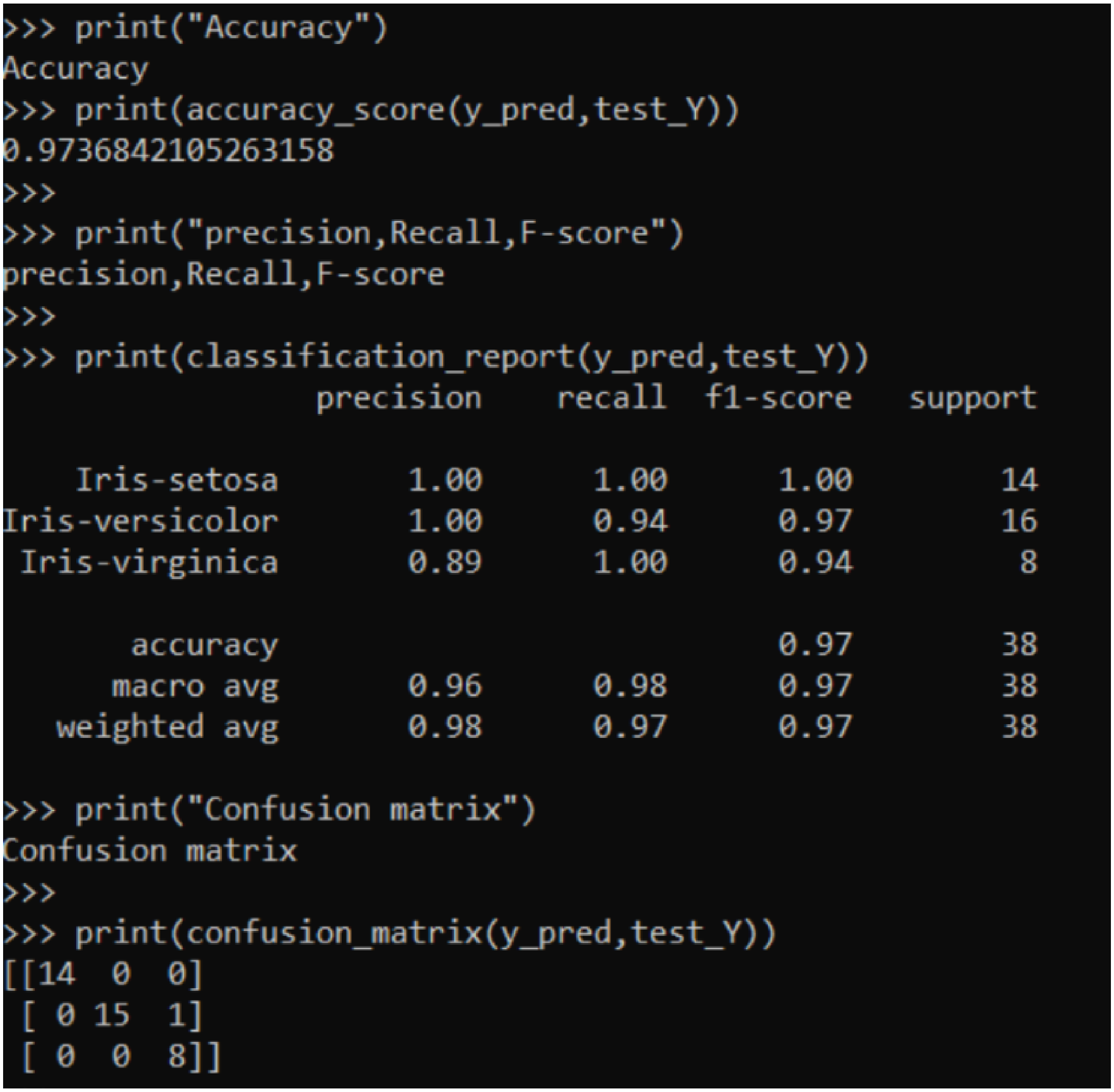


```
>>> print(accuracy_score(y_pred,test_Y))
0.9736842105263158
>>>
>>>
>>> print("precision,Recall,F-score")
precision,Recall,F-score
>>>
>>> print(classification_report(y_pred,test_Y))
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        14
Iris-versicolor       1.00      0.94      0.97        16
 Iris-virginica       0.89      1.00      0.94         8

       accuracy                           0.97        38
      macro avg       0.96      0.98      0.97        38
   weighted avg       0.98      0.97      0.97        38

>>>
>>> print("Confusion matrix")
Confusion matrix
>>>
>>> print(confusion_matrix(y_pred,test_Y))
[[14  0  0]
 [ 0 15  1]
 [ 0  0  8]]
```

Output of GaussianNB classifier with parameter tuning.

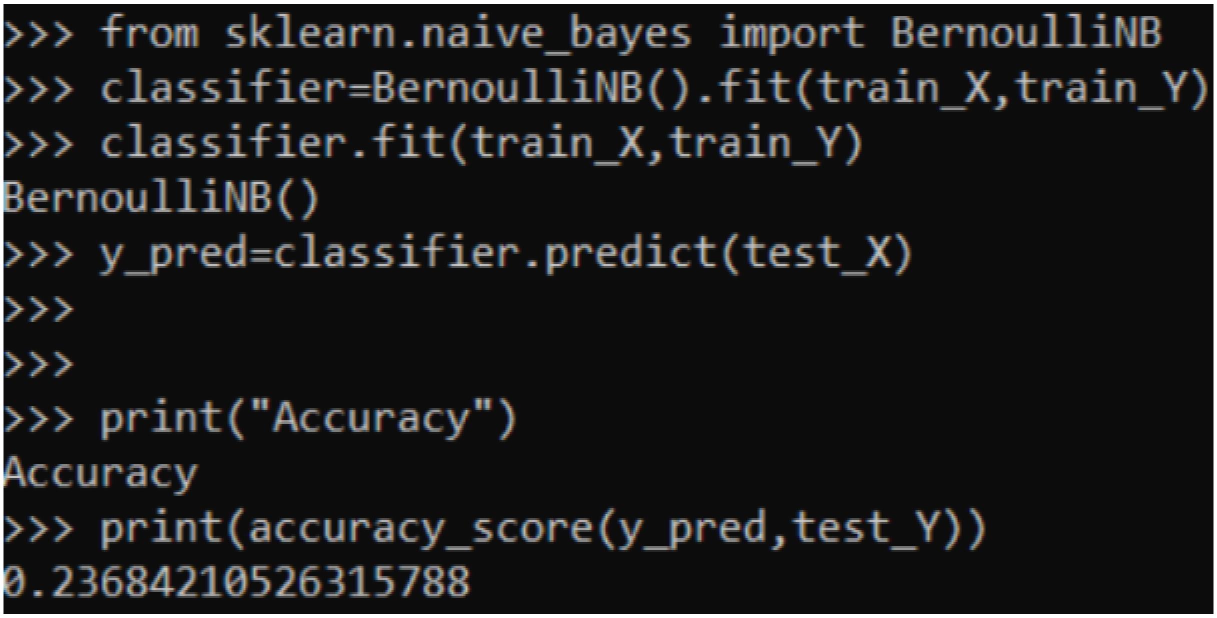


```
>>> classifier= GaussianNB(priors=None,var_smoothing=1e-05).fit(train_X,train_Y)
>>> classifier.fit(train_X,train_Y)
GaussianNB(var_smoothing=1e-05)
>>> y_pred=classifier.predict(test_X)
```



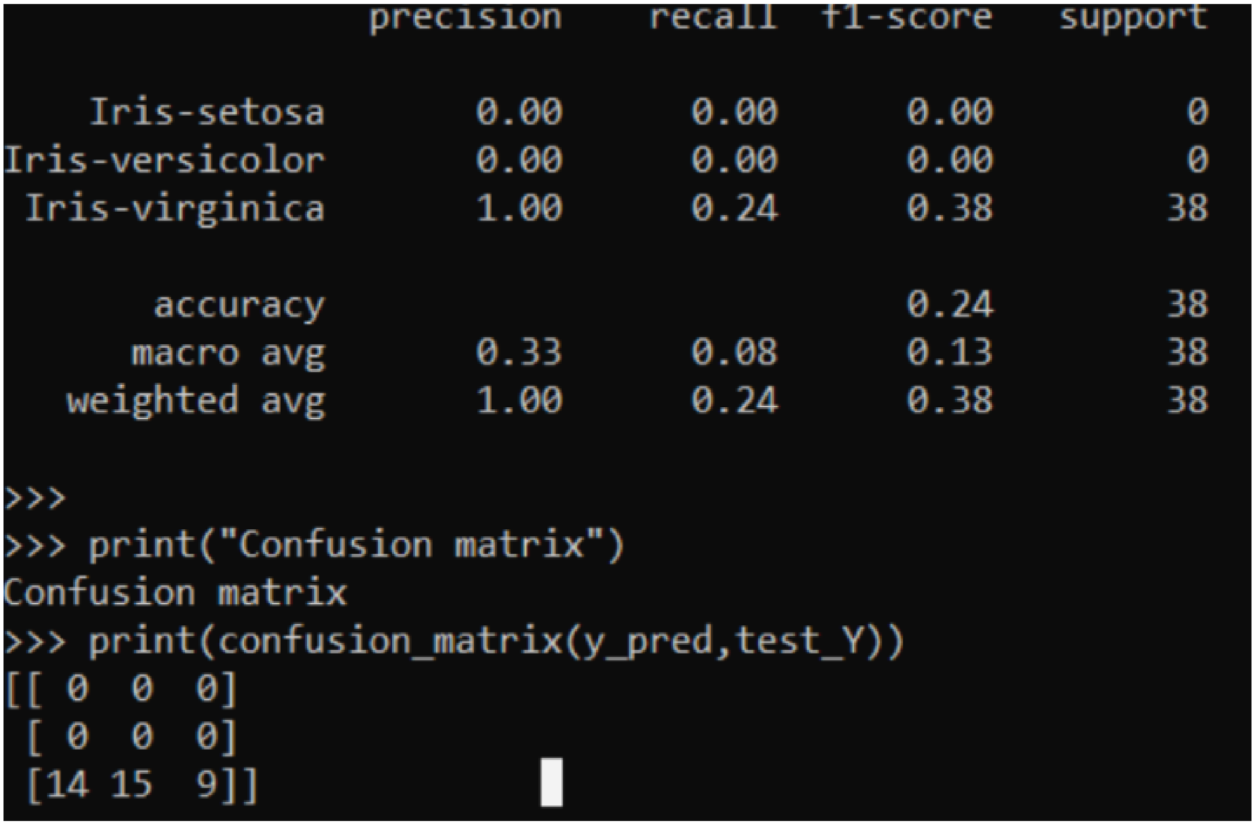
```
>>> print("Accuracy")
Accuracy
>>> print(accuracy_score(y_pred,test_Y))
0.9736842105263158
>>>
>>> print("precision,Recall,F-score")
precision,Recall,F-score
>>>
>>> print(classification_report(y_pred,test_Y))
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        14
Iris-versicolor       1.00      0.94      0.97        16
 Iris-virginica       0.89      1.00      0.94         8

       accuracy                           0.97        38
      macro avg       0.96      0.98      0.97        38
   weighted avg       0.98      0.97      0.97        38

>>> print("Confusion matrix")
Confusion matrix
>>>
>>> print(confusion_matrix(y_pred,test_Y))
[[14  0  0]
 [ 0 15  1]
 [ 0  0  8]]
```

3. Third type of classifier that we will use BernoulliNB classifier and calculate Accuracy, Precision, Recall, F-score, confusion matrix without parameter tuning.



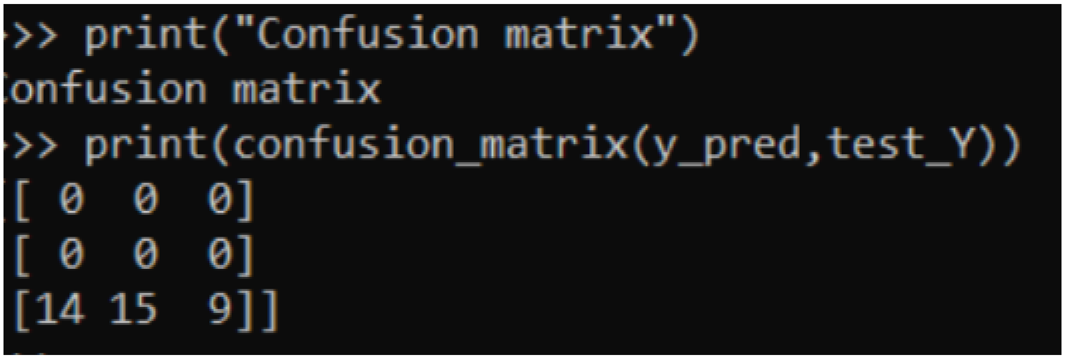
```
>>> from sklearn.naive_bayes import BernoulliNB
>>> classifier=BernoulliNB().fit(train_X,train_Y)
>>> classifier.fit(train_X,train_Y)
BernoulliNB()
>>> y_pred=classifier.predict(test_X)
>>>
>>>
>>> print("Accuracy")
Accuracy
>>> print(accuracy_score(y_pred,test_Y))
0.23684210526315788
```

Output of BernoulliNB classifier without parameter tuning



```
                 precision    recall  f1-score   support

    Iris-setosa       0.00      0.00      0.00         0
Iris-versicolor       0.00      0.00      0.00         0
 Iris-virginica       1.00      0.24      0.38        38

       accuracy                           0.24        38
      macro avg       0.33      0.08      0.13        38
   weighted avg       1.00      0.24      0.38        38

>>>
>>> print("Confusion matrix")
Confusion matrix
>>> print(confusion_matrix(y_pred,test_Y))
[[ 0  0  0]
 [ 0  0  0]
 [14 15  9]]
```

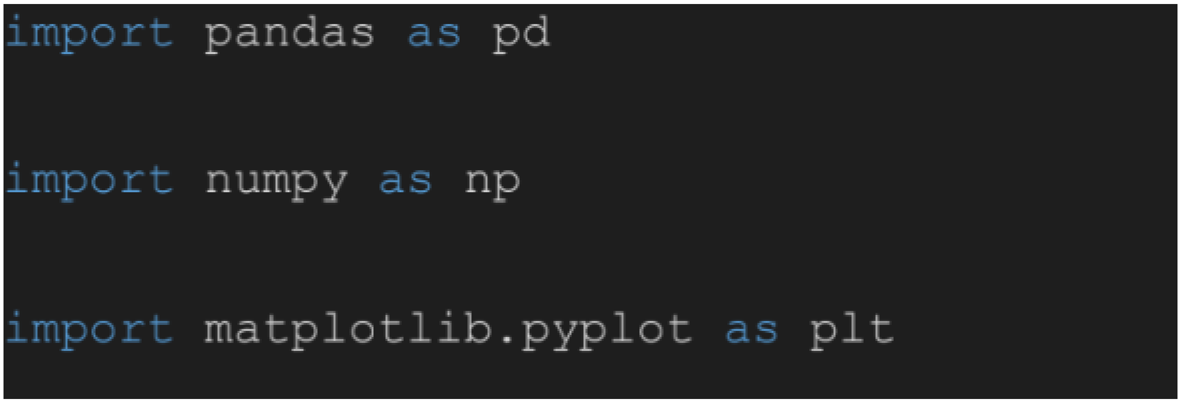
Output of BernoulliNB classifier with parameter tuning



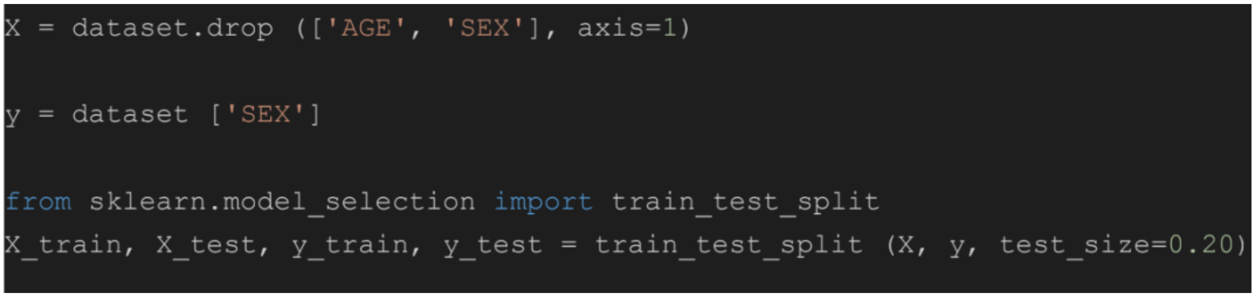
```
>> print("Confusion matrix")
onfusion matrix
>> print(confusion_matrix(y_pred,test_Y))
[[ 0  0  0]
 [ 0  0  0]
 [14 15  9]]
```

Diabetes Dataset

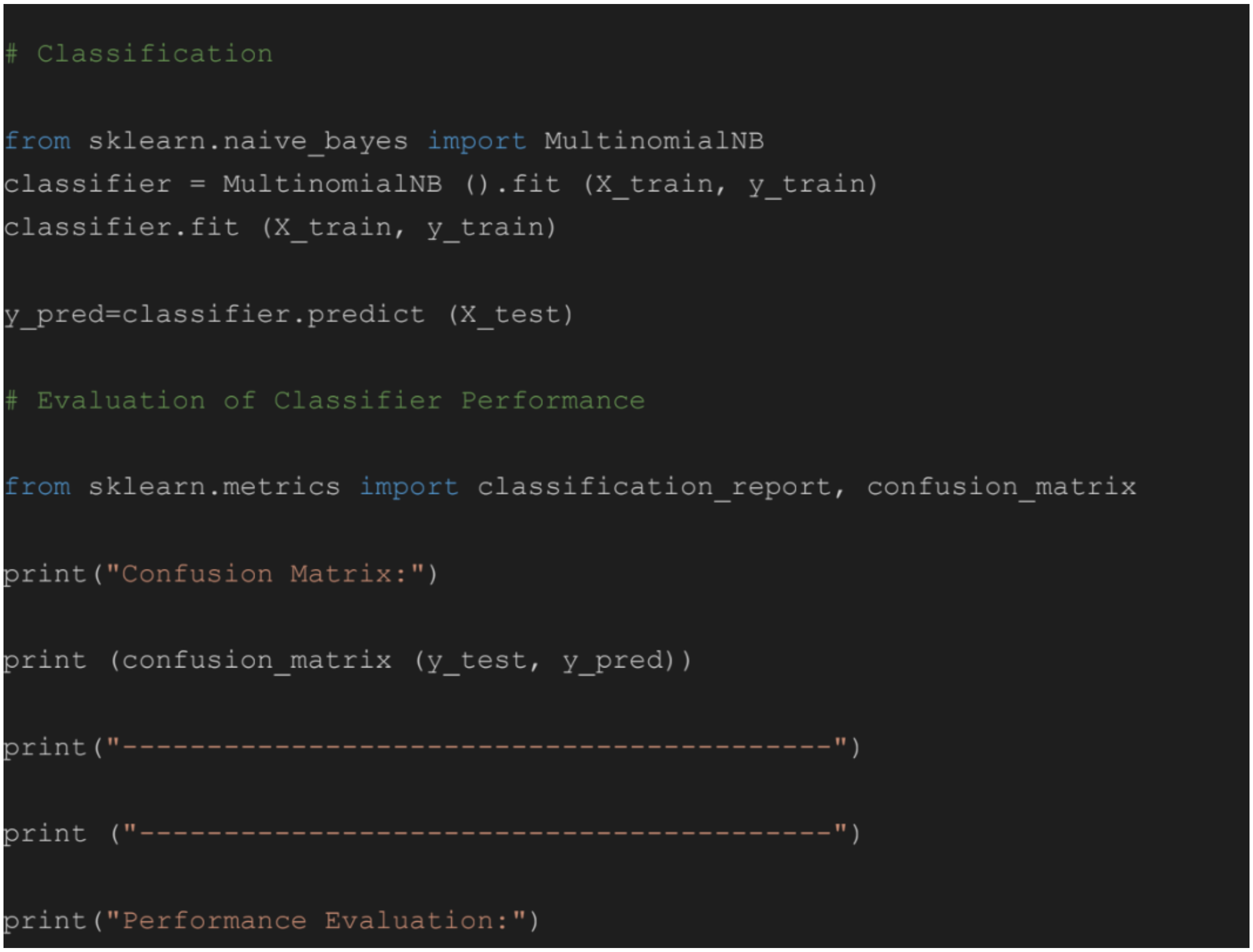
Q1. Without parameter tuning:-
1. Multinomial:--
Code:-



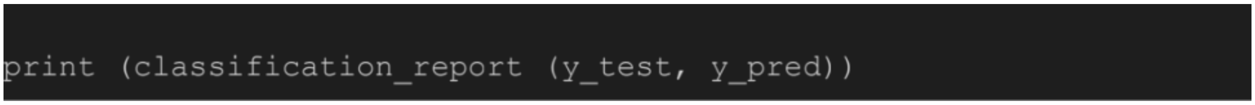
```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt
```



```
X = dataset.drop (['AGE', 'SEX'], axis=1)

y = dataset ['SEX']

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split (X, y, test_size=0.20)
```



```
# Classification

from sklearn.naive_bayes import MultinomialNB
classifier = MultinomialNB ().fit (X_train, y_train)
classifier.fit (X_train, y_train)

y_pred=classifier.predict (X_test)

# Evaluation of Classifier Performance

from sklearn.metrics import classification_report, confusion_matrix

print("Confusion Matrix:")

print (confusion_matrix (y_test, y_pred))

print("-------------------------------------------")

print ("------------------------------------------")

print("Performance Evaluation:")
```



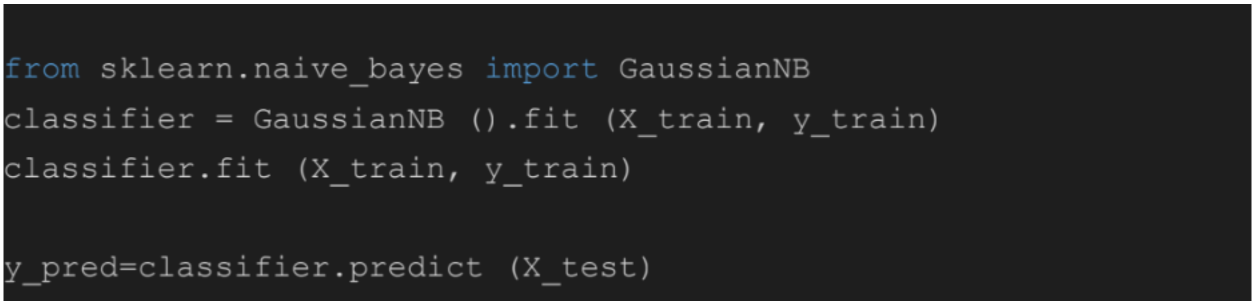
```
print (classification_report (y_test, y_pred))
```

Output:-

```
Confusion Matrix:
[[27 15]
[14 33]]
-----------------------------------------
----------------------------------------
Performance Evaluation:
precision recall f1-score support
1 0.66 0.64 0.65 42
2 0.69 0.70 0.69 47
accuracy 0.67 89
macro avg 0.67 0.67 0.67 89
weighted avg 0.67 0.67 0.67 89
```

2.Gaussian:--

Code:-



```
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB ().fit (X_train, y_train)
classifier.fit (X_train, y_train)

y_pred=classifier.predict (X_test)
```

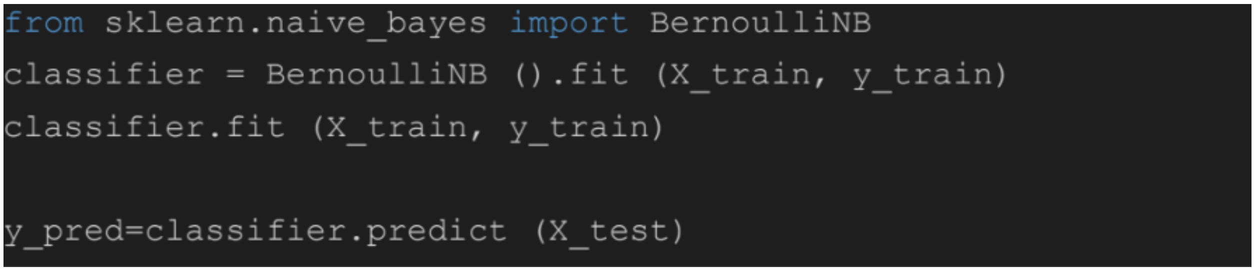
Output:-

```
Confusion Matrix:
[[28 15]
[14 32]]
--------------------------------------
```

```
----------------------------------------
Performance Evaluation:
precision recall f1-score support
1 0.67 0.65 0.66 43
2 0.68 0.70 0.69 46
accuracy 0.67 89
macro avg 0.67 0.67 0.67 89
weighted avg 0.67 0.67 0.67 89
```

3. Bernoulli:---

Code:-



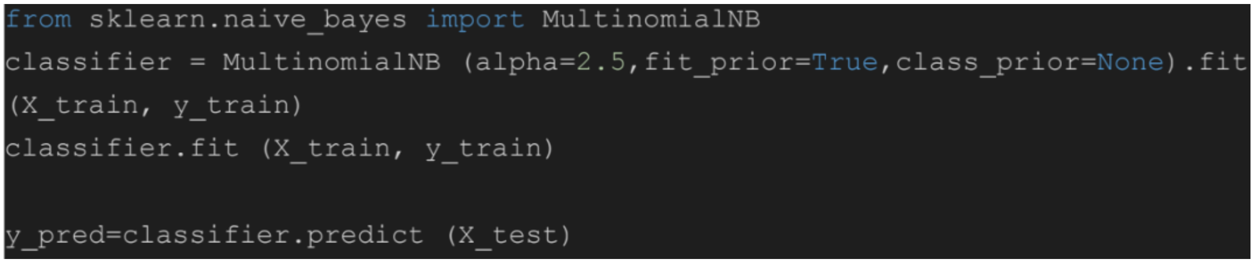
```
from sklearn.naive_bayes import BernoulliNB
classifier = BernoulliNB ().fit (X_train, y_train)
classifier.fit (X_train, y_train)

y_pred=classifier.predict (X_test)
```

Output:-

```
Confusion Matrix:
[[48 0]
[41 0]]
-----------------------------------------
----------------------------------------
Performance Evaluation:
precision recall f1-score support
1 0.54 1.00 0.70 48
2 0.00 0.00 0.00 41
accuracy 0.54 89
macro avg 0.27 0.50 0.35 89
weighted avg 0.29 0.54 0.38 89
```

2. Parameter tuning:---

1.Multonomial:-
Using alpha=2.5,fit_prior=True,class_prior=None :---
Code:-



```
from sklearn.naive_bayes import MultinomialNB
classifier = MultinomialNB (alpha=2.5,fit_prior=True,class_prior=None).fit
(X_train, y_train)
classifier.fit (X_train, y_train)

y_pred=classifier.predict (X_test)
```

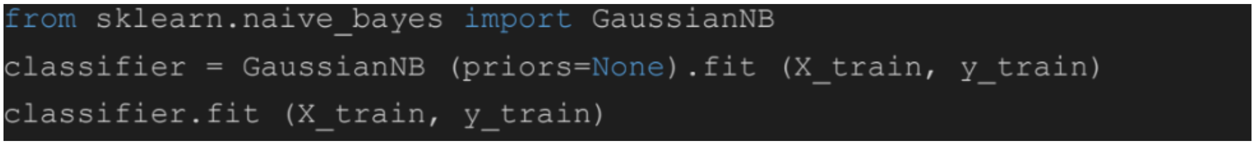
Output:-

```
Confusion Matrix:
[[23 18]
[16 32]]
------------------------------------------
-----------------------------------------
Performance Evaluation:
precision recall f1-score support
1 0.59 0.56 0.57 41
2 0.64 0.67 0.65 48
accuracy 0.62 89
macro avg 0.61 0.61 0.61 89
weighted avg 0.62 0.62 0.62 89
```

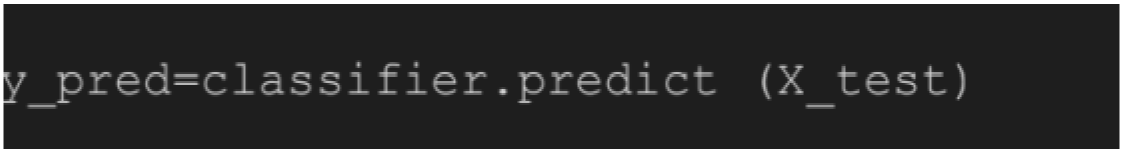
2.Gaussian:-

Using priors=None:---

Code:-



```
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB (priors=None).fit (X_train, y_train)
classifier.fit (X_train, y_train)
```



```
y_pred=classifier.predict (X_test)
```

```
Confusion Matrix:
[[31 15]
[14 29]]
-----------------------------------------
----------------------------------------
Performance Evaluation:
precision recall f1-score support
1 0.69 0.67 0.68 46
2 0.66 0.67 0.67 43
accuracy 0.67 89
macro avg 0.67 0.67 0.67 89
weighted avg 0.67 0.67 0.67 89
```

3.Bernoulli:-

Using alpha=1.0,binarize=0.0,fit_prior=True,class_prior=None:--
Code:-

Output:-

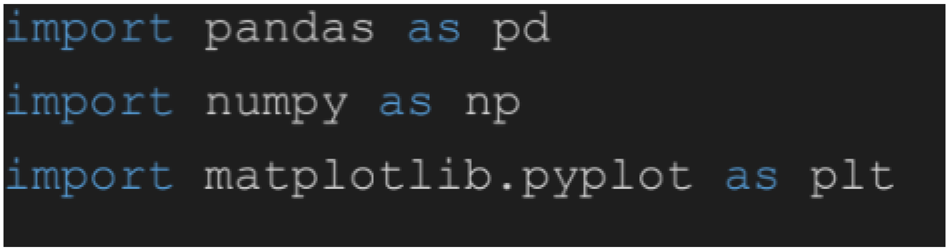
Confusion Matrix:

```
[[47 0]
[42 0]]
----------------------------------------
---------------------------------------
Performance Evaluation:
precision recall f1-score support
1 0.53 1.00 0.69 47
2 0.00 0.00 0.00 42
accuracy 0.53 89
macro avg 0.26 0.50 0.35 89
weighted avg 0.28 0.53 0.37 89
```

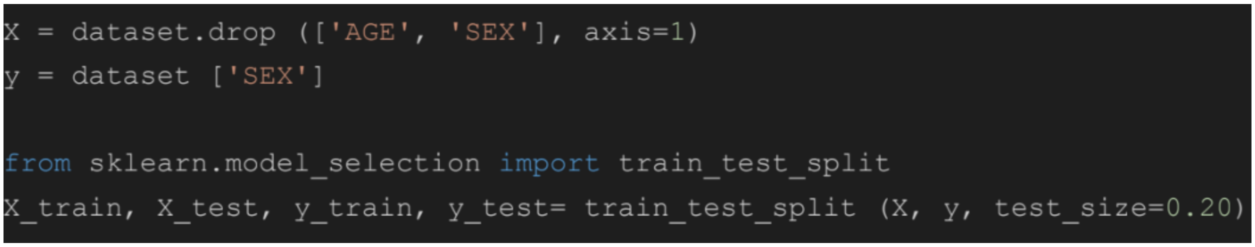
Q2.

Without parameter tuning:-------

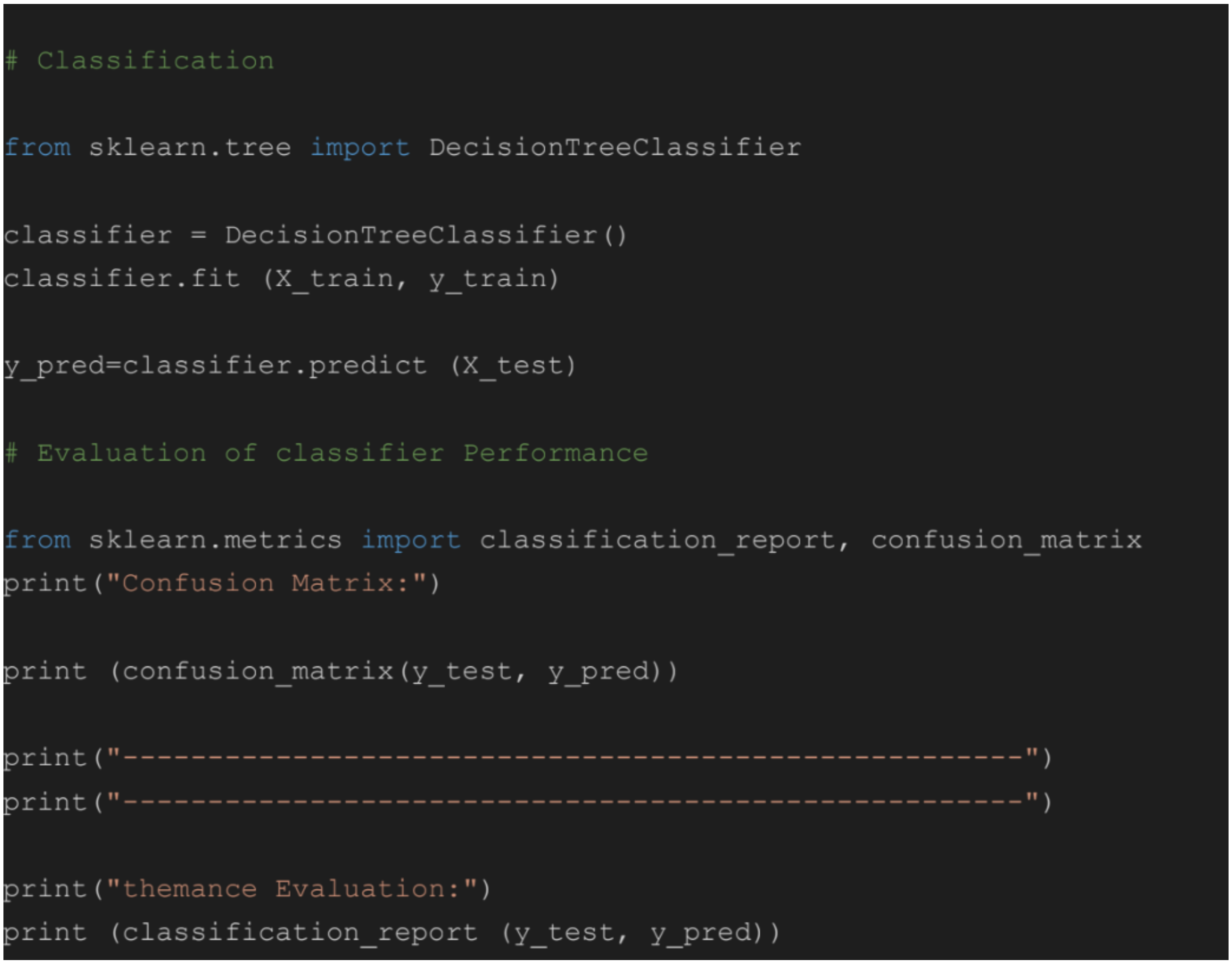
Code:---



```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```



```python
X = dataset.drop (['AGE', 'SEX'], axis=1)
y = dataset ['SEX']

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test= train_test_split (X, y, test_size=0.20)
```



```
# Classification

from sklearn.tree import DecisionTreeClassifier

classifier = DecisionTreeClassifier()
classifier.fit (X_train, y_train)

y_pred=classifier.predict (X_test)

# Evaluation of classifier Performance

from sklearn.metrics import classification_report, confusion_matrix
print("Confusion Matrix:")

print (confusion_matrix(y_test, y_pred))

print("-----------------------------------------------------")
print("-----------------------------------------------------")

print("themance Evaluation:")
print (classification_report (y_test, y_pred))
```

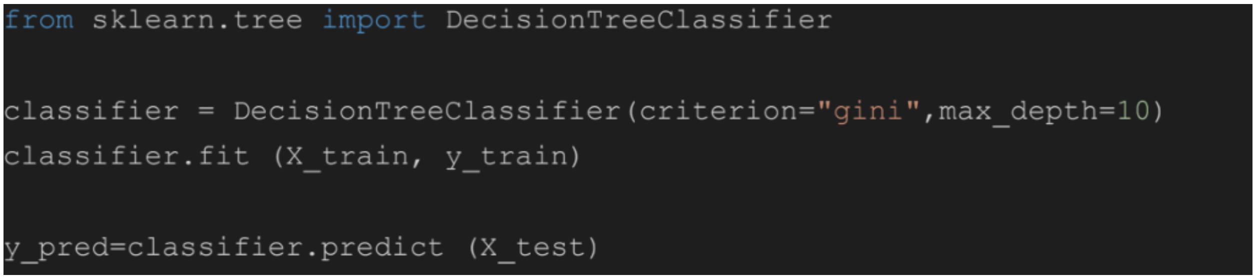
Output:-

```
Confusion Matrix:
[[24 26]
[ 9 30]]
-----------------------------------------------------
-----------------------------------------------------
themance Evaluation:
precision recall f1-score support
1 0.73 0.48 0.58 50
2 0.54 0.77 0.63 39
accuracy 0.61 89
```

```
macro avg 0.63 0.62 0.60 89
weighted avg 0.64 0.61 0.60 89
```

Parameter tuning:-

1.Making criterion=”gini” and max_depth=10

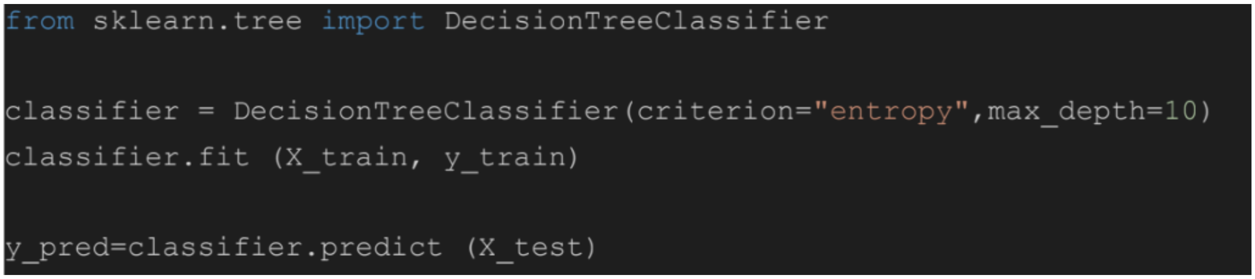


```
from sklearn.tree import DecisionTreeClassifier

classifier = DecisionTreeClassifier(criterion="gini",max_depth=10)
classifier.fit (X_train, y_train)

y_pred=classifier.predict (X_test)
```

Output:-

```
Confusion Matrix:
[[26 21]
[16 26]]
----------------------------------------------------
----------------------------------------------------
themance Evaluation:
precision recall f1-score support
1 0.62 0.55 0.58 47
2 0.55 0.62 0.58 42
accuracy 0.58 89
macro avg 0.59 0.59 0.58 89
weighted avg 0.59 0.58 0.58 89
```

2.Making criterion=”entropy” and max_depth=10
Code:-



```
from sklearn.tree import DecisionTreeClassifier

classifier = DecisionTreeClassifier(criterion="entropy",max_depth=10)
classifier.fit (X_train, y_train)

y_pred=classifier.predict (X_test)
```

Output:-

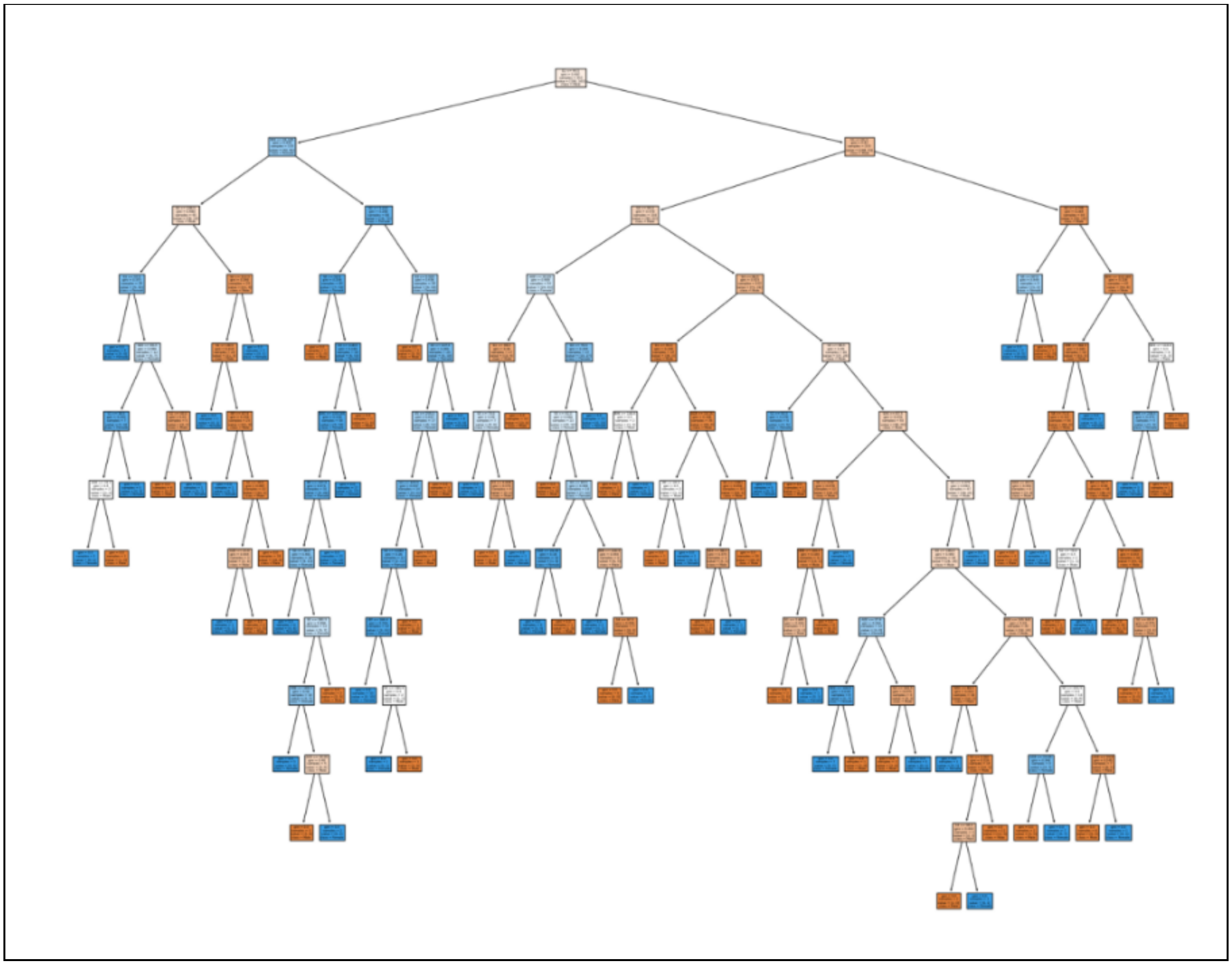
Confusion Matrix:
[[35 14]
[20 20]]

----
themance Evaluation:
precision recall f1-score support

1 0.64 0.71 0.67 49
2 0.59 0.50 0.54 40
accuracy 0.62 89
macro avg 0.61 0.61 0.61 89
weighted avg 0.61 0.62 0.61 89

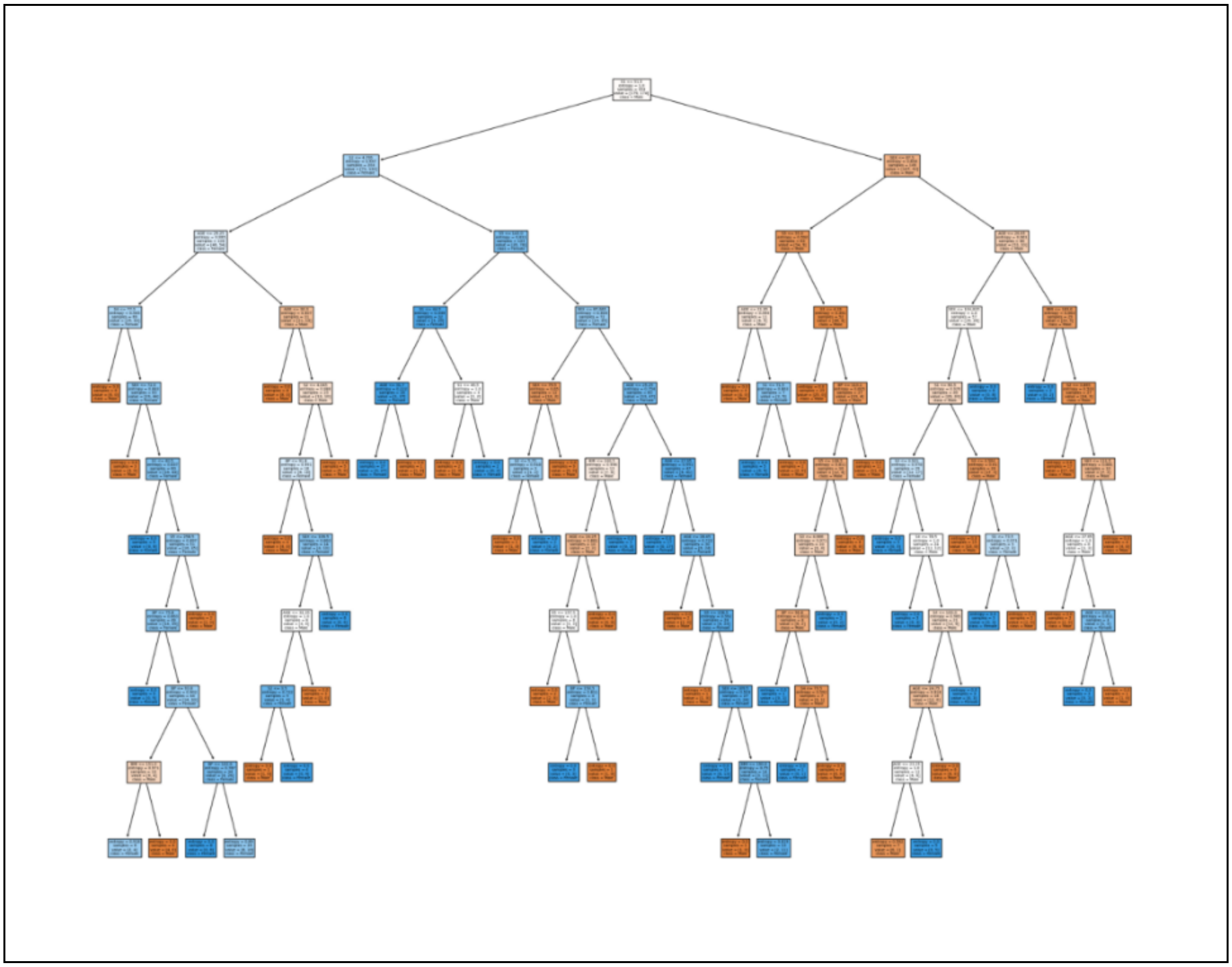
Images:-

1.Without parameter tuning:-



2.Using Parameter tuning:-

1.Making criterion=”gini” and max_depth=10.



2. Making criterion=”entropy” and max_depth=10.