FEDERAL INSTITUTE OF SCIENCE AND TECHNOLOGY (FISAT)™

HORMIS NAGAR, MOOKKANNOOR

ANGAMALY-683577

'FOCUS ON EXCELLENCE'

DATA SCIENCE

....

LABORATORY RECORD

Name: SINCY V.J

Branch: MASTER OF COMPUTER APPLICATION

Semester: 3 **Batch:** B **Roll No:** 47

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SCIENCE AND TECHNOLOGY

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University Exam.Reg. No:

CERTIFICATE

*This is to certify that this is a Bonafide record of the Practical work done and submitted to Kerala Technological University in partial fulfillment for the award of the Master Of Computer Applications is a record of the original research work done by **SINCY V.J** in the **DATA SCIENCE** Laboratory of the Federal Institute of Science and Technology during the academic year 2021-2022.*

Signature of Staff in Charge　　　　　　　　　　Signature of H.O.D

Name:　　　　　　　　　　　　　　　　　　　　Name:

Date:

Date of University practical examination ………………………

Signature of　　　　　　　　　　　　　　　　　Signature of

Internal Examiner　　　　　　　　　　　　　　　External Examiner

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AIM

1: Matrix operations(using vectorixation) and transformation using python and SVD

CODE:

```
a = np.arange(0,4).reshape((2,2))
b = np.eye(2)
print(np.dot(a,b)) ##Matrix multiplication
```

OUTPUT:

```
[[0. 1.]
 [2. 3.]]
```

CODE:

```
x = np.arange(1,10).reshape(3,3)
print(x)
```

OUTPUT:

```
[[1 2 3]
 [4 5 6]
 [7 8 9]]
```

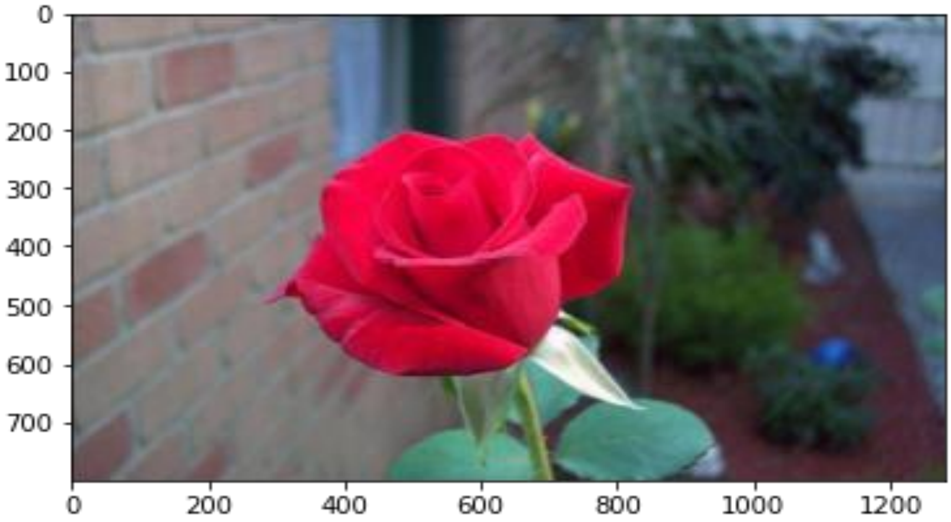
CODE:

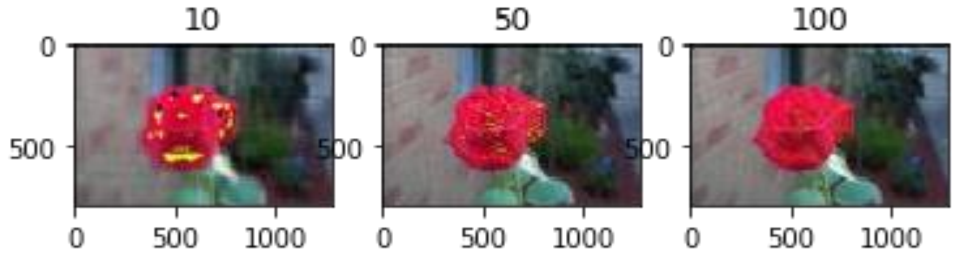
#SVD image compresion

```
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import numpy as np

img_eg = mpimg.imread("rose.jpg")
plt.imshow(img_eg)
print(img_eg.shape) #Operation results: (800, 1280,3)

#Converting image data into two-dimensional matrix and singu-
lar value decomposition
img_temp = img_eg.reshape(800, 1280 * 3)
U,Sigma,VT = np.linalg.svd(img_temp)

# Take the first 10 singular values
sval_nums = 10
```

```
img_re-
struct1 = (U[:,0:sval_nums]).dot(np.diag(Sigma[0:sval_nums])).dot(VT[0:
sval_nums,:])
img_restruct1 = img_restruct1.reshape(800, 1280,3)
img_restruct1.tolist()

# Take the first 50 singular values
sval_nums = 50
img_re-
struct2 = (U[:,0:sval_nums]).dot(np.diag(Sigma[0:sval_nums])).dot(VT[0:
sval_nums,:])
img_restruct2 = img_restruct2.reshape(800, 1280,3)

# Take the first 100 singular values
sval_nums = 100
img_re-
struct3 = (U[:,0:sval_nums]).dot(np.diag(Sigma[0:sval_nums])).dot(VT[0:
sval_nums,:])
img_restruct3 = img_restruct3.reshape(800, 1280,3)

#Exhibition
fig, ax = plt.subplots(nrows=1, ncols=3)
ax[0].imshow(img_restruct1.astype(np.uint8))
ax[0].set(title = "10")
ax[1].imshow(img_restruct2.astype(np.uint8))
ax[1].set(title = "50")
ax[2].imshow(img_restruct3.astype(np.uint8))
ax[2].set(title = "100")
plt.show()
```

OUTPUT:


0
100
200
300
400
500
600
700
0
200
400
600
800
1000
1200

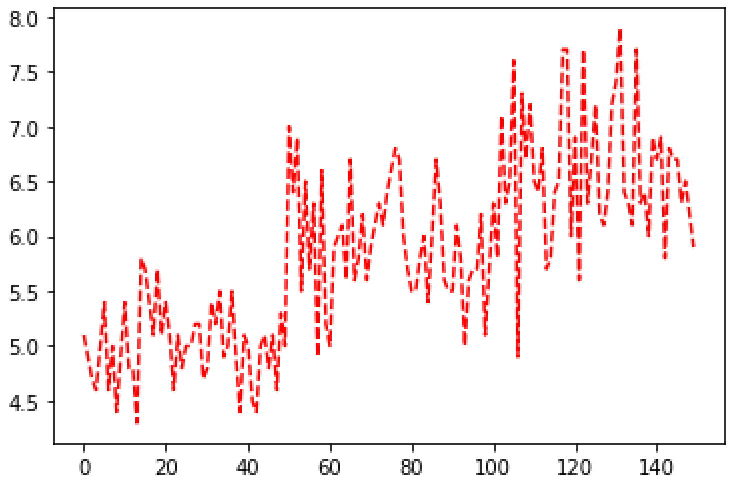

10
50
100
0
500
0
500
1000

AIM
2. Programs using matplotlib / plotly / bokeh / seaborn for data visualisation.
Dataset used: iris.csv

CODE:
```
import pandas as pd
iris = pd.read_csv('iris.csv')
```

```
## Plotting Using Matplotlib
import matplotlib.pyplot as plt
plt.plot(iris["sepal.length"], "r--")
plt.show
```

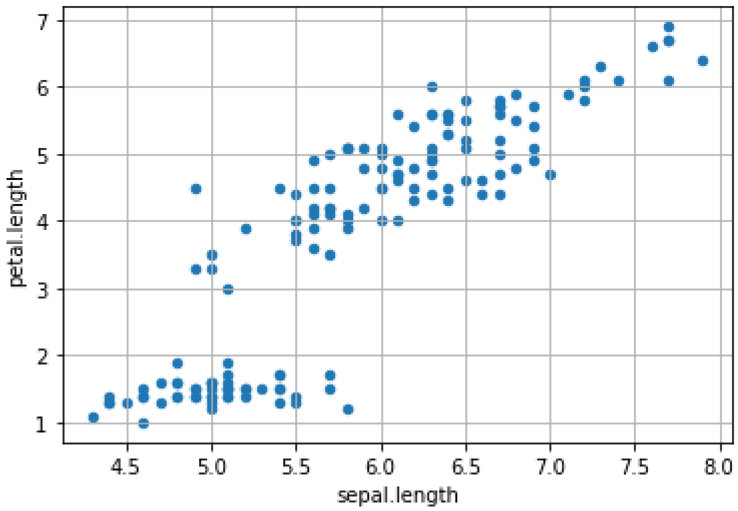
OUTPUT:



CODE:

```
## Scatter Plot

iris.plot(kind ="scatter",
          x ='sepal.length',
          y ='petal.length')
plt.grid()
```

OUTPUT:

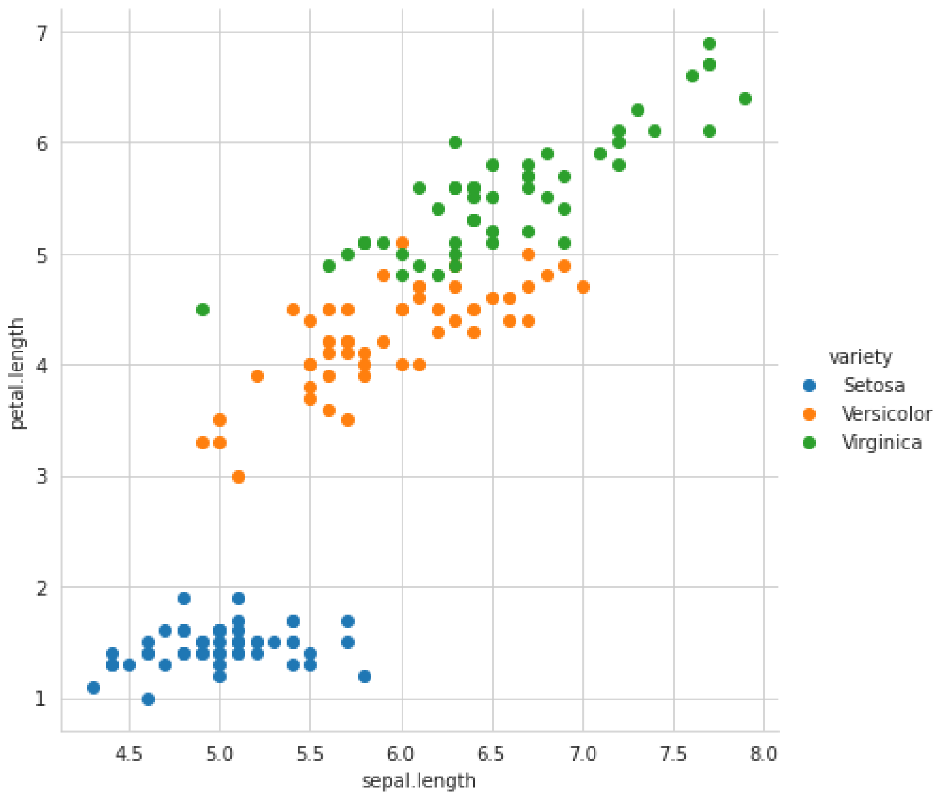


CODE:

Plotting using Seaborn

```
import seaborn as sns
sns.set_style("whitegrid")
sns.FacetGrid(iris, hue ="variety",height = 6).map(plt.scatter, 'sepal.length',
'petal.length').add_legend()
```

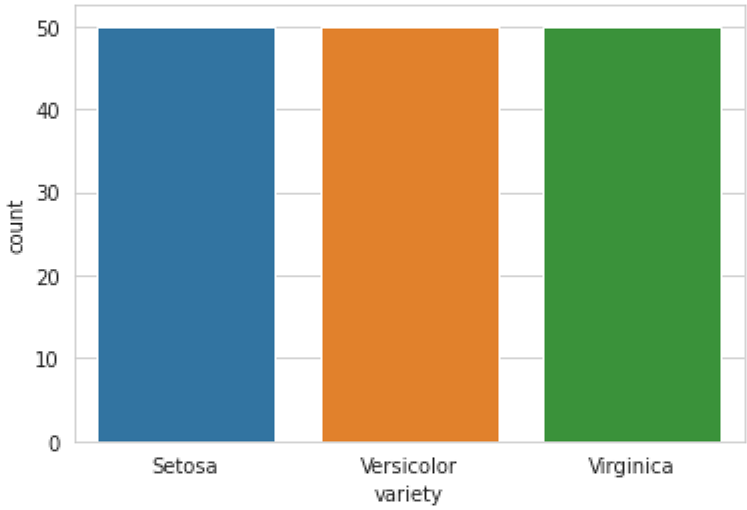
OUTPUT:



CODE:

```
# Distribution Chart
#Visualizing the target(class label) column

sns.countplot(x='variety', data=iris, )
plt.show()
```

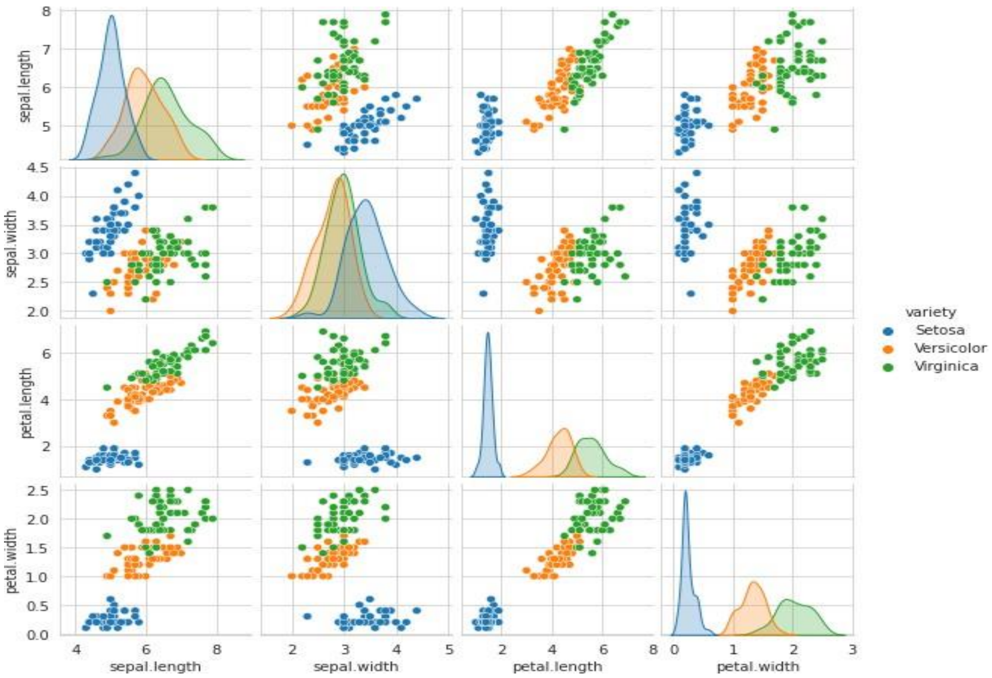
OUTPUT:



CODE:

```
#plotting all the column's relationships using a pairplot. It can be used for multivariate analysis.
sns.pairplot(iris,hue='variety', height=2)
```

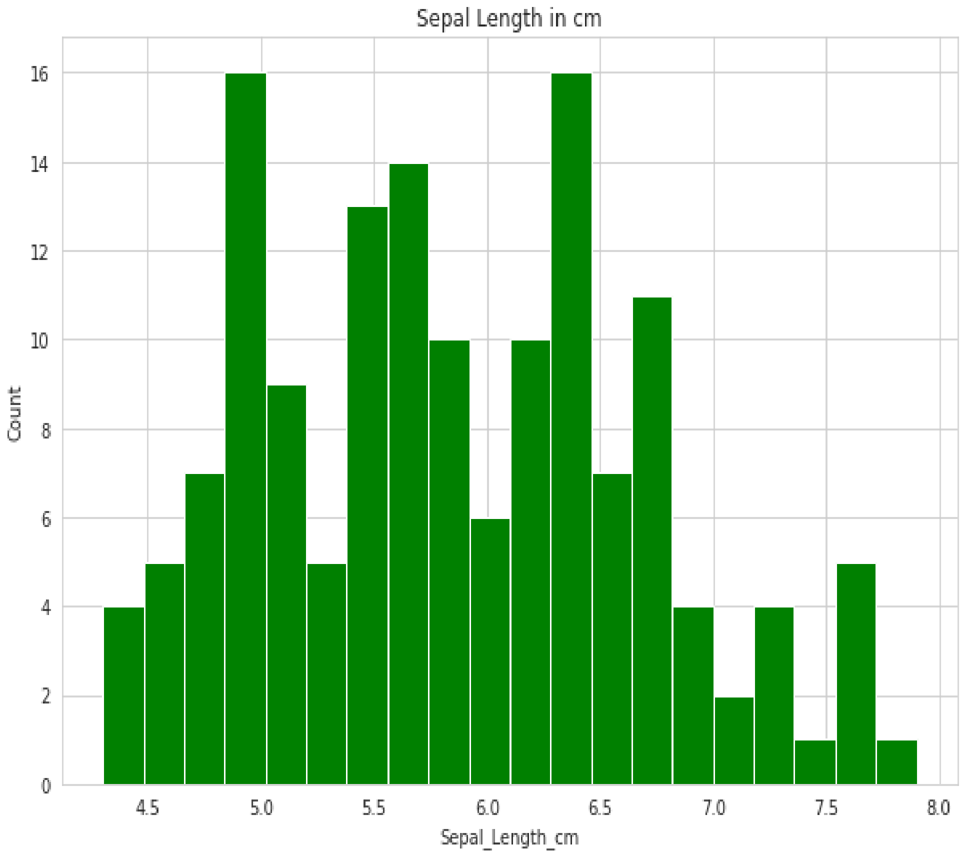
OUTPUT:



#Histogram for Sepal Length

```
plt.figure(figsize = (10, 7))
x = iris["sepal.length"]
plt.hist(x, bins = 20, color = "green")
plt.title("Sepal Length in cm")
plt.xlabel("Sepal_Length_cm")
plt.ylabel("Count")
```

OUTPUT:

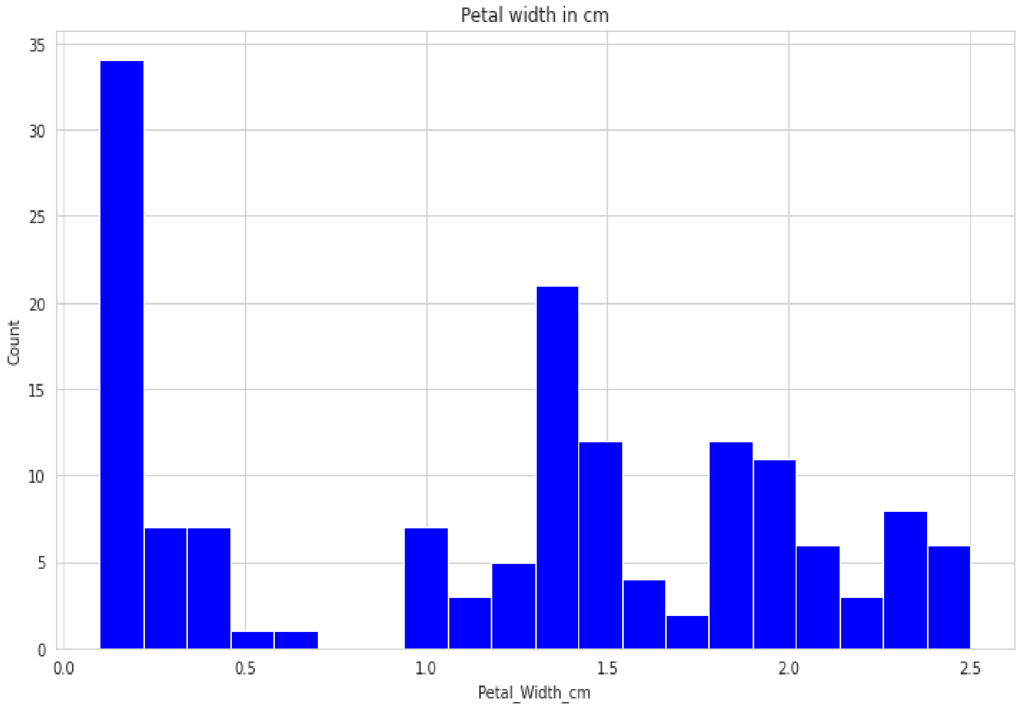


CODE:

#Histogram for Petal Width

```
plt.figure(figsize = (12, 7))
x = iris["petal.width"]

plt.hist(x, bins =20, color = "blue")
plt.title("Petal width in cm")
plt.xlabel("Petal_Width_cm")
plt.ylabel("Count")
```

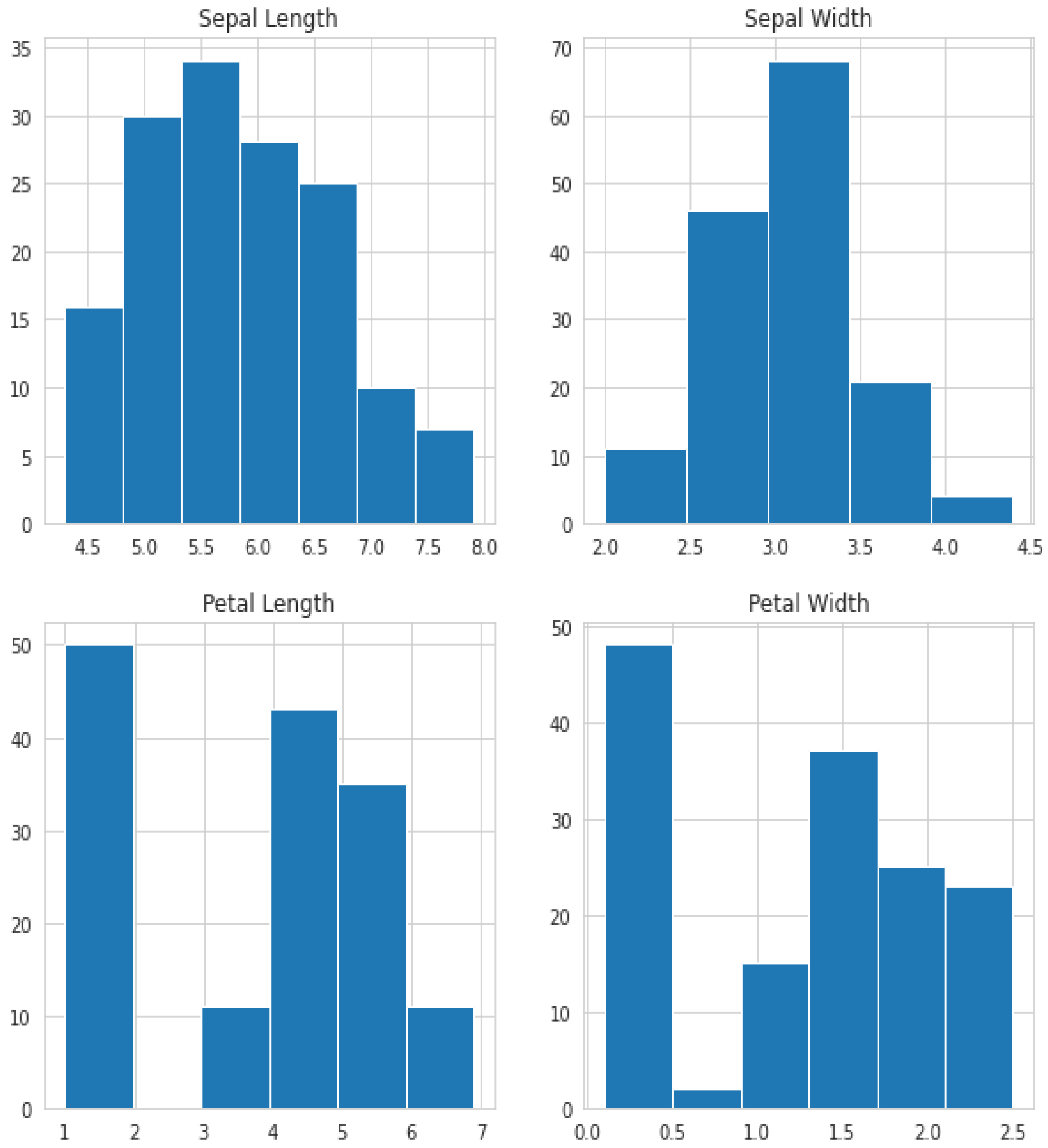
OUTPUT:



CODE:

```
#Histograms allow seeing the distribution of data for various columns.
# It can be used for uni as well as bi-variate analysis.

fig, axes = plt.subplots(2, 2, figsize=(10,10))

axes[0,0].set_title("Sepal Length")
axes[0,0].hist(iris['sepal.length'], bins=7)

axes[0,1].set_title("Sepal Width")
axes[0,1].hist(iris['sepal.width'], bins=5);

axes[1,0].set_title("Petal Length")
axes[1,0].hist(iris['petal.length'], bins=6);

axes[1,1].set_title("Petal Width")
axes[1,1].hist(iris['petal.width'], bins=6);
```

OUTPUT:



CODE:

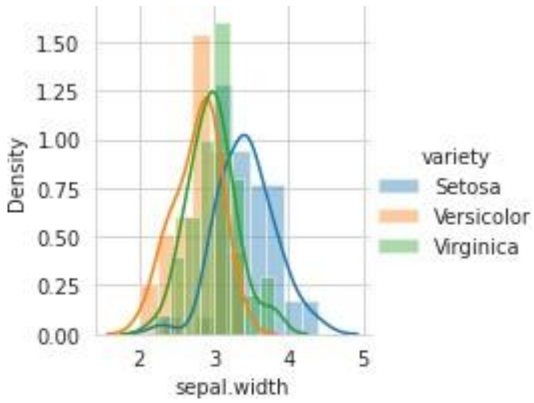
```
#Histograms with Distplot Plot

plot = sns.FacetGrid(iris, hue="variety")
plot.map(sns.distplot, "sepal.length").add_legend()

plot = sns.FacetGrid(iris, hue="variety")
plot.map(sns.distplot, "sepal.width").add_legend()

plot = sns.FacetGrid(iris, hue="variety")
plot.map(sns.distplot, "petal.length").add_legend()


plot = sns.FacetGrid(iris, hue="variety")
```

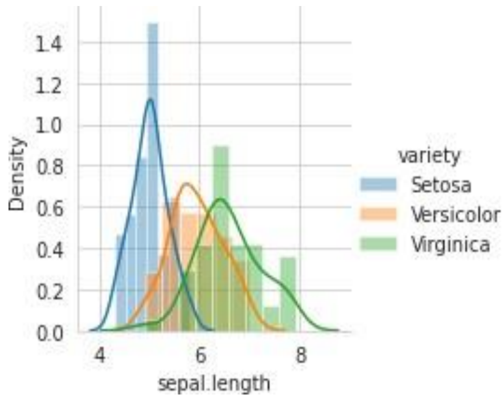
plot.map(sns.distplot, "petal.width").add_legend()

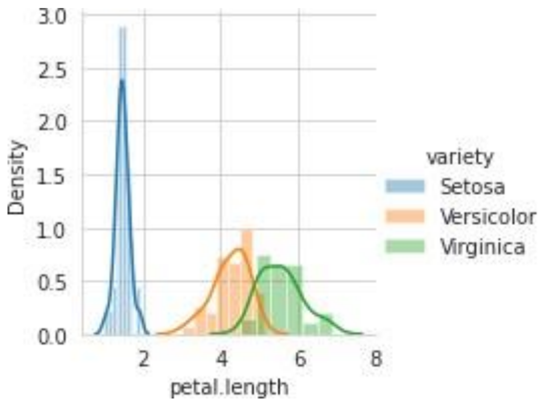
plt.show()

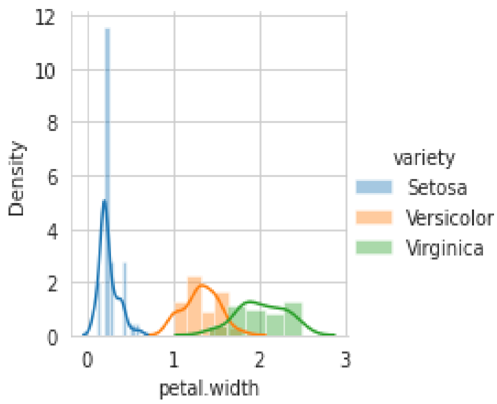
#In the case of Sepal Length, there is a huge amount of overlapping.
#In the case of Sepal Width also, there is a huge amount of overlapping.
#In the case of Petal Length, there is a very little amount of overlapping.
#In the case of Petal Width also, there is a very little amount of overlapping.

OUTPUT:





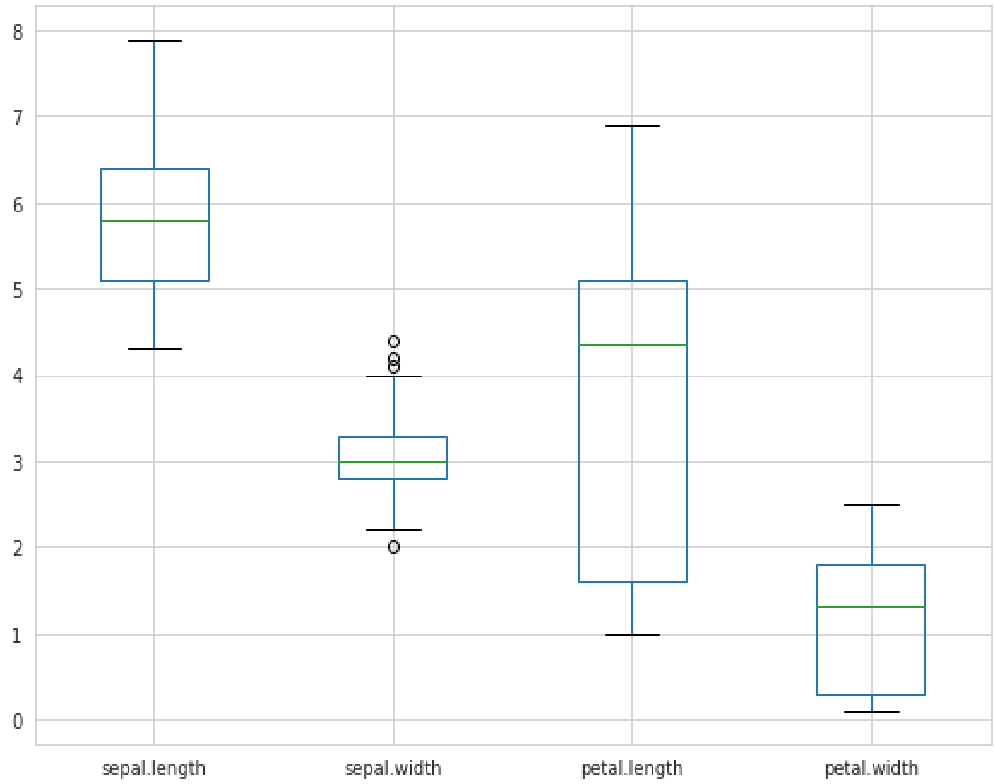




CODE:

```
# Box Plot for Iris Data

plt.figure(figsize = (10, 7))
iris.boxplot()
```

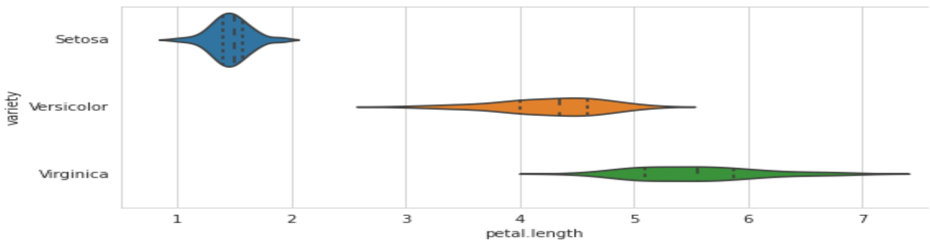
OUTPUT:

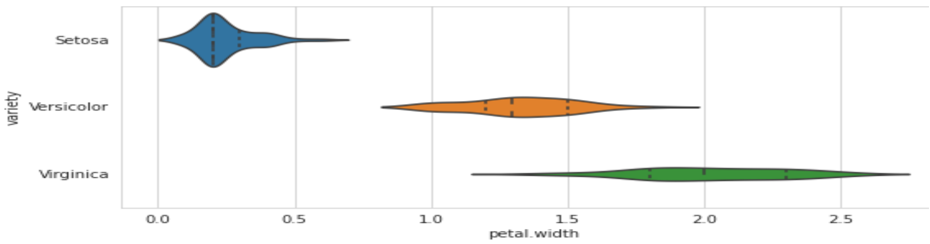


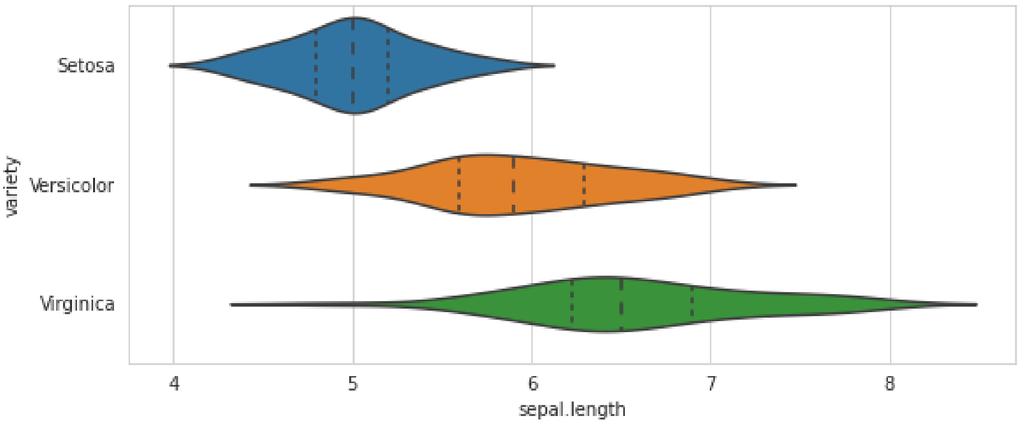
CODE:

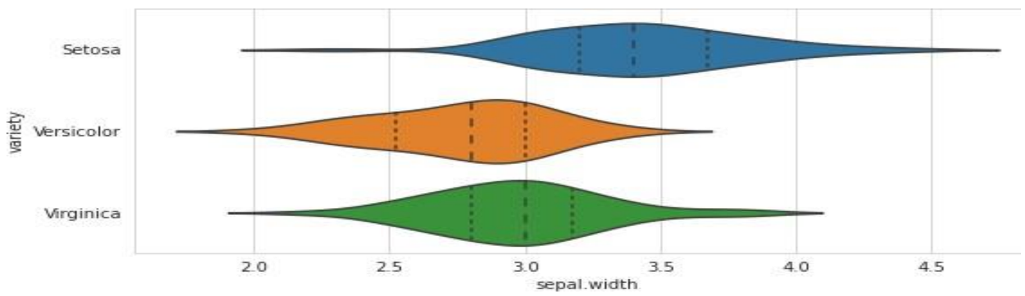
```
import matplotlib.gridspec as gridspec
fig = plt.figure(figsize=(9, 40))
outer = gridspec.GridSpec(4, 1, wspace=0.2, hspace=0.2)
for i, col in enumerate(iris.columns[:-1]):
  inner = gridspec.GridSpecFromSubplotSpec(2, 1,subplot_spec=outer[i], wspace=0.2,
hspace=0.4)
  ax = plt.Subplot(fig, inner[1])
  _ = sns.violinplot(y="variety", x=f"{col}", data=iris, inner='quartile', ax=ax)
  fig.add_subplot(ax)
fig.show()
```

OUTPUT:


Setosa
Versicolor
Virginica
variety
1
2
3
4
5
6
7
petal.length


Setosa
Versicolor
Virginica
variety
0.0
0.5
1.0
1.5
2.0
2.5
petal.width

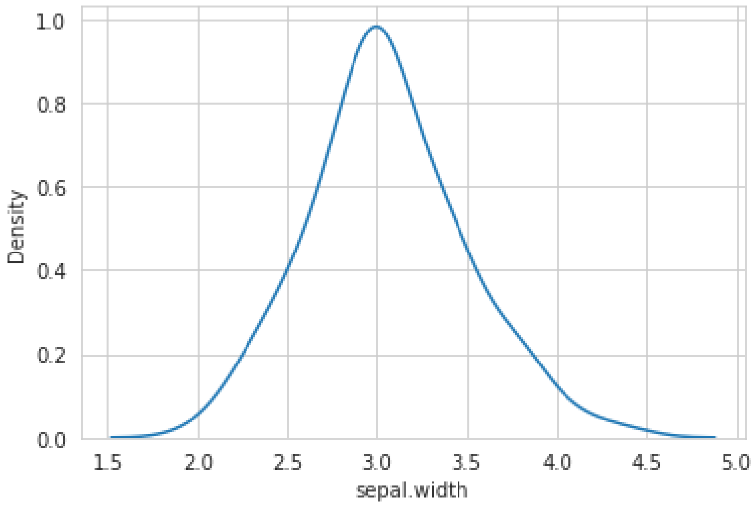

Setosa
Versicolor
Virginica
variety
4
5
6
7
8
sepal.length


Setosa
Versicolor
Virginica
variety
2.0
2.5
3.0
3.5
4.0
4.5
sepal.width

CODE:

```
# Make default density plot
sns.kdeplot(iris['sepal.width'])
```

OUTPUT:



AIM
3. Programs to handle data using pandas

CODE:

```
#Pandas is a Python library.

#Pandas is used to analyze data.

import numpy as np

import pandas as pd

s = pd.Series([1, 3, 5, 6, 8])
print(s)
```

OUTPUT:

```
0    1
1    3
2    5
3    6
4    8
dtype: int64
```

CODE:

```
dict = {"country": ["Brazil", "Russia", "India", "China", "South Africa"],
       "capital": ["Brasilia", "Moscow", "New Dehli", "Beijing", "Pretoria"],
       "area": [8.516, 17.10, 3.286, 9.597, 1.221],
       "population": [200.4, 143.5, 1252, 1357, 52.98] }
b = pd.DataFrame(dict)
print(b)
```

OUTPUT

```
        country    capital    area  population
0        Brazil   Brasilia   8.516      200.40
1        Russia     Moscow  17.100      143.50
2         India  New Dehli   3.286     1252.00
3         China    Beijing   9.597     1357.00
4  South Africa   Pretoria   1.221       52.98
```

CODE:

```
b.index = ["BR", "RU", "IN", "CH", "SA"]
```

print(b)

OUTPUT:

```
        country    capital    area  population
BR        Brazil   Brasilia   8.516      200.40
RU        Russia     Moscow  17.100      143.50
IN         India  New Dehli   3.286     1252.00
CH         China    Beijing   9.597     1357.00
SA  South Africa   Pretoria   1.221       52.98
```

CODE:

import pandas as pd
cars = pd.read_csv('cars1.csv')
print(cars)

OUTPUT:

```
           Car       Model  Volume  Weight  CO2
0       Toyoty        Aygo    1000     790   99
1   Mitsubishi  Space Star    1200    1160   95
2        Skoda      Citigo    1000     929   95
3         Fiat         500     900     865   90
4         Mini      Cooper    1500    1140  105
5        VW        Up!     1000       929   105 6
Skoda  Fabia  1400 1109  90
7     Mercedes     A-Class    1500    1365   92
8         Ford      Fiesta    1500    1112   98
9         Audi          A1    1600    1150   99
10  Hyundai  I20  1100 980  99
11      Suzuki       Swift    1300     990  101
12        Ford      Fiesta    1000    1112   99
13       Honda       Civic    1600    1252   94
14      Hundai         I30    1600    1326   97
15        Opel       Astra    1600    1330   97
16         BMW           1  1600  1365  99
17       Mazda           3    2200    1280  104
18       Skoda       Rapid    1600    1119  104
19        Ford       Focus    2000    1328  105
20        Ford      Mondeo    1600    1584   94
21        Opel    Insignia    2000    1428   99
22    Mercedes     C-Class    2100    1365   99
23       Skoda     Octavia    1600    1415   99
24       Volvo         S60    2000    1415   99
25    Mercedes         CLA    1500    1465  102
26        Audi          A4    2000    1490  104
27        Audi          A6    2000    1725  114
28       Volvo         V70    1600    1523  109
29         BMW           5    2000    1705  114
30    Mercedes     E-Class    2100    1605  115
31       Volvo        XC70    2000    1746  117
32        Ford       B-Max    1600    1235  104
33         BMW         216    1600    1390  108
```

CODE:

```
import pandas as pd
cars = pd.read_csv('cars1.csv')
cars = pd.read_csv('/cars1.csv')
print(cars)

# Print out first 4 observations
print(cars[0:4])

# Print out fifth and sixth observation
print(cars[4:6])

import pandas as pd
cars = pd.read_csv('cars1.csv', index_col = 0) #first column is taen as index column


print(cars.iloc[2])
```

OUTPUT:

```
Model      Citigo
Volume       1000
Weight        929
CO2            95
Name: Skoda, dtype: object
```

CODE:

```
#Slicing dataframe
import pandas as pd

df = pd.DataFrame([['Jay','M',18],['Jennifer','F',17],
                  ['Preity','F',19],['Neil','M',17]],
                 columns = ['Name','Gender','Age'])
print(df)
df1 = df.iloc[2:,:]
df2 = df.iloc[:2,:]
print(df1)
print(df2)
```

OUTPUT

```
      Name Gender  Age
0      Jay      M   18
1  Jennifer      F   17
2   Preity      F   19
3     Neil      M   17
```

```
     Name Gender  Age
2  Preity      F   19
3    Neil      M   17
       Name Gender  Age
0       Jay      M   18
1  Jennifer      F   17
```

CODE:

```
import pandas as pd
import numpy as np

#Create a series with 4 random numbers
s = pd.Series(np.random.randn(4))
print(s)

print ("The actual data series is:")
print( s.values)
```

OUTPUT:

```
0  -1.138968
1  -1.097746
2   0.109717
3   1.159537
dtype: float64
The actual data series is:
[-1.13896826 -1.09774589  0.10971687  1.15953676]
CodeText
```

CODE:

```
print (s.head(2))
```

OUTPUT:

```
0   -1.138968
1   -1.097746
dtype: float64
```

CODE:

```
print(s.tail(3))
```

OUTPUT:

```
1   -1.097746
2    0.109717
3    1.159537
dtype: float64
```

CODE:

```
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack']),
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

# Create a DataFrame
df = pd.DataFrame(d)
print(df)
print ("The transpose of the data series is:")
print(df.T)
```

OUTPUT:

```
   Name  Age  Rating
0    Tom   25    4.23
1  James   26    3.24
2  Ricky   25    3.98
3    Vin   23    2.56
4  Steve   30    3.20
5  Smith   29    4.60
6   Jack   23    3.80
The transpose of the data series is:
           0      1      2     3      4      5     6
Name      Tom  James  Ricky   Vin  Steve  Smith  Jack
Age        25     26     25    23     30     29    23
Rating  4.23   3.24   3.98  2.56    3.2    4.6   3.8
```

CODE:

```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack']),
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}
#Create a DataFrame
df = pd.DataFrame(d)
print(df)
print ("Row axis labels and column axis labels are:")
print (df.axes)
```

OUTPUT:

```
  Name  Age  Rating
0    Tom   25    4.23
1  James   26    3.24
2  Ricky   25    3.98
3    Vin   23    2.56
4  Steve   30    3.20
5  Smith   29    4.60
6   Jack   23    3.80
Row axis labels and column axis labels are:
[RangeIndex(start=0, stop=7, step=1), Index(['Name', 'Age',
'Rating'], dtype='object')]
```

CODE:

```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack']),
   'Age':pd.Series([25,26,25,23,30,29,23]),
'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])
   }

#Create a DataFrame
df = pd.DataFrame(d)
print ("Our object is:")
print (df)
print ("The dimension of the object is:")
print (df.ndim)
```

OUTPUT:

```
   Name  Age  Rating
0    Tom   25    4.23
1  James   26    3.24
2  Ricky   25    3.98
3    Vin   23    2.56
4  Steve   30    3.20
5  Smith   29    4.60
6   Jack   30    3.80
Our object is:
The shape of the object is:
(7, 3)
```

CODE:

```
print (df.size)
```

OUTPUT:

21

CODE:

```
print (df.values)
```

OUTPUT:

```
[['Tom' 25 4.23]
 ['James' 26 3.24]
 ['Ricky' 25 3.98]
 ['Vin' 23 2.56]
 ['Steve' 30 3.2]
 ['Smith' 29 4.6]
 ['Jack' 30 3.8]]
```

CODE:

```
df.isnull().sum() #sum returns the number of missing values
```

OUTPUT:

```
Name      0
Age       0
Rating    0
dtype: int64
```

CODE:

```
df = pd.DataFrame(np.arange(12).reshape(3, 4), columns=['A', 'B', 'C', 'D'])
print(df)
```

OUTPUT:

```
  A  B   C   D
0  0  1   2   3
1  4  5   6   7
2  8  9  10  11
```

AIM

4: Program to implement k-NN classification using any standard dataset available in the public domain and find the accuracy of the algorithm.

CODE:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
import pandas as pd


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

OUTPUT:

```
    sepal.length  sepal.width  petal.length  petal.width   variety
0            5.1          3.5           1.4          0.2    Setosa
1            4.9          3.0           1.4          0.2    Setosa
2            4.7          3.2           1.3          0.2    Setosa
3            4.6          3.1           1.5          0.2    Setosa
4            5.0          3.6           1.4          0.2    Setosa
..           ...          ...           ...          ...       ...
145          6.7          3.0           5.2          2.3 Virginica
146          6.3          2.5           5.0          1.9 Virginica
147          6.5          3.0           5.2          2.0 Virginica
148          6.2          3.4           5.4          2.3 Virginica
149          5.9          3.0           5.1          1.8 Virginica

[150 rows x 5 columns]
```

CODE:

```
df['variety'].value_counts()
```

OUTPUT:

```
Setosa        50
Versicolor    50
Virginica     50
Name: variety, dtype: int64
```

CODE:

```
X = df.drop('variety', axis=1)
y = df['variety']
# splitting to trainset and Test set in the ratio 70:30

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30)


print(X_train)
print(" ")
```

print(X_test)

OUTPUT:

```
  sepal.length  sepal.width  petal.length  petal.width
46            5.1          3.8           1.6          0.2
95            5.7          3.0           4.2          1.2
67            5.8          2.7           4.1          1.0
45            4.8          3.0           1.4          0.3
143           6.8          3.2           5.9          2.3
..            ...          ...           ...          ...
116           6.5          3.0           5.5          1.8
41            4.5          2.3           1.3          0.3
62            6.0          2.2           4.0          1.0
91            6.1          3.0           4.6          1.4
123           6.3          2.7           4.9          1.8

[105 rows x 4 columns]

     sepal.length  sepal.width  petal.length  petal.width
25            5.0          3.0           1.6          0.2
141           6.9          3.1           5.1          2.3
125           7.2          3.2           6.0          1.8
102           7.1          3.0           5.9          2.1
128           6.4          2.8           5.6          2.1
122           7.7          2.8           6.7          2.0
76            6.8          2.8           4.8          1.4
103           6.3          2.9           5.6          1.8
14            5.8          4.0           1.2          0.2
37            4.9          3.6           1.4          0.1
100           6.3          3.3           6.0          2.5
63            6.1          2.9           4.7          1.4
64            5.6          2.9           3.6          1.3
61            5.9          3.0           4.2          1.5
17            5.1          3.5           1.4          0.3
74            6.4          2.9           4.3          1.3
111           6.4          2.7           5.3          1.9
120           6.9          3.2           5.7          2.3
79            5.7          2.6           3.5          1.0
85            6.0          3.4           4.5          1.6
49            5.0          3.3           1.4          0.2
21            5.1          3.7           1.5          0.4
110           6.5          3.2           5.1          2.0
149           5.9          3.0           5.1          1.8
72            6.3          2.5           4.9          1.5
11            4.8          3.4           1.6          0.2
36            5.5          3.5           1.3          0.2
6             4.6          3.4           1.4          0.3
68            6.2          2.2           4.5          1.5
144           6.7          3.3           5.7          2.5
43            5.0          3.5           1.6          0.6
80            5.5          2.4           3.8          1.1
32            5.2          4.1           1.5          0.1
7             5.0          3.4           1.5          0.2
55            5.7          2.8           4.5          1.3


129           7.2          3.0           5.8          1.6
117           7.7          3.8           6.7          2.2
```

```
12          4.8          3.0          1.4          0.1
```

CODE:

```
print("Number transactions X_train dataset: ", X_train.shape)
print("Number transactions y_train dataset: ", y_train.shape)
print("Number transactions X_test dataset: ", X_test.shape)
print("Number transactions y_test dataset: ", y_test.shape)
```

OUTPUT:

```
Number transactions X_train dataset: (105, 4)
Number transactions y_train dataset: (105,)
Number transactions X_test dataset: (45, 4)
Number transactions y_test dataset:  (45,)
```

CODE:

```
classifier = KNeighborsClassifier(n_neighbors=5)
classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)
print(y_pred)
print(' ')
print(y_test)
```

OUTPUT:

```
['Setosa' 'Virginica''Virginica''Virginica''Virginica''Virginica'
 'Versicolor''Virginica''Setosa''Setosa''Virginica' 'Versicolor'
'Versicolor''Versicolor''Setosa''Versicolor''Virginica''Virginica
'Versicolor''Versicolor''Setosa''Setosa' 'Virginica''Virginica'
'Virginica''Setosa''Setosa''Setosa''Versicolor''Virginica''Setosa
 'Setosa' 'Virginica' 'Versicolor' 'Setosa' 'Setosa' 'Virginica'
'Versicolor''Virginica''Versicolor''Virginica''Setosa''Virginica'
 'Virginica' 'Setosa']

63     Versicolor
64     Versicolor

61     Versicolor
17         Setosa
74     Versicolor
111     Virginica
120     Virginica
79     Versicolor
85     Versicolor
49         Setosa
21         Setosa
110     Virginica
149     Virginica
72     Versicolor
11         Setosa
36         Setosa
6          Setosa



68     Versicolor
```

```
144     Virginica
43         Setosa
47         Setosa
77     Versicolor
80     Versicolor
32         Setosa
7          Setosa
148     Virginica
88     Versicolor
137     Virginica
55     Versicolor
112     Virginica
29         Setosa
129     Virginica
117     Virginica
12         Setosa
Name: variety, dtype: object
```

CODE:

```
from sklearn.metrics import confusion_matrix
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

OUTPUT:

```
[[15  0  0]
 [ 0 11  2]
 [ 0  0 17]]
              precision    recall  f1-score   support

      Setosa       1.00      1.00      1.00        15
  Versicolor       1.00      0.85      0.92        13
   Virginica       0.89      1.00      0.94        17
accuracy                             0.96        45
macro avg          0.96      0.95      0.95        45
weighted avg       0.96      0.96      0.95        45
```

CODE:

```
weather=['Sunny','Sunny','Overcast','Rainy','Rainy','Rainy',
'Over cast','Sunny','Sunny', 'Rainy','Sunny','Overcast','Over-
cast','Rainy']

# Second Feature
temp=['Hot','Hot','Hot','Mild','Cool','Cool','Cool','Mild',
'Cool'
,'Mild','Mild','Mild','Hot','Mild']

# Label or target varible

play=['No','No','Yes','Yes','Yes','No','Yes','No','Yes','Yes',
'Ye s','Yes','Yes','No']
```

```
 from sklearn import preprocessing
#creating labelEncoder
le = preprocessing.LabelEncoder()
# Converting string labels into numbers.
weather_encoded=le.fit_transform(weather)
print(weather_encoded)
```

OUTPUT:

```
[2 2 0 1 1 1 0 2 2 1 2 0 0 1]
```

CODE:

```
temp_encoded=le.fit_transform(temp) print(temp_en-
coded)
print(" ") la-
bel=le.fit_transform(play)
print(label)
```

OUTPUT:

```
[1 1 1 2 0 0 0 2 0 2 2 2 1 2]

[0 0 1 1 1 0 1 0 1 1 1 1 1 0]
```

CODE:

```
features=list(zip(weather_encoded,temp_encoded))
print(features)
```

OUTPUT:

```
[(2, 1), (2, 1), (0, 1), (1, 2), (1, 0), (1, 0), (0, 0), (2, 2),
(2, 0), (1, 2), (2, 2), (0, 2), (0, 1), (1, 2)]
```

CODE:

```
from sklearn.neighbors import KNeighborsClassifier

model = KNeighborsClassifier(n_neighbors=3)


from sklearn.neighbors import KNeighborsClassifier

model = KNeighborsClassifier(n_neighbors=3)

# Train the model using the training sets
model.fit(features,label)
predicted= model.predict([[0,1]]) # 0:Overcast, 1:Hot
print(predicted)
```

OUTPUT:

```
[1]
```

AIM

5: Program to implement Naïve Bayes Algorithm using any standard dataset available in the public domain and find the accuracy of the algorithm.

CODE:

Dataset used: Social_Network_Ads.csv

```
import pandas as pd
dataset = pd.read_csv("/content/Social_Network_Ads.csv")
print(dataset.describe())
print(dataset.head())
X = dataset.iloc[:, [1, 2, 3]].values
y = dataset.iloc[:, -1].values
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
X[:,0] = le.fit_transform(X[:,0])
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_si ze = 0.20, random_state = 0)
```

OUTPUT:

```
            User ID         Age  EstimatedSalary   Purchased
count  4.000000e+02  400.000000       400.000000  400.000000
mean   1.569154e+07   37.655000     69742.500000    0.357500
std    7.165832e+04   10.482877     34096.960282    0.479864
min    1.556669e+07   18.000000     15000.000000    0.000000
25%    1.562676e+07   29.750000     43000.000000    0.000000
50%    1.569434e+07   37.000000     70000.000000    0.000000
75%    1.575036e+07   46.000000     88000.000000    1.000000
max    1.581524e+07   60.000000    150000.000000    1.000000
    User ID  Gender  Age  EstimatedSalary  Purchased
0  15624510    Male   19            19000          0
1  15810944    Male   35            20000          0
2  15668575  Female   26            43000          0
3  15603246  Female   27            57000          0
4  15804002    Male   19            76000          0
```

CODE:

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

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

OUTPUT:

```
GaussianNB()
```

CODE:

```
y_pred  =  classifier.predict(X_test)


y_pred
```

OUTPUT:

```
array([0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0,
0, 1,
       0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0,
0, 0,
       1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0,
0, 1,
       0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1])
```

CODE:

```
y_pred  =  classifier.predict(X_test)


y_test
```

OUTPUT:

```
array([0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
0, 1,
       0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0,
0, 0,
       1, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1,
0, 1,
       0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1])
```

CODE:

```
from sklearn.metrics import confusion_matrix,accuracy_score
cm = confusion_matrix(y_test, y_pred)
ac = accuracy_score(y_test,y_pred)
print(cm)
print(ac)
```

OUTPUT:

```
[[56  2]
 [ 4 18]]
0.925
```

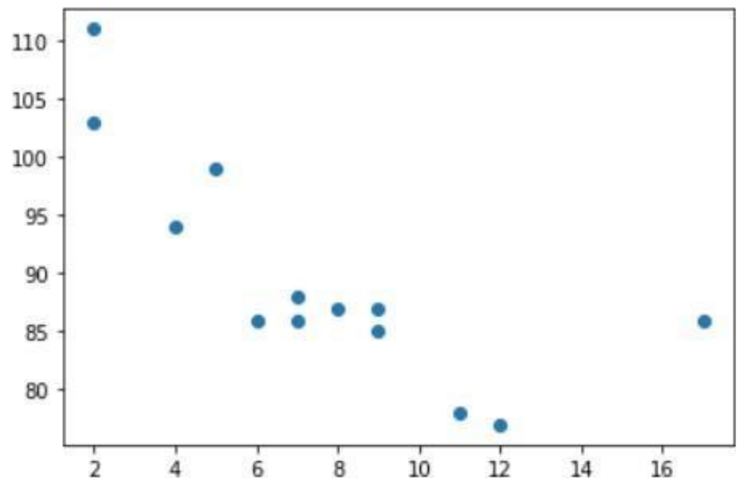
AIM

6: Program to implement linear and multiple regression techniques using any standard dataset available in the public domain and evaluate its performance.

CODE:

```
import matplotlib.pyplot as plt
x = [5,7,8,7,2,17,2,9,4,11,12,9,6]
y = [99,86,87,88,111,86,103,87,94,78,77,85,86]

plt.scatter(x, y)
plt.show()
```

OUTPUT:



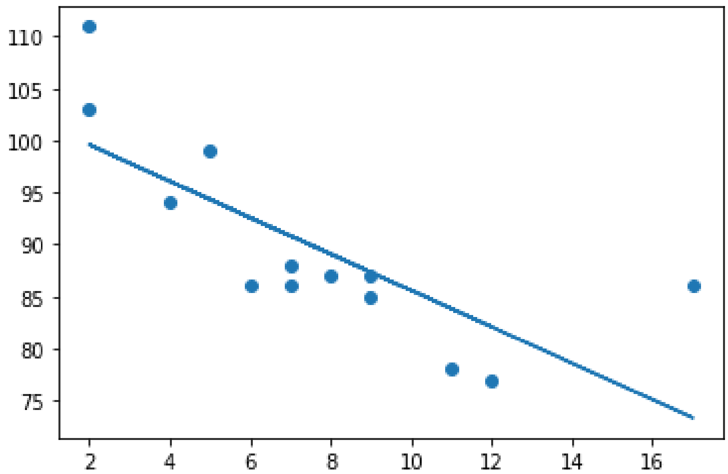
CODE:

```
import matplotlib.pyplot as plt
from scipy import stats

x = [5,7,8,7,2,17,2,9,4,11,12,9,6]
y = [99,86,87,88,111,86,103,87,94,78,77,85,86]

+slope, intercept, r, p, std_err = stats.linregress(x, y) # r
corre lation coefficiant # p probability of hypothesis

def myfunc(x):
```

```
return slope * x + intercept

mymodel = list(map(myfunc, x))


plt.scatter(x, y)
plt.plot(x, mymodel)
plt.show()
```

OUTPUT:

-0.758591524376155



CODE:

```
import pandas
import warnings
warnings.filterwarnings("ignore")

df = pandas.read_csv("cars1.csv")


X = df[['Weight', 'Volume']]
y = df['CO2']
```

```
from sklearn import linear_model
regr = linear_model.LinearRegression()
regr.fit(X, y)
```

OUTPUT:

```
LinearRegression()
```

CODE:

```
predictedCO2 = regr.predict([[2300, 1000]])
print(predictedCO2)
```

OUTPUT:

```
[104.86715554]
```

AIM

7. Program to implement text classification using Support vector machine.

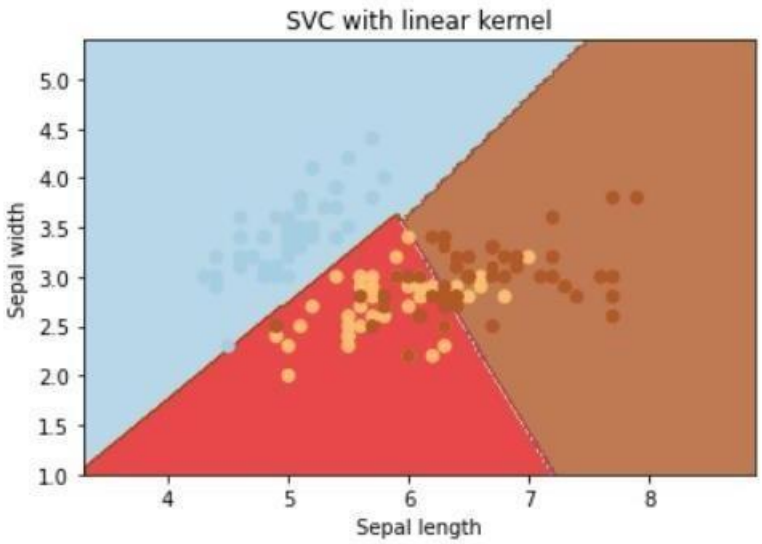
CODE:

Dataset used: iris.csv

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn import svm, datasets

# import some data to play with
iris = datasets.load_iris()
X = iris.data[:, :2] # we only take the first two features.
We could
 # avoid this ugly slicing by using a two-dim dataset
y = iris.target

# we create an instance of SVM and fit out data. We do not
scale our
# data since we want to plot the support vectors
C = 1.0 # SVM regularization parameter

svc = svm.SVC(kernel='linear', C=1,gamma='auto').fit(X, y)

# create a mesh to plot in
#x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
#y_min, y_))max = X[:, 1].min() - 1, X[:, 1].max() + 1
#h = (x_max / x_min)/100
#xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
#np.arange(y_min, y_max, h


plt.subplot(1, 1, 1)
Z = svc.predict(np.c_ravel[xx.(), yy.ravel()])
Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, cmap=plt.cm.Paired, alpha=0.8)

plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.Paired)
plt.xlabel('Sepal length')
plt.ylabel('Sepal width')
plt.xlim(xx.min(), xx.max())
```

```
plt.title('SVC with linear kernel')
plt.show()
```

OUTPUT:



CODE:

Dataset used: True.csv, Fake.csv

```
 #Importing Libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.metrics import accuracy_score, confusion_matrix,class
ification_report

from sklearn.svm import LinearSVC

import csv
true = pd.read_csv("True.csv")
fake = pd.read_csv("Fake.csv")
```

```
 fake['target'] = 'fake'
true['target'] = 'true'
#News dataset
news = pd.concat([fake, true]).reset_index(drop = True)
news.head()
news.dropna()
```

OUTPUT:

	title	text	subject	date	target
0	you were wrong! 70-year-old men don t change ...	News	"December 31	2017"	fake
165	look at me! I m violating the U.S. flag code ...	News	"October 29	2017"	fake
277	particularly those where people are dying. Ob...	News	"September 29	2017"	fake
294	utterly and completely misunderstanding it. T...	News	"September 25	2017"	fake
379	I salute you.Featured image via David Becker/...	News	"September 10	2017"	fake
...	...	...	...	...	...
39998	rescuers pulled Maria s body from the rubble....	worldnews	"September 21	2017 "	true
40742	adding she had a Spanish passport but chose t...	worldnews	"September 14	2017 "	true
40788	adding the Rohingya belong in camps for displ...	worldnews	"September 14	2017 "	true
40824	said Reick. "	worldnews	"September 14	2017 "	true
41394	in general. "	worldnews	"September 7	2017 "	true

236 rows × 5 columns

CODE:

```
#Train-test split
x_train,x_test,y_train,y_test = train_test_split(news['text'], new
s.target, test_size=0.2, random_state=1)


#Term frequency(TF)=count(word)/total(words)6+    0ZXCVBNM,./
#TF-
IDF: we can even reduce the weightage of more common words like (t
he, is, an etc.) which occurs in all document.
#This is called as TF-
IDF i.e Term Frequency times inverse document frequency.
#count vectorizer : involves counting the number of occurrences ea
ch word appears in a document
```

```
pipe2 = Pipeline([('vect', CountVectorizer()), ('tfidf', TfidfTran
sformer()), ('model', LinearSVC())])


model_svc = pipe2.fit(x_train.astype('U'), y_train.astype('U'))
svc_pred = model_svc.predict(x_test.astype('U'))

print("Accuracy of SVM Classifier: {}%".format(round(accuracy_scor
e(y_test, svc_pred)*100,2)))
print("\nConfusion Matrix of SVM Classifier:\n")
print(confusion_matrix(y_test, svc_pred))
print("\nClassification Report of SVM Classifier:\n")
print(classification_report(y_test, svc_pred))
```

OUTPUT:

```
Accuracy of SVM Classifier: 51.43%

Confusion Matrix of SVM Classifier:

[[4302    3]
 [4085   26]]

Classification Report of SVM Classifier:

              precision    recall  f1-score   support

        fake       0.51      1.00      0.68      4305
        true       0.90      0.01      0.01      4111

    accuracy                           0.51      8416
   macro avg       0.70      0.50      0.35      8416
weighted avg       0.70      0.51      0.35      8416
```

AIM

8. Program to implement decision trees using any standard dataset available in the public domain and find the accuracy of the algorithm.

CODE:

Dataset used: iris

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris

data=load_iris()
X=data.data
y=data.target
print(X.shape,y.shape)
```

OUTPUT:

```
(150, 4) (150,)
```

CODE:

```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier#for checking testi
ng results
from sklearn.metrics import classification_report, confusion_matri
x#for visualizing tree
from sklearn.tree import plot_tree
X_train, X_test, y_train, y_test = train_test_split(X , y, test_si
ze = 25, random_state = 10)

clf=DecisionTreeClassifier()
clf.fit(X_train,y_train)
```

OUTPUT:

```
DecisionTreeClassifier()
```

CODE:

```
y_pred =clf.predict(X_test)
print("Classification report - \n", classification_report(y_test,y
_pred))
```

OUTPUT:

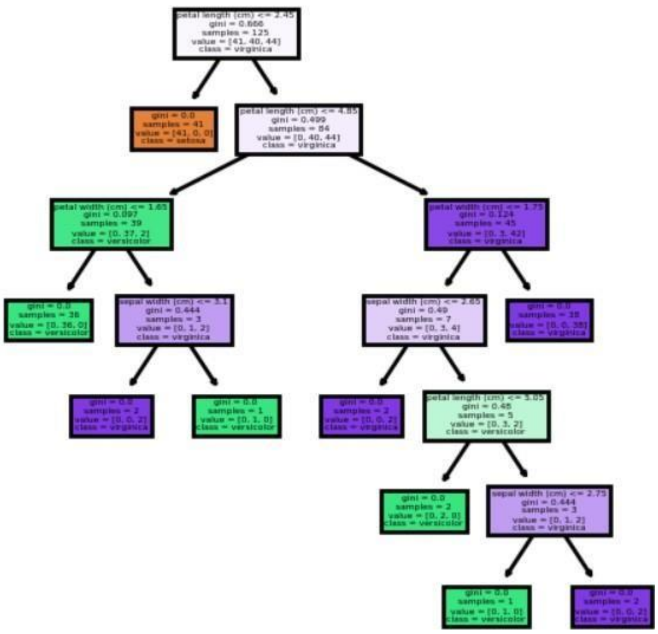
```
Classification report -
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         9
           1       1.00      0.90      0.95        10
           2       0.86      1.00      0.92         6

    accuracy                           0.96        25
   macro avg       0.95      0.97      0.96        25
weighted avg       0.97      0.96      0.96        25
```

CODE:

```
cm = confusion_matrix(y_test, y_pred)
print(cm)
from sklearn import tree
fig,axes = plt.subplots(nrows=1,ncols=1,figsize =(3,3),dpi=200)
tree.plot_tree(clf,feature_names=data.feature_names,class_names=da
ta.target_names,filled=True)
plt.show() fig.savefig("/con-
tent/iris_tree.png")
```

OUTPUT:

```
[[9 0 0]
 [0 9 1]
 [0 0 6]]
```



AIM

9. Program to implement k-means clustering technique using any standard dataset available in the public domain.

CODE:

Dataset used: GENERAL.csv

```
# importing the libraries
import numpy as  np
import pandas as pd
%matplotlib inline
import matplotlib.pyplot as plt da-

taset= pd.read_csv('./CC GENERAL.csv')

# checking the presence of null values
print(dataset.isnull().sum())
 #CREDIT_LIMIT                           1
 #MINIMUM_PAYMENTS                     313
```

OUTPUT:

```
CUST_ID                              0
BALANCE                              0
BALANCE_FREQUENCY                    0
PURCHASES                            0
ONEOFF_PURCHASES                     0
INSTALLMENTS_PURCHASES               0
CASH_ADVANCE                         0
PURCHASES_FREQUENCY                  0
ONEOFF_PURCHASES_FREQUENCY           0
PURCHASES_INSTALLMENTS_FREQUENCY     0
CASH_ADVANCE_FREQUENCY               0
CASH_ADVANCE_TRX                     0
PURCHASES_TRX                        0
CREDIT_LIMIT                         1
PAYMENTS                             0
MINIMUM_PAYMENTS                   313
PRC_FULL_PAYMENT                     0
TENURE                               0
dtype: int64
```

CODE:

```
dataset['CREDIT_LIMIT'].fillna(dataset.CREDIT_LIMIT.mean(), inplac
e = True) dataset['MINIMUM_PAYMENTS'].fillna(dataset.MINIMUM_PAY-
MENTS.mean()
, inplace = True) # unfilled vaues replaced using mean

print(dataset.isnull().sum()) print(dataset.de-

scribe())
```

OUTPUT:

```
CUST_ID                             0
BALANCE                             0
BALANCE_FREQUENCY                   0
PURCHASES                           0
ONEOFF_PURCHASES                    0
INSTALLMENTS_PURCHASES              0
CASH_ADVANCE                        0
PURCHASES_FREQUENCY                 0
ONEOFF_PURCHASES_FREQUENCY          0
PURCHASES_INSTALLMENTS_FREQUENCY    0
CASH_ADVANCE_FREQUENCY              0
CASH_ADVANCE_TRX                    0
PURCHASES_TRX                       0
CREDIT_LIMIT                        0
PAYMENTS                            0
MINIMUM_PAYMENTS                    0
PRC_FULL_PAYMENT                    0
TENURE                              0
dtype: int64
            BALANCE  BALANCE_FREQUENCY  ...  PRC_FULL_PAYMENT       TENURE
count   8950.000000        8950.000000  ...       8950.000000  8950.000000
mean    1564.474828           0.877271  ...          0.153715    11.517318
std     2081.531879           0.236904  ...          0.292499     1.338331
min        0.000000           0.000000  ...          0.000000     6.000000
25%      128.281915           0.888889  ...          0.000000    12.000000
50%      873.385231           1.000000  ...          0.000000    12.000000
75%     2054.140036           1.000000  ...          0.142857    12.000000
max    19043.138560           1.000000  ...          1.000000    12.000000
```

CODE:

```
dataset.drop(['CUST_ID'], axis= 1, inplace = True) #no relevance f
or custid

# No Categorical Values found
X = dataset.iloc[:,:].values
```

```
# Using standard scaler
from sklearn.preprocessing import StandardScaler
standardscaler= StandardScaler()
X = standardscaler.fit_transform(X) #scaling the values
print(X)
```

OUTPUT:

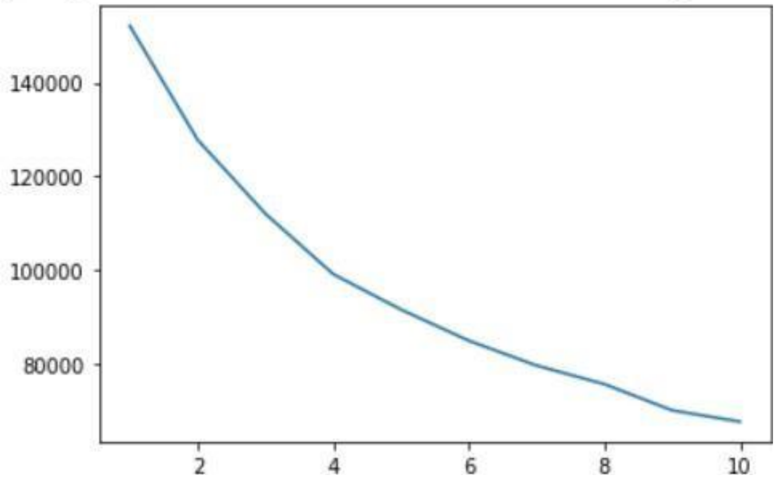
```
[[-0.73198937 -0.24943448 -0.42489974 ... -0.31096755 -0.52555097
   0.36067954]
 [ 0.78696085  0.13432467 -0.46955188 ...  0.08931021  0.2342269
   0.36067954]
 [ 0.44713513  0.51808382 -0.10766823 ... -0.10166318 -0.52555097
   0.36067954]
 ...
 [-0.7403981  -0.18547673 -0.40196519 ... -0.33546549  0.32919999
  -4.12276757]
 [-0.74517423 -0.18547673 -0.46955188 ... -0.34690648  0.32919999
  -4.12276757]
 [-0.57257511 -0.88903307  0.04214581 ... -0.33294642 -0.52555097
  -4.12276757]]
```

CODE:

```
"""K MEANS CLUSTERING """
#Inertia, or the within-
cluster sum of squares criterion, can be recognized as a measure o
f how internally coherent clusters are
from sklearn.cluster import KMeans
wss= []
for i in range(1, 11):
    kmeans= KMeans(n_clusters = i, init = 'k-
means++', random_state = 0)
    kmeans.fit(X) wss.ap-
    pend(kmeans.inertia_)
plt.plot(range(1,11), wss) # selecting 4
```

OUTPUT:

[<matplotlib.lines.Line2D at 0x7f74661e8a90>]



CODE:

```
wss_mean=np.array(wss).mean()
print(wss)
print(wss_mean)
print([abs(wss_mean-x) for x in wss])
k=np.argmin([abs(wss_mean-x) for x in wss])+1
```

OUTPUT:

```
[152149.99999999983, 127784.92103208725, 111986.41162208859,
99073.93826774803, 91502.98328256077, 84851.13240432573,
79532.40237691796, 75568.97609993909, 69954.91393943134,
67546.56302862825]
95995.22420537268
[56154.775794627145, 31789.69682671457, 15991.187416715911,

3078.714062375351, 4492.240922811907, 11144.091801046947,

16462.82182845472, 20426.248105433595, 26040.31026594134,

28448.661176744426]
```

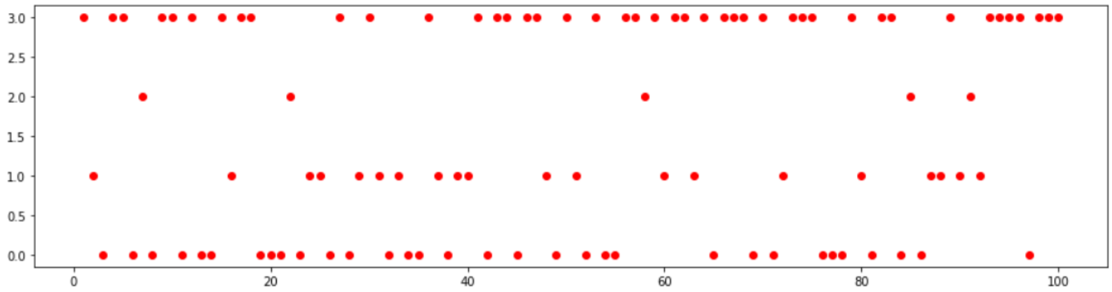
CODE:

```
kmeans = KMeans(n_clusters = k, init= 'k-
means++', random_state =  0)
kmeans.fit(X)

Y_pred_K= kmeans.predict(X)
print(Y_pred_K)
```

```
#showing the clusters of first 100 persons
plt.figure(figsize=(16,4))
plt.plot(range(1,100+1),Y_pred_K[:100],'ro')
```

OUTPUT:

```
[3 1 0 ... 0 3 3]
[<matplotlib.lines.Line2D at 0x7f745836e290>]
```



AIM

10:Programs on feedforward network to classify any standard dataset available in the public domain.

Dataset used: HR_comma_sep.csv

CODE:

```
import numpy as np
import pandas as pd

# Load data
data=pd.read_csv('HR_comma_sep.csv')
data.head()
```

OUTPUT:

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_spend_company	Work_accident	left	promotion_last_5years	sales	salary
0	0.38	0.53	2	157	3	0	1	0	sales	low
1	0.80	0.86	5	262	6	0	1	0	sales	medium
2	0.11	0.88	7	272	4	0	1	0	sales	medium
3	0.72	0.87	5	223	5	0	1	0	sales	low
4	0.37	0.52	2	159	3	0	1	0	sales	low

CODE:

```
from sklearn import preprocessing
# Creating labelEncoder
le = preprocessing.LabelEncoder()
# Converting string labels into numbers.
data['salary']=le.fit_transform(data['salary'])
data['sales']=le.fit_transform(data['sales'])
```

```
X=data[['satisfaction_level', 'last_evaluation', 'number_project', 'average_montly_hour
s', 'time_spend_company', 'Work_accident', 'promotion_last_5years', 'sales', 'salary']]

y=data['left']
# Import train_test_split function
from sklearn.model_selection import train_test_split
# Split dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42
) # 70% training and 30% test

from sklearn.neural_network import MLPClassifier
# Create model object
clf = MLPClassifier(hidden_layer_sizes=(6,5),
                    random_state=5,
                    verbose=False,
                    learning_rate_init=0.01)
# Fit data onto the model
clf.fit(X_train,y_train)
```

OUTPUT:

```
MLPClassifier(hidden_layer_sizes=(6, 5), learning_rate_init=0.01,
              random_state=5)
```

CODE:

```
ypred=clf.predict(X_test)
# Import accuracy score
from sklearn.metrics import accuracy_score
# Calcuate accuracy
accuracy_score(y_test,ypred)
```

OUTPUT:

```
0.9386666666666666
```

Aim:

11:Programs on convolutional neural network to classify images from any standard dataset in the public domain.

CODE:

```
import numpy as np
import pandas as pd

# Load data
data=pd.read_csv('HR_comma_sep.csv')

data.head()
```

Output:

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_spend_company	Work_accident	left	promotion_last_5years	sales	salary
0	0.38	0.53	2	157	3	0	1	0	sales	low
1	0.80	0.86	5	262	6	0	1	0	sales	medium
2	0.11	0.88	7	272	4	0	1	0	sales	medium
3	0.72	0.87	5	223	5	0	1	0	sales	low
4	0.37	0.52	2	159	3	0	1	0	sales	low

CODE:

```
from sklearn import preprocessing

# Creating labelEncoder
le = preprocessing.LabelEncoder()

# Converting string labels into numbers.
data['salary']=le.fit_transform(data['salary'])
data['sales']=le.fit_transform(data['sales'])

X=data[['satisfaction_level', 'last_evaluation', 'number_project', 'average_montly_hours',
```

```
'time_spend_company', 'Work_accident', 'promotion_last_5years', 'sales', 'salary']]
y=data['left']

# Import train_test_split function
from sklearn.model_selection import train_test_split

# Split dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)  #
70% training and 30% test

from sklearn.neural_network import MLPClassifier

# Create model object
clf = MLPClassifier(hidden_layer_sizes=(6,5),
                random_state=5,
                verbose=False,
                learning_rate_init=0.01)

# Fit data onto the model
clf.fit(X_train,y_train)

ypred=clf.predict(X_test)
```

OUTPUT:

```
MLPClassifier(hidden_layer_sizes=(6, 5), learning_rate_init=0.01,
              random_state=5)
```

CODE:

```
# Import accuracy score
from sklearn.metrics import accuracy_score
# Calcuate accuracy
print ("Accuracy:",accuracy_score(y_test,ypred))
```

OUTPUT:

```
Accuracy: 0.9386666666666666
```

CODE:

```
from sklearn.metrics import classification_report, confusion_matrix
print(confusion_matrix(y_test, ypred))
print(classification_report(y_test, ypred))
```

OUTPUT:

```
[[3248  180]
 [  96  976]]
              precision    recall  f1-score   support

           0       0.97      0.95      0.96      3428
           1       0.84      0.91      0.88      1072

    accuracy                           0.94      4500
   macro avg       0.91      0.93      0.92      4500
weighted avg       0.94      0.94      0.94      4500
```