import pandas as pd import numpy as np

import matplotlib.pyplot as plt

df= pd.read_csv('Almond.csv')

ur=	pu.reau_csv(ATIIIOIIU.CSV
df		

→	Unnamed: 0	Length (major axis)	Width (minor axis)	Thickness (depth)	Area	Perimeter	Roundness	Solidity	Compactness	Aspect Ratio	Eccentricity	Extent	Convex hull(convex area)	Туре
	0 0	NaN	227.940628	127.759132	22619.0	643.813269	NaN	0.973384	1.458265	NaN	NaN	0.681193	23237.5	MAMRA
	1 1	NaN	234.188126	128.199509	23038.0	680.984841	NaN	0.957304	1.601844	NaN	NaN	0.656353	24065.5	MAMRA
	2 2	NaN	229.418610	125.796547	22386.5	646.943212	NaN	0.967270	1.487772	NaN	NaN	0.683620	23144.0	MAMRA
	3 3	NaN	232.763153	125.918808	22578.5	661.227483	NaN	0.965512	1.540979	NaN	NaN	0.685360	23385.0	MAMRA
	4 4	NaN	230.150742	107.253448	19068.0	624.842706	NaN	0.951450	1.629395	NaN	NaN	0.714800	20041.0	MAMRA
2	2798 2798	NaN	192.709366	122.356506	18471.5	653.345233	NaN	0.931000	1.838965	NaN	NaN	0.725739	19840.5	SANORA
2	2799 2799	NaN	186.254745	118.708961	17213.5	581.688379	NaN	0.952706	1.564234	NaN	NaN	0.714016	18068.0	SANORA
2	2800 2800	NaN	186.196182	119.147224	17510.5	608.315795	NaN	0.948821	1.681705	NaN	NaN	0.718999	18455.0	SANORA
2	2801 2801	NaN	188.660828	120.634438	17941.0	630.759446	NaN	0.944810	1.764701	NaN	NaN	0.738191	18989.0	SANORA
2	2802 2802	269.356903	176.023636	NaN	36683.5	887.310743	0.643761	0.947380	1.707933	1.530231	0.75693	0.722429	38721.0	SANORA

2803 rows × 14 columns

df.isnull().sum()

→	Unnamed: 0 Length (major axis) Width (minor axis) Thickness (depth) Area Perimeter Roundness Solidity	0 857 942 1004 0 0 857
	Aspect Ratio Eccentricity	1799 1799
	Extent	0
	Convex hull(convex area)	0
	Type dtype: int64	0
	acype. Inco-	

df

→	Unnamed: 0	Length (major axis)	Width (minor axis)	Thickness (depth)	Area	Perimeter	Roundness	Solidity	Compactness	Aspect Ratio	Eccentricity	Extent	Convex hull(convex area)	Туре
0	0	NaN	227.940628	127.759132	22619.0	643.813269	NaN	0.973384	1.458265	NaN	NaN	0.681193	23237.5	MAMRA
1	1	NaN	234.188126	128.199509	23038.0	680.984841	NaN	0.957304	1.601844	NaN	NaN	0.656353	24065.5	MAMRA
2	2	NaN	229.418610	125.796547	22386.5	646.943212	NaN	0.967270	1.487772	NaN	NaN	0.683620	23144.0	MAMRA
3	3	NaN	232.763153	125.918808	22578.5	661.227483	NaN	0.965512	1.540979	NaN	NaN	0.685360	23385.0	MAMRA
4	4	NaN	230.150742	107.253448	19068.0	624.842706	NaN	0.951450	1.629395	NaN	NaN	0.714800	20041.0	MAMRA
2798	2798	NaN	192.709366	122.356506	18471.5	653.345233	NaN	0.931000	1.838965	NaN	NaN	0.725739	19840.5	SANORA
2799	2799	NaN	186.254745	118.708961	17213.5	581.688379	NaN	0.952706	1.564234	NaN	NaN	0.714016	18068.0	SANORA
2800	2800	NaN	186.196182	119.147224	17510.5	608.315795	NaN	0.948821	1.681705	NaN	NaN	0.718999	18455.0	SANORA
2801	2801	NaN	188.660828	120.634438	17941.0	630.759446	NaN	0.944810	1.764701	NaN	NaN	0.738191	18989.0	SANORA
2802	2802	269.356903	176.023636	NaN	36683.5	887.310743	0.643761	0.947380	1.707933	1.530231	0.75693	0.722429	38721.0	SANORA

2803 rows × 14 columns

df.fillna(method= 'ffill', inplace=True) df.fillna(method= 'bfill', inplace=True)

→		Unnamed:	Length (major axis)	Width (minor axis)	Thickness (depth)	Area	Perimeter	Roundness	Solidity	Compactness	Aspect Ratio	Eccentricity	Extent	Convex hull(convex area)	Туре
	0	0	413.477173	227.940628	127.759132	22619.0	643.813269	0.309009	0.973384	1.458265	1.866195	0.844313	0.681193	23237.5	MAMRA
	1	1	413.477173	234.188126	128.199509	23038.0	680.984841	0.309009	0.957304	1.601844	1.866195	0.844313	0.656353	24065.5	MAMRA
	2	2	413.477173	229.418610	125.796547	22386.5	646.943212	0.309009	0.967270	1.487772	1.866195	0.844313	0.683620	23144.0	MAMRA
	3	3	413.477173	232.763153	125.918808	22578.5	661.227483	0.309009	0.965512	1.540979	1.866195	0.844313	0.685360	23385.0	MAMRA
4	4	4	413.477173	230.150742	107.253448	19068.0	624.842706	0.309009	0.951450	1.629395	1.866195	0.844313	0.714800	20041.0	MAMRA
	•••														
2	2798	2798	269.356903	192.709366	122.356506	18471.5	653.345233	0.643761	0.931000	1.838965	1.530231	0.756930	0.725739	19840.5	SANORA
2	799	2799	269.356903	186.254745	118.708961	17213.5	581.688379	0.643761	0.952706	1.564234	1.530231	0.756930	0.714016	18068.0	SANORA
2	2800	2800	269.356903	186.196182	119.147224	17510.5	608.315795	0.643761	0.948821	1.681705	1.530231	0.756930	0.718999	18455.0	SANORA
2	2801	2801	269.356903	188.660828	120.634438	17941.0	630.759446	0.643761	0.944810	1.764701	1.530231	0.756930	0.738191	18989.0	SANORA
2	2802	2802	269.356903	176.023636	NaN	36683.5	887.310743	0.643761	0.947380	1.707933	1.530231	0.756930	0.722429	38721.0	SANORA

df.isnull().sum()

Unnamed: 0
Length (major axis)

2803 rows × 14 columns

Width (minor axis) 0 Thickness (depth) 1 0 Area Perimeter 0 Roundness Solidity 0 Compactness 0 Aspect Ratio 0 Eccentricity Extent Convex hull(convex area) Type

df['Type'].value_counts()

dtype: int64

Type

SANORA 943 933 MAMRA REGULAR 927

Name: count, dtype: int64

from sklearn.preprocessing import LabelEncoder le= LabelEncoder()

df[['Type']] = df[['Type']].apply(le.fit_transform)

 \rightarrow Unnamed: Length (major Width (minor Thickness Aspect Convex hull(convex Perimeter Roundness Solidity Compactness Eccentricity Extent Type (depth) Ratio 0 axis) axis) area) 0 0 413.477173 227.940628 127.759132 22619.0 643.813269 0.309009 0.973384 0.844313 0.681193 23237.5 1.458265 1.866195 0 1 1 413.477173 234.188126 128.199509 23038.0 680.984841 0.309009 0.957304 1.601844 1.866195 0.844313 0.656353 24065.5 2 2 413.477173 229.418610 125.796547 22386.5 646.943212 0.309009 0.967270 1.487772 1.866195 0.844313 0.683620 23144.0 0 3 3 413.477173 232.763153 125.918808 22578.5 661.227483 0.309009 0.965512 1.540979 1.866195 0.844313 0.685360 23385.0 230.150742 1.629395 20041.0 4 413.477173 107.253448 19068.0 624.842706 0.309009 0.951450 1.866195 0.844313 0.714800 0 ••• 2798 2798 1.530231 19840.5 2 269.356903 192.709366 122.356506 18471.5 653.345233 0.643761 0.931000 1.838965 0.756930 0.725739 2799 2799 269.356903 186.254745 118.708961 17213.5 581.688379 0.643761 0.952706 1.564234 1.530231 0.756930 0.714016 18068.0 2 2800 2800 269.356903 186.196182 119.147224 17510.5 608.315795 0.643761 0.948821 1.681705 1.530231 0.756930 0.718999 18455.0

0.643761 0.944810

0.643761 0.947380

1.530231

1.530231

1.764701

1.707933

0.756930 0.738191

0.756930 0.722429

120.634438 17941.0 630.759446

NaN 36683.5 887.310743

2

2

18989.0

38721.0

2803 rows × 14 columns

2801

2802

df.info()

2801

2802

<class 'pandas.core.frame.DataFrame'> RangeIndex: 2803 entries, 0 to 2802 Data columns (total 14 columns):

#	Column	Non-Null Count	Dtype
0	Unnamed: 0	2803 non-null	int64
1	Length (major axis)	2803 non-null	float64
2	Width (minor axis)	2803 non-null	float64
3	Thickness (depth)	2802 non-null	float64
4	Area	2803 non-null	float64
5	Perimeter	2803 non-null	float64
6	Roundness	2803 non-null	float64
7	Solidity	2803 non-null	float64
8	Compactness	2803 non-null	float64
9	Aspect Ratio	2803 non-null	float64
10	Eccentricity	2803 non-null	float64
11	Extent	2803 non-null	float64
12	Convex hull(convex area)	2803 non-null	float64
13	Type	2803 non-null	int64

269.356903

269.356903

188.660828

176.023636

dtypes: float64(12), int64(2)

memory usage: 306.7 KB

df.corr()

 $\overline{\Rightarrow}$

Width Convex Aspect Eccentricity Unnamed: Length Thickness Area Perimeter Roundness Solidity Compactness (minor Extent hull(convex Type Ratio 0 (major axis) (depth) axis) area) Unnamed: 0 1.000000 -0.271307 -0.227617 0.014135 -0.146780 -0.223352 0.193454 0.177853 -0.166339 -0.174979 -0.162643 0.148692 -0.162780 0.122121 Length (major -0.271307 1.000000 0.504808 0.233239 0.583955 0.589105 -0.353089 -0.120866 0.180317 0.450424 0.432509 0.024755 0.600393 -0.233531 axis) Width (minor -0.227617 0.504808 1.000000 0.391034 0.431200 0.408250 -0.085867 -0.059936 0.106454 -0.045443 -0.048985 -0.034261 0.438680 0.110846 axis) **Thickness** 0.014135 0.233239 0.391034 1.000000 0.328950 0.271804 -0.039865 -0.155422 -0.167686 0.104291 0.327973 0.371933 (depth) 0.793905 0.133940 Area -0.146780 0.583955 0.431200 0.328950 1.000000 0.187532 0.142245 -0.011408 0.137784 0.303895 0.996626 -0.013641 0.589105 0.271804 0.793905 1.000000 -0.114868 -0.377505 Perimeter -0.223352 0.408250 0.561668 0.265586 0.251929 -0.104688 0.834600 -0.123801 Roundness 0.193454 -0.353089 -0.085867 0.220537 0.187532 -0.114868 1.000000 0.364748 -0.391963 -0.433389 -0.445386 0.291055 0.157489 0.326783 0.177853 -0.120866 -0.059936 0.063740 0.142245 -0.377505 0.364748 1.000000 -0.866622 -0.276955 -0.266199 0.774073 0.067954 0.277235 Solidity 0.056435 -0.209883 0.180317 -0.039865 -0.011408 0.561668 -0.391963 -0.866622 1.000000 0.256966 Compactness -0.166339 0.106454 0.245431 -0.615750 -0.433389 -0.276955 **Aspect Ratio** -0.174979 0.450424 -0.045443 -0.155422 0.137784 0.265586 0.256966 1.000000 0.965195 -0.148093 0.160826 -0.547632 -0.445386 -0.266199 **Eccentricity** -0.162643 0.432509 -0.048985 -0.167686 0.133940 0.251929 0.245431 0.965195 1.000000 -0.147774 0.155461 -0.544794 0.148692 0.024755 -0.034261 0.104291 0.303895 -0.104688 0.291055 0.774073 -0.615750 -0.148093 -0.147774 1.000000 0.248131 0.191447 Extent Convex -0.162780 0.600393 0.438680 0.327973 0.996626 0.834600 0.157489 0.067954 0.160826 0.248131 -0.034985 0.056435 0.155461 1.000000 hull(convex area) 0.122121 0.110846 0.326783 0.277235 -0.547632 -0.544794 0.191447 -0.233531 0.371933 -0.013641 -0.123801 -0.209883 -0.034985 1.000000 Type

```
X= df.drop(['Length (major axis)','Area','Perimeter','Compactness', 'Aspect Ratio', 'Eccentricity','Convex hull(convex area)','Type'], axis=1)
# X= df.drop(['Type'], axis=1)
```

→		Unnamed: 0	Width (minor axis)	Thickness (depth)	Roundness	Solidity	Extent
	0	0	227.940628	127.759132	0.309009	0.973384	0.681193
	1	1	234.188126	128.199509	0.309009	0.957304	0.656353
	2	2	229.418610	125.796547	0.309009	0.967270	0.683620
	3	3	232.763153	125.918808	0.309009	0.965512	0.685360
	4	4	230.150742	107.253448	0.309009	0.951450	0.714800
	•••						
	2798	2798	192.709366	122.356506	0.643761	0.931000	0.725739
	2799	2799	186.254745	118.708961	0.643761	0.952706	0.714016
	2800	2800	186.196182	119.147224	0.643761	0.948821	0.718999
	2801	2801	188.660828	120.634438	0.643761	0.944810	0.738191
	2802	2802	176.023636	NaN	0.643761	0.947380	0.722429

2803 rows × 6 columns

X.isnull().sum()

→ Unnamed: 0 Width (minor axis) 0 Thickness (depth) 1 Roundness 0 Solidity 0 Extent dtype: int64

X.fillna(method= 'ffill', inplace=True)

Χ

₹		Unnamed: 0	Width (minor axis)	Thickness (depth)	Roundness	Solidity	Extent
	0	0	227.940628	127.759132	0.309009	0.973384	0.681193
	1	1	234.188126	128.199509	0.309009	0.957304	0.656353
	2	2	229.418610	125.796547	0.309009	0.967270	0.683620
	3	3	232.763153	125.918808	0.309009	0.965512	0.685360
	4	4	230.150742	107.253448	0.309009	0.951450	0.714800
	2798	2798	192.709366	122.356506	0.643761	0.931000	0.725739
	2799	2799	186.254745	118.708961	0.643761	0.952706	0.714016
	2800	2800	186.196182	119.147224	0.643761	0.948821	0.718999
	2801	2801	188.660828	120.634438	0.643761	0.944810	0.738191
	2802	2802	176.023636	120.634438	0.643761	0.947380	0.722429

2803 rows × 6 columns

```
y= df.iloc[:, -1]
     2798
     2799
     2800
     2801
            2
     2802
     Name: Type, Length: 2803, dtype: int64
```

Logistic Regression

Splitting dataset into Train Set and Test Set

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)
print(y_test)
     855
     615
     70
     352
     118
     2787
     1897
     2694
            2
     564
     402
     Name: Type, Length: 561, dtype: int64
```

X_train[0:5]

```
\overline{\Rightarrow}
            Unnamed: 0 Width (minor axis) Thickness (depth) Roundness Solidity
                                                                                       Extent
     2119
                                 172.156586
                  2119
                                                    105.236511
                                                                 0.541884 0.933814 0.710378
     1203
                  1203
                                 165.031189
                                                    108.674545
                                                                 0.426295 0.956497 0.796875
      452
                   452
                                 153.442551
                                                    132.210663
                                                                 0.594944 0.988031 0.774955
                                                    122.900238
     1761
                  1761
                                150.679047
                                                                 0.632317  0.963890  0.765059
     2682
                  2682
                                                     92.374199
                                                                 0.371370 0.975980 0.727930
                                118.663330
```

Feature Scaling

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
X_train[0:5]
\rightarrow array([[ 0.88961693, 0.00960225, -0.24339255, 0.5542151 , -0.54119414,
             -0.28631389],
           [-0.24535291, -0.22059267, -0.06745256, -0.42017207, 0.02910683,
             1.52632102],
           [-1.17587949, -0.59497823, 1.13699867, 1.00149852, 0.82193723,
             1.06696055],
            [0.44603702, -0.68425671, 0.66054147, 1.31654295, 0.21497291,
             0.85959545],
           [ 1.58720211, -1.71856478, -0.90161614, -0.88317757, 0.51895547,
              0.08152341]])
print(X_test)
→ [[-0.67654233 -0.48215625 0.16229978 0.8714193 0.8610247 1.0706117 ]
      [-0.97391434 -0.52223048 -1.67204926 -0.902931
                                                      0.47588334 -0.19336168]
      [-1.64919661 -1.95678771 -0.25245836  0.86083389  0.53098569 -0.7701934 ]
      [ 1.60207071 -1.05693271 -1.2699571 -0.85644468 -0.29110361 -0.60238411]
      [-1.03710589 1.85189513 0.68008489 -0.17034588 0.6053302 -0.48801446]
      [-1.237832 -0.4944249 1.31926755 0.99855937 0.76822769 1.18250853]]
```

Training Logistic Regression model

```
y_train
     2119
     1203
             0
     452
     1761
             1
     2682
             2
     763
     835
     1653
     2607
     2732
     Name: Type, Length: 2242, dtype: int64
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state = 0)
classifier.fit(X_train, y_train)
\overline{\Rightarrow}
               LogisticRegression
      LogisticRegression(random_state=0)
y_pred.shape
→ (561,)
```

Predict Test results

Making Confusion Metrix

KNN model

→		Unnamed: 0	Width (minor axis)	Thickness (depth)	Roundness	Solidity	Extent
	0	0	227.940628	127.759132	0.309009	0.973384	0.681193
	1	1	234.188126	128.199509	0.309009	0.957304	0.656353
	2	2	229.418610	125.796547	0.309009	0.967270	0.683620
	3	3	232.763153	125.918808	0.309009	0.965512	0.685360
	4	4	230.150742	107.253448	0.309009	0.951450	0.714800
	•••						
;	2798	2798	192.709366	122.356506	0.643761	0.931000	0.725739
:	2799	2799	186.254745	118.708961	0.643761	0.952706	0.714016
;	2800	2800	186.196182	119.147224	0.643761	0.948821	0.718999
;	2801	2801	188.660828	120.634438	0.643761	0.944810	0.738191
:	2802	2802	176.023636	120.634438	0.643761	0.947380	0.722429

2803 rows × 6 columns

У

Name: Type, Length: 2803, dtype: int64

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)

X_train

→		Unnamed: 0	Width (minor axis)	Thickness (depth)	Roundness	Solidity	Extent
	2119	2119	172.156586	105.236511	0.541884	0.933814	0.710378
	1203	1203	165.031189	108.674545	0.426295	0.956497	0.796875
	452	452	153.442551	132.210663	0.594944	0.988031	0.774955
	1761	1761	150.679047	122.900238	0.632317	0.963890	0.765059
	2682	2682	118.663330	92.374199	0.371370	0.975980	0.727930
	•••						
	763	763	186.861343	121.848526	0.431527	0.981826	0.762699
	835	835	193.119461	113.428879	0.359518	0.969854	0.737407
	1653	1653	137.745041	139.815720	0.524458	0.982817	0.731298
	2607	2607	219.880615	130.854446	0.375444	0.981745	0.753098
	2732	2732	150.463547	78.389381	0.415667	0.964881	0.717213

2242 rows × 6 columns

y_train

2119 1
1203 0
452 2
1761 1
2682 2
...
763 2
835 2
1653 1
2607 2
2732 2
Name: Type, Length: 2242, dtype: int64

X_test

3	Unnamed: 0	Width (minor axis)	Thickness (depth)	Roundness	Solidity	Extent
85	855	156.934814	113.164124	0.579513	0.989586	0.775129
615	615	155.694366	77.319206	0.369027	0.974267	0.714813
70	70	111.289436	105.059357	0.578257	0.976459	0.687287
352	352	126.405533	96.050156	0.412739	0.975364	0.718381
118	118	236.790970	99.237144	0.530404	0.986294	0.755431
278	7 2787	213.362000	120.094116	0.386465	0.933771	0.714018
189	7 1897	180.785843	115.628510	0.588775	0.988657	0.760362
269	4 2694	139.143326	85.176468	0.374541	0.943761	0.695295
564	4 564	229.182465	123.282135	0.455931	0.979416	0.700753
402	402	156.555054	135.772369	0.594595	0.985895	0.780469

561 rows × 6 columns

y_test

-		
→ *	855	2
	615	2
	70	0
	352	2
	118	0

```
2787
             2
     1897
     2694
     564
             2
             2
     402
     Name: Type, Length: 561, dtype: int64
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
X_train
 → array([[ 0.88961693, 0.00960225, -0.24339255, 0.5542151 , -0.54119414,
             -0.28631389],
            [-0.24535291, -0.22059267, -0.06745256, -0.42017207, 0.02910683,
             1.52632102],
            [-1.17587949, -0.59497823, 1.13699867, 1.00149852, 0.82193723,
             1.06696055],
            [ 0.31221961, -1.10210607, 1.52618435, 0.40732183, 0.69084101,
              0.15208594],
            [ 1.49427335, 1.55138717, 1.06759484, -0.84883196, 0.66388936,
              0.60893615],
            [1.64915461, -0.69121871, -1.61728348, -0.5097687, 0.23989943,
             -0.1430791 ]])
X_test
 \Rightarrow array([[-0.67654233, -0.48215625, 0.16229978, 0.8714193, 0.8610247,
             1.0706117 ],
            [-0.97391434, -0.52223048, -1.67204926, -0.902931, 0.47588334,
            [-1.64919661, -1.95678771, -0.25245836, 0.86083389, 0.53098569,
             -0.7701934 ],
            [ 1.60207071, -1.05693271, -1.2699571 , -0.85644468, -0.29110361,
             -0.60238411],
            [-1.03710589, 1.85189513, 0.68008489, -0.17034588, 0.6053302,
             -0.48801446],
            [-1.237832 , -0.4944249 , 1.31926755, 0.99855937, 0.76822769,
              1.18250853]])
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 3, metric = 'euclidean')
classifier.fit(X_train, y_train)
\overline{\Rightarrow}
                       KNeighborsClassifier
      KNeighborsClassifier(metric='euclidean', n_neighbors=3)
y_pred= classifier.predict(X_test)
print(np.concatenate((y_pred, y_test)))
 → [2 2 0 ... 2 2 2]
Making Confusion Metrix
```

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

[[174 0 3] [2 178 1] [2 3 198]] 0.9803921568627451

SVM Classifier Model

Χ

→		Unnamed: 0	Width (minor axis)	Thickness (depth)	Roundness	Solidity	Extent
	0	0	227.940628	127.759132	0.309009	0.973384	0.681193
	1	1	234.188126	128.199509	0.309009	0.957304	0.656353
	2	2	229.418610	125.796547	0.309009	0.967270	0.683620
	3	3	232.763153	125.918808	0.309009	0.965512	0.685360
	4	4	230.150742	107.253448	0.309009	0.951450	0.714800
	•••						
	2798	2798	192.709366	122.356506	0.643761	0.931000	0.725739
	2799	2799	186.254745	118.708961	0.643761	0.952706	0.714016
	2800	2800	186.196182	119.147224	0.643761	0.948821	0.718999
	2801	2801	188.660828	120.634438	0.643761	0.944810	0.738191
	2802	2802	176.023636	120.634438	0.643761	0.947380	0.722429
,	2000						

2803 rows × 6 columns

У		
→	0	0
	1	0
	2	0
	3	0
	4	0
	2798	2
	2799	2
	2800	2
	2801	2

```
2802 2
Name: Type, Length: 2803, dtype: int64
```

Splitting dataset into Train Set and Test Set

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)
```

X_train

→		Unnamed: 0	Width (minor axis)	Thickness (depth)	Roundness	Solidity	Extent
	2119	2119	172.156586	105.236511	0.541884	0.933814	0.710378
	1203	1203	165.031189	108.674545	0.426295	0.956497	0.796875
	452	452	153.442551	132.210663	0.594944	0.988031	0.774955
	1761	1761	150.679047	122.900238	0.632317	0.963890	0.765059
	2682	2682	118.663330	92.374199	0.371370	0.975980	0.727930
	•••						
	763	763	186.861343	121.848526	0.431527	0.981826	0.762699
	835	835	193.119461	113.428879	0.359518	0.969854	0.737407
	1653	1653	137.745041	139.815720	0.524458	0.982817	0.731298
	2607	2607	219.880615	130.854446	0.375444	0.981745	0.753098
	2732	2732	150.463547	78.389381	0.415667	0.964881	0.717213

y_train

```
2119 1
1203 0
452 2
1761 1
2682 2
...
763 2
835 2
1653 1
2607 2
2732 2
Name: Type, Length: 2242, dtype: int64
```

2242 rows × 6 columns

X_test

		Unnamed: 0	Width (minor axis)	Thickness (depth)	Roundness	Solidity	Extent
	855	855	156.934814	113.164124	0.579513	0.989586	0.775129
	615	615	155.694366	77.319206	0.369027	0.974267	0.714813
	70	70	111.289436	105.059357	0.578257	0.976459	0.687287
	352	352	126.405533	96.050156	0.412739	0.975364	0.718381
	118	118	236.790970	99.237144	0.530404	0.986294	0.755431
	•••						
	2787	2787	213.362000	120.094116	0.386465	0.933771	0.714018
	1897	1897	180.785843	115.628510	0.588775	0.988657	0.760362
	2694	2694	139.143326	85.176468	0.374541	0.943761	0.695295
	564	564	229.182465	123.282135	0.455931	0.979416	0.700753
	402	402	156.555054	135.772369	0.594595	0.985895	0.780469

561 rows × 6 columns

y_test

```
→ 855
    615
           2
    70
           0
    352
           2
    118
           0
    2787
          2
    1897
          1
    2694
           2
    564
           2
    402
    Name: Type, Length: 561, dtype: int64
```

Feature Scaling

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

X_train

```
[ 1.64915461, -0.69121871, -1.61728348, -0.5097687 , 0.23989943,
            -0.1430791 ]])
X_test
\rightarrow array([[-0.67654233, -0.48215625, 0.16229978, 0.8714193, 0.8610247,
             1.0706117 ],
           [-0.97391434, -0.52223048, -1.67204926, -0.902931, 0.47588334,
            -0.19336168],
           [-1.64919661, -1.95678771, -0.25245836, 0.86083389, 0.53098569,
            -0.7701934 ],
           [ 1.60207071, -1.05693271, -1.2699571 , -0.85644468, -0.29110361,
            -0.60238411],
           [-1.03710589, 1.85189513, 0.68008489, -0.17034588, 0.6053302,
            -0.48801446],
           [-1.237832 , -0.4944249 , 1.31926755, 0.99855937, 0.76822769,
             1.18250853]])

    Training SVM classifier model on training set

from sklearn.svm import SVC
classifier = SVC(kernel = 'rbf', random_state = 0)
classifier.fit(X_train, y_train)
             SVC
     SVC(random_state=0)
Predicting Test set result
y_pred= classifier.predict(X_test)
print(np.concatenate((y_pred, y_test)))
→ [2 2 0 ... 2 2 2]
Making Confusion Metrix
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
→ [[163 1 13]
      [ 1 180 0]
      [ 12 0 191]]
     0.9518716577540107

    Training Naive Bayes Classification model

from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(X_train, y_train)
      ▼ GaussianNB
     GaussianNB()
Predicting Test set result
y_pred= classifier.predict(X_test)
print(np.concatenate((y_pred, y_test)))
→ [2 0 0 ... 2 2 2]
Making Confusion Metrix
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
→ [[118 3 56]
      [ 7 171 3]
     [ 38 22 143]]
     0.7700534759358288
from sklearn.naive_bayes import BernoulliNB
classifier = BernoulliNB()
classifier.fit(X_train, y_train)
\overline{\mathbf{T}}
      ▼ BernoulliNB
     BernoulliNB()
y_pred= classifier.predict(X_test)
```

print(np.concatenate((y_pred, y_test)))

cm = confusion_matrix(y_test, y_pred)

accuracy_score(y_test, y_pred)

from sklearn.metrics import confusion_matrix, accuracy_score

→ [2 0 0 ... 2 2 2]

```
[[ 84 41 52]
[ 17 164 0]
[ 58 42 103]]
0.6256684491978609
```

Training Decision Tree Classification model

```
from sklearn.tree import DecisionTreeClassifier
classifier = DecisionTreeClassifier(criterion = 'entropy', random_state = 0)
classifier.fit(X_train, y_train)

The decisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', random_state=0)
```

Predicting Test set result

```
y_pred= classifier.predict(X_test)
print(np.concatenate((y_pred, y_test)))

→ [2 2 0 ... 2 2 2]
```

Making Confusion Metrix

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

→ [[177 0 0]
        [ 0 181 0]
        [ 1 0 202]]
        0.9982174688057041
```

Training Random Forest Classification model

```
from sklearn.ensemble import RandomForestClassifier
classifier = RandomForestClassifier(n_estimators = 9, criterion = 'entropy', random_state = 0)
classifier.fit(X_train, y_train)

RandomForestClassifier
RandomForestClassifier(criterion='entropy', n_estimators=9, random_state=0)
```

Predicting Test set result

```
y_pred= classifier.predict(X_test)
print(np.concatenate((y_pred, y_test)))

→ [2 2 0 ... 2 2 2]
```

Making Confusion Metrix

```
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
→ [[177 0 0]
      [ 0 181 0]
      [ 0 0 203]]
     1.0
my_dict= {
    "Logistic Regression":0.768270944741533,
    "KNN": 0.9893048128342246,
    "SVM": 0.9590017825311943,
    "Naive Bayes (Gaussain)": 0.7789661319073083,
    "Naive Bayes (Bernoulli)": 0.7023172905525846,
    "Decision Tree": 0.9946524064171123,
    "Random Forest": 0.9893048128342246
# X on drop target variable
# my_dict= {
      "Logistic Regression": 0.7005347593582888,
      "KNN": 0.9803921568627451,
      "SVM": 0.9518716577540107,
      "Naive Bayes (Gaussain)": 0.7700534759358288,
      "Naive Bayes (Bernoulli)": 0.6256684491978609,
      "Decision Tree": 0.9982174688057041,
      "Random Forest": 1
# }
# when X drop many columns
Series= pd.Series(my_dict)
Series
→ Logistic Regression
                               0.768271
                               0.989305
                               0.959002
     Naive Bayes (Gaussain)
                               0.778966
```

0.702317

Naive Bayes (Bernoulli)

Decision Tree Random Forest dtype: float64 0.994652 0.989305