Breast _cancer_classification and handling imbalance dataset

In [1]:

```
import pandas as pd
from sklearn.datasets import load_breast_cancer
import warnings
warnings.filterwarnings("ignore")
```

Import Data

In [2]:

```
cancer_data=load_breast_cancer()
cancer_data
Out[2]:
{'data': array([[1.799e+01, 1.038e+01, 1.228e+02, ..., 2.654e-01, 4.601e-0
       1.189e-01],
      [2.057e+01, 1.777e+01, 1.329e+02, ..., 1.860e-01, 2.750e-01,
       8.902e-02],
      [1.969e+01, 2.125e+01, 1.300e+02, ..., 2.430e-01, 3.613e-01,
       8.758e-02],
      . . . ,
      [1.660e+01, 2.808e+01, 1.083e+02, ..., 1.418e-01, 2.218e-01,
       7.820e-02],
      [2.060e+01, 2.933e+01, 1.401e+02, ..., 2.650e-01, 4.087e-01,
       1.240e-01],
      [7.760e+00, 2.454e+01, 4.792e+01, ..., 0.000e+00, 2.871e-01,
       7.039e-02]]),
 1, 1, 1,
      0. 0. 1. 0. 1. 1. 1. 1. 0. 0. 1. 0. 0. 1. 1. 1. 1. 0. 1. 0. 0.
```

In []:

In [3]:

```
cancer_data_df=pd.DataFrame(data=cancer_data.data,columns=cancer_data.feature_names)
cancer_data_df['target']=cancer_data.target
cancer_data_df
```

Out[3]:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	me symme
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	0.14710	0.24
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	0.07017	0.18
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740	0.12790	0.20
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	0.2
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	0.18
564	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	0.17
565	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	0.17
566	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	0.1
567	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	0.20
568	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	0.1
569 rows × 31 columns									
4									•

3. Data Understanding

In [4]:

cancer_data_df.shape

Out[4]:

(569, 31)

In [5]:

cancer_data_df.isna().sum()

Out[5]:

mean radius 0 mean texture 0 mean perimeter 0 0 mean area 0 mean smoothness mean compactness 0 0 mean concavity 0 mean concave points mean symmetry 0 mean fractal dimension 0 radius error 0 texture error 0 0 perimeter error area error 0 0 smoothness error compactness error 0 0 concavity error concave points error 0 symmetry error fractal dimension error 0 worst radius 0 worst texture 0 worst perimeter 0 0 worst area worst smoothness 0 worst compactness 0 worst concavity worst concave points 0 worst symmetry 0 worst fractal dimension 0 target 0 dtype: int64

3.Data Understanding

In [6]:

cancer_data_df.shape

Out[6]:

(569, 31)

In [7]:

cancer_data_df.isna().sum()

Out[7]:

mean radius	0
mean texture	0
mean perimeter	0
mean area	0
mean smoothness	0
mean compactness	0
mean concavity	0
mean concave points	0
mean symmetry	0
mean fractal dimension	0
radius error	0
texture error	0
perimeter error	0
area error	0
smoothness error	0
compactness error	0
concavity error	0
concave points error	0
symmetry error	0
fractal dimension error	0
worst radius	0
worst texture	0
worst perimeter	0
worst area	0
worst smoothness	0
worst compactness	0
worst concavity	0
worst concave points	0
worst symmetry	0
worst fractal dimension	0
target	0
dtype: int64	

In [8]:

cancer_data_df.dtypes

Out[8]:

mean radius float64 float64 mean texture float64 mean perimeter float64 mean area float64 mean smoothness float64 mean compactness float64 mean concavity float64 mean concave points float64 mean symmetry float64 mean fractal dimension radius error float64 texture error float64 float64 perimeter error float64 area error float64 smoothness error compactness error float64 float64 concavity error float64 concave points error float64 symmetry error fractal dimension error float64 worst radius float64 float64 worst texture float64 worst perimeter worst area float64 worst smoothness float64 worst compactness float64 float64 worst concavity float64 worst concave points float64 worst symmetry worst fractal dimension float64 target int32 dtype: object

4. Model Building

In [9]:

```
x=cancer_data_df.drop(labels='target',axis=1)
y=cancer_data_df[['target']]
```

In [29]:

```
pm sklearn.model_selection import train_test_split
train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20,random_state=12,stratify=y)
```

```
In [30]:
x_train.shape,y_train.shape
Out[30]:
((455, 30), (455, 1))
In [31]:
x_test.shape,y_test.shape
Out[31]:
((114, 30), (114, 1))
```

5.Model Training

```
In [32]:
```

```
from sklearn.ensemble import AdaBoostClassifier
adb_classifier=AdaBoostClassifier(base_estimator=None)
adb_classifier.fit(x_train,y_train)
```

Out[32]:

AdaBoostClassifier()

6.Model Testing | 7.Model Evaluation

Train data

```
In [33]:
```

```
from sklearn.metrics import confusion_matrix,accuracy_score,classification_report
```

```
In [34]:
```

```
y_pred_train=adb_classifier.predict(x_train)
print(confusion_matrix(y_train,y_pred_train))
print('Accuracy Score:',accuracy_score(y_train,y_pred_train))

[[170     0]
     [     0     285]]
```

Test data

Accuracy Score: 1.0

In [35]:

```
y_pred_test=adb_classifier.predict(x_test)
print(confusion_matrix(y_test,y_pred_test))
print('Accuracy Score:',accuracy_score(y_test,y_pred_test))
print(classification_report(y_test,y_pred_test))
```

[[41 1] [1 71]]

Accuracy Score: 0.9824561403508771

•	precision	recall	f1-score	support
0	0.98	0.98	0.98	42
1	0.99	0.99	0.99	72
accuracy			0.98	114
macro avg	0.98	0.98	0.98	114
weighted avg	0.98	0.98	0.98	114

Handling imbalance dataset

In [36]:

cancer_data_df

Out[36]:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	me symme	
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	0.14710	0.24	
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	0.07017	0.18	
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740	0.12790	0.20	
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	0.2	
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	0.18	
564	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	0.17	
565	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	0.17	
566	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	0.1	
567	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	0.23	
568	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	0.1	
569 r	569 rows × 31 columns									

localhost:8888/notebooks/ADA Boost technique-Breast Cancer Data.ipynb

In [37]:

```
cancer_data_df['target'].value_counts()
```

Out[37]:

1 3570 212

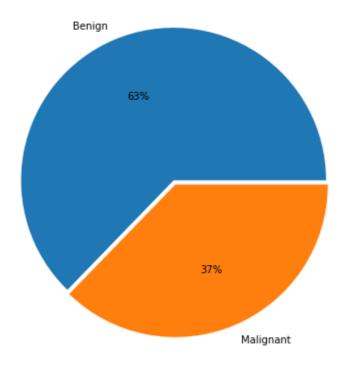
Name: target, dtype: int64

In [38]:

```
from matplotlib import pyplot as plt
plt.figure(figsize=(8,7))
plt.pie(x=cancer_data_df['target'].value_counts(),explode=[0.03,0],labels=['Benign','Malign
plt.show
```

Out[38]:

<function matplotlib.pyplot.show(close=None, block=None)>

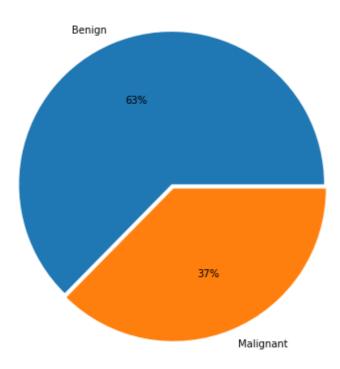


In [39]:

```
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,random_state=12,stratify=
```

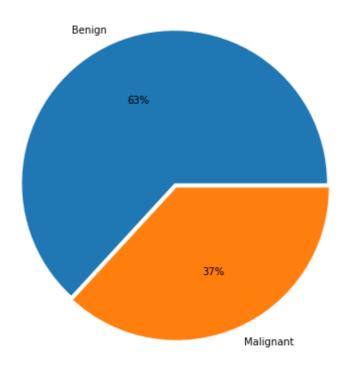
In [40]:

```
plt.figure(figsize=(8,7))
plt.pie(x=y_train.value_counts(),explode=[0.03,0],labels=['Benign','Malignant'],autopct='%1
plt.show()
```



```
In [41]:
```

```
plt.figure(figsize=(8,7))
plt.pie(x=y_test.value_counts(),explode=[0.03,0],labels=['Benign','Malignant'],autopct='%1.
plt.show()
```



In [42]:

```
from sklearn.linear_model import LogisticRegression
logistic_model=LogisticRegression(class_weight={0:3,1:1})
logistic_model.fit(x_train,y_train)
```

Out[42]:

LogisticRegression(class_weight={0: 3, 1: 1})

In [64]:

```
%%time
logistic_model.fit(x_train,y_train)
```

Wall time: 23.9 ms

Out[64]:

LogisticRegression(class_weight={0: 3, 1: 1})

In [43]:

```
y_pred=logistic_model.predict(x_train)
```

Data preprocession for continous data

In [58]:

```
from sklearn.preprocessing import MinMaxScaler
minmax_scaler=MinMaxScaler()
minmax_scaler=minmax_scaler.fit_transform(x)
x_scaled=pd.DataFrame(data=minmax_scaler,columns=x.columns)
x_scaled
```

Out[58]:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	
0	0.521037	0.022658	0.545989	0.363733	0.593753	0.792037	0.703140	0.731113	
1	0.643144	0.272574	0.615783	0.501591	0.289880	0.181768	0.203608	0.348757	
2	0.601496	0.390260	0.595743	0.449417	0.514309	0.431017	0.462512	0.635686	
3	0.210090	0.360839	0.233501	0.102906	0.811321	0.811361	0.565604	0.522863	
4	0.629893	0.156578	0.630986	0.489290	0.430351	0.347893	0.463918	0.518390	
564	0.690000	0.428813	0.678668	0.566490	0.526948	0.296055	0.571462	0.690358	
565	0.622320	0.626987	0.604036	0.474019	0.407782	0.257714	0.337395	0.486630	
566	0.455251	0.621238	0.445788	0.303118	0.288165	0.254340	0.216753	0.263519	
567	0.644564	0.663510	0.665538	0.475716	0.588336	0.790197	0.823336	0.755467	
568	0.036869	0.501522	0.028540	0.015907	0.000000	0.074351	0.000000	0.000000	
569 rows × 30 columns									
4									

In [59]:

```
pm sklearn.model_selection import train_test_split
train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20,random_state=12,stratify=y)
```

In [60]:

```
from sklearn.linear_model import LogisticRegression
logistic_model=LogisticRegression(class_weight={0:3,1:1})
logistic_model.fit(x_train,y_train)
```

Out[60]:

LogisticRegression(class_weight={0: 3, 1: 1})

```
In [66]:
%%time
logistic_model.fit(x_train,y_train)
Wall time: 21 ms
Out[66]:
LogisticRegression(class_weight={0: 3, 1: 1})
In [67]:
y_pred=logistic_model.predict(x_train)
In [62]:
confusion_matrix(y_train,y_pred)
Out[62]:
In [63]:
accuracy_score(y_train,y_pred)
Out[63]:
0.9494505494505494
In [ ]:
In [ ]:
In [ ]:
```