Breast cancer dataset

Problem Statement: Analysing Diagnosis based on remaining parameters.

Out[2]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	po
0	842302	М	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740	
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	
564	926424	M	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	
565	926682	M	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	
566	926954	M	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	
567	927241	M	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	
568	92751	В	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	

569 rows × 33 columns

This DataFrame has 569 Rows and 33 columns

In [5]: 1 df.head()

Out[5]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	o point
0	842302	М	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	
1	842517	М	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	
2	84300903	М	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	
3	84348301	М	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	
4	84358402	М	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	
4										

In [6]: 1 df.tail()

Out[6]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	point
564	926424	М	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	
565	926682	М	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	
566	926954	М	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	
567	927241	М	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	
568	92751	В	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	
4										

In [7]:

1 df.describe()

Out[7]:

	id	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	co points_
count	5.690000e+02	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.0
mean	3.037183e+07	14.127292	19.289649	91.969033	654.889104	0.096360	0.104341	0.088799	0.0
std	1.250206e+08	3.524049	4.301036	24.298981	351.914129	0.014064	0.052813	0.079720	0.0
min	8.670000e+03	6.981000	9.710000	43.790000	143.500000	0.052630	0.019380	0.000000	0.0
25%	8.692180e+05	11.700000	16.170000	75.170000	420.300000	0.086370	0.064920	0.029560	0.0
50%	9.060240e+05	13.370000	18.840000	86.240000	551.100000	0.095870	0.092630	0.061540	0.0
75%	8.813129e+06	15.780000	21.800000	104.100000	782.700000	0.105300	0.130400	0.130700	0.0
max	9.113205e+08	28.110000	39.280000	188.500000	2501.000000	0.163400	0.345400	0.426800	0.2
4									•

In [8]: 1 df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 33 columns):

#	Column	Non-Null Count	Dtype
0	id	569 non-null	int64
1	diagnosis	569 non-null	object
2	radius_mean	569 non-null	float64
3	texture_mean	569 non-null	float64
4	perimeter_mean	569 non-null	float64
5	area_mean	569 non-null	float64
6	smoothness_mean	569 non-null	float64
7	compactness_mean	569 non-null	float64
8	concavity_mean	569 non-null	float64
9	concave points_mean	569 non-null	float64
10	symmetry_mean	569 non-null	float64
11	<pre>fractal_dimension_mean</pre>	569 non-null	float64
12	radius_se	569 non-null	float64
13	texture_se	569 non-null	float64
14	perimeter_se	569 non-null	float64
15	area_se	569 non-null	float64
16	smoothness_se	569 non-null	float64
17	compactness_se	569 non-null	float64
18	concavity_se	569 non-null	float64
19	concave points_se	569 non-null	float64
20	symmetry_se	569 non-null	float64
21	<pre>fractal_dimension_se</pre>	569 non-null	float64
22	radius_worst	569 non-null	float64
23	texture_worst	569 non-null	float64
24	perimeter_worst	569 non-null	float64
25	area_worst	569 non-null	float64
26	smoothness_worst	569 non-null	float64
27	compactness_worst	569 non-null	float64
28	concavity_worst	569 non-null	float64
29	concave points_worst	569 non-null	float64
30	symmetry_worst	569 non-null	float64
31	<pre>fractal_dimension_worst</pre>	569 non-null	float64
32	Unnamed: 32	0 non-null	float64
dtvp	es: float64(31), int64(1)	, object(1)	

dtypes: float64(31), int64(1), object(1)

memory usage: 146.8+ KB

```
In [9]:
             1 convert={'diagnosis':{'M':1,'B':2}}
               df=df.replace(convert)
             3
                df
             IVO
                     ೦೦೦೦೦
                                             44.410
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                                                                                                                                             U.4ZU4L
                                    2
            109
                    864018
                                             11.340
                                                            21.26
                                                                             72.48
                                                                                        396.5
                                                                                                         0.08759
                                                                                                                             0.06575
                                                                                                                                             0.05133
            110
                    864033
                                    2
                                              9.777
                                                            16.99
                                                                             62.50
                                                                                        290.2
                                                                                                         0.10370
                                                                                                                             0.08404
                                                                                                                                             0.04334
            111
                     86408
                                    2
                                             12.630
                                                            20.76
                                                                             82.15
                                                                                        480.4
                                                                                                         0.09933
                                                                                                                             0.12090
                                                                                                                                             0.10650
                                    2
            112
                     86409
                                             14.260
                                                            19.65
                                                                             97.83
                                                                                        629.9
                                                                                                         0.07837
                                                                                                                             0.22330
                                                                                                                                             0.30030
            113
                    864292
                                    2
                                             10.510
                                                            20.19
                                                                             68.64
                                                                                        334.2
                                                                                                         0.11220
                                                                                                                             0.13030
                                                                                                                                             0.06476
            114
                                    2
                                              8.726
                                                                                        230.9
                    864496
                                                            15.83
                                                                             55.84
                                                                                                         0.11500
                                                                                                                             0.08201
                                                                                                                                             0.04132
                                    2
                                                            21.53
                                                                                                         0.09768
                                                                                                                             0.07849
                                                                                                                                             0.03328
            115
                    864685
                                             11.930
                                                                             76.53
                                                                                        438.6
            116
                    864726
                                    2
                                              8.950
                                                            15.76
                                                                             58.74
                                                                                        245.2
                                                                                                         0.09462
                                                                                                                             0.12430
                                                                                                                                             0.09263
            117
                    864729
                                    1
                                             14.870
                                                            16.67
                                                                             98.64
                                                                                        682.5
                                                                                                         0.11620
                                                                                                                             0.16490
                                                                                                                                             0.16900
            118
                                                            22.91
                                                                           105.70
                                                                                        782.6
                                                                                                         0.11550
                                                                                                                             0.17520
                                                                                                                                             0.21330
                    864877
                                    1
                                             15.780
                                                                                                                                            0.07293
            119
                    865128
                                    1
                                             17.950
                                                            20.01
                                                                            114.20
                                                                                        982.0
                                                                                                         0.08402
                                                                                                                             0.06722
             1 features=df.columns[2:31]
In [10]:
In [11]:
             1 target=df.columns[1]
In [28]:
             1 x=np.array(df[features])
                y=np.array(df[target])
```

0.9473684210526315

Decision Tree

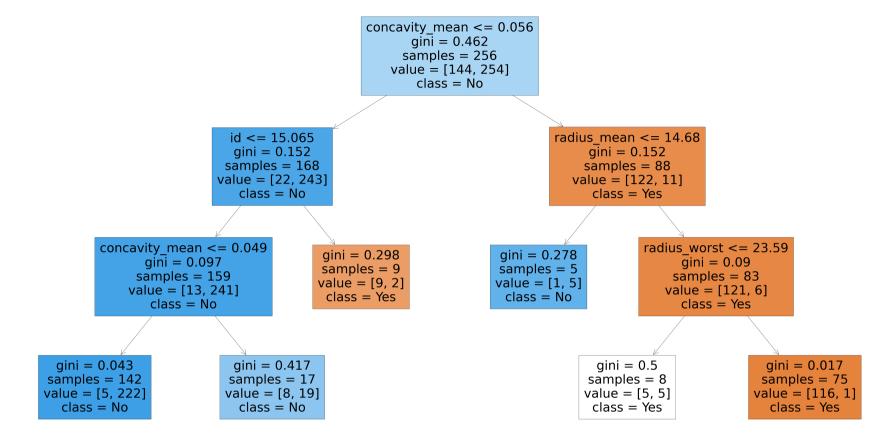
```
In [20]: 1 score=clf.score(x_test,y_test)
2 print(score)
```

0.9181286549707602

Random Forest

```
In [21]:
           1 from sklearn.ensemble import RandomForestClassifier
           2 rfc=RandomForestClassifier()
           3 rfc.fit(x train,y train)
Out[21]:
          ▼ RandomForestClassifier
          RandomForestClassifier()
           1 rf=RandomForestClassifier()
In [22]:
In [30]:
           1 x=df.drop('diagnosis',axis=1)
           2 y=df['diagnosis']
In [31]:
           1 params={'max_depth':[2,3,5,10,20],
                     'min samples leaf':[5,10,20,50,100,200],
           2
                     'n_estimators':[10,25,30,50,100,200]}
           3
```

```
In [35]:
                                                                                1 from sklearn.tree import plot tree
                                                                                2 from sklearn.tree import DecisionTreeClassifier
                                                                                3 plt.figure(figsize=(80,40))
                                                                                4 plot tree(rf best.estimators [5], feature names=x.columns, class names=['Yes', 'No'], filled=True)
Out[35]: [Text(0.5, 0.875, 'concavity mean <= 0.056\ngini = 0.462\nsamples = 256\nvalue = [144, 254]\nclass = No'),
                                                                            Text(0.3, 0.625, 'id <= 15.065 \neq 0.152 = 168 \neq 0.152 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168 = 168
                                                                            Text(0.2, 0.375, 'concavity mean \leq 0.049\ngini = 0.097\nsamples = 159\nvalue = [13, 241]\nclass = No'),
                                                                            Text(0.1, 0.125, 'gini = 0.043\nsamples = 142\nvalue = [5, 222]\nclass = No'),
                                                                            Text(0.3, 0.125, 'gini = 0.417 \setminus samples = 17 \setminus value = [8, 19] \setminus class = No'),
                                                                            Text(0.4, 0.375, 'gini = 0.298 \cap g = 9 \cap g = [9, 2] \cap g = Yes'),
                                                                            Text(0.7, 0.625, 'radius mean <= 14.68\ngini = 0.152\nsamples = 88\nvalue = [122, 11]\nclass = Yes'),
                                                                            Text(0.6, 0.375, 'gini = 0.278 \setminus s = 5 \setminus g = [1, 5] \setminus s = No'),
                                                                            Text(0.8, 0.375, 'radius worst \leq 23.59 \cdot 10^{-10} = 0.09 \cdot 10^{-
                                                                            Text(0.7, 0.125, 'gini = 0.5\nsamples = 8\nvalue = [5, 5]\nclass = Yes'),
                                                                           Text(0.9, 0.125, 'gini = 0.017 \setminus samples = 75 \setminus gini = [116, 1] \setminus samples = 75 \setminus gini = [116, 1] \setminus samples = 75 \setminus gini = [116, 1] \setminus samples = 75 \setminus gini = [116, 1] \setminus samples = 75 \setminus gini = [116, 1] \setminus samples = 75 \setminus gini = [116, 1] \setminus samples = 75 \setminus gini = [116, 1] \setminus samples = 75 \setminus gini = [116, 1] \setminus samples = 75 \setminus gini = [116, 1] \setminus samples = 75 \setminus gini = [116, 1] \setminus samples = 75 \setminus gini = [116, 1] \setminus samples = 75 \setminus gini = [116, 1] \setminus samples = 75 \setminus samples =
```



Conclusion

The Accuracy for LogisticRegression is 0.9473684210526315

The Accuracy for DecisionTree is 0.9181286549707602

The Accuracy for RandomForest is 0.9623115577889447

In []: