

# Breast Cancer Detection

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This project leverages machine learning to develop a predictive model for early detection of breast cancer. Using a dataset of medical attributes such as tumor size, texture, and cell features, the model classifies whether a tumor is benign or malignant. The goal is to enhance diagnostic precision, reduce invasive procedures, and improve patient outcomes through data-driven insights.

The dataset used can be found at <https://www.kaggle.com/datasets/uciml/breast-cancer-wisconsin-data>

## 1 Part 1: Data Pre-processing

I) Importing the dataset and exploring its properties.

```
[1]: #Importing all the necessary libraries.  
import numpy as np  
import pandas as pd  
import matplotlib.pyplot as plt  
%matplotlib inline  
import seaborn as sns  
import warnings  
warnings.filterwarnings('ignore')
```

```
[2]: df = pd.read_csv('breast_cancer_kaggle.csv')  
df.sample(5)
```

```
[2]:
```

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	\
125	86561	B	13.85	17.21	88.44	588.7	
64	85922302	M	12.68	23.84	82.69	499.0	
272	8910988	M	21.75	20.99	147.30	1491.0	
321	894618	M	20.16	19.66	131.10	1274.0	
99	862548	M	14.42	19.77	94.48	642.5	

	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	\
125	0.08785	0.06136	0.01420	0.01141	
64	0.11220	0.12620	0.11280	0.06873	
272	0.09401	0.19610	0.21950	0.10880	
321	0.08020	0.08564	0.11550	0.07726	
99	0.09752	0.11410	0.09388	0.05839	

	texture_worst	perimeter_worst	area_worst	smoothness_worst	\
125	23.58	100.3	725.9	0.1157	
64	33.47	111.8	888.3	0.1851	
272	28.18	195.9	2384.0	0.1272	
321	23.03	150.2	1657.0	0.1054	
99	30.86	109.5	826.4	0.1431	

	compactness_worst	concavity_worst	concave points_worst	symmetry_worst	\
125	0.1350	0.08115	0.05104	0.2364	
64	0.4061	0.40240	0.17160	0.3383	
272	0.4725	0.58070	0.18410	0.2833	
321	0.1537	0.26060	0.14250	0.3055	
99	0.3026	0.31940	0.15650	0.2718	

	fractal_dimension_worst	Unnamed: 32
125	0.07182	NaN
64	0.10310	NaN
272	0.08858	NaN
321	0.05933	NaN
99	0.09353	NaN

[5 rows x 33 columns]

```
[3]: df.shape
```

```
[3]: (569, 33)
```

```
[4]: df.columns
```

```
[4]: Index(['id', 'diagnosis', 'radius_mean', 'texture_mean', 'perimeter_mean',
        'area_mean', 'smoothness_mean', 'compactness_mean', 'concavity_mean',
        'concave points_mean', 'symmetry_mean', 'fractal_dimension_mean',
        'radius_se', 'texture_se', 'perimeter_se', 'area_se', 'smoothness_se',
        'compactness_se', 'concavity_se', 'concave points_se', 'symmetry_se',
        'fractal_dimension_se', 'radius_worst', 'texture_worst',
        'perimeter_worst', 'area_worst', 'smoothness_worst',
        'compactness_worst', 'concavity_worst', 'concave points_worst',
        'symmetry_worst', 'fractal_dimension_worst', 'Unnamed: 32'],
        dtype='object')
```

```
[5]: 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   fractal_dimension_mean 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   fractal_dimension_se   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   fractal_dimension_worst 569 non-null    float64
32   Unnamed: 32           0 non-null    float64

```

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

memory usage: 146.8+ KB

```
[6]: #Finding the statistical summary of the dataset.
df.describe()
```

```
[6]:
```

	id	radius_mean	texture_mean	perimeter_mean	area_mean	\
count	5.690000e+02	569.000000	569.000000	569.000000	569.000000	
mean	3.037183e+07	14.127292	19.289649	91.969033	654.889104	
std	1.250206e+08	3.524049	4.301036	24.298981	351.914129	
min	8.670000e+03	6.981000	9.710000	43.790000	143.500000	
25%	8.692180e+05	11.700000	16.170000	75.170000	420.300000	
50%	9.060240e+05	13.370000	18.840000	86.240000	551.100000	
75%	8.813129e+06	15.780000	21.800000	104.100000	782.700000	

max	9.113205e+08	28.110000	39.280000	188.500000	2501.000000
-----	--------------	-----------	-----------	------------	-------------

	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	\
count	569.000000	569.000000	569.000000	569.000000	
mean	0.096360	0.104341	0.088799	0.048919	
std	0.014064	0.052813	0.079720	0.038803	
min	0.052630	0.019380	0.000000	0.000000	
25%	0.086370	0.064920	0.029560	0.020310	
50%	0.095870	0.092630	0.061540	0.033500	
75%	0.105300	0.130400	0.130700	0.074000	
max	0.163400	0.345400	0.426800	0.201200	

	symmetry_mean	...	texture_worst	perimeter_worst	area_worst	\
count	569.000000	...	569.000000	569.000000	569.000000	
mean	0.181162	...	25.677223	107.261213	880.583128	
std	0.027414	...	6.146258	33.602542	569.356993	
min	0.106000	...	12.020000	50.410000	185.200000	
25%	0.161900	...	21.080000	84.110000	515.300000	
50%	0.179200	...	25.410000	97.660000	686.500000	
75%	0.195700	...	29.720000	125.400000	1084.000000	
max	0.304000	...	49.540000	251.200000	4254.000000	

	smoothness_worst	compactness_worst	concavity_worst	\
count	569.000000	569.000000	569.000000	
mean	0.132369	0.254265	0.272188	
std	0.022832	0.157336	0.208624	
min	0.071170	0.027290	0.000000	
25%	0.116600	0.147200	0.114500	
50%	0.131300	0.211900	0.226700	
75%	0.146000	0.339100	0.382900	
max	0.222600	1.058000	1.252000	

	concave points_worst	symmetry_worst	fractal_dimension_worst	\
count	569.000000	569.000000	569.000000	
mean	0.114606	0.290076	0.083946	
std	0.065732	0.061867	0.018061	
min	0.000000	0.156500	0.055040	
25%	0.064930	0.250400	0.071460	
50%	0.099930	0.282200	0.080040	
75%	0.161400	0.317900	0.092080	
max	0.291000	0.663800	0.207500	

Unnamed: 32	
count	0.0
mean	NaN
std	NaN
min	NaN

25%	NaN
50%	NaN
75%	NaN
max	NaN

[8 rows x 32 columns]

```
[7]: print(df.dtypes)
```

```
id                int64
diagnosis         object
radius_mean      float64
texture_mean     float64
perimeter_mean   float64
area_mean        float64
smoothness_mean  float64
compactness_mean float64
concavity_mean   float64
concave points_mean float64
symmetry_mean    float64
fractal_dimension_mean float64
radius_se        float64
texture_se       float64
perimeter_se     float64
area_se          float64
smoothness_se    float64
compactness_se   float64
concavity_se     float64
concave points_se float64
symmetry_se      float64
fractal_dimension_se float64
radius_worst     float64
texture_worst    float64
perimeter_worst  float64
area_worst       float64
smoothness_worst float64
compactness_worst float64
concavity_worst  float64
concave points_worst float64
symmetry_worst   float64
fractal_dimension_worst float64
Unnamed: 32      float64
dtype: object
```

```
[8]: #Finding the categorical variables.
df.select_dtypes(include='object').columns
```

```
[8]: Index(['diagnosis'], dtype='object')
```

```
[9]: '''There is only one column with a categorical variable, that is the diagnosis_
      ↪column.'''
```

```
[9]: 'There is only one column with a categorical variable, that is the diagnosis
      column.'
```

```
[10]: len(df.select_dtypes(include='object').columns)
```

```
[10]: 1
```

```
[11]: df.select_dtypes(include=['float64','int64']).columns
```

```
[11]: Index(['id', 'radius_mean', 'texture_mean', 'perimeter_mean', 'area_mean',
            'smoothness_mean', 'compactness_mean', 'concavity_mean',
            'concave points_mean', 'symmetry_mean', 'fractal_dimension_mean',
            'radius_se', 'texture_se', 'perimeter_se', 'area_se', 'smoothness_se',
            'compactness_se', 'concavity_se', 'concave points_se', 'symmetry_se',
            'fractal_dimension_se', 'radius_worst', 'texture_worst',
            'perimeter_worst', 'area_worst', 'smoothness_worst',
            'compactness_worst', 'concavity_worst', 'concave points_worst',
            'symmetry_worst', 'fractal_dimension_worst', 'Unnamed: 32'],
            dtype='object')
```

```
[12]: len(df.select_dtypes(include=['float64','int64']).columns)
```

```
[12]: 32
```

II) Dealing with missing values.

```
[13]: missing_data = df.isnull()
      print(missing_data.head())
      for column in missing_data.columns.values.tolist():
          print(column)
          print(missing_data[column].value_counts())
          print(" ")
```

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	\
0	False	False	False	False	False	False	
1	False	False	False	False	False	False	
2	False	False	False	False	False	False	
3	False	False	False	False	False	False	
4	False	False	False	False	False	False	

	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	\
0	False	False	False	False	
1	False	False	False	False	
2	False	False	False	False	
3	False	False	False	False	
4	False	False	False	False	

	texture_worst	perimeter_worst	area_worst	smoothness_worst	\
0	False	False	False	False	
1	False	False	False	False	
2	False	False	False	False	
3	False	False	False	False	
4	False	False	False	False	

	compactness_worst	concavity_worst	concave points_worst	symmetry_worst	\
0	False	False	False	False	
1	False	False	False	False	
2	False	False	False	False	
3	False	False	False	False	
4	False	False	False	False	

	fractal_dimension_worst	Unnamed: 32
0	False	True
1	False	True
2	False	True
3	False	True
4	False	True

[5 rows x 33 columns]

id

id

False 569

Name: count, dtype: int64

diagnosis

diagnosis

False 569

Name: count, dtype: int64

radius\_mean

radius\_mean

False 569

Name: count, dtype: int64

texture\_mean

texture\_mean

False 569

Name: count, dtype: int64

perimeter\_mean

perimeter\_mean

False 569

Name: count, dtype: int64

```
area_mean
area_mean
False      569
Name: count, dtype: int64
```

```
smoothness_mean
smoothness_mean
False      569
Name: count, dtype: int64
```

```
compactness_mean
compactness_mean
False      569
Name: count, dtype: int64
```

```
concavity_mean
concavity_mean
False      569
Name: count, dtype: int64
```

```
concave points_mean
concave points_mean
False      569
Name: count, dtype: int64
```

```
symmetry_mean
symmetry_mean
False      569
Name: count, dtype: int64
```

```
fractal_dimension_mean
fractal_dimension_mean
False      569
Name: count, dtype: int64
```

```
radius_se
radius_se
False      569
Name: count, dtype: int64
```

```
texture_se
texture_se
False      569
Name: count, dtype: int64
```

```
perimeter_se
perimeter_se
False      569
```



Name: count, dtype: int64

area\_se

area\_se

False 569

Name: count, dtype: int64

smoothness\_se

smoothness\_se

False 569

Name: count, dtype: int64

compactness\_se

compactness\_se

False 569

Name: count, dtype: int64

concavity\_se

concavity\_se

False 569

Name: count, dtype: int64

concave points\_se

concave points\_se

False 569

Name: count, dtype: int64

symmetry\_se

symmetry\_se

False 569

Name: count, dtype: int64

fractal\_dimension\_se

fractal\_dimension\_se

False 569

Name: count, dtype: int64

radius\_worst

radius\_worst

False 569

Name: count, dtype: int64

texture\_worst

texture\_worst

False 569

Name: count, dtype: int64

perimeter\_worst

```
perimeter_worst
False      569
Name: count, dtype: int64
```

```
area_worst
area_worst
False      569
Name: count, dtype: int64
```

```
smoothness_worst
smoothness_worst
False      569
Name: count, dtype: int64
```

```
compactness_worst
compactness_worst
False      569
Name: count, dtype: int64
```

```
concavity_worst
concavity_worst
False      569
Name: count, dtype: int64
```

```
concave points_worst
concave points_worst
False      569
Name: count, dtype: int64
```

```
symmetry_worst
symmetry_worst
False      569
Name: count, dtype: int64
```

```
fractal_dimension_worst
fractal_dimension_worst
False      569
Name: count, dtype: int64
```

```
Unnamed: 32
Unnamed: 32
True        569
Name: count, dtype: int64
```

```
[14]: df.isnull().values.sum()
```

```
[14]: 569
```

```
[15]: df.columns[df.isnull().any()]
```

```
[15]: Index(['Unnamed: 32'], dtype='object')
```

```
[16]: '''There is one column with null values.'''
```

```
[16]: 'There is one column with null values.'
```

```
[17]: #Dropping the column.  
df = df.drop(columns='Unnamed: 32')
```

```
[18]: df.shape
```

```
[18]: (569, 32)
```

III) Dealing with categorical data.

```
[19]: df.select_dtypes(include='object').columns
```

```
[19]: Index(['diagnosis'], dtype='object')
```

```
[20]: df['diagnosis'].unique()
```

```
[20]: array(['M', 'B'], dtype=object)
```

```
[21]: '''There are only two unique values, malignant and benign.'''
```

```
[21]: 'There are only two unique values, malignant and benign.'
```

```
[22]: # One hot encoding  
dataset = pd.get_dummies(data = df, drop_first=True)  
dataset.head()
```

```
[22]:
```

	id	radius_mean	texture_mean	perimeter_mean	area_mean	\
0	842302	17.99	10.38	122.80	1001.0	
1	842517	20.57	17.77	132.90	1326.0	
2	84300903	19.69	21.25	130.00	1203.0	
3	84348301	11.42	20.38	77.58	386.1	
4	84358402	20.29	14.34	135.10	1297.0	

	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	\
0	0.11840	0.27760	0.3001	0.14710	
1	0.08474	0.07864	0.0869	0.07017	
2	0.10960	0.15990	0.1974	0.12790	
3	0.14250	0.28390	0.2414	0.10520	
4	0.10030	0.13280	0.1980	0.10430	

	symmetry_mean	...	texture_worst	perimeter_worst	area_worst	\
0	0.2419	...	17.33	184.60	2019.0	
1	0.1812	...	23.41	158.80	1956.0	
2	0.2069	...	25.53	152.50	1709.0	
3	0.2597	...	26.50	98.87	567.7	
4	0.1809	...	16.67	152.20	1575.0	

	smoothness_worst	compactness_worst	concavity_worst	concave	points_worst	\
0	0.1622	0.6656	0.7119		0.2654	
1	0.1238	0.1866	0.2416		0.1860	
2	0.1444	0.4245	0.4504		0.2430	
3	0.2098	0.8663	0.6869		0.2575	
4	0.1374	0.2050	0.4000		0.1625	

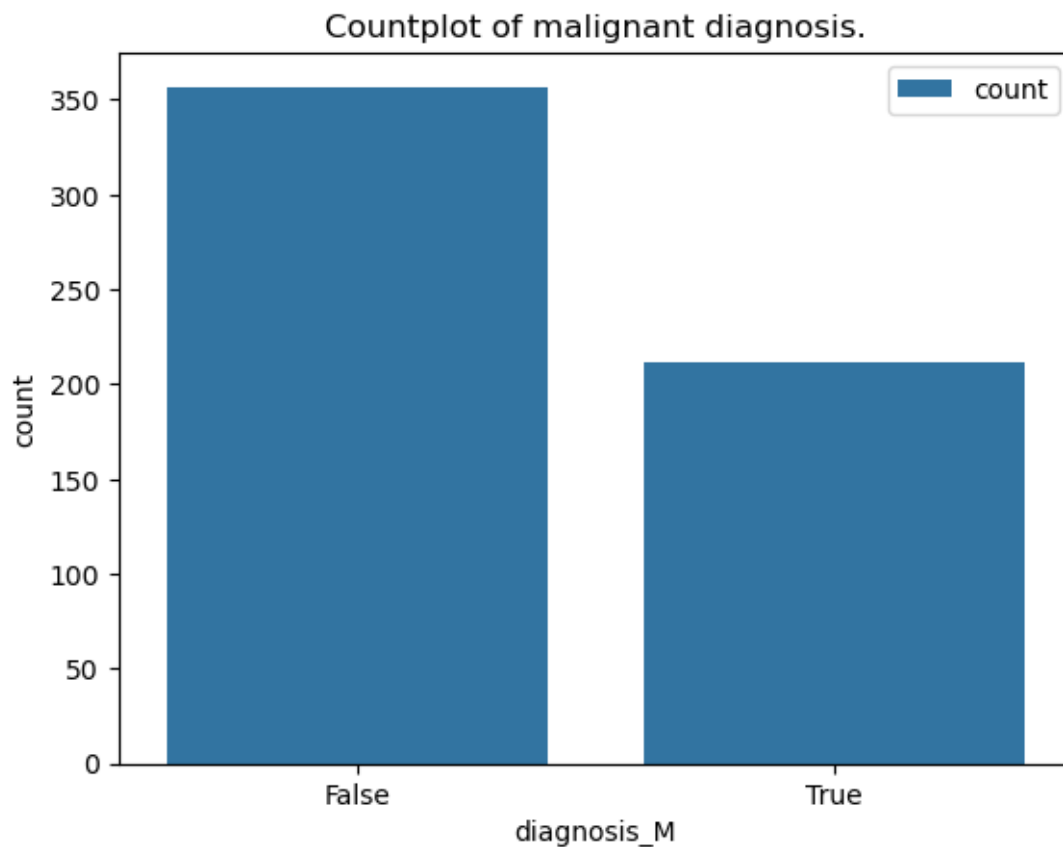
  

	symmetry_worst	fractal_dimension_worst	diagnosis_M
0	0.4601	0.11890	True
1	0.2750	0.08902	True
2	0.3613	0.08758	True
3	0.6638	0.17300	True
4	0.2364	0.07678	True

[5 rows x 32 columns]

IV) Visualization.

```
[23]: sns.countplot(dataset,x='diagnosis_M', label='count')
plt.title('Countplot of malignant diagnosis.')
plt.show()
```



```
[24]: #Count of benign values.
      (dataset.diagnosis_M==0).sum()
```

```
[24]: 357
```

```
[25]: #Count of malignant values.
      (dataset.diagnosis_M==1).sum()
```

```
[25]: 212
```

V) Correlation matrix and heatmap.

```
[26]: dataset_2 = dataset.drop(columns= 'diagnosis_M')
```

```
[27]: dataset_2.head(2)
```

```
[27]:
```

	id	radius_mean	texture_mean	perimeter_mean	area_mean	\
0	842302	17.99	10.38	122.8	1001.0	
1	842517	20.57	17.77	132.9	1326.0	

	smoothness_mean	compactness_mean	concavity_mean	concave	points_mean	\

0	0.11840	0.27760	0.3001	0.14710
1	0.08474	0.07864	0.0869	0.07017

	symmetry_mean	...	radius_worst	texture_worst	perimeter_worst	\
0	0.2419	...	25.38	17.33	184.6	
1	0.1812	...	24.99	23.41	158.8	

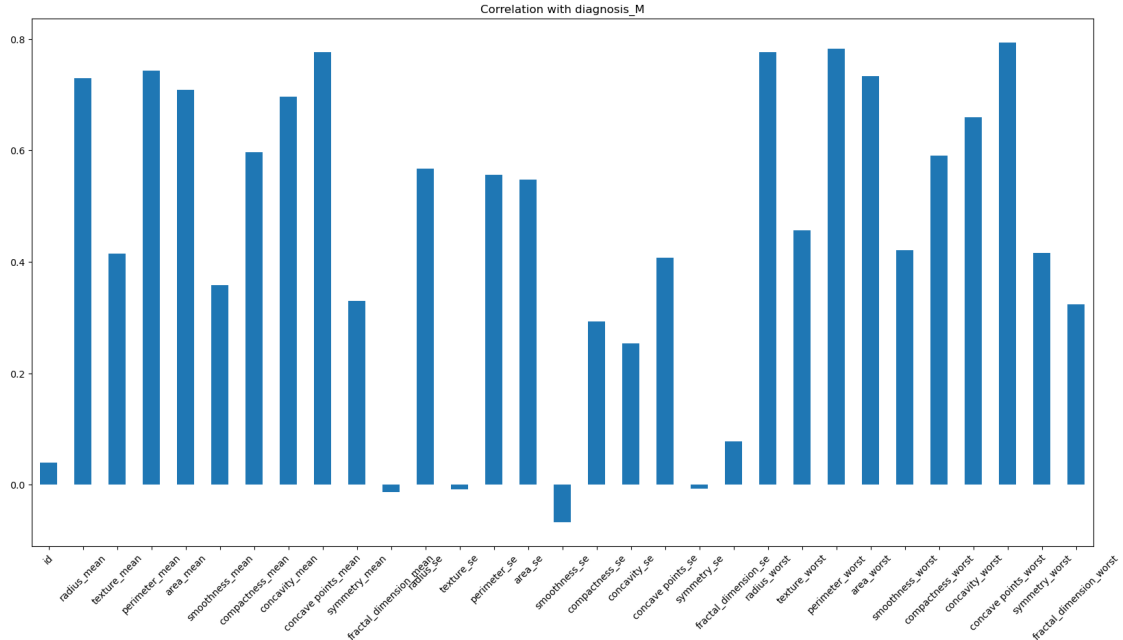
	area_worst	smoothness_worst	compactness_worst	concavity_worst	\
0	2019.0	0.1622	0.6656	0.7119	
1	1956.0	0.1238	0.1866	0.2416	

	concave points_worst	symmetry_worst	fractal_dimension_worst
0	0.2654	0.4601	0.11890
1	0.1860	0.2750	0.08902

[2 rows x 31 columns]

```
[28]: dataset_2.corrwith(dataset['diagnosis_M']).plot.bar(
      figsize=(20,10),
      title = 'Correlation with diagnosis_M',
      rot = 45)
```

```
[28]: <Axes: title={'center': 'Correlation with diagnosis_M'}>
```



```
[29]: corr = dataset.corr()
```

```
[30]: corr
```

```
[30]:
```

	id	radius_mean	texture_mean	perimeter_mean	\
id	1.000000	0.074626	0.099770	0.073159	
radius_mean	0.074626	1.000000	0.323782	0.997855	
texture_mean	0.099770	0.323782	1.000000	0.329533	
perimeter_mean	0.073159	0.997855	0.329533	1.000000	
area_mean	0.096893	0.987357	0.321086	0.986507	
smoothness_mean	-0.012968	0.170581	-0.023389	0.207278	
compactness_mean	0.000096	0.506124	0.236702	0.556936	
concavity_mean	0.050080	0.676764	0.302418	0.716136	
concave points_mean	0.044158	0.822529	0.293464	0.850977	
symmetry_mean	-0.022114	0.147741	0.071401	0.183027	
fractal_dimension_mean	-0.052511	-0.311631	-0.076437	-0.261477	
radius_se	0.143048	0.679090	0.275869	0.691765	
texture_se	-0.007526	-0.097317	0.386358	-0.086761	
perimeter_se	0.137331	0.674172	0.281673	0.693135	
area_se	0.177742	0.735864	0.259845	0.744983	
smoothness_se	0.096781	-0.222600	0.006614	-0.202694	
compactness_se	0.033961	0.206000	0.191975	0.250744	
concavity_se	0.055239	0.194204	0.143293	0.228082	
concave points_se	0.078768	0.376169	0.163851	0.407217	
symmetry_se	-0.017306	-0.104321	0.009127	-0.081629	
fractal_dimension_se	0.025725	-0.042641	0.054458	-0.005523	
radius_worst	0.082405	0.969539	0.352573	0.969476	
texture_worst	0.064720	0.297008	0.912045	0.303038	
perimeter_worst	0.079986	0.965137	0.358040	0.970387	
area_worst	0.107187	0.941082	0.343546	0.941550	
smoothness_worst	0.010338	0.119616	0.077503	0.150549	
compactness_worst	-0.002968	0.413463	0.277830	0.455774	
concavity_worst	0.023203	0.526911	0.301025	0.563879	
concave points_worst	0.035174	0.744214	0.295316	0.771241	
symmetry_worst	-0.044224	0.163953	0.105008	0.189115	
fractal_dimension_worst	-0.029866	0.007066	0.119205	0.051019	
diagnosis_M	0.039769	0.730029	0.415185	0.742636	

	area_mean	smoothness_mean	compactness_mean	\
id	0.096893	-0.012968	0.000096	
radius_mean	0.987357	0.170581	0.506124	
texture_mean	0.321086	-0.023389	0.236702	
perimeter_mean	0.986507	0.207278	0.556936	
area_mean	1.000000	0.177028	0.498502	
smoothness_mean	0.177028	1.000000	0.659123	
compactness_mean	0.498502	0.659123	1.000000	
concavity_mean	0.685983	0.521984	0.883121	
concave points_mean	0.823269	0.553695	0.831135	
symmetry_mean	0.151293	0.557775	0.602641	

fractal_dimension_mean	-0.283110	0.584792	0.565369
radius_se	0.732562	0.301467	0.497473
texture_se	-0.066280	0.068406	0.046205
perimeter_se	0.726628	0.296092	0.548905
area_se	0.800086	0.246552	0.455653
smoothness_se	-0.166777	0.332375	0.135299
compactness_se	0.212583	0.318943	0.738722
concavity_se	0.207660	0.248396	0.570517
concave points_se	0.372320	0.380676	0.642262
symmetry_se	-0.072497	0.200774	0.229977
fractal_dimension_se	-0.019887	0.283607	0.507318
radius_worst	0.962746	0.213120	0.535315
texture_worst	0.287489	0.036072	0.248133
perimeter_worst	0.959120	0.238853	0.590210
area_worst	0.959213	0.206718	0.509604
smoothness_worst	0.123523	0.805324	0.565541
compactness_worst	0.390410	0.472468	0.865809
concavity_worst	0.512606	0.434926	0.816275
concave points_worst	0.722017	0.503053	0.815573
symmetry_worst	0.143570	0.394309	0.510223
fractal_dimension_worst	0.003738	0.499316	0.687382
diagnosis_M	0.708984	0.358560	0.596534

	concavity_mean	concave points_mean	symmetry_mean \
id	0.050080	0.044158	-0.022114
radius_mean	0.676764	0.822529	0.147741
texture_mean	0.302418	0.293464	0.071401
perimeter_mean	0.716136	0.850977	0.183027
area_mean	0.685983	0.823269	0.151293
smoothness_mean	0.521984	0.553695	0.557775
compactness_mean	0.883121	0.831135	0.602641
concavity_mean	1.000000	0.921391	0.500667
concave points_mean	0.921391	1.000000	0.462497
symmetry_mean	0.500667	0.462497	1.000000
fractal_dimension_mean	0.336783	0.166917	0.479921
radius_se	0.631925	0.698050	0.303379
texture_se	0.076218	0.021480	0.128053
perimeter_se	0.660391	0.710650	0.313893
area_se	0.617427	0.690299	0.223970
smoothness_se	0.098564	0.027653	0.187321
compactness_se	0.670279	0.490424	0.421659
concavity_se	0.691270	0.439167	0.342627
concave points_se	0.683260	0.615634	0.393298
symmetry_se	0.178009	0.095351	0.449137
fractal_dimension_se	0.449301	0.257584	0.331786
radius_worst	0.688236	0.830318	0.185728
texture_worst	0.299879	0.292752	0.090651



perimeter_worst	0.729565	0.855923	0.219169
area_worst	0.675987	0.809630	0.177193
smoothness_worst	0.448822	0.452753	0.426675
compactness_worst	0.754968	0.667454	0.473200
concavity_worst	0.884103	0.752399	0.433721
concave points_worst	0.861323	0.910155	0.430297
symmetry_worst	0.409464	0.375744	0.699826
fractal_dimension_worst	0.514930	0.368661	0.438413
diagnosis_M	0.696360	0.776614	0.330499

	...	texture_worst	perimeter_worst	area_worst	\
id	...	0.064720	0.079986	0.107187	
radius_mean	...	0.297008	0.965137	0.941082	
texture_mean	...	0.912045	0.358040	0.343546	
perimeter_mean	...	0.303038	0.970387	0.941550	
area_mean	...	0.287489	0.959120	0.959213	
smoothness_mean	...	0.036072	0.238853	0.206718	
compactness_mean	...	0.248133	0.590210	0.509604	
concavity_mean	...	0.299879	0.729565	0.675987	
concave points_mean	...	0.292752	0.855923	0.809630	
symmetry_mean	...	0.090651	0.219169	0.177193	
fractal_dimension_mean	...	-0.051269	-0.205151	-0.231854	
radius_se	...	0.194799	0.719684	0.751548	
texture_se	...	0.409003	-0.102242	-0.083195	
perimeter_se	...	0.200371	0.721031	0.730713	
area_se	...	0.196497	0.761213	0.811408	
smoothness_se	...	-0.074743	-0.217304	-0.182195	
compactness_se	...	0.143003	0.260516	0.199371	
concavity_se	...	0.100241	0.226680	0.188353	
concave points_se	...	0.086741	0.394999	0.342271	
symmetry_se	...	-0.077473	-0.103753	-0.110343	
fractal_dimension_se	...	-0.003195	-0.001000	-0.022736	
radius_worst	...	0.359921	0.993708	0.984015	
texture_worst	...	1.000000	0.365098	0.345842	
perimeter_worst	...	0.365098	1.000000	0.977578	
area_worst	...	0.345842	0.977578	1.000000	
smoothness_worst	...	0.225429	0.236775	0.209145	
compactness_worst	...	0.360832	0.529408	0.438296	
concavity_worst	...	0.368366	0.618344	0.543331	
concave points_worst	...	0.359755	0.816322	0.747419	
symmetry_worst	...	0.233027	0.269493	0.209146	
fractal_dimension_worst	...	0.219122	0.138957	0.079647	
diagnosis_M	...	0.456903	0.782914	0.733825	
		smoothness_worst	compactness_worst	concavity_worst	\
id		0.010338	-0.002968	0.023203	
radius_mean		0.119616	0.413463	0.526911	

texture_mean	0.077503	0.277830	0.301025
perimeter_mean	0.150549	0.455774	0.563879
area_mean	0.123523	0.390410	0.512606
smoothness_mean	0.805324	0.472468	0.434926
compactness_mean	0.565541	0.865809	0.816275
concavity_mean	0.448822	0.754968	0.884103
concave points_mean	0.452753	0.667454	0.752399
symmetry_mean	0.426675	0.473200	0.433721
fractal_dimension_mean	0.504942	0.458798	0.346234
radius_se	0.141919	0.287103	0.380585
texture_se	-0.073658	-0.092439	-0.068956
perimeter_se	0.130054	0.341919	0.418899
area_se	0.125389	0.283257	0.385100
smoothness_se	0.314457	-0.055558	-0.058298
compactness_se	0.227394	0.678780	0.639147
concavity_se	0.168481	0.484858	0.662564
concave points_se	0.215351	0.452888	0.549592
symmetry_se	-0.012662	0.060255	0.037119
fractal_dimension_se	0.170568	0.390159	0.379975
radius_worst	0.216574	0.475820	0.573975
texture_worst	0.225429	0.360832	0.368366
perimeter_worst	0.236775	0.529408	0.618344
area_worst	0.209145	0.438296	0.543331
smoothness_worst	1.000000	0.568187	0.518523
compactness_worst	0.568187	1.000000	0.892261
concavity_worst	0.518523	0.892261	1.000000
concave points_worst	0.547691	0.801080	0.855434
symmetry_worst	0.493838	0.614441	0.532520
fractal_dimension_worst	0.617624	0.810455	0.686511
diagnosis_M	0.421465	0.590998	0.659610

	concave points_worst	symmetry_worst \
id	0.035174	-0.044224
radius_mean	0.744214	0.163953
texture_mean	0.295316	0.105008
perimeter_mean	0.771241	0.189115
area_mean	0.722017	0.143570
smoothness_mean	0.503053	0.394309
compactness_mean	0.815573	0.510223
concavity_mean	0.861323	0.409464
concave points_mean	0.910155	0.375744
symmetry_mean	0.430297	0.699826
fractal_dimension_mean	0.175325	0.334019
radius_se	0.531062	0.094543
texture_se	-0.119638	-0.128215
perimeter_se	0.554897	0.109930
area_se	0.538166	0.074126

smoothness_se	-0.102007	-0.107342
compactness_se	0.483208	0.277878
concavity_se	0.440472	0.197788
concave points_se	0.602450	0.143116
symmetry_se	-0.030413	0.389402
fractal_dimension_se	0.215204	0.111094
radius_worst	0.787424	0.243529
texture_worst	0.359755	0.233027
perimeter_worst	0.816322	0.269493
area_worst	0.747419	0.209146
smoothness_worst	0.547691	0.493838
compactness_worst	0.801080	0.614441
concavity_worst	0.855434	0.532520
concave points_worst	1.000000	0.502528
symmetry_worst	0.502528	1.000000
fractal_dimension_worst	0.511114	0.537848
diagnosis_M	0.793566	0.416294

	fractal_dimension_worst	diagnosis_M
id	-0.029866	0.039769
radius_mean	0.007066	0.730029
texture_mean	0.119205	0.415185
perimeter_mean	0.051019	0.742636
area_mean	0.003738	0.708984
smoothness_mean	0.499316	0.358560
compactness_mean	0.687382	0.596534
concavity_mean	0.514930	0.696360
concave points_mean	0.368661	0.776614
symmetry_mean	0.438413	0.330499
fractal_dimension_mean	0.767297	-0.012838
radius_se	0.049559	0.567134
texture_se	-0.045655	-0.008303
perimeter_se	0.085433	0.556141
area_se	0.017539	0.548236
smoothness_se	0.101480	-0.067016
compactness_se	0.590973	0.292999
concavity_se	0.439329	0.253730
concave points_se	0.310655	0.408042
symmetry_se	0.078079	-0.006522
fractal_dimension_se	0.591328	0.077972
radius_worst	0.093492	0.776454
texture_worst	0.219122	0.456903
perimeter_worst	0.138957	0.782914
area_worst	0.079647	0.733825
smoothness_worst	0.617624	0.421465
compactness_worst	0.810455	0.590998
concavity_worst	0.686511	0.659610

```

concave_points_worst      0.511114      0.793566
symmetry_worst            0.537848      0.416294
fractal_dimension_worst   1.000000      0.323872
diagnosis_M               0.323872      1.000000

```

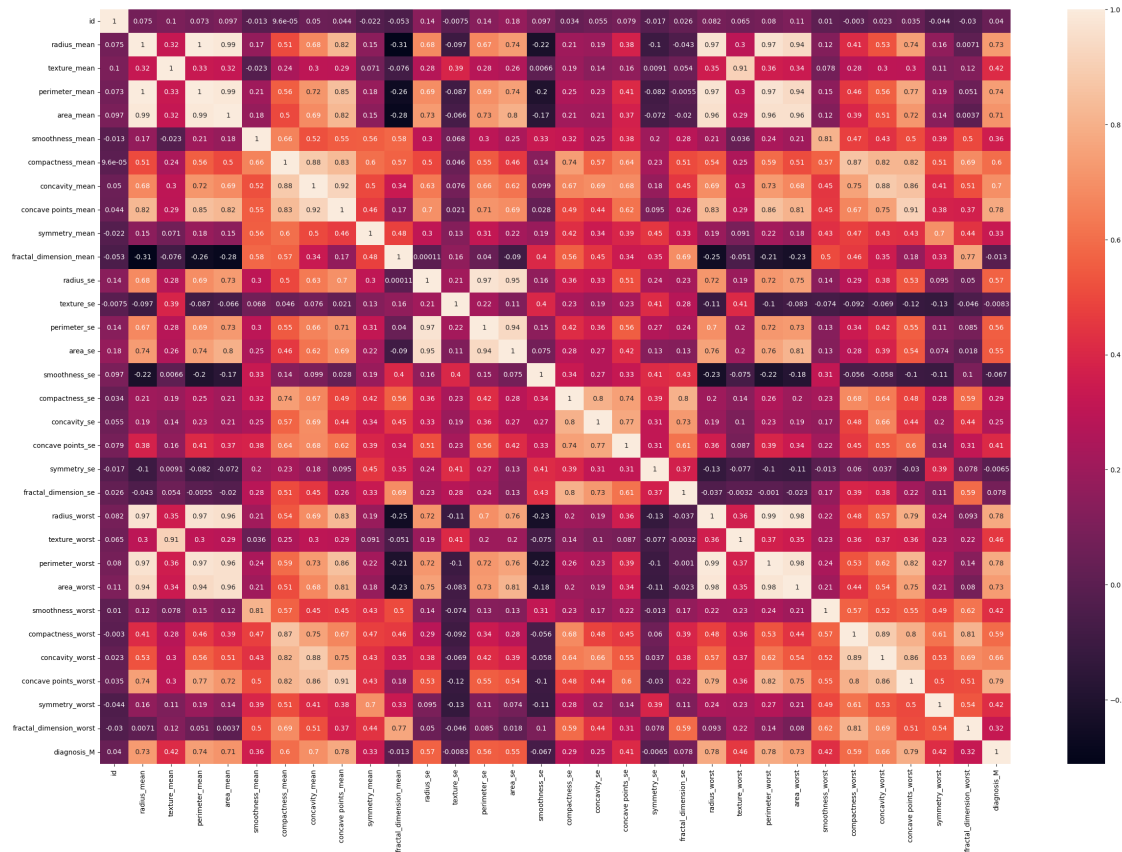
[32 rows x 32 columns]

```

[31]: plt.figure(figsize=(30,20))
      sns.heatmap(corr, annot=True)

```

[31]: <Axes: >



## VI) Splitting the dataset into train and test sets.

```

[32]: dataset.head()

```

```

[32]:      id  radius_mean  texture_mean  perimeter_mean  area_mean  \
0    842302      17.99      10.38      122.80      1001.0
1    842517      20.57      17.77      132.90      1326.0
2    8430093      19.69      21.25      130.00      1203.0
3    84348301      11.42      20.38      77.58      386.1

```

4	84358402	20.29	14.34	135.10	1297.0
---	----------	-------	-------	--------	--------

	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	\
0	0.11840	0.27760	0.3001	0.14710	
1	0.08474	0.07864	0.0869	0.07017	
2	0.10960	0.15990	0.1974	0.12790	
3	0.14250	0.28390	0.2414	0.10520	
4	0.10030	0.13280	0.1980	0.10430	

	symmetry_mean	...	texture_worst	perimeter_worst	area_worst	\
0	0.2419	...	17.33	184.60	2019.0	
1	0.1812	...	23.41	158.80	1956.0	
2	0.2069	...	25.53	152.50	1709.0	
3	0.2597	...	26.50	98.87	567.7	
4	0.1809	...	16.67	152.20	1575.0	

	smoothness_worst	compactness_worst	concavity_worst	concave points_worst	\
0	0.1622	0.6656	0.7119	0.2654	
1	0.1238	0.1866	0.2416	0.1860	
2	0.1444	0.4245	0.4504	0.2430	
3	0.2098	0.8663	0.6869	0.2575	
4	0.1374	0.2050	0.4000	0.1625	

	symmetry_worst	fractal_dimension_worst	diagnosis_M
0	0.4601	0.11890	True
1	0.2750	0.08902	True
2	0.3613	0.08758	True
3	0.6638	0.17300	True
4	0.2364	0.07678	True

[5 rows x 32 columns]

```
[33]: #Matrix of features.
X = dataset.iloc[:,1:-1].values
```

```
[34]: X.shape
```

```
[34]: (569, 30)
```

```
[35]: #Dependent variable.
y = dataset.iloc[:, -1].values
```

```
[36]: y.shape
```

```
[36]: (569,)
```

```
[37]: from sklearn.model_selection import train_test_split
```

```
[38]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
↳ random_state=101)
```

```
[39]: X_train.shape
```

```
[39]: (455, 30)
```

```
[40]: X_test
```

```
[40]: array([[1.236e+01, 1.854e+01, 7.901e+01, ..., 8.442e-02, 2.983e-01,
        7.185e-02],
        [1.404e+01, 1.598e+01, 8.978e+01, ..., 7.453e-02, 2.725e-01,
        7.234e-02],
        [1.291e+01, 1.633e+01, 8.253e+01, ..., 8.235e-02, 3.024e-01,
        6.949e-02],
        ...,
        [1.128e+01, 1.339e+01, 7.300e+01, ..., 8.611e-02, 2.102e-01,
        6.784e-02],
        [1.487e+01, 2.021e+01, 9.612e+01, ..., 1.017e-01, 2.369e-01,
        6.599e-02],
        [1.822e+01, 1.887e+01, 1.187e+02, ..., 1.776e-01, 2.812e-01,
        8.198e-02]])
```

```
[41]: y_train.shape
```

```
[41]: (455,)
```

```
[42]: y_test
```

```
[42]: array([False, False, False,  True, False, False, False,  True, False,
        False,  True, False, False, False,  True, False, False, False,
         True,  True, False, False, False, False,  True, False,  True,
        False,  True,  True, False,  True, False,  True, False, False,
         True,  True,  True,  True,  True, False, False, False, False,
        False,  True, False,  True, False,  True, False, False,  True,
        False, False,  True,  True, False, False,  True,  True, False,
        False,  True, False, False,  True,  True, False,  True, False,
        False, False,  True,  True, False,  True,  True, False, False,
        False, False, False, False, False,  True, False,  True,  True,
        False,  True,  True, False, False, False, False, False,  True,
         True,  True, False, False, False, False, False, False, False,
        False, False, False, False, False,  True])
```

VII) Feature scaling.

```
[43]: from sklearn.preprocessing import StandardScaler
```

```
[44]: scaler = StandardScaler()
```

```
[45]: X_train = scaler.fit_transform(X_train)
      X_test = scaler.transform(X_test)
```

```
[46]: X_train
```

```
[46]: array([[ 0.02090193,  0.28562106,  0.01889271, ...,  0.28708398,
            -0.59963793, -0.32285831],
            [-0.53400124, -1.40599342, -0.51656117, ..., -0.50392051,
             0.88583908,  0.43518026],
            [-0.2551693 , -0.43868901, -0.3137073 , ..., -0.99299632,
             -0.22946024, -0.68461207],
            ...,
            [ 0.53715513,  0.08001046,  0.48846929, ...,  0.56225563,
             -0.41534346, -1.1291307 ],
            [ 1.28254744,  0.49590463,  1.24364806, ...,  1.36496632,
             1.21947563,  0.77994255],
            [-0.11437297, -0.1466285 , -0.12892951, ...,  0.20346828,
             -0.09918311,  0.32007679]])
```

```
[47]: X_test
```

```
[47]: array([[ -0.48706913, -0.17933928, -0.519373 , ..., -0.46515324,
             0.11370878, -0.69173752],
            [-0.02326947, -0.7774792 , -0.08675198, ..., -0.61550946,
             -0.29618755, -0.66488004],
            [-0.33522996, -0.69570226, -0.37797783, ..., -0.49662314,
             0.17884735, -0.82109189],
            ...,
            [-0.78522606, -1.38262858, -0.76078919, ..., -0.43946041,
             -1.28597597, -0.91153034],
            [ 0.20586965,  0.21085357,  0.16792001, ..., -0.20244792,
             -0.86178093, -1.01293101],
            [ 1.13070827, -0.1022353 ,  1.07493791, ...,  0.95144869,
             -0.15796669, -0.13650031]])
```

## 2 Part 2: Building the models.

I) Logistic Regression.

```
[48]: from sklearn.linear_model import LogisticRegression
```

```
[49]: model_lr = LogisticRegression(random_state=0)
```

```
[50]: model_lr.fit(X_train, y_train)
```

```
[50]: LogisticRegression(random_state=0)
```

```
[51]: y_pred = model_lr.predict(X_test)
```

```
[52]: from sklearn.metrics import accuracy_score, confusion_matrix, f1_score, \
      ↪ precision_score, recall_score
```

```
[53]: acc = accuracy_score(y_test, y_pred)
      f1 = f1_score(y_test, y_pred)
      prec = precision_score(y_test, y_pred)
      rec = recall_score(y_test, y_pred)
```

```
[54]: results = pd.DataFrame(['Logistic Regression', acc, f1, prec, rec],
                             columns= ['Model', 'Accuracy', 'F1 Score', 'Precision', \
      ↪ 'Recall'])
```

```
[55]: results
```

```
[55]:
```

	Model	Accuracy	F1 Score	Precision	Recall
0	Logistic Regression	0.991228	0.987952	1.0	0.97619

```
[56]: cm = confusion_matrix(y_test, y_pred)
      print(cm)
```

```
[[72  0]
 [ 1 41]]
```

Cross Validation.

```
[57]: from sklearn.model_selection import cross_val_score
```

```
[58]: accuracies = cross_val_score(estimator=model_lr, X=X_train, y = y_train, cv=10)
```

```
[59]: print("Accuracy is {:.2f}%".format(accuracies.mean()*100))
      print("Standard deviation is {:.2f}%".format(accuracies.std()*100))
```

Accuracy is 97.16%

Standard deviation is 2.18%

II) Random Forest Classifier

```
[60]: from sklearn.ensemble import RandomForestClassifier
```

```
[61]: classifier_rf = RandomForestClassifier(random_state=0)
      classifier_rf.fit(X_train, y_train)
```

```
[61]: RandomForestClassifier(random_state=0)
```

```
[62]: y_pred = classifier_rf.predict(X_test)
```

```
[63]: acc = accuracy_score(y_test, y_pred)
      f1 = f1_score(y_test, y_pred)
```



```
prec = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
```

```
[64]: model_results = pd.DataFrame([[ 'Random Forest', acc, f1, prec, rec]],
                                   columns= [ 'Model', 'Accuracy', 'F1 Score', 'Precision',
                                   ↪ 'Recall'])
```

```
[65]: model_results
```

```
[65]:          Model  Accuracy  F1 Score  Precision  Recall
0  Random Forest  0.973684  0.963855    0.97561  0.952381
```

```
[66]: cm = confusion_matrix(y_test, y_pred)
      print(cm)
```

```
[[71  1]
 [ 2 40]]
```

Cross Validation.

```
[67]: accuracies = cross_val_score(estimator=classifier_rf, X=X_train,y = y_train,
                                   ↪cv=10)
      print("Accuracy is {:.2f}%".format(accuracies.mean()*100))
      print("Standard deviation is {:.2f}%".format(accuracies.std()*100))
```

```
Accuracy is 95.63%
Standard deviation is 3.23%
```

```
[68]: '''Based on accuracy, Logistic Regression is the best model.'''
```

```
[68]: 'Based on accuracy, Logistic Regression is the best model.'
```

### 3 Part 3: Using Randomized Search to find the best parameters.(Logistic Regression)

```
[69]: from sklearn.model_selection import RandomizedSearchCV
```

```
[70]: parameters = {'penalty':['l1', 'l2', 'elasticnet', 'none'],
                    'C':[0.25,0.5, 0.75, 1, 1.25, 1.5, 1.75, 2.0],
                    'solver':['newton-cg','lbfgs','liblinear', 'sag', 'saga']}
```

```
[71]: parameters
```

```
[71]: {'penalty': ['l1', 'l2', 'elasticnet', 'none'],
      'C': [0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75, 2.0],
      'solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga']}
```

```
[72]: random_search = RandomizedSearchCV(estimator=model_lr, param_distributions=␣  
    ↪parameters, n_iter=10, scoring='roc_auc',n_jobs=-1, cv=10, verbose=3)
```

```
[73]: random_search.fit(X_train, y_train)
```

Fitting 10 folds for each of 10 candidates, totalling 100 fits

```
[73]: RandomizedSearchCV(cv=10, estimator=LogisticRegression(random_state=0),  
    n_jobs=-1,  
    param_distributions={'C': [0.25, 0.5, 0.75, 1, 1.25, 1.5,  
        1.75, 2.0],  
        'penalty': ['l1', 'l2', 'elasticnet',  
            'none'],  
        'solver': ['newton-cg', 'lbfgs',  
            'liblinear', 'sag',  
            'saga']},  
    scoring='roc_auc', verbose=3)
```

```
[74]: random_search.best_estimator_
```

```
[74]: LogisticRegression(C=1.5, random_state=0, solver='saga')
```

```
[75]: random_search.best_score_
```

```
[75]: 0.9939075630252102
```

```
[76]: random_search.best_params_
```

```
[76]: {'solver': 'saga', 'penalty': 'l2', 'C': 1.5}
```

## 4 Part 4: Final Model.

```
[77]: model = LogisticRegression(C=1.  
    ↪25, class_weight=None, dual=False, fit_intercept=True, intercept_scaling=1, l1_ratio=None,␣  
    ↪max_iter=100, multi_class='auto', n_jobs=None, penalty='l1', random_state=0, solver='saga', tol=0  
    ↪0001, verbose=0, warm_start=False)  
model.fit(X_train, y_train)
```

```
[77]: LogisticRegression(C=1.25, penalty='l1', random_state=0, solver='saga')
```

```
[78]: y_pred = model.predict(X_test)
```

```
[79]: acc = accuracy_score(y_test, y_pred)  
f1 = f1_score(y_test, y_pred)  
prec = precision_score(y_test, y_pred)  
rec = recall_score(y_test, y_pred)
```

```
final_model_results = pd.DataFrame(['Final Logistic Regression', acc, f1, \
    prec, rec]),
    columns= ['Model', 'Accuracy', 'F1 Score', 'Precision', \
    'Recall'])
final_model_results
```

```
[79]:
```

	Model	Accuracy	F1 Score	Precision	Recall
0	Final Logistic Regression	0.991228	0.987952	1.0	0.97619

```
[80]: accuracies = cross_val_score(estimator=model, X=X_train,y = y_train, cv=10)
print("Accuracy is {:.2f}%".format(accuracies.mean()*100))
print("Standard deviation is {:.2f}%".format(accuracies.std()*100))
```

Accuracy is 97.16%  
Standard deviation is 2.18%

## 5 Part 5: Predicting a single observation.

```
[81]: dataset.head()
```

```
[81]:
```

	id	radius_mean	texture_mean	perimeter_mean	area_mean	\
0	842302	17.99	10.38	122.80	1001.0	
1	842517	20.57	17.77	132.90	1326.0	
2	84300903	19.69	21.25	130.00	1203.0	
3	84348301	11.42	20.38	77.58	386.1	
4	84358402	20.29	14.34	135.10	1297.0	

	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	\
0	0.11840	0.27760	0.3001	0.14710	
1	0.08474	0.07864	0.0869	0.07017	
2	0.10960	0.15990	0.1974	0.12790	
3	0.14250	0.28390	0.2414	0.10520	
4	0.10030	0.13280	0.1980	0.10430	

	symmetry_mean	...	texture_worst	perimeter_worst	area_worst	\
0	0.2419	...	17.33	184.60	2019.0	
1	0.1812	...	23.41	158.80	1956.0	
2	0.2069	...	25.53	152.50	1709.0	
3	0.2597	...	26.50	98.87	567.7	
4	0.1809	...	16.67	152.20	1575.0	

	smoothness_worst	compactness_worst	concavity_worst	concave points_worst	\
0	0.1622	0.6656	0.7119	0.2654	
1	0.1238	0.1866	0.2416	0.1860	
2	0.1444	0.4245	0.4504	0.2430	
3	0.2098	0.8663	0.6869	0.2575	
4	0.1374	0.2050	0.4000	0.1625	

	symmetry_worst	fractal_dimension_worst	diagnosis_M
0	0.4601	0.11890	True
1	0.2750	0.08902	True
2	0.3613	0.08758	True
3	0.6638	0.17300	True
4	0.2364	0.07678	True

[5 rows x 32 columns]

```
[82]: single_obsv = [[17.99, 10.38, 122.80, 1001.0, 0.11840, 0.27760, 0.
↪3001, 0.14710, 0.2419, 0.07871, 1.0950, 0.9053, 8.589, 153.40, 0.
↪006399, 0.04904, 0.05373, 0.01587, 0.03003, 0.006193, 25.38,
17.33, 184.60, 2019.0, 0.1622, 0.6656, 0.7119, 0.2654, 0.4601, 0.11890]]
```

```
[83]: single_obsv
```

```
[83]: [[17.99,
10.38,
122.8,
1001.0,
0.1184,
0.2776,
0.3001,
0.1471,
0.2419,
0.07871,
1.095,
0.9053,
8.589,
153.4,
0.006399,
0.04904,
0.05373,
0.01587,
0.03003,
0.006193,
25.38,
17.33,
184.6,
2019.0,
0.1622,
0.6656,
0.7119,
0.2654,
0.4601,
0.1189]]
```

```
[84]: model.predict(scaler.transform(single_obs))
```

```
[84]: array([ True])
```

```
[85]: '''The cancer is malignant.'''
```

```
[85]: 'The cancer is malignant.'
```