

# Breast Cancer Prediction

```
In [1]: # importing the libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [2]: #importing the dataset
df = pd.read_csv('C:/Users/zizhe/Desktop/Leo Zhao/Breast Cancer Prediction/data.csv')
df.head()
```

```
Out[2]:
```

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

5 rows × 33 columns

## Data Preprocessing Part 1

```
In [3]: # dropping unnecessary columns
df.drop(['Unnamed: 32', 'id'], axis=1, inplace=True)
```

```
In [4]: df.head()
```

Out[4]:

	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean
0	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710
1	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017
2	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790
3	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520
4	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430

5 rows × 31 columns



```
In [5]: #checking for the missing values  
df.isnull().sum()
```

```
Out[5]: diagnosis          0
        radius_mean       0
        texture_mean      0
        perimeter_mean    0
        area_mean         0
        smoothness_mean   0
        compactness_mean  0
        concavity_mean    0
        concave points_mean 0
        symmetry_mean     0
        fractal_dimension_mean 0
        radius_se         0
        texture_se        0
        perimeter_se      0
        area_se           0
        smoothness_se     0
        compactness_se    0
        concavity_se      0
        concave points_se 0
        symmetry_se       0
        fractal_dimension_se 0
        radius_worst      0
        texture_worst     0
        perimeter_worst   0
        area_worst        0
        smoothness_worst  0
        compactness_worst 0
        concavity_worst   0
        concave points_worst 0
        symmetry_worst    0
        fractal_dimension_worst 0
        dtype: int64
```

```
In [ ]: # This information is useful for data cleaning and preprocessing because you can decide how to handle or impute missing
```

```
In [6]: #checking the data types of the columns
        df.dtypes
```

```
Out[6]: 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
dtype: object
```

```
In [19]: # checking the data description
df.describe()
```

Out[19]:

	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	symmr
<b>count</b>	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	
<b>mean</b>	14.127292	19.289649	91.969033	654.889104	0.096360	0.104341	0.088799	0.048919	
<b>std</b>	3.524049	4.301036	24.298981	351.914129	0.014064	0.052813	0.079720	0.038803	
<b>min</b>	6.981000	9.710000	43.790000	143.500000	0.052630	0.019380	0.000000	0.000000	
<b>25%</b>	11.700000	16.170000	75.170000	420.300000	0.086370	0.064920	0.029560	0.020310	
<b>50%</b>	13.370000	18.840000	86.240000	551.100000	0.095870	0.092630	0.061540	0.033500	
<b>75%</b>	15.780000	21.800000	104.100000	782.700000	0.105300	0.130400	0.130700	0.074000	
<b>max</b>	28.110000	39.280000	188.500000	2501.000000	0.163400	0.345400	0.426800	0.201200	

8 rows × 30 columns

```
In [11]: # Remove any leading or trailing spaces from column names
df.columns = df.columns.str.strip()
```

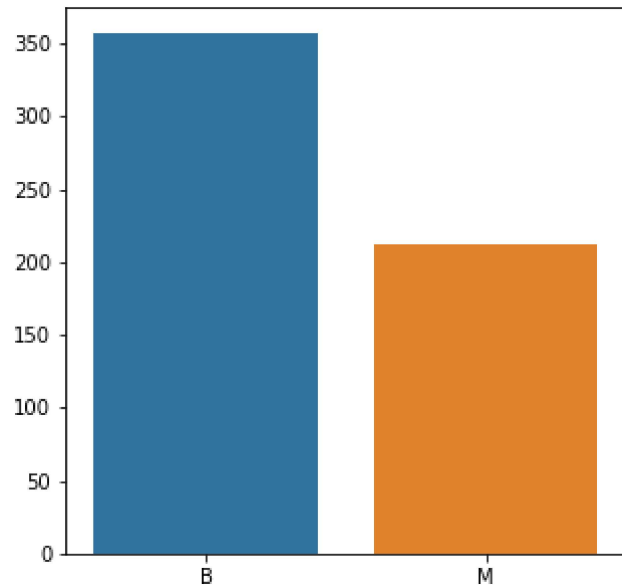
```
In [12]: # Check the corrected column names
print(df.columns)
```

```
Index(['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'],
      dtype='object')
```

## Exploratory Data Analysis

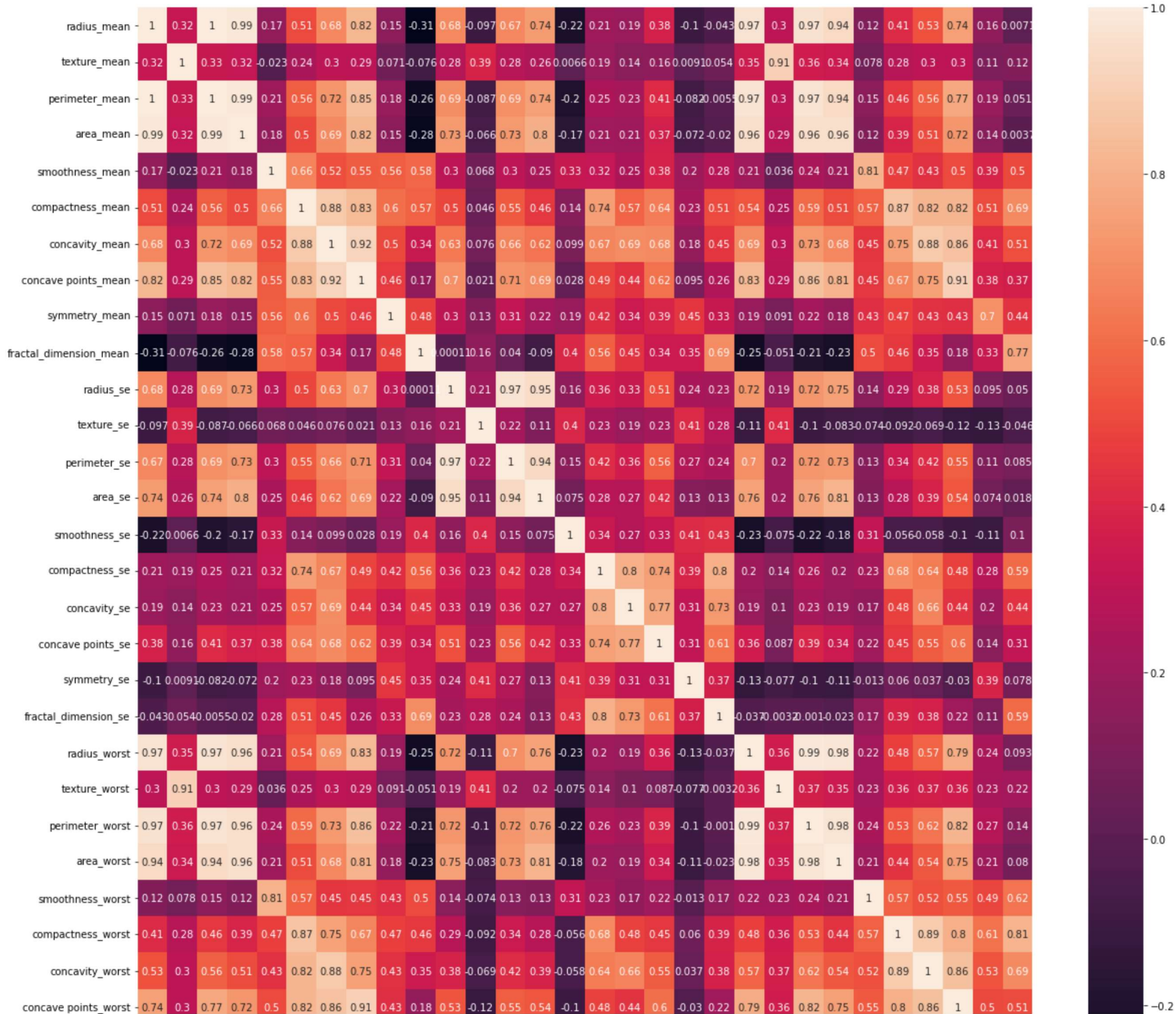
```
In [17]: # bar plot for the number of diagnosis
plt.figure(figsize=(5,5))
```

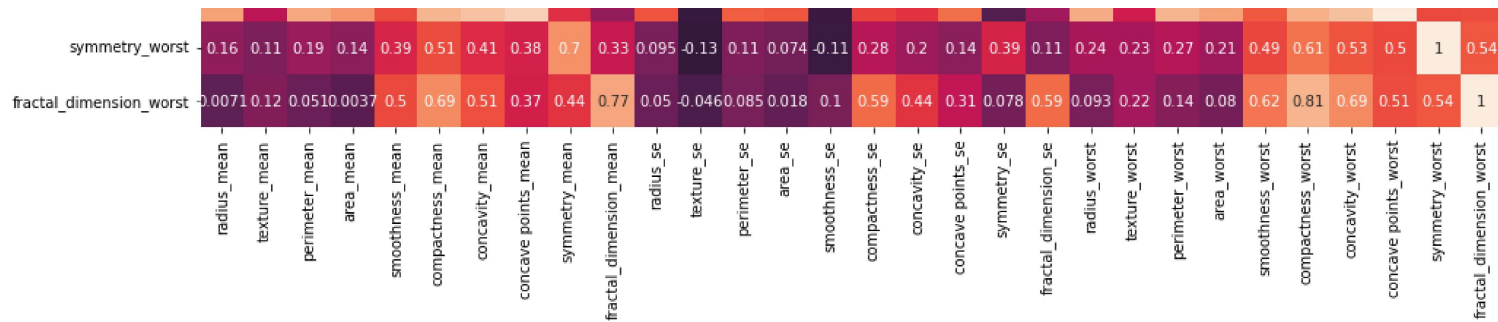
Out[17]: <AxesSubplot:>



```
In [21]: # create a heatmap to check the correlation.  
plt.figure(figsize=(20,20)) size to 20 inches by 20 inches, making it a large heatmap to display correlations clearly.  
sns.heatmap(df.corr(),annot=True)
```

Out[21]: <AxesSubplot:>





## Train Test Split

```
In [22]: #split a DataFrame 'df' into training and testing datasets for machine Learning purposes.

from sklearn.model_selection import train_test_split

X_train,X_test,y_train,y_test = train_test_split(df.drop(['diagnosis'],axis=1),df['diagnosis'],test_size=0.3,random_sta
```

## Using Decision Tree Classifier

```
In [23]: from sklearn.tree import DecisionTreeClassifier
dtree = DecisionTreeClassifier()
dtree.fit(X_train,y_train)
```

```
Out[23]: DecisionTreeClassifier()
```

```
In [24]: #predicting the diagnosis
y_pred = dtree.predict(X_test)
```

## Model Evaluation

```
In [25]: # printing samples from predicted and actual values
print('Predicted values: ',y_pred[:10])
print('Actual values: ',y_test[:10])
```



```
Predicted values: ['B' 'M' 'M' 'B' 'B' 'M' 'M' 'M' 'B' 'B']
Actual values: 204    B
70      M
131     M
431     B
540     B
567     M
369     M
29      M
81      B
477     B
Name: diagnosis, dtype: object
```

```
In [26]: # model evaluation
print(dtreescore(X_test,y_test))
```

```
0.9415204678362573
```

```
In [ ]: # 0.94 means that the model is making correct predictions for approximately 94% of the samples in the test data.
```

## Using logistic regression

```
In [28]: from sklearn.linear_model import LogisticRegression
logmodel = LogisticRegression()
logmodel.fit(X_train,y_train)
```

```
C:\Users\zizhe\New folder\lib\site-packages\sklearn\linear_model\_logistic.py:814: ConvergenceWarning: lbfgs failed to
converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

```
Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
    n_iter_i = _check_optimize_result(
```

```
LogisticRegression()
```

```
In [30]: yhat = logmodel.predict(X_test)
```

## Model Evaluation

```
In [31]: # printing samples from predicted and actual values
print('Predicted values: ',yhat[:10])
print('Actual values: ',y_test[:10])
```

```
Predicted values: ['B' 'M' 'M' 'B' 'B' 'M' 'M' 'M' 'B' 'B']
Actual values: 204    B
70           M
131          M
431          B
540          B
567          M
369          M
29           M
81           B
477          B
Name: diagnosis, dtype: object
```

```
In [ ]: #The numbers "204" and "477" you see in the output are actually indices or row numbers from your test dataset.
# In the context of your printed actual values,
# these numbers represent the row numbers or positions of the corresponding samples in your DataFrame.
```

```
In [32]: # model evaluation
print(logmodel.score(X_test,y_test))

0.9707602339181286
```

```
In [ ]: # Conclusion
```

```
In [ ]: # From both the models we can see that the accuracy is 94% and 97% respectively.
# But we can see that the recall value for the logistic regression is 97% which is better than the decision tree classifier.
# So we can say that the logistic regression is better than the decision tree classifier.
```