

```
## Breast Cancer Detection
```

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

```
# reading data set and converting them to data frame df
df = pd.read_csv("data.csv")
```

```
# print data set using head function and it will give 5 row only , if want more pass the integer inside head function
df.head()
```



```
id diagnosis radius_mean texture_mean perimeter_mean area_mean smoothness
```

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

5 rows × 33 columns

```
df.info() # provides summary of data set
```



```
<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
```

```
df.isna().sum() # returns all the column with null value cnt
```



```
id 0
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
Unnamed: 32    569
dtype: int64
```

df.shape # returns the no of rows and column

(569, 32)

df = df.dropna(axis=1)

df.shape

(569, 32)

df.describe()


	id	radius_mean	texture_mean	perimeter_mean	area_mean	smoothne
count	5.690000e+02	569.000000	569.000000	569.000000	569.000000	569
mean	3.037183e+07	14.127292	19.289649	91.969033	654.889104	C
std	1.250206e+08	3.524049	4.301036	24.298981	351.914129	C
min	8.670000e+03	6.981000	9.710000	43.790000	143.500000	C
25%	8.692180e+05	11.700000	16.170000	75.170000	420.300000	C
50%	9.060240e+05	13.370000	18.840000	86.240000	551.100000	C
75%	8.813129e+06	15.780000	21.800000	104.100000	782.700000	C
max	9.113205e+08	28.110000	39.280000	188.500000	2501.000000	C

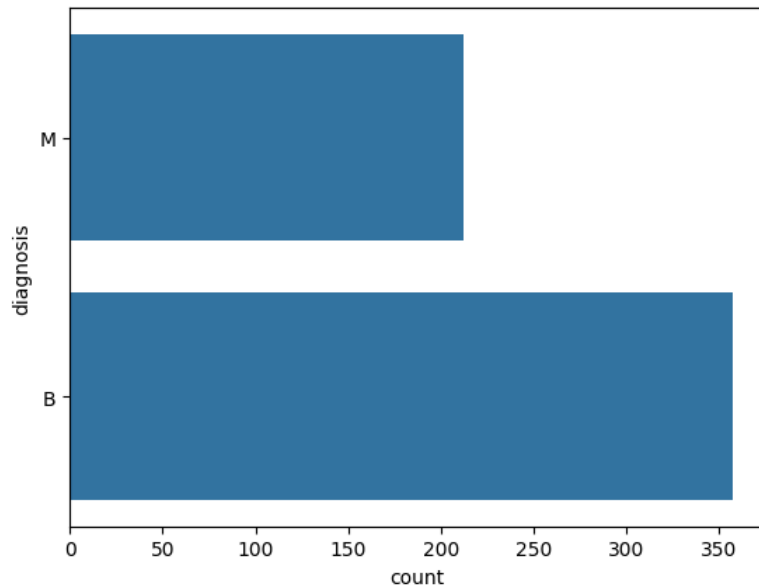
8 rows × 31 columns

df['diagnosis'].value_counts()

diagnosis
B 357
M 212
Name: count, dtype: int64

sns.countplot(df['diagnosis'] , label = "count")

 <Axes: xlabel='count', ylabel='diagnosis'>



```
# label encoding(convert the value of M and B into 1 and 0)
from sklearn.preprocessing import LabelEncoder
labelencoder_Y = LabelEncoder()
df.iloc[:,1]=labelencoder_Y.fit_transform(df.iloc[:,1].values)
```


```
df.head()
```

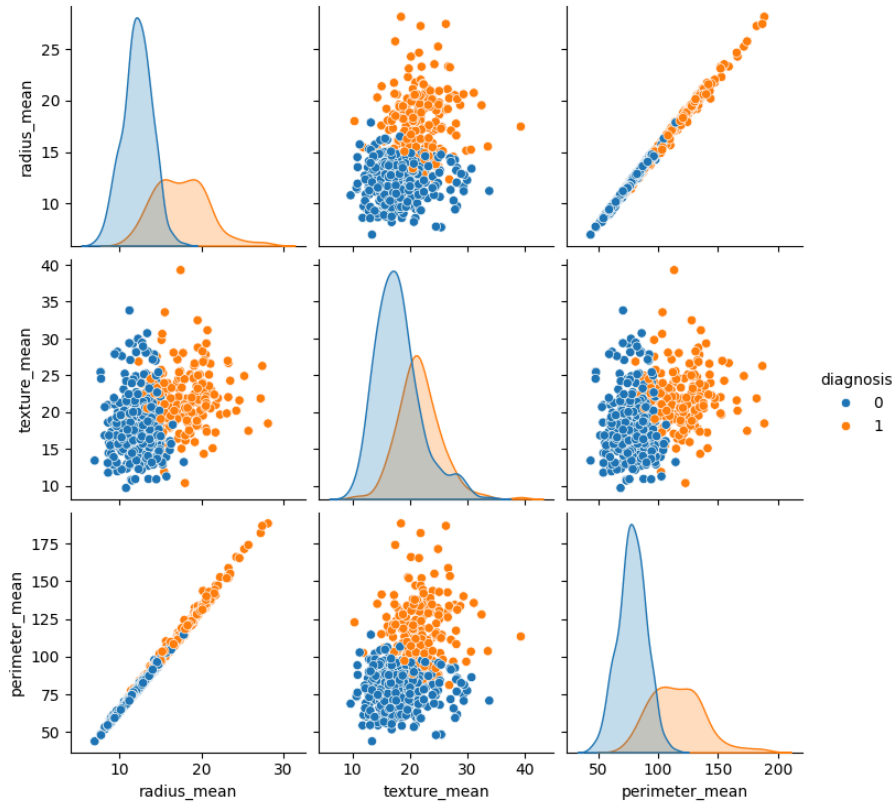


	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothr
0	842302	1	17.99	10.38	122.80	1001.0	
1	842517	1	20.57	17.77	132.90	1326.0	
2	84300903	1	19.69	21.25	130.00	1203.0	
3	84348301	1	11.42	20.38	77.58	386.1	
4	84358402	1	20.29	14.34	135.10	1297.0	

5 rows × 32 columns

```
sns.pairplot(df.iloc[:,1:5], hue ="diagnosis")
```

 <seaborn.axisgrid.PairGrid at 0x7fbf7bc1beb0>



```
df.iloc[:,1:32].corr()
```



	diagnosis	radius_mean	texture_mean	perimeter_mean	area_me
diagnosis	1.000000	0.730029	0.415185	0.742636	0.7089
radius_mean	0.730029	1.000000	0.323782	0.997855	0.9873
texture_mean	0.415185	0.323782	1.000000	0.329533	0.3210
perimeter_mean	0.742636	0.997855	0.329533	1.000000	0.9865
area_mean	0.708984	0.987357	0.321086	0.986507	1.0000
smoothness_mean	0.358560	0.170581	-0.023389	0.207278	0.1770
compactness_mean	0.596534	0.506124	0.236702	0.556936	0.4985
concavity_mean	0.696360	0.676764	0.302418	0.716136	0.6859
concave points_mean	0.776614	0.822529	0.293464	0.850977	0.8232
symmetry_mean	0.330499	0.147741	0.071401	0.183027	0.1512
fractal_dimension_mean	-0.012838	-0.311631	-0.076437	-0.261477	-0.2831
radius_se	0.567134	0.679090	0.275869	0.691765	0.7325
texture_se	-0.008303	-0.097317	0.386358	-0.086761	-0.0662
perimeter_se	0.556141	0.674172	0.281673	0.693135	0.7266
area_se	0.548236	0.735864	0.259845	0.744983	0.8000
smoothness_se	-0.067016	-0.222600	0.006614	-0.202694	-0.1667
compactness_se	0.292999	0.206000	0.191975	0.250744	0.2125
concavity_se	0.253730	0.194204	0.143293	0.228082	0.2076
concave points_se	0.408042	0.376169	0.163851	0.407217	0.3723
symmetry_se	-0.006522	-0.104321	0.009127	-0.081629	-0.0724
fractal_dimension_se	0.077972	-0.042641	0.054458	-0.005523	-0.0198
radius_worst	0.776454	0.969539	0.352573	0.969476	0.9627
texture_worst	0.456903	0.297008	0.912045	0.303038	0.2874
perimeter_worst	0.782914	0.965137	0.358040	0.970387	0.9591
area_worst	0.733825	0.941082	0.343546	0.941550	0.9592
smoothness_worst	0.421465	0.119616	0.077503	0.150549	0.1235
compactness_worst	0.590998	0.413463	0.277830	0.455774	0.3904
concavity_worst	0.659610	0.526911	0.301025	0.563879	0.5126
concave points_worst	0.793566	0.744214	0.295316	0.771241	0.7220
symmetry_worst	0.416294	0.163953	0.105008	0.189115	0.1435
fractal_dimension_worst	0.323872	0.007066	0.119205	0.051019	0.0037

31 rows × 31 columns

```
plt.figure(figsize=(10,10))

sns.heatmap(df.iloc[:,1:5].corr() , annot=True ,fmt="%")
```

<Axes: >



```
# split the data set in to x and y , x = all row and col except output
X = df.iloc[:,2:31].values
Y = df.iloc[:,1].values
```

```
print(X)
```

```
[[ 17.99  10.38 122.8 ... 0.7119 0.2654 0.4601]
 [ 20.57  17.77 132.9 ... 0.2416 0.186 0.275 ]
 [ 19.69  21.25 130. ... 0.4504 0.243 0.3613]
 ...
 [ 16.6  28.08 108.3 ... 0.3403 0.1418 0.2218]
 [ 20.6  29.33 140.1 ... 0.9387 0.265 0.4087]
 [ 7.76  24.54 47.92 ... 0. 0. 0.2871]]
```

```
#splitted the data set in to 80percent training and 20 percent testing rom sklearn.model_selection import train_test_split
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)
```

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

```
def models(X_train,Y_train):
    #logistic regression
    from sklearn.linear_model import LogisticRegression
    log=LogisticRegression(random_state=0)
    log.fit(X_train,Y_train)

    #LEAVE THIS

    #Decision Tree
    from sklearn.tree import DecisionTreeClassifier
```

```

from sklearn.tree import DecisionTreeClassifier
tree=DecisionTreeClassifier(random_state=0,criterion="entropy")
tree.fit(X_train,Y_train)

#Random Forest
from sklearn.ensemble import RandomForestClassifier
forest=RandomForestClassifier(random_state=0,criterion="entropy",n_estimators=10)
forest.fit(X_train,Y_train)

print('[0]logistic regression accuracy:',log.score(X_train,Y_train))
print('[1]Decision tree accuracy:',tree.score(X_train,Y_train))
print('[2]Random forest accuracy:',forest.score(X_train,Y_train))

return log, tree,forest

```

Generate

print hello world using rot13



Close

Generate is available for a limited time for unsubscribed users. [Upgrade to Colab Pro](#)

model= models(X_train, Y_train)



```

[0]Logistic Regression accuracy 0.9912087912087912
[1]Decision Tree accuracy 1.0
[2]Random Forest accuracy 0.9978021978021978

```

Generate

a slider using jupyter widgets



Close

Generate is available for a limited time for unsubscribed users. [Upgrade to Colab Pro](#)

```

def eshi(X_train, Y_train):
    # Import necessary libraries
    from sklearn.linear_model import LogisticRegression
    from sklearn.tree import DecisionTreeClassifier
    from sklearn.ensemble import RandomForestClassifier
    from sklearn.preprocessing import LabelEncoder

    # Initialize models
    log = LogisticRegression(random_state=0)
    tree = DecisionTreeClassifier(random_state=0, criterion="entropy")
    forest = RandomForestClassifier(random_state=0, criterion="entropy", n_estimators=10)

    # Encode the labels in Y_train
    le = LabelEncoder()
    Y_train_encoded = le.fit_transform(Y_train)

    # Fit the models
    log.fit(X_train, Y_train_encoded)
    tree.fit(X_train, Y_train_encoded)
    forest.fit(X_train, Y_train_encoded)

    # Print training accuracy
    print('[0] Logistic Regression accuracy', log.score(X_train, Y_train_encoded))
    print('[1] Decision Tree accuracy', tree.score(X_train, Y_train_encoded))
    print('[2] Random Forest accuracy', forest.score(X_train, Y_train_encoded))

    return log, tree, forest, le

# Train the models
log, tree, forest, le = eshi(X_train, Y_train)

# Encode the Y_test labels
Y_test_encoded = le.transform(Y_test)

# Import necessary metrics
from sklearn.metrics import accuracy_score, classification_report

```