Breast Cancer Classification Using Machine Learning

Problem Statement

Find out whether the cancer is benign or malignant

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

import warnings
warnings.filterwarnings('ignore')
```

Reading the dataset

In [2]:
```
df = pd.read_csv('data/data.csv')
df.head()
```

Out[2]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mea
0	842302	M	17.99	10.38	122.80	1001.0	0.1184
1	842517	M	20.57	17.77	132.90	1326.0	0.0847
2	84300903	M	19.69	21.25	130.00	1203.0	0.1096
3	84348301	M	11.42	20.38	77.58	386.1	0.1425
4	84358402	M	20.29	14.34	135.10	1297.0	0.1003

5 rows × 33 columns

Attribute Information:

Features are computed from a digitized image of a fine needle aspirate (FNA) of a breast mass. They describe characteristics of the cell nuclei present in the image.

- 1 ID number
- 2 Diagnosis (M = malignant, B = benign)
- 3 - 32 (Ten real-valued features are computed for each cell nucleus):
  - radius (mean of distances from center to points on the perimeter)
  - texture (standard deviation of gray-scale values)

- perimeter
- area
- smoothness (local variation in radius lengths)
- compactness (perimeter^2 / area - 1.0)
- concavity (severity of concave portions of the contour)
- concave points (number of concave portions of the contour)
- symmetry
- fractal dimension ("coastline approximation" - 1)

The mean, standard error and "worst" or largest (mean of the three largest values) of these features were computed for each image, resulting in 30 features.

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

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

We have 569 observations and 33 columns in this dataset

In [4]:
```
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
```

- Every feature other than our target diagonsis is numerical variables

Exploratory Data Analysis

In [5]:
```
#statistical summary of features
df.describe().T
```

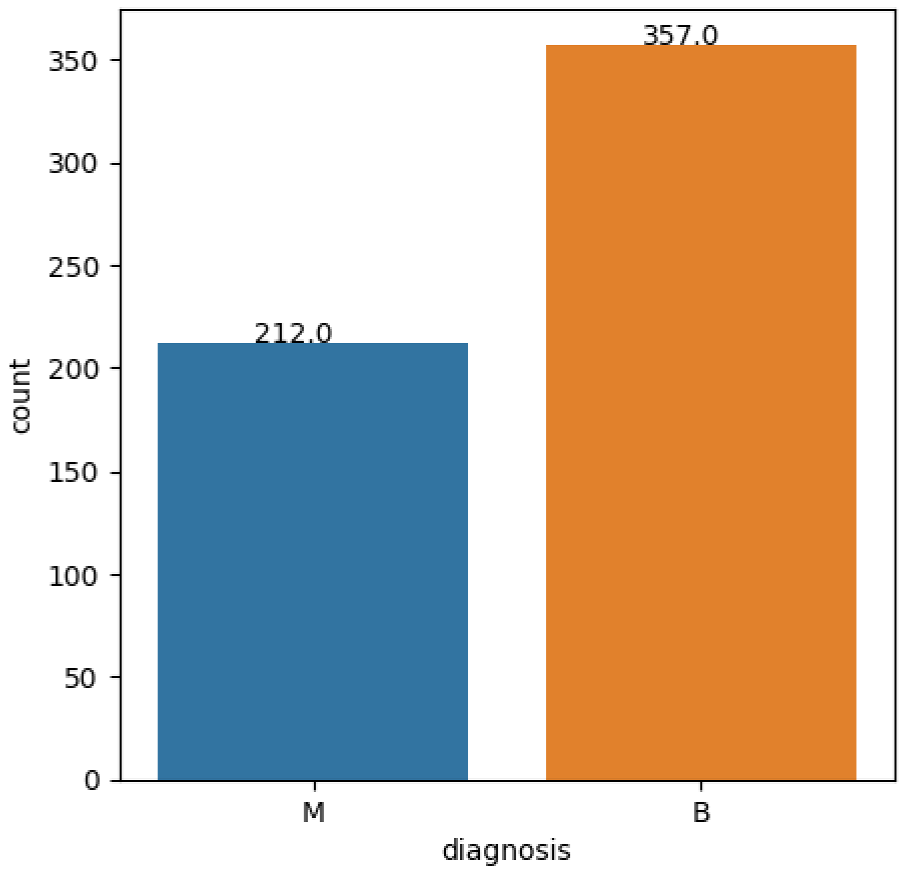
Out[5]:

	count	mean	std	min	25%	
id	569.0	3.037183e+07	1.250206e+08	8670.000000	869218.000000	906024.0
radius_mean	569.0	1.412729e+01	3.524049e+00	6.981000	11.700000	13.3
texture_mean	569.0	1.928965e+01	4.301036e+00	9.710000	16.170000	18.8
perimeter_mean	569.0	9.196903e+01	2.429898e+01	43.790000	75.170000	86.2
area_mean	569.0	6.548891e+02	3.519141e+02	143.500000	420.300000	551.1
smoothness_mean	569.0	9.636028e-02	1.406413e-02	0.052630	0.086370	0.0
compactness_mean	569.0	1.043410e-01	5.281276e-02	0.019380	0.064920	0.0
concavity_mean	569.0	8.879932e-02	7.971981e-02	0.000000	0.029560	0.0
concave points_mean	569.0	4.891915e-02	3.880284e-02	0.000000	0.020310	0.0
symmetry_mean	569.0	1.811619e-01	2.741428e-02	0.106000	0.161900	0.1
fractal_dimension_mean	569.0	6.279761e-02	7.060363e-03	0.049960	0.057700	0.0
radius_se	569.0	4.051721e-01	2.773127e-01	0.111500	0.232400	0.3
texture_se	569.0	1.216853e+00	5.516484e-01	0.360200	0.833900	1.1
perimeter_se	569.0	2.866059e+00	2.021855e+00	0.757000	1.606000	2.2
area_se	569.0	4.033708e+01	4.549101e+01	6.802000	17.850000	24.5
smoothness_se	569.0	7.040979e-03	3.002518e-03	0.001713	0.005169	0.0
compactness_se	569.0	2.547814e-02	1.790818e-02	0.002252	0.013080	0.0
concavity_se	569.0	3.189372e-02	3.018606e-02	0.000000	0.015090	0.0
concave points_se	569.0	1.179614e-02	6.170285e-03	0.000000	0.007638	0.0
symmetry_se	569.0	2.054230e-02	8.266372e-03	0.007882	0.015160	0.0
fractal_dimension_se	569.0	3.794904e-03	2.646071e-03	0.000895	0.002248	0.0
radius_worst	569.0	1.626919e+01	4.833242e+00	7.930000	13.010000	14.9
texture_worst	569.0	2.567722e+01	6.146258e+00	12.020000	21.080000	25.4
perimeter_worst	569.0	1.072612e+02	3.360254e+01	50.410000	84.110000	97.6
area_worst	569.0	8.805831e+02	5.693570e+02	185.200000	515.300000	686.5
smoothness_worst	569.0	1.323686e-01	2.283243e-02	0.071170	0.116600	0.1
compactness_worst	569.0	2.542650e-01	1.573365e-01	0.027290	0.147200	0.2
concavity_worst	569.0	2.721885e-01	2.086243e-01	0.000000	0.114500	0.2
concave points_worst	569.0	1.146062e-01	6.573234e-02	0.000000	0.064930	0.0
symmetry_worst	569.0	2.900756e-01	6.186747e-02	0.156500	0.250400	0.2
fractal_dimension_worst	569.0	8.394582e-02	1.806127e-02	0.055040	0.071460	0.0
Unnamed: 32	0.0	NaN	NaN	NaN	NaN	

- Column Id is not relevent our machine learnig problem
- Last column Unnamed: 32 is full of NaN values
- Column diagnosis is our target variable

In [6]:
```
#dropping unnecessary columns
df = df.drop(['id', 'Unnamed: 32'], axis=1)
```

In [3]:
```
plt.figure(figsize=(5,5))
ax = sns.countplot(x=df['diagnosis'])
for p in ax.patches:
       ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x()+0.25, p.get_height()

plt.savefig('count_plot.jpg')
plt.show()
```

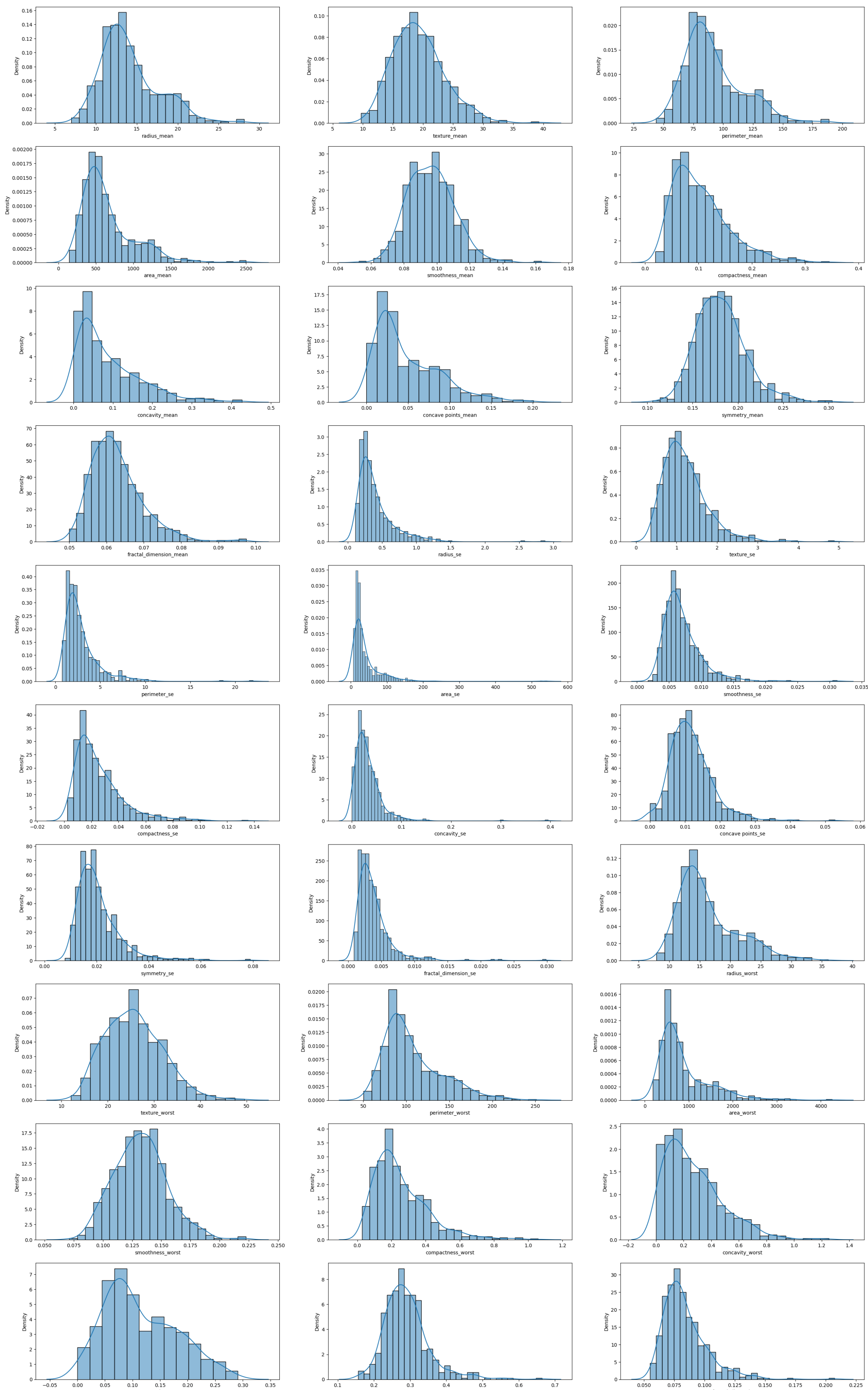


- There is not that much imbalance in this dataset

In [8]:
```
#selecting only numerical features
num_feat = df.select_dtypes(include=['float64', 'int64']).columns
num_feat
```

Out[8]:
```
Index(['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')
```

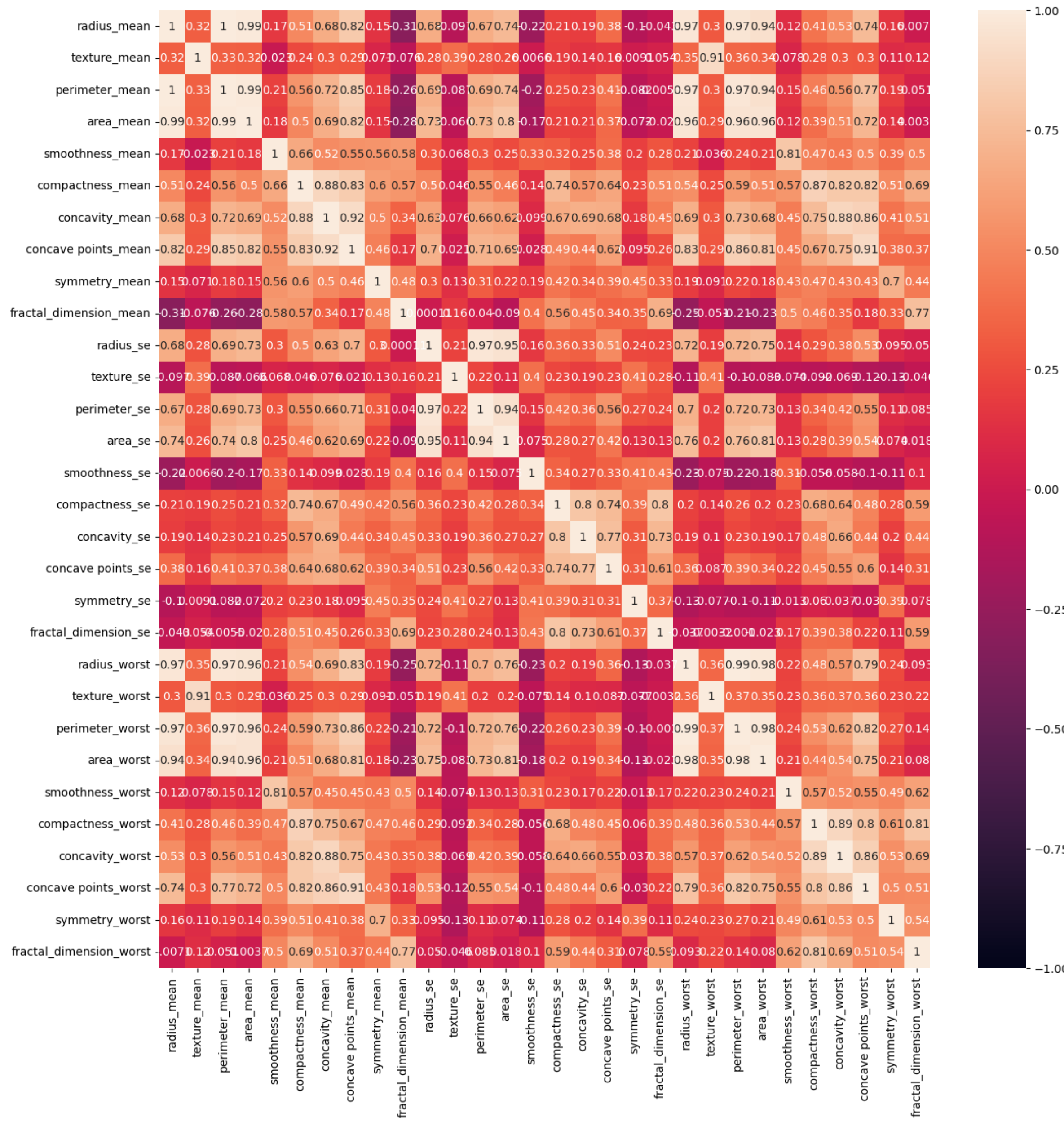
In [9]:
```
#plotting distributions of numerical features
plt.figure(figsize=(30,50))

for i, col in enumerate(num_feat, 1):
    plt.subplot(10, 3, i)
    sns.histplot(df[col], kde=True, stat="density", kde_kws=dict(cut=3))
```


Density
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

- Features 'radius_mean', 'texture_mean', 'perimeter_mean', 'smoothness_mean', 'symmetry_mean', 'texture_worst' and 'smoothness_worst', follow normal distribution.
- Other features follows right skewed distribution.
- Most of the features has outliers

In [10]:
```python
#correlation heatmap
plt.figure(figsize=(15,15))
sns.heatmap(df.corr(), annot=True, vmax=1, vmin=-1)
```

Out[10]: <AxesSubplot: >



- There are multicollinearity in this dataset. Several features show strong posistive correlation.

In [11]:
```
#finding correlated features

def correlation(dataset, threshold):
    col_corr = set()  # Set of all the names of correlated columns
    corr_matrix = dataset.corr()
    for i in range(len(corr_matrix.columns)):
        for j in range(i):
            if abs(corr_matrix.iloc[i, j]) > threshold:
                colname = corr_matrix.columns[i]  # getting the name of column
                col_corr.add(colname)
    return col_corr
```

In [12]:
```
correlatd_col = correlation(df, 0.8) #we are setting threshold as 0.8

print('Features showing multicollinearity : ')
correlatd_col
```

```
Features showing multicollinearity :
```

Out[12]:
```
{'area_mean',
 'area_se',
 'area_worst',
 'compactness_worst',
 'concave points_mean',
 'concave points_worst',
 'concavity_mean',
 'concavity_se',
 'concavity_worst',
 'fractal_dimension_se',
 'fractal_dimension_worst',
 'perimeter_mean',
 'perimeter_se',
 'perimeter_worst',
 'radius_worst',
 'smoothness_worst',
 'texture_worst'}
```

Data Preprocessing

In [13]:
```
#making copy of dataframe for preprocessing
data = df.copy()
```

Handling null values

In [14]:
```
#checking for null values
data.isnull().sum()
```

Out[14]:
```
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
```

- There are no null values in the dataset

Handling duplicated observations

In [15]:
```
#checking for duplicated observations
data.duplicated().sum()
```

Out[15]:
```
0
```

- There are no duplicate observations

Dealing Multicollinearity

In [16]:
```
#removig columns with multicollinearity

data = data.drop(correlatd_col, axis=1)
data.shape
```

Out[16]:
```
(569, 14)
```

- We have removed 17 columns that showed multicollinearity

Encoding categorical variable

In [17]:
```
data['diagnosis'].unique()
```

Out[17]:
```
array(['M', 'B'], dtype=object)
```

In [18]:
```
#doing one-hot encoding

data['diagnosis'] = pd.get_dummies(data.diagnosis, drop_first=True)
data.head()
```

Out[18]:

	diagnosis	radius_mean	texture_mean	smoothness_mean	compactness_mean	symmetry_mean
0	1	17.99	10.38	0.11840	0.27760	0.2419
1	1	20.57	17.77	0.08474	0.07864	0.1812
2	1	19.69	21.25	0.10960	0.15990	0.2069
3	1	11.42	20.38	0.14250	0.28390	0.2597
4	1	20.29	14.34	0.10030	0.13280	0.1809

In [19]:
```
data['diagnosis'].unique()
```

Out[19]:
```
array([1, 0], dtype=uint8)
```

- 1 represents Malignant
- 0 represents Benign

Seperating features and matrix

In [20]:
```
X = data.drop('diagnosis', axis=1)
y = data['diagnosis']
```

Splitting dataset into test and train set

In [21]:
```
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_sta
```

In [22]:
```
print('Shape of Train set: ', X_train.shape)
print('Shape of Test set: ', X_test.shape)
```

```
Shape of Train set:  (455, 13)
Shape of Test set:  (114, 13)
```

- There are 455 observations in test set and 114 observations in train set

In [23]:
```
X_train.head()
```

Out[23]:

	radius_mean	texture_mean	smoothness_mean	compactness_mean	symmetry_mean	fractal_
560	14.05	27.15	0.09929	0.11260	0.1537	
428	11.13	16.62	0.08151	0.03834	0.1511	
198	19.18	22.49	0.08523	0.14280	0.1767	
203	13.81	23.75	0.13230	0.17680	0.2251	
41	10.95	21.35	0.12270	0.12180	0.1895	

Feature scaling

In [24]:
```
#standardizing the dataset
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [25]:
```
X_train
```

Out[25]:
```
array([[-0.01330339,  1.7757658 ,  0.22879041, ...,  0.79264996,
         0.03869712, -1.08014517],
       [-0.8448276 , -0.6284278 , -1.01982093, ..., -0.92858668,
        -0.04989848, -0.85773964],
       [ 1.44755936,  0.71180168, -0.75858166, ...,  0.10046365,
        -0.7911067 ,  0.4967602 ],
       ...,
       [-0.46608541, -1.49375484, -1.56687843, ..., -0.63701388,
         1.02323128, -1.02997851],
       [-0.50025764, -1.62161319, -0.42149874, ..., -1.00532536,
        -1.14798474,  0.35796577],
       [ 0.96060511,  1.21181916,  0.62275607, ...,  0.69523115,
        -1.12801953, -1.23064515]])
```

- Now the dataset is standardized (mean = 0 and standard deviation = 1).

Building Machine Learning Models

1. Logistic regression

Model training

In [26]:
```
#instantiating the model
from sklearn.linear_model import LogisticRegression

logReg = LogisticRegression(random_state=5)
```

```
#training the model with train set
logReg.fit(X_train, y_train)
```

Out[26]:

```
LogisticRegression
LogisticRegression(random_state=5)
```

Model evaluation

In [27]:

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

#prediction for test data
y_pred = logReg.predict(X_test)


#evaluting the model
acc = accuracy_score(y_test, y_pred)
pre = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
```

In [28]:

```
#storing evaluation metrics to a dataframe

results = pd.DataFrame([['Logistic Regression', acc, pre, rec, f1]],
                       columns=['Model', 'Accuracy', 'Precision', 'Recall', 'F1 Sco

results
```

Out[28]:

	Model	Accuracy	Precision	Recall	F1 Score
0	Logistic Regression	0.947368	0.933333	0.933333	0.933333

- With default parameters Model is giving accuracy of 94.7%

In [29]:

```
#printing confusion matrix
confusion_matrix(y_test, y_pred)
```

Out[29]:

```
array([[66,  3],
       [ 3, 42]], dtype=int64)
```

- There are 108 correct predictions (66 TP and 42 TN)
- 6 predictions are wrong (3 FP and 3 FN)

Cross validation

In [30]:

```
from sklearn.model_selection import cross_val_score

accuracies = cross_val_score(estimator=logReg, 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 95.84 %
Standard Deviation is 2.28 %
```

- Our model has accuracy with in the cross validation score

2. Random Forest Classifier

Model Training

In [31]:
```
#instantiating the model
from sklearn.ensemble import RandomForestClassifier

ranForest = RandomForestClassifier(random_state=5)

#training the model
ranForest.fit(X_train, y_train)
```

Out[31]:
```
▾ RandomForestClassifier
RandomForestClassifier(random_state=5)
```

In [32]:
```
#model prediction with test data
y_pred = ranForest.predict(X_test)
```

Model Evaluation

In [33]:
```
#evaluting the model
acc = accuracy_score(y_test, y_pred)
pre = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
```

In [34]:
```
#storing evaluation metrics to a dataframe

rf_results = pd.DataFrame([['Random Forest Classifier', acc, pre, rec, f1]],
                          columns=['Model', 'Accuracy', 'Precision', 'Recall', 'F1 Sco

results = results.append(rf_results, ignore_index=True)
results
```

Out[34]:

	Model	Accuracy	Precision	Recall	F1 Score
0	Logistic Regression	0.947368	0.933333	0.933333	0.933333
1	Random Forest Classifier	0.929825	0.911111	0.911111	0.911111

- Random Forest Classifier has lower scores than Logistic regression

In [35]:
```
#printing confusion matrix
confusion_matrix(y_test, y_pred)
```

Out[35]:
```
array([[65,  4],
       [ 4, 41]], dtype=int64)
```

- Random Forest Classifier made 106 correct and 8 wrong predictions

Cross Validation

In [36]:
```
from sklearn.model_selection import cross_val_score

accuracies = cross_val_score(estimator=ranForest, 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 94.28 %
Standard Deviation is 3.01 %
```

- Random Forest has lower accuracy and higher standard deviaion.
- Since Logistic regression has better performance we will take it as the final model and tune it for better performance.

Hyperparameter Tuning

In [37]:
```
#specifying differnet hyperparameters for random search cross validation
from sklearn.model_selection import RandomizedSearchCV

params = {'penalty': ['l1', 'l2', 'elasticnet', 'none'], 'C': [0.1, 0.25, 0.5, 0.75
         'solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga']}
```

In [38]:
```
random_search = RandomizedSearchCV(estimator=logReg, param_distributions=params, cv
random_search.fit(X_train, y_train)
```

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

Out[38]:
```
▸ RandomizedSearchCV
▸ estimator: LogisticRegression
  ▸ LogisticRegression
```

In [39]:
```
#finding the best estimator
random_search.best_estimator_
```

Out[39]:
```
▾ LogisticRegression
LogisticRegression(C=1.5, penalty='none', random_state=5, solver='saga')
```

In [40]:
```
#finding best score
random_search.best_score_
```

Out[40]:
```
0.9915658504781224
```

In [41]:
```
#finding best params
random_search.best_params_
```

Out[41]:
```
{'solver': 'saga', 'penalty': 'none', 'C': 1.5}
```

- We got the best params value as optimization algorithm = saga, norm of the penalty = None and regularization parameter C = 1.5

Final Model

In [42]:
```
#training the model with best hyperparameters

classifier = LogisticRegression(solver='sag', penalty=None, C=1.5)
classifier.fit(X_train, y_train)
```

Out[42]:
```
LogisticRegression
LogisticRegression(C=1.5, penalty=None, solver='sag')
```

In [43]:
```
#making predictions with test data
y_pred = classifier.predict(X_test)
```

Model evaluation

In [44]:
```
#calculating evaluation metrics
acc = accuracy_score(y_test, y_pred)
pre = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

#storing evaluation metrics to a dataframe

lg_results = pd.DataFrame([['Tuned Logistic Regression', acc, pre, rec, f1]],
                          columns=['Model', 'Accuracy', 'Precision', 'Recall', 'F1 Sco

results = results.append(lg_results, ignore_index=True)
results
```

Out[44]:

	Model	Accuracy	Precision	Recall	F1 Score
0	Logistic Regression	0.947368	0.933333	0.933333	0.933333
1	Random Forest Classifier	0.929825	0.911111	0.911111	0.911111
2	Tuned Logistic Regression	0.947368	0.914894	0.955556	0.934783

- The tuned model has same accuracy as default logistic regression while there is a decrease in precision score. There are improvement in Recall and F1 score

In [45]:
```
#printing confusion matrix
confusion_matrix(y_test, y_pred)
```

Out[45]:
```
array([[65,  4],
       [ 2, 43]], dtype=int64)
```

- The model predicted 108 correct prediction while 8 were wrong
- Two predictions are False Positive while 4 are False Negative

Making a Sample Prediction

Sample Observations are:

radius_mean = 11.13, texture_mean = 16.62, smoothness_mean = 0.08151, compactness_mean = 0.03834, symmetry_mean = 0.1511, fractal_dimension_mean = 0.06148, radius_se = 0.1415, texture_se = 0.9671, smoothness_se = 0.005883, compactness_se = 0.006263, concave points_se = 0.006189, symmetry_se = 0.02009, symmetry_worst = 0.2383

In [69]:
```
sample_obs = [11.13, 16.62, 0.08151, 0.03834, 0.1511, 0.06148, 0.1415, 0.9671, 0.00

#making prediction
classifier.predict(scaler.transform([sample_obs]))
```

Out[69]:
```
array([0], dtype=uint8)
```

- Breast Cancer with the given observations is Benign
- With this information the patient can get correct treatment for the disease.