Importing required libraries

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
```

Load the dataset

In [2]:
```
df = pd.read_csv("C:/Users/ADMIN/Desktop/Data Science/Datasets/Datasets/breast-canc
```

View the first few observations of the dataset

In [3]:
```
df.head()
```

Out[3]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothn
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 × 32 columns

Droping unnecessary columns

In [4]:
```
df = df.drop(columns = "id")
```

Checking for unique levels of diagnosis

In [5]:
```
df.diagnosis.unique()
```

Out[5]:
```
array(['M', 'B'], dtype=object)
```

Label Encoding

In [6]:
```
df['diagnosis'] = df['diagnosis'].apply(lambda val: 1 if val == 'M' else 0)
```

In [7]:
```
df.diagnosis.unique()
```

Out[7]:
```
array([1, 0], dtype=int64)
```

Assess the structure of the dataset

In [8]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 31 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   diagnosis                569 non-null    int64  
 1   radius_mean              569 non-null    float64
 2   texture_mean             569 non-null    float64
 3   perimeter_mean           569 non-null    float64
 4   area_mean                569 non-null    float64
 5   smoothness_mean          569 non-null    float64
 6   compactness_mean         569 non-null    float64
 7   concavity_mean           569 non-null    float64
 8   concave points_mean      569 non-null    float64
 9   symmetry_mean            569 non-null    float64
 10  fractal_dimension_mean   569 non-null    float64
 11  radius_se                569 non-null    float64
 12  texture_se               569 non-null    float64
 13  perimeter_se             569 non-null    float64
 14  area_se                  569 non-null    float64
 15  smoothness_se            569 non-null    float64
 16  compactness_se           569 non-null    float64
 17  concavity_se             569 non-null    float64
 18  concave points_se        569 non-null    float64
 19  symmetry_se              569 non-null    float64
 20  fractal_dimension_se     569 non-null    float64
 21  radius_worst             569 non-null    float64
 22  texture_worst            569 non-null    float64
 23  perimeter_worst          569 non-null    float64
 24  area_worst               569 non-null    float64
 25  smoothness_worst         569 non-null    float64
 26  compactness_worst        569 non-null    float64
 27  concavity_worst          569 non-null    float64
 28  concave points_worst     569 non-null    float64
 29  symmetry_worst           569 non-null    float64
 30  fractal_dimension_worst  569 non-null    float64
dtypes: float64(30), int64(1)
memory usage: 137.9 KB
```

Checking for null values

In [9]:
```
df.isna().sum()
```

Out[9]:
```
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
```

Checking for duplicates

In [10]:
```
df.duplicated().sum()
```

Out[10]:
```
0
```

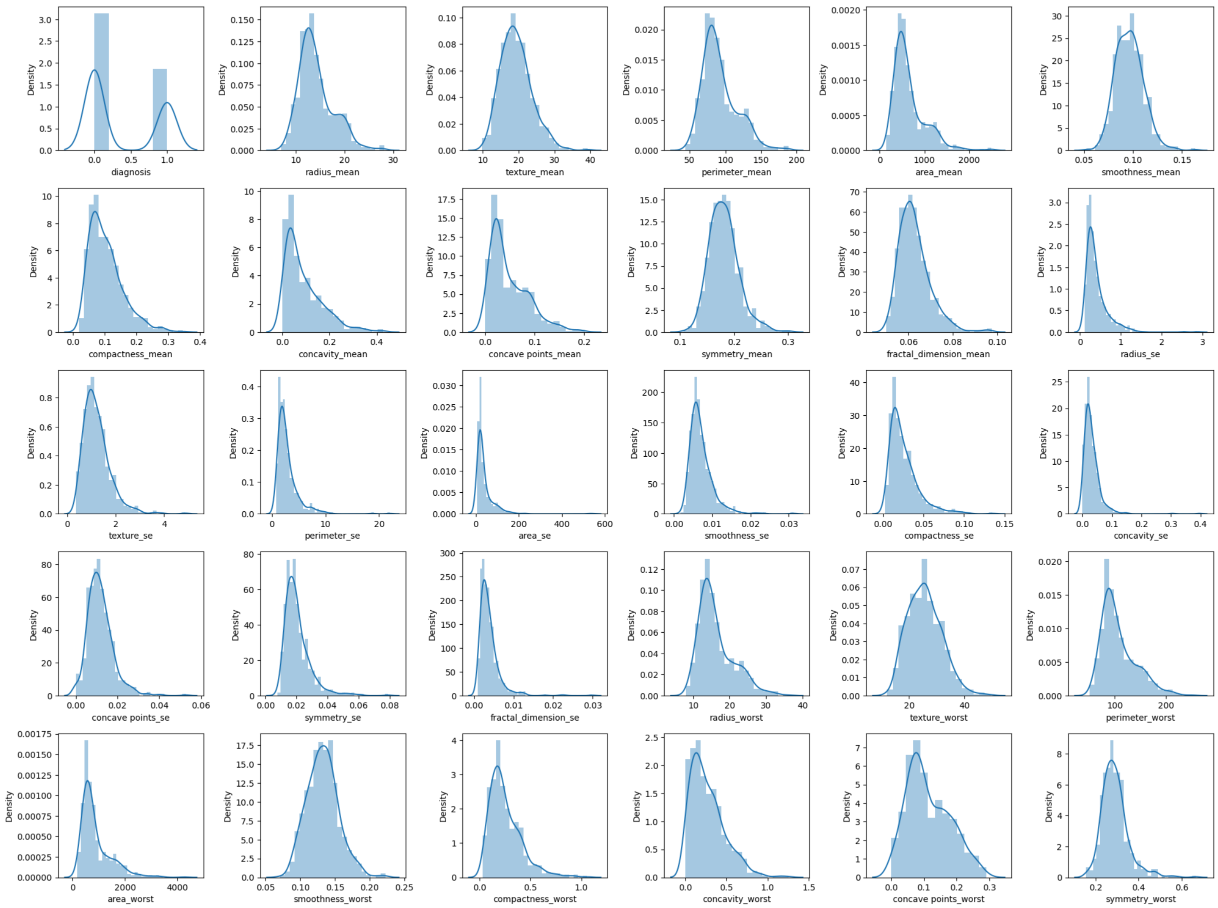
Exploratory Data Analysis (EDA)

In [11]:
```
plt.figure(figsize = (20, 15))
plotnumber = 1

for column in df:
    if plotnumber <= 30:
        ax = plt.subplot(5, 6, plotnumber)
        sns.distplot(df[column])
        plt.xlabel(column)

    plotnumber += 1

plt.tight_layout()
plt.show()
```



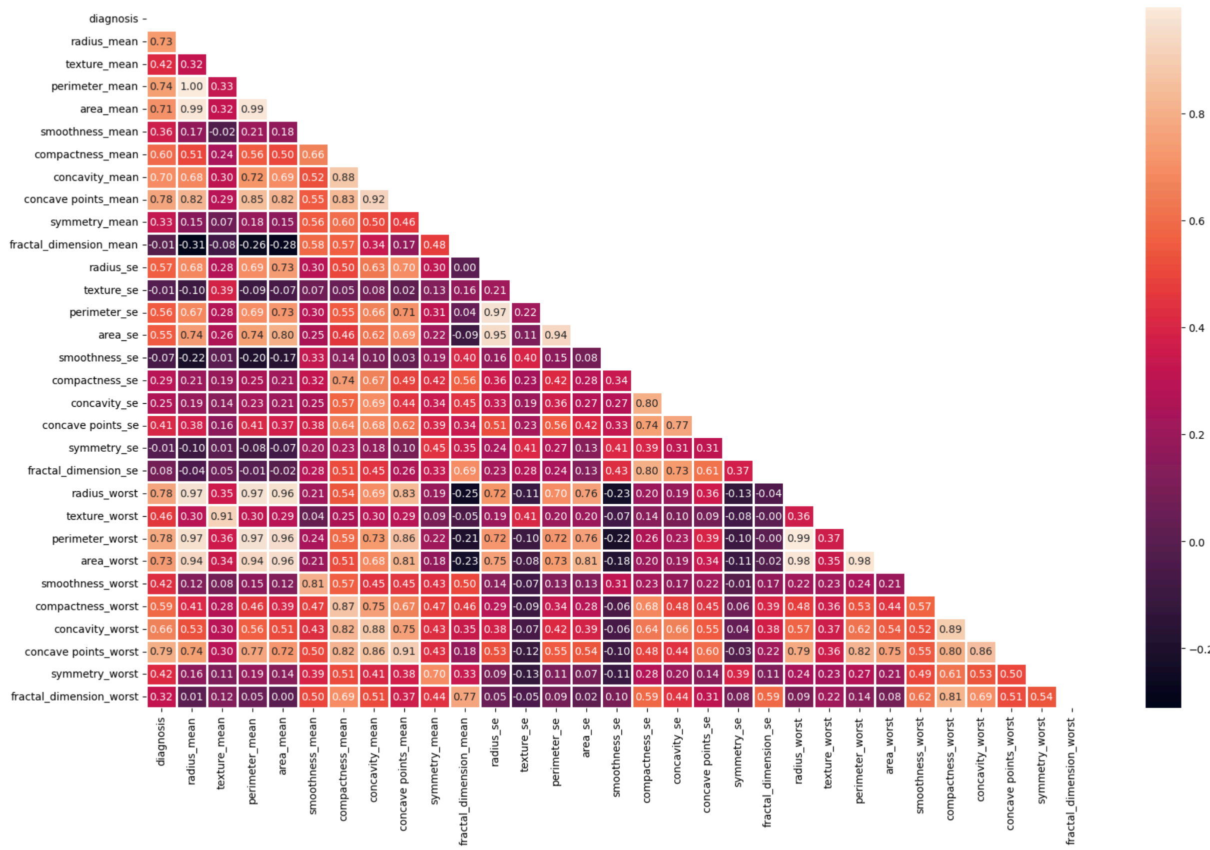
Heatmap

In [12]:

```
plt.figure(figsize = (20, 12))

corr = df.corr()
mask = np.triu(np.ones_like(corr, dtype = bool))

sns.heatmap(corr, mask = mask, linewidths = 1, annot = True, fmt = ".2f")
plt.show()
```



Distribution of the Study Outcome

In [13]:
```
df['diagnosis'].value_counts()
```

Out[13]:
```
diagnosis
0    357
1    212
Name: count, dtype: int64
```

Defining the X and y features

In [15]:
```
X = df.drop(columns = ['diagnosis'])
y = df['diagnosis']
```

Handling Class Imbalance

In [16]:
```
## Load the required module
from imblearn.over_sampling import RandomOverSampler

## Initialize the RandomOverSampler
ros = RandomOverSampler(random_state = 42)

## Apply the RandomOverSampler
X_resampled, y_resampled = ros.fit_resample(X, y)

## Print the oversampled data
dict(zip(*np.unique(y_resampled, return_counts = True)))
```

Out[16]: {0: 357, 1: 357}

Splitting data into training and test set

In [18]:
```
## Loading the required libraries
from sklearn.model_selection import train_test_split

## Splitting
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled, test_
```

Standardization

In [19]:
```
## Load the required module
from sklearn.preprocessing import StandardScaler

## Initialize the standard scaler
scaler = StandardScaler()

## Apply the standard scaler
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Training various Machine Learning models

1. Logistic Regression

In [22]:
```
## Load the required module
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score, precision_score, recall_score, accuracy_score

## Initialize the model
log = LogisticRegression()

## Fit the model
log.fit(X_train, y_train)

## Model predictions
log_pred = log.predict(X_test)
log_score = accuracy_score(y_test, log_pred)

## Evaluate performance
print("Classification Report:\n", classification_report(y_test, log_pred))
print("F1 Score:", f1_score(y_test, log_pred))
print("Precision:", precision_score(y_test, log_pred))
print("Recall:", recall_score(y_test, log_pred))
print("Accuracy:", accuracy_score(y_test, log_pred))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.97      0.99      0.98       119
           1       0.99      0.96      0.97        96

    accuracy                           0.98       215
   macro avg       0.98      0.97      0.98       215
weighted avg       0.98      0.98      0.98       215

F1 Score: 0.9735449735449735
Precision: 0.989247311827957
Recall: 0.9583333333333334
Accuracy: 0.9767441860465116
```

2. K Nearest Neighbors

In [24]:
```python
## Load the required modules
from sklearn.neighbors import KNeighborsClassifier

## Initialize the model
knn = KNeighborsClassifier()

## Fit the model
knn.fit(X_train, y_train)

## Model predictions
knn_pred = knn.predict(X_test)
knn_score = accuracy_score(y_test, knn_pred)

## Evaluate performance
print("Classification Report:\n", classification_report(y_test, knn_pred))
print("F1 Score:", f1_score(y_test, knn_pred))
print("Precision:", precision_score(y_test, knn_pred))
print("Recall:", recall_score(y_test, knn_pred))
print("Accuracy:", accuracy_score(y_test, knn_pred))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.94      0.98      0.96       119
           1       0.98      0.93      0.95        96

    accuracy                           0.96       215
   macro avg       0.96      0.96      0.96       215
weighted avg       0.96      0.96      0.96       215

F1 Score: 0.9518716577540107
Precision: 0.978021978021978
Recall: 0.9270833333333334
Accuracy: 0.958139534883721
```

3. Support Vector Machines

In [23]:
```python
## Load the required module
from sklearn.svm import SVC
```

```
from sklearn.model_selection import GridSearchCV

## Initialize the model
svc = SVC()

## Define parameters
parameters = {
    'gamma' : [0.0001, 0.001, 0.01, 0.1],
    'C' : [0.01, 0.05, 0.5, 0.1, 1, 10, 15, 20]
}

## Fit the model using the best parameters
grid_search = GridSearchCV(svc, parameters)
grid_search.fit(X_train, y_train)

## Model predictions
svm_pred = grid_search.predict(X_test)
svm_score = accuracy_score(y_test, svm_pred)

## Evaluate performance
print("Classification Report:\n", classification_report(y_test, svm_pred))
print("F1 Score:", f1_score(y_test, svm_pred))
print("Precision:", precision_score(y_test, svm_pred))
print("Recall:", recall_score(y_test, svm_pred))
print("Accuracy:", accuracy_score(y_test, svm_pred))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.95      0.99      0.97       119
           1       0.99      0.94      0.96        96

    accuracy                           0.97       215
   macro avg       0.97      0.96      0.97       215
weighted avg       0.97      0.97      0.97       215

F1 Score: 0.9625668449197861
Precision: 0.989010989010989
Recall: 0.9375
Accuracy: 0.9674418604651163
```

4. Stochastic Gradient Descent Classifier

In [25]:

```
## Load the required module
from sklearn.linear_model import SGDClassifier

## Initialize the model
sgd = SGDClassifier()

## Define the parameters
parameters = {
    'alpha' : [0.0001, 0.001, 0.01, 0.1, 1],
    'loss' : ['hinge', 'log_loss'], # Changed 'log' to 'log_loss'
    'penalty' : ['l1', 'l2']
}
```

```python
## Fit the model with parameters
grid_search = GridSearchCV(sgd, parameters, cv = 10, n_jobs = -1)
grid_search.fit(X_train, y_train)

## Make Predictions
sdg_pred = grid_search.predict(X_test)
sdg_score = accuracy_score(y_test, sdg_pred)

## Evaluate performance
print("Classification Report:\n", classification_report(y_test, sdg_pred))
print("F1 Score:", f1_score(y_test, sdg_pred))
print("Precision:", precision_score(y_test, sdg_pred))
print("Recall:", recall_score(y_test, sdg_pred))
print("Accuracy:", accuracy_score(y_test, sdg_pred))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.97      0.99      0.98       119
           1       0.99      0.96      0.97        96

    accuracy                           0.98       215
   macro avg       0.98      0.97      0.98       215
weighted avg       0.98      0.98      0.98       215

F1 Score: 0.9735449735449735
Precision: 0.989247311827957
Recall: 0.9583333333333334
Accuracy: 0.9767441860465116
```

5. Decision Tree Classifier

In [26]:
```python
## Load the required module
from sklearn.tree import DecisionTreeClassifier

## Initialize the model
dtc = DecisionTreeClassifier()

## Define the parameters
parameters = {
    'criterion' : ['gini', 'entropy'],
    'max_depth' : range(2, 32, 1),
    'min_samples_leaf' : range(1, 10, 1),
    'min_samples_split' : range(2, 10, 1),
    'splitter' : ['best', 'random']
}

## Fit the models with parameters
grid_search_dt = GridSearchCV(dtc, parameters, cv = 5, n_jobs = -1, verbose = 1)
grid_search_dt.fit(X_train, y_train)

## Make Predictions
dtc_pred = grid_search_dt.predict(X_test)
dtc_score = accuracy_score(y_test, dtc_pred)

## Evaluate performance
```

```
print("Classification Report:\n", classification_report(y_test, dtc_pred))
print("F1 Score:", f1_score(y_test, dtc_pred))
print("Precision:", precision_score(y_test, dtc_pred))
print("Recall:", recall_score(y_test, dtc_pred))
print("Accuracy:", accuracy_score(y_test, dtc_pred))
```

```
Fitting 5 folds for each of 8640 candidates, totalling 43200 fits
Classification Report:
               precision    recall  f1-score   support

           0       0.94      0.97      0.96       119
           1       0.97      0.93      0.95        96

    accuracy                           0.95       215
   macro avg       0.96      0.95      0.95       215
weighted avg       0.95      0.95      0.95       215

F1 Score: 0.9468085106382979
Precision: 0.967391304347826
Recall: 0.9270833333333334
Accuracy: 0.9534883720930233
```

6. Random Forest Classifier

In [29]:

```
## Load the required module
from sklearn.ensemble import RandomForestClassifier

## Initialize the model
rf = RandomForestClassifier(criterion = 'entropy', max_depth = 11, max_features = '

## Fit the model
rf.fit(X_train, y_train)

## Make predictions
rf_pred = rf.predict(X_test)
rf_score = accuracy_score(y_test, rf_pred)

## Evaluate performance
print("Classification Report:\n", classification_report(y_test, rf_pred))
print("F1 Score:", f1_score(y_test, rf_pred))
print("Precision:", precision_score(y_test, rf_pred))
print("Recall:", recall_score(y_test, rf_pred))
print("Accuracy:", accuracy_score(y_test, rf_pred))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.97      0.97      0.97       119
           1       0.96      0.97      0.96        96

    accuracy                           0.97       215
   macro avg       0.97      0.97      0.97       215
weighted avg       0.97      0.97      0.97       215

F1 Score: 0.9637305699481865
Precision: 0.9587628865979382
Recall: 0.96875
Accuracy: 0.9674418604651163
```

7. Voting Classifier

In [32]:
```
## Load the required module
from sklearn.ensemble import VotingClassifier

## Define the base models
classifiers = [('Logistic Regression', log), ('K Nearest Neighbours', knn), ('Suppo
               ('Decision Tree', dtc)]

## Initialize the voting classifier
vc = VotingClassifier(estimators = classifiers)

## Fit the model
vc.fit(X_train, y_train)

## Model predictions
vc_pred = vc.predict(X_test)
vc_score = accuracy_score(y_test, vc_pred)

## Evaluate performance
print("Classification Report:\n", classification_report(y_test, vc_pred))
print("F1 Score:", f1_score(y_test, vc_pred))
print("Precision:", precision_score(y_test, vc_pred))
print("Recall:", recall_score(y_test, vc_pred))
print("Accuracy:", accuracy_score(y_test, vc_pred))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.95      0.99      0.97       119
           1       0.99      0.94      0.96        96

    accuracy                           0.97       215
   macro avg       0.97      0.96      0.97       215
weighted avg       0.97      0.97      0.97       215

F1 Score: 0.9625668449197861
Precision: 0.989010989010989
Recall: 0.9375
Accuracy: 0.9674418604651163
```

8. Ada Boost Classifier

In [33]:
```
## Load the required model
from sklearn.ensemble import AdaBoostClassifier

## Initialize the model
ada = AdaBoostClassifier(estimator=DecisionTreeClassifier(max_depth = 1), n_estimat

## Fit the model
ada.fit(X_train, y_train)

## Model predictions
ada_pred = ada.predict(X_test)

## Evaluate performance
ada_score = accuracy_score(y_test, ada_pred)
print("Classification Report:\n", classification_report(y_test, ada_pred))
print("F1 Score:", f1_score(y_test, ada_pred))
print("Precision:", precision_score(y_test, ada_pred))
print("Recall:", recall_score(y_test, ada_pred))
print("Accuracy:", accuracy_score(y_test, ada_pred))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.98      0.97      0.97       119
           1       0.96      0.98      0.97        96

    accuracy                           0.97       215
   macro avg       0.97      0.97      0.97       215
weighted avg       0.97      0.97      0.97       215

F1 Score: 0.9690721649484536
Precision: 0.9591836734693877
Recall: 0.9791666666666666
Accuracy: 0.9720930232558139
```

9. Gradient Boosting Classifier

In [34]:
```
## Load the required module
from sklearn.ensemble import GradientBoostingClassifier

## Initialize the model
gbc = GradientBoostingClassifier()

## Define the parameters
parameters = {
    'loss': ['deviance', 'exponential'],
    'learning_rate': [0.001, 0.1, 1, 10],
    'n_estimators': [100, 150, 180, 200]
}

## Fit the model using gridsearch
grid_search_gbc = GridSearchCV(gbc, parameters, cv = 5, n_jobs = -1, verbose = 1)
grid_search_gbc.fit(X_train, y_train)
```

```
## Make predictions
gbc_pred = grid_search_gbc.predict(X_test)

## Evaluate performance
gbc_score = accuracy_score(y_test, gbc_pred)
print("Classification Report:\n", classification_report(y_test, gbc_pred))
print("F1 Score:", f1_score(y_test, gbc_pred))
print("Precision:", precision_score(y_test, gbc_pred))
print("Recall:", recall_score(y_test, gbc_pred))
print("Accuracy:", accuracy_score(y_test, gbc_pred))
```

```
Fitting 5 folds for each of 32 candidates, totalling 160 fits
Classification Report:
               precision    recall  f1-score   support

           0       0.98      0.97      0.97       119
           1       0.96      0.98      0.97        96

    accuracy                           0.97       215
   macro avg       0.97      0.97      0.97       215
weighted avg       0.97      0.97      0.97       215

F1 Score: 0.9690721649484536
Precision: 0.9591836734693877
Recall: 0.9791666666666666
Accuracy: 0.9720930232558139
```

10. Stochastic Gradient Boosting (SGB)

In [39]:
```
## Initialize the model
sgbc = GradientBoostingClassifier(max_depth=4, subsample=0.9, max_features=0.75, n_

## Fit the model
sgbc.fit(X_train, y_train)

## Model predictions
sgbc_pred = sgbc.predict(X_test)

## Evaluate performance
sgbc_score = accuracy_score(y_test, sgbc_pred)
print("Classification Report:\n", classification_report(y_test, sgbc_pred))
print("F1 Score:", f1_score(y_test, sgbc_pred))
print("Precision:", precision_score(y_test, sgbc_pred))
print("Recall:", recall_score(y_test, sgbc_pred))
print("Accuracy:", accuracy_score(y_test, sgbc_pred))
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.97      0.98       119
           1       0.97      0.98      0.97        96

    accuracy                           0.98       215
   macro avg       0.98      0.98      0.98       215
weighted avg       0.98      0.98      0.98       215

F1 Score: 0.9740932642487047
Precision: 0.9690721649484536
Recall: 0.9791666666666666
Accuracy: 0.9767441860465116
```

Extreme Gradient Boosting

Model Comparison

In [40]:

```
models = pd.DataFrame({
    'Model': ['Logistic Regression', 'KNN', 'SVC', 'SGD Classifier', 'Decision Tree
              'Gradient Boosting Classifier', 'Stochastic Gradient Boosting'],
    'Score': [log_score, knn_score, svm_score, sdg_score, dtc_score, rf_score, vc_s
})

models.sort_values(by = 'Score', ascending = False)
```

Out[40]:

	Model	Score
0	Logistic Regression	0.976744
3	SGD Classifier	0.976744
8	Gradient Boosting Classifier	0.976744
9	Stochastic Gradient Boosting	0.976744
7	Ada Boost Classifier	0.972093
2	SVC	0.967442
5	Random Forest Classifier	0.967442
6	Voting Classifier	0.967442
1	KNN	0.958140
4	Decision Tree Classifier	0.953488

Best model for diagnosing breast cancer is "Gradient Boosting Classifier" with an accuracy of 97.44%.

In [41]:

```
## Lets save our model using pickle
import pickle as pkl
pkl.dump(grid_search_gbc, open("breast_cancer_model1.sav","wb"))
```