

In [26]:

```
1 import seaborn as sns
2 import numpy as np
3 import pandas as pd
4 import matplotlib.pyplot as plt
5 import time
6 %matplotlib inline
7
8 from sklearn.linear_model import LogisticRegression
9 from sklearn.naive_bayes import GaussianNB
10 from sklearn.svm import SVC
11 from sklearn.neighbors import KNeighborsClassifier
12 from sklearn.model_selection import train_test_split, GridSearchCV
13 from sklearn.ensemble import VotingClassifier, BaggingClassifier, RandomForestClassifier
14 from xgboost import XGBClassifier
15 from sklearn.metrics import classification_report, confusion_matrix
16
17 from sklearn.datasets import load_breast_cancer
18
19 import warnings
20 warnings.filterwarnings("ignore")
```

In [2]:

```
1 dataset = load_breast_cancer()
2 df = pd.DataFrame(dataset.data, columns=dataset.feature_names)
3 df['target'] = dataset.target
```

In [3]: 1 df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 31 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   mean radius                           569 non-null    float64
1   mean texture                          569 non-null    float64
2   mean perimeter                        569 non-null    float64
3   mean area                            569 non-null    float64
4   mean smoothness                       569 non-null    float64
5   mean compactness                      569 non-null    float64
6   mean concavity                        569 non-null    float64
7   mean concave points                   569 non-null    float64
8   mean symmetry                         569 non-null    float64
9   mean fractal dimension                569 non-null    float64
10  radius error                          569 non-null    float64
11  texture error                         569 non-null    float64
12  perimeter error                       569 non-null    float64
13  area error                           569 non-null    float64
14  smoothness error                     569 non-null    float64
15  compactness error                    569 non-null    float64
16  concavity error                      569 non-null    float64
17  concave points error                 569 non-null    float64
18  symmetry error                       569 non-null    float64
19  fractal dimension error              569 non-null    float64
20  worst radius                         569 non-null    float64
21  worst texture                        569 non-null    float64
22  worst perimeter                      569 non-null    float64
23  worst area                           569 non-null    float64
24  worst smoothness                     569 non-null    float64
25  worst compactness                    569 non-null    float64
26  worst concavity                      569 non-null    float64
27  worst concave points                 569 non-null    float64
28  worst symmetry                       569 non-null    float64
29  worst fractal dimension              569 non-null    float64
30  target                              569 non-null    int32
dtypes: float64(30), int32(1)
memory usage: 135.7 KB
```

The dataset has 569 rows and 31 features with 30 features are floats and 1 target feature of integer.

In [4]:

1	<code>df.describe(include="all").T</code>
---	-------------------------------------------

Out[4]:

	count	mean	std	min	25%	50%	75%
mean radius	569.0	14.127292	3.524049	6.981000	11.700000	13.370000	15.780000
mean texture	569.0	19.289649	4.301036	9.710000	16.170000	18.840000	21.800000
mean perimeter	569.0	91.969033	24.298981	43.790000	75.170000	86.240000	104.100000
mean area	569.0	654.889104	351.914129	143.500000	420.300000	551.100000	782.700000
mean smoothness	569.0	0.096360	0.014064	0.052630	0.086370	0.095870	0.105300
mean compactness	569.0	0.104341	0.052813	0.019380	0.064920	0.092630	0.130400
mean concavity	569.0	0.088799	0.079720	0.000000	0.029560	0.061540	0.130700
mean concave points	569.0	0.048919	0.038803	0.000000	0.020310	0.033500	0.074000
mean symmetry	569.0	0.181162	0.027414	0.106000	0.161900	0.179200	0.195700
mean fractal dimension	569.0	0.062798	0.007060	0.049960	0.057700	0.061540	0.066120
radius error	569.0	0.405172	0.277313	0.111500	0.232400	0.324200	0.478900
texture error	569.0	1.216853	0.551648	0.360200	0.833900	1.108000	1.474000
perimeter error	569.0	2.866059	2.021855	0.757000	1.606000	2.287000	3.357000
area error	569.0	40.337079	45.491006	6.802000	17.850000	24.530000	45.190000
smoothness error	569.0	0.007041	0.003003	0.001713	0.005169	0.006380	0.008140
compactness error	569.0	0.025478	0.017908	0.002252	0.013080	0.020450	0.032450
concavity error	569.0	0.031894	0.030186	0.000000	0.015090	0.025890	0.042050
concave points error	569.0	0.011796	0.006170	0.000000	0.007638	0.010930	0.014710
symmetry error	569.0	0.020542	0.008266	0.007882	0.015160	0.018730	0.023480
fractal dimension error	569.0	0.003795	0.002646	0.000895	0.002248	0.003187	0.004550
worst radius	569.0	16.269190	4.833242	7.930000	13.010000	14.970000	18.790000
worst texture	569.0	25.677223	6.146258	12.020000	21.080000	25.410000	29.720000
worst perimeter	569.0	107.261213	33.602542	50.410000	84.110000	97.660000	125.400000
worst area	569.0	880.583128	569.356993	185.200000	515.300000	686.500000	1084.000000
worst smoothness	569.0	0.132369	0.022832	0.071170	0.116600	0.131300	0.146000
worst compactness	569.0	0.254265	0.157336	0.027290	0.147200	0.211900	0.339100
worst concavity	569.0	0.272188	0.208624	0.000000	0.114500	0.226700	0.382900

	count	mean	std	min	25%	50%	75%
worst concave points	569.0	0.114606	0.065732	0.000000	0.064930	0.099930	0.161400
worst symmetry	569.0	0.290076	0.061867	0.156500	0.250400	0.282200	0.317900
worst fractal dimension	569.0	0.083946	0.018061	0.055040	0.071460	0.080040	0.092080
target	569.0	0.627417	0.483918	0.000000	0.000000	1.000000	1.000000

In [5]: 1 df.isnull().sum()

```
Out[5]: mean radius          0
mean texture            0
mean perimeter          0
mean area               0
mean smoothness         0
mean compactness        0
mean concavity          0
mean concave points     0
mean symmetry           0
mean fractal dimension  0
radius error            0
texture error           0
perimeter error         0
area error              0
smoothness error        0
compactness error       0
concavity error         0
concave points error    0
symmetry error          0
fractal dimension error 0
worst radius            0
worst texture           0
worst perimeter         0
worst area              0
worst smoothness        0
worst compactness       0
worst concavity         0
worst concave points    0
worst symmetry          0
worst fractal dimension 0
target                  0
dtype: int64
```

In [6]:

1 df

Out[6]:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	symmetry
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	0.14710	0
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	0.07017	0
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740	0.12790	0
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	0
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	0
...
564	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	0
565	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	0
566	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	0
567	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	0
568	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	0

569 rows × 31 columns

In [7]:

```

1 s = pd.value_counts(df.target)
2
3 # For class 0
4 num_benign = s[0]
5 # For class 1
6 num_malign = s[1]
7 total_cases = len(df)
8
9 percent_b = num_benign / total_cases
10 percent_m = num_malign / total_cases
11
12 print("Distribution between Benign and Malignant\nPercent Benign: {0:.3}

```

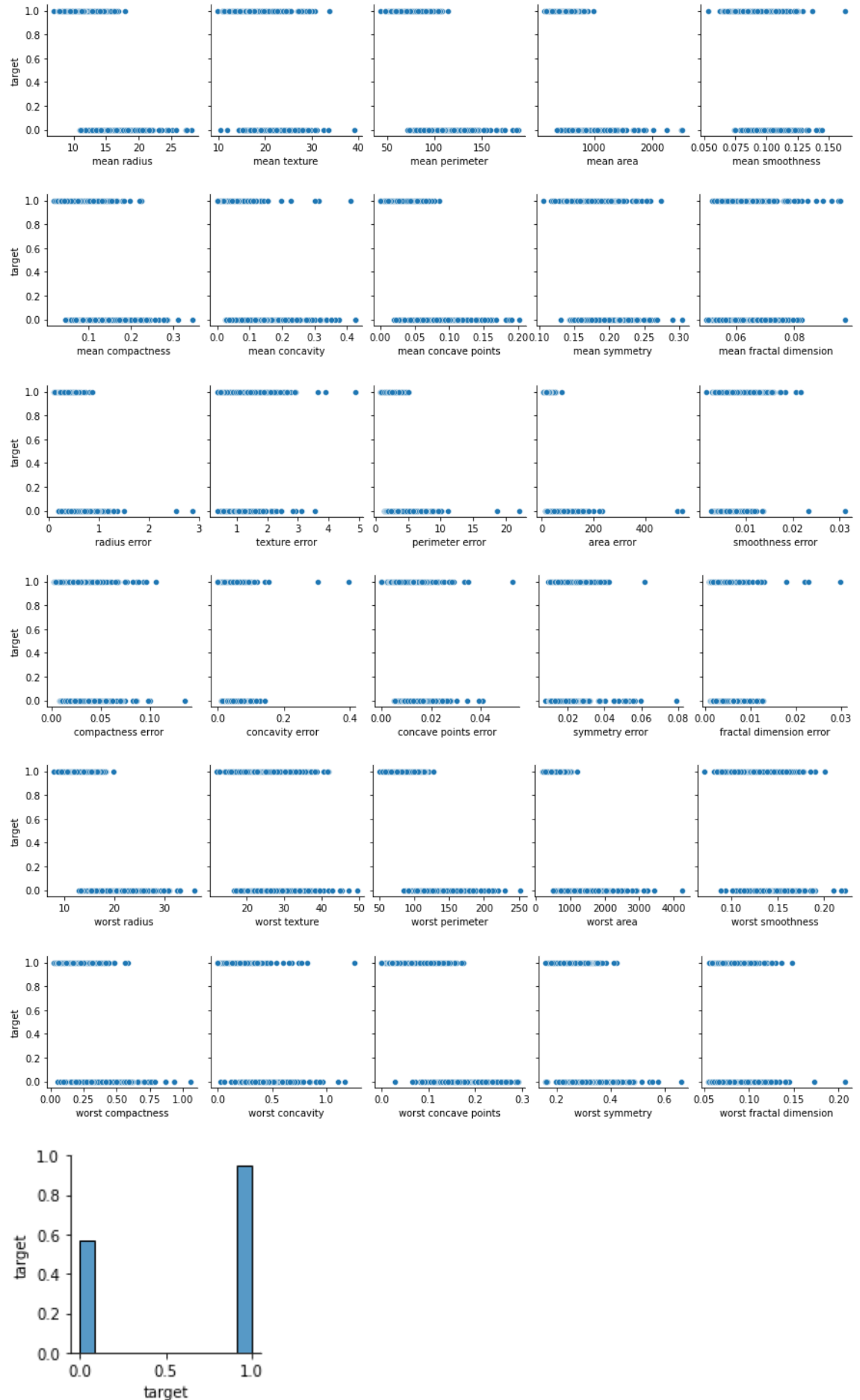
Distribution between Benign and Malignant
Percent Benign: 0.373
Percent Malignant: 0.627

In [8]:

```

1 for i in range(0, len(df.columns),5):
2     sns.pairplot(data=df,x_vars=df.columns[i:i+5],y_vars=['target'])

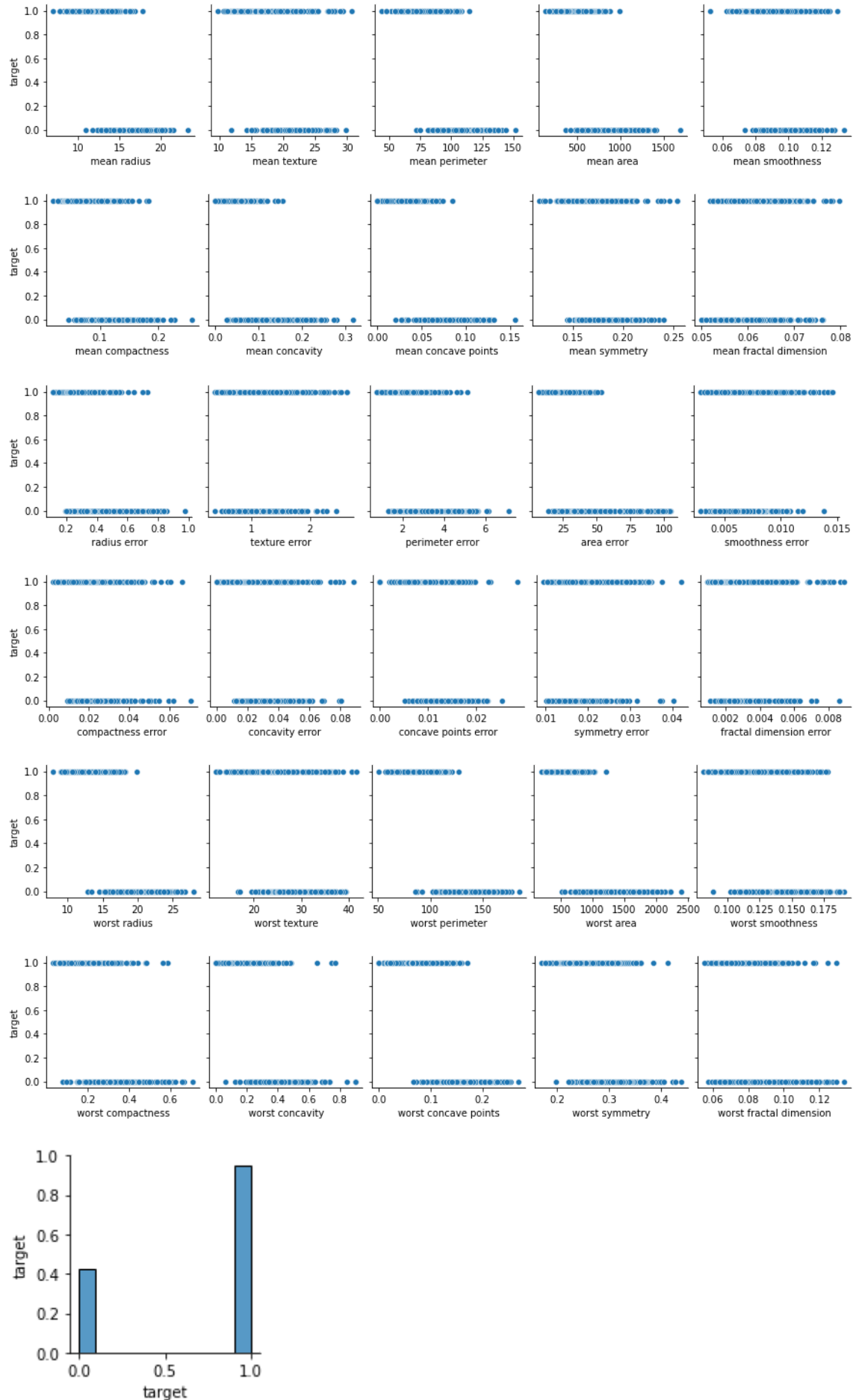
```



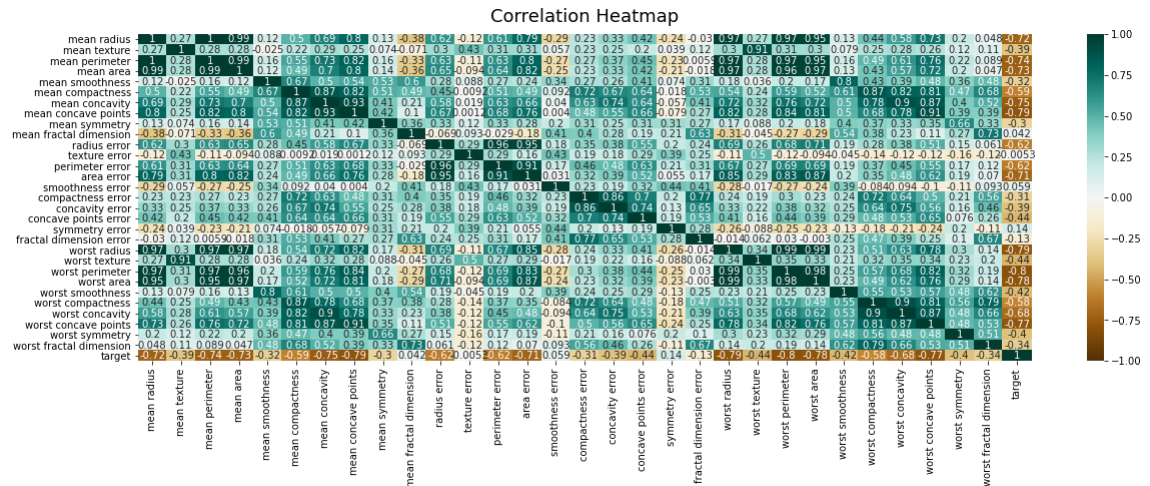
```
In [9]: 1 q1 = df.quantile(0.2)
        2 q3 = df.quantile(0.8)
        3 iqr = q3-q1
        4
        5 df= df[~((df<(q1 - 1.5 * iqr)) | (df > (q3 + 1.5 * iqr ))).any(axis=1)]
```



```
In [10]: 1 for i in range(0, len(df.columns), 5):
2         sns.pairplot(data=df, x_vars=df.columns[i:i+5], y_vars=['target'])
```



```
In [11]: 1 plt.figure(figsize=(20,6))
2 heatmap=sns.heatmap(df.corr(),vmin=-1, vmax=1, annot=True,cmap='BrBG')
3 heatmap.set_title('Correlation Heatmap', fontdict = {'fontsize':18},pac
```



From the heatmap, mean radius, mean perimeter, mean concave points, radius error, perimeter error, concave points error, worst radius, worst texture, worst perimeter, worst area has a correlation score that exceed the p-value of 0.8. Therefore, the features are excluded.

```
In [12]: 1 features = list(df.columns)
2 features = ['mean texture','mean area','mean smoothness','mean compactness',
3            'mean fractal dimension','texture error','area error','smoothness error',
4            'concavity error','concave points error','symmetry error','fractal dimension error',
5            'worst compactness','worst concavity','worst concave points',
6            'target']
X = df[features]
```

```
In [13]: 1 X.head()
```

```
Out[13]:
```

	mean texture	mean area	mean smoothness	mean compactness	mean concavity	mean symmetry	mean fractal dimension	texture error	area error
1	17.77	1326.0	0.08474	0.07864	0.0869	0.1812	0.05667	0.7339	74.0
2	21.25	1203.0	0.10960	0.15990	0.1974	0.2069	0.05999	0.7869	94.0
4	14.34	1297.0	0.10030	0.13280	0.1980	0.1809	0.05883	0.7813	94.4
5	15.70	477.1	0.12780	0.17000	0.1578	0.2087	0.07613	0.8902	27.1
6	19.98	1040.0	0.09463	0.10900	0.1127	0.1794	0.05742	0.7732	53.9

5 rows × 21 columns

```
In [14]: 1 # Normalization:
2 X = (X - np.min(X)) / (np.max(X) - np.min(X))
3 y = df['target']
```

```
In [15]: 1 # Prepare training data for building the model
2 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)
3
```

```
In [16]: 1 # LogReg Model
2 lr = LogisticRegression()
3 lr.fit(X_train, y_train)
4 lr_pred = lr.predict(X_test)
5 print(classification_report(y_test, lr_pred))
```

	precision	recall	f1-score	support
0	1.00	0.83	0.91	30
1	0.93	1.00	0.96	64
accuracy			0.95	94
macro avg	0.96	0.92	0.94	94
weighted avg	0.95	0.95	0.95	94

```
In [17]: 1 knn = KNeighborsClassifier()
2 knn_model = knn.fit(X_train,y_train)
3 knn_pred = knn.predict(X_test)
4 print(classification_report(y_test,knn_pred))
```

	precision	recall	f1-score	support
0	0.96	0.83	0.89	30
1	0.93	0.98	0.95	64
accuracy			0.94	94
macro avg	0.94	0.91	0.92	94
weighted avg	0.94	0.94	0.93	94

```
In [20]: 1 gnb = GaussianNB()
2 gnb_model = gnb.fit(X_train,y_train)
3 gnb_pred = gnb.predict(X_test)
4 print(classification_report(y_test,gnb_pred))
```

	precision	recall	f1-score	support
0	0.84	0.90	0.87	30
1	0.95	0.92	0.94	64
accuracy			0.91	94
macro avg	0.90	0.91	0.90	94
weighted avg	0.92	0.91	0.92	94

```
In [21]: 1 svm = SVC()
2 svm_model = svm.fit(X_train,y_train)
3 svm_pred = svm.predict(X_test)
4 print(classification_report(y_test,svm_pred))
```

	precision	recall	f1-score	support
0	0.96	0.90	0.93	30
1	0.95	0.98	0.97	64
accuracy			0.96	94
macro avg	0.96	0.94	0.95	94
weighted avg	0.96	0.96	0.96	94

Voting Classifier

```
In [23]: 1 models = [('svm', svm), ('KNN', knn), ('GaussianNB', gnb)]
2 hv = VotingClassifier(models, voting='hard')
3
4 hv_model = hv.fit(X_train, y_train)
5 hv_pred = hv.predict(X_test)
6 print(classification_report(y_test,hv_pred))
```

	precision	recall	f1-score	support
0	0.96	0.90	0.93	30
1	0.95	0.98	0.97	64
accuracy			0.96	94
macro avg	0.96	0.94	0.95	94
weighted avg	0.96	0.96	0.96	94

```
In [32]: 1 bagging = BaggingClassifier()
2 bagging.fit(X_train, y_train)
3 bag_pred = bagging.predict(X_test)
4 print(classification_report(y_test, bag_pred))
```

	precision	recall	f1-score	support
0	0.91	0.97	0.94	30
1	0.98	0.95	0.97	64
accuracy			0.96	94
macro avg	0.95	0.96	0.95	94
weighted avg	0.96	0.96	0.96	94

```
In [34]: 1 start = time.time()
2 param_dist = {'max_depth': [2, 3, 4],
3               'bootstrap': [True, False],
4               'max_features': ['auto', 'sqrt', 'log2', None],
5               'criterion': ['gini', 'entropy']}
6 fit_rf = RandomForestClassifier()
7 cv_rf = GridSearchCV(fit_rf, cv=10, param_grid = param_dist, n_jobs = 3)
8
9 cv_rf.fit(X_train, y_train)
10 print('Best Parameters using grid search: \n', cv_rf.best_params_)
11 end = time.time()
12 print('Time taken in grid search: {0: .2f}'.format(end-start))
```

Best Parameters using grid search:

```
{'bootstrap': False, 'criterion': 'gini', 'max_depth': 4, 'max_features': 'sqrt'}
```

Time taken in grid search: 25.41

```
In [37]: 1 rf_pred = cv_rf.predict(X_test)
2 print(classification_report(y_test, rf_pred))
```

	precision	recall	f1-score	support
0	0.90	0.90	0.90	30
1	0.95	0.95	0.95	64
accuracy			0.94	94
macro avg	0.93	0.93	0.93	94
weighted avg	0.94	0.94	0.94	94

```
In [38]: 1 xgb = XGBClassifier()
2 xgb_model = xgb.fit(X_train, y_train)
3 xgb_pred = xgb.predict(X_test)
4 print(classification_report(y_test, xgb_pred))
```

	precision	recall	f1-score	support
0	0.91	0.97	0.94	30
1	0.98	0.95	0.97	64
accuracy			0.96	94
macro avg	0.95	0.96	0.95	94
weighted avg	0.96	0.96	0.96	94

Summary

Voting Classifier is the best model out of the 3 models. The three models has the same f1-score which is 0.97, so we look to precision and recall values. Out of the three models, voting classifier achieved the best score between precision and recall. Voting classifier scores 0.95 which is the lowest of out the three models, however the recall score of 0.98 which scored highest among all 3 models, improving the quality of the model. Hence, The best model is the Voting Classifier model out of all 3 models. The three models has same weighted avg score, scoring 0.96 on precision, recall, and f1-score, therefore it cant be used for comparison.

In []:

1