

Projet_classification_final (1)

March 9, 2023

```
[1]: import pandas as pd
from sklearn.feature_selection import SelectFromModel
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn import tree
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neural_network import MLPClassifier
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.model_selection import cross_val_score
from sklearn.feature_selection import SelectKBest, mutual_info_classif, chi2, \
    f_classif
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score, \
    recall_score, classification_report
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import GridSearchCV
from sklearn.tree import export_graphviz
import warnings
warnings.filterwarnings("ignore")
from sklearn.tree import export_graphviz
import graphviz
from sklearn.model_selection import LeaveOneOut
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import RFECV
import matplotlib.pyplot as plt
```

```
[2]: data = pd.read_csv('data.csv')
```

```
[3]: data.head(3)
```

```
[3]:      id diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
0    842302         M         17.99         10.38             122.8        1001.0
```

1	842517	M	20.57	17.77	132.9	1326.0
2	84300903	M	19.69	21.25	130.0	1203.0

	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	\
0	0.11840	0.27760	0.3001	0.14710	
1	0.08474	0.07864	0.0869	0.07017	
2	0.10960	0.15990	0.1974	0.12790	

...	texture_worst	perimeter_worst	area_worst	smoothness_worst	\
0	17.33	184.6	2019.0	0.1622	
1	23.41	158.8	1956.0	0.1238	
2	25.53	152.5	1709.0	0.1444	

	compactness_worst	concavity_worst	concave points_worst	symmetry_worst	\
0	0.6656	0.7119	0.2654	0.4601	
1	0.1866	0.2416	0.1860	0.2750	
2	0.4245	0.4504	0.2430	0.3613	

	fractal_dimension_worst	Unnamed: 32
0	0.11890	NaN
1	0.08902	NaN
2	0.08758	NaN

[3 rows x 33 columns]

[4]: data.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

```

```
[5]: data.describe()
```

```

[5]:
      count  5.690000e+02  569.000000  569.000000  569.000000  569.000000 \
mean    3.037183e+07    14.127292    19.289649    91.969033   654.889104
std     1.250206e+08     3.524049     4.301036    24.298981   351.914129
min     8.670000e+03     6.981000     9.710000    43.790000   143.500000
25%     8.692180e+05    11.700000    16.170000    75.170000   420.300000
50%     9.060240e+05    13.370000    18.840000    86.240000   551.100000
75%     8.813129e+06    15.780000    21.800000   104.100000   782.700000
max     9.113205e+08    28.110000    39.280000   188.500000  2501.000000

      smoothness_mean  compactness_mean  concavity_mean  concave points_mean \
count          569.000000          569.000000          569.000000          569.000000
mean           0.096360           0.104341           0.088799           0.048919
std            0.014064           0.052813           0.079720           0.038803
min            0.052630           0.019380           0.000000           0.000000
25%            0.086370           0.064920           0.029560           0.020310
50%            0.095870           0.092630           0.061540           0.033500
75%            0.105300           0.130400           0.130700           0.074000
max            0.163400           0.345400           0.426800           0.201200

      symmetry_mean  ... texture_worst  perimeter_worst  area_worst \
count          569.000000  ...          569.000000          569.000000          569.000000
mean           0.181162  ...          25.677223          107.261213          880.583128
std            0.027414  ...           6.146258           33.602542          569.356993
min            0.106000  ...          12.020000           50.410000          185.200000

```

25%	0.161900	...	21.080000	84.110000	515.300000
50%	0.179200	...	25.410000	97.660000	686.500000
75%	0.195700	...	29.720000	125.400000	1084.000000
max	0.304000	...	49.540000	251.200000	4254.000000

	smoothness_worst	compactness_worst	concavity_worst	\
count	569.000000	569.000000	569.000000	
mean	0.132369	0.254265	0.272188	
std	0.022832	0.157336	0.208624	
min	0.071170	0.027290	0.000000	
25%	0.116600	0.147200	0.114500	
50%	0.131300	0.211900	0.226700	
75%	0.146000	0.339100	0.382900	
max	0.222600	1.058000	1.252000	

	concave points_worst	symmetry_worst	fractal_dimension_worst	\
count	569.000000	569.000000	569.000000	
mean	0.114606	0.290076	0.083946	
std	0.065732	0.061867	0.018061	
min	0.000000	0.156500	0.055040	
25%	0.064930	0.250400	0.071460	
50%	0.099930	0.282200	0.080040	
75%	0.161400	0.317900	0.092080	
max	0.291000	0.663800	0.207500	

```

      Unnamed: 32
count      0.0
mean      NaN
std       NaN
min       NaN
25%       NaN
50%       NaN
75%       NaN
max       NaN

```

[8 rows x 32 columns]

```
[6]: data.columns
```

```
[6]: Index(['id', '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', 'Unnamed: 32'],  
dtype='object')
```

1 Data Preprocessing

1.0.1 Missing values

```
[7]: data.isna().sum()
```

```
[7]: 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
```

```
[8]: # suppression de la colonne Unnamed : 32  
     data.drop('Unnamed: 32',axis = 1,inplace = True)
```

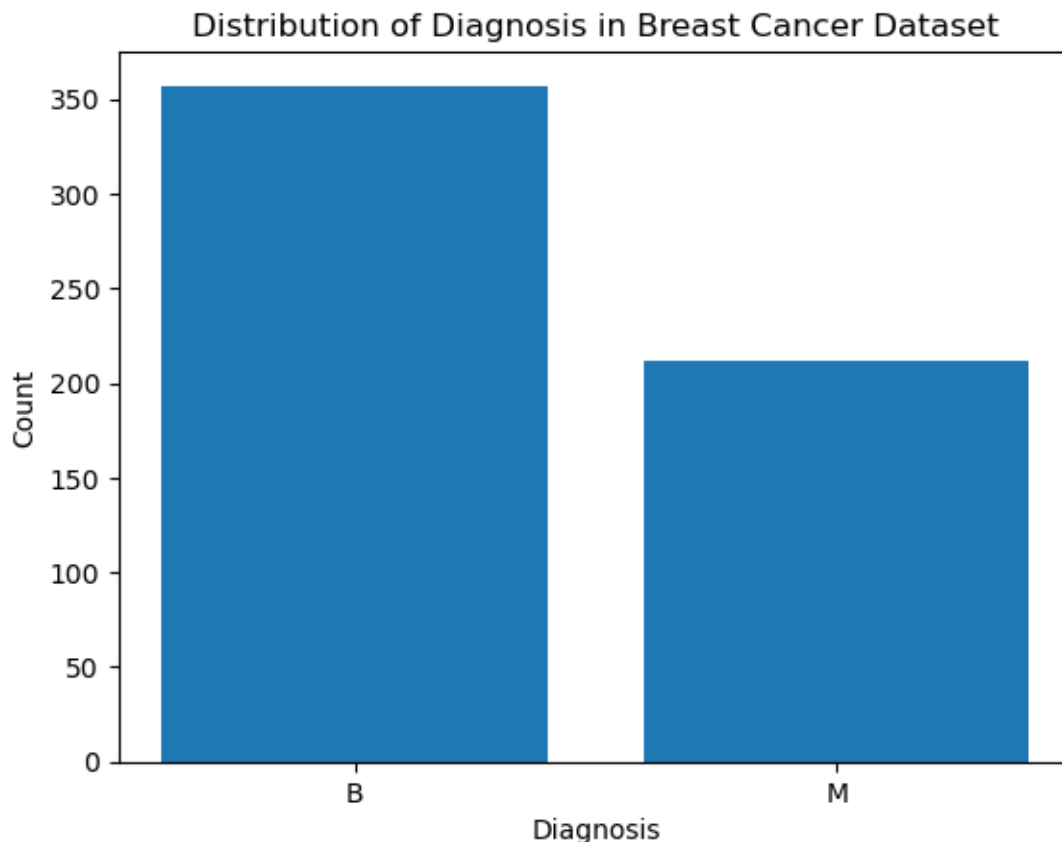
```
[9]: data.drop('id',axis = 1,inplace = True)
```

```
[10]: data.columns
```

```
[10]: 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')
```

1.0.2 Unbalanced data

```
[11]: counts = data['diagnosis'].value_counts()  
plt.bar(counts.index, counts.values)  
plt.xlabel('Diagnosis')  
plt.ylabel('Count')  
plt.title('Distribution of Diagnosis in Breast Cancer Dataset')  
plt.show()
```

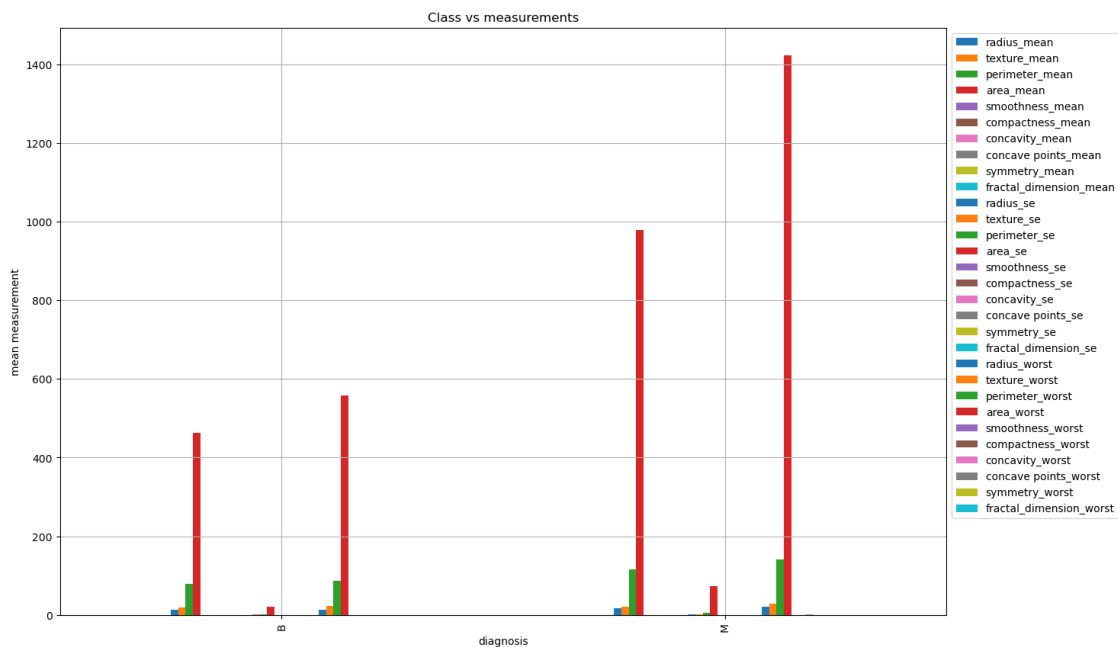


1.0.3 Normalization

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

```
[13]: data.groupby(by = "diagnosis").mean()
      data.groupby(by="diagnosis").mean().plot(kind="bar", figsize=(15,10))
      plt.title('Class vs measurements')
      plt.ylabel('mean measurement')
      plt.grid(True)
      plt.legend(loc="upper left", bbox_to_anchor=(1,1))
```

```
[13]: <matplotlib.legend.Legend at 0x220339e2730>
```



```
[14]: scaler = MinMaxScaler(feature_range=(0, 1))
      X = scaler.fit_transform(X)
      np.set_printoptions(precision=5)
```

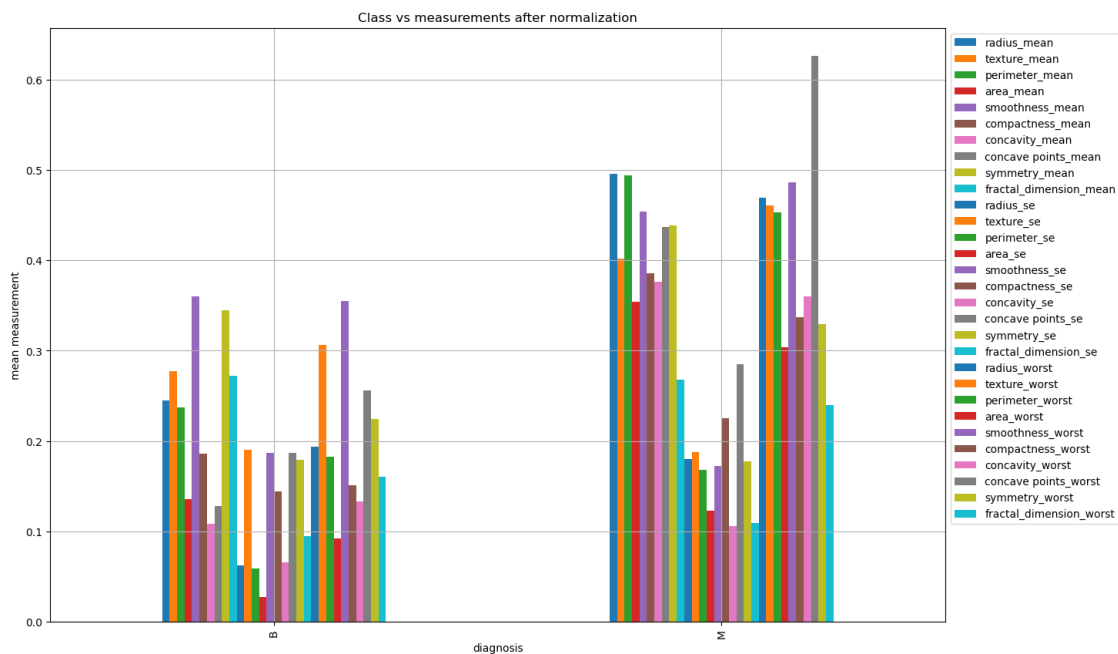
```
[15]: #Save new dataset
      feature_columns = ['radius_mean', 'texture_mean', 'perimeter_mean',
                        'area_mean', 'smoothness_mean', 'compactness_mean', 'concavity_mean',
                        'concave points_mean', 'symmetry_mean', 'fractal_dimension_mean',
                        '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']
```

```
df = pd.DataFrame(X, columns = feature_columns)
X = pd.DataFrame(X, columns = feature_columns)
df['diagnosis'] = y
```

```
[16]: df.groupby(by = "diagnosis").mean()
df.groupby(by="diagnosis").mean().plot(kind="bar", figsize=(15,10))
plt.title('Class vs measurements after normalization')
plt.ylabel('mean measurement')
plt.grid(True)
plt.legend(loc="upper left", bbox_to_anchor=(1,1))
```

```
[16]: <matplotlib.legend.Legend at 0x2202d2f3fd0>
```



```
[17]: df['diagnosis'] = df['diagnosis'].map({'B':0, 'M':1})
```

```
[18]: # split of the data
X = df.drop('diagnosis',axis = True)
y = df['diagnosis']
```


1.0.4 Data balancing

```
[19]: # Under sampler
```

```
[20]: pip install imblearn
```

Requirement already satisfied: imblearn in c:\users\21261\anaconda3\lib\site-packages (0.0)

Requirement already satisfied: imbalanced-learn in

c:\users\21261\anaconda3\lib\site-packages (from imblearn) (0.10.1)

Requirement already satisfied: scipy>=1.3.2 in

c:\users\21261\anaconda3\lib\site-packages (from imbalanced-learn->imblearn) (1.9.1)

Requirement already satisfied: joblib>=1.1.1 in

c:\users\21261\anaconda3\lib\site-packages (from imbalanced-learn->imblearn) (1.2.0)

Requirement already satisfied: numpy>=1.17.3 in

c:\users\21261\anaconda3\lib\site-packages (from imbalanced-learn->imblearn) (1.21.5)

Requirement already satisfied: scikit-learn>=1.0.2 in

c:\users\21261\anaconda3\lib\site-packages (from imbalanced-learn->imblearn) (1.0.2)

Requirement already satisfied: threadpoolctl>=2.0.0 in

c:\users\21261\anaconda3\lib\site-packages (from imbalanced-learn->imblearn) (2.2.0)

Note: you may need to restart the kernel to use updated packages.

```
[84]: from imblearn.under_sampling import RandomUnderSampler
      rus = RandomUnderSampler(random_state=0)
      X_resampled, y_resampled = rus.fit_resample(X, y)
```

```
[85]: X_resampled
```

```
[85]:
```

	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	\
0	0.308060	0.425769	0.297975	0.177094	0.314977	
1	0.264991	0.293879	0.249050	0.146554	0.282567	
2	0.373373	0.355090	0.361620	0.227953	0.390358	
3	0.082967	0.241123	0.079331	0.038515	0.462851	
4	0.223816	0.252959	0.213461	0.117413	0.407240	
..	
419	0.659709	0.520122	0.685578	0.510498	0.517017	
420	0.690000	0.428813	0.678668	0.566490	0.526948	
421	0.622320	0.626987	0.604036	0.474019	0.407782	
422	0.455251	0.621238	0.445788	0.303118	0.288165	
423	0.644564	0.663510	0.665538	0.475716	0.588336	
	compactness_mean	concavity_mean	concave	points_mean	symmetry_mean	\
0	0.176676	0.111317		0.168191	0.378283	

1	0.069873	0.004358	0.014533	0.321717
2	0.196522	0.159888	0.246074	0.215657
3	0.168395	0.000000	0.000000	0.467172
4	0.128918	0.089246	0.160984	0.230303
..
419	0.626403	0.743674	0.732604	0.550000
420	0.296055	0.571462	0.690358	0.336364
421	0.257714	0.337395	0.486630	0.349495
422	0.254340	0.216753	0.263519	0.267677
423	0.790197	0.823336	0.755467	0.675253

	fractal_dimension_mean	...	radius_worst	texture_worst	\
0	0.152064	...	0.256848	0.527719	
1	0.180918	...	0.198150	0.294776	
2	0.158382	...	0.287442	0.438699	
3	0.442713	...	0.079687	0.287313	
4	0.231466	...	0.180719	0.249733	
..	
419	0.396588	...	0.581999	0.463486	
420	0.132056	...	0.623266	0.383262	
421	0.113100	...	0.560655	0.699094	
422	0.137321	...	0.393099	0.589019	
423	0.425442	...	0.633582	0.730277	

	perimeter_worst	area_worst	smoothness_worst	compactness_worst	\
0	0.241994	0.126229	0.297365	0.139525	
1	0.175059	0.093123	0.215479	0.037789	
2	0.266398	0.147070	0.333025	0.108188	
3	0.067732	0.032393	0.494156	0.100620	
4	0.169381	0.082653	0.403685	0.074424	
..	
419	0.640918	0.401543	0.459156	0.379651	
420	0.576174	0.452664	0.461137	0.178527	
421	0.520892	0.379915	0.300007	0.159997	
422	0.379949	0.230731	0.282177	0.273705	
423	0.668310	0.402035	0.619626	0.815758	

	concavity_worst	concave points_worst	symmetry_worst	\
0	0.182268	0.440550	0.257441	
1	0.004456	0.030144	0.185295	
2	0.135783	0.349485	0.158486	
3	0.000000	0.000000	0.173467	
4	0.121486	0.377663	0.198502	
..	
419	0.527077	0.873540	0.268874	
420	0.328035	0.761512	0.097575	
421	0.256789	0.559450	0.198502	

422	0.271805	0.487285	0.128721
423	0.749760	0.910653	0.497142

	fractal_dimension_worst
0	0.092680
1	0.060803
2	0.071822
3	0.220451
4	0.104486
..	...
419	0.286567
420	0.105667
421	0.074315
422	0.151909
423	0.452315

[424 rows x 30 columns]

```
[86]: y_resampled
```

```
[86]: 0      0
      1      0
      2      0
      3      0
      4      0
      ..
      419    1
      420    1
      421    1
      422    1
      423    1
      Name: diagnosis, Length: 424, dtype: int64
```

1.1 Feature selection

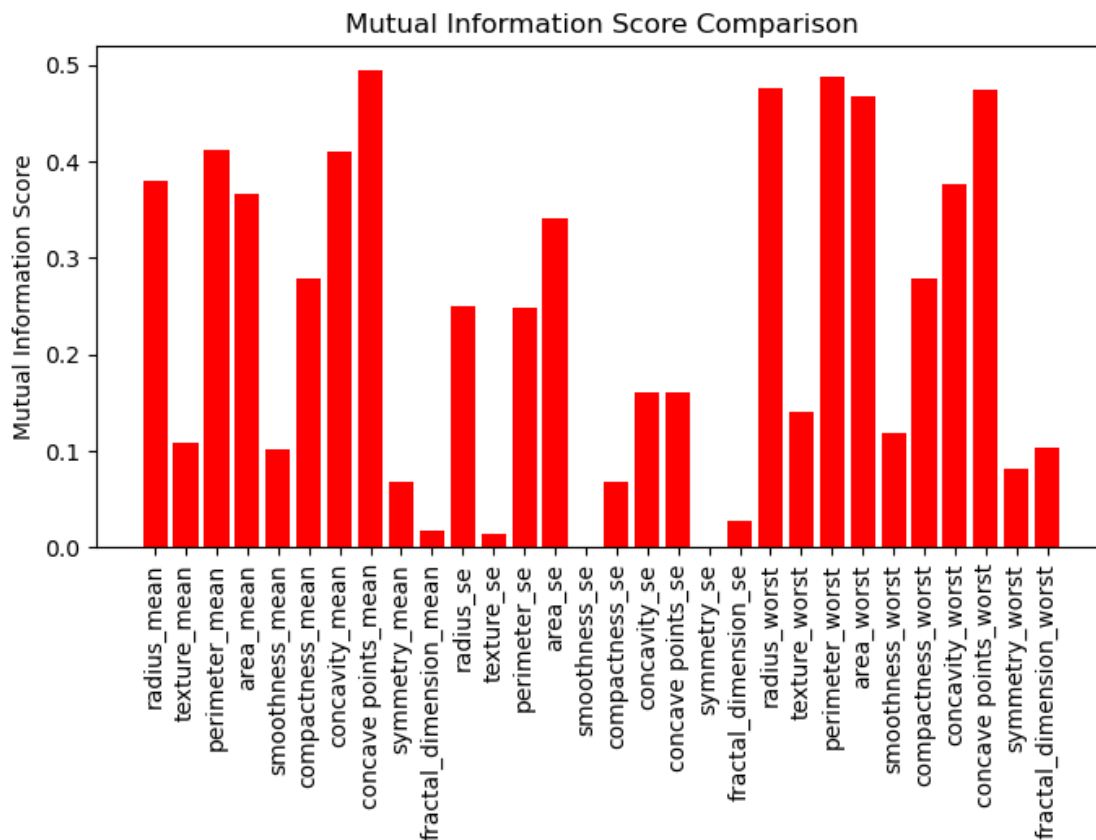
1.1.1 Information gain

```
[24]: MI_score = mutual_info_classif(X_resampled, y_resampled , random_state=0)
      for feature in zip(feature_columns, MI_score):
          if feature[1]>0.30:
              print(feature)
```

```
('radius_mean', 0.3790613211089362)
('perimeter_mean', 0.4120872655607555)
('area_mean', 0.3662171010510915)
('concavity_mean', 0.410597450084802)
('concave points_mean', 0.49467688911271535)
('area_se', 0.3414216405120378)
```

```
( 'radius_worst', 0.4764124126823539)
( 'perimeter_worst', 0.4878617892664423)
( 'area_worst', 0.46675770778085424)
( 'concavity_worst', 0.3762803586441521)
( 'concave points_worst', 0.4739511039507369)
```

```
[25]: plt.figure(figsize=(8,4))
plt.bar(x=feature_columns, height=MI_score, color='red')
plt.xticks(rotation='vertical')
plt.ylabel('Mutual Information Score')
plt.title('Mutual Information Score Comparison')
plt.show()
```



```
[26]: selected_features = [feature_columns[i] for i in range(len(feature_columns)) if
    ↪MI_score[i] > 0.3 ]
X_selected = X_resampled[selected_features]
```

```
[27]: selected_features
```

```
[27]: ['radius_mean',
      'perimeter_mean',
      'area_mean',
      'concavity_mean',
      'concave points_mean',
      'area_se',
      'radius_worst',
      'perimeter_worst',
      'area_worst',
      'concavity_worst',
      'concave points_worst']
```

```
[28]: X_selected
```

```
[28]:
```

	radius_mean	perimeter_mean	area_mean	concavity_mean	\
0	0.308060	0.297975	0.177094	0.111317	
1	0.264991	0.249050	0.146554	0.004358	
2	0.373373	0.361620	0.227953	0.159888	
3	0.082967	0.079331	0.038515	0.000000	
4	0.223816	0.213461	0.117413	0.089246	
..	
419	0.659709	0.685578	0.510498	0.743674	
420	0.690000	0.678668	0.566490	0.571462	
421	0.622320	0.604036	0.474019	0.337395	
422	0.455251	0.445788	0.303118	0.216753	
423	0.644564	0.665538	0.475716	0.823336	

	concave points_mean	area_se	radius_worst	perimeter_worst	area_worst	\
0	0.168191	0.025024	0.256848	0.241994	0.126229	
1	0.014533	0.029227	0.198150	0.175059	0.093123	
2	0.246074	0.028088	0.287442	0.266398	0.147070	
3	0.000000	0.041181	0.079687	0.067732	0.032393	
4	0.160984	0.020654	0.180719	0.169381	0.082653	
..	
419	0.732604	0.209186	0.581999	0.640918	0.401543	
420	0.690358	0.283710	0.623266	0.576174	0.452664	
421	0.486630	0.172279	0.560655	0.520892	0.379915	
422	0.263519	0.077976	0.393099	0.379949	0.230731	
423	0.755467	0.148335	0.633582	0.668310	0.402035	

	concavity_worst	concave points_worst
0	0.182268	0.440550
1	0.004456	0.030144
2	0.135783	0.349485
3	0.000000	0.000000
4	0.121486	0.377663
..

419	0.527077	0.873540
420	0.328035	0.761512
421	0.256789	0.559450
422	0.271805	0.487285
423	0.749760	0.910653

[424 rows x 11 columns]

1.1.2 KNN using information gain

```
[29]: X_train, X_test, y_train, y_test = train_test_split(X_selected, y_resampled,
↳ test_size=0.2, random_state=0)
```

```
[114]: def knn(X_train,X_test,y_train,y_test):
    knn = KNeighborsClassifier(n_neighbors=5)
    knn.fit(X_train, y_train)
    y_pred = knn.predict(X_test)
    accuracy = metrics.accuracy_score(y_test, y_pred)
    precision_score = metrics.precision_score(y_test, y_pred)
    recall_score = metrics.recall_score(y_test, y_pred)
    f1_score = metrics.f1_score(y_test,y_pred)
    print("Accuracy du KNN : " , accuracy)
    print("precision score du KNN : ", precision_score )
    print("recall score du KNN : ", recall_score )
    print("f1 score du KNN : ",f1_score)
```

```
[115]: knn(X_train, X_test, y_train, y_test)
```

```
Accuracy du KNN :  0.972027972027972
precision score du KNN :  0.9841269841269841
recall score du KNN :  0.9538461538461539
f1 score du KNN :  0.96875
```

1.1.3 KNN avec grid search

```
[32]: #creat a new KNN model
def knn_grid_search(X_selected, y_resampled):
    Knn2 = KNeighborsClassifier()
    grid_param={'n_neighbors': range(1,31),
    'weights' : ['uniform', 'distance'],
    'metric' : ['euclidean', 'manhattan', 'minkowski']}
    grid = GridSearchCV(Knn2, grid_param, cv = 10, scoring = 'accuracy')
    grid.fit(X_selected,y_resampled)

    grid1 = GridSearchCV(Knn2, grid_param, cv = 10, scoring = 'precision')
    grid1.fit(X_selected,y_resampled)

    grid2 = GridSearchCV(Knn2, grid_param, cv = 10, scoring = 'recall')
```

```

grid2.fit(X_selected,y_resampled)

grid3 = GridSearchCV(Knn2, grid_param, cv = 10, scoring = 'f1')
grid3.fit(X_selected,y_resampled)

print('grid best score accuracy',grid.best_score_)
print('grid best score precision',grid1.best_score_)
print('grid best score recall',grid2.best_score_)
print('grid best score f1 score',grid3.best_score_)

print(grid.best_params_)
print(grid.best_estimator_)

```

```

[33]: knn_grid_search(X_selected, y_resampled)

grid best score accuracy 0.9529346622369876
grid best score precision 0.9802130325814536
grid best score recall 0.9482683982683981
grid best score f1 score 0.9525095824954022
{'metric': 'manhattan', 'n_neighbors': 21, 'weights': 'distance'}
KNeighborsClassifier(metric='manhattan', n_neighbors=21, weights='distance')

```

1.1.4 SVM based on information gain

```

[34]: def svm(X_train, X_test, y_train, y_test):
    svm = SVC()
    svm.fit(X_train, y_train)
    y_pred = svm.predict(X_test)
    print(classification_report(y_test, y_pred))

```

```

[35]: svm(X_train, X_test, y_train, y_test)

```

	precision	recall	f1-score	support
0	0.96	0.94	0.95	48
1	0.92	0.95	0.93	37
accuracy			0.94	85
macro avg	0.94	0.94	0.94	85
weighted avg	0.94	0.94	0.94	85

1.1.5 SVM with grid search

```

[36]: def svm_grid_search(X_train,X_test,y_train ,y_test):
    param_grid = {'C': [0.1, 1, 10], 'kernel': ['linear', 'rbf', 'poly'],
    ↪ 'gamma': ['scale', 'auto']}
    svm = GridSearchCV(SVC(), param_grid=param_grid, cv=5, n_jobs=-1)

```

```

svm.fit(X_train, y_train)
best_params = svm.best_params_
best_accuracy = svm.best_score_
y_pred = svm.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(classification_report(y_test, y_pred))
print("Accuracy : ",accuracy)

```

```
[37]: svm_grid_search(X_train,X_test,y_train ,y_test)
```

	precision	recall	f1-score	support
0	0.94	1.00	0.97	48
1	1.00	0.92	0.96	37
accuracy			0.96	85
macro avg	0.97	0.96	0.96	85
weighted avg	0.97	0.96	0.96	85

Accuracy : 0.9647058823529412

1.1.6 Decision tree

```
[125]: X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled,
↳test_size=0.2, random_state=0)
```

```
[126]: clf = tree.DecisionTreeClassifier()
clf.fit(X_train, y_train)
y_pred= clf.predict(X_test)
acc2 = metrics.accuracy_score(y_test, y_pred)
precision = metrics.precision_score(y_test, y_pred)
recall = metrics.recall_score(y_test, y_pred)
f1_score = metrics.f1_score(y_test , y_pred)
print("Accuracy:", acc2)
print("Precision: ",precision)
print("Recall: ",recall)
print("F1 score : ",f1_score)

```

Accuracy: 0.9529411764705882

Precision: 0.9459459459459459

Recall: 0.9459459459459459

F1 score : 0.9459459459459459

```
[127]: from sklearn import tree
clf = tree.DecisionTreeClassifier()
clf.fit(X_train, y_train)
fig = plt.figure(figsize=(15,15))
_ = tree.plot_tree(clf,
```

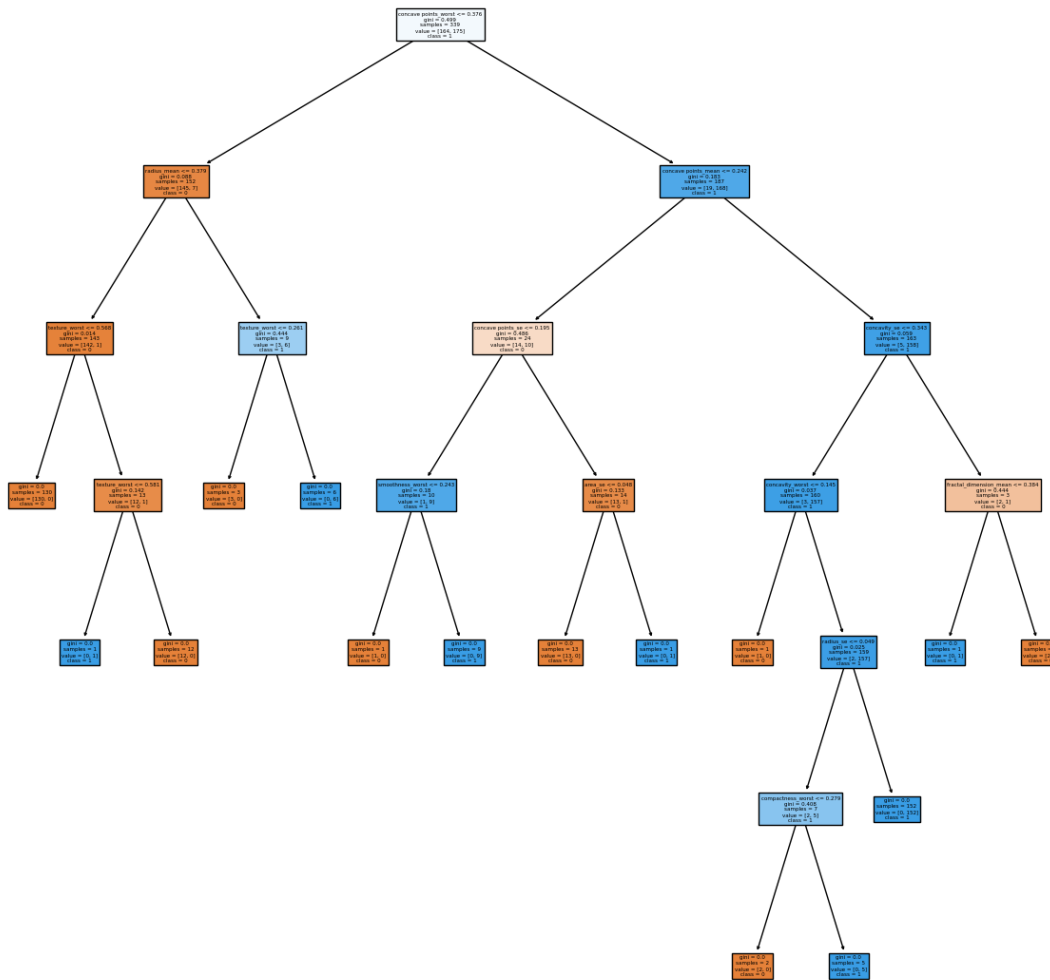


```

feature_names=feature_columns

',
class_names=["0", "1"],
filled=True)

```



```

[128]: from sklearn import tree
import matplotlib.pyplot as plt

clf = tree.DecisionTreeClassifier()
clf.fit(X_train, y_train)

fig, ax = plt.subplots(figsize=(20,20))
_ = tree.plot_tree(clf,

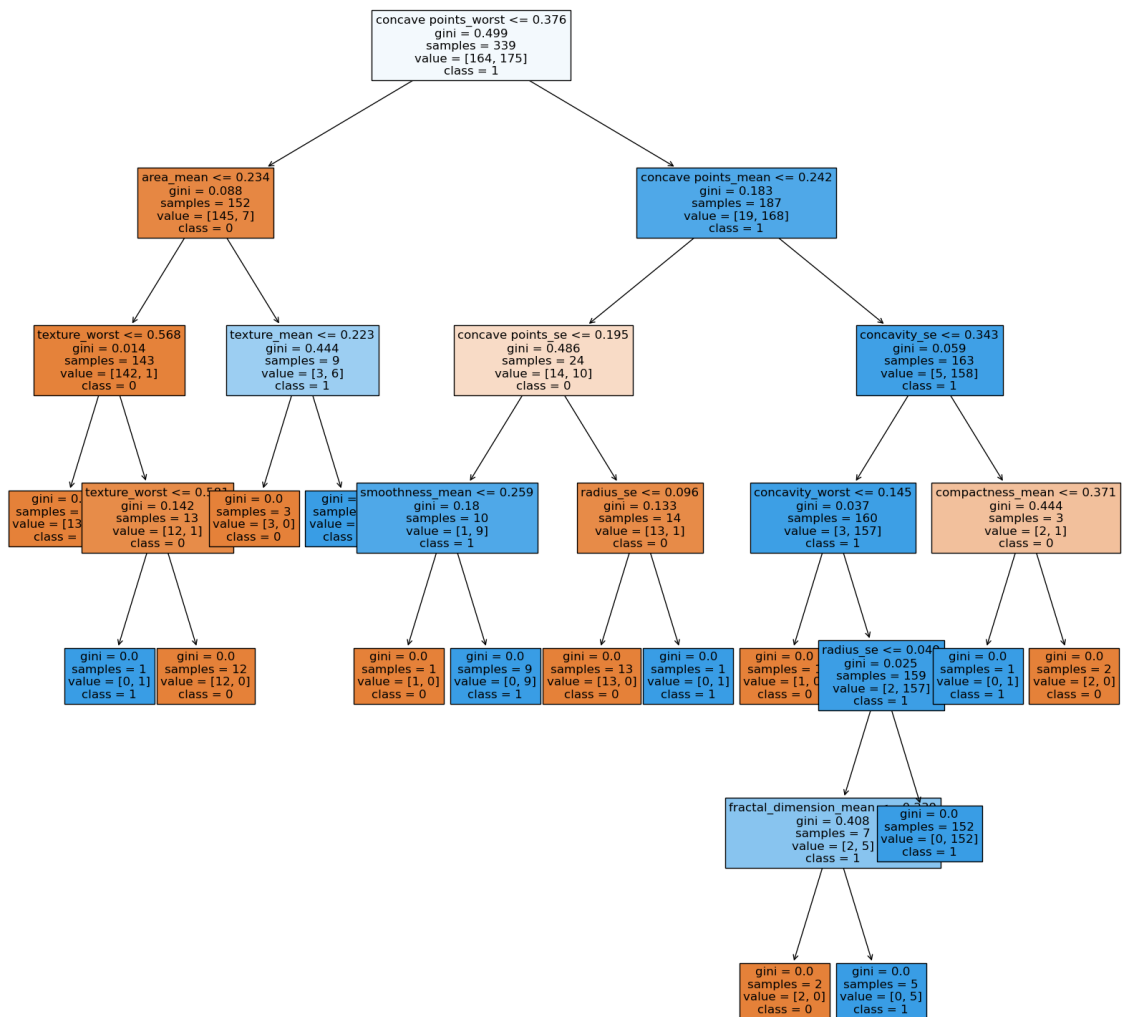
```

```

feature_names=feature_columns,
class_names=["0", "1"],
filled=True,
fontsize=12)

plt.show()

```



```

[42]: #Grid search
DT = tree.DecisionTreeClassifier()
params = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [2, 4, 6, 8, 10],
    'min_samples_split': [2, 4, 6, 8, 10],

```

```

    'min_samples_leaf': [1, 2, 3, 4, 5]
}
grid = GridSearchCV(DT, params, cv = 10, scoring = 'accuracy')
grid.fit(X_resampled,y_resampled)

grid1 = GridSearchCV(DT, params, cv = 10, scoring = 'precision')
grid1.fit(X_resampled,y_resampled)

grid2 = GridSearchCV(DT, params, cv = 10, scoring = 'recall')
grid2.fit(X_resampled,y_resampled)

grid3 = GridSearchCV(DT, params, cv = 10, scoring = 'f1')
grid3.fit(X_resampled,y_resampled)

print("Accuracy",grid.best_score_)
print("Precision",grid1.best_score_)
print("Recall",grid2.best_score_)
print("f1 score",grid3.best_score_)

print(grid.best_params_)
print(grid.best_estimator_)

```

```

Accuracy 0.9553156146179402
Precision 0.9654761904761905
Recall 0.958008658008658
f1 score 0.9526802258055802
{'criterion': 'entropy', 'max_depth': 4, 'min_samples_leaf': 3,
 'min_samples_split': 2}
DecisionTreeClassifier(criterion='entropy', max_depth=4, min_samples_leaf=3)

```

```

[129]: # Use a pruning algorithm to prune the decision tree
clf = tree.DecisionTreeClassifier()
path = clf.cost_complexity_pruning_path(X_train, y_train)
ccp_alphas = path.ccp_alphas[:-1]
clfs = []
for ccp_alpha in ccp_alphas:
    clf = tree.DecisionTreeClassifier(ccp_alpha=ccp_alpha)
    clf.fit(X_train, y_train)
    clfs.append(clf)
# Evaluate the pruned decision tree using the testing data
acc_scores = []
for clf in clfs:
    y_pred = clf.predict(X_test)
    acc_score = accuracy_score(y_test, y_pred)
    prec_score = precision_score(y_test, y_pred)
    acc_scores.append(acc_score)
# Find the best pruning parameter based on accuracy score

```

```

best_clf = clfs[acc_scores.index(max(acc_scores))]
# Evaluate the best pruned decision tree using the testing data
y_pred = best_clf.predict(X_test)
acc_score = accuracy_score(y_test, y_pred)
precision = precision_score(y_test , y_pred)
recall = recall_score(y_test , y_pred)
f1_score = metrics.f1_score(y_test , y_pred)

print("Accuracy score: {:.2f}".format(acc_score))
print("precision score: {:.2f}".format(precision))
print("recall score: {:.2f}".format(recall))
print("f1 score: {:.2f}".format(f1_score))

#print("ccp_alpha: {:.3f}".format(ccp_alphas[acc_scores.
↪index(max(acc_scores))]))

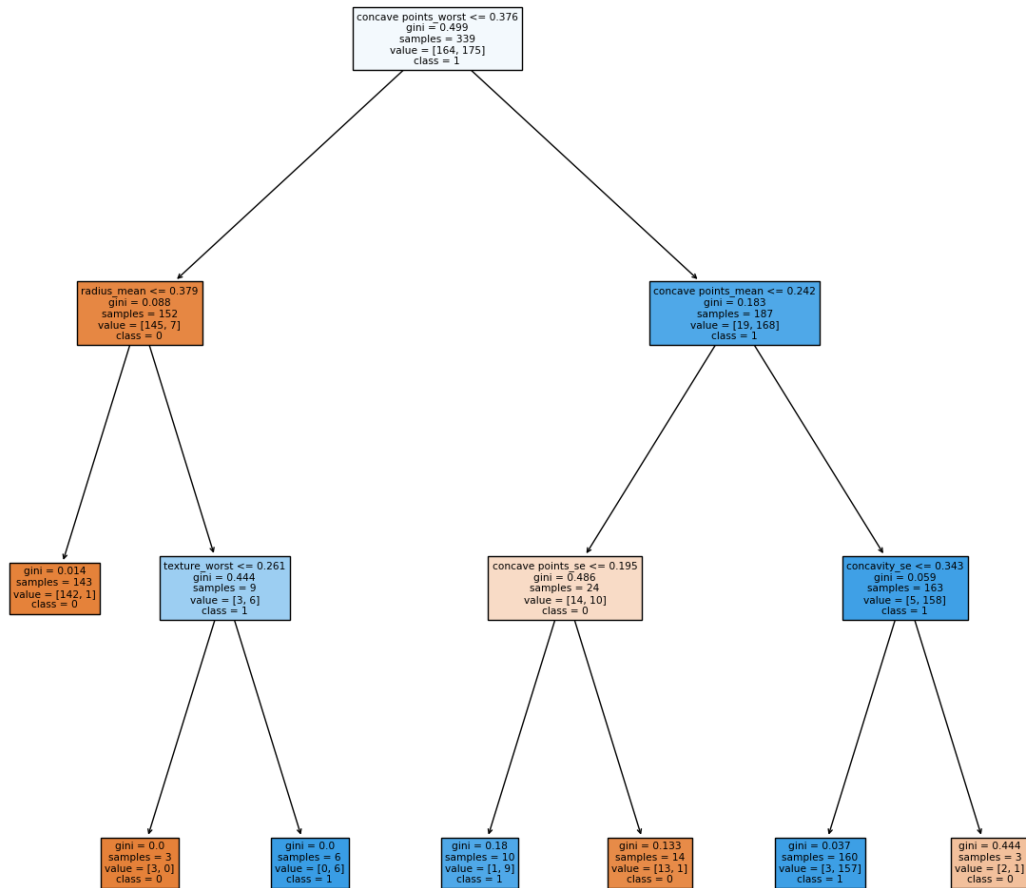
```

Accuracy score: 0.96
 precision score: 0.95
 recall score: 0.97
 f1 score: 0.96

```

[130]: from sklearn import tree
fig = plt.figure(figsize=(15,15))
_ = tree.plot_tree(best_clf,
    feature_names=feature_columns,
    class_names=["0","1"],filled=True)

```



1.2 Correlation

[45]: X_resampled

```
[45]:
```

	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	\
0	0.308060	0.425769	0.297975	0.177094	0.314977	
1	0.264991	0.293879	0.249050	0.146554	0.282567	
2	0.373373	0.355090	0.361620	0.227953	0.390358	
3	0.082967	0.241123	0.079331	0.038515	0.462851	
4	0.223816	0.252959	0.213461	0.117413	0.407240	
..	
419	0.659709	0.520122	0.685578	0.510498	0.517017	
420	0.690000	0.428813	0.678668	0.566490	0.526948	

421	0.622320	0.626987	0.604036	0.474019	0.407782
422	0.455251	0.621238	0.445788	0.303118	0.288165
423	0.644564	0.663510	0.665538	0.475716	0.588336

	compactness_mean	concavity_mean	concave	points_mean	symmetry_mean \
0	0.176676	0.111317		0.168191	0.378283
1	0.069873	0.004358		0.014533	0.321717
2	0.196522	0.159888		0.246074	0.215657
3	0.168395	0.000000		0.000000	0.467172
4	0.128918	0.089246		0.160984	0.230303
..
419	0.626403	0.743674		0.732604	0.550000
420	0.296055	0.571462		0.690358	0.336364
421	0.257714	0.337395		0.486630	0.349495
422	0.254340	0.216753		0.263519	0.267677
423	0.790197	0.823336		0.755467	0.675253

	fractal_dimension_mean	...	radius_worst	texture_worst \
0	0.152064	...	0.256848	0.527719
1	0.180918	...	0.198150	0.294776
2	0.158382	...	0.287442	0.438699
3	0.442713	...	0.079687	0.287313
4	0.231466	...	0.180719	0.249733
..
419	0.396588	...	0.581999	0.463486
420	0.132056	...	0.623266	0.383262
421	0.113100	...	0.560655	0.699094
422	0.137321	...	0.393099	0.589019
423	0.425442	...	0.633582	0.730277

	perimeter_worst	area_worst	smoothness_worst	compactness_worst \
0	0.241994	0.126229	0.297365	0.139525
1	0.175059	0.093123	0.215479	0.037789
2	0.266398	0.147070	0.333025	0.108188
3	0.067732	0.032393	0.494156	0.100620
4	0.169381	0.082653	0.403685	0.074424
..
419	0.640918	0.401543	0.459156	0.379651
420	0.576174	0.452664	0.461137	0.178527
421	0.520892	0.379915	0.300007	0.159997
422	0.379949	0.230731	0.282177	0.273705
423	0.668310	0.402035	0.619626	0.815758

	concavity_worst	concave	points_worst	symmetry_worst \
0	0.182268		0.440550	0.257441
1	0.004456		0.030144	0.185295
2	0.135783		0.349485	0.158486

3	0.000000	0.000000	0.173467
4	0.121486	0.377663	0.198502
..
419	0.527077	0.873540	0.268874
420	0.328035	0.761512	0.097575
421	0.256789	0.559450	0.198502
422	0.271805	0.487285	0.128721
423	0.749760	0.910653	0.497142

	fractal_dimension_worst
0	0.092680
1	0.060803
2	0.071822
3	0.220451
4	0.104486
..	...
419	0.286567
420	0.105667
421	0.074315
422	0.151909
423	0.452315

[424 rows x 30 columns]

```
[46]: y_resampled
```

```
[46]: 0      0
      1      0
      2      0
      3      0
      4      0
      ..
     419    1
     420    1
     421    1
     422    1
     423    1
```

Name: diagnosis, Length: 424, dtype: int64

```
[47]: df_corr = pd.DataFrame(X_resampled , columns = X_resampled.columns)
```

```
[48]: df_corr['diagnosis'] = y_resampled
```

```
[49]: df_corr
```

```
[49]:      radius_mean  texture_mean  perimeter_mean  area_mean  smoothness_mean  \
0      0.308060      0.425769      0.297975      0.177094      0.314977
```

1	0.264991	0.293879	0.249050	0.146554	0.282567
2	0.373373	0.355090	0.361620	0.227953	0.390358
3	0.082967	0.241123	0.079331	0.038515	0.462851
4	0.223816	0.252959	0.213461	0.117413	0.407240
..
419	0.659709	0.520122	0.685578	0.510498	0.517017
420	0.690000	0.428813	0.678668	0.566490	0.526948
421	0.622320	0.626987	0.604036	0.474019	0.407782
422	0.455251	0.621238	0.445788	0.303118	0.288165
423	0.644564	0.663510	0.665538	0.475716	0.588336

	compactness_mean	concavity_mean	concave	points_mean	symmetry_mean	\
0	0.176676	0.111317		0.168191	0.378283	
1	0.069873	0.004358		0.014533	0.321717	
2	0.196522	0.159888		0.246074	0.215657	
3	0.168395	0.000000		0.000000	0.467172	
4	0.128918	0.089246		0.160984	0.230303	
..	
419	0.626403	0.743674		0.732604	0.550000	
420	0.296055	0.571462		0.690358	0.336364	
421	0.257714	0.337395		0.486630	0.349495	
422	0.254340	0.216753		0.263519	0.267677	
423	0.790197	0.823336		0.755467	0.675253	

	fractal_dimension_mean	...	texture_worst	perimeter_worst	area_worst	\
0	0.152064	...	0.527719	0.241994	0.126229	
1	0.180918	...	0.294776	0.175059	0.093123	
2	0.158382	...	0.438699	0.266398	0.147070	
3	0.442713	...	0.287313	0.067732	0.032393	
4	0.231466	...	0.249733	0.169381	0.082653	
..	
419	0.396588	...	0.463486	0.640918	0.401543	
420	0.132056	...	0.383262	0.576174	0.452664	
421	0.113100	...	0.699094	0.520892	0.379915	
422	0.137321	...	0.589019	0.379949	0.230731	
423	0.425442	...	0.730277	0.668310	0.402035	

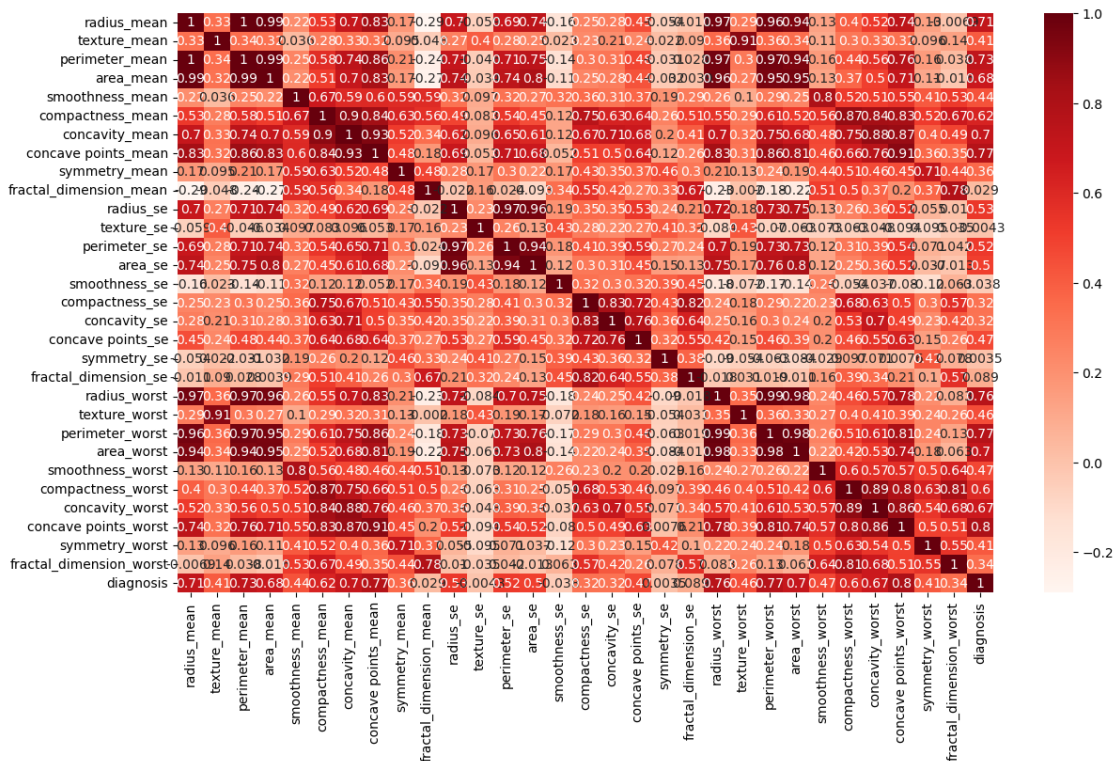
	smoothness_worst	compactness_worst	concavity_worst	\
0	0.297365	0.139525	0.182268	
1	0.215479	0.037789	0.004456	
2	0.333025	0.108188	0.135783	
3	0.494156	0.100620	0.000000	
4	0.403685	0.074424	0.121486	
..	
419	0.459156	0.379651	0.527077	
420	0.461137	0.178527	0.328035	
421	0.300007	0.159997	0.256789	

422	0.282177	0.273705	0.271805
423	0.619626	0.815758	0.749760

	concave points_worst	symmetry_worst	fractal_dimension_worst	diagnosis
0	0.440550	0.257441	0.092680	0
1	0.030144	0.185295	0.060803	0
2	0.349485	0.158486	0.071822	0
3	0.000000	0.173467	0.220451	0
4	0.377663	0.198502	0.104486	0
..
419	0.873540	0.268874	0.286567	1
420	0.761512	0.097575	0.105667	1
421	0.559450	0.198502	0.074315	1
422	0.487285	0.128721	0.151909	1
423	0.910653	0.497142	0.452315	1

[424 rows x 31 columns]

```
[50]: # Matrice de corrélation
#Using Pearson Correlation
plt.figure(figsize=(14,8))
cor = df_corr.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.Reds)
plt.show()
```



```
[51]: #Correlation with output variable
cor_target = abs(corr["diagnosis"])
#Selecting highly correlated features
relevant_features = list(corr_target[abs(corr_target) > 0.5].index)
relevant_features.remove('diagnosis')
relevant_features
# we choose the variables that have a correlation higher to 0.5 with our target_
↪variable
```

```
[51]: ['radius_mean',
'perimeter_mean',
'area_mean',
'compactness_mean',
'concavity_mean',
'concave points_mean',
'radius_se',
'perimeter_se',
'area_se',
'radius_worst',
'perimeter_worst',
'area_worst',
'compactness_worst',
'concavity_worst',
'concave points_worst']
```

```
[52]: X_selected_corr = X_resampled[relevant_features]
```

```
[53]: X_selected_corr
```

```
[53]:
```

	radius_mean	perimeter_mean	area_mean	compactness_mean	concavity_mean	\
0	0.308060	0.297975	0.177094	0.176676	0.111317	
1	0.264991	0.249050	0.146554	0.069873	0.004358	
2	0.373373	0.361620	0.227953	0.196522	0.159888	
3	0.082967	0.079331	0.038515	0.168395	0.000000	
4	0.223816	0.213461	0.117413	0.128918	0.089246	
..	
419	0.659709	0.685578	0.510498	0.626403	0.743674	
420	0.690000	0.678668	0.566490	0.296055	0.571462	
421	0.622320	0.604036	0.474019	0.257714	0.337395	
422	0.455251	0.445788	0.303118	0.254340	0.216753	
423	0.644564	0.665538	0.475716	0.790197	0.823336	
	concave points_mean	radius_se	perimeter_se	area_se	radius_worst	\
0	0.168191	0.044288	0.046082	0.025024	0.256848	
1	0.014533	0.058084	0.045422	0.029227	0.198150	

2	0.246074	0.043744	0.039533	0.028088	0.287442
3	0.000000	0.146804	0.113556	0.041181	0.079687
4	0.160984	0.048380	0.046412	0.020654	0.180719
..
419	0.732604	0.308057	0.376997	0.209186	0.581999
420	0.690358	0.385479	0.325873	0.283710	0.623266
421	0.486630	0.236828	0.209490	0.172279	0.560655
422	0.263519	0.124896	0.125713	0.077976	0.393099
423	0.755467	0.222524	0.236300	0.148335	0.633582

	perimeter_worst	area_worst	compactness_worst	concavity_worst	\
0	0.241994	0.126229	0.139525	0.182268	
1	0.175059	0.093123	0.037789	0.004456	
2	0.266398	0.147070	0.108188	0.135783	
3	0.067732	0.032393	0.100620	0.000000	
4	0.169381	0.082653	0.074424	0.121486	
..	
419	0.640918	0.401543	0.379651	0.527077	
420	0.576174	0.452664	0.178527	0.328035	
421	0.520892	0.379915	0.159997	0.256789	
422	0.379949	0.230731	0.273705	0.271805	
423	0.668310	0.402035	0.815758	0.749760	

	concave points_worst
0	0.440550
1	0.030144
2	0.349485
3	0.000000
4	0.377663
..	...
419	0.873540
420	0.761512
421	0.559450
422	0.487285
423	0.910653

[424 rows x 15 columns]

```
[54]: # splitting the data
X_train, X_test, y_train, y_test = train_test_split(X_selected_corr,
↪y_resampled, test_size=0.2, random_state=0)
```

1.2.1 KNN based on correlation

```
[55]: knn(X_train, X_test, y_train, y_test)
```

Accuracy du KNN : 0.9529411764705882
precision score du KNN : 0.9459459459459459

```
recall score du KNN : 0.9459459459459459
f1 score du KNN : 0.9459459459459459
```

1.2.2 KNN with grid search

```
[56]: knn_grid_search(X_selected_corr, y_resampled)
```

```
grid best score accuracy 0.9552602436323365
grid best score precision 0.9765424430641823
grid best score recall 0.938961038961039
grid best score f1 score 0.9543019563155696
{'metric': 'manhattan', 'n_neighbors': 16, 'weights': 'distance'}
KNeighborsClassifier(metric='manhattan', n_neighbors=16, weights='distance')
```

1.2.3 SVM based on correlation

```
[57]: svm(X_train, X_test, y_train, y_test)
```

	precision	recall	f1-score	support
0	0.96	0.96	0.96	48
1	0.95	0.95	0.95	37
accuracy			0.95	85
macro avg	0.95	0.95	0.95	85
weighted avg	0.95	0.95	0.95	85

1.2.4 SVM with grid search

```
[58]: svm_grid_search(X_train,X_test,y_train ,y_test)
```

	precision	recall	f1-score	support
0	0.98	0.98	0.98	48
1	0.97	0.97	0.97	37
accuracy			0.98	85
macro avg	0.98	0.98	0.98	85
weighted avg	0.98	0.98	0.98	85

```
Accuracy : 0.9764705882352941
```

2 Select Kbest

```
[59]: selector = SelectKBest(chi2, k=10)
X_new = selector.fit_transform(X_resampled, y_resampled)
mask = selector.get_support()
```

```
selected_features = X_resampled.columns[mask]
selected = selected_features.values
selected
```

```
[59]: array(['perimeter_mean', 'area_mean', 'concavity_mean',
        'concave points_mean', 'radius_worst', 'perimeter_worst',
        'area_worst', 'concavity_worst', 'concave points_worst',
        'diagnosis'], dtype=object)
```

```
[60]: X_selected_kbest = X_resampled[selected]
```

```
[61]: X_selected_kbest.drop('diagnosis',axis = 1, inplace = True)
```

```
[62]: X_selected_kbest
```

```
[62]:
```

	perimeter_mean	area_mean	concavity_mean	concave points_mean \
0	0.297975	0.177094	0.111317	0.168191
1	0.249050	0.146554	0.004358	0.014533
2	0.361620	0.227953	0.159888	0.246074
3	0.079331	0.038515	0.000000	0.000000
4	0.213461	0.117413	0.089246	0.160984
..
419	0.685578	0.510498	0.743674	0.732604
420	0.678668	0.566490	0.571462	0.690358
421	0.604036	0.474019	0.337395	0.486630
422	0.445788	0.303118	0.216753	0.263519
423	0.665538	0.475716	0.823336	0.755467

	radius_worst	perimeter_worst	area_worst	concavity_worst \
0	0.256848	0.241994	0.126229	0.182268
1	0.198150	0.175059	0.093123	0.004456
2	0.287442	0.266398	0.147070	0.135783
3	0.079687	0.067732	0.032393	0.000000
4	0.180719	0.169381	0.082653	0.121486
..
419	0.581999	0.640918	0.401543	0.527077
420	0.623266	0.576174	0.452664	0.328035
421	0.560655	0.520892	0.379915	0.256789
422	0.393099	0.379949	0.230731	0.271805
423	0.633582	0.668310	0.402035	0.749760

	concave points_worst
0	0.440550
1	0.030144
2	0.349485
3	0.000000
4	0.377663

```

..
419          0.873540
420          0.761512
421          0.559450
422          0.487285
423          0.910653

```

[424 rows x 9 columns]

```

[63]: # splitting the data
X_train, X_test, y_train, y_test = train_test_split(X_selected_kbest,
↳ y_resampled, test_size=0.2, random_state=0)

```

2.0.1 KNN based on selectKbest

```

[64]: knn(X_train, X_test, y_train, y_test)

```

```

Accuracy du KNN : 0.9411764705882353
precision score du KNN : 0.9210526315789473
recall score du KNN : 0.9459459459459459
f1 score du KNN : 0.9333333333333332

```

2.0.2 KNN with grid search

```

[65]: knn_grid_search(X_selected_kbest, y_resampled)

```

```

grid best score accuracy 0.95531561461794
grid best score precision 0.9802130325814536
grid best score recall 0.9528138528138529
grid best score f1 score 0.9546179401993357
{'metric': 'manhattan', 'n_neighbors': 29, 'weights': 'distance'}
KNeighborsClassifier(metric='manhattan', n_neighbors=29, weights='distance')

```

2.0.3 SVM

```

[66]: svm(X_train, X_test, y_train, y_test)

```

	precision	recall	f1-score	support
0	0.96	0.94	0.95	48
1	0.92	0.95	0.93	37
accuracy			0.94	85
macro avg	0.94	0.94	0.94	85
weighted avg	0.94	0.94	0.94	85

2.0.4 SVM with grid search

```
[67]: svm_grid_search(X_train,X_test,y_train ,y_test)
```

	precision	recall	f1-score	support
0	0.96	1.00	0.98	48
1	1.00	0.95	0.97	37
accuracy			0.98	85
macro avg	0.98	0.97	0.98	85
weighted avg	0.98	0.98	0.98	85

Accuracy : 0.9764705882352941

2.1 Wrappers

```
[68]: import joblib
import sys
sys.modules['sklearn.externals.joblib'] = joblib
from mlxtend.feature_selection import SequentialFeatureSelector as SFS
from mlxtend.feature_selection import ExhaustiveFeatureSelector as EFS
```

```
[69]: X_train, X_test, y_train, y_test = train_test_split( X_resampled, y_resampled,
↳test_size=0.33, random_state=42)
# create the classifier with n_estimators = 100

clf = RandomForestClassifier(n_estimators=100, random_state=0)

# fit the model to the training set

clf.fit(X_train, y_train)

# view the feature scores

feature_scores = pd.Series(clf.feature_importances_, index=X_train.columns).
↳sort_values(ascending=False)

selected = feature_scores[feature_scores.values > 0.01]
selected_features = selected.index.values
```

```
[70]: selected_features
```

```
[70]: array(['diagnosis', 'concave points_mean', 'radius_worst',
'concave points_worst', 'area_worst', 'perimeter_worst',
'concavity_mean', 'radius_mean', 'perimeter_mean',
```

```
'concavity_worst', 'area_se', 'compactness_mean'], dtype=object)
```

```
[71]: X_selected_rf = X_resampled[selected_features]
```

```
[72]: X_selected_rf.drop('diagnosis',axis =1,inplace = True)
```

```
[73]: X_selected_rf
```

```
[73]:
```

	concave points_mean	radius_worst	concave points_worst	area_worst	\
0	0.168191	0.256848	0.440550	0.126229	
1	0.014533	0.198150	0.030144	0.093123	
2	0.246074	0.287442	0.349485	0.147070	
3	0.000000	0.079687	0.000000	0.032393	
4	0.160984	0.180719	0.377663	0.082653	
..	
419	0.732604	0.581999	0.873540	0.401543	
420	0.690358	0.623266	0.761512	0.452664	
421	0.486630	0.560655	0.559450	0.379915	
422	0.263519	0.393099	0.487285	0.230731	
423	0.755467	0.633582	0.910653	0.402035	

	perimeter_worst	concavity_mean	radius_mean	perimeter_mean	\
0	0.241994	0.111317	0.308060	0.297975	
1	0.175059	0.004358	0.264991	0.249050	
2	0.266398	0.159888	0.373373	0.361620	
3	0.067732	0.000000	0.082967	0.079331	
4	0.169381	0.089246	0.223816	0.213461	
..	
419	0.640918	0.743674	0.659709	0.685578	
420	0.576174	0.571462	0.690000	0.678668	
421	0.520892	0.337395	0.622320	0.604036	
422	0.379949	0.216753	0.455251	0.445788	
423	0.668310	0.823336	0.644564	0.665538	

	concavity_worst	area_se	compactness_mean
0	0.182268	0.025024	0.176676
1	0.004456	0.029227	0.069873
2	0.135783	0.028088	0.196522
3	0.000000	0.041181	0.168395
4	0.121486	0.020654	0.128918
..
419	0.527077	0.209186	0.626403
420	0.328035	0.283710	0.296055
421	0.256789	0.172279	0.257714
422	0.271805	0.077976	0.254340
423	0.749760	0.148335	0.790197

[424 rows x 11 columns]

```
[74]: # splitting the data
X_train, X_test, y_train, y_test = train_test_split(X_selected_rf, y_resampled,
↳ test_size=0.2, random_state=0)
```

2.1.1 KNN based on Random forest wrapper

```
[75]: knn(X_train, X_test, y_train, y_test)
```

Accuracy du KNN : 0.9529411764705882
precision score du KNN : 0.9459459459459459
recall score du KNN : 0.9459459459459459
f1 score du KNN : 0.9459459459459459

```
[76]: knn_grid_search(X_selected_rf, y_resampled)
```

grid best score accuracy 0.9529346622369876
grid best score precision 0.9758840282524492
grid best score recall 0.9482683982683981
grid best score f1 score 0.9526342347386023
{'metric': 'manhattan', 'n_neighbors': 8, 'weights': 'distance'}
KNeighborsClassifier(metric='manhattan', n_neighbors=8, weights='distance')

2.2 SVM

```
[77]: svm(X_train, X_test, y_train, y_test)
```

	precision	recall	f1-score	support
0	0.96	0.94	0.95	48
1	0.92	0.95	0.93	37
accuracy			0.94	85
macro avg	0.94	0.94	0.94	85
weighted avg	0.94	0.94	0.94	85

```
[78]: svm_grid_search(X_train,X_test,y_train ,y_test)
```

	precision	recall	f1-score	support
0	0.98	0.98	0.98	48
1	0.97	0.97	0.97	37
accuracy			0.98	85
macro avg	0.98	0.98	0.98	85
weighted avg	0.98	0.98	0.98	85

Accuracy : 0.9764705882352941

2.3 Wrapper the Recursive Feature Elimination :

```
[79]: from sklearn.feature_selection import RFE
      from sklearn.svm import SVC

      # Initialize an SVM classifier and an RFE feature selector
      svm = SVC(kernel='linear')
      rfe = RFE(estimator=svm, n_features_to_select=10, step=1)

      # Fit the RFE selector to the data and get the selected feature indices
      rfe.fit(X_resampled, y_resampled)
      selected_indices = rfe.get_support(indices=True)

      selected_names = [X_resampled.columns[i] for i, selected in enumerate(rfe.
      ↪support_) if selected]

      # Print the selected feature names
      print('Selected features:', selected_names)
```

Selected features: ['radius_mean', 'perimeter_mean', 'radius_se',
'concavity_se', 'concave points_se', 'radius_worst', 'texture_worst',
'area_worst', 'concavity_worst', 'diagnosis']

```
[80]: X_selected_rfe = X_resampled[selected_names]
```

```
[81]: X_selected_rfe.drop('diagnosis',axis=1,inplace=True)
```

```
[82]: X_selected_rfe
```

```
[82]:
```

	radius_mean	perimeter_mean	radius_se	concavity_se	concave points_se	\
0	0.308060	0.297975	0.044288	0.052904	0.224285	
1	0.264991	0.249050	0.058084	0.004697	0.055389	
2	0.373373	0.361620	0.043744	0.054369	0.224095	
3	0.082967	0.079331	0.146804	0.000000	0.000000	
4	0.223816	0.213461	0.048380	0.049949	0.224474	
..	
419	0.659709	0.685578	0.308057	0.198106	0.497064	
420	0.690000	0.678668	0.385479	0.131263	0.464861	
421	0.622320	0.604036	0.236828	0.099747	0.317863	
422	0.455251	0.445788	0.124896	0.119444	0.294942	
423	0.644564	0.665538	0.222524	0.179722	0.315211	

	radius_worst	texture_worst	area_worst	concavity_worst
0	0.256848	0.527719	0.126229	0.182268
1	0.198150	0.294776	0.093123	0.004456

2	0.287442	0.438699	0.147070	0.135783
3	0.079687	0.287313	0.032393	0.000000
4	0.180719	0.249733	0.082653	0.121486
..
419	0.581999	0.463486	0.401543	0.527077
420	0.623266	0.383262	0.452664	0.328035
421	0.560655	0.699094	0.379915	0.256789
422	0.393099	0.589019	0.230731	0.271805
423	0.633582	0.730277	0.402035	0.749760

[424 rows x 9 columns]

```
[83]: # splitting the data
X_train, X_test, y_train, y_test = train_test_split(X_selected_rfe,
↪ y_resampled, test_size=0.2, random_state=0)
```

2.4 KNN

```
[84]: knn(X_train, X_test, y_train, y_test)
```

```
Accuracy du KNN : 0.9294117647058824
precision score du KNN : 0.918918918918919
recall score du KNN : 0.918918918918919
f1 score du KNN : 0.918918918918919
```

```
[85]: knn_grid_search(X_selected_rfe, y_resampled)
```

```
grid best score accuracy 0.9599667774086378
grid best score precision 0.9684523809523811
grid best score recall 0.9623376623376624
grid best score f1 score 0.9598331126238102
{'metric': 'manhattan', 'n_neighbors': 14, 'weights': 'distance'}
KNeighborsClassifier(metric='manhattan', n_neighbors=14, weights='distance')
```

2.5 SVM

```
[86]: def svm(X_train, X_test, y_train, y_test):
    svm = SVC()
    svm.fit(X_train, y_train)
    y_pred = svm.predict(X_test)
    print(classification_report(y_test, y_pred))
```

```
[87]: svm(X_train, X_test, y_train, y_test)
```

	precision	recall	f1-score	support
0	0.94	0.96	0.95	48
1	0.94	0.92	0.93	37

accuracy			0.94	85
macro avg	0.94	0.94	0.94	85
weighted avg	0.94	0.94	0.94	85

```
[88]: svm_grid_search(X_train,X_test,y_train ,y_test)
```

	precision	recall	f1-score	support
0	0.94	0.96	0.95	48
1	0.94	0.92	0.93	37

accuracy			0.94	85
macro avg	0.94	0.94	0.94	85
weighted avg	0.94	0.94	0.94	85

Accuracy : 0.9411764705882353

3 Unbalanced data methods Smote

```
[89]: df['diagnosis'].value_counts()
```

```
[89]: 0    357
      1    212
      Name: diagnosis, dtype: int64
```

```
[90]: df
```

```
[90]:
```

	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	\
0	0.521037	0.022658	0.545989	0.363733	0.593753	
1	0.643144	0.272574	0.615783	0.501591	0.289880	
2	0.601496	0.390260	0.595743	0.449417	0.514309	
3	0.210090	0.360839	0.233501	0.102906	0.811321	
4	0.629893	0.156578	0.630986	0.489290	0.430351	
..	
564	0.690000	0.428813	0.678668	0.566490	0.526948	
565	0.622320	0.626987	0.604036	0.474019	0.407782	
566	0.455251	0.621238	0.445788	0.303118	0.288165	
567	0.644564	0.663510	0.665538	0.475716	0.588336	
568	0.036869	0.501522	0.028540	0.015907	0.000000	
	compactness_mean	concavity_mean	concave	points_mean	symmetry_mean	\
0	0.792037	0.703140		0.731113	0.686364	
1	0.181768	0.203608		0.348757	0.379798	
2	0.431017	0.462512		0.635686	0.509596	
3	0.811361	0.565604		0.522863	0.776263	
4	0.347893	0.463918		0.518390	0.378283	
..	

564	0.296055	0.571462	0.690358	0.336364
565	0.257714	0.337395	0.486630	0.349495
566	0.254340	0.216753	0.263519	0.267677
567	0.790197	0.823336	0.755467	0.675253
568	0.074351	0.000000	0.000000	0.266162

	fractal_dimension_mean	...	texture_worst	perimeter_worst	area_worst	\
0	0.605518	...	0.141525	0.668310	0.450698	
1	0.141323	...	0.303571	0.539818	0.435214	
2	0.211247	...	0.360075	0.508442	0.374508	
3	1.000000	...	0.385928	0.241347	0.094008	
4	0.186816	...	0.123934	0.506948	0.341575	
..	
564	0.132056	...	0.383262	0.576174	0.452664	
565	0.113100	...	0.699094	0.520892	0.379915	
566	0.137321	...	0.589019	0.379949	0.230731	
567	0.425442	...	0.730277	0.668310	0.402035	
568	0.187026	...	0.489072	0.043578	0.020497	

	smoothness_worst	compactness_worst	concavity_worst	\
0	0.601136	0.619292	0.568610	
1	0.347553	0.154563	0.192971	
2	0.483590	0.385375	0.359744	
3	0.915472	0.814012	0.548642	
4	0.437364	0.172415	0.319489	
..	
564	0.461137	0.178527	0.328035	
565	0.300007	0.159997	0.256789	
566	0.282177	0.273705	0.271805	
567	0.619626	0.815758	0.749760	
568	0.124084	0.036043	0.000000	

	concave points_worst	symmetry_worst	fractal_dimension_worst	diagnosis
0	0.912027	0.598462	0.418864	1
1	0.639175	0.233590	0.222878	1
2	0.835052	0.403706	0.213433	1
3	0.884880	1.000000	0.773711	1
4	0.558419	0.157500	0.142595	1
..
564	0.761512	0.097575	0.105667	1
565	0.559450	0.198502	0.074315	1
566	0.487285	0.128721	0.151909	1
567	0.910653	0.497142	0.452315	1
568	0.000000	0.257441	0.100682	0

[569 rows x 31 columns]

[93]: X

```
[93]:      radius_mean  texture_mean  perimeter_mean  area_mean  smoothness_mean  \
0      0.521037      0.022658      0.545989      0.363733      0.593753
1      0.643144      0.272574      0.615783      0.501591      0.289880
2      0.601496      0.390260      0.595743      0.449417      0.514309
3      0.210090      0.360839      0.233501      0.102906      0.811321
4      0.629893      0.156578      0.630986      0.489290      0.430351
..      ...      ...      ...      ...      ...
564     0.690000      0.428813      0.678668      0.566490      0.526948
565     0.622320      0.626987      0.604036      0.474019      0.407782
566     0.455251      0.621238      0.445788      0.303118      0.288165
567     0.644564      0.663510      0.665538      0.475716      0.588336
568     0.036869      0.501522      0.028540      0.015907      0.000000

      compactness_mean  concavity_mean  concave points_mean  symmetry_mean  \
0      0.792037      0.703140      0.731113      0.686364
1      0.181768      0.203608      0.348757      0.379798
2      0.431017      0.462512      0.635686      0.509596
3      0.811361      0.565604      0.522863      0.776263
4      0.347893      0.463918      0.518390      0.378283
..      ...      ...      ...      ...
564     0.296055      0.571462      0.690358      0.336364
565     0.257714      0.337395      0.486630      0.349495
566     0.254340      0.216753      0.263519      0.267677
567     0.790197      0.823336      0.755467      0.675253
568     0.074351      0.000000      0.000000      0.266162

      fractal_dimension_mean  ...  radius_worst  texture_worst  \
0      0.605518  ...      0.620776      0.141525
1      0.141323  ...      0.606901      0.303571
2      0.211247  ...      0.556386      0.360075
3      1.000000  ...      0.248310      0.385928
4      0.186816  ...      0.519744      0.123934
..      ...  ...      ...      ...
564     0.132056  ...      0.623266      0.383262
565     0.113100  ...      0.560655      0.699094
566     0.137321  ...      0.393099      0.589019
567     0.425442  ...      0.633582      0.730277
568     0.187026  ...      0.054287      0.489072

      perimeter_worst  area_worst  smoothness_worst  compactness_worst  \
0      0.668310      0.450698      0.601136      0.619292
1      0.539818      0.435214      0.347553      0.154563
2      0.508442      0.374508      0.483590      0.385375
3      0.241347      0.094008      0.915472      0.814012
4      0.506948      0.341575      0.437364      0.172415
```

```

..          ...          ...          ...          ...
564          0.576174      0.452664      0.461137      0.178527
565          0.520892      0.379915      0.300007      0.159997
566          0.379949      0.230731      0.282177      0.273705
567          0.668310      0.402035      0.619626      0.815758
568          0.043578      0.020497      0.124084      0.036043

```

```

          concavity_worst  concave points_worst  symmetry_worst  \
0          0.568610          0.912027          0.598462
1          0.192971          0.639175          0.233590
2          0.359744          0.835052          0.403706
3          0.548642          0.884880          1.000000
4          0.319489          0.558419          0.157500
..          ...          ...          ...
564          0.328035          0.761512          0.097575
565          0.256789          0.559450          0.198502
566          0.271805          0.487285          0.128721
567          0.749760          0.910653          0.497142
568          0.000000          0.000000          0.257441

```

```

          fractal_dimension_worst
0          0.418864
1          0.222878
2          0.213433
3          0.773711
4          0.142595
..          ...
564          0.105667
565          0.074315
566          0.151909
567          0.452315
568          0.100682

```

[569 rows x 30 columns]

[114]: y

```

[114]: 0      1
       1      1
       2      1
       3      1
       4      1
       ..
       564    1
       565    1
       566    1
       567    1

```

```
568      0
Name: diagnosis, Length: 569, dtype: int64
```

```
[115]: from imblearn.over_sampling import SMOTE
oversample = SMOTE(k_neighbors=3)
X_smote, y_smote = oversample.fit_resample(X, y)
```

```
[116]: X_smote
```

```
[116]:      radius_mean  texture_mean  perimeter_mean  area_mean  smoothness_mean  \
0      0.521037      0.022658      0.545989      0.363733      0.593753
1      0.643144      0.272574      0.615783      0.501591      0.289880
2      0.601496      0.390260      0.595743      0.449417      0.514309
3      0.210090      0.360839      0.233501      0.102906      0.811321
4      0.629893      0.156578      0.630986      0.489290      0.430351
..      ...
709     0.367634      0.581892      0.376596      0.227153      0.538995
710     0.556667      0.317027      0.537899      0.409033      0.273154
711     0.427079      0.383549      0.421857      0.274840      0.440676
712     0.435488      0.330092      0.453632      0.281896      0.477590
713     0.349033      0.365141      0.348066      0.210141      0.407677

      compactness_mean  concavity_mean  concave points_mean  symmetry_mean  \
0      0.792037      0.703140      0.731113      0.686364
1      0.181768      0.203608      0.348757      0.379798
2      0.431017      0.462512      0.635686      0.509596
3      0.811361      0.565604      0.522863      0.776263
4      0.347893      0.463918      0.518390      0.378283
..      ...
709     0.438382      0.386852      0.384937      0.575483
710     0.183928      0.210193      0.278150      0.452697
711     0.325105      0.253603      0.294954      0.512528
712     0.540719      0.545367      0.478627      0.566299
713     0.285548      0.253641      0.285680      0.414782

      fractal_dimension_mean  ...  radius_worst  texture_worst  \
0      0.605518  ...      0.620776      0.141525
1      0.141323  ...      0.606901      0.303571
2      0.211247  ...      0.556386      0.360075
3      1.000000  ...      0.248310      0.385928
4      0.186816  ...      0.519744      0.123934
..      ...
709     0.407227  ...      0.366481      0.666169
710     0.014982  ...      0.500331      0.363063
711     0.221357  ...      0.411742      0.509960
712     0.362368  ...      0.336391      0.298011
713     0.272496  ...      0.292908      0.497094
```


	perimeter_worst	area_worst	smoothness_worst	compactness_worst	\
0	0.668310	0.450698	0.601136	0.619292	
1	0.539818	0.435214	0.347553	0.154563	
2	0.508442	0.374508	0.483590	0.385375	
3	0.241347	0.094008	0.915472	0.814012	
4	0.506948	0.341575	0.437364	0.172415	
..	
709	0.401470	0.208288	0.631406	0.599183	
710	0.475312	0.322063	0.211934	0.183422	
711	0.387724	0.235170	0.490489	0.322270	
712	0.355222	0.184625	0.454784	0.414086	
713	0.306903	0.155099	0.478750	0.311564	

	concavity_worst	concave points_worst	symmetry_worst	\
0	0.568610	0.912027	0.598462	
1	0.192971	0.639175	0.233590	
2	0.359744	0.835052	0.403706	
3	0.548642	0.884880	1.000000	
4	0.319489	0.558419	0.157500	
..	
709	0.546024	0.617763	0.512624	
710	0.242989	0.413138	0.262584	
711	0.268737	0.472589	0.415778	
712	0.481531	0.626685	0.370250	
713	0.315265	0.522470	0.292343	

	fractal_dimension_worst
0	0.418864
1	0.222878
2	0.213433
3	0.773711
4	0.142595
..	...
709	0.454898
710	0.067407
711	0.213753
712	0.250317
713	0.271976

[714 rows x 30 columns]

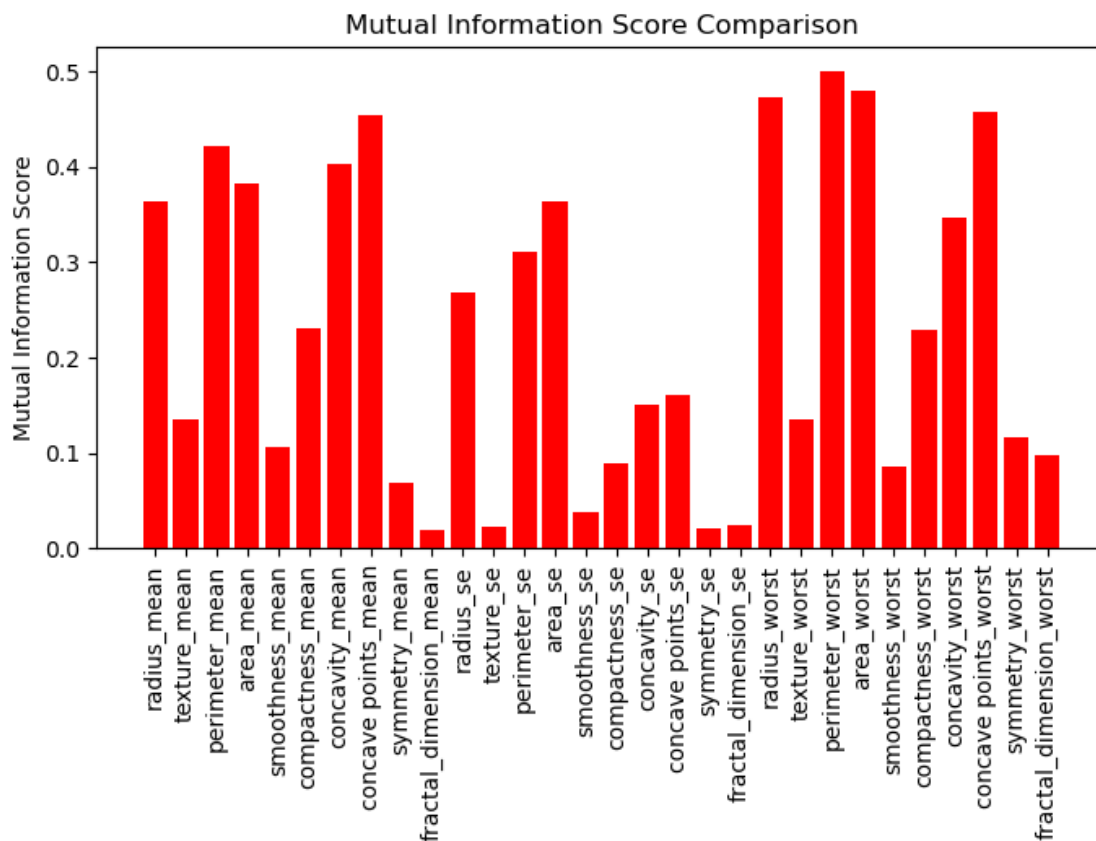
```
[117]: y_smote.value_counts()
```

```
[117]: 1    357
0    357
Name: diagnosis, dtype: int64
```

```
[118]: # information gain
MI_score = mutual_info_classif(X_smote, y_smote , random_state=0)
for feature in zip(feature_columns, MI_score):
    if feature[1]>0.30:
        print(feature)
```

```
('radius_mean', 0.36267197586780675)
('perimeter_mean', 0.42227347410878435)
('area_mean', 0.3830290669088263)
('concavity_mean', 0.40219732276547515)
('concave points_mean', 0.4534264220811439)
('perimeter_se', 0.3102076682911583)
('area_se', 0.3633570139714395)
('radius_worst', 0.4733901657815698)
('perimeter_worst', 0.5001892273843289)
('area_worst', 0.47923049764730474)
('concavity_worst', 0.34669874006624646)
('concave points_worst', 0.45661096537561363)
```

```
[119]: plt.figure(figsize=(8,4))
plt.bar(x=feature_columns, height=MI_score, color='red')
plt.xticks(rotation='vertical')
plt.ylabel('Mutual Information Score')
plt.title('Mutual Information Score Comparison')
plt.show()
```



```
[120]: selected_features = [feature_columns[i] for i in range(len(feature_columns)) if
    ↪MI_score[i] > 0.3 ]
X_selected = X_smote[selected_features]
```

```
[121]: X_selected
```

```
[121]:
```

	radius_mean	perimeter_mean	area_mean	concavity_mean	\
0	0.521037	0.545989	0.363733	0.703140	
1	0.643144	0.615783	0.501591	0.203608	
2	0.601496	0.595743	0.449417	0.462512	
3	0.210090	0.233501	0.102906	0.565604	
4	0.629893	0.630986	0.489290	0.463918	
...	
709	0.367634	0.376596	0.227153	0.386852	
710	0.556667	0.537899	0.409033	0.210193	
711	0.427079	0.421857	0.274840	0.253603	
712	0.435488	0.453632	0.281896	0.545367	
713	0.349033	0.348066	0.210141	0.253641	

```

concave points_mean  perimeter_se  area_se  radius_worst  \

```

0	0.731113	0.369034	0.273811	0.620776
1	0.348757	0.124440	0.125660	0.606901
2	0.635686	0.180370	0.162922	0.556386
3	0.522863	0.126655	0.038155	0.248310
4	0.518390	0.220563	0.163688	0.519744
..
709	0.384937	0.107996	0.053709	0.366481
710	0.278150	0.203343	0.135932	0.500331
711	0.294954	0.087632	0.060754	0.411742
712	0.478627	0.111577	0.053725	0.336391
713	0.285680	0.081291	0.036075	0.292908

	perimeter_worst	area_worst	concavity_worst	concave	points_worst
0	0.668310	0.450698	0.568610		0.912027
1	0.539818	0.435214	0.192971		0.639175
2	0.508442	0.374508	0.359744		0.835052
3	0.241347	0.094008	0.548642		0.884880
4	0.506948	0.341575	0.319489		0.558419
..
709	0.401470	0.208288	0.546024		0.617763
710	0.475312	0.322063	0.242989		0.413138
711	0.387724	0.235170	0.268737		0.472589
712	0.355222	0.184625	0.481531		0.626685
713	0.306903	0.155099	0.315265		0.522470

[714 rows x 12 columns]

```
[122]: X_train, X_test, y_train, y_test = train_test_split(X_selected, y_smote,
↳ test_size=0.2, random_state=0)
```

```
[123]: knn(X_train, X_test, y_train, y_test)
```

```
Accuracy du KNN : 0.951048951048951
precision score du KNN : 0.9393939393939394
recall score du KNN : 0.9538461538461539
f1 score du KNN : 0.9465648854961831
```

```
[124]: knn_grid_search(X_selected, y_smote)
```

```
grid best score accuracy 0.9692488262910798
grid best score precision 0.971979836979837
grid best score recall 0.9804761904761904
grid best score f1 score 0.9696325594357622
{'metric': 'euclidean', 'n_neighbors': 1, 'weights': 'uniform'}
KNeighborsClassifier(metric='euclidean', n_neighbors=1)
```

```
[125]: svm(X_train, X_test, y_train, y_test)
```

```
precision    recall  f1-score   support
```

0	0.97	0.96	0.97	78
1	0.95	0.97	0.96	65
accuracy			0.97	143
macro avg	0.96	0.97	0.96	143
weighted avg	0.97	0.97	0.97	143

```
[126]: svm_grid_search(X_train,X_test,y_train ,y_test)
```

	precision	recall	f1-score	support
0	0.97	0.99	0.98	78
1	0.98	0.97	0.98	65
accuracy			0.98	143
macro avg	0.98	0.98	0.98	143
weighted avg	0.98	0.98	0.98	143

Accuracy : 0.9790209790209791

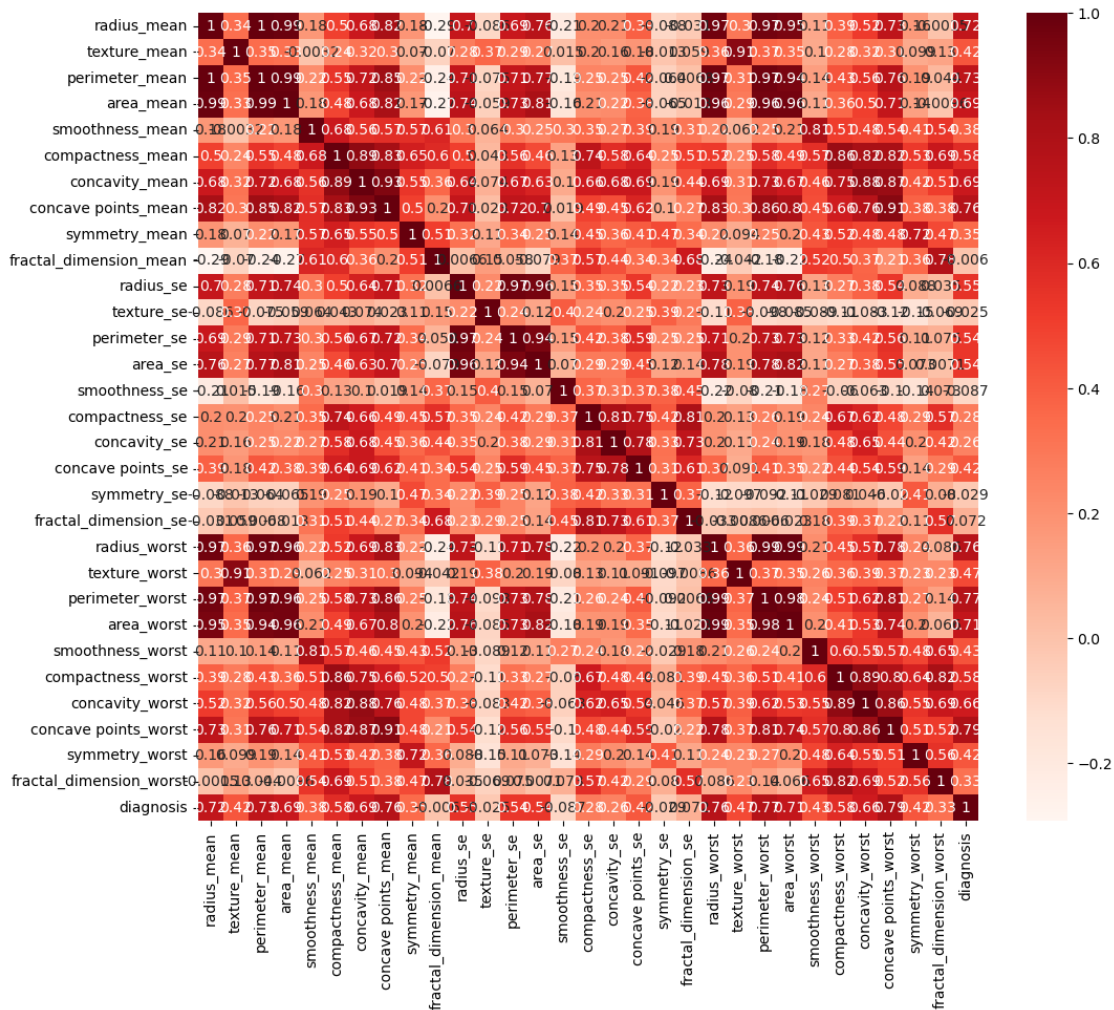
```
[127]: data_smote = pd.DataFrame(X_smote, columns = X_smote.columns)
```

```
[128]: data_smote["diagnosis"] = y_smote
```

```
[129]: data_smote['diagnosis'].value_counts()
```

```
[129]: 1    357
      0    357
      Name: diagnosis, dtype: int64
```

```
[130]: #Using Pearson Correlation
plt.figure(figsize=(12,10))
cor = data_smote.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.Red)
plt.show()
```



```
[131]: #Correlation with output variable
cor_target = abs(cor["diagnosis"])
#Selecting highly correlated features
relevant_features = list(cor_target[abs(cor_target) > 0.5].index)
relevant_features.remove('diagnosis')
relevant_features
# we choose the variables that have a correlation higher to 0.5 with our target_
↪variable
```

```
[131]: ['radius_mean',
'perimeter_mean',
'area_mean',
'compactness_mean',
'concavity_mean',
'concave points_mean',
```

```

'radius_se',
'perimeter_se',
'area_se',
'radius_worst',
'perimeter_worst',
'area_worst',
'compactness_worst',
'concavity_worst',
'concave points_worst']

```

```
[132]: X_selected_corr = X_smote[relevant_features]
```

```
[133]: X_selected_corr
```

```
[133]:
```

	radius_mean	perimeter_mean	area_mean	compactness_mean	concavity_mean	\
0	0.521037	0.545989	0.363733	0.792037	0.703140	
1	0.643144	0.615783	0.501591	0.181768	0.203608	
2	0.601496	0.595743	0.449417	0.431017	0.462512	
3	0.210090	0.233501	0.102906	0.811361	0.565604	
4	0.629893	0.630986	0.489290	0.347893	0.463918	
..	
709	0.367634	0.376596	0.227153	0.438382	0.386852	
710	0.556667	0.537899	0.409033	0.183928	0.210193	
711	0.427079	0.421857	0.274840	0.325105	0.253603	
712	0.435488	0.453632	0.281896	0.540719	0.545367	
713	0.349033	0.348066	0.210141	0.285548	0.253641	

	concave points_mean	radius_se	perimeter_se	area_se	radius_worst	\
0	0.731113	0.356147	0.369034	0.273811	0.620776	
1	0.348757	0.156437	0.124440	0.125660	0.606901	
2	0.635686	0.229622	0.180370	0.162922	0.556386	
3	0.522863	0.139091	0.126655	0.038155	0.248310	
4	0.518390	0.233822	0.220563	0.163688	0.519744	
..	
709	0.384937	0.100471	0.107996	0.053709	0.366481	
710	0.278150	0.204485	0.203343	0.135932	0.500331	
711	0.294954	0.104716	0.087632	0.060754	0.411742	
712	0.478627	0.083650	0.111577	0.053725	0.336391	
713	0.285680	0.063979	0.081291	0.036075	0.292908	

	perimeter_worst	area_worst	compactness_worst	concavity_worst	\
0	0.668310	0.450698	0.619292	0.568610	
1	0.539818	0.435214	0.154563	0.192971	
2	0.508442	0.374508	0.385375	0.359744	
3	0.241347	0.094008	0.814012	0.548642	
4	0.506948	0.341575	0.172415	0.319489	
..	

709	0.401470	0.208288	0.599183	0.546024
710	0.475312	0.322063	0.183422	0.242989
711	0.387724	0.235170	0.322270	0.268737
712	0.355222	0.184625	0.414086	0.481531
713	0.306903	0.155099	0.311564	0.315265

	concave points_worst
0	0.912027
1	0.639175
2	0.835052
3	0.884880
4	0.558419
..	...
709	0.617763
710	0.413138
711	0.472589
712	0.626685
713	0.522470

[714 rows x 15 columns]

```
[134]: # splitting the data
X_train, X_test, y_train, y_test = train_test_split(X_selected_corr, y_smote,
↳ test_size=0.2, random_state=0)
```

```
[135]: knn(X_train, X_test, y_train, y_test)
```

Accuracy du KNN : 0.958041958041958
precision score du KNN : 0.9402985074626866
recall score du KNN : 0.9692307692307692
f1 score du KNN : 0.9545454545454547

```
[136]: knn_grid_search(X_selected_corr, y_smote)
```

grid best score accuracy 0.9621870109546166
grid best score precision 0.9686363636363635
grid best score recall 0.9748412698412698
grid best score f1 score 0.9628758759094641
{'metric': 'manhattan', 'n_neighbors': 1, 'weights': 'uniform'}
KNeighborsClassifier(metric='manhattan', n_neighbors=1)

```
[137]: svm(X_train, X_test, y_train, y_test)
```

	precision	recall	f1-score	support
0	0.97	0.96	0.97	78
1	0.95	0.97	0.96	65
accuracy			0.97	143

macro avg	0.96	0.97	0.96	143
weighted avg	0.97	0.97	0.97	143

```
[138]: svm_grid_search(X_train,X_test,y_train ,y_test)
```

	precision	recall	f1-score	support
0	0.97	0.97	0.97	78
1	0.97	0.97	0.97	65
accuracy			0.97	143
macro avg	0.97	0.97	0.97	143
weighted avg	0.97	0.97	0.97	143

Accuracy : 0.972027972027972

```
[139]: # Select Kbest
selector = SelectKBest(chi2, k=10)
X_new = selector.fit_transform(X_smote, y_smote)
mask = selector.get_support()
selected_features = X_smote.columns[mask]
selected = selected_features.values
selected
```

```
[139]: array(['perimeter_mean', 'area_mean', 'concavity_mean',
            'concave points_mean', 'radius_worst', 'perimeter_worst',
            'area_worst', 'concavity_worst', 'concave points_worst',
            'diagnosis'], dtype=object)
```

```
[140]: X_selected_kbest_smote = X_smote[selected]
```

```
[141]: X_selected_kbest_smote
```

```
[141]:      perimeter_mean  area_mean  concavity_mean  concave points_mean \
0      0.545989    0.363733      0.703140      0.731113
1      0.615783    0.501591      0.203608      0.348757
2      0.595743    0.449417      0.462512      0.635686
3      0.233501    0.102906      0.565604      0.522863
4      0.630986    0.489290      0.463918      0.518390
..      ...          ...          ...          ...
709    0.376596    0.227153      0.386852      0.384937
710    0.537899    0.409033      0.210193      0.278150
711    0.421857    0.274840      0.253603      0.294954
712    0.453632    0.281896      0.545367      0.478627
713    0.348066    0.210141      0.253641      0.285680
```

```
      radius_worst  perimeter_worst  area_worst  concavity_worst \
```

0	0.620776	0.668310	0.450698	0.568610
1	0.606901	0.539818	0.435214	0.192971
2	0.556386	0.508442	0.374508	0.359744
3	0.248310	0.241347	0.094008	0.548642
4	0.519744	0.506948	0.341575	0.319489
..
709	0.366481	0.401470	0.208288	0.546024
710	0.500331	0.475312	0.322063	0.242989
711	0.411742	0.387724	0.235170	0.268737
712	0.336391	0.355222	0.184625	0.481531
713	0.292908	0.306903	0.155099	0.315265

	concave	points_worst	diagnosis
0		0.912027	1
1		0.639175	1
2		0.835052	1
3		0.884880	1
4		0.558419	1
..	
709		0.617763	1
710		0.413138	1
711		0.472589	1
712		0.626685	1
713		0.522470	1

[714 rows x 10 columns]

```
[142]: # splitting the data
X_train, X_test, y_train, y_test = train_test_split(X_selected_kbest_smote, y_smote, test_size=0.2, random_state=0)
```

```
[143]: knn(X_train, X_test, y_train, y_test)
```

```
Accuracy du KNN : 1.0
precision score du KNN : 1.0
recall score du KNN : 1.0
f1 score du KNN : 1.0
```

```
[144]: knn_grid_search(X_selected_kbest_smote, y_smote)
```

```
grid best score accuracy 1.0
grid best score precision 1.0
grid best score recall 1.0
grid best score f1 score 1.0
{'metric': 'euclidean', 'n_neighbors': 1, 'weights': 'uniform'}
KNeighborsClassifier(metric='euclidean', n_neighbors=1)
```

```
[145]: svm(X_train, X_test, y_train, y_test)
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	78
1	1.00	1.00	1.00	65
accuracy			1.00	143
macro avg	1.00	1.00	1.00	143
weighted avg	1.00	1.00	1.00	143

```
[146]: svm_grid_search(X_train, X_test, y_train, y_test)
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	78
1	1.00	1.00	1.00	65
accuracy			1.00	143
macro avg	1.00	1.00	1.00	143
weighted avg	1.00	1.00	1.00	143

Accuracy : 1.0

3.0.1 wrapper

```
[147]: X_smote
```

```
[147]:
```

	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	\
0	0.521037	0.022658	0.545989	0.363733	0.593753	
1	0.643144	0.272574	0.615783	0.501591	0.289880	
2	0.601496	0.390260	0.595743	0.449417	0.514309	
3	0.210090	0.360839	0.233501	0.102906	0.811321	
4	0.629893	0.156578	0.630986	0.489290	0.430351	
..	
709	0.367634	0.581892	0.376596	0.227153	0.538995	
710	0.556667	0.317027	0.537899	0.409033	0.273154	
711	0.427079	0.383549	0.421857	0.274840	0.440676	
712	0.435488	0.330092	0.453632	0.281896	0.477590	
713	0.349033	0.365141	0.348066	0.210141	0.407677	
	compactness_mean	concavity_mean	concave	points_mean	symmetry_mean	\
0	0.792037	0.703140		0.731113	0.686364	
1	0.181768	0.203608		0.348757	0.379798	
2	0.431017	0.462512		0.635686	0.509596	
3	0.811361	0.565604		0.522863	0.776263	
4	0.347893	0.463918		0.518390	0.378283	
..	
709	0.438382	0.386852		0.384937	0.575483	

710	0.183928	0.210193	0.278150	0.452697
711	0.325105	0.253603	0.294954	0.512528
712	0.540719	0.545367	0.478627	0.566299
713	0.285548	0.253641	0.285680	0.414782

	fractal_dimension_mean	...	texture_worst	perimeter_worst	area_worst	\
0	0.605518	...	0.141525	0.668310	0.450698	
1	0.141323	...	0.303571	0.539818	0.435214	
2	0.211247	...	0.360075	0.508442	0.374508	
3	1.000000	...	0.385928	0.241347	0.094008	
4	0.186816	...	0.123934	0.506948	0.341575	
..	
709	0.407227	...	0.666169	0.401470	0.208288	
710	0.014982	...	0.363063	0.475312	0.322063	
711	0.221357	...	0.509960	0.387724	0.235170	
712	0.362368	...	0.298011	0.355222	0.184625	
713	0.272496	...	0.497094	0.306903	0.155099	

	smoothness_worst	compactness_worst	concavity_worst	\
0	0.601136	0.619292	0.568610	
1	0.347553	0.154563	0.192971	
2	0.483590	0.385375	0.359744	
3	0.915472	0.814012	0.548642	
4	0.437364	0.172415	0.319489	
..	
709	0.631406	0.599183	0.546024	
710	0.211934	0.183422	0.242989	
711	0.490489	0.322270	0.268737	
712	0.454784	0.414086	0.481531	
713	0.478750	0.311564	0.315265	

	concave points_worst	symmetry_worst	fractal_dimension_worst	diagnosis
0	0.912027	0.598462	0.418864	1
1	0.639175	0.233590	0.222878	1
2	0.835052	0.403706	0.213433	1
3	0.884880	1.000000	0.773711	1
4	0.558419	0.157500	0.142595	1
..
709	0.617763	0.512624	0.454898	1
710	0.413138	0.262584	0.067407	1
711	0.472589	0.415778	0.213753	1
712	0.626685	0.370250	0.250317	1
713	0.522470	0.292343	0.271976	1

[714 rows x 31 columns]

[148]: y_smote

```
[148]: 0      1
      1      1
      2      1
      3      1
      4      1
      ..
      709    1
      710    1
      711    1
      712    1
      713    1
      Name: diagnosis, Length: 714, dtype: int64
```

```
[149]: X_train, X_test, y_train, y_test = train_test_split( X_smote, y_smote,
      ↪test_size=0.33, random_state=42)
      # create the classifier with n_estimators = 100

      clf = RandomForestClassifier(n_estimators=100, random_state=0)

      # fit the model to the training set

      clf.fit(X_train, y_train)

      # view the feature scores

      feature_scores = pd.Series(clf.feature_importances_, index=X_train.columns).
      ↪sort_values(ascending=False)

      selected = feature_scores[feature_scores.values > 0.01]
      selected_features = selected.index.values
```

```
[150]: selected_features
```

```
[150]: array(['diagnosis', 'radius_worst', 'concave points_worst', 'area_worst',
      'concave points_mean', 'perimeter_worst', 'concavity_mean',
      'perimeter_mean', 'radius_mean', 'concavity_worst', 'area_se',
      'texture_mean'], dtype=object)
```

```
[151]: X_selected_rf_smote = X_smote[selected_features]
```

```
[152]: # splitting the data
      X_train, X_test, y_train, y_test = train_test_split(X_selected_rf_smote,
      ↪y_smote, test_size=0.2, random_state=0)
```

```
[153]: knn(X_train, X_test, y_train, y_test)
```

```

Accuracy du KNN : 1.0
precision score du KNN : 1.0
recall score du KNN : 1.0
f1 score du KNN : 1.0

```

```
[154]: knn_grid_search(X_selected_rf_smote , y_smote)
```

```

grid best score accuracy 1.0
grid best score precision 1.0
grid best score recall 1.0
grid best score f1 score 1.0
{'metric': 'euclidean', 'n_neighbors': 1, 'weights': 'uniform'}
KNeighborsClassifier(metric='euclidean', n_neighbors=1)

```

```
[155]: svm(X_train, X_test, y_train, y_test)
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	78
1	1.00	1.00	1.00	65
accuracy			1.00	143
macro avg	1.00	1.00	1.00	143
weighted avg	1.00	1.00	1.00	143

```
[156]: svm_grid_search(X_train, X_test, y_train, y_test)
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	78
1	1.00	1.00	1.00	65
accuracy			1.00	143
macro avg	1.00	1.00	1.00	143
weighted avg	1.00	1.00	1.00	143

```
Accuracy : 1.0
```

3.0.2 Wrapper recursive features elemiation

```

[109]: from sklearn.feature_selection import RFE
        from sklearn.svm import SVC

        # Initialize an SVM classifier and an RFE feature selector
        svm = SVC(kernel='linear')
        rfe = RFE(estimator=svm, n_features_to_select=10, step=1)

        # Fit the RFE selector to the data and get the selected feature indices

```

```

rfe.fit(X_smote, y_smote)
selected_indices = rfe.get_support(indices=True)

selected_names = [X_resampled.columns[i] for i, selected in enumerate(rfe.
    ↪support_) if selected]

# Print the selected feature names
print('Selected features:', selected_names)

```

Selected features: ['radius_mean', 'concave points_mean', 'radius_se', 'radius_worst', 'texture_worst', 'perimeter_worst', 'area_worst', 'smoothness_worst', 'concave points_worst', 'symmetry_worst']

```
[110]: X_selected_rfe_smote = X_smote[selected_names]
```

```
[111]: X_selected_rfe_smote
```

```
[111]:
```

	radius_mean	concave points_mean	radius_se	radius_worst	texture_worst	\
0	0.521037	0.731113	0.356147	0.620776	0.141525	
1	0.643144	0.348757	0.156437	0.606901	0.303571	
2	0.601496	0.635686	0.229622	0.556386	0.360075	
3	0.210090	0.522863	0.139091	0.248310	0.385928	
4	0.629893	0.518390	0.233822	0.519744	0.123934	
..	
709	0.388456	0.256380	0.108656	0.306150	0.437301	
710	0.306098	0.470705	0.103634	0.315222	0.302132	
711	0.365918	0.223111	0.077374	0.332806	0.236218	
712	0.638719	0.306977	0.205080	0.579789	0.377599	
713	0.687596	0.715509	0.286213	0.660887	0.364345	

	perimeter_worst	area_worst	smoothness_worst	concave points_worst	\
0	0.668310	0.450698	0.601136	0.912027	
1	0.539818	0.435214	0.347553	0.639175	
2	0.508442	0.374508	0.483590	0.835052	
3	0.241347	0.094008	0.915472	0.884880	
4	0.506948	0.341575	0.437364	0.558419	
..	
709	0.298084	0.161883	0.332679	0.402120	
710	0.298679	0.170446	0.761657	0.685184	
711	0.318329	0.183558	0.519499	0.444969	
712	0.554043	0.385231	0.346674	0.506193	
713	0.660659	0.466581	0.378645	0.802264	

	symmetry_worst
0	0.598462
1	0.233590
2	0.403706
3	1.000000

```

4          0.157500
..          ...
709        0.265297
710        0.328455
711        0.340645
712        0.139067
713        0.254533

```

[714 rows x 10 columns]

```
[116]: # splitting the data
X_train, X_test, y_train, y_test = train_test_split(X_selected_rfe_smote,
↪y_smote, test_size=0.2, random_state=0)
```

```
[117]: knn(X_train, X_test, y_train, y_test)
```

```

Accuracy du KNN :  0.972027972027972
precision score du KNN :  0.9841269841269841
recall score du KNN :  0.9538461538461539
f1 score du KNN :  0.96875

```

```
[162]: knn_grid_search(X_selected_rfe_smote,y_smote)
```

```

grid best score accuracy 1.0
grid best score precision 1.0
grid best score recall 1.0
grid best score f1 score 1.0
{'metric': 'euclidean', 'n_neighbors': 1, 'weights': 'uniform'}
KNeighborsClassifier(metric='euclidean', n_neighbors=1)

```

```
[163]: def svm(X_train, X_test, y_train, y_test):
        svm = SVC()
        svm.fit(X_train, y_train)
        y_pred = svm.predict(X_test)
        print(classification_report(y_test, y_pred))
```

```
[164]: svm(X_train, X_test, y_train, y_test)
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	78
1	1.00	1.00	1.00	65
accuracy			1.00	143
macro avg	1.00	1.00	1.00	143
weighted avg	1.00	1.00	1.00	143

```
[165]: svm_grid_search(X_train, X_test, y_train, y_test)
```


	precision	recall	f1-score	support
0	1.00	1.00	1.00	78
1	1.00	1.00	1.00	65
accuracy			1.00	143
macro avg	1.00	1.00	1.00	143
weighted avg	1.00	1.00	1.00	143

Accuracy : 1.0

```
[166]: ## Decision tree
```

```
[122]: # splitting the data
X_train, X_test, y_train, y_test = train_test_split(X_smote, y_smote,
↳test_size=0.2, random_state=0)
```

```
[123]: clf = tree.DecisionTreeClassifier()
clf.fit(X_train, y_train)
y_pred= clf.predict(X_test)
acc2 = metrics.accuracy_score(y_test, y_pred)
precision = metrics.precision_score(y_test, y_pred)
recall = metrics.recall_score(y_test, y_pred)
f1_score = metrics.f1_score(y_test , y_pred)
print("Accuracy:", acc2)
print("Precision: ",precision)
print("Recall: ",recall)
print("F1 score : ",f1_score)
```

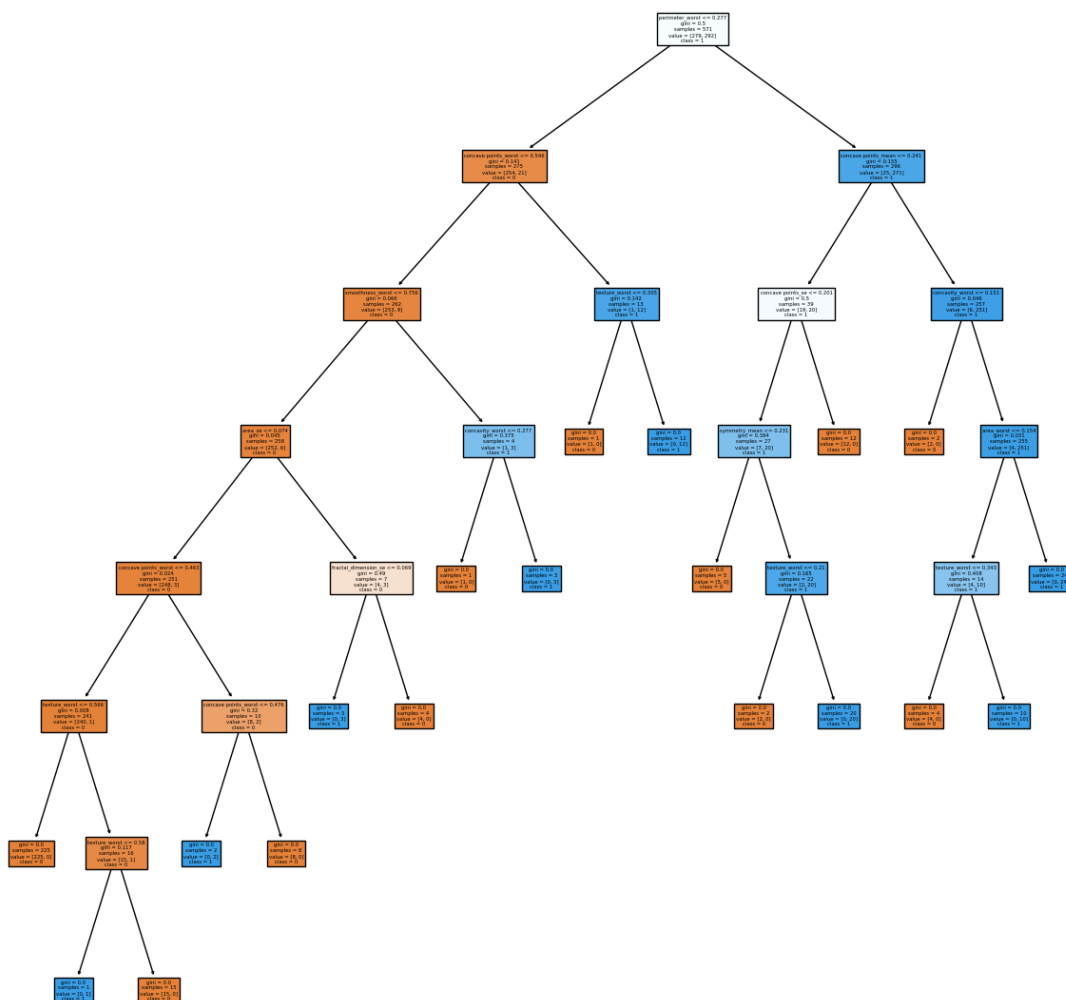
Accuracy: 0.951048951048951

Precision: 0.9264705882352942

Recall: 0.9692307692307692

F1 score : 0.9473684210526316

```
[120]: from sklearn import tree
clf = tree.DecisionTreeClassifier()
clf.fit(X_train, y_train)
fig = plt.figure(figsize=(15,15))
_ = tree.plot_tree(clf,
feature_names=feature_columns
,
class_names=["0","1"],
filled=True)
```



```
[131]: #Grid search
DT = tree.DecisionTreeClassifier()
params = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [2, 4, 6, 8, 10],
    'min_samples_split': [2, 4, 6, 8, 10],
    'min_samples_leaf': [1, 2, 3, 4, 5]
}
grid = GridSearchCV(DT, params, cv = 10, scoring = 'accuracy')
grid.fit(X_smote,y_smote)

grid1 = GridSearchCV(DT, params, cv = 10, scoring = 'precision')
grid1.fit(X_smote,y_smote)
```

```

grid2 = GridSearchCV(DT, params, cv = 10, scoring = 'recall')
grid2.fit(X_smote,y_smote)

grid3 = GridSearchCV(DT, params, cv = 10, scoring = 'f1')
grid3.fit(X_smote,y_smote)

print("Accuracy",grid.best_score_)
print("Precision",grid1.best_score_)
print("Recall",grid2.best_score_)
print("f1 score",grid3.best_score_)

print(grid.best_params_)
print(grid.best_estimator_)

```

```

Accuracy 0.9594483568075116
Precision 0.966233582704171
Recall 0.9804761904761905
f1 score 0.9619993310401753
{'criterion': 'entropy', 'max_depth': 8, 'min_samples_leaf': 3,
 'min_samples_split': 8}
DecisionTreeClassifier(criterion='entropy', max_depth=8, min_samples_leaf=3,
                        min_samples_split=8)

```

```

[132]: # Use a pruning algorithm to prune the decision tree
clf = tree.DecisionTreeClassifier()
path = clf.cost_complexity_pruning_path(X_train, y_train)
ccp_alphas = path.ccp_alphas[:-1]
clfs = []
for ccp_alpha in ccp_alphas:
    clf = tree.DecisionTreeClassifier(ccp_alpha=ccp_alpha)
    clf.fit(X_train, y_train)
    clfs.append(clf)
# Evaluate the pruned decision tree using the testing data
acc_scores = []
for clf in clfs:
    y_pred = clf.predict(X_test)
    acc_score = accuracy_score(y_test, y_pred)
    prec_score = precision_score(y_test , y_pred)
    acc_scores.append(acc_score)
# Find the best pruning parameter based on accuracy score
best_clf = clfs[acc_scores.index(max(acc_scores))]
# Evaluate the best pruned decision tree using the testing data
y_pred = best_clf.predict(X_test)
acc_score = accuracy_score(y_test, y_pred)
precision = precision_score(y_test , y_pred)
recall = recall_score(y_test , y_pred)

```

```

f1_score = metrics.f1_score(y_test , y_pred)

print("Accuracy score: {:.2f}".format(acc_score))
print("precision score: {:.2f}".format(precision))
print("recall score: {:.2f}".format(recall))
print("f1 score: {:.2f}".format(f1_score))

#print("ccp_alpha: {:.3f}".format(ccp_alphas[acc_scores.
↪index(max(acc_scores))]))

```

```

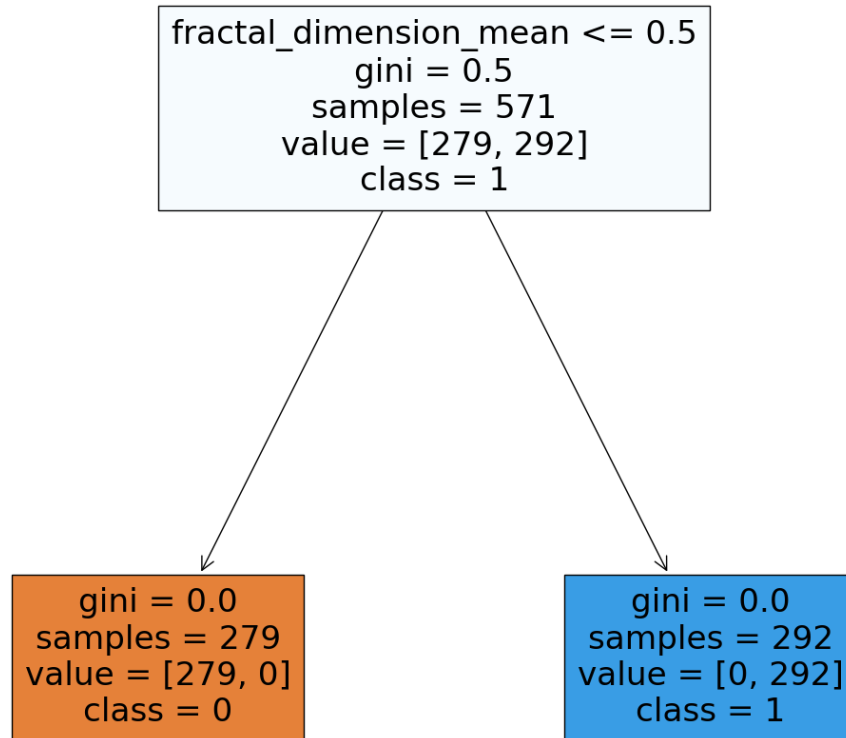
Accuracy score: 0.96
precision score: 0.95
recall score: 0.97
f1 score: 0.96

```

```

[171]: from sklearn import tree
fig = plt.figure(figsize=(15,15))
_ = tree.plot_tree(best_clf,
    feature_names=feature_columns,
    class_names=["0","1"],filled=True)

```



3.1 Unbalanced data Over sampler methods

[172]: X

```

[172]:      radius_mean  texture_mean  perimeter_mean  area_mean  smoothness_mean  \
0      0.521037    0.022658    0.545989    0.363733    0.593753
1      0.643144    0.272574    0.615783    0.501591    0.289880
2      0.601496    0.390260    0.595743    0.449417    0.514309
3      0.210090    0.360839    0.233501    0.102906    0.811321
4      0.629893    0.156578    0.630986    0.489290    0.430351
..      ...          ...          ...          ...          ...
564    0.690000    0.428813    0.678668    0.566490    0.526948
565    0.622320    0.626987    0.604036    0.474019    0.407782
  
```

566	0.455251	0.621238	0.445788	0.303118	0.288165
567	0.644564	0.663510	0.665538	0.475716	0.588336
568	0.036869	0.501522	0.028540	0.015907	0.000000

	compactness_mean	concavity_mean	concave	points_mean	symmetry_mean \
0	0.792037	0.703140		0.731113	0.686364
1	0.181768	0.203608		0.348757	0.379798
2	0.431017	0.462512		0.635686	0.509596
3	0.811361	0.565604		0.522863	0.776263
4	0.347893	0.463918		0.518390	0.378283
..
564	0.296055	0.571462		0.690358	0.336364
565	0.257714	0.337395		0.486630	0.349495
566	0.254340	0.216753		0.263519	0.267677
567	0.790197	0.823336		0.755467	0.675253
568	0.074351	0.000000		0.000000	0.266162

	fractal_dimension_mean	...	radius_worst	texture_worst \
0	0.605518	...	0.620776	0.141525
1	0.141323	...	0.606901	0.303571
2	0.211247	...	0.556386	0.360075
3	1.000000	...	0.248310	0.385928
4	0.186816	...	0.519744	0.123934
..
564	0.132056	...	0.623266	0.383262
565	0.113100	...	0.560655	0.699094
566	0.137321	...	0.393099	0.589019
567	0.425442	...	0.633582	0.730277
568	0.187026	...	0.054287	0.489072

	perimeter_worst	area_worst	smoothness_worst	compactness_worst \
0	0.668310	0.450698	0.601136	0.619292
1	0.539818	0.435214	0.347553	0.154563
2	0.508442	0.374508	0.483590	0.385375
3	0.241347	0.094008	0.915472	0.814012
4	0.506948	0.341575	0.437364	0.172415
..
564	0.576174	0.452664	0.461137	0.178527
565	0.520892	0.379915	0.300007	0.159997
566	0.379949	0.230731	0.282177	0.273705
567	0.668310	0.402035	0.619626	0.815758
568	0.043578	0.020497	0.124084	0.036043

	concavity_worst	concave	points_worst	symmetry_worst \
0	0.568610		0.912027	0.598462
1	0.192971		0.639175	0.233590
2	0.359744		0.835052	0.403706

3	0.548642	0.884880	1.000000
4	0.319489	0.558419	0.157500
..
564	0.328035	0.761512	0.097575
565	0.256789	0.559450	0.198502
566	0.271805	0.487285	0.128721
567	0.749760	0.910653	0.497142
568	0.000000	0.000000	0.257441

	fractal_dimension_worst
0	0.418864
1	0.222878
2	0.213433
3	0.773711
4	0.142595
..	...
564	0.105667
565	0.074315
566	0.151909
567	0.452315
568	0.100682

[569 rows x 30 columns]

[173]: y

```
[173]: 0      1
      1      1
      2      1
      3      1
      4      1
      ..
      564    1
      565    1
      566    1
      567    1
      568    0
```

Name: diagnosis, Length: 569, dtype: int64

3.2 Over sampling

```
[174]: from imblearn.over_sampling import RandomOverSampler
      rus = RandomOverSampler()
      X_oversampling, y_oversampling = rus.fit_resample(X, y)
```

[175]: X_oversampling

```

[175]:      radius_mean  texture_mean  perimeter_mean  area_mean  smoothness_mean  \
0      0.521037      0.022658      0.545989      0.363733      0.593753
1      0.643144      0.272574      0.615783      0.501591      0.289880
2      0.601496      0.390260      0.595743      0.449417      0.514309
3      0.210090      0.360839      0.233501      0.102906      0.811321
4      0.629893      0.156578      0.630986      0.489290      0.430351
..      ...      ...      ...      ...      ...
709     0.692366      0.425093      0.695253      0.535949      0.578406
710     0.394671      0.255665      0.410545      0.241697      0.730071
711     0.395617      0.153872      0.405708      0.237922      0.493545
712     0.313739      0.516402      0.305853      0.186299      0.381421
713     0.434427      0.400068      0.431276      0.282630      0.434865

      compactness_mean  concavity_mean  concave points_mean  symmetry_mean  \
0      0.792037      0.703140      0.731113      0.686364
1      0.181768      0.203608      0.348757      0.379798
2      0.431017      0.462512      0.635686      0.509596
3      0.811361      0.565604      0.522863      0.776263
4      0.347893      0.463918      0.518390      0.378283
..      ...      ...      ...      ...
709     0.580701      0.658388      0.776342      0.556566
710     0.641126      0.573571      0.617296      0.675758
711     0.595424      0.486645      0.484891      0.737879
712     0.201613      0.202085      0.223111      0.277273
713     0.334397      0.244377      0.278976      0.555556

      fractal_dimension_mean  ...  radius_worst  texture_worst  \
0      0.605518  ...      0.620776      0.141525
1      0.141323  ...      0.606901      0.303571
2      0.211247  ...      0.556386      0.360075
3      1.000000  ...      0.248310      0.385928
4      0.186816  ...      0.519744      0.123934
..      ...  ...      ...      ...
709     0.339090  ...      0.651014      0.445629
710     0.547599  ...      0.348630      0.283582
711     0.428812  ...      0.360726      0.188166
712     0.184288  ...      0.322305      0.619670
713     0.188500  ...      0.410530      0.523987

      perimeter_worst  area_worst  smoothness_worst  compactness_worst  \
0      0.668310      0.450698      0.601136      0.619292
1      0.539818      0.435214      0.347553      0.154563
2      0.508442      0.374508      0.483590      0.385375
3      0.241347      0.094008      0.915472      0.814012
4      0.506948      0.341575      0.437364      0.172415
..      ...      ...      ...      ...
709     0.605558      0.465936      0.521891      0.528189

```


710	0.345585	0.182757	0.695569	0.410406
711	0.371981	0.195561	0.447930	0.551183
712	0.289805	0.177276	0.365383	0.162034
713	0.394890	0.243266	0.451232	0.269921

	concavity_worst	concave points_worst	symmetry_worst	\
0	0.568610	0.912027	0.598462	
1	0.192971	0.639175	0.233590	
2	0.359744	0.835052	0.403706	
3	0.548642	0.884880	1.000000	
4	0.319489	0.558419	0.157500	
..	
709	0.563339	0.832302	0.446087	
710	0.353754	0.765979	0.333728	
711	0.503594	0.822337	0.611473	
712	0.253115	0.406873	0.214075	
713	0.238978	0.450859	0.377489	

	fractal_dimension_worst
0	0.418864
1	0.222878
2	0.213433
3	0.773711
4	0.142595
..	...
709	0.299488
710	0.420176
711	0.291355
712	0.124164
713	0.138725

[714 rows x 30 columns]

```
[176]: y_oversampling
```

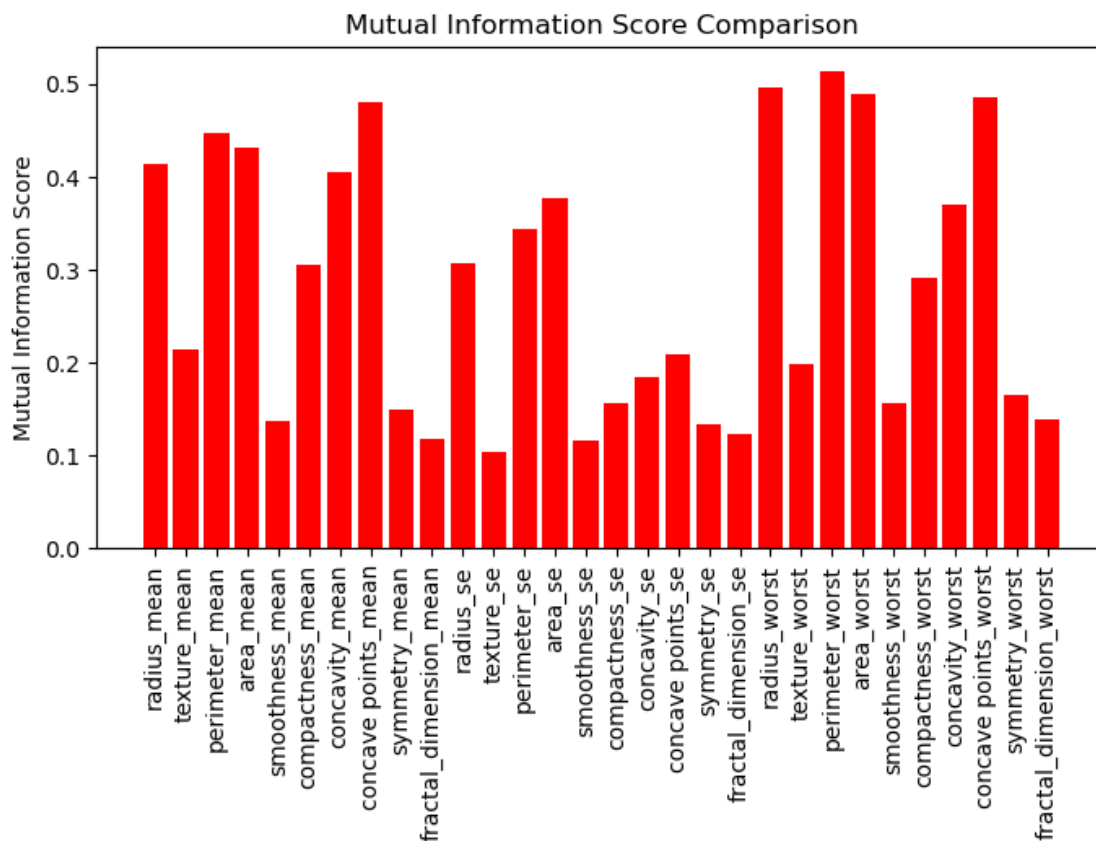
```
[176]: 0      1
      1      1
      2      1
      3      1
      4      1
      ..
      709    1
      710    1
      711    1
      712    1
      713    1
```

Name: diagnosis, Length: 714, dtype: int64

```
[177]: # information gain
MI_score = mutual_info_classif(X_oversampling, y_oversampling , random_state=0)
for feature in zip(feature_columns, MI_score):
    if feature[1]>0.30:
        print(feature)

('radius_mean', 0.4133085495567619)
('perimeter_mean', 0.4473629655717368)
('area_mean', 0.43171828371890686)
('compactness_mean', 0.305059643908004)
('concavity_mean', 0.40517789650428226)
('concave points_mean', 0.480230407000652)
('radius_se', 0.30735060999231867)
('perimeter_se', 0.3438191837108908)
('area_se', 0.37763026802866495)
('radius_worst', 0.49623541498187906)
('perimeter_worst', 0.5139462061728981)
('area_worst', 0.48930203610532796)
('concavity_worst', 0.36912822036724213)
('concave points_worst', 0.48558750895509517)

[178]: plt.figure(figsize=(8,4))
plt.bar(x=feature_columns, height=MI_score, color='red')
plt.xticks(rotation='vertical')
plt.ylabel('Mutual Information Score')
plt.title('Mutual Information Score Comparison')
plt.show()
```



```
[179]: selected_features = [feature_columns[i] for i in range(len(feature_columns)) if
    ↪MI_score[i] > 0.3 ]
X_selected_over = X_oversampling[selected_features]
```

```
[180]: X_selected_over
```

```
[180]:
```

	radius_mean	perimeter_mean	area_mean	compactness_mean	concavity_mean	\
0	0.521037	0.545989	0.363733	0.792037	0.703140	
1	0.643144	0.615783	0.501591	0.181768	0.203608	
2	0.601496	0.595743	0.449417	0.431017	0.462512	
3	0.210090	0.233501	0.102906	0.811361	0.565604	
4	0.629893	0.630986	0.489290	0.347893	0.463918	
..	
709	0.692366	0.695253	0.535949	0.580701	0.658388	
710	0.394671	0.410545	0.241697	0.641126	0.573571	
711	0.395617	0.405708	0.237922	0.595424	0.486645	
712	0.313739	0.305853	0.186299	0.201613	0.202085	
713	0.434427	0.431276	0.282630	0.334397	0.244377	

```

concave points_mean  radius_se  perimeter_se  area_se  radius_worst  \

```

0	0.731113	0.356147	0.369034	0.273811	0.620776
1	0.348757	0.156437	0.124440	0.125660	0.606901
2	0.635686	0.229622	0.180370	0.162922	0.556386
3	0.522863	0.139091	0.126655	0.038155	0.248310
4	0.518390	0.233822	0.220563	0.163688	0.519744
..
709	0.776342	0.185660	0.160251	0.138566	0.651014
710	0.617296	0.198334	0.155680	0.098353	0.348630
711	0.484891	0.118523	0.123781	0.071177	0.360726
712	0.223111	0.124932	0.099138	0.067871	0.322305
713	0.278976	0.116495	0.098337	0.068880	0.410530

	perimeter_worst	area_worst	concavity_worst	concave	points_worst
0	0.668310	0.450698	0.568610		0.912027
1	0.539818	0.435214	0.192971		0.639175
2	0.508442	0.374508	0.359744		0.835052
3	0.241347	0.094008	0.548642		0.884880
4	0.506948	0.341575	0.319489		0.558419
..
709	0.605558	0.465936	0.563339		0.832302
710	0.345585	0.182757	0.353754		0.765979
711	0.371981	0.195561	0.503594		0.822337
712	0.289805	0.177276	0.253115		0.406873
713	0.394890	0.243266	0.238978		0.450859

[714 rows x 14 columns]

```
[181]: y_oversampling
```

```
[181]: 0      1
      1      1
      2      1
      3      1
      4      1
      ..
      709    1
      710    1
      711    1
      712    1
      713    1
```

Name: diagnosis, Length: 714, dtype: int64

```
[182]: X_train, X_test, y_train, y_test = train_test_split(X_selected_over,
↳ y_oversampling, test_size=0.2, random_state=0)
```

```
[183]: knn(X_train, X_test, y_train, y_test)
```

Accuracy du KNN : 0.9370629370629371

```
precision score du KNN : 0.9375
recall score du KNN : 0.9230769230769231
f1 score du KNN : 0.9302325581395349
```

```
[184]: knn_grid_search(X_selected_over,y_oversampling)
```

```
grid best score accuracy 0.9706964006259782
grid best score precision 0.9677298249819597
grid best score recall 0.9888888888888889
grid best score f1 score 0.9714095547561736
{'metric': 'manhattan', 'n_neighbors': 7, 'weights': 'distance'}
KNeighborsClassifier(metric='manhattan', n_neighbors=7, weights='distance')
```

3.2.1 SVM

```
[185]: svm(X_train, X_test, y_train, y_test)
```

	precision	recall	f1-score	support
0	0.96	0.96	0.96	78
1	0.95	0.95	0.95	65
accuracy			0.96	143
macro avg	0.96	0.96	0.96	143
weighted avg	0.96	0.96	0.96	143

```
[186]: svm_grid_search(X_train, X_test, y_train, y_test)
```

	precision	recall	f1-score	support
0	0.97	0.97	0.97	78
1	0.97	0.97	0.97	65
accuracy			0.97	143
macro avg	0.97	0.97	0.97	143
weighted avg	0.97	0.97	0.97	143

```
Accuracy : 0.972027972027972
```

4 Correlation

```
[187]: X_oversampling
```

```
[187]: radius_mean texture_mean perimeter_mean area_mean smoothness_mean \
0      0.521037      0.022658      0.545989      0.363733      0.593753
1      0.643144      0.272574      0.615783      0.501591      0.289880
2      0.601496      0.390260      0.595743      0.449417      0.514309
3      0.210090      0.360839      0.233501      0.102906      0.811321
```

4	0.629893	0.156578	0.630986	0.489290	0.430351
..
709	0.692366	0.425093	0.695253	0.535949	0.578406
710	0.394671	0.255665	0.410545	0.241697	0.730071
711	0.395617	0.153872	0.405708	0.237922	0.493545
712	0.313739	0.516402	0.305853	0.186299	0.381421
713	0.434427	0.400068	0.431276	0.282630	0.434865

	compactness_mean	concavity_mean	concave	points_mean	symmetry_mean \
0	0.792037	0.703140		0.731113	0.686364
1	0.181768	0.203608		0.348757	0.379798
2	0.431017	0.462512		0.635686	0.509596
3	0.811361	0.565604		0.522863	0.776263
4	0.347893	0.463918		0.518390	0.378283
..
709	0.580701	0.658388		0.776342	0.556566
710	0.641126	0.573571		0.617296	0.675758
711	0.595424	0.486645		0.484891	0.737879
712	0.201613	0.202085		0.223111	0.277273
713	0.334397	0.244377		0.278976	0.555556

	fractal_dimension_mean	...	radius_worst	texture_worst \
0	0.605518	...	0.620776	0.141525
1	0.141323	...	0.606901	0.303571
2	0.211247	...	0.556386	0.360075
3	1.000000	...	0.248310	0.385928
4	0.186816	...	0.519744	0.123934
..
709	0.339090	...	0.651014	0.445629
710	0.547599	...	0.348630	0.283582
711	0.428812	...	0.360726	0.188166
712	0.184288	...	0.322305	0.619670
713	0.188500	...	0.410530	0.523987

	perimeter_worst	area_worst	smoothness_worst	compactness_worst \
0	0.668310	0.450698	0.601136	0.619292
1	0.539818	0.435214	0.347553	0.154563
2	0.508442	0.374508	0.483590	0.385375
3	0.241347	0.094008	0.915472	0.814012
4	0.506948	0.341575	0.437364	0.172415
..
709	0.605558	0.465936	0.521891	0.528189
710	0.345585	0.182757	0.695569	0.410406
711	0.371981	0.195561	0.447930	0.551183
712	0.289805	0.177276	0.365383	0.162034
713	0.394890	0.243266	0.451232	0.269921

	concavity_worst	concave	points_worst	symmetry_worst	\
0	0.568610		0.912027	0.598462	
1	0.192971		0.639175	0.233590	
2	0.359744		0.835052	0.403706	
3	0.548642		0.884880	1.000000	
4	0.319489		0.558419	0.157500	
..	
709	0.563339		0.832302	0.446087	
710	0.353754		0.765979	0.333728	
711	0.503594		0.822337	0.611473	
712	0.253115		0.406873	0.214075	
713	0.238978		0.450859	0.377489	

	fractal_dimension_worst
0	0.418864
1	0.222878
2	0.213433
3	0.773711
4	0.142595
..	...
709	0.299488
710	0.420176
711	0.291355
712	0.124164
713	0.138725

[714 rows x 30 columns]

```
[188]: y_oversampling
```

```
[188]: 0      1
      1      1
      2      1
      3      1
      4      1
      ..
      709    1
      710    1
      711    1
      712    1
      713    1
      Name: diagnosis, Length: 714, dtype: int64
```

```
[190]: data_over = pd.DataFrame(X_oversampling , columns = X_oversampling.columns)
```

```
[191]: data_over
```

```

[191]:      radius_mean  texture_mean  perimeter_mean  area_mean  smoothness_mean  \
0      0.521037      0.022658      0.545989      0.363733      0.593753
1      0.643144      0.272574      0.615783      0.501591      0.289880
2      0.601496      0.390260      0.595743      0.449417      0.514309
3      0.210090      0.360839      0.233501      0.102906      0.811321
4      0.629893      0.156578      0.630986      0.489290      0.430351
..      ...      ...      ...      ...      ...
709     0.692366      0.425093      0.695253      0.535949      0.578406
710     0.394671      0.255665      0.410545      0.241697      0.730071
711     0.395617      0.153872      0.405708      0.237922      0.493545
712     0.313739      0.516402      0.305853      0.186299      0.381421
713     0.434427      0.400068      0.431276      0.282630      0.434865

      compactness_mean  concavity_mean  concave points_mean  symmetry_mean  \
0      0.792037      0.703140      0.731113      0.686364
1      0.181768      0.203608      0.348757      0.379798
2      0.431017      0.462512      0.635686      0.509596
3      0.811361      0.565604      0.522863      0.776263
4      0.347893      0.463918      0.518390      0.378283
..      ...      ...      ...      ...
709     0.580701      0.658388      0.776342      0.556566
710     0.641126      0.573571      0.617296      0.675758
711     0.595424      0.486645      0.484891      0.737879
712     0.201613      0.202085      0.223111      0.277273
713     0.334397      0.244377      0.278976      0.555556

      fractal_dimension_mean  ...  radius_worst  texture_worst  \
0      0.605518  ...      0.620776      0.141525
1      0.141323  ...      0.606901      0.303571
2      0.211247  ...      0.556386      0.360075
3      1.000000  ...      0.248310      0.385928
4      0.186816  ...      0.519744      0.123934
..      ...  ...      ...      ...
709     0.339090  ...      0.651014      0.445629
710     0.547599  ...      0.348630      0.283582
711     0.428812  ...      0.360726      0.188166
712     0.184288  ...      0.322305      0.619670
713     0.188500  ...      0.410530      0.523987

      perimeter_worst  area_worst  smoothness_worst  compactness_worst  \
0      0.668310      0.450698      0.601136      0.619292
1      0.539818      0.435214      0.347553      0.154563
2      0.508442      0.374508      0.483590      0.385375
3      0.241347      0.094008      0.915472      0.814012
4      0.506948      0.341575      0.437364      0.172415
..      ...      ...      ...      ...
709     0.605558      0.465936      0.521891      0.528189

```


710	0.345585	0.182757	0.695569	0.410406
711	0.371981	0.195561	0.447930	0.551183
712	0.289805	0.177276	0.365383	0.162034
713	0.394890	0.243266	0.451232	0.269921

	concavity_worst	concave points_worst	symmetry_worst	\
0	0.568610	0.912027	0.598462	
1	0.192971	0.639175	0.233590	
2	0.359744	0.835052	0.403706	
3	0.548642	0.884880	1.000000	
4	0.319489	0.558419	0.157500	
..	
709	0.563339	0.832302	0.446087	
710	0.353754	0.765979	0.333728	
711	0.503594	0.822337	0.611473	
712	0.253115	0.406873	0.214075	
713	0.238978	0.450859	0.377489	

	fractal_dimension_worst
0	0.418864
1	0.222878
2	0.213433
3	0.773711
4	0.142595
..	...
709	0.299488
710	0.420176
711	0.291355
712	0.124164
713	0.138725

[714 rows x 30 columns]

```
[192]: data_over['diagnosis'] = y_oversampling
```

```
[193]: data_over
```

```
[193]:
```

	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	\
0	0.521037	0.022658	0.545989	0.363733	0.593753	
1	0.643144	0.272574	0.615783	0.501591	0.289880	
2	0.601496	0.390260	0.595743	0.449417	0.514309	
3	0.210090	0.360839	0.233501	0.102906	0.811321	
4	0.629893	0.156578	0.630986	0.489290	0.430351	
..	
709	0.692366	0.425093	0.695253	0.535949	0.578406	
710	0.394671	0.255665	0.410545	0.241697	0.730071	
711	0.395617	0.153872	0.405708	0.237922	0.493545	

712	0.313739	0.516402	0.305853	0.186299	0.381421
713	0.434427	0.400068	0.431276	0.282630	0.434865

	compactness_mean	concavity_mean	concave	points_mean	symmetry_mean	\
0	0.792037	0.703140		0.731113	0.686364	
1	0.181768	0.203608		0.348757	0.379798	
2	0.431017	0.462512		0.635686	0.509596	
3	0.811361	0.565604		0.522863	0.776263	
4	0.347893	0.463918		0.518390	0.378283	
..	
709	0.580701	0.658388		0.776342	0.556566	
710	0.641126	0.573571		0.617296	0.675758	
711	0.595424	0.486645		0.484891	0.737879	
712	0.201613	0.202085		0.223111	0.277273	
713	0.334397	0.244377		0.278976	0.555556	

	fractal_dimension_mean	...	texture_worst	perimeter_worst	area_worst	\
0	0.605518	...	0.141525	0.668310	0.450698	
1	0.141323	...	0.303571	0.539818	0.435214	
2	0.211247	...	0.360075	0.508442	0.374508	
3	1.000000	...	0.385928	0.241347	0.094008	
4	0.186816	...	0.123934	0.506948	0.341575	
..	
709	0.339090	...	0.445629	0.605558	0.465936	
710	0.547599	...	0.283582	0.345585	0.182757	
711	0.428812	...	0.188166	0.371981	0.195561	
712	0.184288	...	0.619670	0.289805	0.177276	
713	0.188500	...	0.523987	0.394890	0.243266	

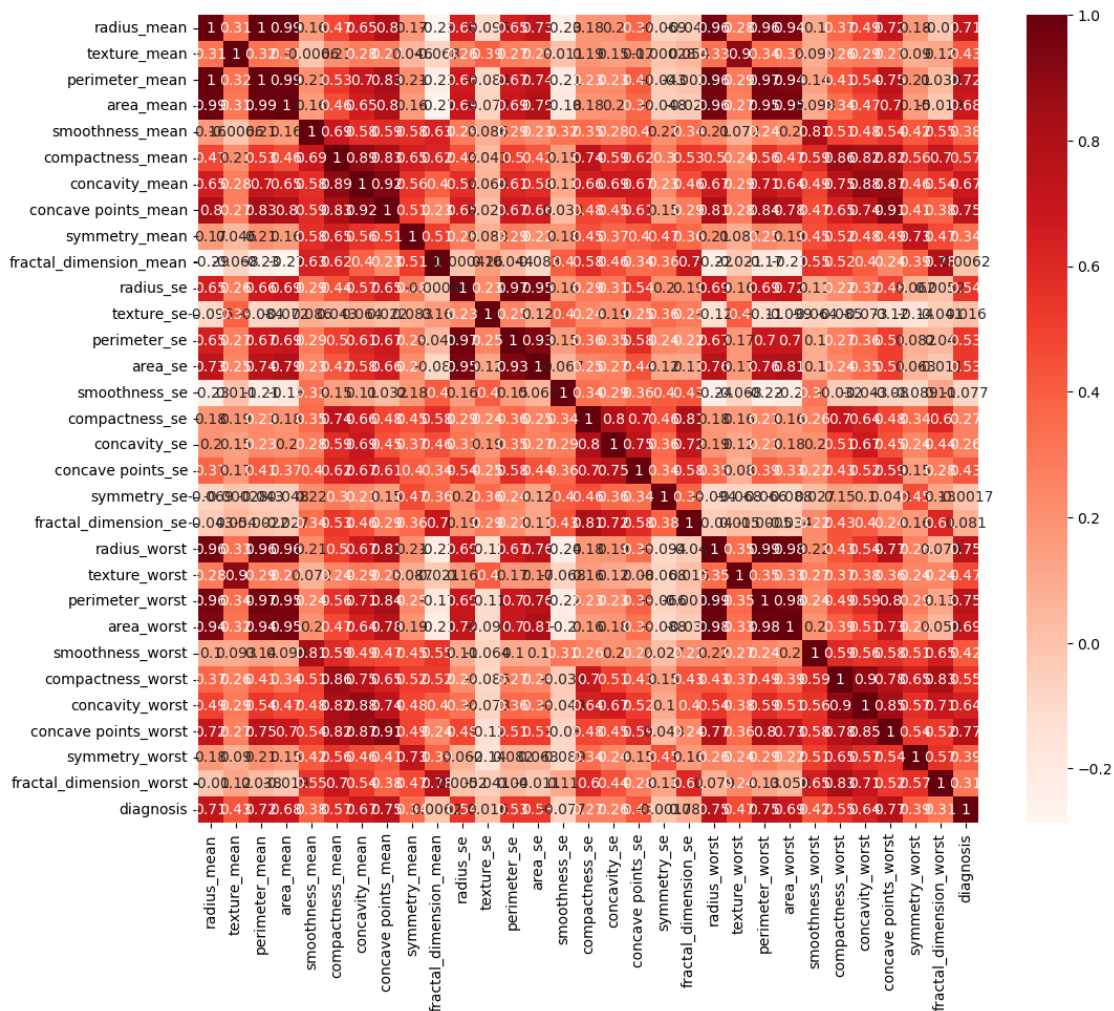
	smoothness_worst	compactness_worst	concavity_worst	\
0	0.601136	0.619292	0.568610	
1	0.347553	0.154563	0.192971	
2	0.483590	0.385375	0.359744	
3	0.915472	0.814012	0.548642	
4	0.437364	0.172415	0.319489	
..	
709	0.521891	0.528189	0.563339	
710	0.695569	0.410406	0.353754	
711	0.447930	0.551183	0.503594	
712	0.365383	0.162034	0.253115	
713	0.451232	0.269921	0.238978	

	concave	points_worst	symmetry_worst	fractal_dimension_worst	diagnosis
0		0.912027	0.598462	0.418864	1
1		0.639175	0.233590	0.222878	1
2		0.835052	0.403706	0.213433	1
3		0.884880	1.000000	0.773711	1

4	0.558419	0.157500	0.142595	1
..
709	0.832302	0.446087	0.299488	1
710	0.765979	0.333728	0.420176	1
711	0.822337	0.611473	0.291355	1
712	0.406873	0.214075	0.124164	1
713	0.450859	0.377489	0.138725	1

[714 rows x 31 columns]

```
[194]: #Using Pearson Correlation
plt.figure(figsize=(12,10))
cor = data_over.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.Reds)
plt.show()
```



```
[195]: #Correlation with output variable
cor_target = abs(cor["diagnosis"])
#Selecting highly correlated features
relevant_features = list(cor_target[abs(cor_target) > 0.5].index)
relevant_features.remove('diagnosis')
relevant_features
# we choose the variables that have a correlation higher to 0.5 with our target_
↪variable
```

```
[195]: ['radius_mean',
        'perimeter_mean',
        'area_mean',
        'compactness_mean',
        'concavity_mean',
        'concave points_mean',
        'radius_se',
        'perimeter_se',
        'area_se',
        'radius_worst',
        'perimeter_worst',
        'area_worst',
        'compactness_worst',
        'concavity_worst',
        'concave points_worst']
```

```
[196]: data_corr_over = data_over[relevant_features]
data_corr_over
```

```
[196]:
```

	radius_mean	perimeter_mean	area_mean	compactness_mean	concavity_mean	\
0	0.521037	0.545989	0.363733	0.792037	0.703140	
1	0.643144	0.615783	0.501591	0.181768	0.203608	
2	0.601496	0.595743	0.449417	0.431017	0.462512	
3	0.210090	0.233501	0.102906	0.811361	0.565604	
4	0.629893	0.630986	0.489290	0.347893	0.463918	
..	
709	0.692366	0.695253	0.535949	0.580701	0.658388	
710	0.394671	0.410545	0.241697	0.641126	0.573571	
711	0.395617	0.405708	0.237922	0.595424	0.486645	
712	0.313739	0.305853	0.186299	0.201613	0.202085	
713	0.434427	0.431276	0.282630	0.334397	0.244377	

	concave points_mean	radius_se	perimeter_se	area_se	radius_worst	\
0	0.731113	0.356147	0.369034	0.273811	0.620776	
1	0.348757	0.156437	0.124440	0.125660	0.606901	
2	0.635686	0.229622	0.180370	0.162922	0.556386	
3	0.522863	0.139091	0.126655	0.038155	0.248310	
4	0.518390	0.233822	0.220563	0.163688	0.519744	

```

..          ...          ...          ...          ...          ...
709          0.776342    0.185660    0.160251    0.138566    0.651014
710          0.617296    0.198334    0.155680    0.098353    0.348630
711          0.484891    0.118523    0.123781    0.071177    0.360726
712          0.223111    0.124932    0.099138    0.067871    0.322305
713          0.278976    0.116495    0.098337    0.068880    0.410530

```

```

      perimeter_worst  area_worst  compactness_worst  concavity_worst  \
0          0.668310    0.450698          0.619292          0.568610
1          0.539818    0.435214          0.154563          0.192971
2          0.508442    0.374508          0.385375          0.359744
3          0.241347    0.094008          0.814012          0.548642
4          0.506948    0.341575          0.172415          0.319489
..          ...          ...          ...          ...
709          0.605558    0.465936          0.528189          0.563339
710          0.345585    0.182757          0.410406          0.353754
711          0.371981    0.195561          0.551183          0.503594
712          0.289805    0.177276          0.162034          0.253115
713          0.394890    0.243266          0.269921          0.238978

```

```

      concave points_worst
0          0.912027
1          0.639175
2          0.835052
3          0.884880
4          0.558419
..          ...
709          0.832302
710          0.765979
711          0.822337
712          0.406873
713          0.450859

```

[714 rows x 15 columns]

```

[197]: X_over_corr = X_oversampling[relevant_features]
X_over_corr

```

```

[197]:      radius_mean  perimeter_mean  area_mean  compactness_mean  concavity_mean  \
0          0.521037          0.545989    0.363733          0.792037          0.703140
1          0.643144          0.615783    0.501591          0.181768          0.203608
2          0.601496          0.595743    0.449417          0.431017          0.462512
3          0.210090          0.233501    0.102906          0.811361          0.565604
4          0.629893          0.630986    0.489290          0.347893          0.463918
..          ...          ...          ...          ...          ...
709          0.692366          0.695253    0.535949          0.580701          0.658388
710          0.394671          0.410545    0.241697          0.641126          0.573571

```

711	0.395617	0.405708	0.237922	0.595424	0.486645
712	0.313739	0.305853	0.186299	0.201613	0.202085
713	0.434427	0.431276	0.282630	0.334397	0.244377

	concave	points_mean	radius_se	perimeter_se	area_se	radius_worst \
0		0.731113	0.356147	0.369034	0.273811	0.620776
1		0.348757	0.156437	0.124440	0.125660	0.606901
2		0.635686	0.229622	0.180370	0.162922	0.556386
3		0.522863	0.139091	0.126655	0.038155	0.248310
4		0.518390	0.233822	0.220563	0.163688	0.519744
..	
709		0.776342	0.185660	0.160251	0.138566	0.651014
710		0.617296	0.198334	0.155680	0.098353	0.348630
711		0.484891	0.118523	0.123781	0.071177	0.360726
712		0.223111	0.124932	0.099138	0.067871	0.322305
713		0.278976	0.116495	0.098337	0.068880	0.410530

	perimeter_worst	area_worst	compactness_worst	concavity_worst \
0	0.668310	0.450698	0.619292	0.568610
1	0.539818	0.435214	0.154563	0.192971
2	0.508442	0.374508	0.385375	0.359744
3	0.241347	0.094008	0.814012	0.548642
4	0.506948	0.341575	0.172415	0.319489
..	
709	0.605558	0.465936	0.528189	0.563339
710	0.345585	0.182757	0.410406	0.353754
711	0.371981	0.195561	0.551183	0.503594
712	0.289805	0.177276	0.162034	0.253115
713	0.394890	0.243266	0.269921	0.238978

	concave points_worst
0	0.912027
1	0.639175
2	0.835052
3	0.884880
4	0.558419
..	...
709	0.832302
710	0.765979
711	0.822337
712	0.406873
713	0.450859

[714 rows x 15 columns]

4.1 KNN based on correlation

```
[198]: # splitting the data
X_train, X_test, y_train, y_test = train_test_split(X_over_corr,
↳ y_oversampling, test_size=0.2, random_state=0)
```

```
[199]: knn(X_train, X_test, y_train, y_test)
```

```
Accuracy du KNN : 0.951048951048951
precision score du KNN : 0.9393939393939394
recall score du KNN : 0.9538461538461539
f1 score du KNN : 0.9465648854961831
```

```
[200]: knn_grid_search(X_over_corr, y_oversampling)
```

```
grid best score accuracy 0.9692292644757433
grid best score precision 0.9686692312059959
grid best score recall 0.9888888888888889
grid best score f1 score 0.9697774346105428
{'metric': 'manhattan', 'n_neighbors': 1, 'weights': 'uniform'}
KNeighborsClassifier(metric='manhattan', n_neighbors=1)
```

4.2 SVM BASED ON CORRELATION

```
[201]: svm(X_train,X_test,y_train ,y_test)
```

	precision	recall	f1-score	support
0	0.96	0.96	0.96	78
1	0.95	0.95	0.95	65
accuracy			0.96	143
macro avg	0.96	0.96	0.96	143
weighted avg	0.96	0.96	0.96	143

```
[202]: svm_grid_search(X_train,X_test,y_train ,y_test)
```

	precision	recall	f1-score	support
0	0.97	0.97	0.97	78
1	0.97	0.97	0.97	65
accuracy			0.97	143
macro avg	0.97	0.97	0.97	143
weighted avg	0.97	0.97	0.97	143

```
Accuracy : 0.972027972027972
```

```
[208]: X_oversampling
```

```

[208]:      radius_mean  texture_mean  perimeter_mean  area_mean  smoothness_mean  \
0      0.521037      0.022658      0.545989      0.363733      0.593753
1      0.643144      0.272574      0.615783      0.501591      0.289880
2      0.601496      0.390260      0.595743      0.449417      0.514309
3      0.210090      0.360839      0.233501      0.102906      0.811321
4      0.629893      0.156578      0.630986      0.489290      0.430351
..      ...      ...      ...      ...      ...
709    0.692366      0.425093      0.695253      0.535949      0.578406
710    0.394671      0.255665      0.410545      0.241697      0.730071
711    0.395617      0.153872      0.405708      0.237922      0.493545
712    0.313739      0.516402      0.305853      0.186299      0.381421
713    0.434427      0.400068      0.431276      0.282630      0.434865

      compactness_mean  concavity_mean  concave points_mean  symmetry_mean  \
0      0.792037      0.703140      0.731113      0.686364
1      0.181768      0.203608      0.348757      0.379798
2      0.431017      0.462512      0.635686      0.509596
3      0.811361      0.565604      0.522863      0.776263
4      0.347893      0.463918      0.518390      0.378283
..      ...      ...      ...      ...
709    0.580701      0.658388      0.776342      0.556566
710    0.641126      0.573571      0.617296      0.675758
711    0.595424      0.486645      0.484891      0.737879
712    0.201613      0.202085      0.223111      0.277273
713    0.334397      0.244377      0.278976      0.555556

      fractal_dimension_mean  ... texture_worst  perimeter_worst  area_worst  \
0      0.605518  ...      0.141525      0.668310      0.450698
1      0.141323  ...      0.303571      0.539818      0.435214
2      0.211247  ...      0.360075      0.508442      0.374508
3      1.000000  ...      0.385928      0.241347      0.094008
4      0.186816  ...      0.123934      0.506948      0.341575
..      ...  ...      ...      ...      ...
709    0.339090  ...      0.445629      0.605558      0.465936
710    0.547599  ...      0.283582      0.345585      0.182757
711    0.428812  ...      0.188166      0.371981      0.195561
712    0.184288  ...      0.619670      0.289805      0.177276
713    0.188500  ...      0.523987      0.394890      0.243266

      smoothness_worst  compactness_worst  concavity_worst  \
0      0.601136      0.619292      0.568610
1      0.347553      0.154563      0.192971
2      0.483590      0.385375      0.359744
3      0.915472      0.814012      0.548642
4      0.437364      0.172415      0.319489
..      ...      ...      ...
709    0.521891      0.528189      0.563339

```


710	0.695569	0.410406	0.353754
711	0.447930	0.551183	0.503594
712	0.365383	0.162034	0.253115
713	0.451232	0.269921	0.238978

	concave	points_worst	symmetry_worst	fractal_dimension_worst	diagnosis
0		0.912027	0.598462	0.418864	1
1		0.639175	0.233590	0.222878	1
2		0.835052	0.403706	0.213433	1
3		0.884880	1.000000	0.773711	1
4		0.558419	0.157500	0.142595	1
..	
709		0.832302	0.446087	0.299488	1
710		0.765979	0.333728	0.420176	1
711		0.822337	0.611473	0.291355	1
712		0.406873	0.214075	0.124164	1
713		0.450859	0.377489	0.138725	1

[714 rows x 31 columns]

```
[209]: X_oversampling.drop('diagnosis',axis = 1,inplace = True)
```

5 DT

```
[124]: X_train, X_test, y_train, y_test = train_test_split(X_oversampling,
↳ y_oversampling, test_size=0.2, random_state=0)
clf = tree.DecisionTreeClassifier()
clf.fit(X_train, y_train)
y_pred= clf.predict(X_test)
acc2 = metrics.accuracy_score(y_test, y_pred)
precision = metrics.precision_score(y_test, y_pred)
recall = metrics.recall_score(y_test, y_pred)
f1_score = metrics.f1_score(y_test , y_pred)
print("Accuracy:", acc2)
print("Precision: ",precision)
print("Recall: ",recall)
print("F1 score : ",f1_score)
```

Accuracy: 0.951048951048951

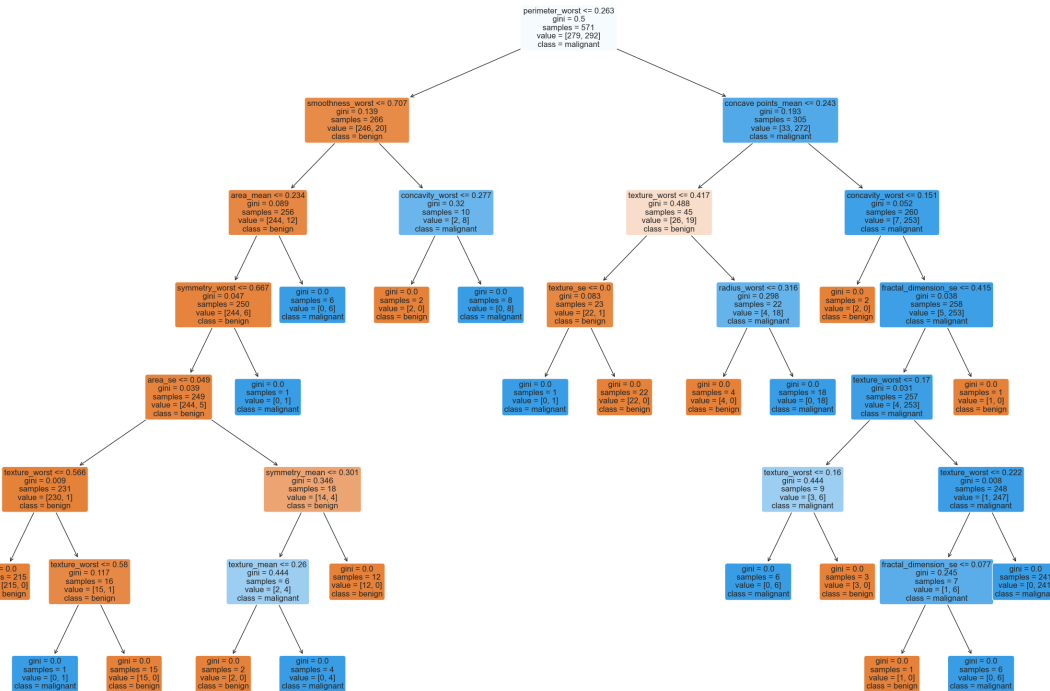
Precision: 0.9393939393939394

Recall: 0.9538461538461539

F1 score : 0.9465648854961831

```
[211]: clf = tree.DecisionTreeClassifier()
clf.fit(X_train, y_train)
sns.set(font_scale=100, style="whitegrid", rc={"axes.grid": False})
fig, ax = plt.subplots(figsize=(30, 20))
```

```
tree.plot_tree(clf, feature_names=X_oversampling.columns,
               class_names=['benign', 'malignant'], filled=True, rounded=True, fontsize=12,
               ax=ax)
plt.show()
```



[133]: #Grid search

```
DT = tree.DecisionTreeClassifier()
params = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [2, 4, 6, 8, 10],
    'min_samples_split': [2, 4, 6, 8, 10],
    'min_samples_leaf': [1, 2, 3, 4, 5]
}
grid = GridSearchCV(DT, params, cv = 10, scoring = 'accuracy')
grid.fit(X_oversampling, y_oversampling)

grid1 = GridSearchCV(DT, params, cv = 10, scoring = 'precision')
grid1.fit(X_oversampling, y_oversampling)

grid2 = GridSearchCV(DT, params, cv = 10, scoring = 'recall')
grid2.fit(X_oversampling, y_oversampling)

grid3 = GridSearchCV(DT, params, cv = 10, scoring = 'f1')
```

```

grid3.fit(X_oversampling,y_oversampling)

print("Accuracy",grid.best_score_)
print("Precision",grid1.best_score_)
print("Recall",grid2.best_score_)
print("f1 score",grid3.best_score_)

print(grid.best_params_)
print(grid.best_estimator_)

```

```

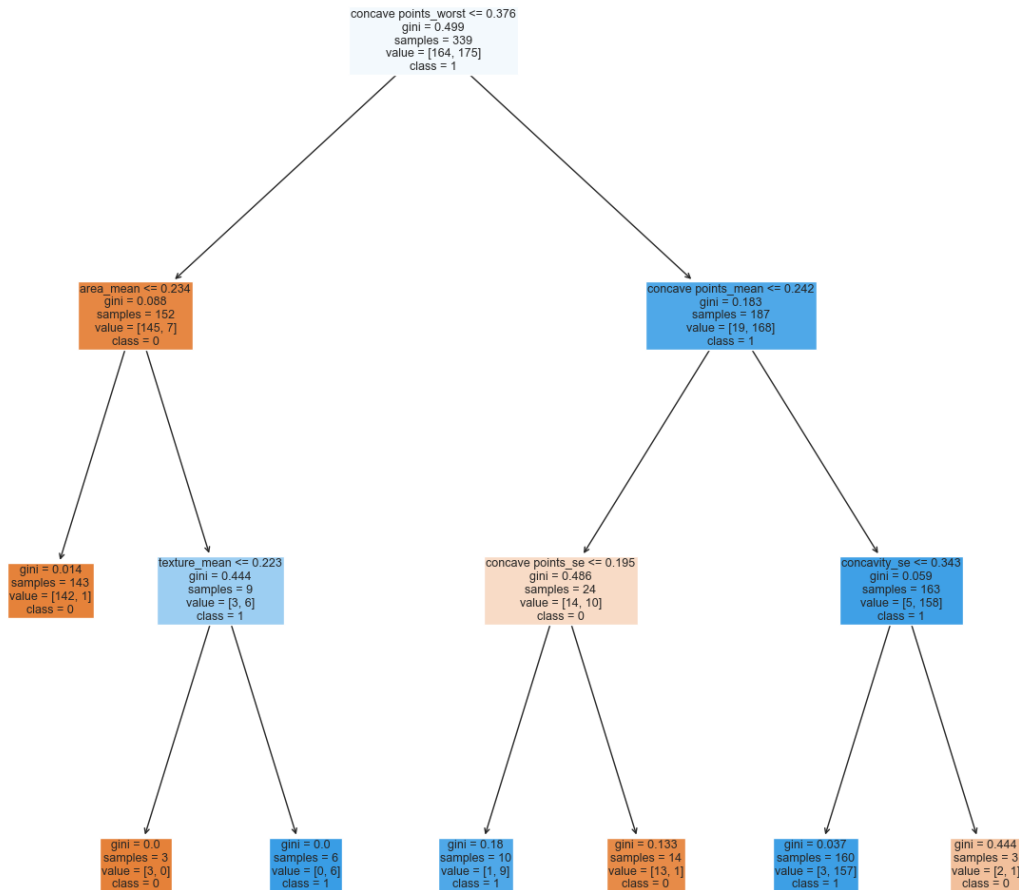
Accuracy 0.9650430359937403
Precision 0.9637876952582834
Recall 0.9861111111111111
f1 score 0.966697748712026
{'criterion': 'entropy', 'max_depth': 6, 'min_samples_leaf': 5,
 'min_samples_split': 6}
DecisionTreeClassifier(criterion='entropy', max_depth=6, min_samples_leaf=5,
                       min_samples_split=6)

```

```

[134]: from sklearn import tree
sns.set(font_scale=2, style="whitegrid", rc={"axes.grid": False})
fig, ax = plt.subplots(figsize=(15, 15))
tree.plot_tree(best_clf, feature_names=feature_columns, class_names=["0", "1"],
               filled=True, ax=ax)
plt.show()

```



6 Select Kbest

```
[216]: selector = SelectKBest(chi2, k=10)
X_new = selector.fit_transform(X_oversampling, y_oversampling)
mask = selector.get_support()
selected_features = X_oversampling.columns[mask]
selected = selected_features.values
selected
```

```
[216]: array(['radius_mean', 'perimeter_mean', 'area_mean', 'concavity_mean',
            'concave points_mean', 'radius_worst', 'perimeter_worst',
            'area_worst', 'concavity_worst', 'concave points_worst'],
```

```
dtype=object)
```

```
[217]: X_selected_kbest_oversampling = X_oversampling[selected]  
X_selected_kbest_oversampling
```

```
[217]:
```

	radius_mean	perimeter_mean	area_mean	concavity_mean	\
0	0.521037	0.545989	0.363733	0.703140	
1	0.643144	0.615783	0.501591	0.203608	
2	0.601496	0.595743	0.449417	0.462512	
3	0.210090	0.233501	0.102906	0.565604	
4	0.629893	0.630986	0.489290	0.463918	
..	
709	0.692366	0.695253	0.535949	0.658388	
710	0.394671	0.410545	0.241697	0.573571	
711	0.395617	0.405708	0.237922	0.486645	
712	0.313739	0.305853	0.186299	0.202085	
713	0.434427	0.431276	0.282630	0.244377	

	concave points_mean	radius_worst	perimeter_worst	area_worst	\
0	0.731113	0.620776	0.668310	0.450698	
1	0.348757	0.606901	0.539818	0.435214	
2	0.635686	0.556386	0.508442	0.374508	
3	0.522863	0.248310	0.241347	0.094008	
4	0.518390	0.519744	0.506948	0.341575	
..	
709	0.776342	0.651014	0.605558	0.465936	
710	0.617296	0.348630	0.345585	0.182757	
711	0.484891	0.360726	0.371981	0.195561	
712	0.223111	0.322305	0.289805	0.177276	
713	0.278976	0.410530	0.394890	0.243266	

	concavity_worst	concave points_worst
0	0.568610	0.912027
1	0.192971	0.639175
2	0.359744	0.835052
3	0.548642	0.884880
4	0.319489	0.558419
..
709	0.563339	0.832302
710	0.353754	0.765979
711	0.503594	0.822337
712	0.253115	0.406873
713	0.238978	0.450859

```
[714 rows x 10 columns]
```

```
[218]: # splitting the data
X_train, X_test, y_train, y_test = \
    train_test_split(X_selected_kbest_oversampling, y_oversampling, test_size=0.
    2, random_state=0)
```

```
[219]: knn(X_train, X_test, y_train, y_test)
```

```
Accuracy du KNN : 0.9440559440559441
precision score du KNN : 0.9384615384615385
recall score du KNN : 0.9384615384615385
f1 score du KNN : 0.9384615384615385
```

```
[220]: knn_grid_search(X_selected_kbest_oversampling, y_oversampling)
```

```
grid best score accuracy 0.9706377151799688
grid best score precision 0.9598742822272234
grid best score recall 0.9916666666666668
grid best score f1 score 0.9714854980390385
{'metric': 'euclidean', 'n_neighbors': 1, 'weights': 'uniform'}
KNeighborsClassifier(metric='euclidean', n_neighbors=1)
```

6.1 SVM

```
[221]: svm(X_train, X_test, y_train, y_test)
```

	precision	recall	f1-score	support
0	0.96	0.95	0.95	78
1	0.94	0.95	0.95	65
accuracy			0.95	143
macro avg	0.95	0.95	0.95	143
weighted avg	0.95	0.95	0.95	143

```
[222]: svm_grid_search(X_train,X_test,y_train ,y_test)
```

	precision	recall	f1-score	support
0	0.96	0.96	0.96	78
1	0.95	0.95	0.95	65
accuracy			0.96	143
macro avg	0.96	0.96	0.96	143
weighted avg	0.96	0.96	0.96	143

```
Accuracy : 0.958041958041958
```

6.2 Wrappers

```
[223]: X_train, X_test, y_train, y_test = train_test_split(X_oversampling,
    ↪y_oversampling, test_size=0.33, random_state=42)
clf = RandomForestClassifier(n_estimators=100, random_state=0)
clf.fit(X_train, y_train)
# Calculate feature importances and select features with scores greater than 0.
    ↪01
feature_scores = pd.Series(clf.feature_importances_, index=X_train.columns).
    ↪sort_values(ascending=False)
selected = feature_scores[feature_scores.values > 0.01]
selected_features = selected.index.values
selected_features
```

```
[223]: array(['perimeter_worst', 'radius_worst', 'concave points_worst',
    'perimeter_mean', 'area_worst', 'concave points_mean', 'area_se',
    'concavity_mean', 'area_mean', 'concavity_worst', 'radius_se',
    'radius_mean', 'perimeter_se', 'texture_worst',
    'compactness_worst', 'fractal_dimension_worst', 'smoothness_worst',
    'texture_mean'], dtype=object)
```

```
[224]: X_selected_randomforest = X_oversampling[selected_features]
X_selected_randomforest
```

```
[224]:
```

	perimeter_worst	radius_worst	concave points_worst	perimeter_mean	\
0	0.668310	0.620776	0.912027	0.545989	
1	0.539818	0.606901	0.639175	0.615783	
2	0.508442	0.556386	0.835052	0.595743	
3	0.241347	0.248310	0.884880	0.233501	
4	0.506948	0.519744	0.558419	0.630986	
..	
709	0.605558	0.651014	0.832302	0.695253	
710	0.345585	0.348630	0.765979	0.410545	
711	0.371981	0.360726	0.822337	0.405708	
712	0.289805	0.322305	0.406873	0.305853	
713	0.394890	0.410530	0.450859	0.431276	

	area_worst	concave points_mean	area_se	concavity_mean	area_mean	\
0	0.450698	0.731113	0.273811	0.703140	0.363733	
1	0.435214	0.348757	0.125660	0.203608	0.501591	
2	0.374508	0.635686	0.162922	0.462512	0.449417	
3	0.094008	0.522863	0.038155	0.565604	0.102906	
4	0.341575	0.518390	0.163688	0.463918	0.489290	
..	
709	0.465936	0.776342	0.138566	0.658388	0.535949	
710	0.182757	0.617296	0.098353	0.573571	0.241697	
711	0.195561	0.484891	0.071177	0.486645	0.237922	

712	0.177276	0.223111	0.067871	0.202085	0.186299
713	0.243266	0.278976	0.068880	0.244377	0.282630

	concavity_worst	radius_se	radius_mean	perimeter_se	texture_worst \
0	0.568610	0.356147	0.521037	0.369034	0.141525
1	0.192971	0.156437	0.643144	0.124440	0.303571
2	0.359744	0.229622	0.601496	0.180370	0.360075
3	0.548642	0.139091	0.210090	0.126655	0.385928
4	0.319489	0.233822	0.629893	0.220563	0.123934
..
709	0.563339	0.185660	0.692366	0.160251	0.445629
710	0.353754	0.198334	0.394671	0.155680	0.283582
711	0.503594	0.118523	0.395617	0.123781	0.188166
712	0.253115	0.124932	0.313739	0.099138	0.619670
713	0.238978	0.116495	0.434427	0.098337	0.523987

	compactness_worst	fractal_dimension_worst	smoothness_worst \
0	0.619292	0.418864	0.601136
1	0.154563	0.222878	0.347553
2	0.385375	0.213433	0.483590
3	0.814012	0.773711	0.915472
4	0.172415	0.142595	0.437364
..
709	0.528189	0.299488	0.521891
710	0.410406	0.420176	0.695569
711	0.551183	0.291355	0.447930
712	0.162034	0.124164	0.365383
713	0.269921	0.138725	0.451232

	texture_mean
0	0.022658
1	0.272574
2	0.390260
3	0.360839
4	0.156578
..	...
709	0.425093
710	0.255665
711	0.153872
712	0.516402
713	0.400068

[714 rows x 18 columns]

```
[225]: # splitting the data
X_train, X_test, y_train, y_test = train_test_split(X_selected_randomforest, y,
↳ y_oversampling, test_size=0.2, random_state=0)
```


6.3 KNN BASED ON RANDOM FOREST

```
[226]: knn(X_train, X_test, y_train, y_test)
```

```
Accuracy du KNN : 0.951048951048951
precision score du KNN : 0.953125
recall score du KNN : 0.9384615384615385
f1 score du KNN : 0.9457364341085271
```

```
[227]: knn_grid_search(X_selected_randomforest, y_oversampling)
```

```
grid best score accuracy 0.9846439749608763
grid best score precision 0.9833247533247531
grid best score recall 0.9888888888888889
grid best score f1 score 0.9846619289557742
{'metric': 'manhattan', 'n_neighbors': 10, 'weights': 'distance'}
KNeighborsClassifier(metric='manhattan', n_neighbors=10, weights='distance')
```

6.4 SVM

```
[228]: svm(X_train, X_test, y_train, y_test)
```

	precision	recall	f1-score	support
0	0.94	0.99	0.96	78
1	0.98	0.92	0.95	65
accuracy			0.96	143
macro avg	0.96	0.96	0.96	143
weighted avg	0.96	0.96	0.96	143

```
[229]: svm_grid_search(X_train,X_test,y_train ,y_test)
```

	precision	recall	f1-score	support
0	0.96	0.99	0.97	78
1	0.98	0.95	0.97	65
accuracy			0.97	143
macro avg	0.97	0.97	0.97	143
weighted avg	0.97	0.97	0.97	143

```
Accuracy : 0.972027972027972
```

6.5 Wrapper the Recursive Feature Elimination

```
[230]: from sklearn.feature_selection import RFE
from sklearn.svm import SVC

# Initialize an SVM classifier and an RFE feature selector
svm = SVC(kernel='linear')
rfe = RFE(estimator=svm, n_features_to_select=10, step=1)

# Fit the RFE selector to the data and get the selected feature indices
rfe.fit(X_oversampling, y_oversampling)
selected_indices = rfe.get_support(indices=True)

selected_names = [X_oversampling.columns[i] for i, selected in enumerate(rfe.
    ↳support_) if selected]

# Print the selected feature names
print('Selected features:', selected_names)
```

Selected features: ['radius_mean', 'concave points_mean', 'radius_se',
'perimeter_se', 'radius_worst', 'texture_worst', 'perimeter_worst',
'area_worst', 'smoothness_worst', 'concave points_worst']

```
[231]: X_selected_RFE = X_oversampling[selected_names]
X_selected_RFE
```

```
[231]:
```

	radius_mean	concave points_mean	radius_se	perimeter_se	radius_worst	\
0	0.521037	0.731113	0.356147	0.369034	0.620776	
1	0.643144	0.348757	0.156437	0.124440	0.606901	
2	0.601496	0.635686	0.229622	0.180370	0.556386	
3	0.210090	0.522863	0.139091	0.126655	0.248310	
4	0.629893	0.518390	0.233822	0.220563	0.519744	
..	
709	0.692366	0.776342	0.185660	0.160251	0.651014	
710	0.394671	0.617296	0.198334	0.155680	0.348630	
711	0.395617	0.484891	0.118523	0.123781	0.360726	
712	0.313739	0.223111	0.124932	0.099138	0.322305	
713	0.434427	0.278976	0.116495	0.098337	0.410530	

	texture_worst	perimeter_worst	area_worst	smoothness_worst	\
0	0.141525	0.668310	0.450698	0.601136	
1	0.303571	0.539818	0.435214	0.347553	
2	0.360075	0.508442	0.374508	0.483590	
3	0.385928	0.241347	0.094008	0.915472	
4	0.123934	0.506948	0.341575	0.437364	
..	
709	0.445629	0.605558	0.465936	0.521891	
710	0.283582	0.345585	0.182757	0.695569	

711	0.188166	0.371981	0.195561	0.447930
712	0.619670	0.289805	0.177276	0.365383
713	0.523987	0.394890	0.243266	0.451232

```

concave points_worst
0          0.912027
1          0.639175
2          0.835052
3          0.884880
4          0.558419
..          ...
709        0.832302
710        0.765979
711        0.822337
712        0.406873
713        0.450859

```

[714 rows x 10 columns]

```

[232]: # splitting the data
X_train, X_test, y_train, y_test = \
    train_test_split(X_selected_RFE, y_oversampling, test_size=0.2,
                    random_state=0)

```

```

[233]: knn(X_train, X_test, y_train, y_test)

```

```

Accuracy du KNN : 0.958041958041958
precision score du KNN : 0.9682539682539683
recall score du KNN : 0.9384615384615385
f1 score du KNN : 0.953125

```

```

[236]: knn_grid_search(X_selected_RFE, y_oversampling)

```

```

grid best score accuracy 0.9846048513302035
grid best score precision 0.9857936507936508
grid best score recall 0.9916666666666668
grid best score f1 score 0.9847723735973783
{'metric': 'euclidean', 'n_neighbors': 17, 'weights': 'distance'}
KNeighborsClassifier(metric='euclidean', n_neighbors=17, weights='distance')

```

```

[237]: def svm(X_train, X_test, y_train, y_test):
        svm = SVC()
        svm.fit(X_train, y_train)
        y_pred = svm.predict(X_test)
        print(classification_report(y_test, y_pred))

```

```

[238]: svm(X_train, X_test, y_train, y_test)

```

```

precision    recall  f1-score   support

```

0	0.96	0.99	0.97	78
1	0.98	0.95	0.97	65
accuracy			0.97	143
macro avg	0.97	0.97	0.97	143
weighted avg	0.97	0.97	0.97	143

```
[239]: svm_grid_search(X_train,X_test,y_train ,y_test)
```

	precision	recall	f1-score	support
0	0.96	0.99	0.97	78
1	0.98	0.95	0.97	65
accuracy			0.97	143
macro avg	0.97	0.97	0.97	143
weighted avg	0.97	0.97	0.97	143

Accuracy : 0.972027972027972

6.6 Comparaison

6.6.1 using data set before balancing

```
[73]: X
```

```
[73]:
```

	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	\
0	0.521037	0.022658	0.545989	0.363733	0.593753	
1	0.643144	0.272574	0.615783	0.501591	0.289880	
2	0.601496	0.390260	0.595743	0.449417	0.514309	
3	0.210090	0.360839	0.233501	0.102906	0.811321	
4	0.629893	0.156578	0.630986	0.489290	0.430351	
..	
564	0.690000	0.428813	0.678668	0.566490	0.526948	
565	0.622320	0.626987	0.604036	0.474019	0.407782	
566	0.455251	0.621238	0.445788	0.303118	0.288165	
567	0.644564	0.663510	0.665538	0.475716	0.588336	
568	0.036869	0.501522	0.028540	0.015907	0.000000	
	compactness_mean	concavity_mean	concave	points_mean	symmetry_mean	\
0	0.792037	0.703140		0.731113	0.686364	
1	0.181768	0.203608		0.348757	0.379798	
2	0.431017	0.462512		0.635686	0.509596	
3	0.811361	0.565604		0.522863	0.776263	
4	0.347893	0.463918		0.518390	0.378283	
..	

564	0.296055	0.571462	0.690358	0.336364
565	0.257714	0.337395	0.486630	0.349495
566	0.254340	0.216753	0.263519	0.267677
567	0.790197	0.823336	0.755467	0.675253
568	0.074351	0.000000	0.000000	0.266162

	fractal_dimension_mean	...	radius_worst	texture_worst	\
0	0.605518	...	0.620776	0.141525	
1	0.141323	...	0.606901	0.303571	
2	0.211247	...	0.556386	0.360075	
3	1.000000	...	0.248310	0.385928	
4	0.186816	...	0.519744	0.123934	
..	
564	0.132056	...	0.623266	0.383262	
565	0.113100	...	0.560655	0.699094	
566	0.137321	...	0.393099	0.589019	
567	0.425442	...	0.633582	0.730277	
568	0.187026	...	0.054287	0.489072	

	perimeter_worst	area_worst	smoothness_worst	compactness_worst	\
0	0.668310	0.450698	0.601136	0.619292	
1	0.539818	0.435214	0.347553	0.154563	
2	0.508442	0.374508	0.483590	0.385375	
3	0.241347	0.094008	0.915472	0.814012	
4	0.506948	0.341575	0.437364	0.172415	
..	
564	0.576174	0.452664	0.461137	0.178527	
565	0.520892	0.379915	0.300007	0.159997	
566	0.379949	0.230731	0.282177	0.273705	
567	0.668310	0.402035	0.619626	0.815758	
568	0.043578	0.020497	0.124084	0.036043	

	concavity_worst	concave points_worst	symmetry_worst	\
0	0.568610	0.912027	0.598462	
1	0.192971	0.639175	0.233590	
2	0.359744	0.835052	0.403706	
3	0.548642	0.884880	1.000000	
4	0.319489	0.558419	0.157500	
..	
564	0.328035	0.761512	0.097575	
565	0.256789	0.559450	0.198502	
566	0.271805	0.487285	0.128721	
567	0.749760	0.910653	0.497142	
568	0.000000	0.000000	0.257441	

	fractal_dimension_worst
0	0.418864

```

1          0.222878
2          0.213433
3          0.773711
4          0.142595
..          ...
564        0.105667
565        0.074315
566        0.151909
567        0.452315
568        0.100682

```

[569 rows x 30 columns]

[76]: y

```

[76]: 0      1
      1      1
      2      1
      3      1
      4      1
      ..
      564    1
      565    1
      566    1
      567    1
      568    0
Name: diagnosis, Length: 569, dtype: int64

```

```

[77]: # splitting the data
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.25,
↳random_state=0)

```

```

[78]: knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
accuracy_knn = metrics.accuracy_score(y_test, y_pred)
precision_score_knn = metrics.precision_score(y_test, y_pred)
recall_score_knn = metrics.recall_score(y_test, y_pred)
f1_score_knn = metrics.f1_score(y_test,y_pred)
print("Accuracy du KNN : " , accuracy_knn)
print("precision score du KNN : ", precision_score_knn )
print("recall score du KNN : ", recall_score_knn )
print("f1 score du KNN : ",f1_score_knn)

```

```

Accuracy du KNN :  0.972027972027972
precision score du KNN :  1.0
recall score du KNN :  0.9245283018867925
f1 score du KNN :  0.9607843137254902

```

```
[79]: svm = SVC()
svm.fit(X_train, y_train)
y_pred = svm.predict(X_test)
accuracy_svm = metrics.accuracy_score(y_test, y_pred)
precision_score_svm = metrics.precision_score(y_test, y_pred)
recall_score_svm = metrics.recall_score(y_test, y_pred)
f1_score_svm = metrics.f1_score(y_test, y_pred)
print("Accuracy : " , accuracy_svm)
print("precision score : ", precision_score_svm )
print("recall score ", recall_score_svm )
print("f1 score ", f1_score_svm)
```

Accuracy du KNN : 0.972027972027972
precision score du KNN : 0.9803921568627451
recall score du KNN : 0.9433962264150944
f1 score du KNN : 0.9615384615384616

```
[80]: clf = tree.DecisionTreeClassifier()
clf.fit(X_train, y_train)
y_pred= clf.predict(X_test)
accuracy_dt = metrics.accuracy_score(y_test, y_pred)
precision_score_dt = metrics.precision_score(y_test, y_pred)
recall_score_dt = metrics.recall_score(y_test, y_pred)
f1_score_dt = metrics.f1_score(y_test , y_pred)
print("Accuracy:", accuracy_dt)
print("Precision: ", precision_score_dt)
print("Recall: ", recall_score_dt)
print("F1 score : ", f1_score_dt)
```

Accuracy: 0.9090909090909091
Precision: 0.8225806451612904
Recall: 0.9622641509433962
F1 score : 0.8869565217391304

```
[81]: acc = [accuracy_knn , accuracy_svm , accuracy_dt]
pre = [precision_score_knn, precision_score_svm, precision_score_dt]
rec = [recall_score_knn , recall_score_svm, recall_score_dt]
f1 = [f1_score_knn , f1_score_svm, f1_score_dt]
```

```
[82]: n=3
r = np.arange(n)
width = 0.15

plt.bar(r, acc, color = 'b',
        width = width, edgecolor = 'black',
        label='accuracy')
plt.bar(r + width, pre, color = 'g',
        width = width, edgecolor = 'black',
```

```

label='Precision')

plt.bar(r + 2*width, rec, color = 'c',
        width = width, edgecolor = 'black',
        label='Recall')

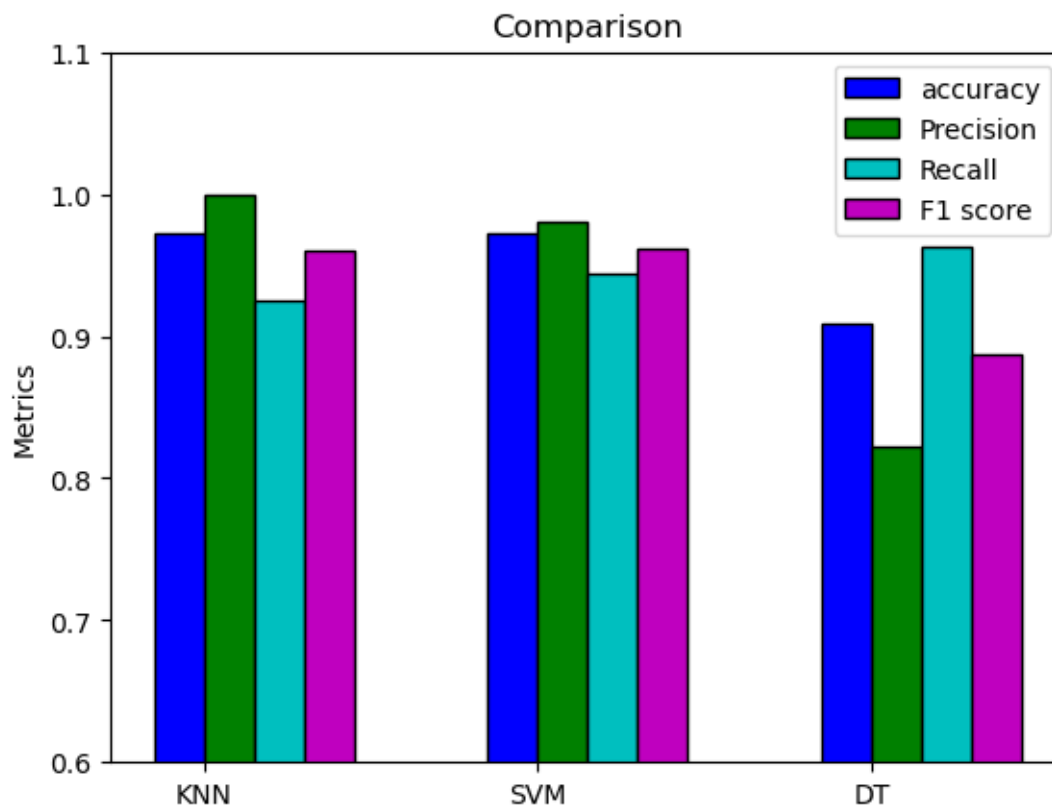
plt.bar(r + 3*width, f1, color = 'm',
        width = width, edgecolor = 'black',
        label='F1 score')

plt.xlabel("")
plt.ylabel("Metrics")
plt.title("Comparison")

# plt.grid(linestyle='--')
plt.xticks(r + width/2,['KNN','SVM','DT'])
plt.legend()
plt.ylim(0.6,1.1)

plt.show()

```



6.7 balanced data : Under sampling

[87]: X_resampled

```
[87]:      radius_mean  texture_mean  perimeter_mean  area_mean  smoothness_mean  \
0      0.308060      0.425769      0.297975      0.177094      0.314977
1      0.264991      0.293879      0.249050      0.146554      0.282567
2      0.373373      0.355090      0.361620      0.227953      0.390358
3      0.082967      0.241123      0.079331      0.038515      0.462851
4      0.223816      0.252959      0.213461      0.117413      0.407240
..      ...
419    0.659709      0.520122      0.685578      0.510498      0.517017
420    0.690000      0.428813      0.678668      0.566490      0.526948
421    0.622320      0.626987      0.604036      0.474019      0.407782
422    0.455251      0.621238      0.445788      0.303118      0.288165
423    0.644564      0.663510      0.665538      0.475716      0.588336

      compactness_mean  concavity_mean  concave points_mean  symmetry_mean  \
0      0.176676      0.111317      0.168191      0.378283
1      0.069873      0.004358      0.014533      0.321717
2      0.196522      0.159888      0.246074      0.215657
3      0.168395      0.000000      0.000000      0.467172
4      0.128918      0.089246      0.160984      0.230303
..      ...
419    0.626403      0.743674      0.732604      0.550000
420    0.296055      0.571462      0.690358      0.336364
421    0.257714      0.337395      0.486630      0.349495
422    0.254340      0.216753      0.263519      0.267677
423    0.790197      0.823336      0.755467      0.675253

      fractal_dimension_mean  ...  radius_worst  texture_worst  \
0      0.152064  ...      0.256848      0.527719
1      0.180918  ...      0.198150      0.294776
2      0.158382  ...      0.287442      0.438699
3      0.442713  ...      0.079687      0.287313
4      0.231466  ...      0.180719      0.249733
..      ...
419    0.396588  ...      0.581999      0.463486
420    0.132056  ...      0.623266      0.383262
421    0.113100  ...      0.560655      0.699094
422    0.137321  ...      0.393099      0.589019
423    0.425442  ...      0.633582      0.730277

      perimeter_worst  area_worst  smoothness_worst  compactness_worst  \
0      0.241994      0.126229      0.297365      0.139525
1      0.175059      0.093123      0.215479      0.037789
2      0.266398      0.147070      0.333025      0.108188
```

3	0.067732	0.032393	0.494156	0.100620
4	0.169381	0.082653	0.403685	0.074424
..
419	0.640918	0.401543	0.459156	0.379651
420	0.576174	0.452664	0.461137	0.178527
421	0.520892	0.379915	0.300007	0.159997
422	0.379949	0.230731	0.282177	0.273705
423	0.668310	0.402035	0.619626	0.815758

	concavity_worst	concave	points_worst	symmetry_worst	\
0	0.182268		0.440550	0.257441	
1	0.004456		0.030144	0.185295	
2	0.135783		0.349485	0.158486	
3	0.000000		0.000000	0.173467	
4	0.121486		0.377663	0.198502	
..	
419	0.527077		0.873540	0.268874	
420	0.328035		0.761512	0.097575	
421	0.256789		0.559450	0.198502	
422	0.271805		0.487285	0.128721	
423	0.749760		0.910653	0.497142	

	fractal_dimension_worst
0	0.092680
1	0.060803
2	0.071822
3	0.220451
4	0.104486
..	...
419	0.286567
420	0.105667
421	0.074315
422	0.151909
423	0.452315

[424 rows x 30 columns]

```
[88]: y_resampled
```

```
[88]: 0      0
      1      0
      2      0
      3      0
      4      0
      ..
      419    1
      420    1
```

```
421    1
422    1
423    1
Name: diagnosis, Length: 424, dtype: int64
```

```
[89]: # splitting the data
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled,
↳ test_size=0.25, random_state=0)
```

```
[90]: knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
accuracy_knn = metrics.accuracy_score(y_test, y_pred)
precision_score_knn = metrics.precision_score(y_test, y_pred)
recall_score_knn = metrics.recall_score(y_test, y_pred)
f1_score_knn = metrics.f1_score(y_test, y_pred)
print("Accuracy du KNN : ", accuracy_knn)
print("precision score du KNN : ", precision_score_knn )
print("recall score du KNN : ", recall_score_knn )
print("f1 score du KNN : ", f1_score_knn)
```

```
Accuracy du KNN : 0.9716981132075472
precision score du KNN : 0.9767441860465116
recall score du KNN : 0.9545454545454546
f1 score du KNN : 0.9655172413793104
```

```
[91]: svm = SVC()
svm.fit(X_train, y_train)
y_pred = svm.predict(X_test)
accuracy_svm = metrics.accuracy_score(y_test, y_pred)
precision_score_svm = metrics.precision_score(y_test, y_pred)
recall_score_svm = metrics.recall_score(y_test, y_pred)
f1_score_svm = metrics.f1_score(y_test, y_pred)
print("Accuracy : ", accuracy_svm)
print("precision score : ", precision_score_svm )
print("recall score : ", recall_score_svm )
print("f1 score : ", f1_score_svm)
```

```
Accuracy du KNN : 0.9716981132075472
precision score du KNN : 0.9767441860465116
recall score du KNN : 0.9545454545454546
f1 score du KNN : 0.9655172413793104
```

```
[ ]: clf = tree.DecisionTreeClassifier()
clf.fit(X_train, y_train)
clf = tree.DecisionTreeClassifier()
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
accuracy_dt = metrics.accuracy_score(y_test, y_pred)
```

```

precision_score_dt = metrics.precision_score(y_test, y_pred)
recall_score_dt = metrics.recall_score(y_test, y_pred)
f1_score_dt = metrics.f1_score(y_test , y_pred)
print("Accuracy:", accuracy_dt)
print("Precision: ",precision_score_dt)
print("Recall: ",recall_score_dt)
print("F1 score : ",f1_score_dt)
y_pred= clf.predict(X_test)
accuracy_dt = metrics.accuracy_score(y_test, y_pred)
precision_score_dt = metrics.precision_score(y_test, y_pred)
recall_score_dt = metrics.recall_score(y_test, y_pred)
f1_score_dt = metrics.f1_score(y_test , y_pred)
print("Accuracy:", accuracy_dt)
print("Precision: ",precision_score_dt)
print("Recall: ",recall_score_dt)
print("F1 score : ",f1_score_dt)clf = tree.DecisionTreeClassifier()
clf.fit(X_train, y_train)
y_pred= clf.predict(X_test)
accuracy_dt = metrics.accuracy_score(y_test, y_pred)
precision_score_dt = metrics.precision_score(y_test, y_pred)
recall_score_dt = metrics.recall_score(y_test, y_pred)
f1_score_dt = metrics.f1_score(y_test , y_pred)
print("Accuracy:", accuracy_dt)
print("Precision: ",precision_score_dt)
print("Recall: ",recall_score_dt)
print("F1 score : ",f1_score_dt)

```

```

[92]: clf = tree.DecisionTreeClassifier()
      clf.fit(X_train, y_train)
      y_pred= clf.predict(X_test)
      accuracy_dt = metrics.accuracy_score(y_test, y_pred)
      precision_score_dt = metrics.precision_score(y_test, y_pred)
      recall_score_dt = metrics.recall_score(y_test, y_pred)
      f1_score_dt = metrics.f1_score(y_test , y_pred)
      print("Accuracy:", accuracy_dt)
      print("Precision: ",precision_score_dt)
      print("Recall: ",recall_score_dt)
      print("F1 score : ",f1_score_dt)

```

Accuracy: 0.9150943396226415
 Precision: 0.926829268292683
 Recall: 0.8636363636363636
 F1 score : 0.8941176470588236

```

[93]: acc = [accuracy_knn , accuracy_svm , accuracy_dt]
      pre = [precision_score_knn,precision_score_svm,precision_score_dt]
      rec = [recall_score_knn , recall_score_svm, recall_score_dt]
      f1 = [f1_score_knn , f1_score_svm, f1_score_dt]

```

```
[94]: n=3
r = np.arange(n)
width = 0.15

plt.bar(r, acc, color = 'b',
        width = width, edgecolor = 'black',
        label='accuracy')
plt.bar(r + width, pre, color = 'g',
        width = width, edgecolor = 'black',
        label='Precision')

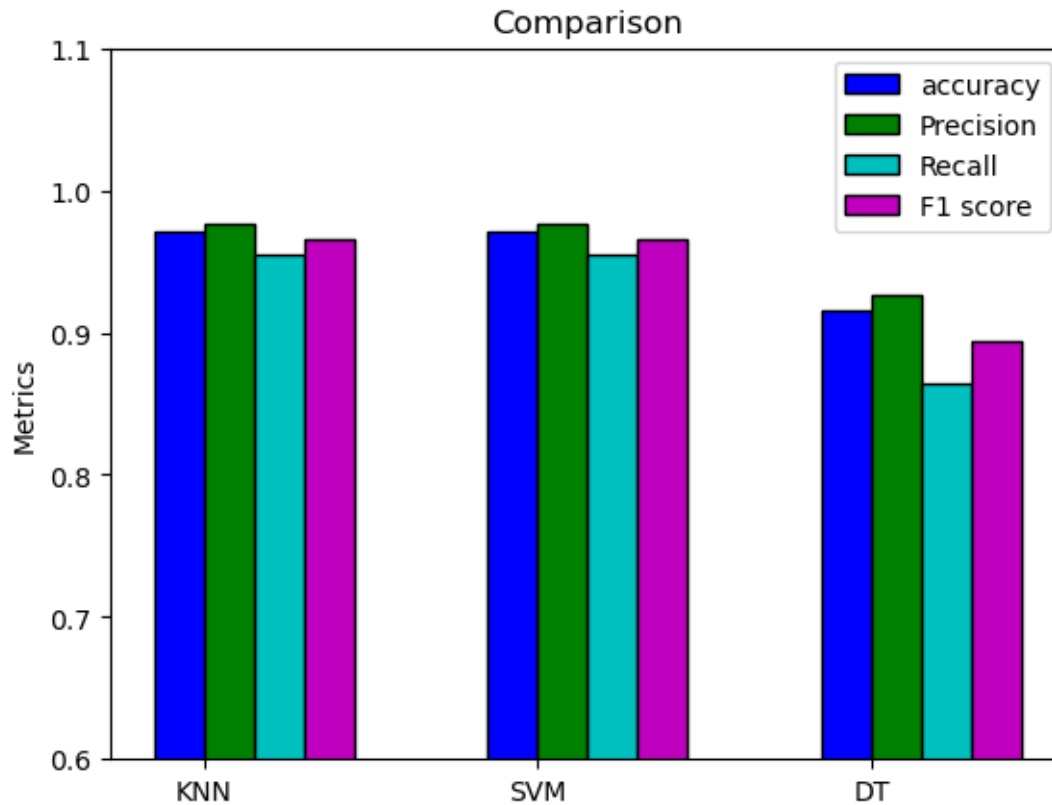
plt.bar(r + 2*width, rec, color = 'c',
        width = width, edgecolor = 'black',
        label='Recall')

plt.bar(r + 3*width, f1, color = 'm',
        width = width, edgecolor = 'black',
        label='F1 score')

plt.xlabel("")
plt.ylabel("Metrics")
plt.title("Comparison")

# plt.grid(linestyle='--')
plt.xticks(r + width/2,['KNN','SVM','DT'])
plt.legend()
plt.ylim(0.6,1.1)

plt.show()
```



6.8 Balanced data random over sampler

```
[95]: from imblearn.over_sampling import RandomOverSampler
      rus = RandomOverSampler()
      X_oversampling, y_oversampling = rus.fit_resample(X, y)
```

```
[96]: # splitting the data
      X_train, X_test, y_train, y_test = train_test_split(X_oversampling, y_oversampling, test_size=0.25, random_state=0)
```

```
[103]: knn = KNeighborsClassifier(n_neighbors=5)
      knn.fit(X_train, y_train)
      y_pred = knn.predict(X_test)
      accuracy_knn = metrics.accuracy_score(y_test, y_pred)
      precision_score_knn = metrics.precision_score(y_test, y_pred)
      recall_score_knn = metrics.recall_score(y_test, y_pred)
      f1_score_knn = metrics.f1_score(y_test, y_pred)
      print("Accuracy du KNN : ", accuracy_knn)
      print("precision score du KNN : ", precision_score_knn)
      print("recall score du KNN : ", recall_score_knn)
```

```

print("f1 score du KNN : ",f1_score_knn)

svm = SVC()
svm.fit(X_train, y_train)
y_pred = svm.predict(X_test)
accuracy_svm = metrics.accuracy_score(y_test, y_pred)
precision_score_svm = metrics.precision_score(y_test, y_pred)
recall_score_svm = metrics.recall_score(y_test, y_pred)
f1_score_svm = metrics.f1_score(y_test,y_pred)
print("Accuracy SVM : " , accuracy_svm)
print("precision score SVM : ", precision_score_svm )
print("recall score SVM ", recall_score_svm )
print("f1 score du SVM: ",f1_score_svm)

clf = tree.DecisionTreeClassifier()
clf.fit(X_train, y_train)
y_pred= clf.predict(X_test)
accuracy_dt = metrics.accuracy_score(y_test, y_pred)
precision_score_dt = metrics.precision_score(y_test, y_pred)
recall_score_dt = metrics.recall_score(y_test, y_pred)
f1_score_dt = metrics.f1_score(y_test , y_pred)
print("Accuracy DT:", accuracy_dt)
print("Precision DT: ",precision_score_dt)
print("Recall DT",recall_score_dt)
print("F1 score DT: ",f1_score_dt)

```

```

Accuracy du KNN : 0.9664804469273743
precision score du KNN : 0.9629629629629629
recall score du KNN : 0.9629629629629629
f1 score du KNN : 0.9629629629629629
Accuracy SVM : 0.9664804469273743
precision score SVM : 0.9518072289156626
recall score SVM 0.9753086419753086
f1 score du SVM: 0.9634146341463414
Accuracy DT: 0.9664804469273743
Precision DT: 0.9411764705882353
Recall DT 0.9876543209876543
F1 score DT: 0.963855421686747

```

```

[104]: acc = [accuracy_knn , accuracy_svm , accuracy_dt]
pre = [precision_score_knn,precision_score_svm,precision_score_dt]
rec = [recall_score_knn , recall_score_svm, recall_score_dt]
f1 = [f1_score_knn , f1_score_svm, f1_score_dt]

n=3
r = np.arange(n)
width = 0.15

```

```

plt.bar(r, acc, color = 'b',
        width = width, edgecolor = 'black',
        label='accuracy')
plt.bar(r + width, pre, color = 'g',
        width = width, edgecolor = 'black',
        label='Precision')

plt.bar(r + 2*width, rec, color = 'c',
        width = width, edgecolor = 'black',
        label='Recall')

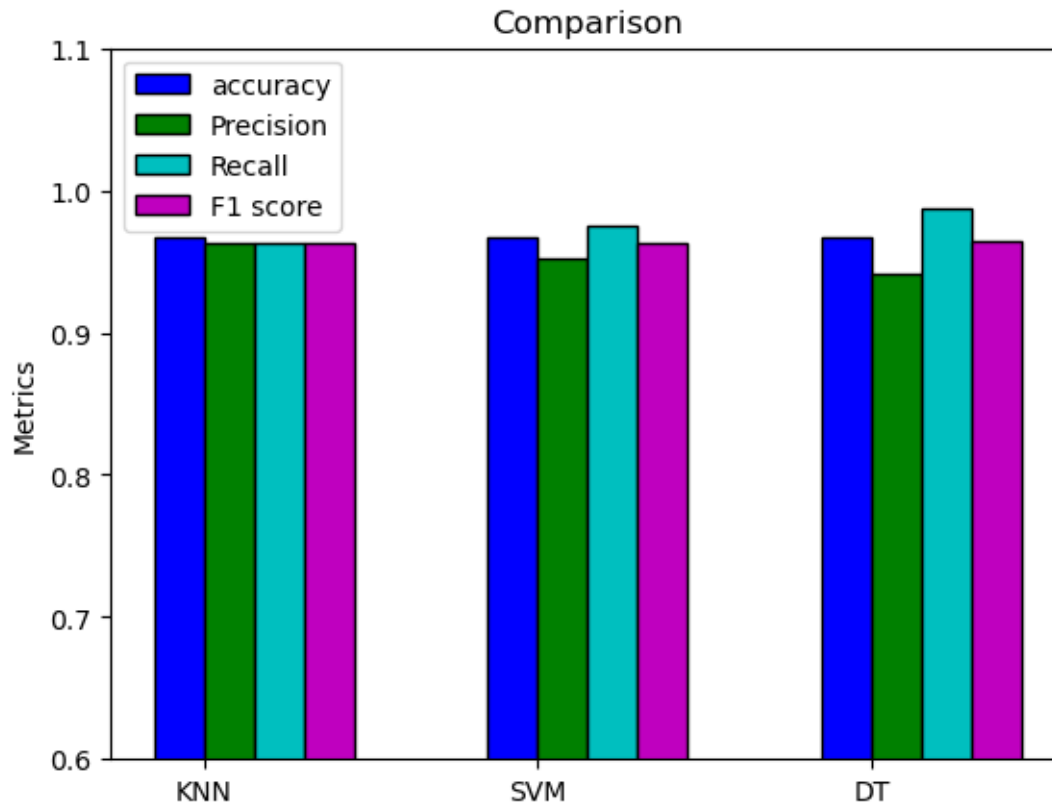
plt.bar(r + 3*width, f1, color = 'm',
        width = width, edgecolor = 'black',
        label='F1 score')

plt.xlabel("")
plt.ylabel("Metrics")
plt.title("Comparison")

# plt.grid(linestyle='--')
plt.xticks(r + width/2,['KNN','SVM','DT'])
plt.legend()
plt.ylim(0.6,1.1)

plt.show()

```

6.9 Balanced data SMOTE

```
[105]: from imblearn.over_sampling import SMOTE
oversample = SMOTE(k_neighbors=3)
X_smote, y_smote = oversample.fit_resample(X, y)
```

```
[106]: # splitting the data
X_train, X_test, y_train, y_test = train_test_split(X_smote, y_smote,
    ↪ test_size=0.25, random_state=0)
```

```
[107]: knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
accuracy_knn = metrics.accuracy_score(y_test, y_pred)
precision_score_knn = metrics.precision_score(y_test, y_pred)
recall_score_knn = metrics.recall_score(y_test, y_pred)
f1_score_knn = metrics.f1_score(y_test, y_pred)
print("Accuracy du KNN : ", accuracy_knn)
print("precision score du KNN : ", precision_score_knn )
print("recall score du KNN : ", recall_score_knn )
print("f1 score du KNN : ", f1_score_knn)
```

```

svm = SVC()
svm.fit(X_train, y_train)
y_pred = svm.predict(X_test)
accuracy_svm = metrics.accuracy_score(y_test, y_pred)
precision_score_svm = metrics.precision_score(y_test, y_pred)
recall_score_svm = metrics.recall_score(y_test, y_pred)
f1_score_svm = metrics.f1_score(y_test, y_pred)
print("Accuracy SVM : " , accuracy_svm)
print("precision score SVM : ", precision_score_svm )
print("recall score SVM ", recall_score_svm )
print("f1 score du SVM: ", f1_score_svm)

clf = tree.DecisionTreeClassifier()
clf.fit(X_train, y_train)
y_pred= clf.predict(X_test)
accuracy_dt = metrics.accuracy_score(y_test, y_pred)
precision_score_dt = metrics.precision_score(y_test, y_pred)
recall_score_dt = metrics.recall_score(y_test, y_pred)
f1_score_dt = metrics.f1_score(y_test , y_pred)
print("Accuracy DT:", accuracy_dt)
print("Precision DT: ", precision_score_dt)
print("Recall DT", recall_score_dt)
print("F1 score DT: ", f1_score_dt)

```

```

Accuracy du KNN : 0.9720670391061452
precision score du KNN : 0.9634146341463414
recall score du KNN : 0.9753086419753086
f1 score du KNN : 0.9693251533742332
Accuracy SVM : 0.9776536312849162
precision score SVM : 0.9753086419753086
recall score SVM 0.9753086419753086
f1 score du SVM: 0.9753086419753086
Accuracy DT: 0.9441340782122905
Precision DT: 0.9080459770114943
Recall DT 0.9753086419753086
F1 score DT: 0.9404761904761905

```

```

[108]: acc = [accuracy_knn , accuracy_svm , accuracy_dt]
pre = [precision_score_knn, precision_score_svm, precision_score_dt]
rec = [recall_score_knn , recall_score_svm, recall_score_dt]
f1 = [f1_score_knn , f1_score_svm, f1_score_dt]

n=3
r = np.arange(n)
width = 0.15

```

```

plt.bar(r, acc, color = 'b',
        width = width, edgecolor = 'black',
        label='accuracy')
plt.bar(r + width, pre, color = 'g',
        width = width, edgecolor = 'black',
        label='Precision')

plt.bar(r + 2*width, rec, color = 'c',
        width = width, edgecolor = 'black',
        label='Recall')

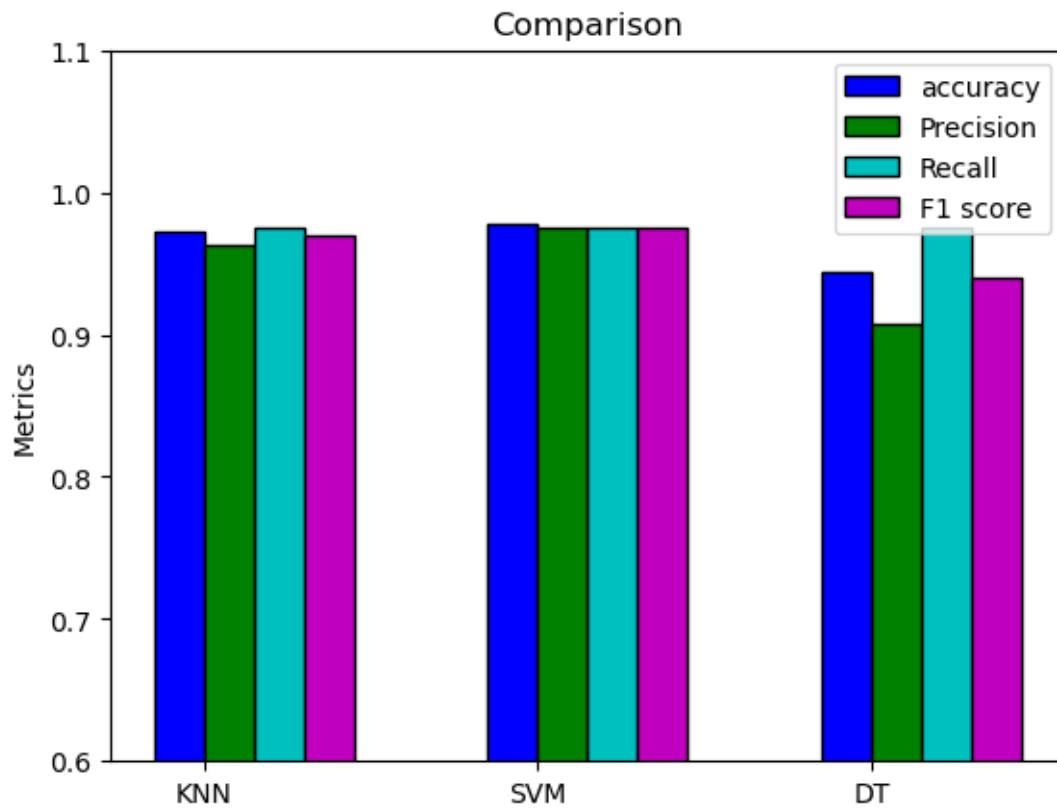
plt.bar(r + 3*width, f1, color = 'm',
        width = width, edgecolor = 'black',
        label='F1 score')

plt.xlabel("")
plt.ylabel("Metrics")
plt.title("Comparison")

# plt.grid(linestyle='--')
plt.xticks(r + width/2,['KNN','SVM','DT'])
plt.legend()
plt.ylim(0.6,1.1)

plt.show()

```



[]:

[]: