Breast Cancer Prediction – K-Nearest Neighbors (KNN) : ML (Binary Classification)

In [438]:
```
# Designed By : ALTAF HUSAIN DATA ANALYST
```

step 1 : import modules

In [439]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
```

```python
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix,classification_report
from sklearn.datasets import load_breast_cancer,load_iris
import warnings
warnings.filterwarnings('ignore')
print("All modules loaded succesfully")
```

```
All modules loaded succesfully
```

step 2 : load data

In [440]:
```python
lbc = load_breast_cancer()
```

In [441]:
```python
lbc.keys()
```

Out[441]:
```
dict_keys(['data', 'target', 'frame', 'target_names', 'DESCR', 'feature_names', 'filename', 'data_module'])
```

In [442]:
```python
df = pd.DataFrame(lbc['data'],columns=lbc['feature_names'])
df['Target'] = lbc['target']
```

In [443]:
```python
df.sample(5)
```

Out[443]:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst texture	per
162	19.59	18.15	130.70	1214.0	0.11200	0.16660	0.25080	0.12860	0.2027	0.06082	...	26.39	
167	16.78	18.80	109.30	886.3	0.08865	0.09182	0.08422	0.06576	0.1893	0.05534	...	26.30	
249	11.52	14.93	73.87	406.3	0.10130	0.07808	0.04328	0.02929	0.1883	0.06168	...	21.19	
108	22.27	19.67	152.80	1509.0	0.13260	0.27680	0.42640	0.18230	0.2556	0.07039	...	28.01	
84	12.00	15.65	76.95	443.3	0.09723	0.07165	0.04151	0.01863	0.2079	0.05968	...	24.90	

5 rows × 31 columns

In [444]:
```
X = lbc.data
```

In [445]:
```
y = lbc.target
```

In [446]:
```
lbc.target_names
```

Out[446]:
```
array(['malignant', 'benign'], dtype='<U9')
```

In [447]:
```
X
```

Out[447]:
```
array([[1.799e+01, 1.038e+01, 1.228e+02, ..., 2.654e-01, 4.601e-01,
        1.189e-01],
       [2.057e+01, 1.777e+01, 1.329e+02, ..., 1.860e-01, 2.750e-01,
        8.902e-02],
       [1.969e+01, 2.125e+01, 1.300e+02, ..., 2.430e-01, 3.613e-01,
        8.758e-02],
       ...,
       [1.660e+01, 2.808e+01, 1.083e+02, ..., 1.418e-01, 2.218e-01,
        7.820e-02],
       [2.060e+01, 2.933e+01, 1.401e+02, ..., 2.650e-01, 4.087e-01,
        1.240e-01],
       [7.760e+00, 2.454e+01, 4.792e+01, ..., 0.000e+00, 2.871e-01,
        7.039e-02]], shape=(569, 30))
```

In [448]:
```
y
```

Out[448]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0,
       1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0,
       1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1,
       1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0,
       0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1,
       1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0,
       0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0,
       1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1,
       1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0,
       0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0,
       0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0,
       1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1,
       1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1,
       1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
       1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1,
       1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1,
       1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1])
```

Step 3 : EDA

In [449]:
```
df.shape
```

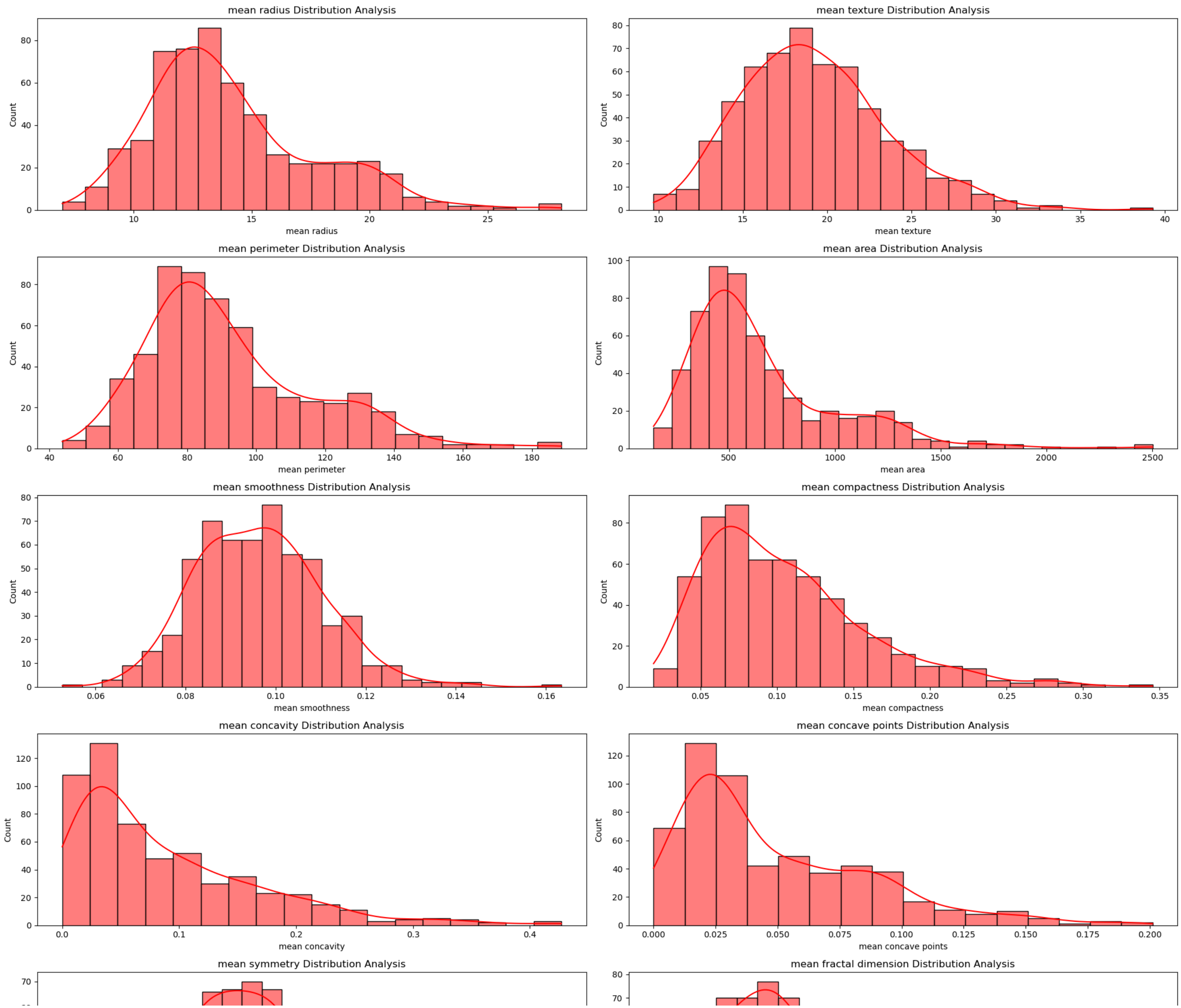
Out[449]:
```
(569, 31)
```

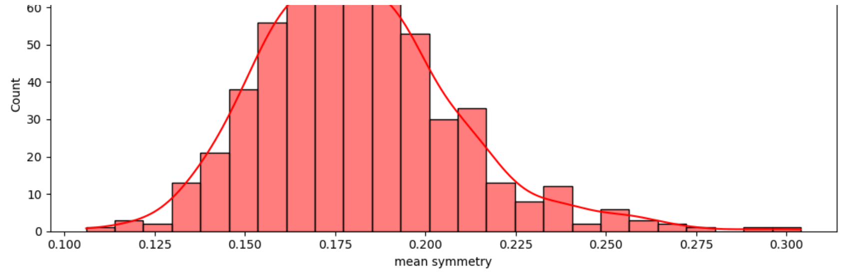
In [450]:
```
X.shape[1]
```

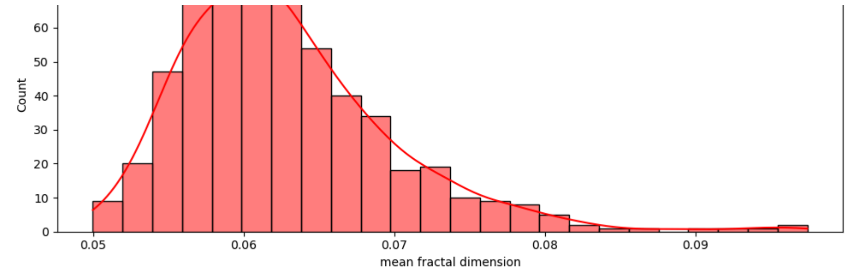
Out[450]:
```
30
```

In [451]:
```
plt.figure(figsize=(20, 60))
for i in range(X.shape[1]):
```

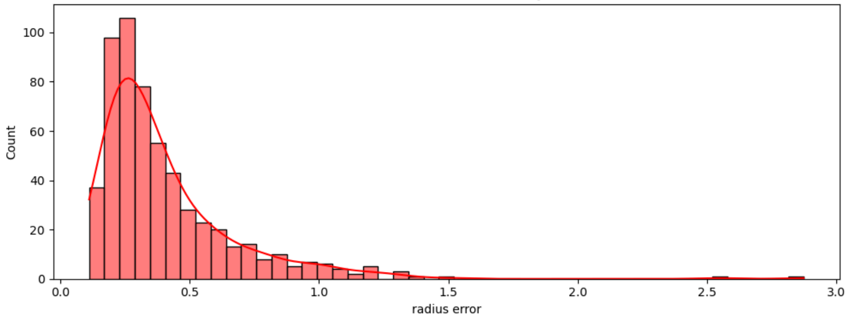
```
    plt.subplot(15,2,i+1)
    plt.title(f'{df.iloc[:, :-1].columns[i]} Distribution Analysis')
    sns.histplot(data=df, x=df.iloc[:, :-1].columns[i], kde=True, color='r')
plt.tight_layout()
plt.show()
```


mean radius Distribution Analysis
Count
mean radius
mean texture Distribution Analysis
Count
mean texture
mean perimeter Distribution Analysis
Count
mean perimeter
mean area Distribution Analysis
Count
mean area
mean smoothness Distribution Analysis
Count
mean smoothness
mean compactness Distribution Analysis
Count
mean compactness
mean concavity Distribution Analysis
Count
mean concavity
mean concave points Distribution Analysis
Count
mean concave points
mean symmetry Distribution Analysis
mean fractal dimension Distribution Analysis

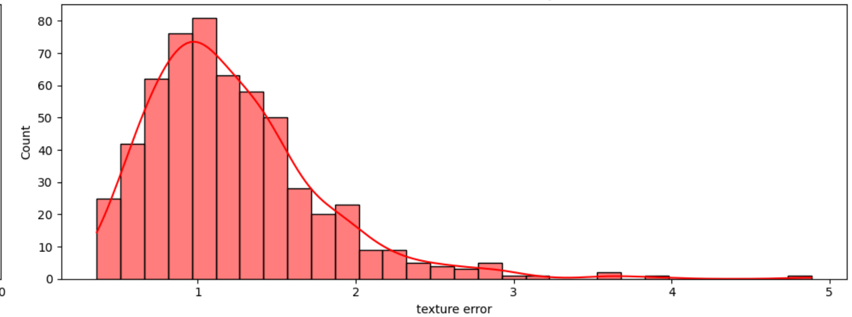




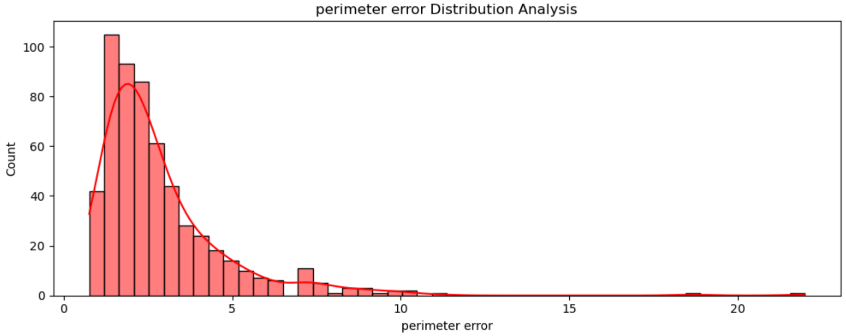
radius error Distribution Analysis



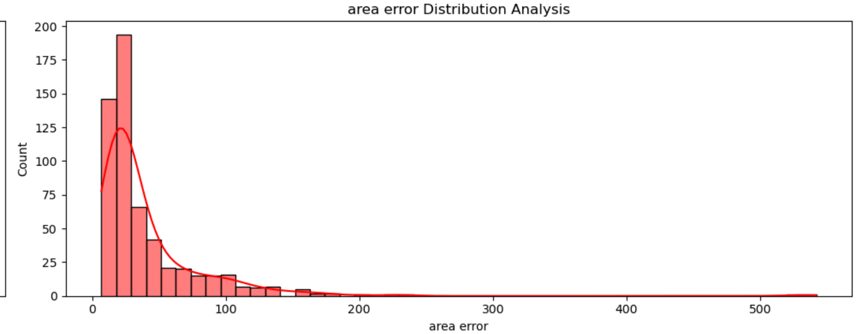
texture error Distribution Analysis



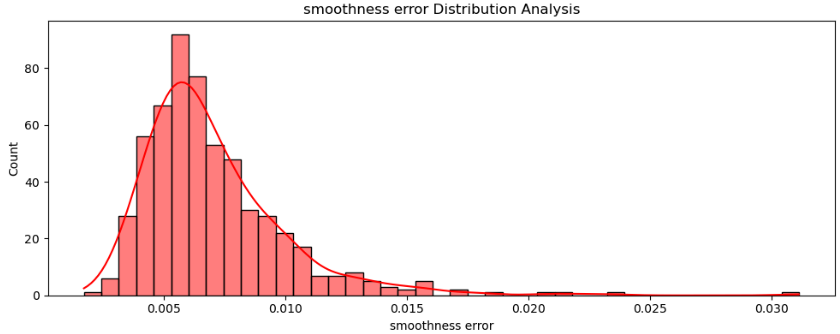
perimeter error Distribution Analysis



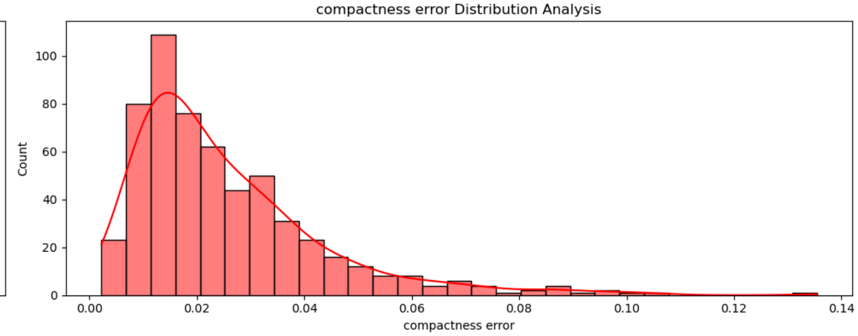
area error Distribution Analysis



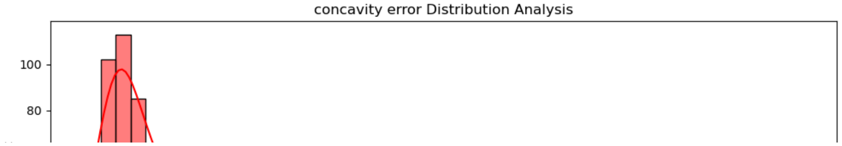
smoothness error Distribution Analysis



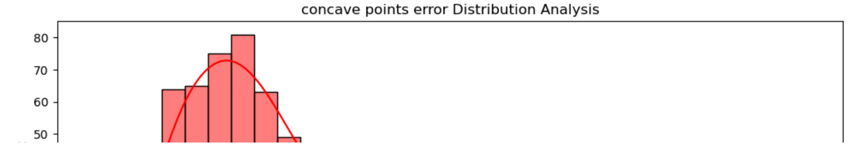
compactness error Distribution Analysis

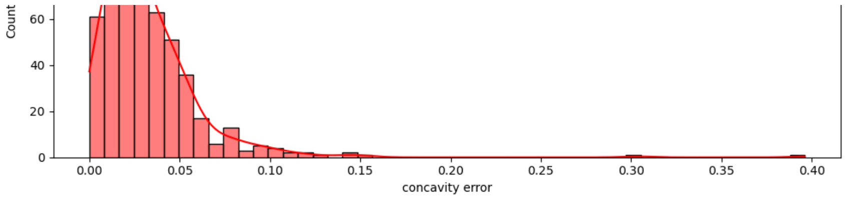


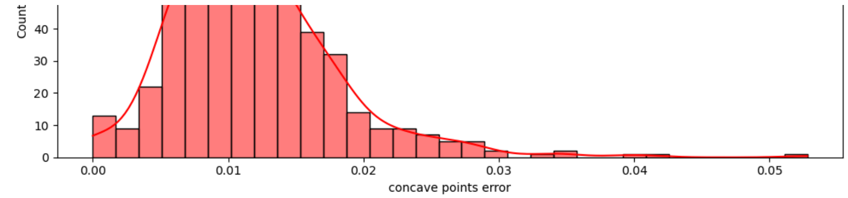
concavity error Distribution Analysis



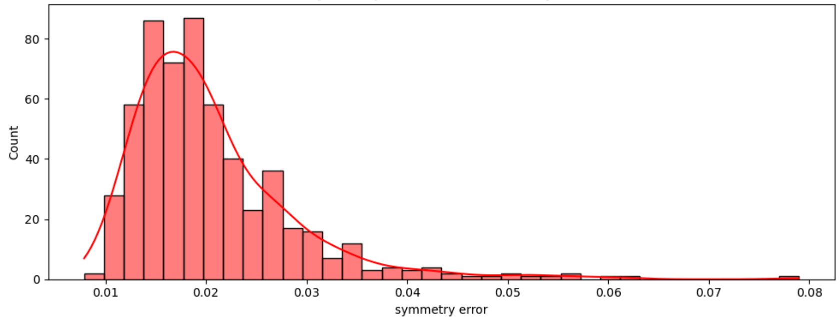
concave points error Distribution Analysis



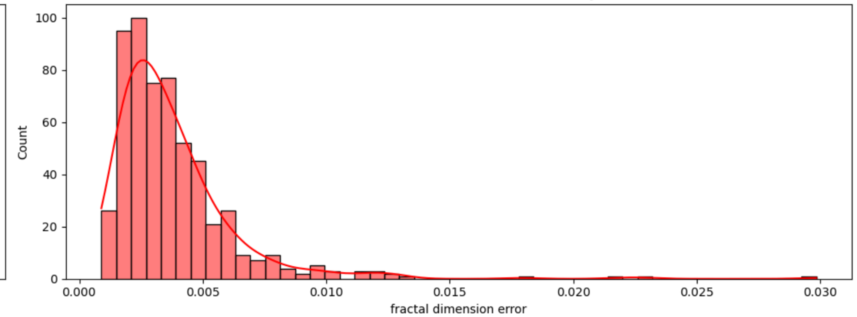




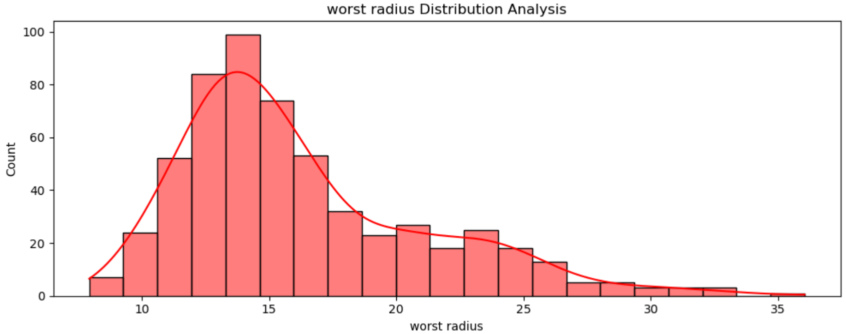
symmetry error Distribution Analysis



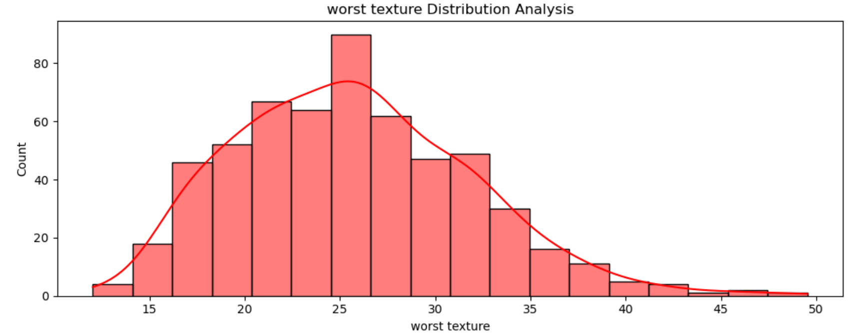
fractal dimension error Distribution Analysis



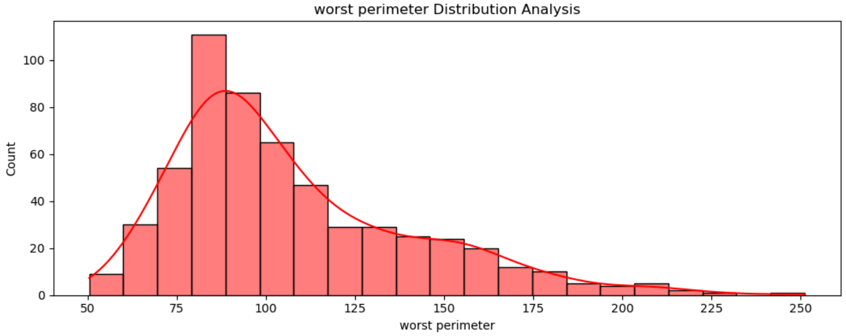
worst radius Distribution Analysis



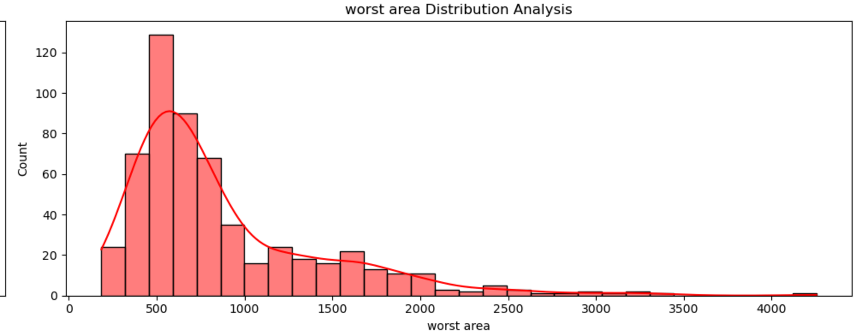
worst texture Distribution Analysis



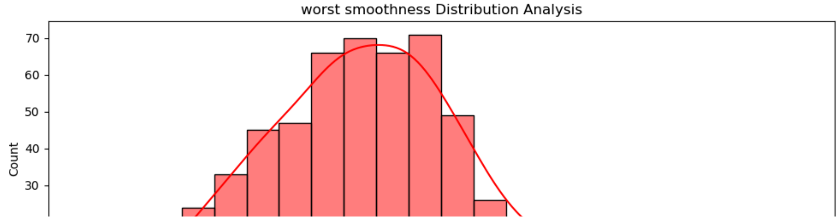
worst perimeter Distribution Analysis



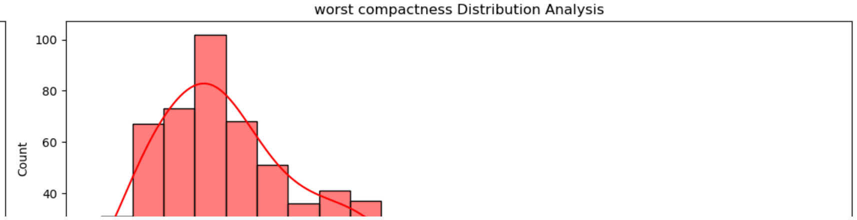
worst area Distribution Analysis

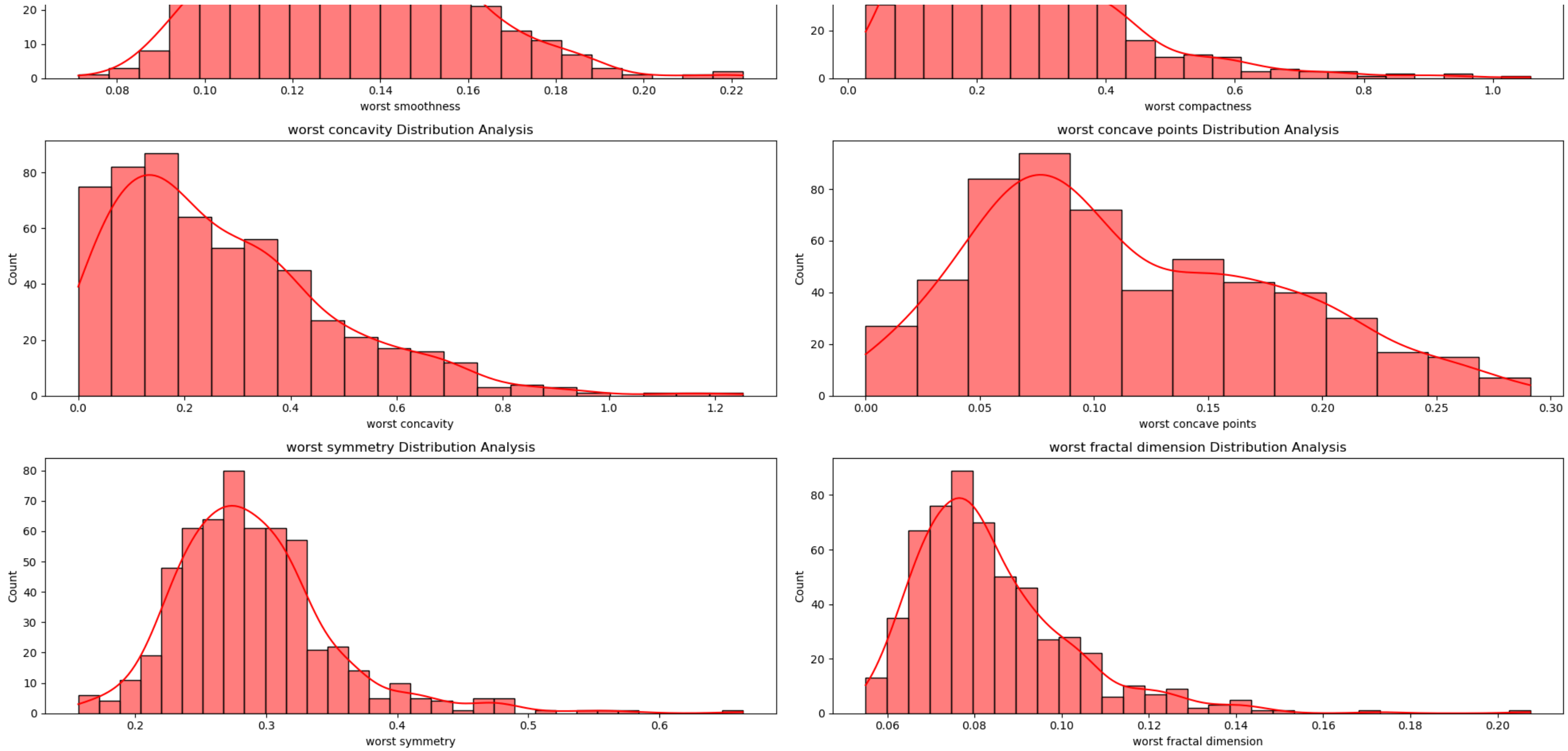


worst smoothness Distribution Analysis

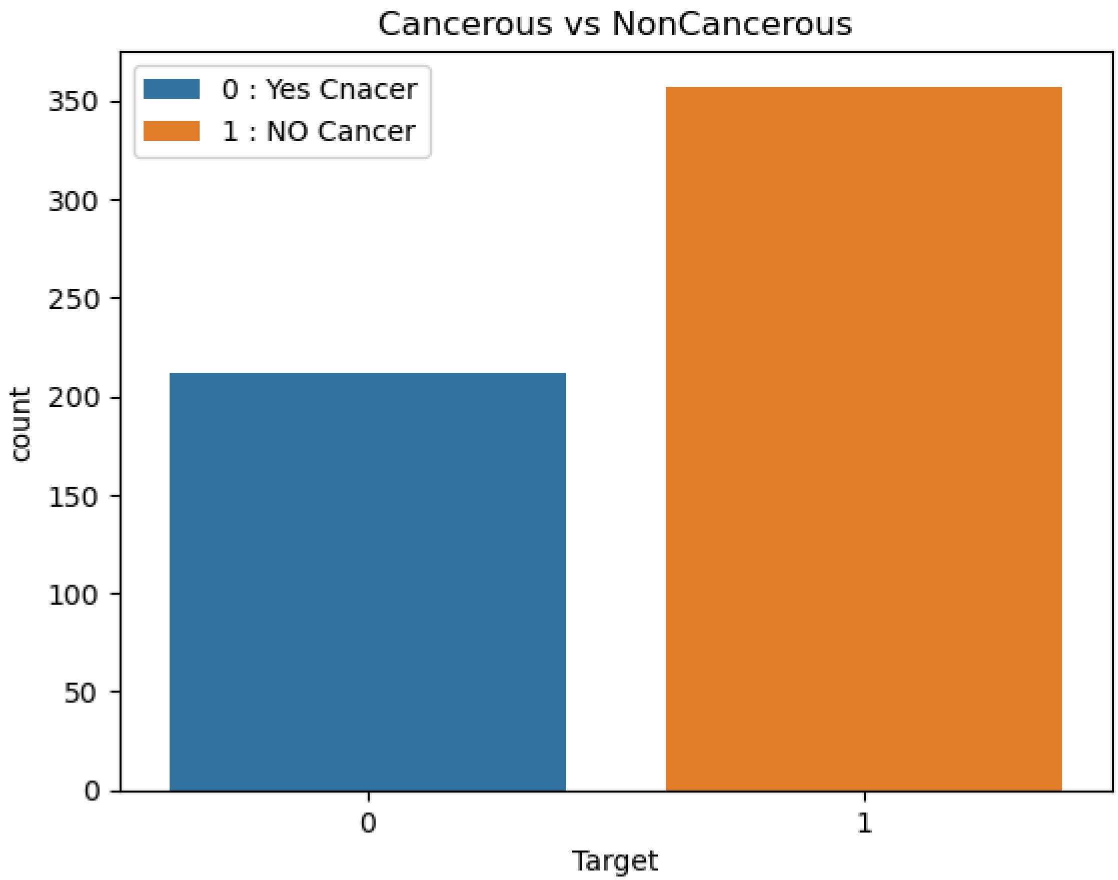


worst compactness Distribution Analysis



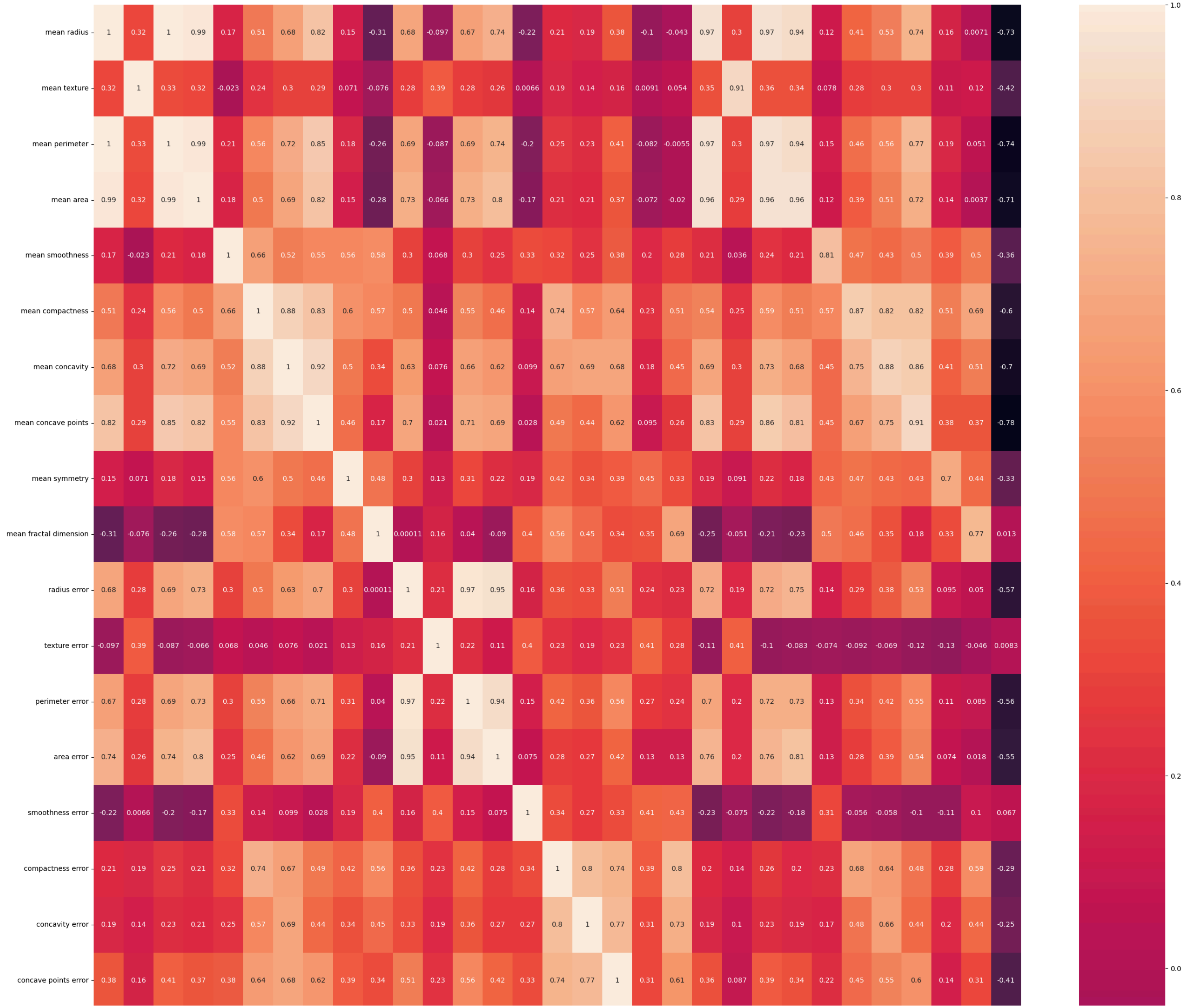


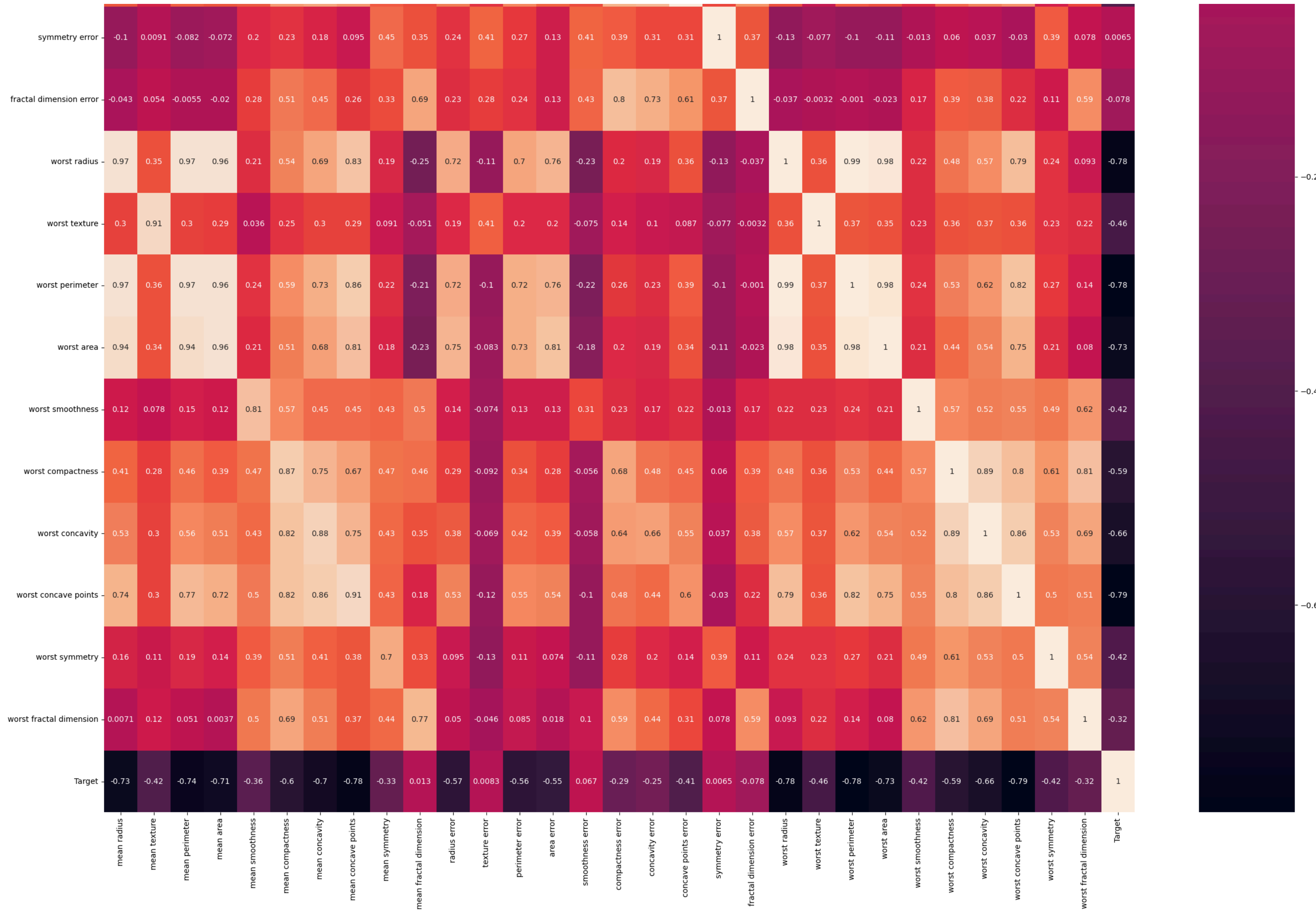
In [452]:
```
plt.title('Cancerous vs NonCancerous')
sns.countplot(data = df,  x = 'Target',hue = 'Target')
plt.legend(("0 : Yes Cnacer","1 : NO Cancer"))
plt.show()
```



In [453]:
```
plt.figure(figsize=(30,45))
sns.heatmap(df.corr(),annot = True)
```

Out[453]: <Axes: >


mean radius
mean texture
mean perimeter
mean area
mean smoothness
mean compactness
mean concavity
mean concave points
mean symmetry
mean fractal dimension
radius error
texture error
perimeter error
area error
smoothness error
compactness error
concavity error
concave points error
1.0
0.8
0.6
0.4
0.2
0.0

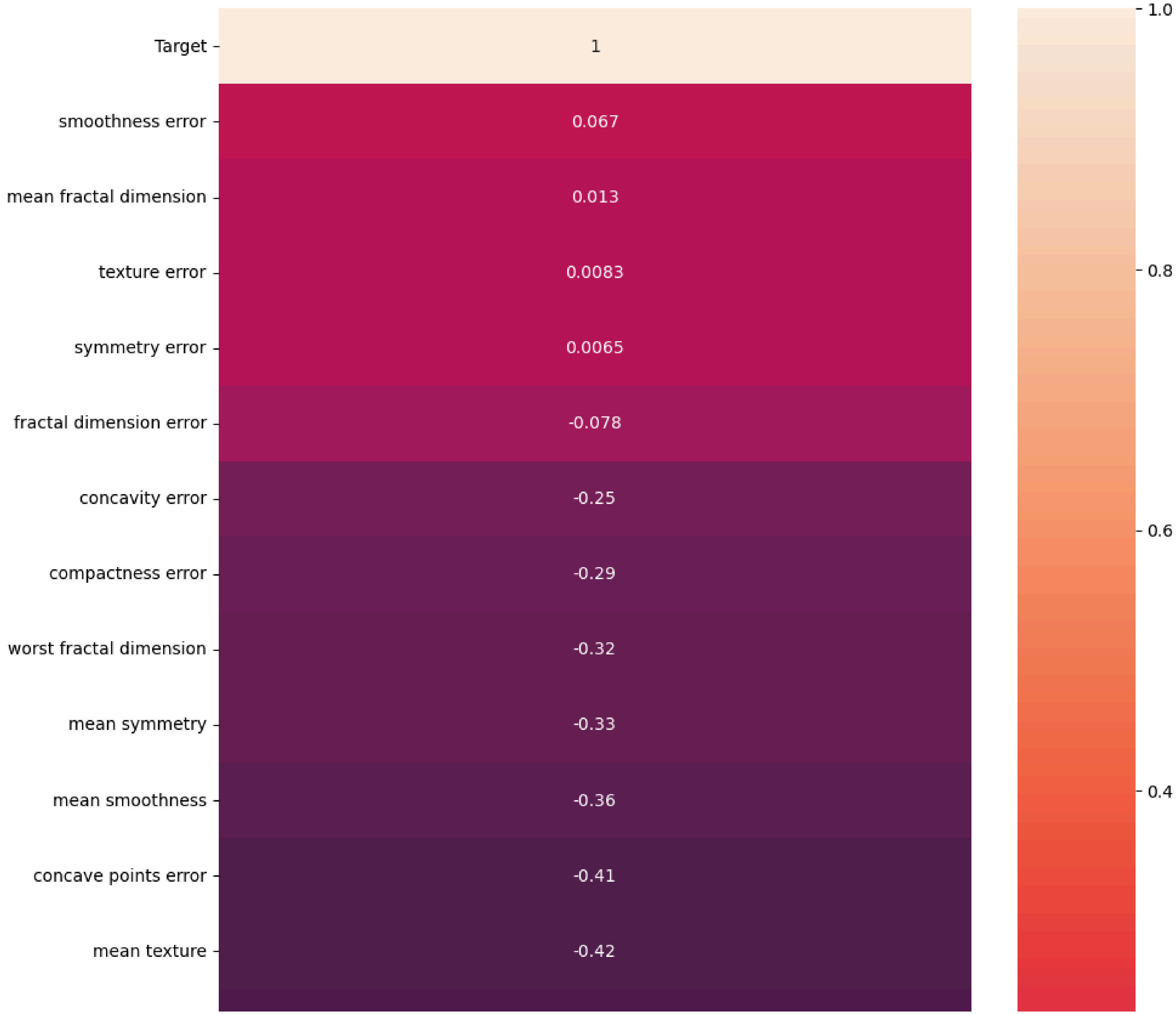


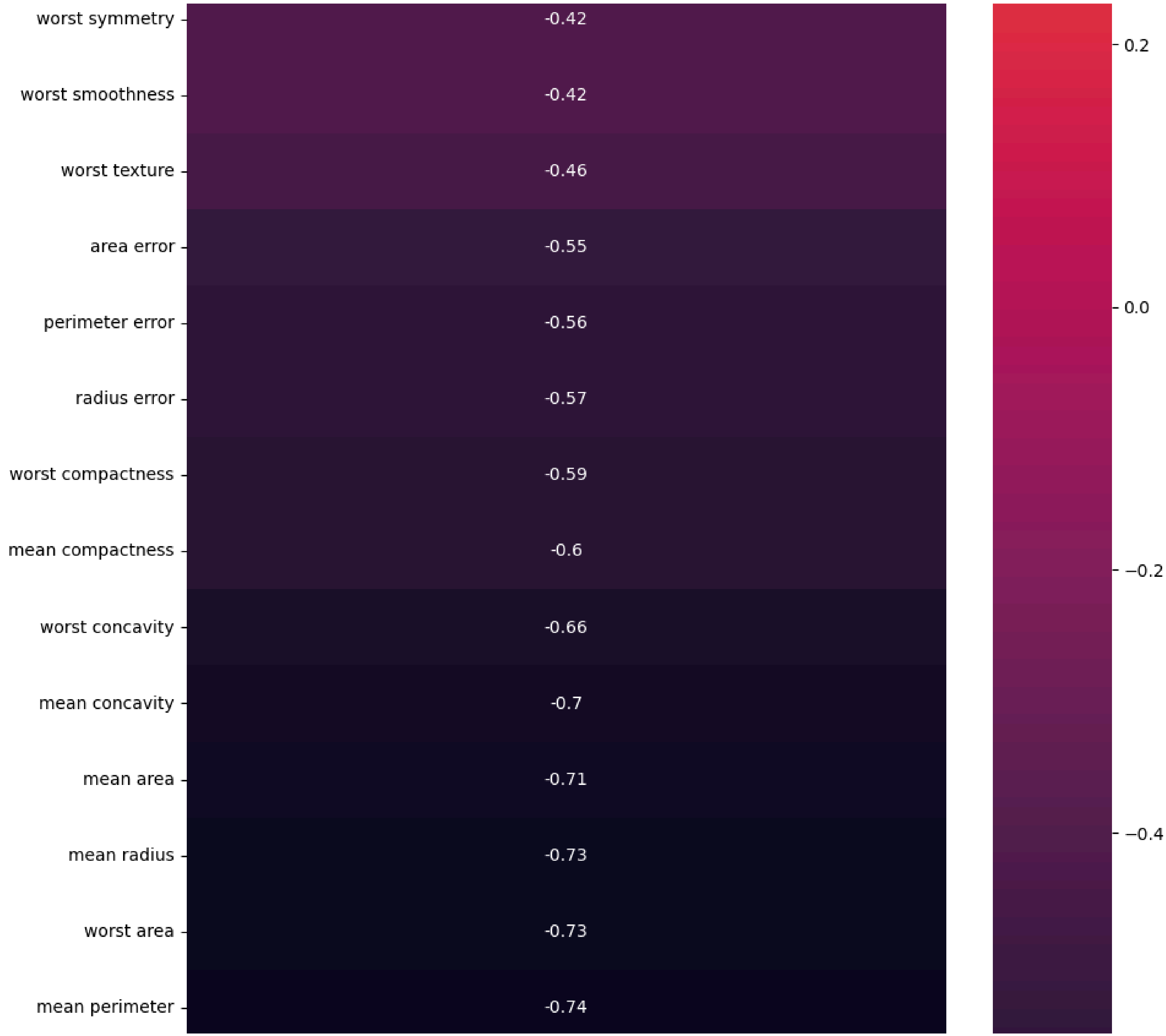
In [454]:
```
df.corr()['Target']
```

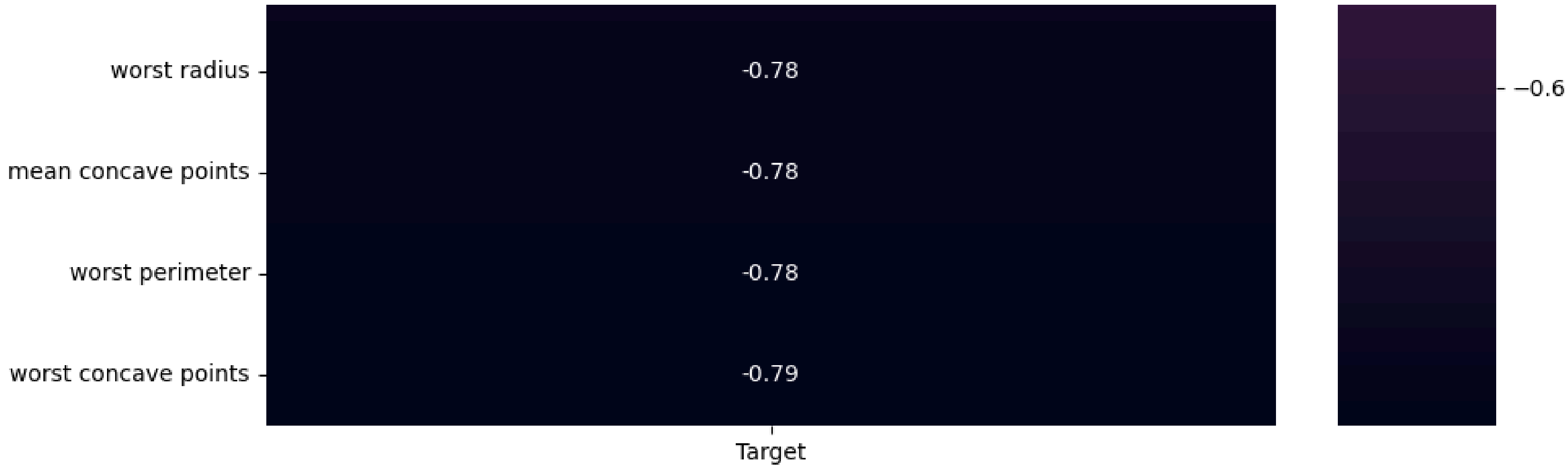
Out[454]:
```
mean radius                -0.730029
mean texture               -0.415185
mean perimeter             -0.742636
mean area                  -0.708984
mean smoothness            -0.358560
mean compactness           -0.596534
mean concavity             -0.696360
mean concave points        -0.776614
mean symmetry              -0.330499
mean fractal dimension      0.012838
radius error               -0.567134
texture error               0.008303
perimeter error            -0.556141
area error                 -0.548236
smoothness error            0.067016
compactness error          -0.292999
concavity error            -0.253730
concave points error       -0.408042
symmetry error              0.006522
fractal dimension error    -0.077972
worst radius               -0.776454
worst texture              -0.456903
worst perimeter            -0.782914
worst area                 -0.733825
worst smoothness           -0.421465
worst compactness          -0.590998
worst concavity            -0.659610
worst concave points       -0.793566
worst symmetry             -0.416294
worst fractal dimension    -0.323872
Target                      1.000000
Name: Target, dtype: float64
```

In [455]:
```
plt.figure(figsize=(10,25))
sns.heatmap(df.corr()[["Target"]].sort_values(by ='Target',ascending=False),annot = True)
```

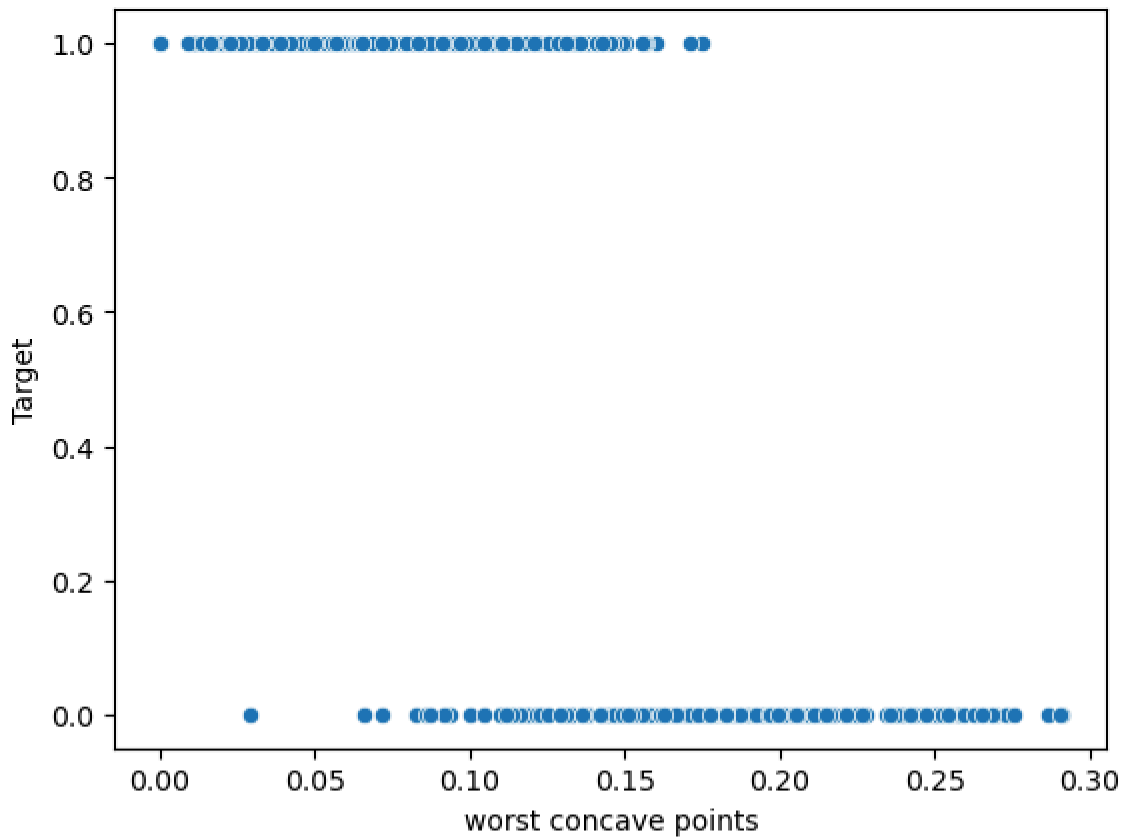
Out[455]:
```
<Axes: >
```


Target
1
smoothness error
0.067
mean fractal dimension
0.013
texture error
0.0083
symmetry error
0.0065
fractal dimension error
-0.078
concavity error
-0.25
compactness error
-0.29
worst fractal dimension
-0.32
mean symmetry
-0.33
mean smoothness
-0.36
concave points error
-0.41
mean texture
-0.42
1.0
0.8
0.6
0.4


worst symmetry
-0.42
worst smoothness
-0.42
worst texture
-0.46
area error
-0.55
perimeter error
-0.56
radius error
-0.57
worst compactness
-0.59
mean compactness
-0.6
worst concavity
-0.66
mean concavity
-0.7
mean area
-0.71
mean radius
-0.73
worst area
-0.73
mean perimeter
-0.74
0.2
0.0
−0.2
−0.4



In [456]:
```
sns.scatterplot(data = df, x = 'worst concave points',y = 'Target' )
plt.show()
```



step 4 : train-test-split

In [457]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.2)
```

step 5 : model building

In [458]:
```
model_k = KNeighborsClassifier()
```

In [459]:
```
model_k.fit(X_train,y_train)
```

Out[459]:

```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

In [460]:
```
y_pred = model_k.predict(X_test)
```

In [461]:
```
y_pred
```

Out[461]:
```
array([1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1,
       1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1,
       1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0,
       1, 0, 0, 1])
```

In [462]:
```
y_test
```

Out[462]:
```
array([1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1,
       1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1,
       1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1,
       1, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0,
       1, 0, 0, 1])
```

In [463]:
```
compare_df = pd.DataFrame({'Actayp y' : y_test,'PRedictes y':y_pred})
compare_df
```

Out[463]:

	Actayp y	PRedictes y
0	1	1
1	1	1
2	0	0
3	0	1
4	1	1
...	...	...
109	0	0
110	1	1
111	0	0
112	0	0
113	1	1

114 rows × 2 columns

Step 6 : Confusion matrix

In [464]:

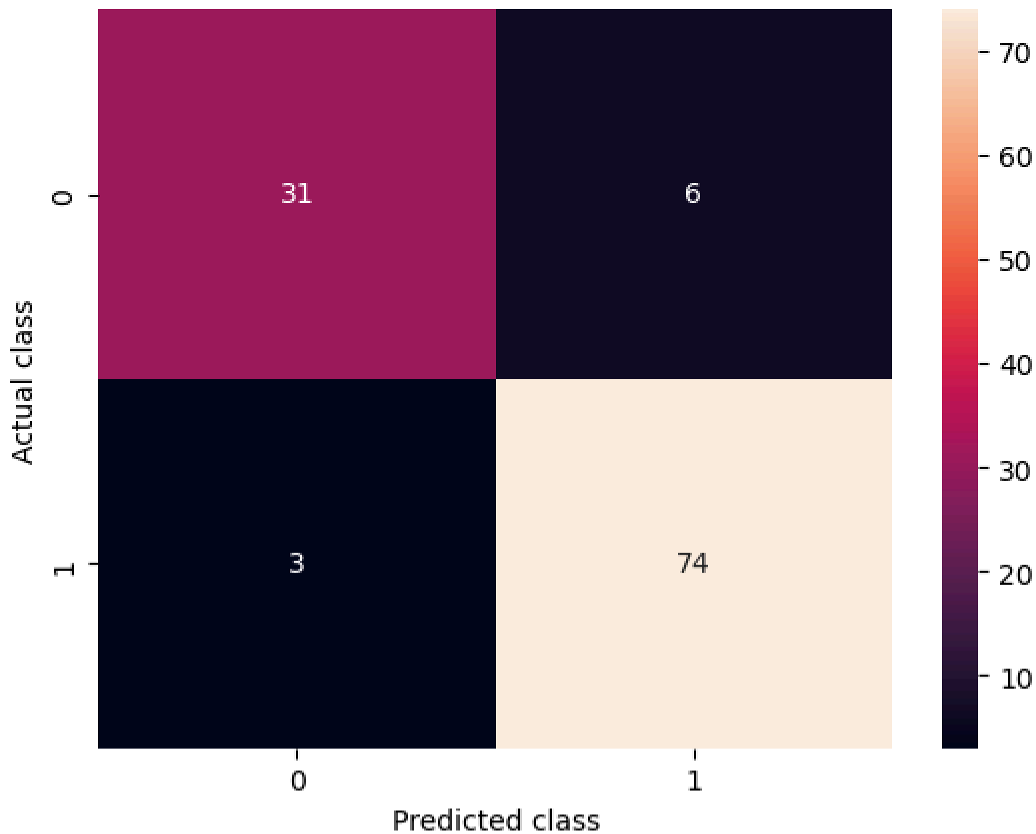
```
cm = confusion_matrix(y_test,y_pred)
cm
```

Out[464]:

```
array([[31,  6],
       [ 3, 74]])
```

In [465]:

```
sns.heatmap(cm,annot= True)
plt.xlabel('Predicted class')
plt.ylabel('Actual class')
plt.show()
```



In [466]:
```
score = round(model_k.score(X_test,y_test)*100,2)
```

In [467]:
```
print('Model Score is :',score)
```

```
Model Score is : 92.11
```

In [468]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.91      0.84      0.87        37
           1       0.93      0.96      0.94        77

    accuracy                           0.92       114
   macro avg       0.92      0.90      0.91       114
weighted avg       0.92      0.92      0.92       114
```

Step 7 : Now finding the best K Value

In [469]:

```python
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.2)

k_dict = {'K_value': [],'Score': []}

for k in range(1,16):
  model_k = KNeighborsClassifier(n_neighbors=k)
  model_k.fit(X_train,y_train)
  y_pred =model_k.predict(X_test)
  score = round(model_k.score(X_test,y_test)*100,2)

  k_dict['K_value'].append(k)
  k_dict['Score'].append(score)

k_df = pd.DataFrame(k_dict)
```

In [470]:

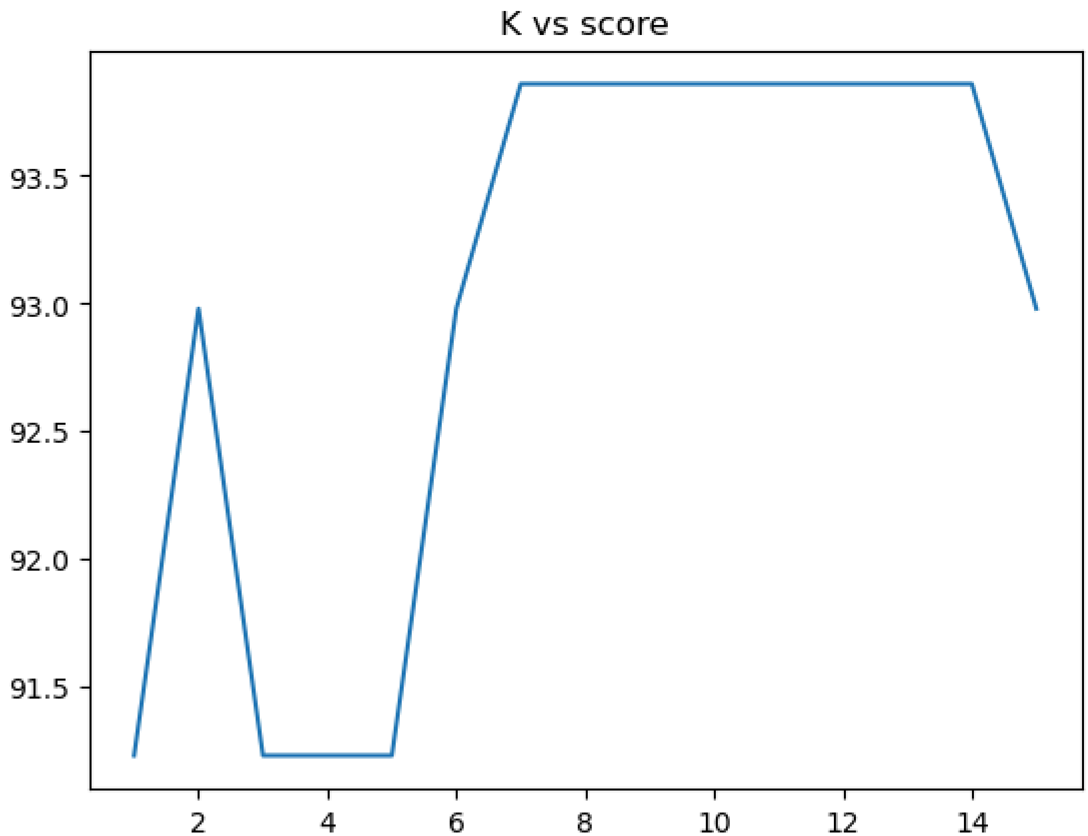
```python
k_df
```

Out[470]:

	K_value	Score
0	1	91.23
1	2	92.98
2	3	91.23
3	4	91.23
4	5	91.23
5	6	92.98
6	7	93.86
7	8	93.86
8	9	93.86
9	10	93.86
10	11	93.86
11	12	93.86
12	13	93.86
13	14	93.86
14	15	92.98

In [471]:

```
plt.plot(k_df['K_value'],k_df['Score'])
plt.title('K vs score')
plt.show()
```



In [472]:
```
best_k_df = k_df[k_df['Score'] == k_df['Score'].max()]
best_k = best_k_df['K_value'].values[0]
print(f"Best K value is : {best_k}")
```

```
Best K value is : 7
```

Step 8 : Model building after best k

In [473]:
```
final_knn = KNeighborsClassifier(n_neighbors=best_k)
final_knn.fit(X_train, y_train)
y_pred_final = final_knn.predict(X_test)
```

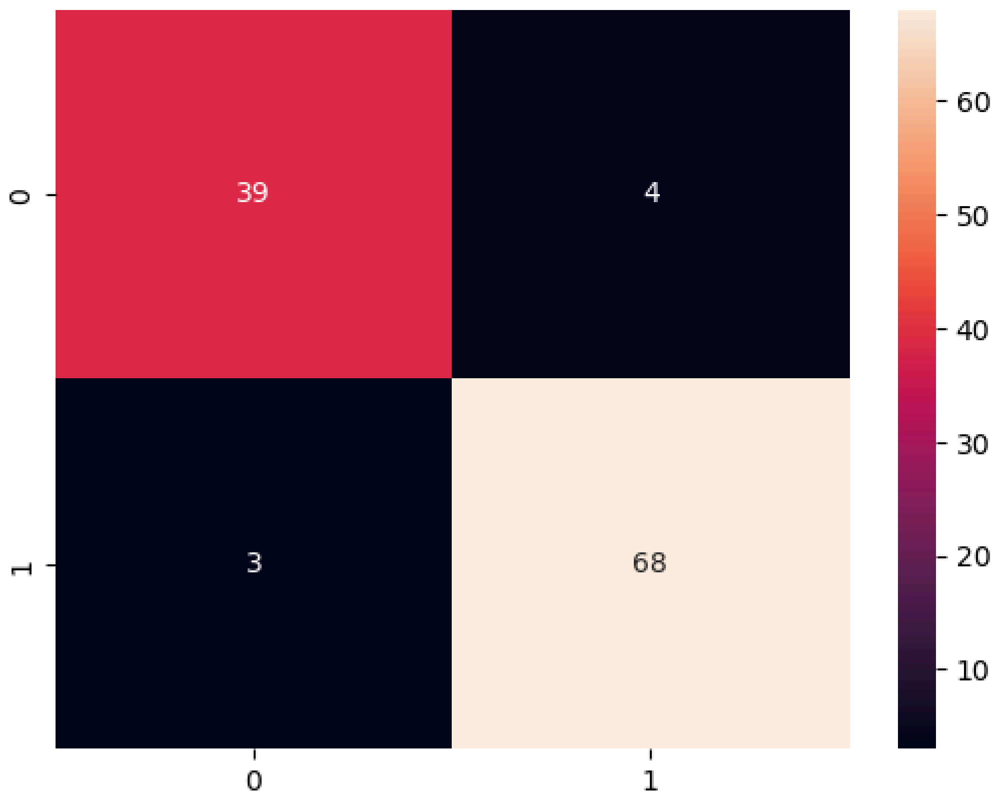
Step 9 : Confusion matirx

In [474]:
```
cm = confusion_matrix(y_test, y_pred_final)
cm
```

Out[474]:
```
array([[39,  4],
       [ 3, 68]])
```

In [475]:
```
sns.heatmap(cm,annot =True)
```

Out[475]: <Axes: >



In [476]:
```
score = round(final_knn.score(X_test,y_test)*100,2)
score
```

Out[476]: 93.86

In [477]:
```
print(classification_report(y_test, y_pred_final))
```

```
              precision    recall  f1-score   support

           0       0.93      0.91      0.92        43
           1       0.94      0.96      0.95        71

    accuracy                           0.94       114
   macro avg       0.94      0.93      0.93       114
weighted avg       0.94      0.94      0.94       114
```

Step 10 : Prediction cancer vs non cancer

In [479]:
```
sample_data = pd.DataFrame(X).sample()
ans = final_knn.predict(sample_data)[0]
probability = round(final_knn.predict_proba(sample_data).max() * 100, 2)

if ans == 0:
    print(f"Cancer with chances of {probability}%")
else:
    print(f"No Cancer with chances of {probability}%")
```

```
No Cancer with chances of 85.71%
```

In [ ]:
```
# Designed By : ALTAF HUSAIN DATA ANALYST
```