In [183…
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [184…
```python
from sklearn.datasets import load_breast_cancer
breast_cancer_dataset = load_breast_cancer()
```

In [185…
```python
breast_cancer_dataset
```

Out[185…
```
{'data': 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]]),
 'target': 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]),
 'frame': None,
 'target_names': array(['malignant', 'benign'], dtype='<U9'),
 'DESCR': '.. _breast_cancer_dataset:\n\nBreast cancer wisconsin (diagnostic) dataset\n------------------------
--------------------\n\n**Data Set Characteristics:**\n\n:Number of Instances: 569\n\n:Number of Attributes: 30
numeric, predictive attributes and the class\n\n:Attribute Information:\n    - radius (mean of distances from c
enter to points on the perimeter)\n    - texture (standard deviation of gray-scale values)\n    - perimeter\n
- area\n    - smoothness (local variation in radius lengths)\n    - compactness (perimeter^2 / area - 1.0)\n
- concavity (severity of concave portions of the contour)\n    - concave points (number of concave portions of
the contour)\n    - symmetry\n    - fractal dimension ("coastline approximation" - 1)\n\n    The mean, standard
error, and "worst" or largest (mean of the three\n    worst/largest values) of these features were computed for
each image,\n    resulting in 30 features.  For instance, field 0 is Mean Radius, field\n    10 is Radius SE, f
ield 20 is Worst Radius.\n\n    - class:\n            - WDBC-Malignant\n            - WDBC-Benign\n\n:Summary S
tatistics:\n\n===================================== ====== ======\n                                           Min
Max\n===================================== ====== ======\nradius (mean):                        6.981  28.11\nt
exture (mean):                       9.71   39.28\nperimeter (mean):                     43.79  188.5\narea (me
an):                          143.5  2501.0\nsmoothness (mean):                    0.053  0.163\ncompactness (m
ean):                  0.019  0.345\nconcavity (mean):                     0.0    0.427\nconcave points (mean)
:              0.0    0.201\nsymmetry (mean):                      0.106  0.304\nfractal dimension (mean):
0.05   0.097\nradius (standard error):              0.112  2.873\ntexture (standard error):             0.36
4.885\nperimeter (standard error):           0.757  21.98\narea (standard error):                6.802  542.2\n
smoothness (standard error):         0.002  0.031\ncompactness (standard error):         0.002  0.135\nconcavi
ty (standard error):           0.0    0.396\nconcave points (standard error):      0.0    0.053\nsymmetry (stan
dard error):           0.008  0.079\nfractal dimension (standard error):   0.001  0.03\nradius (worst):
7.93   36.04\ntexture (worst):                      12.02  49.54\nperimeter (worst):                    50.41
251.2\narea (worst):                         185.2  4254.0\nsmoothness (worst):                   0.071  0.223\
ncompactness (worst):                 0.027  1.058\nconcavity (worst):                    0.0    1.252\nconcav
e points (worst):             0.0    0.291\nsymmetry (worst):                     0.156  0.664\nfractal dimen
sion (worst):            0.055  0.208\n===================================== ====== ======\n\n:Missing Attribut
e Values: None\n\n:Class Distribution: 212 - Malignant, 357 - Benign\n\n:Creator:  Dr. William H. Wolberg, W. N
ick Street, Olvi L. Mangasarian\n\n:Donor: Nick Street\n\n:Date: November, 1995\n\nThis is a copy of UCI ML Bre
```

```
ast Cancer Wisconsin (Diagnostic) datasets.\nhttps://goo.gl/U2Uwz2\n\nFeatures are computed from a digitized im
age of a fine needle\naspirate (FNA) of a breast mass.  They describe\ncharacteristics of the cell nuclei prese
nt in the image.\n\nSeparating plane described above was obtained using\nMultisurface Method-Tree (MSM-T) [K. P
. Bennett, "Decision Tree\nConstruction Via Linear Programming." Proceedings of the 4th\nMidwest Artificial Int
elligence and Cognitive Science Society,\npp. 97-101, 1992], a classification method which uses linear\nprogram
ming to construct a decision tree.  Relevant features\nwere selected using an exhaustive search in the space of
1-4\nfeatures and 1-3 separating planes.\n\nThe actual linear program used to obtain the separating plane\nin t
he 3-dimensional space is that described in:\n[K. P. Bennett and O. L. Mangasarian: "Robust Linear\nProgramming
Discrimination of Two Linearly Inseparable Sets",\nOptimization Methods and Software 1, 1992, 23-34].\n\nThis d
atabase is also available through the UW CS ftp server:\n\nftp ftp.cs.wisc.edu\ncd math-prog/cpo-dataset/machin
e-learn/WDBC/\n\n.. dropdown:: References\n\n  - W.N. Street, W.H. Wolberg and O.L. Mangasarian. Nuclear featur
e extraction\n    for breast tumor diagnosis. IS&T/SPIE 1993 International Symposium on\n    Electronic Imaging
: Science and Technology, volume 1905, pages 861-870,\n    San Jose, CA, 1993.\n  - O.L. Mangasarian, W.N. Stre
et and W.H. Wolberg. Breast cancer diagnosis and\n    prognosis via linear programming. Operations Research, 43
(4), pages 570-577,\n    July-August 1995.\n  - W.H. Wolberg, W.N. Street, and O.L. Mangasarian. Machine learni
ng techniques\n    to diagnose breast cancer from fine-needle aspirates. Cancer Letters 77 (1994)\n    163-171.
\n',
 'feature_names': array(['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', 'symmetry error',
        'fractal dimension error', 'worst radius', 'worst texture',
        'worst perimeter', 'worst area', 'worst smoothness',
        'worst compactness', 'worst concavity', 'worst concave points',
        'worst symmetry', 'worst fractal dimension'], dtype='<U23'),
 'filename': 'breast_cancer.csv',
 'data_module': 'sklearn.datasets.data'}
```

In [186…

```
breast_cancer_dataset.DESCR
```

Out[186…

```
'.. _breast_cancer_dataset:\n\nBreast cancer wisconsin (diagnostic) dataset\n----------------------------------
----------\n\n**Data Set Characteristics:**\n\n:Number of Instances: 569\n\n:Number of Attributes: 30 numeric,
predictive attributes and the class\n\n:Attribute Information:\n    - radius (mean of distances from center to
points on the perimeter)\n    - texture (standard deviation of gray-scale values)\n    - perimeter\n    - area\
n    - smoothness (local variation in radius lengths)\n    - compactness (perimeter^2 / area - 1.0)\n    - conc
avity (severity of concave portions of the contour)\n    - concave points (number of concave portions of the co
ntour)\n    - symmetry\n    - fractal dimension ("coastline approximation" - 1)\n\n    The mean, standard error
, and "worst" or largest (mean of the three\n    worst/largest values) of these features were computed for each
image,\n    resulting in 30 features.  For instance, field 0 is Mean Radius, field\n    10 is Radius SE, field
20 is Worst Radius.\n\n    - class:\n            - WDBC-Malignant\n            - WDBC-Benign\n\n:Summary Statis
tics:\n\n===================================== ====== ======\n                                        Min    Ma
x\n===================================== ====== ======\nradius (mean):                        6.981  28.11\ntex
ture (mean):                       9.71   39.28\nperimeter (mean):                     43.79  188.5\narea (mean
):                          143.5  2501.0\nsmoothness (mean):                    0.053  0.163\ncompactness (mea
n):                   0.019  0.345\nconcavity (mean):                     0.0    0.427\nconcave points (mean):
0.0    0.201\nsymmetry (mean):                      0.106  0.304\nfractal dimension (mean):             0.05
0.097\nradius (standard error):              0.112  2.873\ntexture (standard error):             0.36   4.885\n
perimeter (standard error):           0.757  21.98\narea (standard error):                6.802  542.2\nsmoothn
ess (standard error):          0.002  0.031\ncompactness (standard error):         0.002  0.135\nconcavity (sta
ndard error):           0.0    0.396\nconcave points (standard error):      0.0    0.053\nsymmetry (standard er
ror):            0.008  0.079\nfractal dimension (standard error):   0.001  0.03\nradius (worst):
7.93   36.04\ntexture (worst):                      12.02  49.54\nperimeter (worst):                    50.41
251.2\narea (worst):                         185.2  4254.0\nsmoothness (worst):                   0.071  0.223\
ncompactness (worst):                  0.027  1.058\nconcavity (worst):                    0.0    1.252\nconcav
e points (worst):              0.0    0.291\nsymmetry (worst):                     0.156  0.664\nfractal dimen
sion (worst):            0.055  0.208\n===================================== ====== ======\n\n:Missing Attribut
e Values: None\n\n:Class Distribution: 212 - Malignant, 357 - Benign\n\n:Creator:  Dr. William H. Wolberg, W. N
ick Street, Olvi L. Mangasarian\n\n:Donor: Nick Street\n\n:Date: November, 1995\n\nThis is a copy of UCI ML Bre
ast Cancer Wisconsin (Diagnostic) datasets.\nhttps://goo.gl/U2Uwz2\n\nFeatures are computed from a digitized im
age of a fine needle\naspirate (FNA) of a breast mass.  They describe\ncharacteristics of the cell nuclei prese
nt in the image.\n\nSeparating plane described above was obtained using\nMultisurface Method-Tree (MSM-T) [K. P
. Bennett, "Decision Tree\nConstruction Via Linear Programming." Proceedings of the 4th\nMidwest Artificial Int
elligence and Cognitive Science Society,\npp. 97-101, 1992], a classification method which uses linear\nprogram
ming to construct a decision tree.  Relevant features\nwere selected using an exhaustive search in the space of
1-4\nfeatures and 1-3 separating planes.\n\nThe actual linear program used to obtain the separating plane\nin t
he 3-dimensional space is that described in:\n[K. P. Bennett and O. L. Mangasarian: "Robust Linear\nProgramming
Discrimination of Two Linearly Inseparable Sets",\nOptimization Methods and Software 1, 1992, 23-34].\n\nThis d
atabase is also available through the UW CS ftp server:\n\nftp ftp.cs.wisc.edu\ncd math-prog/cpo-dataset/machin
e-learn/WDBC/\n\n.. dropdown:: References\n\n  - W.N. Street, W.H. Wolberg and O.L. Mangasarian. Nuclear featur
e extraction\n    for breast tumor diagnosis. IS&T/SPIE 1993 International Symposium on\n    Electronic Imaging
: Science and Technology, volume 1905, pages 861-870,\n    San Jose, CA, 1993.\n  - O.L. Mangasarian, W.N. Stre
et and W.H. Wolberg. Breast cancer diagnosis and\n    prognosis via linear programming. Operations Research, 43
(4), pages 570-577,\n    July-August 1995.\n  - W.H. Wolberg, W.N. Street, and O.L. Mangasarian. Machine learni
ng techniques\n    to diagnose breast cancer from fine-needle aspirates. Cancer Letters 77 (1994)\n    163-171.
\n'
```

In [187…

```
breast_cancer_dataset.data
```

Out[187…
```
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]])
```

In [188…
```python
breast_cancer_dataset.feature_names
```

Out[188…
```
array(['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', 'symmetry error',
       'fractal dimension error', 'worst radius', 'worst texture',
       'worst perimeter', 'worst area', 'worst smoothness',
       'worst compactness', 'worst concavity', 'worst concave points',
       'worst symmetry', 'worst fractal dimension'], dtype='<U23')
```

In [189…
```python
breast_cancer_dataset.target
```

Out[189…
```
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])
```

In [190…
```python
data = pd.DataFrame(breast_cancer_dataset.data,columns = breast_cancer_dataset.feature_names)
data['target'] = breast_cancer_dataset.target
```

In [191…
```python
data
```

Out[191...

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst texture	wor perime
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	0.14710	0.2419	0.07871	...	17.33	184.
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	0.07017	0.1812	0.05667	...	23.41	158.
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740	0.12790	0.2069	0.05999	...	25.53	152.
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	0.2597	0.09744	...	26.50	98.
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	0.1809	0.05883	...	16.67	152.
...	...	...	...	...	...	...	...	...	...	...	...	...	
564	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	0.1726	0.05623	...	26.40	166.
565	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	0.1752	0.05533	...	38.25	155.
566	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	0.1590	0.05648	...	34.12	126.
567	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	0.2397	0.07016	...	39.42	184.
568	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	0.1587	0.05884	...	30.37	59.

569 rows × 31 columns

In [192...

```
data.head()
```

Out[192...

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst texture	worst perimeter
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419	0.07871	...	17.33	184.60
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812	0.05667	...	23.41	158.80
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069	0.05999	...	25.53	152.50
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2597	0.09744	...	26.50	98.87
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1809	0.05883	...	16.67	152.20

5 rows × 31 columns

In [193...

```
data.tail()
```

Out[193...

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst texture	wor perime
564	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	0.1726	0.05623	...	26.40	166.
565	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	0.1752	0.05533	...	38.25	155.
566	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	0.1590	0.05648	...	34.12	126.
567	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	0.2397	0.07016	...	39.42	184.
568	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	0.1587	0.05884	...	30.37	59.

5 rows × 31 columns

In [194...

```
data.isnull().sum()
```

Out[194…
```
mean radius                0
mean texture               0
mean perimeter             0
mean area                  0
mean smoothness            0
mean compactness           0
mean concavity             0
mean concave points        0
mean symmetry              0
mean fractal dimension     0
radius error               0
texture error              0
perimeter error            0
area error                 0
smoothness error           0
compactness error          0
concavity error            0
concave points error       0
symmetry error             0
fractal dimension error    0
worst radius               0
worst texture              0
worst perimeter            0
worst area                 0
worst smoothness           0
worst compactness          0
worst concavity            0
worst concave points       0
worst symmetry             0
worst fractal dimension    0
target                     0
dtype: int64
```

In [195…
```
data.describe()
```

Out[195…

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mea fract dimensio
count	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.00000
mean	14.127292	19.289649	91.969033	654.889104	0.096360	0.104341	0.088799	0.048919	0.181162	0.06279
std	3.524049	4.301036	24.298981	351.914129	0.014064	0.052813	0.079720	0.038803	0.027414	0.00706
min	6.981000	9.710000	43.790000	143.500000	0.052630	0.019380	0.000000	0.000000	0.106000	0.04996
25%	11.700000	16.170000	75.170000	420.300000	0.086370	0.064920	0.029560	0.020310	0.161900	0.05770
50%	13.370000	18.840000	86.240000	551.100000	0.095870	0.092630	0.061540	0.033500	0.179200	0.06154
75%	15.780000	21.800000	104.100000	782.700000	0.105300	0.130400	0.130700	0.074000	0.195700	0.06612
max	28.110000	39.280000	188.500000	2501.000000	0.163400	0.345400	0.426800	0.201200	0.304000	0.09744

8 rows × 31 columns

In [196…
```
data.info()
```

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

In [197…
```
data.shape
```

Out[197…
```
(569, 31)
```

In [198…
```
data.corr()
```

Out[198…

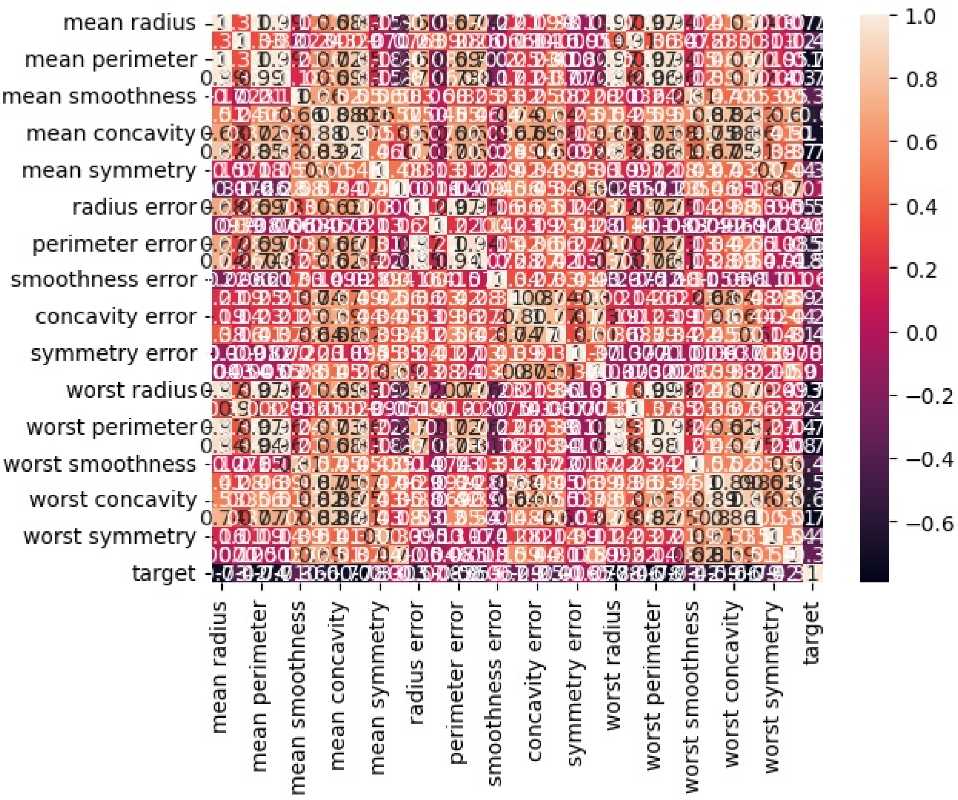
	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...
mean radius	1.000000	0.323782	0.997855	0.987357	0.170581	0.506124	0.676764	0.822529	0.147741	-0.311631	...
mean texture	0.323782	1.000000	0.329533	0.321086	-0.023389	0.236702	0.302418	0.293464	0.071401	-0.076437	...
mean perimeter	0.997855	0.329533	1.000000	0.986507	0.207278	0.556936	0.716136	0.850977	0.183027	-0.261477	...
mean area	0.987357	0.321086	0.986507	1.000000	0.177028	0.498502	0.685983	0.823269	0.151293	-0.283110	...
mean smoothness	0.170581	-0.023389	0.207278	0.177028	1.000000	0.659123	0.521984	0.553695	0.557775	0.584792	...
mean compactness	0.506124	0.236702	0.556936	0.498502	0.659123	1.000000	0.883121	0.831135	0.602641	0.565369	...
mean concavity	0.676764	0.302418	0.716136	0.685983	0.521984	0.883121	1.000000	0.921391	0.500667	0.336783	...
mean concave points	0.822529	0.293464	0.850977	0.823269	0.553695	0.831135	0.921391	1.000000	0.462497	0.166917	...
mean symmetry	0.147741	0.071401	0.183027	0.151293	0.557775	0.602641	0.500667	0.462497	1.000000	0.479921	...
mean fractal dimension	-0.311631	-0.076437	-0.261477	-0.283110	0.584792	0.565369	0.336783	0.166917	0.479921	1.000000	...
radius error	0.679090	0.275869	0.691765	0.732562	0.301467	0.497473	0.631925	0.698050	0.303379	0.000111	...
texture error	-0.097317	0.386358	-0.086761	-0.066280	0.068406	0.046205	0.076218	0.021480	0.128053	0.164174	...
perimeter error	0.674172	0.281673	0.693135	0.726628	0.296092	0.548905	0.660391	0.710650	0.313893	0.039830	...
area error	0.735864	0.259845	0.744983	0.800086	0.246552	0.455653	0.617427	0.690299	0.223970	-0.090170	...
smoothness error	-0.222600	0.006614	-0.202694	-0.166777	0.332375	0.135299	0.098564	0.027653	0.187321	0.401964	...
compactness error	0.206000	0.191975	0.250744	0.212583	0.318943	0.738722	0.670279	0.490424	0.421659	0.559837	...
concavity error	0.194204	0.143293	0.228082	0.207660	0.248396	0.570517	0.691270	0.439167	0.342627	0.446630	...
concave points error	0.376169	0.163851	0.407217	0.372320	0.380676	0.642262	0.683260	0.615634	0.393298	0.341198	...
symmetry error	-0.104321	0.009127	-0.081629	-0.072497	0.200774	0.229977	0.178009	0.095351	0.449137	0.345007	...
fractal dimension error	-0.042641	0.054458	-0.005523	-0.019887	0.283607	0.507318	0.449301	0.257584	0.331786	0.688132	...
worst radius	0.969539	0.352573	0.969476	0.962746	0.213120	0.535315	0.688236	0.830318	0.185728	-0.253691	...
worst texture	0.297008	0.912045	0.303038	0.287489	0.036072	0.248133	0.299879	0.292752	0.090651	-0.051269	...
worst perimeter	0.965137	0.358040	0.970387	0.959120	0.238853	0.590210	0.729565	0.855923	0.219169	-0.205151	...
worst area	0.941082	0.343546	0.941550	0.959213	0.206718	0.509604	0.675987	0.809630	0.177193	-0.231854	...
worst smoothness	0.119616	0.077503	0.150549	0.123523	0.805324	0.565541	0.448822	0.452753	0.426675	0.504942	...
worst compactness	0.413463	0.277830	0.455774	0.390410	0.472468	0.865809	0.754968	0.667454	0.473200	0.458798	...
worst concavity	0.526911	0.301025	0.563879	0.512606	0.434926	0.816275	0.884103	0.752399	0.433721	0.346234	...
worst concave points	0.744214	0.295316	0.771241	0.722017	0.503053	0.815573	0.861323	0.910155	0.430297	0.175325	...
worst symmetry	0.163953	0.105008	0.189115	0.143570	0.394309	0.510223	0.409464	0.375744	0.699826	0.334019	...
worst fractal dimension	0.007066	0.119205	0.051019	0.003738	0.499316	0.687382	0.514930	0.368661	0.438413	0.767297	...
target	-0.730029	-0.415185	-0.742636	-0.708984	-0.358560	-0.596534	-0.696360	-0.776614	-0.330499	0.012838	...

31 rows × 31 columns

In [199…

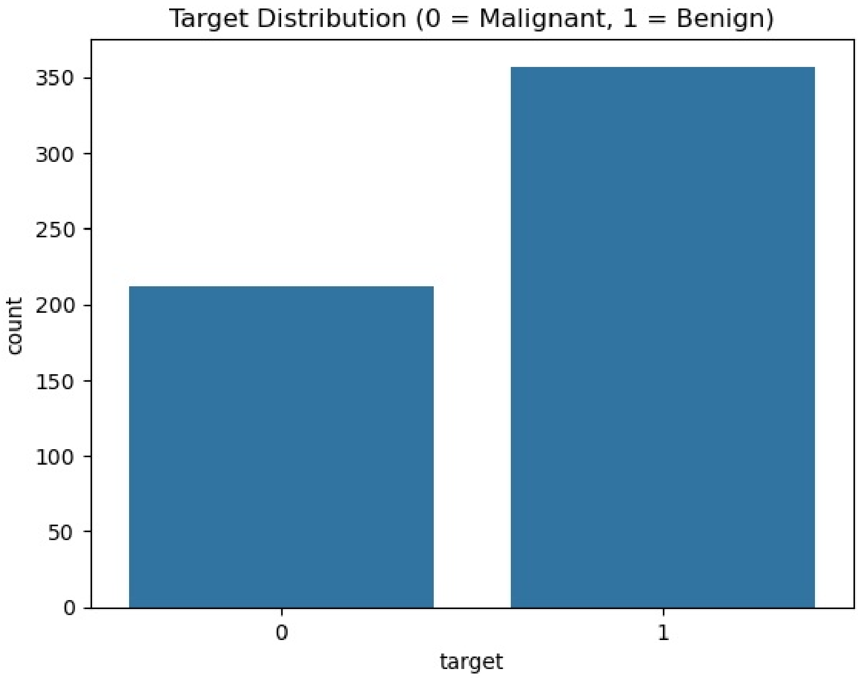
```
sns.heatmap(data.corr(),annot=True)
```

Out[199… <Axes: >



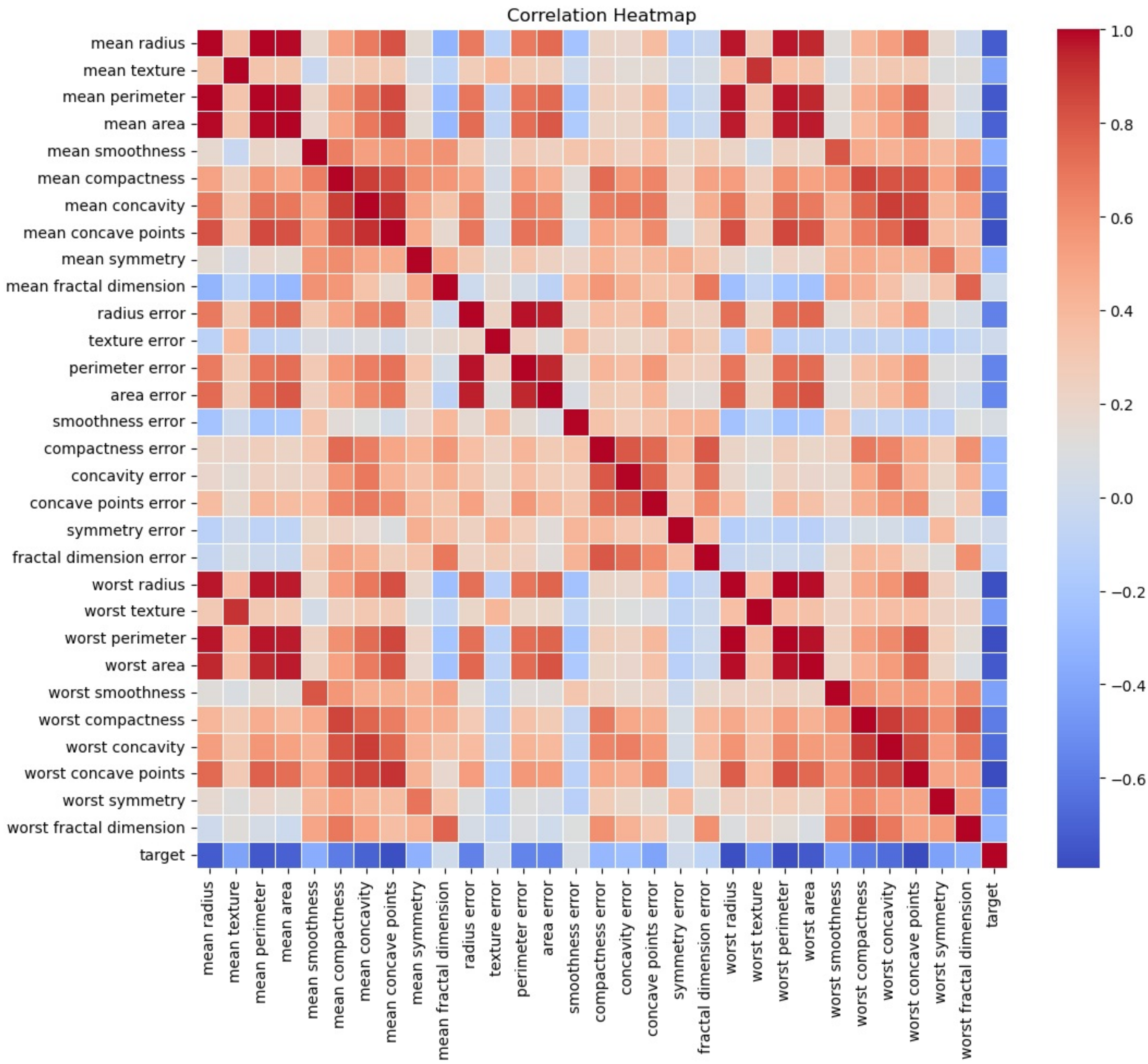
In [200…

```
sns.countplot(x='target', data= data)
plt.title('Target Distribution (0 = Malignant, 1 = Benign)')
plt.show()
```



In [201…

```
# Correlation heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(data.corr(), cmap='coolwarm', linewidths=0.5)
plt.title("Correlation Heatmap")
plt.show()
```



In [202…
```
data['target'].value_counts()
```

Out[202…
```
target
1    357
0    212
Name: count, dtype: int64
```

In [203…
```
#Divide the data into x any y
x = data.iloc[:,:-1] #indepent variable
y= data.iloc[:,-1]#dependent variable
```

In [204…
```
x
```

Out[204…

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst radius	worst texture
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	0.14710	0.2419	0.07871	...	25.380	17.33
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	0.07017	0.1812	0.05667	...	24.990	23.41
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740	0.12790	0.2069	0.05999	...	23.570	25.53
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	0.2597	0.09744	...	14.910	26.50
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	0.1809	0.05883	...	22.540	16.67
...	...	...	...	...	...	...	...	...	...	...	...	...	...
564	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	0.1726	0.05623	...	25.450	26.40
565	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	0.1752	0.05533	...	23.690	38.25
566	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	0.1590	0.05648	...	18.980	34.12
567	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	0.2397	0.07016	...	25.740	39.42
568	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	0.1587	0.05884	...	9.456	30.37

569 rows × 30 columns

In [205…

```
y
```

Out[205…

```
0      0
1      0
2      0
3      0
4      0
      ..
564    0
565    0
566    0
567    0
568    1
Name: target, Length: 569, dtype: int32
```

In [206…

```
# Split into training and testing sets
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.2,random_state=42)
```

In [207…

```
x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

Out[207…

```
((455, 30), (114, 30), (455,), (114,))
```

In [208…

```
x_train
```

Out[208…

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst radius	worst texture
68	9.029	17.33	58.79	250.5	0.10660	0.14130	0.31300	0.04375	0.2111	0.08046	...	10.310	22.65
181	21.090	26.57	142.70	1311.0	0.11410	0.28320	0.24870	0.14960	0.2395	0.07398	...	26.680	33.48
63	9.173	13.86	59.20	260.9	0.07721	0.08751	0.05988	0.02180	0.2341	0.06963	...	10.010	19.23
248	10.650	25.22	68.01	347.0	0.09657	0.07234	0.02379	0.01615	0.1897	0.06329	...	12.250	35.19
60	10.170	14.88	64.55	311.9	0.11340	0.08061	0.01084	0.01290	0.2743	0.06960	...	11.020	17.45
...	...	...	...	...	...	...	...	...	...	...	...	...	...
71	8.888	14.64	58.79	244.0	0.09783	0.15310	0.08606	0.02872	0.1902	0.08980	...	9.733	15.67
106	11.640	18.33	75.17	412.5	0.11420	0.10170	0.07070	0.03485	0.1801	0.06520	...	13.140	29.26
270	14.290	16.82	90.30	632.6	0.06429	0.02675	0.00725	0.00625	0.1508	0.05376	...	14.910	20.65
435	13.980	19.62	91.12	599.5	0.10600	0.11330	0.11260	0.06463	0.1669	0.06544	...	17.040	30.80
102	12.180	20.52	77.22	458.7	0.08013	0.04038	0.02383	0.01770	0.1739	0.05677	...	13.340	32.84

455 rows × 30 columns

In [209…

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

In [210…

```
x_train = scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)
```

In [211…
```python
# Train model (Logistic Regression)
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
```

In [212…
```python
model
```

Out[212…
```
▾ LogisticRegression
LogisticRegression()
```

In [213…
```python
model.fit(x_train,y_train)
```

Out[213…
```
▾ LogisticRegression
LogisticRegression()
```

In [214…
```python
x_train.shape
```

Out[214…
```
(455, 30)
```

In [215…
```python
model.coef_
```

Out[215…
```
array([[-0.43190368, -0.38732553, -0.39343248, -0.46521006, -0.07166728,
         0.54016395, -0.8014581 , -1.11980408,  0.23611852,  0.07592093,
        -1.26817815,  0.18887738, -0.61058302, -0.9071857 , -0.31330675,
         0.68249145,  0.17527452, -0.3112999 ,  0.50042502,  0.61622993,
        -0.87984024, -1.35060559, -0.58945273, -0.84184594, -0.54416967,
         0.01611019, -0.94305313, -0.77821726, -1.20820031, -0.15741387]])
```

In [216…
```python
model.intercept_
```

Out[216…
```
array([0.44558453])
```

In [217…
```python
y_pred = model.predict(x_test)
y_pred
```

Out[217…
```
array([1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1,
       0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1,
       1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1,
       0, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0,
       1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1,
       0, 1, 0, 0])
```

In [218…
```python
# Predictions and Evaluation
from sklearn.metrics import confusion_matrix,accuracy_score,classification_report
```

In [219…
```python
print(confusion_matrix(y_test,y_pred))
```

```
[[41  2]
 [ 1 70]]
```

In [220…
```python
print(accuracy_score(y_test,y_pred))
```

```
0.9736842105263158
```

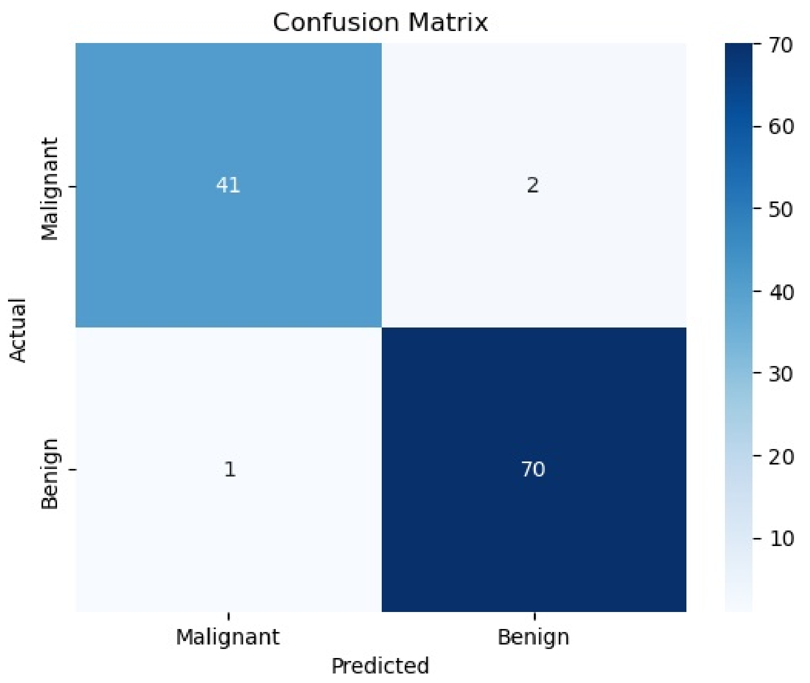
In [221…
```python
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.98      0.95      0.96        43
           1       0.97      0.99      0.98        71

    accuracy                           0.97       114
   macro avg       0.97      0.97      0.97       114
weighted avg       0.97      0.97      0.97       114
```

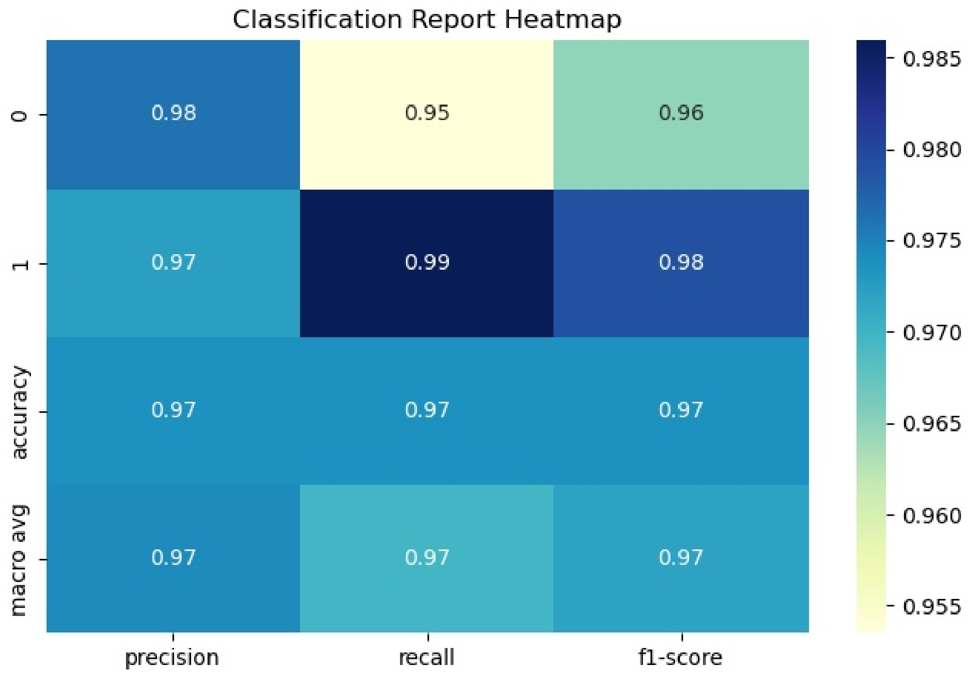
In [222…
```python
import seaborn as sns
conf_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Malignant', 'Benign'],
            yticklabels=['Malignant', 'Benign'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



In [223…

```
# 13. Visualize Classification Report
report_dict = classification_report(y_test, y_pred, output_dict=True)
report_df = pd.DataFrame(report_dict).transpose().drop(columns=['support'])

plt.figure(figsize=(8, 5))
sns.heatmap(report_df.iloc[:-1], annot=True, cmap='YlGnBu', fmt='.2f')
plt.title('Classification Report Heatmap')
plt.show()
```



In [ ]:

In [ ]:

In [ ]:

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js