Cancer Prediction

Dataset Information:

Target Variable (y):

• Diagnosis (M = malignant, B = benign)

Ten features (X) are computed for each cell nucleus:

- 1. radius (mean of distances from center to points on the perimeter)
- 2. texture (standard deviation of gray-scale values)
- 3. perimeter
- 4. area
- 5. smoothness (local variation in radius lengths)
- 6. compactness (perimeter^2 / area 1.0)
- 7. concavity (severity of concave portions of the contour)
- 8. concave points (number of concave portions of the contour)
- 9. symmetry
- 10. fractal dimension (coastline approximation 1)

For each characteristic three measures are given:

- a. Mean
- b. Standard error
- c. Largest/ Worst

Out[3]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoo
0	842302	М	17.99	10.38	122.80	1001.0	
1	842517	M	20.57	17.77	132.90	1326.0	
2	84300903	M	19.69	21.25	130.00	1203.0	
3	84348301	M	11.42	20.38	77.58	386.1	
4	84358402	М	20.29	14.34	135.10	1297.0	

5 rows × 33 columns

<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	<pre>fractal_dimension_se</pre>	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	<pre>fractal_dimension_worst</pre>	569 non-null	float64
32	Unnamed: 32	0 non-null	float64
dtype	es: float64(31), int64(1)	, object(1)	

memory usage: 146.8+ KB

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In [5]:
          Out[5]:
                              id radius_mean texture_mean perimeter_mean
                                                                        area_mean smooth
              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
                                                              75.170000
                                                                        420.300000
                                                16.170000
               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
             8 rows × 32 columns
             # Step 3 : define target (y) and features (X)
 In [6]:
In [7]:
           | cancer.columns
    Out[7]: Index(['id', 'diagnosis', 'radius_mean', 'texture_mean', 'perimeter_me
             an',
                     'area_mean', 'smoothness_mean', 'compactness_mean', 'concavity_
             mean',
                     'concave points_mean', 'symmetry_mean', 'fractal_dimension_mea
             n',
                     'radius_se', 'texture_se', 'perimeter_se', 'area_se', 'smoothne
             ss_se',
                     'compactness_se', 'concavity_se', 'concave points_se', 'symmetr
             y_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')
 In [8]:
           y = cancer['diagnosis']
           X = cancer.drop(['id','diagnosis','Unnamed: 32'],axis=1)
 In [9]:
           # Step 4 : train test split
In [10]:
             from sklearn.model selection import train test split
             X_train, X_test, y_train, y_test = train_test_split(X,y, train_size=0.7
```

```
In [11]: ▶ # check shape of train and test sample
            X_train.shape, X_test.shape, y_train.shape, y_test.shape
   Out[11]: ((398, 30), (171, 30), (398,), (171,))
         ▶ # Step 5 : select model
In [12]:
            from sklearn.linear_model import LogisticRegression
            model = LogisticRegression(max_iter=5000)
         # Step 6 : train or fit model
In [13]:
            model.fit(X_train,y_train)
   Out[13]: LogisticRegression(max_iter=5000)
In [14]:
         M model.intercept_
   Out[14]: array([-29.49840967])
In [15]:
         M model.coef
   Out[15]: array([[-9.04309380e-01, -1.88693401e-01, 2.36465162e-01,
                    -2.39701052e-02, 1.57767489e-01, 1.81651624e-01,
                     4.29904515e-01, 2.49073653e-01, 1.87042677e-01,
                     3.12701310e-02, -8.14808210e-04, -1.27998720e+00,
                    -2.15082640e-01, 1.27945786e-01, 2.75531281e-02,
                    -8.45325440e-02, -1.02460154e-02, 3.18227925e-02,
                     2.66934912e-02, -2.05532877e-02, -2.25545003e-01,
                     4.49709783e-01, 1.79244553e-01, 1.09126700e-02,
                     3.27078006e-01, 5.51684050e-01, 1.06887289e+00,
                     5.06025040e-01, 5.64121521e-01, 6.82532635e-02]])
y_pred = model.predict(X_test)
```

```
In [17]:
      ⋈ y_pred
  Out[17]: array(['B', 'M', 'M', 'B', 'M', 'B', 'M', 'B', 'M', 'B', 'M',
        'Β',
             'M',
             'B',
             'B',
             'Μ',
             'M', 'M', 'B', 'M', 'M', 'B', 'M', 'B', 'M', 'B', 'M', 'B',
        'B',
             'M',
             'B', 'B', 'B', 'M', 'B', 'M', 'B', 'M', 'B', 'M', 'B',
        'B',
             'Β',
             'M',
             'M', 'B', 'M', 'M', 'M', 'B', 'B', 'M', 'B', 'M', 'B', 'M',
        'B',
             'B',
             'B', 'M', 'M', 'M', 'B', 'B', 'B', 'M', 'B', 'M', 'B',
        'B',
             'B', 'B'], dtype=object)
      # Step 8 : model accuracy
In [18]:
        from sklearn.metrics import confusion matrix, accuracy score, classifid
In [19]:
      confusion matrix(y test,y pred)
  Out[19]: array([[97, 5],
             [ 2, 67]], dtype=int64)
In [20]:

    accuracy_score(y_test,y_pred)

  Out[20]: 0.9590643274853801
In [21]:
      print(classification report(y test,y pred))
                 precision
                          recall f1-score
                                      support
                     0.98
                           0.95
                                  0.97
               В
                                         102
                     0.93
                           0.97
               Μ
                                  0.95
                                          69
           accuracy
                                  0.96
                                         171
                     0.96
                           0.96
                                  0.96
                                         171
          macro avg
        weighted avg
                     0.96
                           0.96
                                  0.96
                                         171
```

In []:	M	
In []:	M	