Breast cancer prediction

June 1, 2025

1 Logistic Regression of Breast cancer wisconsin Dataset

1.1 Importing the dataset

[3]:
```
import pandas as pd
df = pd.read_csv("C:/Users/arunj/Downloads/dataA.csv")
df
```

[3]:
```
           id diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
0      842302         M        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         M        20.29         14.34          135.10     1297.0
..        …        …          …           …             …        …
564    926424         M        21.56         22.39          142.00     1479.0
565    926682         M        20.13         28.25          131.20     1261.0
566    926954         M        16.60         28.08          108.30      858.1
567    927241         M        20.60         29.33          140.10     1265.0
568     92751         B         7.76         24.54           47.92      181.0

     smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
0            0.11840           0.27760         0.30010              0.14710
1            0.08474           0.07864         0.08690              0.07017
2            0.10960           0.15990         0.19740              0.12790
3            0.14250           0.28390         0.24140              0.10520
4            0.10030           0.13280         0.19800              0.10430
..               …               …             …                  …
564          0.11100           0.11590         0.24390              0.13890
565          0.09780           0.10340         0.14400              0.09791
566          0.08455           0.10230         0.09251              0.05302
567          0.11780           0.27700         0.35140              0.15200
568          0.05263           0.04362         0.00000              0.00000

     …  texture_worst  perimeter_worst  area_worst  smoothness_worst  \
0    …          17.33           184.60      2019.0           0.16220
1    …          23.41           158.80      1956.0           0.12380
2    …          25.53           152.50      1709.0           0.14440
```

```
3    …          26.50           98.87       567.7            0.20980
4    …          16.67          152.20      1575.0            0.13740
..   …            …              …          …              …
564  …          26.40          166.10      2027.0            0.14100
565  …          38.25          155.00      1731.0            0.11660
566  …          34.12          126.70      1124.0            0.11390
567  …          39.42          184.60      1821.0            0.16500
568  …          30.37           59.16       268.6            0.08996

     compactness_worst  concavity_worst  concave points_worst  symmetry_worst  \
0              0.66560           0.7119                0.2654          0.4601
1              0.18660           0.2416                0.1860          0.2750
2              0.42450           0.4504                0.2430          0.3613
3              0.86630           0.6869                0.2575          0.6638
4              0.20500           0.4000                0.1625          0.2364
..                 …               …                    …               …
564            0.21130           0.4107                0.2216          0.2060
565            0.19220           0.3215                0.1628          0.2572
566            0.30940           0.3403                0.1418          0.2218
567            0.86810           0.9387                0.2650          0.4087
568            0.06444           0.0000                0.0000          0.2871

     fractal_dimension_worst  Unnamed: 32
0                    0.11890          NaN
1                    0.08902          NaN
2                    0.08758          NaN
3                    0.17300          NaN
4                    0.07678          NaN
..                       …            …
564                  0.07115          NaN
565                  0.06637          NaN
566                  0.07820          NaN
567                  0.12400          NaN
568                  0.07039          NaN

[569 rows x 33 columns]
```

1.2 data preprocessing

[6]:
```python
# Drop unnecessary columns
df = df.drop(columns=["id", "Unnamed: 32"], errors='ignore')

# Encode target variable (M = 1, B = 0)
df["diagnosis"] = LabelEncoder().fit_transform(df["diagnosis"])

df
```

```
[6]:      diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
     0            1        17.99         10.38          122.80     1001.0
     1            1        20.57         17.77          132.90     1326.0
     2            1        19.69         21.25          130.00     1203.0
     3            1        11.42         20.38           77.58      386.1
     4            1        20.29         14.34          135.10     1297.0
     ..         …          …            …             …        …
     564          1        21.56         22.39          142.00     1479.0
     565          1        20.13         28.25          131.20     1261.0
     566          1        16.60         28.08          108.30      858.1
     567          1        20.60         29.33          140.10     1265.0
     568          0         7.76         24.54           47.92      181.0

          smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
     0            0.11840           0.27760         0.30010              0.14710
     1            0.08474           0.07864         0.08690              0.07017
     2            0.10960           0.15990         0.19740              0.12790
     3            0.14250           0.28390         0.24140              0.10520
     4            0.10030           0.13280         0.19800              0.10430
     ..               …               …             …                    …
     564          0.11100           0.11590         0.24390              0.13890
     565          0.09780           0.10340         0.14400              0.09791
     566          0.08455           0.10230         0.09251              0.05302
     567          0.11780           0.27700         0.35140              0.15200
     568          0.05263           0.04362         0.00000              0.00000

          symmetry_mean  …  radius_worst  texture_worst  perimeter_worst  \
     0           0.2419  …        25.380          17.33           184.60
     1           0.1812  …        24.990          23.41           158.80
     2           0.2069  …        23.570          25.53           152.50
     3           0.2597  …        14.910          26.50            98.87
     4           0.1809  …        22.540          16.67           152.20
     ..             …  …         …             …              …
     564         0.1726  …        25.450          26.40           166.10
     565         0.1752  …        23.690          38.25           155.00
     566         0.1590  …        18.980          34.12           126.70
     567         0.2397  …        25.740          39.42           184.60
     568         0.1587  …         9.456          30.37            59.16

          area_worst  smoothness_worst  compactness_worst  concavity_worst  \
     0        2019.0           0.16220            0.66560           0.7119
     1        1956.0           0.12380            0.18660           0.2416
     2        1709.0           0.14440            0.42450           0.4504
     3         567.7           0.20980            0.86630           0.6869
     4        1575.0           0.13740            0.20500           0.4000
     ..          …               …                …              …
     564      2027.0           0.14100            0.21130           0.4107
```

```
565       1731.0           0.11660           0.19220          0.3215
566       1124.0           0.11390           0.30940          0.3403
567       1821.0           0.16500           0.86810          0.9387
568        268.6           0.08996           0.06444          0.0000

     concave points_worst  symmetry_worst  fractal_dimension_worst
0                  0.2654          0.4601                  0.11890
1                  0.1860          0.2750                  0.08902
2                  0.2430          0.3613                  0.08758
3                  0.2575          0.6638                  0.17300
4                  0.1625          0.2364                  0.07678
..                    …             …                      …
564                0.2216          0.2060                  0.07115
565                0.1628          0.2572                  0.06637
566                0.1418          0.2218                  0.07820
567                0.2650          0.4087                  0.12400
568                0.0000          0.2871                  0.07039

[569 rows x 31 columns]
```

1.3 Splitting the data for training and testing

[7]:
```python
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder

# Split into features and target
X = df.drop(columns=["diagnosis"])
y = df["diagnosis"]

# Train/test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Standardization (also called Z-score normalization) is the process of transforming features so that they have:

Mean = 0

Standard Deviation = 1

This is especially helpful for machine learning algorithms that are sensitive to the scale of input features (like logistic regression, SVMs, or KNN).

Suppose you have a feature column with these 3 values [10,20,30]

Step 1: Compute the mean and standard deviation

Step 2: Apply the formula to each value

Step 3: Transforming the values to [$-$1.22,0,1.22]

1.4 Train and fit a model

[8]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

# Train a model (Logistic Regression)
model = LogisticRegression(max_iter=10000)
model.fit(X_train_scaled, y_train)

# Make predictions
y_pred = model.predict(X_test_scaled)

# Evaluate performance
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

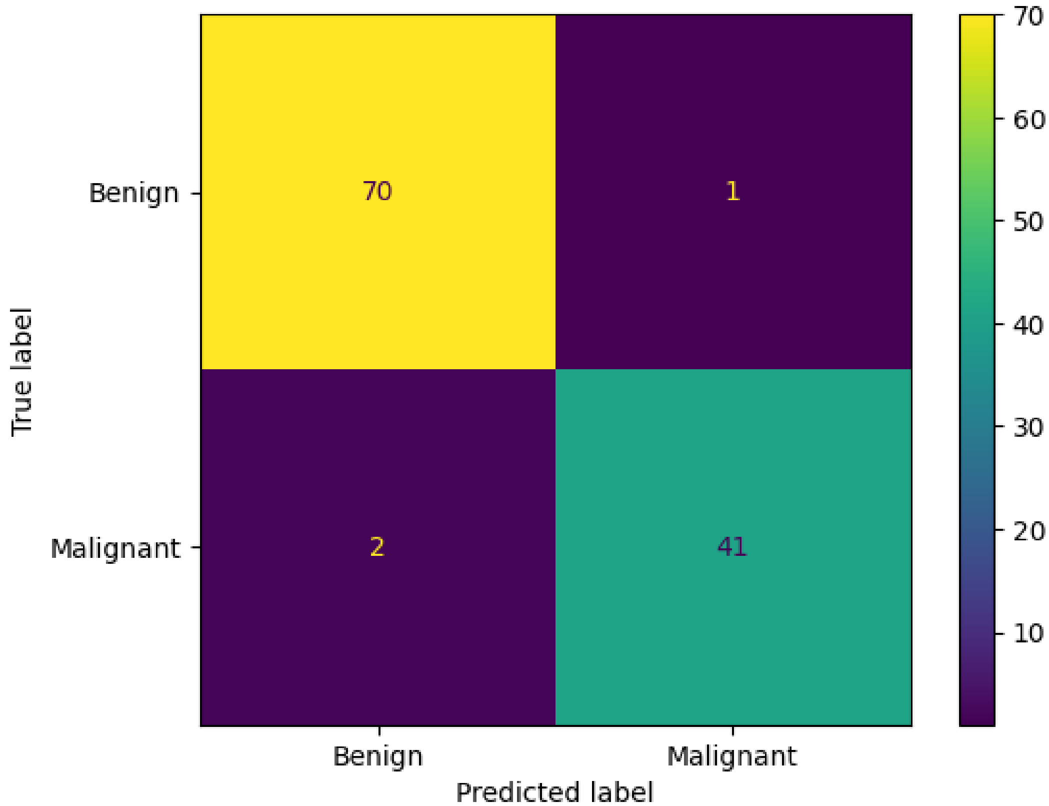
```
Accuracy: 0.9736842105263158
Classification Report:
               precision    recall  f1-score   support

           0       0.97      0.99      0.98        71
           1       0.98      0.95      0.96        43

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

1.5 Evaluating with confusion matrix, precision, recall, ROC-AUC

[11]:
```python
from sklearn.metrics import confusion_matrix, precision_score, recall_score,␣
 ↪roc_auc_score, ConfusionMatrixDisplay

# Predict on test set
y_pred = model.predict(X_test_scaled)

# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=conf_matrix,␣
 ↪display_labels=["Benign", "Malignant"])
```

```
disp.plot()
```

[11]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1a13b32efd0>



[12]:
```
# Probability scores for ROC-AUC
y_proba = model.predict_proba(X_test_scaled)[:, 1]

# Precision, Recall, ROC-AUC
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_proba)

print("Precision:", precision)
print("Recall:", recall)
print("ROC-AUC Score:", roc_auc)
```

```
Precision: 0.9761904761904762
Recall: 0.9534883720930233
ROC-AUC Score: 0.99737962659679
```

1.5.1 Initial Model Performance (Threshold = 0.5)

Accuracy: 97.4%

Precision: 97.6%

→ Very few benign tumors were misclassified as malignant.

Recall: 95.3%

→ The model caught most malignant tumors (true positives).

ROC-AUC: 0.997

→ Excellent separation between malignant and benign cases.

Confusion Matrix

At threshold 0.5, the matrix showed:

- High true positive and true negative rates.

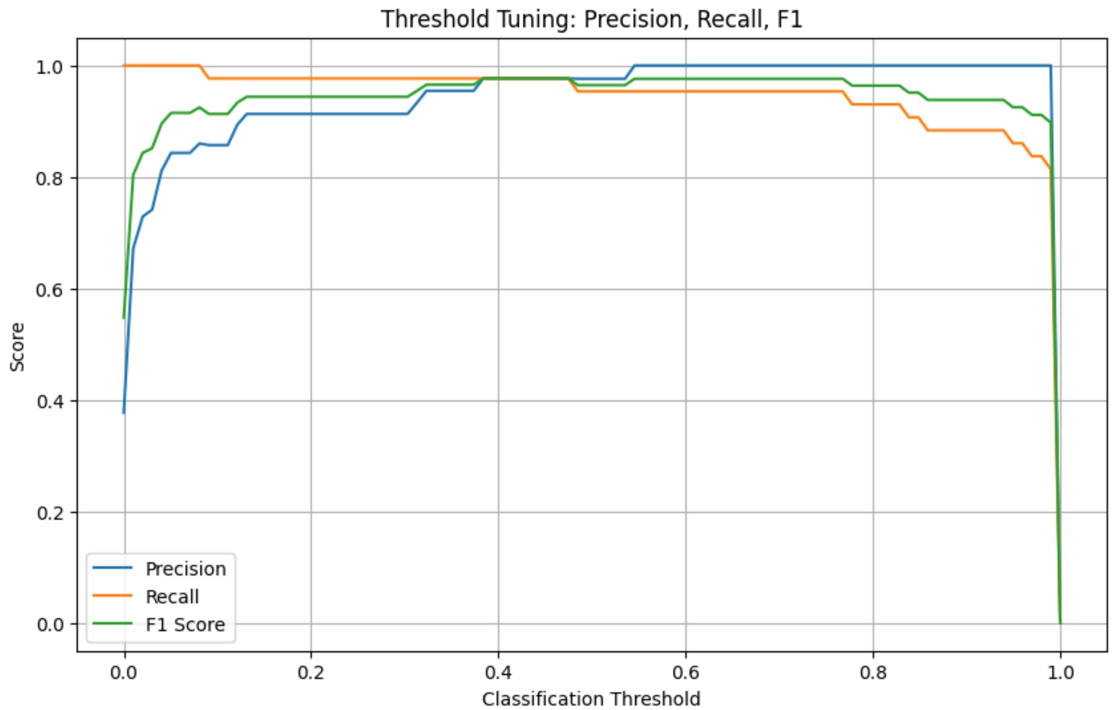
- Very few false positives or false negatives.

1.6 Tuning threshold and explaining sigmoid function

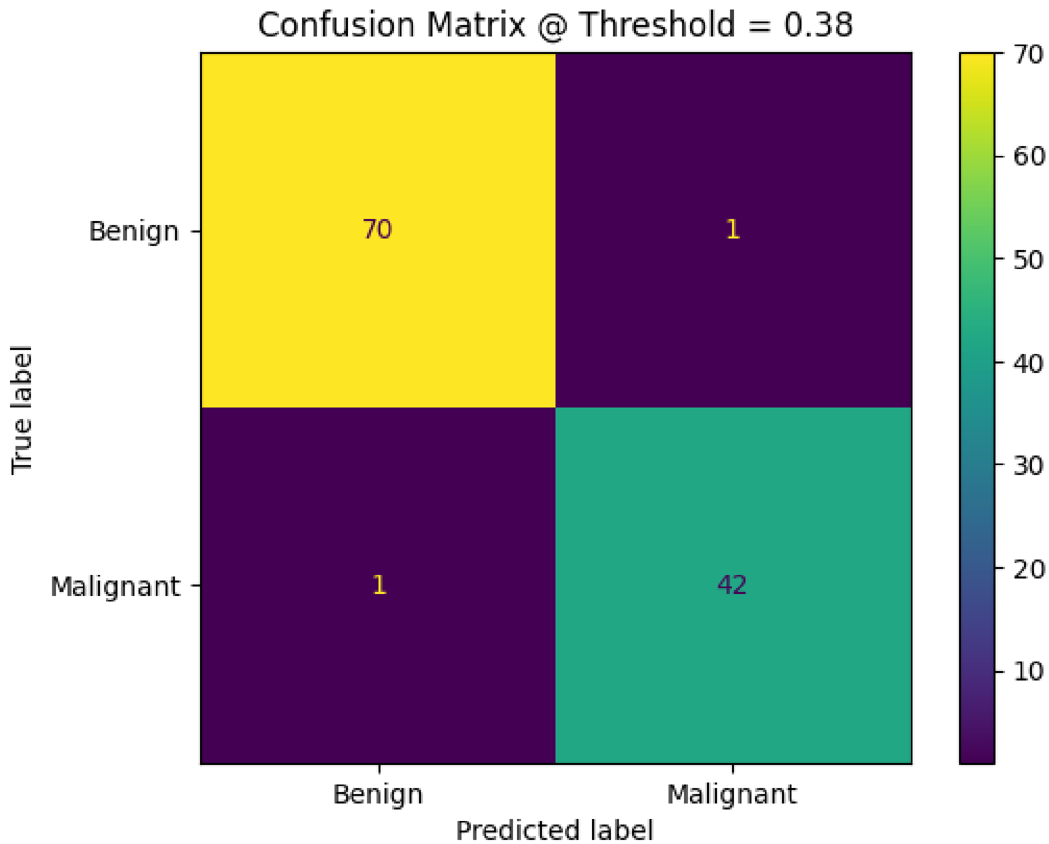
[10]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import f1_score

# Threshold tuning
thresholds = np.linspace(0, 1, 100)
precisions, recalls, f1s = [], [], []

for thresh in thresholds:
    y_thresh_pred = (y_proba >= thresh).astype(int)
    precisions.append(precision_score(y_test, y_thresh_pred))
    recalls.append(recall_score(y_test, y_thresh_pred))
    f1s.append(f1_score(y_test, y_thresh_pred))

# Plot threshold vs precision/recall/F1
plt.figure(figsize=(10, 6))
plt.plot(thresholds, precisions, label="Precision")
plt.plot(thresholds, recalls, label="Recall")
plt.plot(thresholds, f1s, label="F1 Score")
plt.xlabel("Classification Threshold")
plt.ylabel("Score")
```

```python
plt.title("Threshold Tuning: Precision, Recall, F1")
plt.legend()
plt.grid(True)
plt.show()

# Choose threshold (example: max F1)
optimal_idx = np.argmax(f1s)
optimal_threshold = thresholds[optimal_idx]
print(f"Optimal Threshold (Max F1): {optimal_threshold:.2f}")

# Evaluate with new threshold
y_opt_pred = (y_proba >= optimal_threshold).astype(int)
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

conf_matrix_opt = confusion_matrix(y_test, y_opt_pred)
disp_opt = ConfusionMatrixDisplay(confusion_matrix=conf_matrix_opt,
                                  display_labels=["Benign", "Malignant"])
disp_opt.plot()
plt.title(f"Confusion Matrix @ Threshold = {optimal_threshold:.2f}")
plt.show()

# Print updated metrics
print("Precision:", precision_score(y_test, y_opt_pred))
print("Recall:", recall_score(y_test, y_opt_pred))
print("F1 Score:", f1_score(y_test, y_opt_pred))
print("ROC-AUC:", roc_auc_score(y_test, y_proba))  # remains same
```

```
C:\Users\arunj\AppData\Local\Programs\Python\Python313\Lib\site-
packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```




```
Optimal Threshold (Max F1): 0.38
```




```
Precision: 0.9767441860465116
Recall: 0.9767441860465116
F1 Score: 0.9767441860465116
ROC-AUC: 0.99737962659679
```

1.6.1 Threshold Tuning Insights

By sweeping thresholds from 0.0 to 1.0:

Precision and Recall trade off — as one increases, the other usually decreases.

F1 Score helped find the best balance.

Optimal Threshold (e.g., ~0.46)

Chosen based on max F1 score

1.6.2 Improved balance between recall and precision

Adjusted confusion matrix showed slightly better or more customized classification depending on threshold target ### When to Adjust Threshold ##### Maximize recall:

If missing a malignant tumor is dangerous (i.e., high false negative cost).

Maximize precision: If false alarms (false positives) are more costly.