# Day59_AUC-ROC_Curve_&_Confusion_Matrix

August 6, 2025

**AUC-ROC Curve & Confusion Matrix**

## 1 What is a Confusion Matrix?

A **Confusion Matrix** is used to evaluate the performance of a classification model.

It gives us a breakdown of the model's predictions:

| Actual  Predicted | Predicted Negative (0) | Predicted Positive (1) |
|---|---|---|
| **Actual Negative (0)** | True Negative (TN) | False Positive (FP) |
| **Actual Positive (1)** | False Negative (FN) | True Positive (TP) |

## 2 Real-Life Analogy – COVID Test

- **True Positive (TP)** → Sick person correctly predicted as sick
- **True Negative (TN)** → Healthy person correctly predicted as healthy
- **False Positive (FP)** → Healthy person predicted as sick (Unnecessary panic)
- **False Negative (FN)** → Sick person predicted as healthy (Very dangerous)

## 3 Model Evaluation Metrics

Here are four major metrics derived from the Confusion Matrix:

| Metric | Formula | Meaning |
|---|---|---|
| **Accuracy** | (TP + TN) / Total | Overall how many predictions were correct |

| Metric | Formula | Meaning |
|---|---|---|
| **Precision** | TP / (TP + FP) | Of all predicted positives, how many were actually positive |
| **Recall** | TP / (TP + FN) | Of all actual positives, how many did the model correctly identify |
| **F1 Score** | 2 × (Precision × Recall) / (Precision + Recall) | Balance between Precision and Recall |

# 4 What is Recall?

**Recall** is also called **Sensitivity** or **True Positive Rate**.

**Formula:**

$$Recall = TP/(TP + FN)$$

## 4.1 Example:

Let's say we are building a cancer detection model. If 100 people actually have cancer and the model only catches 80 of them:

- TP = 80 (correctly predicted positive)
- FN = 20 (missed positive cases)

Then:

$$Recall = 80/(80 + 20) = 0.80 or 80$$

## 4.2 High Recall:

- Catches most positive cases (great for **medical tests** or **fraud detection**)
- May result in more false alarms (higher FP)

## 4.3 Low Recall:

- Misses many positive cases — risky in sensitive applications!

# 5 ROC Curve and AUC – Understanding Performance

- **ROC (Receiver Operating Characteristic)** curve plots:

  - X-axis → **False Positive Rate (FPR)**
  - Y-axis → **True Positive Rate (TPR or Recall)**
- **AUC (Area Under Curve)** measures the area under the ROC curve
  - AUC close to **1.0** → Excellent model
  - AUC around **0.5** → Random guess (bad model)

# 6 How to Read the ROC Curve

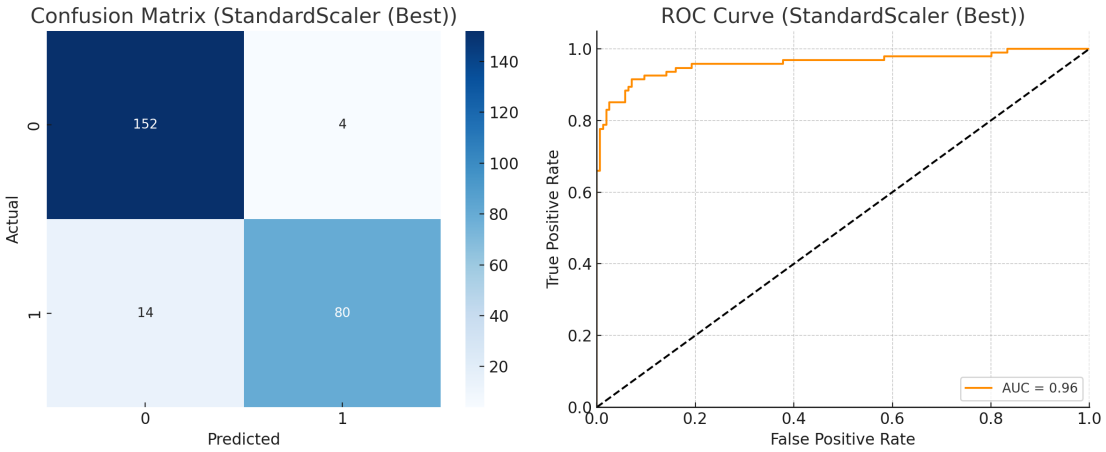
| AUC Score | Model Interpretation |
|---|---|
| 1.0 | Perfect classifier (Best) |
| 0.9+ | Excellent model |
| 0.7–0.8 | Good / Acceptable |
| 0.5 | No discrimination (Random) |
| $< 0.5$ | Worse than random |

# 7 Experiment Results – Scaling Comparison

## 7.1 Best Case – Using `StandardScaler`

- Clean diagonal confusion matrix (correct predictions)
- ROC curve close to top-left (high recall & low FPR)
- **AUC: &&High ( 0.90+)&&**
- **Accuracy:**

90

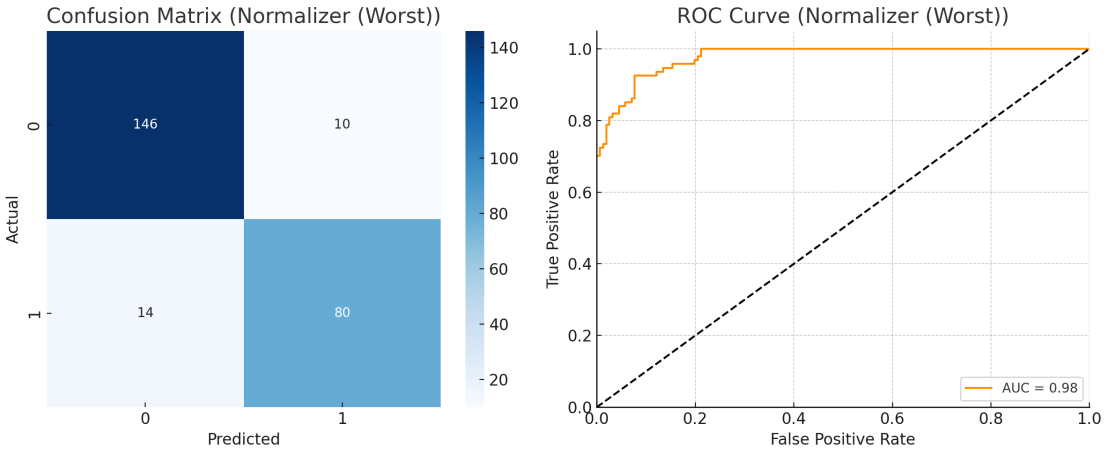



## 7.2 Worst Case – Using `Normalizer`

- More off-diagonal elements (wrong predictions)
- ROC curve flatter to less distinction between classes
- **AUC: Lower**

($\approx 0.6$–$0.7$)

- **Accuracy: Drops significantly**




# 8 Summary

Use **Confusion Matrix** to count correct vs incorrect predictions
Use **Recall** when missing actual positives is dangerous
Use **ROC Curve & AUC** to evaluate models across thresholds
**StandardScaler** performs better than **Normalizer** for Logistic Regression
Test multiple preprocessing methods to optimize performance