Confusion Matrix → Accuracy

accuracy: 90.00%

	true MACET	true LANCAR	class precision
pred. MACET	53	4	92.98%
pred. LANCAR	6	37	86.05%
class recall	89.83%	90.24%	

- pred MACET- true MACET: Jumlah data yang diprediksi macet dan kenyataannya macet (**TP**)
- pred LANCAR-true LANCAR: Jumlah data yang diprediksi lancar dan kenyataannya lancar (**TN**)
- pred MACET-true LANCAR: Jumlah data yang diprediksi macet tapi kenyataannya lancer (**FP**)
- pred LANCAR-true MACET: Jumlah data yang diprediksi lancar tapi kenyataanya macet (**FN**)

$$\text{Accuracy} = \frac{\mathbf{TP} + \mathbf{TN}}{\mathbf{TP} + \mathbf{TN} + \mathbf{FP} + \mathbf{FN}} = \frac{53 + 37}{53 + 37 + 4 + 6} = \frac{90}{100} = 90\%$$

Precision and Recall, and F-measures

- **Precision**: exactness – what % of tuples that the classifier labeled as positive are actually positive

$$precision = \frac{TP}{TP + FP}$$

- **Recall**: completeness – what % of positive tuples did the classifier label as positive?
  - Perfect score is 1.0
  - Inverse relationship between precision & recall

$$recall = \frac{TP}{TP + FN}$$

- **F measure** (F1 or F-score): harmonic mean of precision and recall,

$$F = \frac{2 \times precision \times recall}{precision + recall}$$

- **Fß**: weighted measure of precision and recall
  - assigns ß times as much weight to recall as to precision

$$F_\beta = \frac{(1 + \beta^2) \times precision \times recall}{\beta^2 \times precision + recall}$$

Sensitivity and Specificity

Binary classification should be both sensitive and specific as much as possible:

1. Sensitivity measures the proportion of true ’positives’ that are correctly identified (True Positive Rate (TP Rate) or Recall)

$$Sensitivity = \frac{Number\ of\ 'True\ Positives'}{Number\ of\ 'True\ Positives' + Number\ of\ 'False\ Negatives'},$$

2. Specificity measures the proportion of true ’negatives’ that are correctly identified (False Negative Rate (FN Rate or Precision)

$$Specificity = \frac{Number\ of\ 'True\ Negatives'}{Number\ of\ 'True\ Negatives' + Number\ of\ 'False\ Positives'},$$

PPV and NPV

We need to know the probability that the classifier will give the correct diagnosis, but the sensitivity and specificity do not give us this information

- Positive Predictive Value (PPV) is the proportion of cases with 'positive' test results that are correctly diagnosed

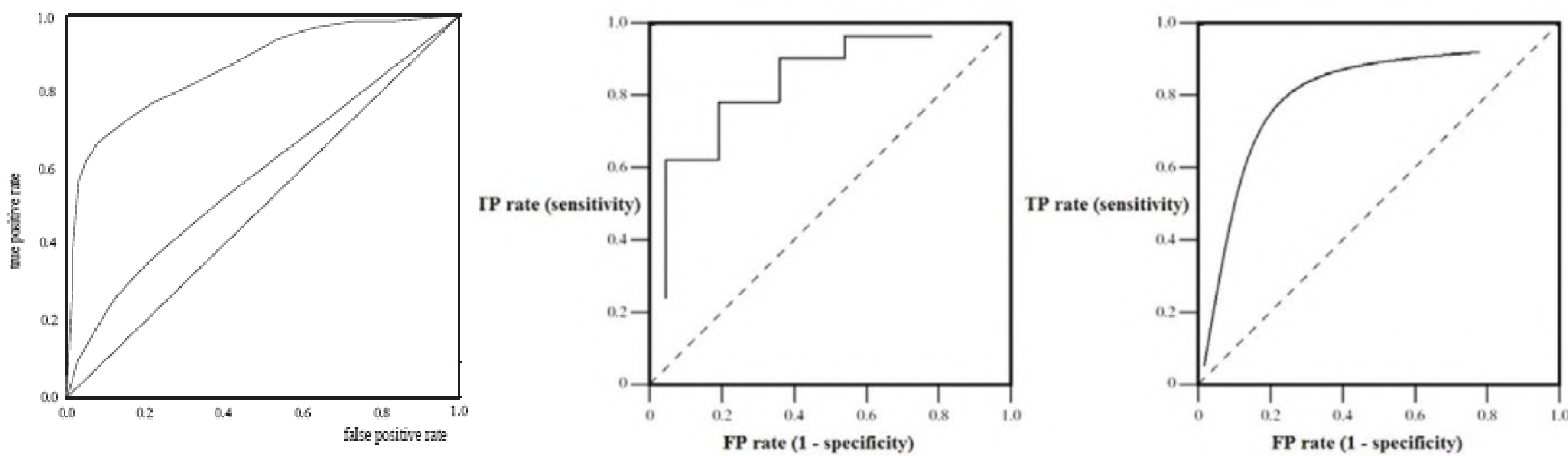
$$PPV = \frac{Number\ of\ 'True\ Positives'}{Number\ of\ 'True\ Positives' + Number\ of\ 'False\ Positives'},$$

- Negative Predictive Value (NPV) is the proportion of cases with 'negative' test results that are correctly diagnosed

$$NPV = \frac{Number\ of\ 'True\ Negatives'}{Number\ of\ 'True\ Negatives' + Number\ of\ 'False\ Negatives'}.$$

Kurva ROC - AUC (Area Under Curve)

- ROC (Receiver Operating Characteristics) curves: for visual comparison of classification models
  - Originated from signal detection theory
- ROC curves are two-dimensional graphs in which the TP rate is plotted on the Y-axis and the FP rate is plotted on the X-axis
- ROC curve depicts relative trade-offs between benefits ('true positives') and costs ('false positives')
- Two types of ROC curves: discrete and continuous



Kurva ROC - AUC (Area Under Curve)