General Notes
Evaluation Metrics

1 — Precision: It is implied as the measure of the correctly identified positive cases from all the predicted positive cases.
(TP/(TP+FP))
Thus, it is useful when the costs of False Positives is high.

2 — Recall: It is the measure of the correctly identified positive cases
True positive rate
(TP/TP+FN)
from all the actual positive cases. **It is important when the cost of False Negatives is high.**

Recall is more important where Overlooked Cases (False Negatives) are **more costly** than False Alarms (False Positive). The focus in these problems is finding the positive cases.

Precision is more important where False Alarms (False Positives) are more costly than Overlooked Cases (False Negatives).

<u>**About Accuracy Vs F1-Score**</u>

3 — Accuracy: One of the more obvious metrics, it is the measure of all the correctly identified cases. It is most used when all the classes are equally important.

$$\text{Accuracy} = \frac{\textbf{True Positive + True Negative}}{\textbf{(True Positive + False Positive + True Negative + False Negative)}}$$

$$= \frac{25 + 65}{(25 + 5 + 65 + 5)} = \frac{90}{100} = 0.90$$

4 — F1-score: This is the harmonic mean of Precision and Recall and gives a better measure of the incorrectly classified cases than the Accuracy Metric.

$$\text{F1-score} = \left(\frac{\text{Recall}^{-1} + \text{Precision}^{-1}}{2}\right)^{-1} = 2 * \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})}$$

F1-Score
We use the Harmonic Mean since it penalises the extreme values.

Accuracy is used when the True Positives and True negatives are more important while F1-score is used when the False Negatives and False Positives are crucial

Accuracy can be used when the class distribution is similar while F1-score is a better metric when there are imbalanced classes as in the above case.

<u>About F1-Score Vs mAP</u>

F measure gives the same weight to the precision and recall while mAP choose the best precision from all recalls

Links:
https://neptune.ai/blog/f1-score-accuracy-roc-auc-pr-auc

ROC curve intuition:
https://towardsdatascience.com/demystifying-roc-curves-df809474529a#:~:text=When%20the%20class%20distribution%20in,minimizes%20the%20mis%2Dclassification%20cost.