Experiment No:4

Aim: Implementation of confusion matri0078

Theory:

Confusion matrix is a very popular measure used while solving classification problems. It can be applied to binary classification as well as for multiclass classification problems. An example of a confusion matrix for binary classification is shown in Table 5.1.

Table 5.1. Confusion matrix for binary classification.

Empty Cell	Empty Cell	**Predicted**	
Actual		Negative	Positive
	Negative	TN	FP
	Positive	FN	TP

Confusion matrices represent counts from predicted and actual values. The output “TN” stands for True Negative which shows the number of negative examples classified accurately. Similarly, “TP” stands for True Positive which indicates the number of positive examples classified accurately. The term “FP” shows False Positive value, i.e., the number of actual negative examples classified as positive; and “FN” means a False Negative value which is the number of actual positive examples classified as negative.

Methods of evaluation

3.1 Confusion matrix

The confusion matrix, also known as the error matrix, is depicted by a matrix describing the performance of a classification model on a set of test data (Fig. 3.5).

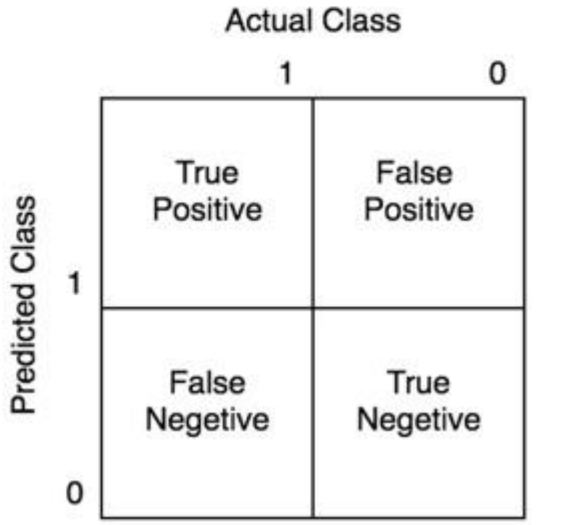

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Figure 3.5. Confusion matrix visualization.

True positive (TP): Observation is predicted positive and is actually positive. False positive (FP): Observation is predicted positive and is actually negative. True negative (TN): Observation is predicted negative and is actually negative. False negative (FN): Observation is predicted negative and is actually positive.

3.2 Accuracy

Accuracy gives the proportion of the total number of predictions that were correct:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

3.3 Precision

Precision or the positive predictive value, is the fraction of positive values out of the total predicted positive instances. In other words, precision is the proportion of positive values that were correctly identified:

$$\text{Precision} = \frac{TP}{TP + FP}$$

3.4 Sensitivity

Sensitivity, recall, or the TP rate (TPR) is the fraction of positive values out of the total actual positive instances (i.e., the proportion of actual positive cases that are correctly identified):

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

3.5 Specificity

Specificity gives the fraction of negative values out of the total actual negative instances. In other words, it is the proportion of actual negative cases that are correctly identified. The FP rate is given by (1 – specificity):

$$\text{Specificity} = \frac{TN}{TN + FP}$$

3.6 F1 score

The *F*1 score, *F* score, or *F* measure is the harmonic mean of precision and sensitivity it gives importance to both factors:

$$F1\ \text{Score} = 2 \times \frac{\text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}}$$

3.7 Root mean square error

The root mean square error is defined as the measure of the differences between values that are predicted by a model and values that are actually observed. Here, *N* is the number of observations [8]:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} \left(\text{Predicted}_i - \text{Actual}_i\right)^2}{N}}$$

3.8 AUC-ROC curve

The receiver operating characteristics (ROC) curve is the plot between sensitivity and the FP rate for various threshold values. The area under curve (AUC) is the area under this ROC curve; it is used to measure the quality of a classification model [9]. The larger the area, the better the performance.

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