Confusion Matrix:

In the field of machine learning and specifically the problem of statistical classification, a confusion matrix, also known as an error matrix.

A confusion matrix is a table that is often used to describe the performance of a classification model (or “classifier”) on a set of test data for which the true values are known. It allows the visualization of the performance of an algorithm.

A confusion matrix is a summary of prediction results on a classification problem.  
The number of correct and incorrect predictions are summarized with count values and broken down by each class. This is the key to the confusion matrix.

The confusion matrix shows the ways in which your classification model is confused when it makes predictions.

Accuracy:

Accuracy = total correct prediction / total data in confusion matrix

OR

Accuracy = TP + TN / TP + TN + FP + FN

**Definition of the Terms:**  
• Positive (P) : Observation is positive (for example: is an apple).  
• Negative (N) : Observation is not positive (for example: is not an apple).  
• True Positive (TP) : Observation is positive, and is predicted to be positive.  
• False Negative (FN) : Observation is positive, but is predicted negative.  
• True Negative (TN) : Observation is negative, and is predicted to be negative.  
• False Positive (FP) : Observation is negative, but is predicted positive.

**Precision, recall and f1-score:**

Besides the accuracy, there are several other performance measures which can be computed from the confusion matrix. Some of the main ones are obtained using the function **classification\_report**

**from** sklearn.metrics **import** classification\_report  
  
print(classification\_report(y\_test, y\_pred))

**Precision** :

*When it predicts the positive result, how often is it correct*

To get the value of precision we divide the total number of correctly classified positive examples by the total number of predicted positive examples. High Precision indicates an example labeled as positive is indeed positive (small number of FP).  
Precision is given by the relation:

Precision = TP / TP + FP

Recall:

*When it is actually the positive result, how often does it predict correctly*

Recall can be defined as the ratio of the total number of correctly classified positive examples divide to the total number of positive examples. High Recall indicates the class is correctly recognized (small number of FN).

Recall = TP / TP + FN

**High recall, low precision:**This means that most of the positive examples are correctly recognized (low FN) but there are a lot of false positives.

**Low recall, high precision:**This shows that we miss a lot of positive examples (high FN) but those we predict as positive are indeed positive (low FP)

F1-score(measure) = 2 \* Recall \* Precision / Recall + Precision