

**Assignment 4**

**Problem Statement:**

In this assignment, we apply various machine learning evaluation metrics to assess the performance of a classification model. We are provided with a dataset consisting of actual and predicted values for a binary classification task. Using this data, we will create a confusion matrix and calculate key evaluation metrics, including accuracy, precision, recall, and F1 score.

**Task Overview:**

In this assignment, we evaluate a binary classification model's performance by analyzing the confusion matrix. The key steps involved are:

1. **Confusion Matrix** – To visualize the performance of the classification model.
2. **Accuracy** – To measure the proportion of correct predictions.
3. **Precision** – To evaluate the proportion of correct positive predictions.
4. **Recall** – To assess the proportion of actual positives correctly identified by the model.
5. **F1 Score** – To balance precision and recall in a single metric.

**Objective:**

1. **Evaluate Classification Model** – Assess the performance of a classifier using key metrics.
2. **Confusion Matrix Analysis** – Understand the relationship between actual and predicted values.
3. **Use Scikit-Learn for Metrics** – Leverage Python’s scikit-learn library to calculate various evaluation metrics.

**Tools and Resources:**

* **Software Used:** Google Colab
* **Libraries Used:** Numpy, Scikit-learn, Matplotlib, Seaborn

**Key Functions Used:**

1. **Confusion Matrix:** Used to compare actual vs. predicted values.
2. **Accuracy Score:** Calculated using the accuracy\_score function to determine the overall accuracy of the model.
3. **Precision Score:** Computed using the precision\_score function to evaluate the percentage of true positives among predicted positives.
4. **Recall Score:** Evaluated using the recall\_score function to determine how well the model identifies true positives.
5. **F1 Score:** Calculated using the f1\_score function to get a balanced view of the model's performance by considering both precision and recall.

**Methodology:**

1. **Step 1: Confusion Matrix**
   * The **confusion matrix** is created using the actual and predicted labels. It provides a visual representation of the number of true positives, false positives, true negatives, and false negatives. This helps in understanding the performance of the classification model.
   * The confusion matrix for the given dataset is as follows:

|  | **Predicted: Positive** | **Predicted: Negative** |
| --- | --- | --- |
| **Actual: Positive** | 4 (True Positive) | 1 (False Negative) |
| **Actual: Negative** | 1 (False Positive) | 4 (True Negative) |

**Step 2: Calculate the Metrics**

* + After creating the confusion matrix, we calculate the following evaluation metrics:
    - **Accuracy:** This metric measures the proportion of correct predictions made by the model. It is calculated using the formula:

True Positives + True Negatives

Accuracy=

Total Samples

* + - **Precision:** Precision evaluates the proportion of correctly predicted positive instances out of all instances predicted as positive. It is calculated using the formula:

True Positives

Precision =

True Positives + False Positives

* + - **Recall:** Recall measures the proportion of actual positive instances correctly identified by the model. It is calculated as:

True Positives

Recall =

True Positives + False Negatives

**F1 Score:** The F1 score is the harmonic mean of precision and recall. It provides a balanced view of the classifier's performance, especially in imbalanced datasets. It is calculated using the formula:

Precision × Recall

F1 = 2 ×

Precision + Recall

1. **Confusion Matrix Visualization:**
   * The confusion matrix is visualized using a heatmap to display the relationship between actual and predicted labels. This provides insights into how well the classifier distinguishes between the two classes (positive and negative).

**Advantages of Using Evaluation Metrics:**

1. **Comprehensive Evaluation:** These metrics provide a thorough evaluation of the classification model, covering various aspects of performance.
2. **Precision and Recall Trade-off:** The F1 score balances precision and recall, making it useful when the dataset is imbalanced.
3. **Model Optimization:** Understanding these metrics helps to fine-tune the model and improve its performance.

**Challenges:**

* **Imbalanced Datasets:** In cases where the classes are imbalanced, accuracy may not be the best metric to assess the model's performance.
* **Interpretation of Metrics:** Understanding the trade-offs between precision, recall, and F1 score can sometimes be difficult for new learners.

**Conclusion:**

In this assignment, I used machine learning evaluation metrics to assess the performance of a binary classification model. The process involved:

* **Confusion Matrix Visualization**: Understanding the model's behavior through the confusion matrix.
* **Computation of Key Metrics**: Calculating accuracy, precision, recall, and F1 score to measure performance.
* **Insights Gained**: These metrics helped in understanding how well the model classified the positive and negative instances.