**Results**

Table 1 depicts the performance metrics of the XGBoost classifier when identifying fraudulent claims for insurance. The metrics consist of the precision, recall rates, and F1-scores for every target category and general accuracy, macro-average, and weighted-average scores.

|  |  |  |  |
| --- | --- | --- | --- |
| Target Class | Precision | Recall | F1-score |
| Genuine Claims (Class 0) | 0.82 | 0.86 | 0.84 |
| Fraudulent Claims (Class 1) | 0.56 | 0.49 | 0.52 |
| Overall Metrics | Accuracy | Macro-average | Weighted-average |
|  | 0.76 | 0.68 | 0.75 |

Table - 1

**Interpretation**

**Class 0 – Genuine Claims:**

* According to the precision rate of 0.82, it is correct approximately 82% of the time when the system identifies a claim as genuine.
* The recall score of 0.86 indicates that this classifier can detect about 86% of all real genuine claims.
* In addition, for genuine claims, its F1-score is 0.84 which provides an even measure on both precision and recall values thus overall good performance in this class.

**Class 1 – Fraudulent Claims:**

* It means that if it predicts that a claim is fraudulent, there are around 56% chances it will be right.
* When we talk about recall score for class one, we mean how many actual fraud cases were captured by the model (49%).
* Additionally, an F1 -score of 0.52 stands for harmonic mean between precision and recall on fraudulent claims hence shows moderate performance in this class.

**Overall Performance:**

* The overall accuracy of the classifier equals to 0.76 indicating that out of all claims made only some have been predicted accurately.
* An average F1-score is given as macro-average F1-score with a value of 0.68 indicting balance in terms of performance on both classes by the classifier.
* Lastly, weighted average F1-score 0.75 takes into account proportionate average based on class dataset.

**Discussion**

The findings indicate the capability of XGBoost classifier to identify authentic claims with high precision and recall. Although the performance in fraud detection can be further improved, it is possible that the model may have potential for real-world use in detecting insurance fraud. It is achievable through exploring methods such as feature engineering and model optimization to improve classifier’s performance and thereby contribute towards an improved accuracy of fraudulent claims detection during processing of insurance claims.