**Churn Prediction Model Performance Report**

**Model:**  Logistic Regression

**Data:** Bank Customer Churn Prediction Dataset

**Objective:** To predict which customers are likely to churn (i.e., close their accounts).

**Results Overview:**

The model achieved an overall accuracy of 81.05% on the test dataset. However, a more detailed examination of the precision, recall, F1-score, and confusion matrix reveals a significant imbalance in the model's performance across the two classes (non-churn vs. churn).

**Detailed Analysis:**

* **Accuracy:** 81.05%. This indicates that the model correctly classified 81.05% of all customers in the test dataset. While this seems like a reasonable result at first glance, it can be misleading in cases with imbalanced classes.
* **Precision:**
  + **Class 0 (Non-Churn):** 0.83. This means that when the model predicted a customer would *not* churn, it was correct 83% of the time.
  + **Class 1 (Churn):** 0.55. This means that when the model predicted a customer *would* churn, it was correct only 55% of the time. This relatively low precision suggests a higher rate of false positives (i.e., the model predicts churn when the customer does not actually churn).
* **Recall:**
  + **Class 0 (Non-Churn):** 0.96. The model correctly identified 96% of all customers who actually did *not* churn. This is a very good recall rate for the non-churn class.
  + **Class 1 (Churn):** 0.20. The model correctly identified only 20% of all customers who *did* churn. This is a *very* poor recall rate for the churn class. This indicates a high rate of false negatives (i.e., the model fails to predict churn for customers who actually churn).
* **F1-Score:**
  + **Class 0 (Non-Churn):** 0.89. This represents the harmonic mean of precision and recall for the non-churn class, indicating a good balance between precision and recall.
  + **Class 1 (Churn):** 0.29. This very low F1-score for the churn class reflects the poor recall performance, indicating that the model struggles to accurately identify churning customers.
* **Support:** Indicates the number of actual occurrences of each class in the test data. 1607 customers did not churn (Class 0), and 393 customers did churn (Class 1). The dataset is clearly imbalanced, with significantly more non-churning customers than churning customers.
* **Confusion Matrix:**

[[1543 64]

[ 315 78]]

* + **True Positives (TP):** 78 (Correctly predicted churn). This small number confirms the low recall for the churn class.
  + **True Negatives (TN):** 1543 (Correctly predicted non-churn).
  + **False Positives (FP):** 64 (Incorrectly predicted churn when the customer did not churn).
  + **False Negatives (FN):** 315 (Incorrectly predicted non-churn when the customer *did* churn). The large number of false negatives is a major concern.

**Interpretation and Key Concerns:**

The model is significantly better at predicting which customers will *not* churn than at predicting which customers *will* churn. The low recall for the churn class (0.20) is a major issue because it means the model is missing a large proportion of actual churning customers. This could lead to missed opportunities to retain valuable customers.

The high number of false negatives (315) is particularly concerning because the cost of *not* identifying a churning customer can be high (lost revenue, decreased customer lifetime value).

The overall accuracy of 81.05% is misleading because it is heavily influenced by the model's strong performance on the majority class (non-churn). The imbalanced dataset is contributing to the poor performance on the minority class (churn).

Churn Prediction Model Performance Report

**Model:** Random Forest

**Data:** Bank Customer Churn Prediction Dataset ([Bank-Customer-Churn-Prediction.csv](https://ppl-ai-file-upload.s3.amazonaws.com/web/direct-files/54217747/c8c1de3e-ee53-47f4-9397-dd6702c034bc/Bank-Customer-Churn-Prediction.csv))

**Objective:** To predict which customers are likely to churn (i.e., close their accounts).

**Results Overview:**

The Random Forest model achieved an overall accuracy of 86.65% on the test dataset. While the accuracy suggests strong performance, a closer look at the precision, recall, F1-score, and confusion matrix is necessary to assess its effectiveness in identifying churning customers, especially given the known class imbalance in the dataset.

**Data Overview:**

The dataset contains 10,000 customer records with the following features:

* customer\_id: Unique identifier for each customer.
* credit\_score: Credit score of the customer.
* country: Country of residence (France, Spain, Germany).
* gender: Gender of the customer (Male, Female).
* age: Age of the customer.
* tenure: Number of years the customer has been with the bank.
* balance: Account balance of the customer.
* products\_number: Number of products the customer uses.
* credit\_card: Whether the customer has a credit card (1 = yes, 0 = no).
* active\_member: Whether the customer is an active member (1 = yes, 0 = no).
* estimated\_salary: Estimated salary of the customer.
* churn: Whether the customer churned (1 = yes, 0 = no) - *Target Variable*.

**Detailed Analysis:**

* **Accuracy:** 86.65%. This indicates that the model correctly classified 86.65% of all customers in the test dataset. This is a high accuracy score.
* **Precision (Churn - Class 1):** 0.7647. This signifies that when the model predicted a customer would churn, it was correct approximately 76.5% of the time. This is a good precision score, meaning there are relatively few false positives (incorrectly predicting churn).
* **Recall (Churn - Class 1):** 0.4631. The model accurately identified only 46.3% of all customers who actually churned. This is a moderate recall score, suggesting the model misses more than half of the customers who actually churn.
* **F1-Score (Churn - Class 1):** 0.5769. The F1-score balances precision and recall. A score of 0.5769 indicates a fair balance between precision and recall for the churn class, but it can be improved.
* **Confusion Matrix:**

[[1551 56]

[ 211 182]]

* + **True Positives (TP):** 182. The model correctly predicted churn for 182 customers who actually churned.
  + **True Negatives (TN):** 1551. The model correctly predicted no churn for 1551 customers who did not churn.
  + **False Positives (FP):** 56. The model incorrectly predicted churn for 56 customers who did not churn.
  + **False Negatives (FN):** 211. The model incorrectly predicted no churn for 211 customers who actually churned.

**Class Distribution:**

Let's analyze the distribution of the Churn column

* non churn(0) = 7963
* churn(1) = 2037

**Interpretation and Key Concerns:**

The model demonstrates high accuracy but struggles to identify all churning customers, with a recall of only 46.31%. It means the model is good at predicting customers who will not churn but isn't as strong with those who will churn, potentially missing key opportunities for retention.

* Accuracy is high due to class imbalance. With approximately 80% of customers *not* churning, the model can achieve a high accuracy simply by predicting "no churn" most of the time. This is why examining precision, recall, and the confusion matrix are crucial.
* The low recall is a significant concern because it represents a lost opportunity to retain customers. The high number of False Negatives (211) signifies customers at high risk are not identified.