MODEL PERFORMANCE REPORT

1. INTRODUCTION

This report provides a detailed evaluation of the machine learning model developed for GST Model Prediction. The model was evaluated using standard metrics such as accuracy, precision, recall, F1-score, and the confusion matrix, which are discussed below. We also provide insights and analysis from the model's predictions to understand its strengths and limitations.

2. MODEL EVALUATION METRICS

2.1 Accuracy

Accuracy represents the percentage of correctly classified instances out of the total instances.

Formula:

Accuracy = True Positives + True Negatives / Total Instances

Model's Accuracy : 97.74%

The model performs well with a relatively high accuracy on test data, indicating that it is generalizing well without significant overfitting.

2.2 Precision, Recall, and F1-Score

Precision measures the percentage of correctly predicted positive instances out of all instances predicted as positive.

Precision = True positives/ (True positives + False positives)

Model's Precision: 0.92

A precision of 0.92 indicates that 92% of the instances predicted as positive are actually positive, showing the model's ability to avoid false positives.

Recall:

Recall (Sensitivity or True Positive Rate) measures the percentage of actual positive instances that were correctly predicted by the model.

Recall = True Positive (TP) / True Positive (TP) + False Negative (FN)

Model's Recall: 0.98

With a recall of 0.98, the model correctly identifies 98% of actual positive instances, but misses only 2%, indicating room for improvement in minimizing false negatives.

F1-Score:

F1-Score is the harmonic mean of precision and recall, providing a balanced measure when you need to account for both false positives and false negatives.

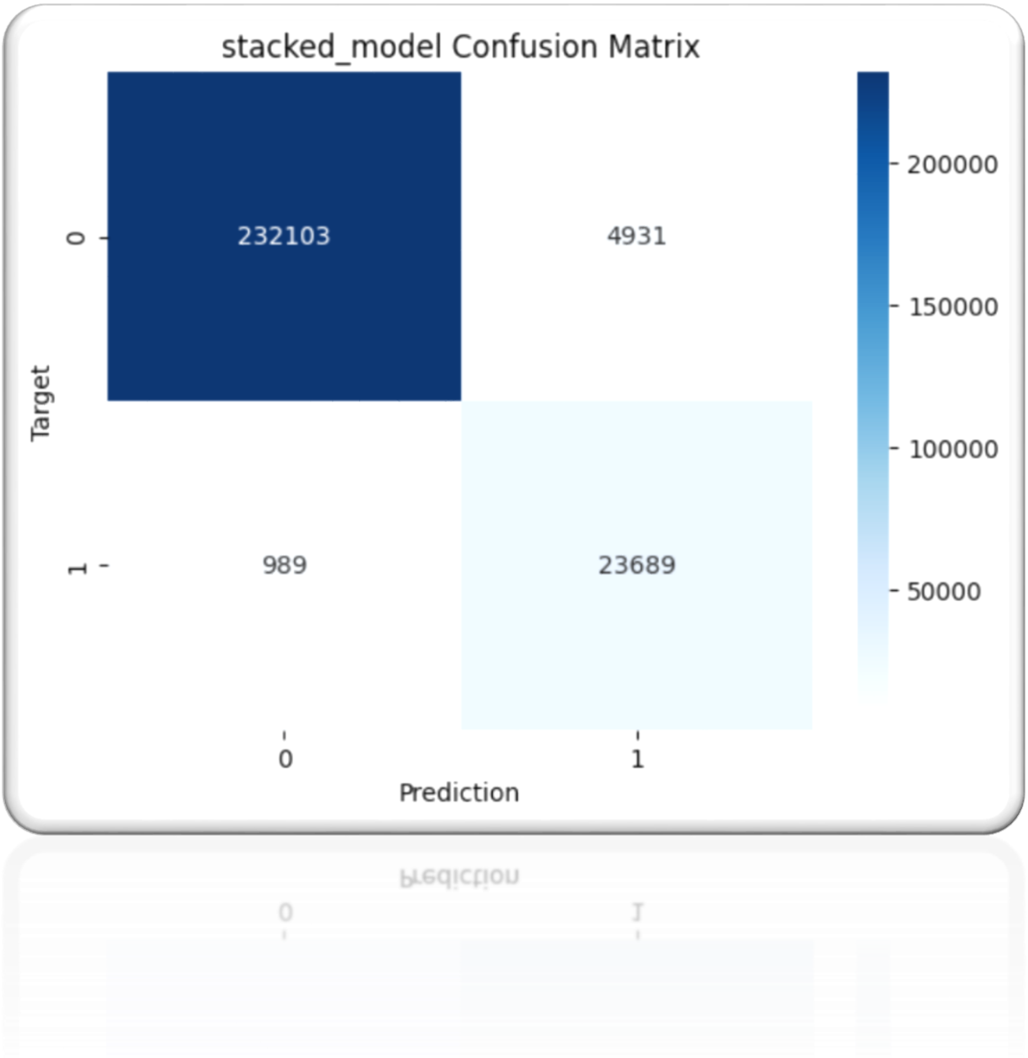
F1-score = 2 * (precision * recall) / (precision + recall)

Model's F1-Score: 0.94

A F1-score of 0.94 balances precision and recall, indicating that the model has a decent ability to handle both false positives and false negatives, making it well-suited for situations where both errors carry significant consequences.

Confusion Matrix:

The confusion matrix provides a summary of the model's performance by showing the number of true positives, true negatives, false positives, and false negatives.



3. INSIGHTS AND ANALYSIS

1.ROC Curve and AUC (Area Under the Curve):

- **AUC Score 0.99:** This is very close to the perfect score of 1.0, which suggests that the model is excellent at distinguishing between positive and negative classes. A high AUC means that the model has a very low probability of making incorrect classifications.

- **True Positive Rate (Recall) vs. False Positive Rate (FPR):** The ROC curve is very close to the top-left corner, meaning the model has high sensitivity (true positive rate) and low false positive rate. This means the model is highly effective at identifying true positive cases with minimal false alarms.

2.Confusion Matrix Insights:

- **True Negatives (TN):** 232,103 instances were correctly classified as negative (0). This shows the model is highly accurate in identifying the negative class.

- **False Positives (FP)**: 4,931 instances were incorrectly classified as positive (1). This is a low number, indicating the model doesn't misclassify many negative samples as positive.

- **False Negatives (FN):** 989 instances were incorrectly classified as negative when they were actually positive. This low FN value shows that the model is good at catching most positive cases.

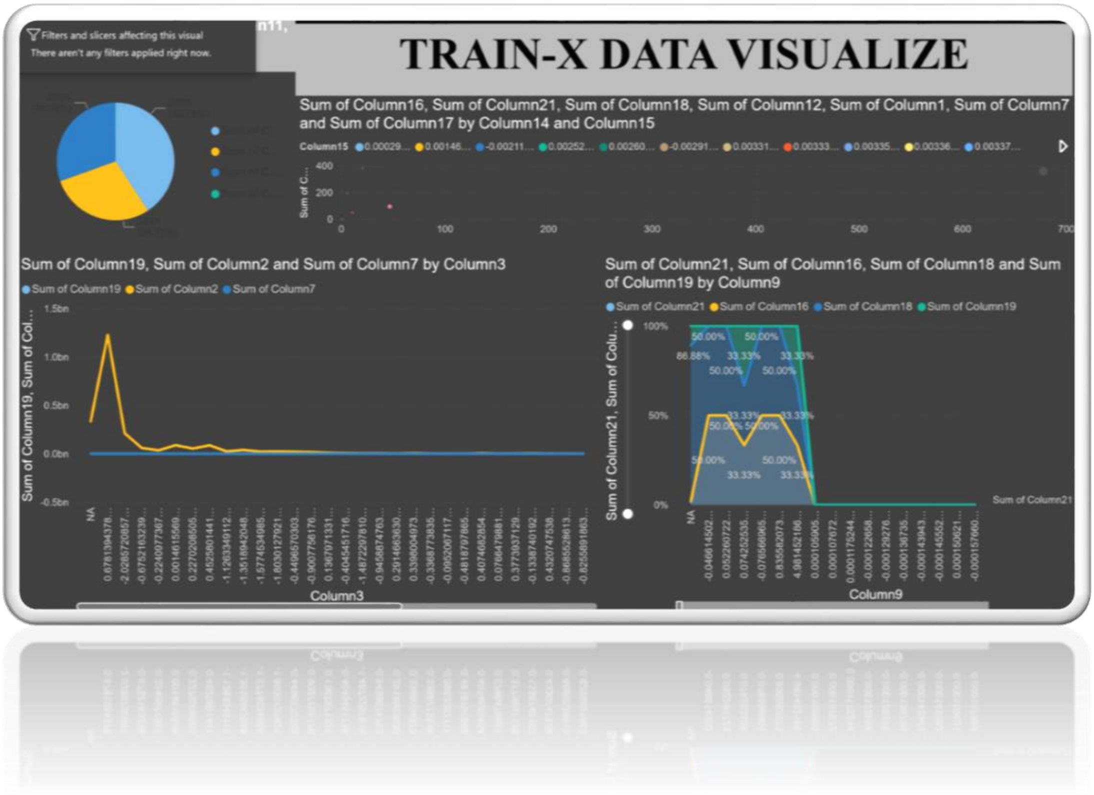
- **True Positives (TP):** 23,689 instances were correctly classified as positive. This reinforces that the model is very strong in capturing the positive class.
  The model's overall misclassification rate is quite low, with relatively fewer false positives and false negatives.

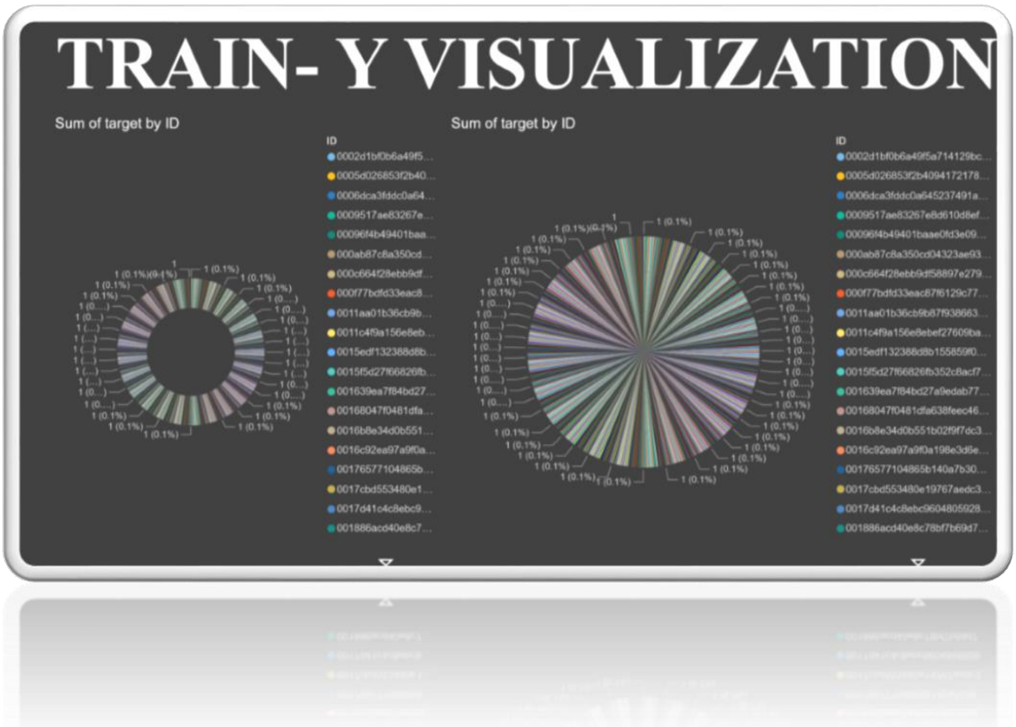
3. Accuracy: 97.74%

- High Accuracy: The accuracy of 97.74% is a very high value, showing that the model is correctly predicting the majority of both the positive and negative classes. However, accuracy alone might be misleading in case of imbalanced data, but the confusion matrix and ROC curve provide additional confidence that the model is performing well across both classes.

4. Model Performance Evaluation:

- Sensitivity (Recall for Positive Class): The model has a high recall, meaning it is correctly identifying most of the positive cases.
- Specificity (Recall for Negative Class): The true negative rate is very high, demonstrating the model's effectiveness in distinguishing negative cases as well.





In this report, we present the visualization of the Train_x and Train_y datasets, which are essential for understanding the underlying patterns and relationships within our data. The Train_x dataset contains the features or independent variables, while the Train_y dataset consists of the target or dependent variable we aim to predict.

Through various visualization techniques—such as scatter plots, histograms, or heatmaps—we can effectively illustrate the distribution of values, identify trends, and highlight correlations between the features and the target variable. These visual representations enable us to discern important insights that inform our model development, guiding feature selection and helping to validate our assumptions. Overall, the visualizations serve as a crucial tool for both exploratory data analysis and communicating our findings.

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