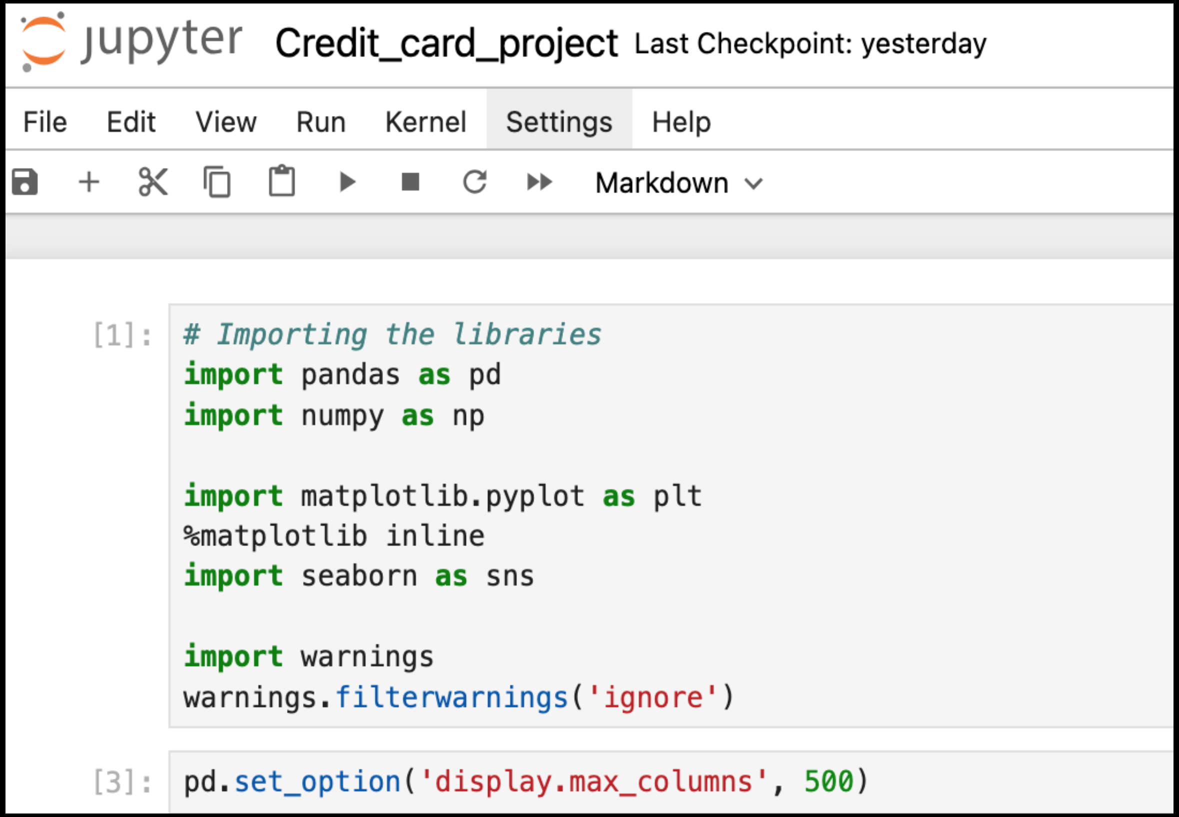
Credit Card Fraud Detection

What Is Credit Card Fraud

- Credit card fraud is when someone uses another person's credit card or account information to make unauthorized purchases or access funds through cash advances.
- Credit card fraud doesn’t just happen online; it happens in brick-and-mortar stores, too.
- We live in a world where cash transactions are quickly being replaced by credit card transactions.

Steps Involved



- importing the required packages into our python environment.

Reading And Understanding the Data

```python
# Reading the dataset
df = pd.read_csv('creditcard.csv')
df.head()
```

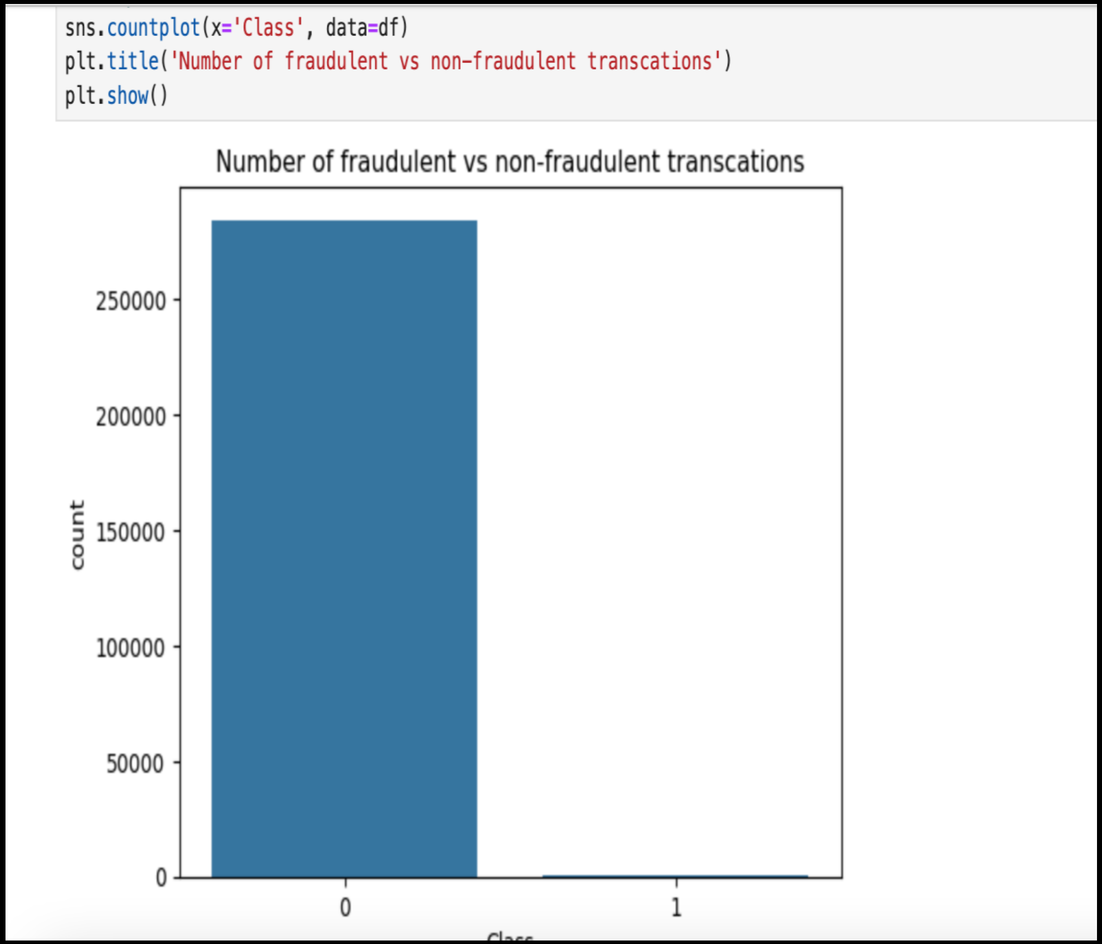
	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V1
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	0.090794	-0.551600	-0.617801	-0.991390	-0.3111
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	-0.166974	1.612727	1.065235	0.489095	-0.1437
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	0.207643	0.624501	0.066084	0.717293	-0.1659
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	-0.054952	-0.226487	0.178228	0.507757	-0.2879
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	0.753074	-0.822843	0.538196	1.345852	-1.1196

Bar plot for the number of fraudulent vs non-fraudulent transactions

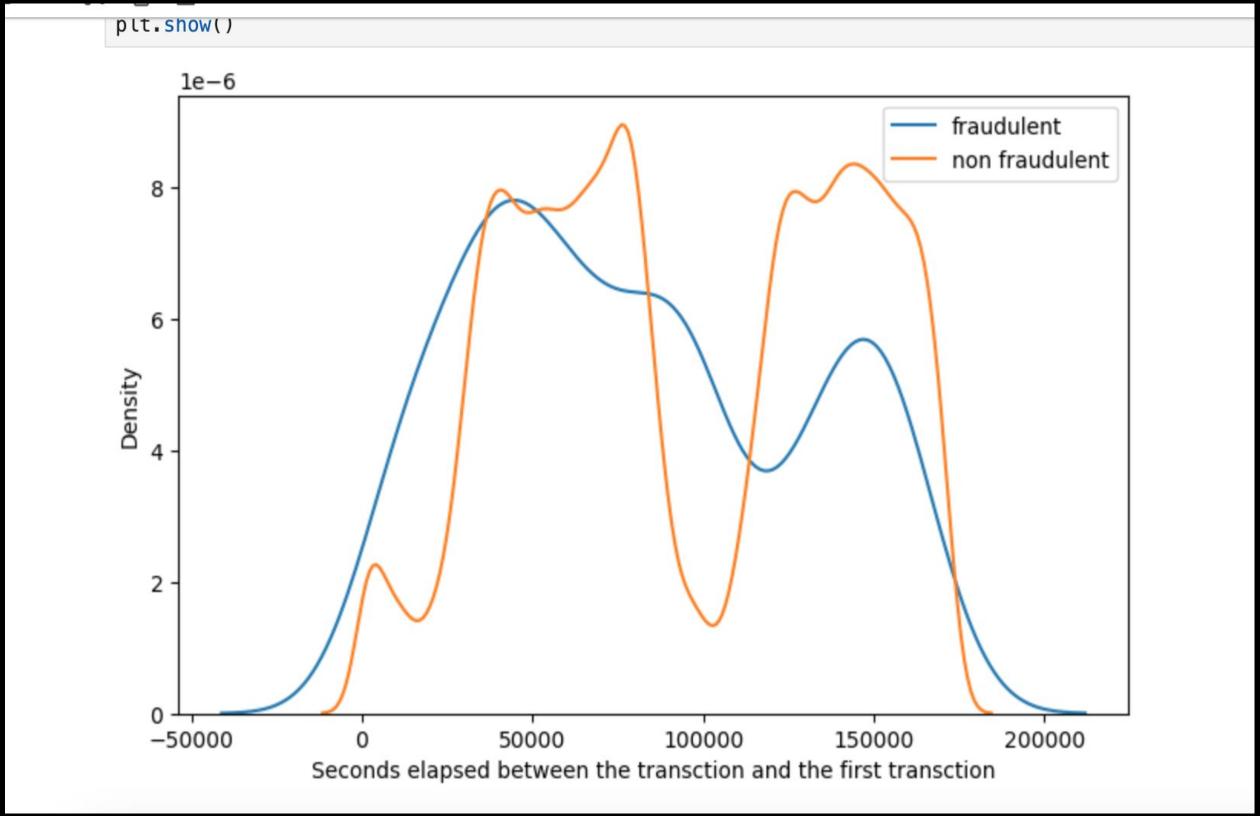
- Distribution of Class

- Class
- 0 – 284315
- 1 – 492

- Normal share – 99.83%
- Fraud share – 0.17%



Observe the distribution of classes with time

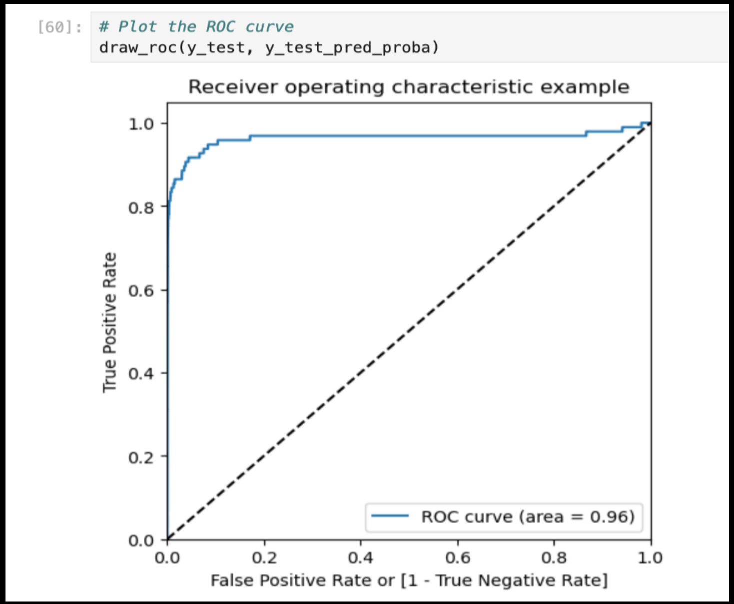


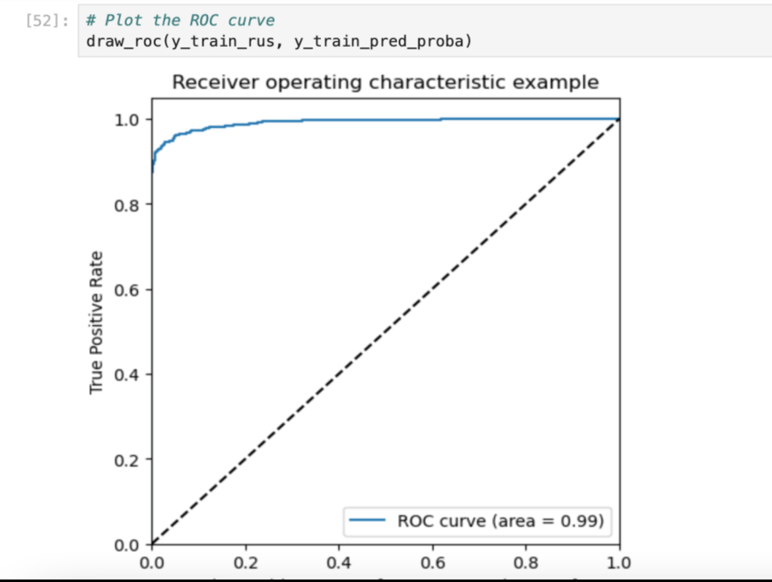
- We do not see any specific pattern for the fraudulent and non-fraudulent transactions with respect to Time. Hence, we can drop the Time column.

Handling the Imbalance data

As we see that the data is heavily imbalanced, We will try several approaches for handling data imbalance:

- Undersampling :- Here for balancing the class distribution, the non-fraudulent transactions count will be reduced to 396 (similar count of fraudulent transactions)
- Oversampling :- Here we will make the same count of non-fraudulent transactions as fraudulent transactions.
- SMOTE :- Synthetic minority oversampling technique. It is another oversampling technique, which uses nearest neighbor algorithm to create synthetic data.
- •Adasyn:- This is similar to SMOTE with minor changes that the new synthetic data is generated on the region of low density of imbalanced data points.





Model building on balanced data with Undersampling

Logistic regression :

Train set

- Accuracy = 0.96
- Sensitivity = 0.92
- Specificity = 0.99
- ROC = 0.99

Test set

- Accuracy = 0.97
- Sensitivity = 0.86
- Specificity = 0.97
- ROC = 0.96

Model building on balanced data with Undersampling

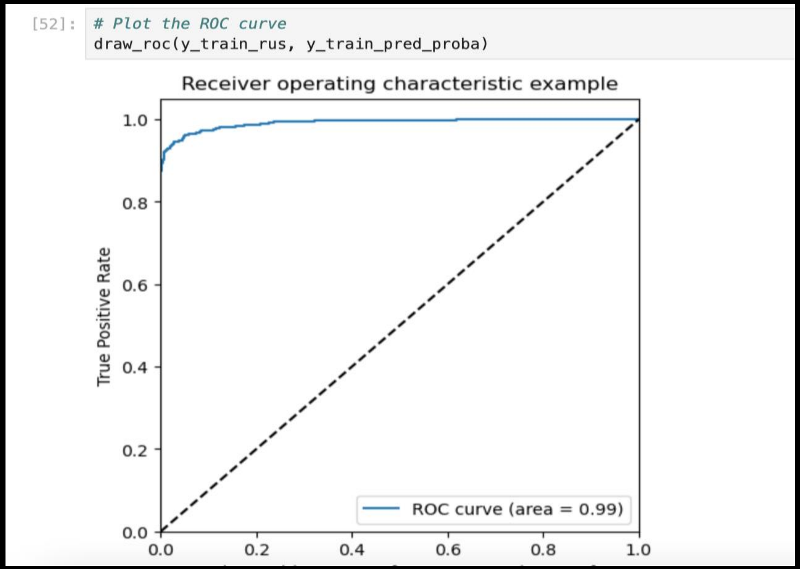
XGBoost :

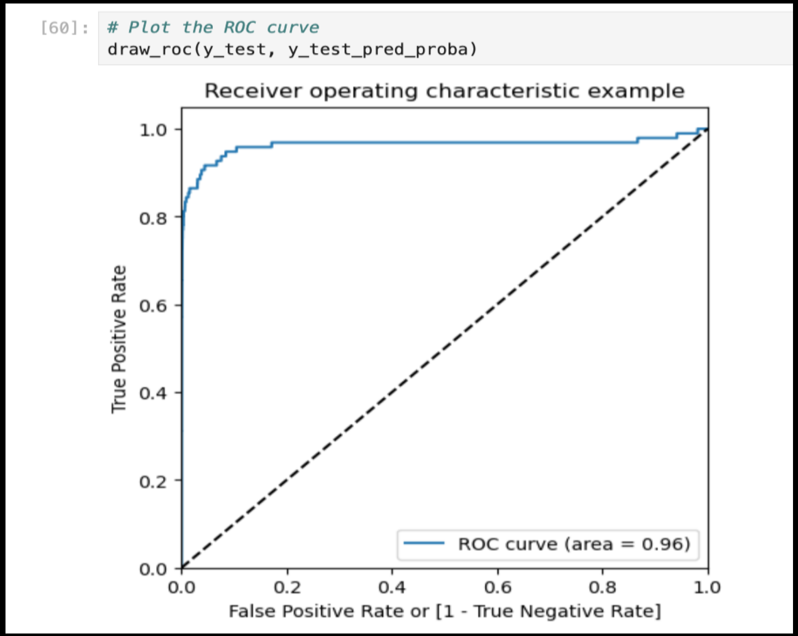
Train set

- Accuracy = 1.0
- Sensitivity = 1.0
- Specificity = 1.0
- ROC-AUC = 1.0

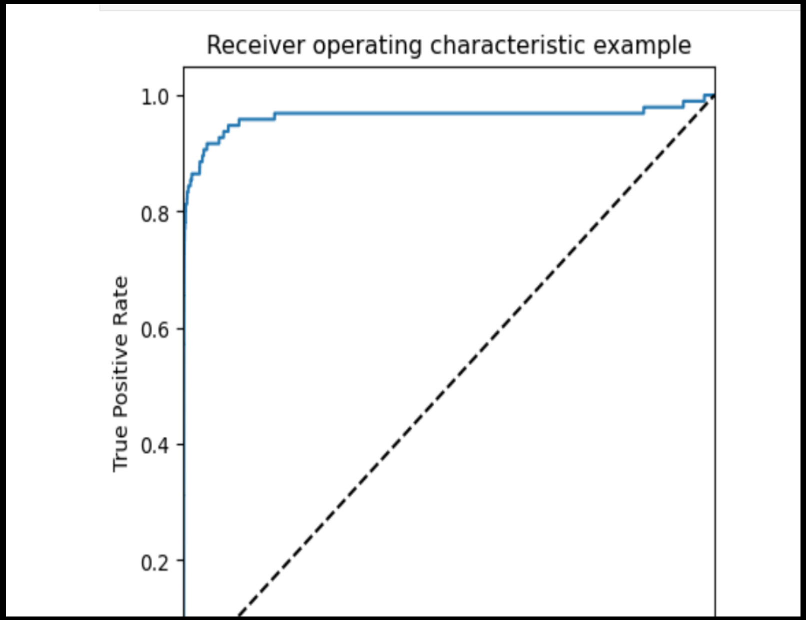
Test set

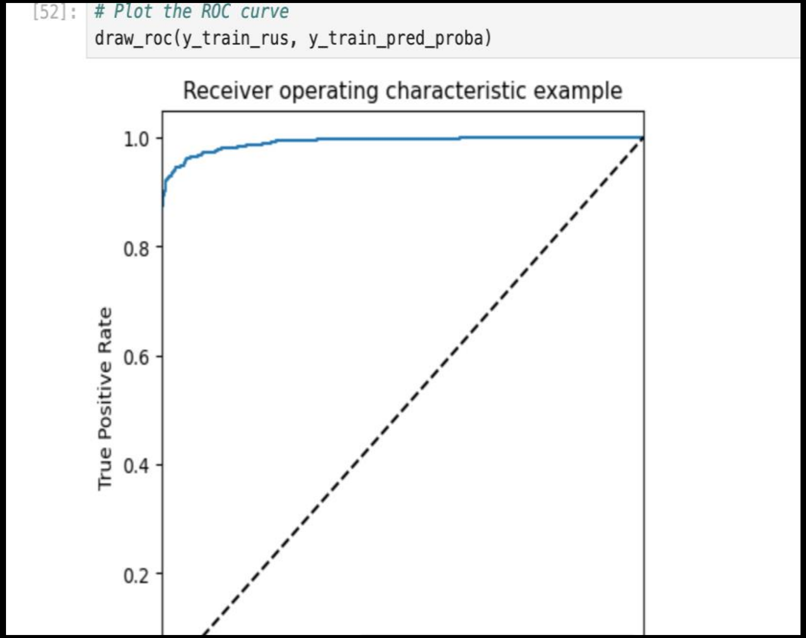
- Accuracy = 0.95
- Sensitivity = 0.93
- Specificity = 0.95
- ROC-AUC = 0.98





Model building on balanced data with Oversampling





Logistic regression:

Train set

- Accuracy = 0.95
- Sensitivity = 0.92
- Specificity = 0.98
- ROC = 0.99

Test set

- Accuracy = 0.98
- Sensitivity = 0.89
- Specificity = 0.98
- ROC = 0.97

Model building on balanced data with Oversampling

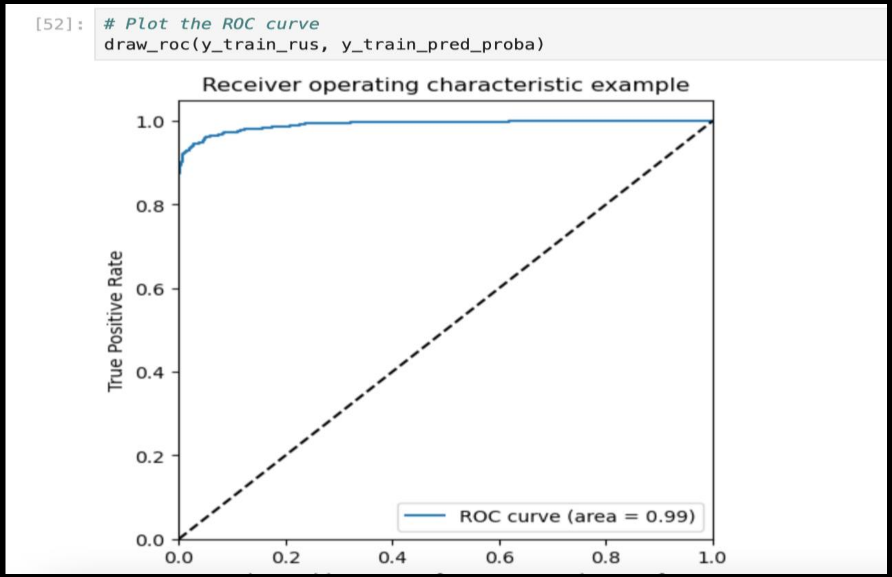
XGboost:

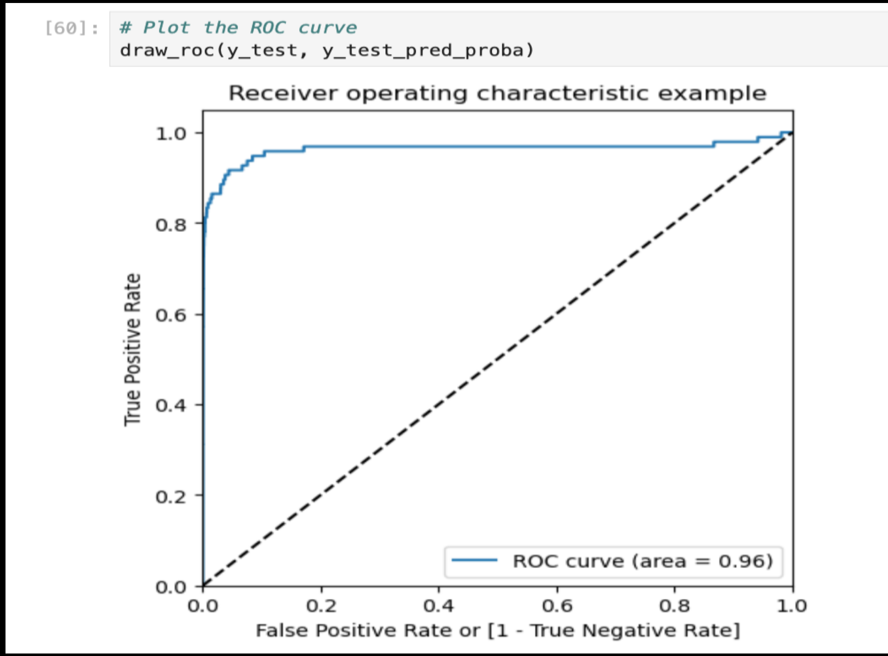
Train set

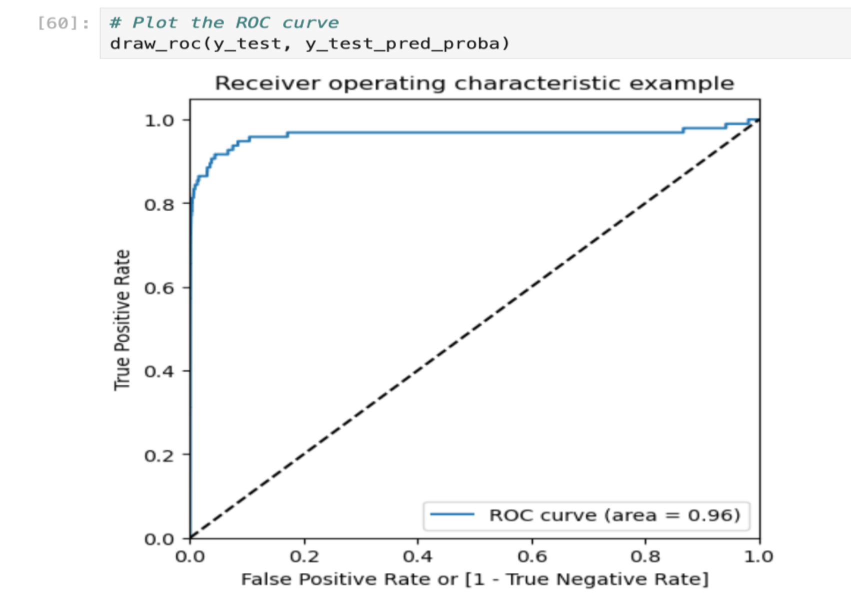
- Accuracy = 1.0
- Sensitivity = 1.0
- Specificity = 1.0
- ROC-AUC = 1.0

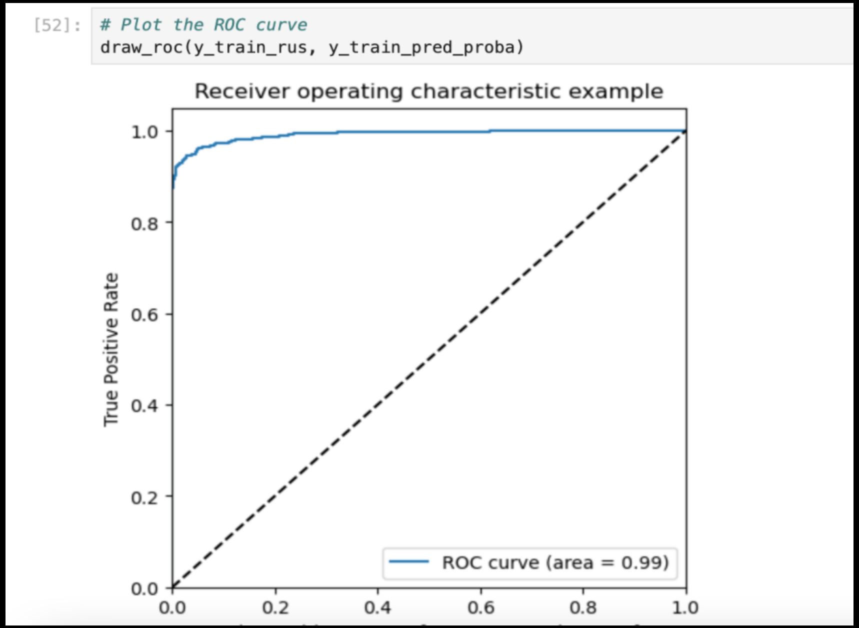
Test set

- Accuracy = 0.99
- Sensitivity = 0.78
- Specificity = 0.99
- ROC-AUC = 0.97









Model building on balanced data with SMOTE

Logistic regression :

Train set

- Accuracy = 0.95
- Sensitivity = 0.92
- Specificity = 0.98
- ROC = 0.99

Test set

- Accuracy = 0.97
- Sensitivity = 0.90
- Specificity = 0.97
- ROC = 0.97

Model building on balanced data with SMOTE

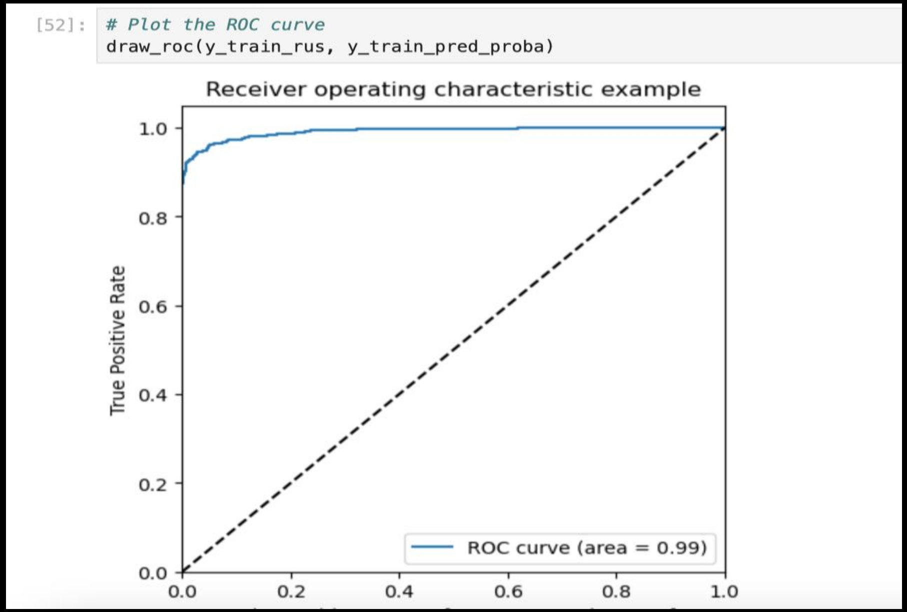
XGboost:

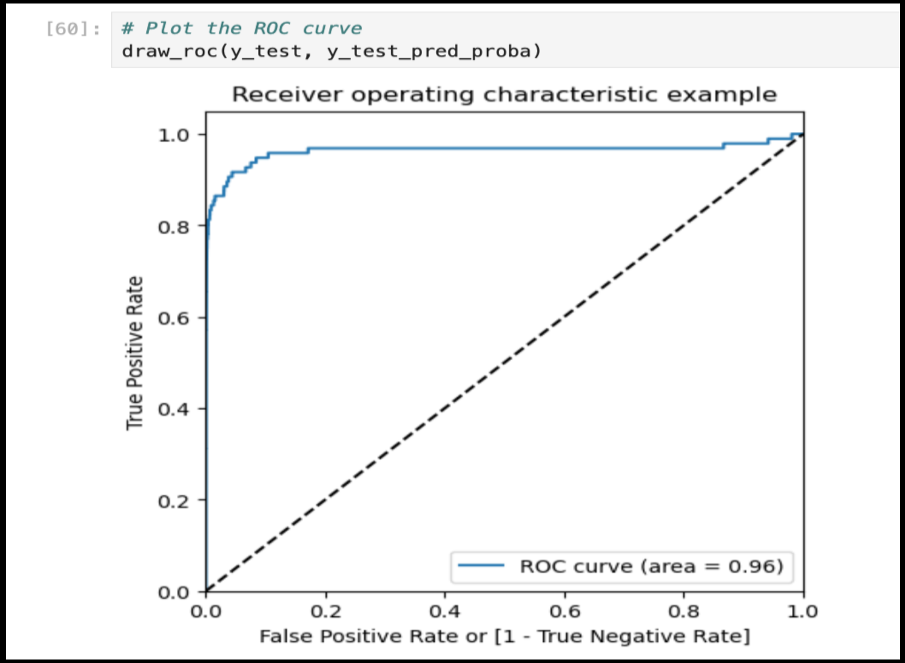
Train set

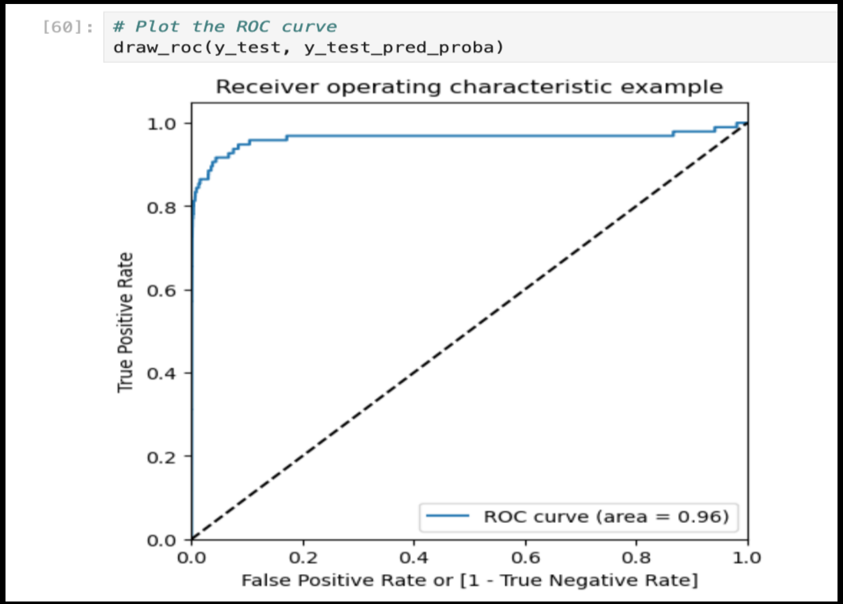
- Accuracy = 0.99
- Sensitivity = 1.0
- Specificity = 0.99
- ROC-AUC = 1.0

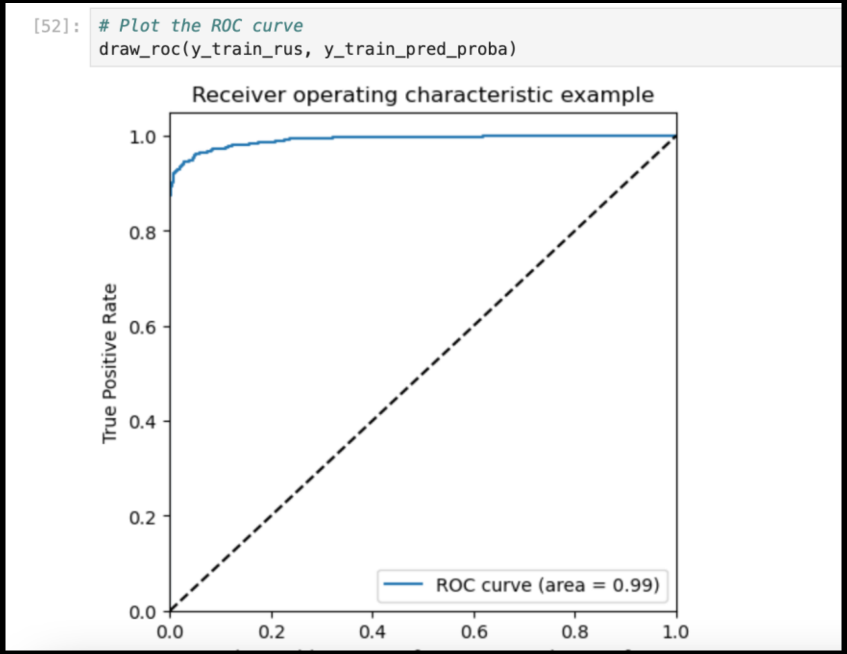
Test set

- Accuracy = 0.99
- Sensitivity = 0.79
- Specificity = 0.99
- ROC-AUC = 0.96









Model building on balanced data with AdaSyn

Logistic regression:

Train set

- Accuracy = 0.89
- Sensitivity = 0.86
- Specificity = 0.91
- ROC = 0.96

Test set

- Accuracy = 0.91
- Sensitivity = 0.96
- Specificity = 0.91
- ROC = 0.97

Model building on balanced data with AdaSyn

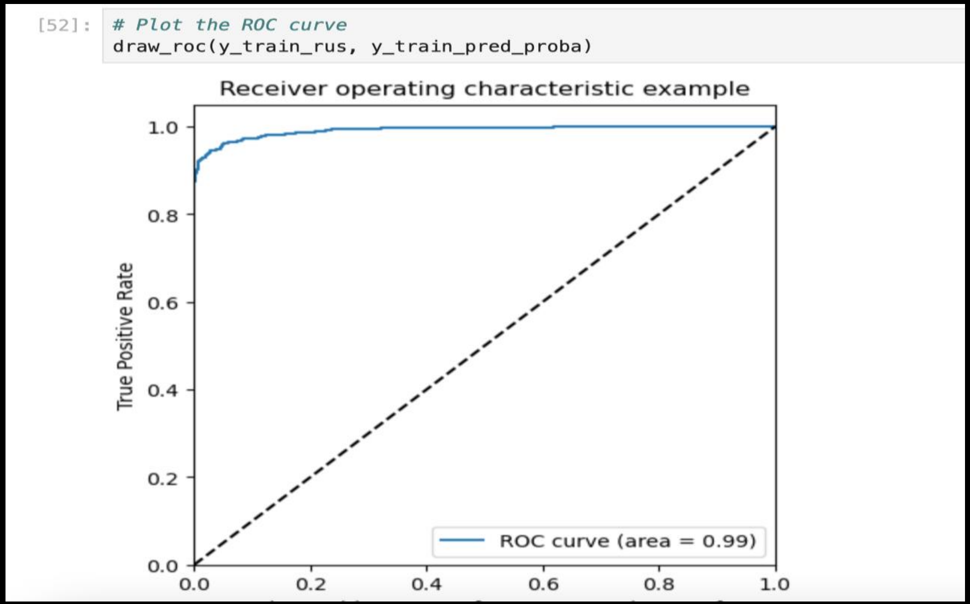
XGboost:

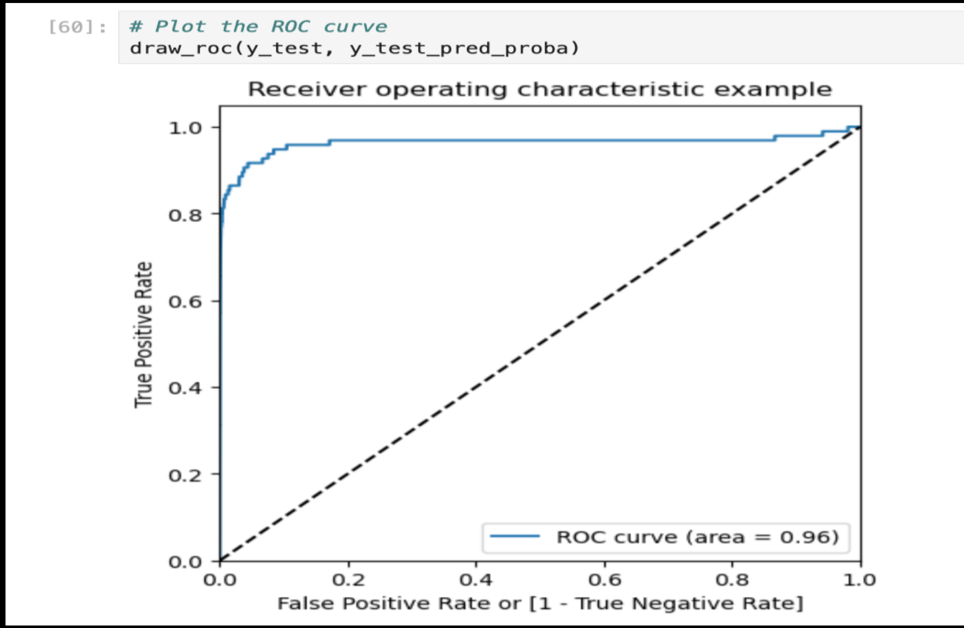
Train set

- Accuracy = 0.99
- Sensitivity = 1.0
- Specificity = 1.0
- ROC-AUC = 1.0

Test set

- Accuracy = 0.99
- Sensitivity = 0.77
- Specificity = 0.99
- ROC-AUC = 0.95





Choosing best model on the balanced data

- Here we balanced the data with various approach such as Undersampling, Oversampling, SMOTE and Adasyn. With every data balancing technique we built several models such as Logistic, XGBoost, Decision Tree, and Random Forest.

- We can see that almost all the models performed more or less good. But we should be interested in the best model.

- Though the Undersampling technique models performed well, we should keep mind that by doing the undersampling some information were lost. Hence, it is better not to consider the undersampling models.

- Whereas the SMOTE and Adasyn models performed well. Among those models the simplest model Logistic regression has ROC score 0.99 in the train set and 0.97 on the test set. We can consider the Logistic model as the best model to choose because of the easy interpretation of the models and also the resource requirements to build the model is lesser than the other heavy models such as Random forest or XGBoost.

- Hence, we can conclude that the Logistic regression model with SMOTE is the best model for its simplicity and less resource requirement.

Print the FPR,TPR & select the best threshold from the roc curve for the best model

We can see that the threshold is 0.53, for which the TPR is the highest and FPR is the lowest and we got the best ROC score.

Print the FPR,TPR & select the best threshold from the roc curve for the best model

[321]:
```
print('Train auc =', metrics.roc_auc_score(y_train_smote, y_train_pred_proba_log_bal_smote))
fpr, tpr, thresholds = metrics.roc_curve(y_train_smote, y_train_pred_proba_log_bal_smote)
threshold = thresholds[np.argmax(tpr-fpr)]
print("Threshold=",threshold)
```

```
Train auc = 0.9897681302852576
Threshold= 0.5322737615586992
```

We can see that the threshold is 0.53, for which the TPR is the highest and FPR is the lowest and we got the best ROC score.

Model deployment plan

Model deployment plan

Deployment Overview:

- Once the model is trained, it can be deployed as:
  - A REST API using Flask or FastAPI
  - Cloud Deployment: Deploy models on cloud platforms like AWS, Azure, or GCP to scale up as needed.
  - Saved and loaded via pickle or joblib
  - Monitoring: Continuously monitor the model's performance in production to ensure it remains effective over time.

```
import joblib
joblib.dump(rf, 'model.pkl')
```

```
['model.pkl']
```


Thank
you